ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

DEVELOPMENT OF A HOME ENERGY MANAGEMENT SYSTEM TO INCREASE RENEWABLE SELF-CONSUMPTION IN HOUSEHOLDS CONSIDERING DEMAND-SIDE FLEXIBILITY

Ph.D. THESIS

Anıl Can DUMAN

Energy Science and Technology Division

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(301162003)

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Thesis Advisor: Prof. Dr. Önder GÜLER

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

TALEP TARAFI ESNEKLİĞİ DİKKATE ALINARAK KONUTLARDA YENİLENEBİLİR ÖZ TÜKETİMİ ARTIRMAYA YÖNELİK BİR EV ENERJİ YÖNETİM SİSTEMİ GELİŞTİRİLMESİ

DOKTORA TEZİ

Anıl Can DUMAN
(301162003)

Enerji Bilim ve Teknoloji Anabilim Dalı

Enerji Bilim ve Teknoloji Programı

Tez Danışmanı: Prof. Dr. Önder GÜLER

OCAK 2024

Anıl Can DUMAN, a Ph.D. student of İTU Graduate School student ID 301162003, successfully defended the thesis entitled "DEVELOPMENT OF A HOME ENERGY MANAGEMENT SYSTEM TO INCREASE RENEWABLE SELF-CONSUMPTION IN HOUSEHOLDS CONSIDERING DEMAND-SIDE FLEXIBILITY", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. Önder GÜLER** Istanbul Technical University	....
Jury Members :	**Prof. Dr. Gülgün KAYAKUTLU** Istanbul Technical University	....
	Prof. Dr. Ozan ERDİNÇ Yildiz Technical University	....
	Asst. Prof. Dr. M. Berker YURTSEVEN Istanbul Technical University	....
	Asst. Prof. Dr. M. Alparslan ZEHİR Marmara University	....

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FOREWORD

I would like to thank everyone, especially my thesis advisor Prof. Dr. Önder Güler, for his valuable guidance and friendship during my study.

November 2023 Anıl Can DUMAN
(Electrical Engineer, M. Sc)

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ABBREVIATIONS

AC	: Air conditioner
B2H	: Battery-to-home
B2V	: Battery-to-vehicle
B2X	: Battery-to-everything
BESS	: Battery energy storage system
DLC	: Direct load control
DPBP	: Discounted payback period
DR	: Demand response
DSM	: Demand-side management
EUAS	: The Electricity Generation Company
EV	: Electric vehicle
EWH	: Electric water heater
FiT	: Feed-in tariff
GEPA	: Solar Energy Potential Atlas
HEMS	: Home energy management system
HOMER	: Hybrid Optimization Model for Electric Renewables
ICT	: Information and communication technology
IEA	: International Energy Agency
ILC	: Indirect load control
IRENA	: International Renewable Energy Agency
IRR	: Internal rate of return
LSE	: Load serving entity
MILP	: Mixed-integer linear programming
NASA	: National Aeronautics and Space Administration
NOCT	: Nominal operating cell temperature
NPV	: Net present value
PI	: Profitability index
PSA	: Power-shiftable appliance
PV	: Photovoltaic
RTP	: Real time pricing

STC **:** Standard test conditions

TARBIL **:** Agricultural Monitoring and Information System

TCA **:** Thermostatically controlled appliance

TOU **:** Time-of-use

V2G **:** Vehicle-to-grid

V2H **:** Vehicle-to-home

V2X **:** Vehicle-to-everything

SYMBOLS

$\dot{c}^{EWH}$	: constant amount of water heat flow capacity in a single time-step [kW/K].
$\dot{c}^{j}$	: Water (for EWH) or air (for AC) heat flow capacity per time interval [kW/K].
$C'_{c,y,d}$	: Daily bill (artificial battery degradation cost removed) [$].
C^{AC}	: House thermal capacitance [kJ/ºC].
$C^{B,O\&M}$	: O&M cost of BESS [$].
$C^{B,ini}$	: Initial cost of BESS [$].
C^{EWH}	: EWH tank thermal capacitance [kJ/ºC].
$C^{HEMS,ini}$	: Initial cost of HEMS [$].
COP^{AC}	: AC coefficient of performance.
COP^{EWH}	: EWH coefficient of performance.
COP^{R}	: Refrigerator coefficient of performance.
COP^{j}	: Coefficient of performance (AC, EWH).
$C^{PV,O\&M}$	: O&M cost of a module [$].
$C^{PV,ini}$	: Initial cost of 1 kW PV array [$].
C^{R}	: Refrigerator thermal capacitance [kJ/ºC].
Cap^{B}, Cap^{V}	: BESS, EV battery capacity [kWh].
Cap^{k}	: Battery capacity [kWh].
$C_{c,y,d}$	: Daily bill (artificial battery degradation cost included) [$].
$C_{c,y}^{ann,with}$	: Annual electricity bill of household with HEMS use [$].
$C_{c,y}^{ann,without}$	: Annual electricity bill of household without HEMS use [$].
$C_{c,y}^{ann}$	: Annual electricity bill of household [$].
$C_{c}^{O\&M}$	: Operation and maintenance cost of PV-BESS-HEMS [$].
C_{c}^{in}	: Monetary savings [$].
$C_{c}^{initial}$	: Initial investment cost of PV-BESS-HEMS [$].
C_{c}^{out}	: Expense costs [$].
$C_{c}^{replacement}$	: Replacement cost of PV-BESS-HEMS [$].
$C^{inv,ini}$	: Initial cost of 1 kW inverter [$].

$\boldsymbol{C^{inv,rep}}$: Replacement cost of inverter [$].

$\boldsymbol{C^{j}}$: Thermal capacitance (house, EWH tank) [kJ/ºC].

$\boldsymbol{C^{labor}}$: Installation labor cost of PV-BESS-HEMS [$].

$\boldsymbol{Cyc^{B}, Cyc^{V}}$: BESS, EV battery lifetime in cycles.

$\boldsymbol{Cyc^{k}}$: Lifetime of battery in cycles.

$\boldsymbol{DoD^{B}, DoD^{V}}$: BESS, EV battery depth of discharge.

$\boldsymbol{DoD^{k}}$: Depth of discharge of battery.

$\boldsymbol{Ht^{NOCT}}$: Solar radiation at which the NOCT is defined [800 W/m^2].

$\boldsymbol{Ht^{STC}}$: Global solar radiation under STC [1000 W/m^2].

$\boldsymbol{L^{B}, L^{V}}$: BESS, EV battery lifetime throughput energy measured for specific DoD [kWh].

$\boldsymbol{L^{inv}}$: Lifetime of inverter [years].

$\boldsymbol{L^{k}}$: Battery lifetime throughput for specific DoD (BESS, EV) [kWh].

$\boldsymbol{NPV_{c}}$: Net present value of PV-BESS-HEMS investment [$].

$\boldsymbol{P^{AC}}$: AC power [kW].

$\boldsymbol{P^{EWH}}$: EWH power [kW].

$\boldsymbol{PL_{t}^{G}, PL_{t}^{2G}}$: Power import, export peak limit [kW].

$\boldsymbol{P^{R}}$: Refrigerator power [kW].

$\boldsymbol{P_{a}^{TSA}}$: Fixed daily energy consumption pattern of TSA a.

$\boldsymbol{P_{c,d,t}^{B,G}, P_{c,d,t}^{V,G}}$: Power drawn from grid by BESS and EV at time t from grid [kW].

$\boldsymbol{P_{c,d,t}^{G}}$: Power drawn from grid by inflexible appliances, TCAs and TSAs at time t [kW].

$\boldsymbol{P^{i}}$: All combination possibilities of a TSA's power consumption in one day.

$\boldsymbol{P^{j}}$: Power (AC, EWH) [kW].

$\boldsymbol{P_{t}^{AC}}$: AC power used [kW].

$\boldsymbol{P_{t}^{B,G}}$: Power drawn from grid by BESS at time t [kW].

$\boldsymbol{P_{t}^{B,ch}, P_{t}^{V,ch}}$: BESS, EV charging power [kW].

$\boldsymbol{P_{t}^{B,dis}, P_{t}^{V,dis}}$: BESS, EV discharging power [kW].

$\boldsymbol{P_{t}^{B,used}}$: BESS power used to supply energy demand of flexible and inflexible appliances and charging of EV [kW].

$\boldsymbol{P_{t}^{B,2G}}$: Power transfer (battery-to-grid) [kW].

$\boldsymbol{P_{t}^{B,2H}}$: Power transfer (battery-to-home) [kW].

$\boldsymbol{P_{t}^{B,2V}}$: Power transfer (battery-to-vehicle) [kW].

P_t^{EWH}	: EWH power used [kW].
P_t^{G}	: Power drawn from grid by inflexible appliances, TSAs and TCAs at time t [kW].
P_t^{G}	: Power purchased from grid [kW].
P_t^{H}	: Power consumption of all appliances except PSAs at time t [kW].
P_t^{H}	: Power consumption of flexible and inflexible appliances except PSAs [kW].
$P_t^{PV,prod}$	: PV production at time t [kW].
$P_t^{PV,used}$	: PV power used to supply energy demand of flexible and inflexible appliances and charging of PSAs [kW].
$P_t^{PV,2B}$	: Power transfer at time t (PV-to-battery) [kW].
$P_t^{PV,2G}$	: Power transfer at time t (PV-to-grid) [kW].
$P_t^{PV,2H}$	: Power transfer at time t (PV-to-home) [kW].
$P_t^{PV,2V}$	: Power transfer at time t (PV-to-vehicle) [kW].
P_t^{R}	: Refrigerator power used [kW].
$P_t^{V,G}$	: Power drawn from grid by EV at time t [kW].
$P_t^{V,used}$	: EV power used to supply energy demand of flexible and inflexible appliances and charging of BESS [kW].
$P_t^{V,2B}$	: Power transfer (vehicle-to-battery) [kW].
$P_t^{V,2G}$	: Power transfer (vehicle-to-grid) [kW].
$P_t^{V,2H}$	: Power transfer (vehicle-to-home) [kW].
P_t^{g}	: Power used by inflexible appliances, TSAs and TCAs [kW].
P_t^{i}	: TSA power used at time t [kW].
P_t^{inf}	: Total power consumption of inflexible appliances at time t [kW].
P_t^{j}	: TCA power used at time t [kW].
$P_t^{k,ch}$	: Power drawn from grid for charging at time t [kW].
$P_t^{k,dis}$	: Discharging power at time t [kW].
$P_t^{k,2H}$	: Power transfer at time t (PSA-to-home) [kW].
P_t^{other}	: Power consumption of inflexible appliances [kW].
P_t^{2G}	: Power transfer (PV+BESS+EV to grid) [kW].
Q^{AC}	: AC heating capacity [kW].
Q^{EWH}	: EWH heating capacity [kW].
Q^{R}	: Refrigerator heating capacity [kW].
R^{AC}	: House envelope thermal resistance [ºC/kW].

$\boldsymbol{R^{B,ch}}$, $\boldsymbol{R^{V,ch}}$: BESS, EV charging rate [kW].

$\boldsymbol{R^{B,dis}}$, $\boldsymbol{R^{V,dis}}$: BESS, EV discharging rate [kW].

$\boldsymbol{R^{EWH}}$: EWH thermal resistance [ºC/kW].

$\boldsymbol{R^{R}}$: Refrigerator thermal resistance [ºC/kW].

$\boldsymbol{Rep^{B}}$, $\boldsymbol{Rep^{V}}$: BESS, EV battery replacement cost including labor [$].

$\boldsymbol{Rep^{k}}$: Replacement cost of battery including labor (BESS, EV) [$].

$\boldsymbol{R^{j}}$: Thermal resistance (house, EWH tank) [ºC/kW].

$\boldsymbol{R^{k,ch}}$: Charging rate (BESS, EV) [kW].

$\boldsymbol{R^{k,dis}}$: Discharging rate (BESS, EV) [kW].

$\boldsymbol{SOE_t^{B}}$, $\boldsymbol{SOE_t^{V}}$: BESS, EV state of energy [kWh].

$\boldsymbol{SP_t^{max}}$, $\boldsymbol{SP_t^{min}}$: AC max. and min. set-point temperature [ºC].

$\boldsymbol{SoE^{B,ini}}$: Initial SoE (at start of the day) [kWh].

$\boldsymbol{SoE^{B,max}}$: BESS maximum battery capacity [kWh].

$\boldsymbol{SoE^{V,ini}}$: Initial SoE (at EV arrival) [kWh].

$\boldsymbol{SoE^{V,max}}$: EV maximum battery capacity [kWh].

$\boldsymbol{SoE^{k,max}}$: Maximum SoE (BESS, EV) [kWh].

$\boldsymbol{SoE_t^{k}}$: SoE at time t [kWh].

$\boldsymbol{T^{R,max}}$, $\boldsymbol{T^{R,min}}$: Refrigerator max. and min. allowed inside temperature [ºC].

$\boldsymbol{T^{amb,NOCT}}$: Ambient temperature at which the NOCT is defined [20 °C].

$\boldsymbol{T^{cell,STC}}$: PV cell temperature under STC [25 °C].

$\boldsymbol{T^{cell,NOCT}}$: Nominal operating cell temperature (NOCT) [45 °C].

$\boldsymbol{T^{hw,max}}$: EWH tank maximum allowed hot water temperature [ºC].

$\boldsymbol{T^{hw,min}}$: EWH tank minimum allowed hot water temperature [ºC].

$\boldsymbol{T^{i,max,j}}$: Max. allowed inside temperature (house, EWH tank) [ºC].

$\boldsymbol{T^{i,min,j}}$: Min. allowed inside temperature (house, EWH tank) [ºC].

$\boldsymbol{T_t^{AC}}$: AC operating temperature [ºC].

$\boldsymbol{T_t^{amb}}$: Ambient temperature [ºC].

$\boldsymbol{T_t^{c}}$: EWH inlet water temperature [ºC].

$\boldsymbol{T_t^{cell}}$: PV cell temperature in the current time step [°C].

$\boldsymbol{T_t^{en,j}}$: Temperature of entering inlet water or outside air at time t [ºC].

$\boldsymbol{T_t^{hw}}$: EWH hot water temperature [ºC].

$\boldsymbol{T_t^{i,j}}$: Temperature inside the EWH tank or house at time t [ºC].

$\boldsymbol{T_t^{in}}$: Refrigerator inside temperature [ºC].

$T_t^{o,j}$: Outside temperature at time t (outside of house) [ºC].

T_t^{out} : Outdoor temperature [ºC].

X_a^{TSA} : Switch vector of binary variable combinations of TSA a.

X^i : Switch vector to choose optimal column in P_i

Y^{PV} : The rated capacity of the PV array under STC [kW].

d^{PV} : PV derating factor [kW].

n_c^B : Number of batteries in BESS.

n_c^{PV} : Number of 1 kW PV arrays.

$p_{a,t}^{TSA}$: Fixed power consumption of TSA a at time t.

p_t^i : Constant power consumption of TSA i at time t.

run_a : Running time of TSA a.

run^i : Operation duration of TSA i.

t_a^{min}, t_a^{max} : Preferred hours of operation range limits of TSA a.

t^{arr}, t^{dep} : Arrival and departure time of EV.

t^{arr}, t^{dep} : EV home arrival and departure time.

$t^{i,max}$: End time of preferred operating range for TSA i.

$t^{i,min}$: Start time of preferred operating range for TSA i.

uc_t : Daily cold water usage times.

uc_t^j : Water usage or air ventilation at time t.

$use_{c,y}^B$: Annual BESS use [kWh].

$x_{a,t}^{TSA}$: Binary variable – 1 if TSA a starts operating at time t, else 0.

x_t^{AC} : Decision variable between 0 – 1, defining AC usage.

x_t^B : Binary variable – 1 if BESS is charging at time t, else 0.

x_t^{EWH} : Decision variable between 0 – 1, defining EWH usage.

x_t^R : Decision variable between 0 – 1, defining refrigerator usage.

x_t^V : Binary variable – 1 if EV is charging at time t, else 0.

x_t^i : Binary variable: if TSA starts running at time t 1, else 0.

x_t^j : Decision variable between 0 – 1, defining usage of TCA.

x_t^k : Binary variable: if PSA is charging at time t 1, else 0.

α^P : Temperature coefficient of power [%/°C].

$\eta^{B,ch}, \eta^{V,ch}$: BESS, EV charging efficiency.

$\eta^{B,dis}, \eta^{V,dis}$: BESS, EV discharging efficiency.

$\eta^{B,rt}, \eta^{V,rt}$: BESS, EV round-trip efficiency [$/kWh].

$\boldsymbol{\eta^{k,ch}}$	: Charging efficiency (BESS, EV).
$\boldsymbol{\eta^{k,dis}}$	: Discharging efficiency (BESS, EV).
$\boldsymbol{\eta^{k,rt}}$	: Round-trip efficiency of battery (BESS, EV) [$/kWh].
$\boldsymbol{\lambda^{B,deg}, \lambda^{V,deg}}$	: BESS, EV battery degradation cost [$/kWh].
$\boldsymbol{\lambda_t^{B,buy}, \lambda_t^{V,buy}}$	: BESS, EV artificial electricity buying price considering battery degradation cost [$/kWh].
$\boldsymbol{\lambda_t^{B,sell}, \lambda_t^{V,sell}}$	: BESS, EV artificial electricity selling price considering battery degradation cost [$/kWh].
$\boldsymbol{\lambda_t^{buy}}$	: Electricity buy price [$/kWh].
$\boldsymbol{\lambda_t^{k,buy}}$	: Penalty cost included electricity buying prices (BESS, EV) [$/kWh].
$\boldsymbol{\lambda_t^{sell}}$	: Electricity sell-back price [$/kWh].
$\boldsymbol{\omega'}$	: Hour angle on tilted surface [°].
$\boldsymbol{\Delta t}$	: Time interval (5 min).
$\boldsymbol{A}$	: Number of appliances.
$\boldsymbol{B}$	: Index for BESS.
$\boldsymbol{E}$	: Index for EV.
$\boldsymbol{H}$	: Monthly average daily global radiation on horizontal surface [kWh·m^{-2}-day].
$\boldsymbol{Hd}$	: Monthly average daily diffuse radiation on horizontal surface [kWh·m^{-2}-day].
$\boldsymbol{Ho}$	: Monthly average daily extraterrestrial radiation [kWh·m^{-2}-day].
$\boldsymbol{Ht}$	: Monthly average daily global radiation on tilted surface [kWh·m^{-2}-day].
$\boldsymbol{I}$	: Number of TSAs.
$\boldsymbol{Isc}$	: Solar constant [kW/m^2].
$\boldsymbol{J}$	: Number of TCAs.
$\boldsymbol{K}$	: Clearness index.
$\boldsymbol{K}$	: Number of PSAs.
$\boldsymbol{R}$	: Ratio of average global solar radiation on a tilted surface to that on horizontal surface.
$\boldsymbol{Rb}$	: Ratio of average beam radiation on a tilted surface to that on horizontal surface.
$\boldsymbol{T}$	: Set of time period.
$\boldsymbol{T}$	: Set of time period.
$\boldsymbol{c}$	: Index for PV-BESS-tilt angle combinations.
$\boldsymbol{d}$	: Index for day.

$\boldsymbol{i}$	: Index for time-shiftable appliances.
$\boldsymbol{j}$	: Index for thermostatically controlled appliances.
$\boldsymbol{k}$	: Index for power-shiftable appliances.
$\boldsymbol{n}$	: Day of the year.
$\boldsymbol{r}$	: Real interest rate.
$\boldsymbol{s}$	: Tilt of surface from horizontal [°].
$\boldsymbol{t}$	: Index for the time intervals of scheduling.
$\boldsymbol{y}$	: Index for year.
$\boldsymbol{\delta}$	: Solar declination [°].
$\boldsymbol{\rho}$	: Ground reflectance.
$\boldsymbol{\varphi}$	: Latitude of the place [°].
$\boldsymbol{\omega}$	: Hour angle [°].

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DEVELOPMENT OF A HOME ENERGY MANAGEMENT SYSTEM TO INCREASE RENEWABLE SELF-CONSUMPTION IN HOUSEHOLDS CONSIDERING DEMAND-SIDE FLEXIBILITY

SUMMARY

The increase in global electrical energy demand and the rapid integration of intermittent renewable resources into the electricity grid has required the improvement and modernization of traditional grid infrastructure to achieve reliable and clean energy. As a result, the concept of smart grid has emerged, where all players in the grid network connect and interact with each other through information and communication technologies (ICT) to increase stability, resource efficiency and sustainability in the areas of energy production, transmission and distribution.

In smart grids, unlike in the traditional grid, it becomes possible to adjust electricity demand according to supply. Demand side management (DSM) stands out as one of the ways to achieve this. DSM refers to a set of strategies for end-users to change their electrical energy usage habits by reducing, increasing or shifting their electrical load demands to a different time period for the purposes of energy efficiency, strategic load increase or load management. The ability of users to perform DSM can be described as their “demand side flexibility”.

Demand response (DR), one of the DSM strategies, refers to balancing the load curve by encouraging end-users to shift their electricity demand to low demand period on the electricity grid. End-users can reduce their electricity bills or benefit from other incentives by actively participating in DR programs through DSM. Additionally, in case they have distributed generation (DG) units, users can increase renewable self-consumption by shifting their electricity consumption to the period of renewable energy production. Today, since feed-in tariff (FiT) rates for selling electricity to grid has decreased significantly, increasing self-consumption becomes a necessity to increase the value of renewable energy system investments. Increasing DR and renewable self-consumption not only offers financial advantages to end-users, but also gives them the opportunity to contribute to a sustainable electricity grid.

Grid-connected rooftop photovoltaic (PV) systems enable the use of solar energy potential in urban areas, provide on-site solutions for electrification and CO_2 reduction, create no land costs, and reduce transmission and distribution costs. Despite these advantages and Türkiye's high solar energy potential, the deployment rate of grid-connected rooftop PV systems in Türkiye has stayed low. At the beginning of this thesis study (2017), the share of rooftop PV capacity (200 MW) in the total installed PV capacity (3700 MW) was only 5%. This was a very low rate compared to examples in other countries (21.5% in China, 70% in Germany and 76.5% in Australia). In addition, most of this amount belonged to industrial and commercial buildings and the share of residential rooftop PVs were very low.

Therefore, one of the aims of this thesis is to accelerate investments in residential rooftop PV systems in Türkiye. This can be achieved through policy mechanisms such

as FiT schemes, purchase subsidies, regulatory supports, information campaigns, etc., as well as through engineering solutions that include smart home automation. For this purpose, a home energy management system (HEMS) tool has been developed to increase residential demand-side flexibility. The developed HEMS performs energy optimization by planning the operating hours of manageable electrical household loads through DSM. To increase self-consumption, HEMS shifts electrical loads to periods of high solar energy production. And to realize DR, it takes advantage of time-based electricity prices by shifting the loads to cheap electricity period. The developed HEMS tool then was modified to a PV-battery sizing model. PV-battery sizing model can perform component sizing for a flexible household load profile due to optimal DR and self-consumption operations of HEMS. Lastly, a nationwide survey was conducted to understand demand-side flexibility in Türkiye, specifically residential end users' perceptions of DR and HEMS usage. The survey aimed to identify the limits of HEMS use and DR participation rather than making assumptions for simulation studies (as is often done in the literature). Survey participants' responses were entered into the HEMS tool and simulated to observe to what extent the daily load curve of Türkiye could change with the use of DR-based HEMS. This Ph.D. thesis consists of four thematically linked scientific publications.

Paper 1 examines the economic feasibility of grid-connected residential rooftop PV systems in Türkiye. This study was conducted to understand the economic reasons for the low prevalence of the systems in the country and to draw conclusions for policy making. Economic analysis of 5 kW rooftop PV systems for a total of nine provinces was made using HOMER Grid software. Simulation results have shown that residential rooftop PV systems were not feasible in Türkiye except for one of the nine selected provinces. To overcome this, first, the amount of FiT rates that could make the systems attractive were calculated, and then, based on solar radiation differences in Türkiye, a regional FiT scheme was proposed, as applied in many other countries. It was also recommended to update FiT rates periodically (as applied in Germany, England, Japan and Australia) taking into account the country's rooftop PV targets and changes in parameters such as PV installation costs, retail electricity prices and grid needs.

In Paper 2, a HEMS model is developed to increase the demand-side flexibility of households through automation, thereby making rooftop PV systems economically attractive. The developed mixed integer linear programming (MILP)-based HEMS model provides optimum DR and PV self-consumption by performing day-ahead load scheduling for cost minimization. HEMS allows bi-directional power flow between the household, battery energy storage system (BESS), electric vehicle (EV) and the grid. The model can calculate the solar radiation falling on an inclined plane using an isotropic model and thus determine the power output that the PV array can produce according to the technical specifications of the array, the inclination angle and the daily outdoor temperature. The proposed HEMS also includes a smart thermostat which can define different air conditioning temperature set-points for different periods of the day based on changing electricity prices, solar radiation, and occupancy level. In this way, DR participation is provided flexibly for air-conditioner owners. Simulation results showed that the proposed HEMS can reduce the daily electricity bill during summer days by between 53.2% (household with time-shiftable appliances (TSAs), thermostatically controlled appliances (TCAs), PV, BESS and EV) and 13.5% (household with TSAs and TCAs) depending on the household type. The smart thermostat integrated into HEMS managed to reduce the daily air conditioning bill by

15% to 24% during the summer months. It was seen that the HEMS could provide more bill reduction under RTP than under TOU. Under RTP, the HEMS achieved to sell a portion of the produced electricity to the grid and perform vehicle-to-grid (V2G).

PV-BESS sizing becomes complicated for a household that wants to install an HEMS due to the load profile changing throughout the year according to HEMS oeprations. Therefore, in Paper 3, a renewable energy system sizing model that can calculate the optimal PV-BESS-PV tilt angle for HEMS-equipped households is developed. The proposed model simulates the load profile of a HEMS-equipped household for a year and repeats the simulations for each PV array capacity-tilt angle-number of batteries combination. The model determines the NPV of each combination and ranks them from highest to lowest. According to the results, under current battery and electricity prices, the optimal system design with the highest NPV for a HEMS-equipped household in Istanbul, Türkiye is 3 kW PV – no battery – 10° tilt angle. The reason why the optimum configuration is without a battery is that electricity prices are very low in Türkiye. The savings made cannot cover the investment made in the battery. In order to make future projections, a sensitivity analysis is conducted according to increasing electricity and decreasing battery prices. Battery use becomes possible if electricity prices increase by 25% or battery prices decrease by 25%. In the case of HEMS use, the NPV of the PV-BESS investment increases from $920 to $2273. This is an important finding, because in many countries PV projects cannot be implemented due to low feasibility in the absence of incentives.

The rising adoption rate of smart home appliances and rising electricity prices make the use of HEMSs increasingly attractive. However, HEMSs have not yet become widespread, and even if they did, there is still not enough information about the future potential for mass adoption of these devices and consumer preferences for their use. Understanding this potential is closely related to appliance usage behavior, electricity tariff perception and DR perception. Since HEMS is a new technology and no DR programs are offered for residential consumers in Türkiye today, surveys can be very useful to understand future user behavior and preferences before the wide-scale deployment of these technologies. Therefore, in Paper 4, we conduct a nationwide survey aiming to understand the perceptions towards HEMS use (which electrical appliances users would want to give management to HEMS, at what time of day they would like HEMS to operate these appliances, etc.), time-based electricity tariffs and DR programs. Then, the responses of the survey participants are simulated using the developed HEMS, and it is investigated to what extent Türkiye's daily load curve could change in case of participation in DR programs with HEMSs in Türkiye. According to the results, 78% of the survey participants are willing to use HEMS. There is a technical potential to reduce daily peak demand by 33% with the use of HEMS for DR purposes. However, this potential may not be possible to achieve, as the average electricity bill savings HEMS owners can achieve is only 6.7%. Yet in simulations, 21% of survey participants (16.4% of total respondents) were able to reduce their bills by over 10% if they used HEMS. 8% of the participants saved more than 15% on their bills, and 3% saved more than 20%. These households may be the target audience of future HEMS market and DR campaigns. Simulations show that if survey participants' device and HEMS usage behaviors are representative of the Turkish population, DR participation of 40% of all residential end-users in winter period and 20% in summer period is required to minimize the peak to average power ratio (PAR) of the Turkish load curve.

TALEP TARAFI ESNEKLİĞİ DİKKATE ALINARAK KONUTLARDA YENİLENEBİLİR ÖZ TÜKETİMİ ARTIRMAYA YÖNELİK BİR EV ENERJİ YÖNETİM SİSTEMİ GELİŞTİRİLMESİ

ÖZET

Küresel elektrik enerjisi talebindeki artış, mevcut şebeke altyapısının verimsizliği ve konvansiyonel kaynakların yarattığı çevresel tahribat nedeniyle kesintili yenilenebilir kaynakların hızlı bir şekilde elektrik şebekesine entegre olmaya başlaması, güvenilir ve temiz enerji elde etmek için geleneksel elektrik şebekesinin iyileştirilmesini, izlenebilirliğini ve modernizasyonunu gerektirmiştir. Bunun sonucunda enerji üretimi, iletimi ve dağıtımı alanlarında istikrarı, kaynak verimliliğini ve sürdürülebilirliği artırmak için şebeke ağındaki tüm oyuncuların bilgi ve iletişim teknolojileri (ICT) aracılığıyla birbirleriyle bağlantı kurduğu ve etkileşimde bulunduğu akıllı şebekeler kavramı ortaya çıkmıştır.

Akıllı şebekelerde gelişmiş takip, iletişim ve kontrol teknikleri sayesinde elektrik enerjisi arzını talebe göre düzenlemek yerine, talebi arza göre düzenleyebilmek mümkün olmuştur. Talep tarafı yönetimi (DSM) olarak adlandırılan bu yaklaşım, son kullanıcıların, enerji verimliliği, stratejik yük artışı veya yük yönetimi için elektrik yük taleplerini azaltarak, artırarak veya farklı zaman dilimlerine kaydırarak elektrik enerjisi kullanım alışkanlıklarını değiştirmesine yönelik bir dizi stratejiyi ifade etmektedir. Kullanıcıların DSM yapabilme yeteneği onların "talep tarafı esnekliği" olarak tanımlanabilir.

DSM stratejilerinden biri olan talep cevabı (DR), elektrik tüketicilerinin, bir sistem operatörü ya da hizmet sağlayıcıdan aldıkları sinyallere göre güç taleplerini elektrik şebekesindeki düşük talep dönemine kaydırarak yük eğrisini dengelemesini ifade etmektedir. Tüketiciler DSM yoluyla DR programlarına aktif olarak katılarak elektrik faturalarını azaltabilir ya da diğer maddi teşviklerden yararlanabilmektedir. Ayrıca, tesislerinde dağıtık üretim (DG) birimlerinin bulunması halinde yine DSM yoluyla elektrik tüketimlerini yenilenebilir enerji üretiminin olduğu zaman aralıklarına kaydırarak yenilenebilir iç tüketimi arttırabilmektedirler. Günümüzde yenilenebilir kaynaklarla üretilen enerjinin tarife garantisi (FiT) oranı önemli ölçüde düştüğünden, yenilenebilir enerji sistem yatırımlarının değerini artırmak için öz tüketimin arttırılması bir gereklilik haline gelmiştir. DR programlarına katılmak ve yenilenebilir iç tüketimi arttırmak son kullanıcılara sadece maddi avantajlar sunmaz, aynı zamanda onlara sürdürülebilir bir elektrik şebekesine katkıda bulunma imkanı da tanır.

Şebekeye bağlı çatı üstü fotovoltaik (PV) sistemler güneş enerjisi potansiyelinin kentsel alanlarda kullanılmasına olanak tanımakta, elektrifikasyon ve CO_2 azaltımı için yerinde çözümler sunmakta, iletim ve dağıtım maliyetlerini azaltmakta ve arazi maliyetlerini ortadan kaldırmaktadır. Bu avantajlarına ve Türkiye'nin yüksek güneş enerjisi potansiyeline rağmen Türkiye'de şebekeye bağlı çatı üstü PV sistemlerin kullanım oranı çok düşüktür. Tez çalışmasının başlangıcında (2017) Türkiye'deki toplam PV kurulu güç 3700 MW iken toplam çatı üstü PV kurulu güç 200 MW'de

kalmıştır. Toplam PV kurulu gücün %5'i dahi etmeyen bu oranın, Çin (%21,5), Almanya (%70) ve Avustralya (%76,5) gibi örneklerle karşılaştırıldığında oldukça düşük olduğu görülmektedir. Ayrıca, bu oranın büyük kısmı endüstriyel ve ticari uygulamalara ait olduğundan, Türkiye'de çatı üstü PV sistemlerin konutlarda yaygınlaşamadığı söylenebilir.

Bu nedenle bu tez çalışmasının amaçlarından biri Türkiye'de konut tipi çatı üstü PV sistemleri ekonomik açıdan cazip hale getirmektir. Bu, politikalar üretme yoluyla başarılabileceği gibi teknolojik çözümlerle de başarılabilir. Makale 1'de, çatı üstü PV sistemleri cazip kılabilmek için garantili satış tarifesi miktarlarının bölgesel farklılıklara göre düzenlenmesi ve PV kurulum maliyetlerinin sübvanse edilmesi gibi politika çözümleri önerilmiştir. Makale 2'de konutlarda talep tarafı esnekliğini artırmaya yönelik bir ev enerji yönetim sistemi (HEMS) aracı geliştirilmiştir. Geliştirilen HEMS, DSM yoluyla yönetilebilir elektrik yüklerin çalışma saatlerini planlayarak hanelerde enerji optimizasyonu gerçekleştirebilmektedir. HEMS, öz tüketimi artırmak için elektrik yükleri güneş enerjisi üretiminin yüksek olduğu periyotlara, DR gerçekleştirmek için ise yükleri elektrik şebekesinin yoğun olmadığı yani elektriğin ucuz olduğu periyotlara kaydırarak zamana bağlı elektrik fiyatlarından yararlanmaktadır. Makale 3'de, geliştirilen HEMS aracı modifiye edilerek HEMS kurulumuna sahip haneler için optimal PV-batarya tasarımı yapabilen bir boyutlandırma modeli geliştirilmiştir. Bu model, HEMS işletimi nedeniyle hanenin elektrik yük profili (günlük değişen elektrik fiyatları, güneş radyasyonu ve sıcaklıklar nedeniyle) her gün değişse bile PV-batarya boyutlandırması yapabilmeyi amaçlamıştır. Makale 4'te Türkiye'deki talep tarafı esnekliğini, özellikle de konut son kullanıcılarının DR ve HEMS kullanımına ilişkin algılarını anlamak için ülke çapında bir anket yürütülmüştür. Anket sayesinde elektrik tüketicilerinin HEMS kullanımı ve DR katılımı tercihleriyle ile ilgili varsayımlar yapmak yerine bu tercihlerin sınırları belirlenmiştir. Ardından, anket katılımcılarının yanıtları geliştirilen HEMS aracıyla simüle edilerek Türkiye'de DR bazlı HEMS kullanımıyla günlük yük eğrisinin ne ölçüde değiştirilebilceği hesaplanmıştır. Bu doktora tez çalışması birbiriyle bağlantılı dört bilimsel yayının bir araya getirilmesiyle hazırlanmıştır.

Makale 1'de, Türkiye'deki şebekeye bağlı konut tipi çatı üstü PV sistemlerinin ekonomik fizibilitesi incelenmektedir. Bu çalışma, sistemlerin Türkiye'deki yaygınlığının düşük olmasının ekonomik nedenlerini anlamak ve politika oluşturmaya yönelik sonuçlar çıkarmak amacıyla yapılmıştır. Çalışmanın başlangıcında Türkiye güneş enerjisi potansiyel atlası (GEPA) üç bölgeye ayrılmış ve ülke çapında bir fizibilite analizi için her bölgeden üçer il seçilmiştir. Toplam dokuz il için 5 kW'lık çatı üstü PV sistemlerin ekonomik analizi HOMER Grid yazılımı kullanılarak yapılmıştır. Simülasyon sonuçları göstermiştir ki, Türkiye'de konut tipi çatı üstü PV sistemler ülkenin güney kesimi haricinde fizibıl değildir. Bunu aşmak için ülkedeki bölgesel güneş ışınımı farklılıkları dikkate alınarak güneş enerjisinden üretilen elektrik için bölgesel alım fiyatı garantisi uygulamaya konulabilir. Ya da, başka ülkelerde uygulanan ancak Türkiye'de uygulanmayan yatırım sübvansiyonları bölgesel olarak sunulabilir. Türkiye'de 2011 yılında lisanssız üretim kanununda değişiklik yapıldığından beri alım fiyatı garantisi sabit kalmıştır. Aralarında Almanya, İngiltere, Japonya ve Avustralya'nın da bulunduğu birçok ülkede bu fiyatlar periyodik olarak güncellenmektedir. Türkiye'de de yerinde üretilen elektrik için alım fiyatı, ülkenin çatı üstü PV hedeflerine ve PV kurulum maliyeti, perakende elektrik fiyatı ve şebeke ihtiyacı gibi parametrelerdeki değişikliklere göre periyodik olarak güncellenebilir.

Makale 2'de, hanelerin talep tarafı esnekliğini otomasyon yoluyla artırmak ve bu sayede çatı üstü PV sistemleri ekonomik olarak cazip hale getirmek amacıyla bir HEMS modeli geliştirilmiştir. Geliştirilen karma tamsayılı doğrusal programlama (MILP) tabanlı bu model, maliyet minimizasyonu için gün öncesi yük çizelgelemesi gerçekleştirerek optimum DR ve PV öz tüketimi sağlayabilmektedir. HEMS, konut, batarya enerji depolama sistemi (BESS), elektrikli araç (EV) ve şebeke arasında çift yönlü güç akışına izin vermekte ve batarya sağlığını korumak için verdiği kararlarda batarya bozunumunu dikkate almaktadır. Model, tüm yönetilebilir elektrikli ev aletlerinin (zamana bağlı kaydırılabilir (TSA), termostatik olarak kaydırılabilir (TCA), güce bağlı kaydırılabilir (PSA)) çalışma saatlerini optimal bir şekilde ayarlayabilmektedir. Ayrıca, batarya bozunumunu da dikkate alarak her türlü bataryadan her şeye (B2X) ve araçtan her şeye (V2X) taleplerine yanıt verebilmektedir. Model, eğik düzleme düşen güneş ışınımını izotropik model kullanarak hesaplayabilmekte ve bu sayede günlük güneş radyasyonu tahmini üzerinden PV dizinin, dizinin eğim açısına, günlük dış sıcaklığa ve dizinin teknik özelliklerine göre üretebileceği güç çıkışını belirleyebilmektedir. Önerilen HEMS, bünyesinde bir akıllı termostat da barındırmaktadır. Bu akıllı termostat, değişen elektrik fiyatları, güneş radyasyonu ve sakinlerin evde bulunup bulunmama durumlarına göre günün farklı zaman dilimleri için farklı klima sıcaklık ayar noktaları tanımlayabilmektedir. Bu sayede klima kullanıcıları için DR katılımı esnek bir şekilde sağlanmaktadır. Simülasyon sonuçları, önerilen HEMS'in hane tipine bağlı olarak yaz aylarında günlük elektrik faturasını %53,2 (TSA'lara, TCA'lara, PV'ye, BESS'e ve EV'ye sahip hane) ile %13,5 (TSA'lara ve TCA'lara sahip hane) arasında azaltmayı başarabileceğini göstermiştir. HEMS'e entegre akıllı termostat, yaz aylarında İstanbul'da günlük klima faturasını %15 ile %24 arasında azaltmayı başarmıştır. Geliştirilen HEMS'in performansı Türkiye'de konut elektrik tüketicileri için başka bir alternatif olmadığı için sadece TOU tarifesine göre test edilebilmiştir. HEMS'in başka tarifeler altındaki performansını görmek için Türkiye'nin TOU tarifesi RTP'ye modifiye edilerek simülasyonlar tekrarlanmıştır. RTP altında, HEMS'in daha fazla fatura düşüşü sağlayabildiği görülmüştür. RTP altında TOU altında mümkün olmayan şebekeye elektrik satma ve araçtan şebekeye (V2G) güç aktarımı mümkün olmuştur.

Makale 3'de HEMS donanımlı evler için optimal PV-BESS-PV eğim açısı hesaplayabilen bir yenilenebilir enerji sistem boyutlandırması modeli geliştirilmiştir. Bunun nedeni, HEMS kullanan hanelerde DSM nedeniyle yıl boyunca günlük olarak değişen yük profilinin PV-BESS boyutlandırmasını daha karmaşık bir hale getirmesidir. Geliştirilen boyutlandırma modeli, bir yıl için hane halkı yük profilini HEMS kullanılması durumu için simüle etmekte ve simülasyonları her bir PV dizisi kapasitesi-eğim açısı-batarya sayısı kombinasyonu için tekrarlamaktadır. Model, her kombinasyonun NPV'sini belirleyerek bunları en yüksekten en düşüğe doğru sıralamaktadır. Sonuçlara göre mevcut akü ve elektrik fiyatları altında İstanbul'da HEMS donanımlı bir ev için en yüksek NPV'ye sahip optimal konfigürasyon, bataryasız 3 kW PV – 10° eğim açılı konfigürasyon olarak bulunmuştur. Optimal konfigürasyonda batarya bulunmamasının nedeni, Türkiye'de elektrik fiyatlarının düşük olmasıdır. Elde edilecek fatura tasarrufları bataryaya yapılacak yatırımı karşılamamaktadır. Çalışmada geleceğe yönelik projeksiyonlar yapabilmek amacıyla artan elektrik ve düşen pil fiyatlarına göre hassasiyet analizi de yapılmıştır. Batarya kullanımı elektrik fiyatlarının %25 artması veya batarya fiyatlarının %25 düşmesi durumlarında mümkün hale gelmiştir. HEMS kullanımı durumunda PV-BESS yatırımının NPV'si 920 $'dan 2273 $'a yükselmiştir. Bu önemli bir bulgudur, çünkü birçok ülkede PV projeleri teşviklerin yokluğunda fizibilitenin düşük olmasından dolayı hayata geçememektedir. HEMS kullanımı, PV sistemleri ekonomik açıdan daha cazip hale getirdiğinden PV-BESS boyutlandırması için yük profillerini simüle etmek isteyen haneler bu boyutlandırma modelinden yararlanabilir. Çalışmada aynı zamanda Türkiye ile aynı enlemde bulunan fakat farklı elektrik fiyatlarına sahip diğer Güney Avrupa ülkelerinde, HEMS kurulumu yapmak isteyen haneler için gerekli olan optimal PV-BESS konfigürasyonları da araştırılmıştır.

Akıllı ev aletlerinin artan kullanımı ve artan elektrik fiyatları, HEMS kullanımını giderek daha cazip hale getirmektedir. Ancak HEMS'ler şu ana kadar yaygınlaşmamıştır ve yaygınlaşsalar bile, bu cihazların kitlesel olarak benimsenmesinin gelecekteki potansiyeli ve kullanımlarına dair tüketici tercihleri hakkında hala yeterince bilgi bulunmamaktadır. Bu potansiyelin anlaşılması, cihaz kullanım davranışı, elektrik tarifesi algısı ve DR katılım eğilimi ile yakından ilgilidir. HEMS yeni bir teknoloji olduğundan ve günümüzde yaygın olarak kullanılmadığından, yapılacak anketler gelecekteki kullanıcı davranışları ve tercihlerini anlamak açısından faydalı olabilir. Literatürde yapılan simülasyon çalışmalarında HEMS ve DR katılımına dair birçok varsayımda bulunulduğundan bu teknolojilere dair tüketici tercihlerinin sınırlarının belirlenmesi sonuçların tutarlığı açısından önem arz etmektedir. Ayrıca günümüzde Türkiye'de konut tüketicilerine yönelik herhangi bir DR programı sunulmamaktadır. Son kullanıcıları DR gerçekleştirmeye motive edecek tek araç TOU tarifesidir. Bu nedenle Makale 4’te Türkiye’de elektrik tüketicilerinin HEMS kullanımına (kullanıcıların hangi elektrikli aletlerinin yönetimini HEMS’e vermek isteyecekleri, HEMS’in bu aletleri günün hangi saatlerinde çalıştırmasını isteyecekleri vb.), zamana bağlı elektrik tarifelerine ve DR programlarına yönelik algılarını anlamayı amaçlayan bir anket yapılmıştır. Ardından, Türkiye genelini temsil eden anket katılımcılarının yanıtları geliştirilen HEMS’de simüle edilerek, Türkiye’de DR programlarına HEMS kullanımı yoluyla katılım durumunda Türkiye’nin günlük yük eğrisinin ne ölçüde değişebileceği araştırılmıştır. Sonuçlara göre anket katılımcılarının %78’i HEMS kullanmaya sıcak bakmaktadır. Katılımcıların beyanına göre Türkiye’de DR amaçlı HEMS kullanımıyla günlük puant talebin %33 oranında azaltılmasına yönelik bir teknik potansiyel bulunmaktadır. Ancak HEMS sahiplerinin elde edebileceği ortalama elektrik faturası tasarrufu yalnızca %6,7 olduğundan bu potansiyele ulaşılması mümkün olmayabilir. Bunu aşmanın yolu konut tüketicileri için daha cazip elektrik tarifelerinin tasarlanması olacaktır. Yine de simülasyonlarda anket katılımcılarının %21'i (toplam yanıt verenlerin %16,4'ü) HEMS kullanmaları durumunda faturalarını %10'un üzerinde azaltmayı başarmıştır. Katılımcıların %8’i %15'in üzerinde, %3’ü ise %20'nin üzerinde fatura tasarrufu sağlamıştır. Bu haneler gelecekteki HEMS pazarının ve DR kampanyalarının hedef kitlesi olabilir. Simülasyonlar, anket katılımcılarının cihaz ve HEMS kullanım davranışlarının Türkiye nüfusunu temsil etmesi durumunda, tepe güç/ortalama güç oranını (PAR) en aza indirmek için tüm konut son kullanıcılarının kış aylarında %40'ının ve yaz aylarında %20'sinin DR katılımının gerekli olduğunu göstermektedir.

1. GENERAL INTRODUCTION

1.1 Motivation

Meeting the rising global demand for electrical energy, improving the existing grid's inefficiencies, and integrating intermittent renewables into the system required upgrading, monitoring, and modernizing the conventional electricity grid for reliable and clean energy. As a result, the concept of smart grid has emerged, in which all players in the grid network connect and interact with each other through information and communication technologies (ICT) to increase stability, resource efficiency and sustainability in the fields of energy production, transmission and distribution [1]. Advanced monitoring, communication and control techniques in smart grids made it possible to manage electrical demand, replacing the concept of "the demand follows the supply" with "the supply follows the demand" [2]. This approach, named demand-side management (DSM), refers to a set of strategies to change electrical energy usage habits of end-users by reducing, increasing or shifting their load demand for energy efficiency, strategic load growth or load management (Figure 1.1) [3]. The ability of users to perform DSM can be described as their "demand side flexibility" [4].

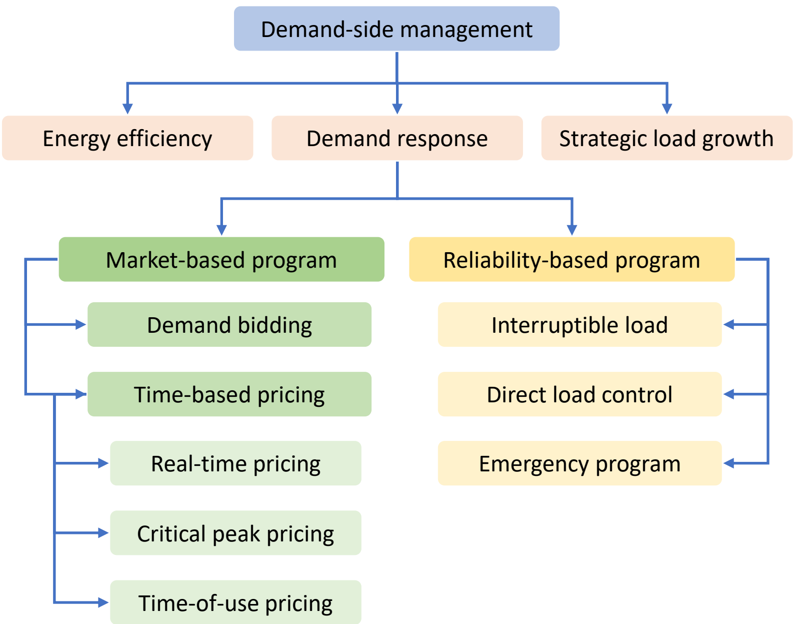

Figure 1.1 : Demand-side management methods [3].

Through DSM, end-users can reduce their electricity bills by performing demand response (DR), which refers to balancing the load curve by shifting demand to low demand period in return for incentives [5]. In addition, they can perform DSM in the presence of distributed generation (DG) units to increase renewable self-consumption. As feed-in tariff (FiT) rates have decreased significantly today, increasing self-consumption becomes more important to increase the value of a renewable energy system investment [6].

This thesis aims to increase demand-side flexibility in residential sector in Türkiye through automated DSM using home energy management systems (HEMSs). In this way, residential end-users can better utilize renewable resources, increase the value of their on-site renewable energy systems and reduce their electricity bills, while the grid-side can reduce investment and operating costs, all of which together contribute to a sustainable future.

1.2 Scope and Research Objectives

Grid-connected rooftop PV systems allows the utilization of solar potential in the urban areas, provide on-site solutions for electrification and CO_2 mitigation, do not cost land, and reduce transmission and distribution costs. Despite these advantages and Türkiye's high solar energy potential, the rooftop PV deployment rate in Türkiye as of 2017 (at the start of the thesis study) was only 200 MW over the entire installed PV capacity of 3700 MW. This amount was not even 5% and most of it belonged to industrial and commercial buildings [7]. This was a very low rate when compared to the examples from other countries (21.5% in China (2017), 70% in Germany (2017) and 76.5% in Australia (2018) as well [8–12].

Therefore, one of the aims of this thesis is to make residential rooftop PV systems economically attractive in Türkiye. This can be achieved through policymaking as well as technological solutions. In Paper 1, policy solutions such as regulating FiT rates according to regional differences, updating FiT rates peridocially and subsidizing PV installation costs are suggested in order to make rooftop PV systems economically viable. In Paper 2, a HEMS tool is developed to increase residential demand-side flexibility. The developed HEMS can perform energy optimization in households by scheduling the working hours of manageable home appliances via DSM. HEMS shifts loads to solar generation period to increase self-consumption and to off-peak hours to benefit from cheaper electricity prices. In Paper 3, the developed HEMS tool was modified to a PV-battery sizing model. PV-battery sizing model can perform component sizing for a flexible household load profile due to optimal DR and self-consumption operations of HEMS. In Paper 4, a nationwide survey was conducted to understand demand-side flexibility in Türkiye, specifically residential end users' perceptions of DR and HEMS usage. The survey aimed to identify the limits of HEMS use and DR participation rather than making assumptions for simulation studies (as is often done in the literature). Survey participants' responses were entered into the HEMS tool and simulated to observe to what extent the daily load curve of Türkiye could change with the use of DR-based HEMS. This doctoral thesis was prepared by bringing together four interrelated scientific publications.

1.3 Linkage of Scientific Papers

This thesis consists of the combination of four scientific papers. The linkage of papers is summarized in Figure 1.2.

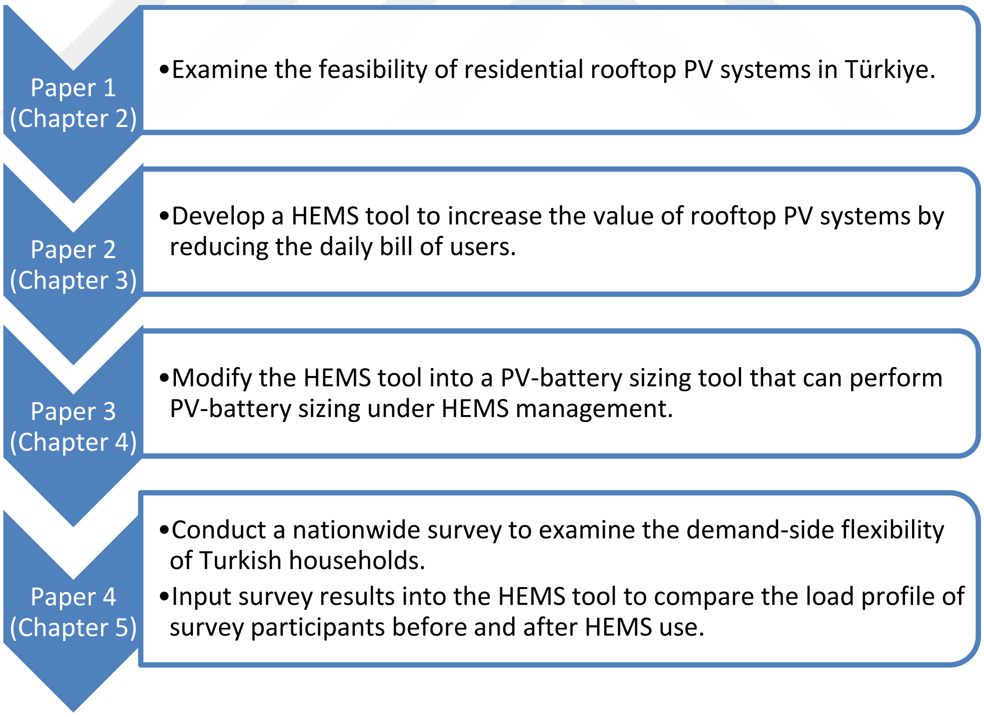

Figure 1.2 : Linkage of scientific papers.

In Paper 1 [13], an economic feasibility of residential rooftop PV systems in Türkiye is examined to understand the low deployment rate of the systems in the country and draw conclusions for policy-making.

In Paper 2 [14], a HEMS tool is developed to make rooftop PV systems economically more viable by enhancing the demand-side flexibility of households. The developed mixed-integer linear programming (MILP)-based HEMS tool can perform day-ahead load scheduling for cost-minimization and provides optimal DR and PV self-consumption. The HEMS allows bi-directional power flow between the home, battery energy storage system (BESS), electric vehicle (EV) and the grid, and takes battery degradation into account to maintain battery health. The HEMS is combined with a smart thermostat to ensure the maintenance of the thermal comfort of household occupants. The developed HEMS tool forms the basis of the following two studies.

In Paper 3 [15], the HEMS tool proposed in Paper 2 has been modified into a PV-battery-PV tilt angle sizing tool for HEMS-equipped households. The proposed tool simulates the household load profile under HEMS management and accordingly determines the optimum PV-battery capacity based on the highest net-present value (NPV) based on site-specific economic and climatic characteristics.

In Paper 4 [16], a nationwide survey is conducted to understand demand-side flexibility in Türkiye. Today, no DR program is offered to residential consumers in Türkiye. In addition, the Turkish time-of-use (TOU) scheme, which is the only tool to motivate end-users to perform DR, is designed for commercial and industrial groups and does not appeal to residential end-users. Therefore, the conducted survey aims to understand Turkish end-users' perceptions regarding DR programs and HEMS use before the large-scale deployments of these technologies.

1.4 Contribution to the Literature

Contributions of the papers to the literature is as follows:

Paper 1: At the time study was conducted, there was no detailed study in the literature on the nationwide feasibility analysis of rooftop PV systems in Türkiye. Paper 1 therefore conducts an economic analysis of grid-connected residential rooftop PV systems in nine provinces of Türkiye under the current FiT scheme. It investigates the low installation rate of the systems (only 5% of the total PV capacity) and makes policy recommendations, including regionalized FiT scheme, to make the systems viable in the country.

Paper 2: The main contribution of the Paper 2 is to combine a HEMS with a smart thermostat to provide efficient DR of air-conditioning with a higher thermal comfort of end-users. The developed HEMS tool is comprehensive and versatile in terms of its capabilities. After examination of the relevant publications, it became apparent that on the basis of HEMSs:

- integration of a smart thermostat into a HEMS
- controlling of all type of residential appliances (time-shiftable, thermostatically controlled, power-shiftable)
- consideration of optimizing self-consumption and DR simultaneously
- consideration of vehicle-to-grid (V2G), vehicle-to-home (V2H), vehicle-to-battery (V2B), battery-to-grid (B2G), battery-to-home (B2H), battery-to-vehicle (B2V), home-to-grid (H2G) operations together
- consideration of battery degradation and prevention of unnecessary energy arbitrage
- consideration of a solar model for a tilted PV array, that considers installed capacity, tilt angle of the PV array as well as the impact of temperature on PV power output

were not evaluated together in a single HEMS framework before. Therefore, a load scheduling optimization-based HEMS which combines all the above-mentioned features is developed. This tool is then formed the basis of the 3rd and 4th papers.

Paper 3: Although there are many studies and software for PV-BESS sizing in the literature, almost none of them perform optimal sizing for HEMS-equipped households since it is a more complicated problem. The sizing model we propose not only closes this gap in the literature, but also is very comprehensive in terms of including PV tilt angle sizing, energy optimization of all types of home appliances (TSAs, TCAs, PSAs) and V2H availability for EVs.

Paper 3 conducts a techno-economic comparison between PV-BESS-equipped households using and not using HEMS. By this means, the effect of using HEMS on the NPV of PV-BESS systems is investigated.

Paper 4: Before the initial deployment of a technology, field tests or surveys can be conducted to understand the perception of the technology. Although field tests are based on actual use, they are costly and difficult to represent the general population. On the other hand, surveys can be conducted at lower costs and with more participants, and it has been stated that their accuracies are not low at all.

As its main contribution, Paper 4 combines information gathered in a survey with an optimization tool to simulate the load mitigation potential of future mass adoption of HEMSs for DR.

The study contributes to the existing literature in the following ways:

- It collects information on residential electrical energy use behaviour, such as: - ownership rate of appliances - running hours of time-shiftable appliances (dishwashers, washing machines, dryers, etc.) - weekly operating frequency of appliances - preferred temperature set-points of refrigerators and air conditioners - frequency of use of electric water heaters (shower times, shower duration, etc.)
- It investigates the consumer perception of electricity tariffs,
- It investigates the residential demand-side flexibility through the willingness to participate in DR and defining operational priorities and limitations of HEMS use, such as: - willingness to use HEMS (if yes, which appliances do users allow HEMS to control) - time intervals users prefer HEMS to shift electrical loads - expectations, concerns, motivational factors, etc.
- It investigates to what extent HEMS-based DR can change the initial load profile. To this end, survey responses are entered into a load scheduling-based HEMS tool to simulate the load profiles of DR-performing households.
- It is comprehensive in scope as it includes DR participation of all major manageable home appliances.

2. ECONOMIC ANALYSIS OF GRID-CONNECTED RESIDENTIAL ROOFTOP PV SYSTEMS IN TÜRKİYE

This chapter presents an economic analysis of grid-connected residential rooftop PVs in Türkiye under the current feed-in tariff (FiT) scheme. Three solar parts are formed on the solar map of Türkiye to discuss the effect of solar radiation differences between regions on the feasibility of PV systems. Nine provinces are selected for a nationwide analysis. 5 kW rooftop PVs are simulated using HOMER Grid. Discounted Payback Period (DPBP), Internal Rate of Return (IRR) and Profitability Index (PI) are used to ensure the viability of the systems from all aspects. DPBP below 8 years, IRR above 13.12%, and PI above 2 are considered feasible.

The results showed that the current DPBP, IRR, and PI of the systems are in the range of 7.75 – 14.43 years, 13.68% – 6.87%, and 2.02 – 1.28, respectively. The systems are attractive only in one province in the southern part, and far from being investable in the northern part. A sensitivity analysis is performed to analyze the effect of varying FiT rates and PV initial costs on the feasibility of the systems and make policy implications. It is recommended to increase the amount of residential PV incentives in Türkiye and develop a regional support mechanism, considering solar differences between regions.

2.1 Introduction

Energy demand grows rapidly worldwide and increased demand brings challenges such as global warming. To overcome the threat, global steps have been taken so far, beginning from Rio Earth Summit in 1992, followed by the Kyoto Protocol in 1997, Rio+20 in 2012 and lastly Paris Agreement in 2015. More than 190 participant countries have agreed on a set of rules to keep global temperature increase below 2 degrees Celsius. The first step to achieve the goal has been determined as the maximization of use of renewable energy sources. The European Union (EU) has already set targets to increase the share of renewables to 32% by 2030 with a 40% reduction in greenhouse gas emissions from 1990 levels [17].

However, except hydropower, there has still been insufficient use of renewable energy worldwide. According to Renewable Energy Global Statement Report published by Renewable Energy Policy Network (REN21), 75.5% of the global electricity production has been provided by fossil fuels and nuclear energy resources by the end of 2017. Wind and solar power have only been accounted for 4.0% and 1.5%, respectively of the remaining share of 24.5% [18].

As reported in 2017 Sectoral Report of Electricity Supply published by Electricity Generation Company (EUAS), Türkiye'ss total installed power generating capacity and electrical energy production were 85360 MW and 292.6 TWh, respectively by the end of 2017. Natural gas covers the largest portion of the total electricity production of the country with a share of 37%. The rest of the share of energy sources is sorted as coal 32.5%, hydropower 20%, wind 6.1%, and the others (including solar) 4.4% [19].

Solar energy stands out as one of the most promising alternatives to increase utilization of renewables, and governments work on incentive mechanisms, regulations and policies to promote solar energy investments. Turkish energy policy also focuses on the exploitation of renewable energy sources not only to overcome global warming but also to reduce the high external dependency of the country on imported energy sources [20]. Although Türkiye continues its efforts to achieve better utilization of solar energy especially in photovoltaic (PV) power plant applications, PV systems have not been adopted sufficiently on building scale in the country and stayed behind EU countries.

Unlike large-scale PV plants, small-scale grid-connected rooftop PV applications offer promising possibilities for the assessment of solar potential in the urban areas, provide on-site solutions, do not cost land, and reduce transmission and distribution costs. Thus, increasing the installation rate of these systems has vital importance, and there is a growing body of research dealing with the feasibility of grid-connected rooftop PVs in the literature.

Rodrigues et al. [21] investigated the feasibility of 5 kW rooftop PV systems for 13 different countries using RETScreen software and showed that the viability of the PV systems is very dependent on incentives and subsidies. La Monaca and Ryan [22] economically analyzed rooftop PVs for Ireland. System Advisory Model (SAM) is used in the simulations, and policy scenarios to reduce the current payback periods in

Ireland were introduced. Li et al. [23] investigated the feasibility of rooftop PV systems in five climatic zones of China for residential apartments. HOMER software was used and the results were evaluated over the levelized cost of energy (LCOE) and the net present value (NPV). Mayr et al. [24] suggested a reverse auction-based subsidy scheme for residential PVs in Austria to increase the efficiency of the FiT. Sagani et al. [25] found that grid-connected PV systems with a capacity below 5 kW are not economically viable in Greece due to the low sale price of electricity. Anagnostopoulos et al. [26] analyzed the effect of FiT cuts on the payback period, internal rate of return and profitability index of the residential rooftop PV systems. Lee et al. [27] studied the economic feasibility of rooftop PVs for a university campus in New England, Connecticut and calculated payback period of the systems as 11 years. Wee [28] discussed the economic impact of rooftop PVs on Hawaiian house prices. Pre-installed PV systems increased the value of the properties, since new PV systems were not subsidized anymore. Gautam et al. [29] studied the potential of rooftop PVs in Nepal and recommended to invest in storage systems to benefit from the excess solar energy corresponding to 85% of the production. Haegermark et al. [30] emphasized the effect of investment subsidies and tax rebates on the profitability of rooftop PV systems. Madmoud and Omar [31] found payback period of 5 kW rooftop systems in Palestine as 4.9 years. Bakhshi and Sadeh [32] also investigated the economic viability of 5 kW rooftop PVs in different cities of Iran and the payback period of the systems was found to be below 3.5 years. Tomar and Tiwari [33] used HOMER software and concluded that grid-connected systems in New Delhi are viable without a need for battery storage. Lee et al. [34] showed that cost of PV systems has reached the break-even point in 18 of 51 cities in the USA, and excellent results were obtained in seven of 51 cities due to the effective solar incentives offered in the USA. Li et al. [35] estimated the payback period of 5 kW PV-battery systems as 18 years without any incentive policies, it is also concluded that PV-battery systems can enable 1.1% shaving of net peak load in Japan. Lopez Prol et al. [36] compared the profitability of grid-connected PV systems in Germany and Spain. Spain’s obvious higher profitability in equal conditions is compensated in reality with a lower cost of equity in Germany. Poruschi et al. [37] discussed the effect of a reduced payback period on social acceptance of PV systems. The study also showed that people are fond of capital subsidies rather than FiT. Watts et al. [38] compared net billing and net metering (NM) schemes for residential PV systems. Talavera et al. [39] investigated the economics of grid-connected PV systems in Spain between 1998 and 2014 based on the evolution of the legislative framework. Batman et al. [40] investigated the feasibility of grid-connected PV systems in Istanbul considering FiT and time-of-use rates. This was one of the few detailed studies conducted for a location in Türkiye, after the current FiT scheme was introduced.

All of these studies have made important contributions to the literature. However, in none of them, the effect of important three parameters, namely FiT, PV initial cost, and solar radiation on the feasibility of rooftop PV systems was examined together at the same time.

In many of the studies, only NPV and LCOE were used as economic indicators. In our opinion, there exist more clear indicators to understand the feasibility of rooftop PVs. For instance, these two parameters cannot tell when an energy system will start to make a profit.

Lastly, as the main lack, none of the studies addresses the case of Türkiye. Different parameters come to the fore for different countries to evaluate the feasibility of rooftop PV systems. In countries where electricity prices are high or subject to change notably, change in electricity prices can be an important parameter to be considered in the sensitivity analysis. In countries in which solar radiation does not differ a lot, a feasibility study made for a single location can give an overall idea for a whole country. Some large countries implement regional incentives, while some prefer to have a nationwide incentive mechanism throughout the country. In some countries, both net metering and net billing are available. Some countries apply only FiT, some of them use only capital/tax incentives and some of them use both. Each study in the literature selects necessary parameters according to their country's own specific conditions. At this point, it is important to define the parameters to be used for a study to be done for Türkiye.

2.2 Content and Contributions

To the best of our knowledge, there are no detailed studies in the literature about the feasibility of rooftop PV systems in Türkiye. The existing very few ones are concentrated in specific locations which do not reflect the feasibility in the whole country [40]. Also, the low number of studies is not because the rooftop PV systems are already feasible in Türkiye. Although the total installed PV capacity has reached 3700 MW in the country, the share of rooftop PV systems remains only 5%. Thus, we found this issue is worth investigating.

Türkiye is relatively a large country with a surface area of 783,562 km^2, which causes solar radiation in the country to differ a lot from north to south. Moreover, Türkiye’s own geographical features add this more. The country contains very different climates within, which causes solar radiation differences to be sharper between regions. For instance, Türkiye lies between latitudes 36° and 42° and the total annual radiation intensity difference between the northern and southern regions is 900 kWh/m^2, whereas it is only 250 kWh/m^2 in Germany where the latitude difference is higher than in Türkiye (47° and 55°) [41].

If we continue with the example of Germany, in such a country a nationwide FiT and support mechanism can be counted as fairly distributed, however, in countries such as Türkiye, the use of nationwide mechanisms for PV systems can cause installations to become concentrated at certain locations. A nationwide model can be suitable for utility-scale PV plants in Türkiye, but it can be an obstacle against the widespread adoption of the grid-connected rooftop PV applications which provide on-site solutions, do not cost land, and reduce transmission and distribution costs. Also, considering that the population of Türkiye is denser in the northern part, where the solar radiation is lower, increases, even more, the importance of this issue.

Therefore, this chapter presents a feasibility analysis of grid-connected residential rooftop PV systems in nine provinces of Türkiye under the current FiT scheme to investigate the low installation rate of the systems in the country. The main contribution of the study is taking into account the different solar potential of the regions for future policy implications. For this reason, three solar parts were formed on the Solar Energy Potential Atlas (GEPA) of Türkiye in the north-south direction, and three representative provinces from each part were selected for a comparative feasibility analysis.

Another contribution is that this study evaluates the effect of varying FiT, PV system initial cost, and solar radiation on the feasibility of rooftop PV systems together at the same time. Also, to guarantee the feasibility of the systems from all aspects, three economic indicators, DPBP, IRR, and PI are used as economic criteria.

Simulations are carried out for PV systems with a capacity of 5 kW using National Renewable Energy Laboratory's (NREL) recently released product HOMER Grid software. HOMER Grid uses the engine of widely-known HOMER and has been developed to optimize the value of behind-the-meter systems. To the best of our knowledge, this study is one of the very first studies in the literature that uses HOMER Grid.

Finally, a sensitivity analysis is conducted considering future changes in FiT and decrease in the initial cost of PVs, and policy recommendations are made, accordingly. Also, the required PV capacity in each province under current conditions is calculated up to 10 kW which FiTs are valid for in Türkiye. Conceptual framework of the methodology used in the study is given in Figure 2.1.

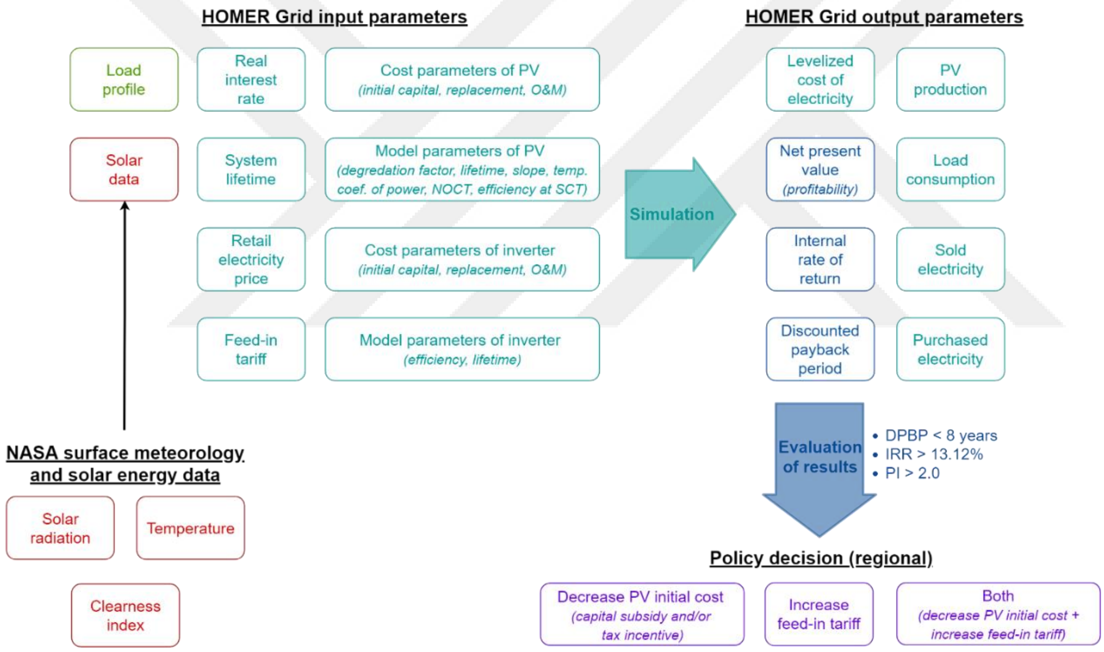

Figure 2.1 : Conceptual framework of the methodology used in the study.

2.3 Renewable Energy Policies in Türkiye

Türkiye has been implementing policies to increase the use of existing natural resources for energy demand. The aim of the current energy strategies is to reduce environmental impacts through measures to maximize the efficient use of renewable energy resources. In 2009, the Strategy Paper on Electricity Market Reform and Security of Supply has been issued to ensure to make the share of electricity generated from renewable sources 30% by 2023 [42].

The target of 30% renewable energy production by 2023 has remained the same in Strategic Plan 2010-2014 published by the Ministry of Energy and Natural Resources (MoENR) and Climate Change Strategy of Türkiye 2010-2020, published by the Ministry of Environment and Urbanization (MoEU). Development of renewable energy technologies has been supported by the Strategic Plan of MoENR, and one of the long-term objectives of Climate Change Strategy has been determined as generating electricity from solar energy [43,44].

The current FiT scheme for renewables has been introduced within the Law on the Use of Renewable Energy Resources for Generating Electricity numbered 6094 and dated 29/12/2010. The base amount of FiT for was identified as 13.3 $ cent/kWh for biomass, biogas, solar PV and concentrated solar power (CSP), 10.5 $ cent/kWh for geothermal and 7.3 $ cent/kWh for wind and hydropower. The law also provides additional incentives for the use of locally produced equipment [45].

The license exemption for electricity generation facilities with a capacity of equal or lower than 1000 kW has been put into practice in line with Electricity Market Law numbered 6446 and dated 14/03/2013. The Ministry of Energy and Natural Resource has enacted Regulation on Technical Assessment of Solar Power License Applications which aims to identify procedures and principles for technical assessment.

2.4 Solar Potential and PV Applications in Türkiye

The global cumulative installed capacity of PV systems has reached 402.5 GW at the end of 2017, whereas it was 303.1 GW in 2016, and 70.5 GW in 2011. By the end of 2017, 375 TWh of electricity has been produced by PV systems that represent more than 2% of the global total electricity demand. In Europe, 4% of the electricity generation has been covered by PV systems. However, the deployment rate of new installations has slowed down in Europe [46].

The solar potential in Türkiye is relatively high and the country has the second-largest potential in Europe after Spain. Türkiye is located between 36° – 42° northern latitudes and 26° – 45° eastern longitudes with a total surface area of 783,562 km^2. The potential implementation capacity of PV systems in Türkiye is assumed to be 450-500 GW regarding annual solar radiation of 1527 kWh/m^2-year and sunshine duration of 2741 hours [47]. In order to reveal the solar energy potential of the country, GEPA (Figure

2.2) has been released by the Electricity Affairs Survey Administration (EIE) in 2010 [48]. Türkiye contains a high potential for solar energy due to its location. The solar radiation level decreases from south to north as expected. In the northern part of the country, sunshine duration notably decreases related to specific climatic and geographic conditions of the region.

By the end of 2016, the total installed PV capacity was only 0.83 GW in Türkiye. In 2017, the country added record 2.6 GW of new PV, and the cumulative capacity has reached 3.42 GW at year's end. With this performance, Türkiye was among the top five countries responsible for approximately 84% of newly installed PV systems with China, the United States, India, and Japan. Although the total capacity has reached 3.42 GW, rooftop PV systems have consisted only 200 MW of this capacity and mainly in industrial and commercial buildings [49].

2.5 Simulations

2.5.1 Selected provinces

The GEPA was separated into three parts, namely southern, central and northern, depending on different solar characteristics. This was due to regionally evaluate the feasibility of residential rooftop PV systems. Three provinces with the highest, median and lowest solar radiation were selected from each part. In Figure 2.2, selected nine provinces and the identified parts are highlighted on GEPA [29]. Daily global horizontal radiation data (including daily radiation and clearness index) of each pilot province are given in Figure 2.3.

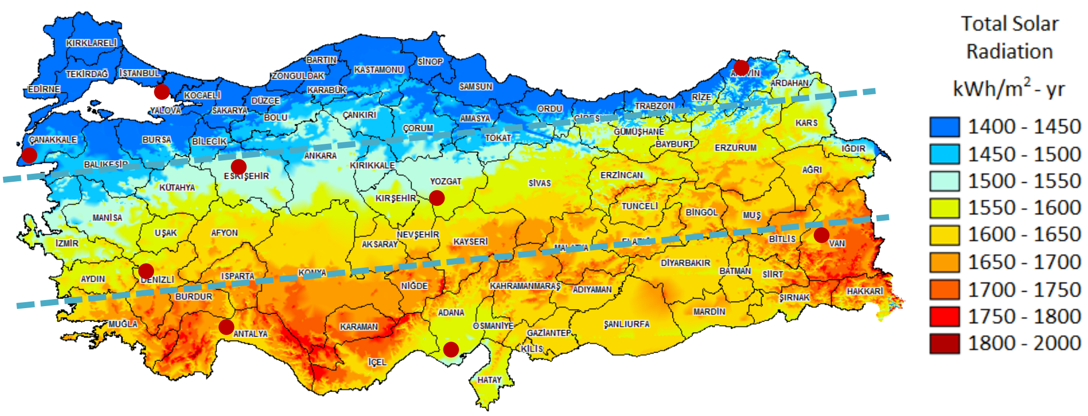

Figure 2.2 : Solar Energy Potential Atlas of Türkiye and the selected provinces.

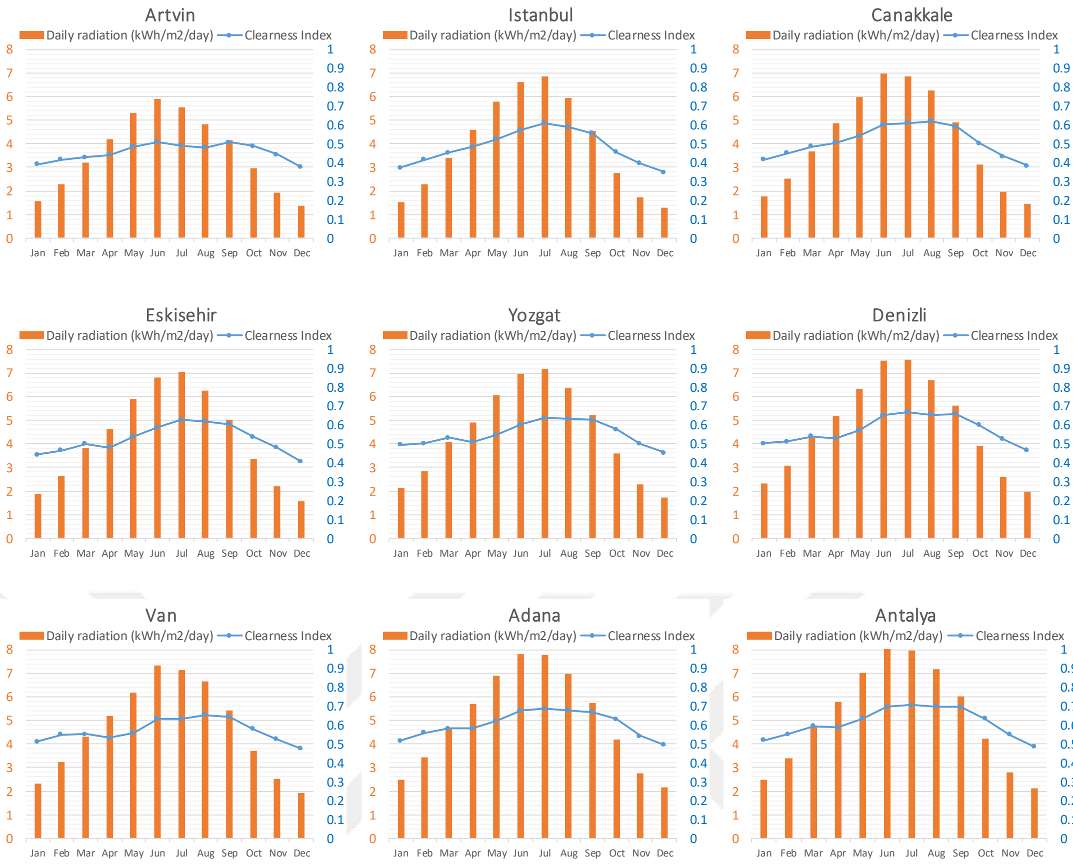

Figure 2.3 : Global horizontal radiation (including daily radiation and clearness index) of each pilot province.

2.5.2 HOMER Grid and input data

HOMER Grid software has been used to evaluate the design of grid-connected PV systems [50]. HOMER Grid, released in 2018, uses the engine of optimization tool HOMER developed by the NREL. HOMER Grid addresses behind-the-meter systems and computes demand charge reduction, energy arbitrage, and self-consumption to optimize an energy system. HOMER Grid's Tariff Builder application makes it possible to model accurate tariff models. Moreover, the library of the software contains 20,000 tariff models from different states of the USA, Canada, and Mexico.

Polycrystalline PV module spot price has been taken as 0.35 $/W in the calculation of the PV system capital cost [51]. The additional cost items such as electrical-structural, net profit, overhead, sales & marketing, permitting, inspection, interconnection, install labor and supply chain have been estimated to be 0.80 $/W. In this estimation, NREL's assumptions were adapted into Turkish conditions considering much lower labor costs [52]. Eventually, residential PV and inverter initial costs have been identified as 1.15 $/W and 0.15 $/W, respectively as well as the replacement costs. Operation and maintenance (O&M) costs of PV module and inverter have been estimated to be 23 $/W-year and 3 $/W-year, respectively. The efficiency of PV and inverter are 17.41% and 97.5%, respectively. PV temperature coefficient is -0.41 and the operating temperature is 45°C. The lifetime of PV panels is 20 years as well as the project lifetime, and inverter lifetime is 10 years. Battery storage is not evaluated in the simulations. The real interest rate was calculated as 3.92% for Türkiye. Schematic diagram of PV system components described in HOMER Grid is given in Figure 2.4.

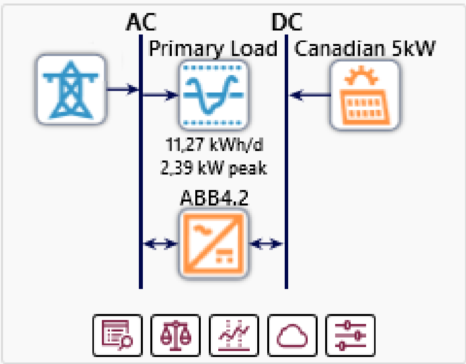

Figure 2.4 : Schematic diagram of the PV system components.

5 kW residential rooftop system was modeled for one side of an average open gable roof. As an autonomous load, an average four-person Turkish household with an average daily consumption of 11.27 kWh was determined. The daily load profile showing the hourly electricity demand for each month is given in Figure 2.5. Seasonal variations were taken into account as the highest load consumption occurs in July whereas the lowest is in December. The consumption trend remains the same in each month with peak consumption between 17:00-20:00.

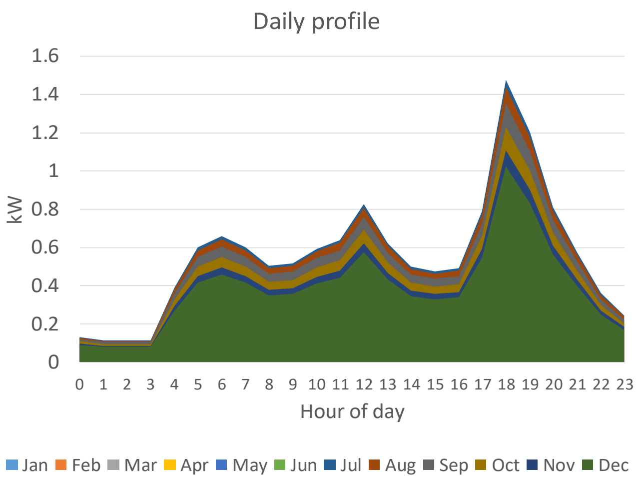

Figure 2.5 : The daily load profile used in the model.

Solar data of each selected province was extracted from Climatological Solar Radiation Data Sets of NREL and NASA Surface Meteorology and Solar Energy Data Sets through HOMER Grid software [53]. Coordinates of the pilot provinces are given in Table 2.1.

Table 2.1 : Coordinates of the pilot provinces.

Part	Pilot province	Latitude (North)	Longitude (East)
Northern	Artvin	41° 12'	41° 49'
	Istanbul	41° 02'	28° 58'
	Canakkale	40° 10'	26° 24'
Central	Eskisehir	39° 53'	30° 32'
	Yozgat	40° 03'	34° 46'
	Denizli	37° 51'	29° 05'
Southern	Van	38° 31'	43° 22'
	Adana	37° 02'	35° 18'
	Antalya	36° 57'	31° 06'

The amount of FiT for solar PV was set at 13.3 $ cent/kWh in Türkiye. If the selected PV components are locally produced, the amount of FiT can rise up to 20 $ cent/kWh. These incentives are applied for the components such as array structural mechanics, PV modules, PV cells, inverters, and materials focusing solar ray on PV modules. In the model, FiT was identified as 14.7 $ cent/kWh, assuming PV modules and PV cells are imported and mounting equipment and inverter are manufactured in Türkiye. The residential electricity price in the country is 10.60 $ cent/kWh including taxes and levies [54].

2.5.3 Economic determinants

The feasibility results in the study are discussed through three economic determinants, namely Discounted Payback Period (DPBP), Internal Rate of Return (IRR) and Profitability Index (PI). DPBP gives the number of years needed to recover the initial cost of a project. It considers the time value of money and is a useful determinant to understand the feasibility of a system. DPBP gives a good idea about how risky an investment is. The longer the DPBP, the higher the risk that the investment will not get the expected return. However, DPBP ignores cash flows occur after the payback period and does not give information about the total profitability of a project. DPBP is calculated as follows [55]:

$$DPBP = ln\left(\frac{1}{1-\frac{C_o \times r}{C_t}}\right) \div ln(1+r) \tag{2.1}$$

where C_0 is the initial investment cost, r is the real interest rate, and C_t is the net cash flow during the time period t.

IRR is described as the interest rate where the total NPC of all the cash flows in the project equals to zero. IRR may fail when comparing projects with different economic scales, but useful with projects with the same initial cost. It should be noted that, in projects with long lifetime, IRR figure could be misleading that interest rates are subject to differ from the assumed values from time to time. IRR should be greater than the initial discount rate to make a profit. IRR is calculated as follows [5]:

$$0 = \sum_{t=1}^{T} \frac{C_t}{(1+IRR)^t} - C_0 \tag{2.2}$$

where T is the project lifetime, C_t is the net cash flow during the time period t, IRR is the internal rate of return, and C_o is the initial investment cost.

The PI is an index to measure the ratio between the present value of future cash flows and the initial investment. PI is a useful method to rank projects. PI equal to 1 indicates the breakeven point for a project, and PI greater than 1 means the project generates value. Increasing PI states increasing profitability as well as decreasing risk for projects with a long lifetime. PI less than 1 means the project destroys value and the revenues do not cover the expenditures. PI is calculated as follows [5]:

$$PI = \frac{NPV}{C_o} + 1 \tag{2.3}$$

where NPV is the total net present value and C_o is the initial investment cost.

2.5.4 Simulation results

HOMER Grid simulation results of 5 kW rooftop systems for the pilot provinces under current conditions are given in Table 2.2. Initial capital cost of 5 kW rooftop PV system with 4 kW inverter is estimated as 6350 $. HOMER Grid takes grid purchases, grid sales, and O&M costs into account when calculating the cash flows. The present worth of the project is calculated by subtracting the cost of grid-only use from the net present cost of the energy system.

Monthly average of electricity purchases and sales in households are given in Figure 2.6. Blue bars represent the energy purchased from the grid and orange bars represent the electricity sold to the grid.

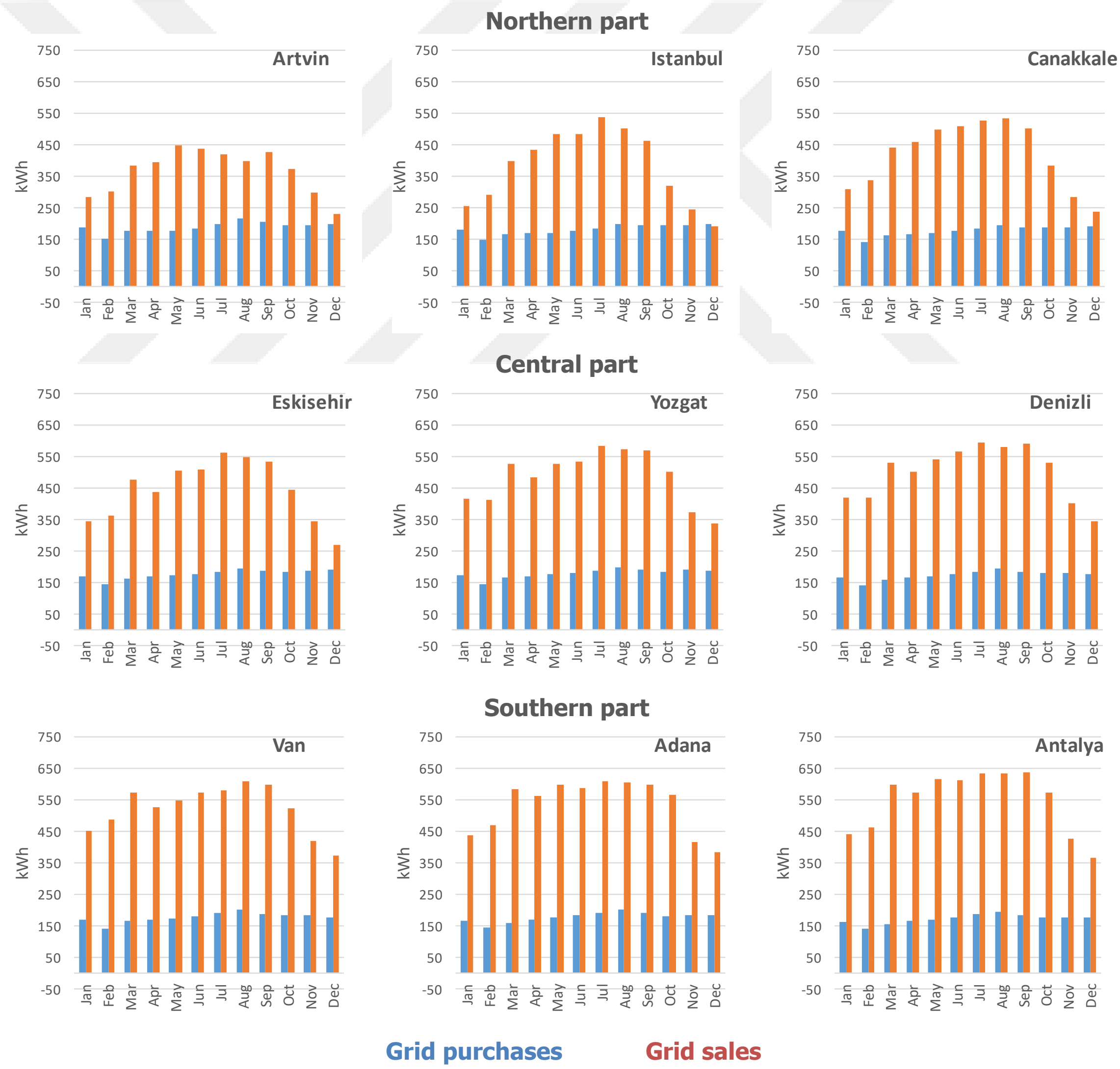

Figure 2.6 : Monthly electricity purchases and sales in the households in each pilot province.

Table 2.2 : HOMER Grid results of 5 kW rooftop PV systems for the pilot provinces under current conditions (criteria met are highlighted in bold).

	Northern part			Central part			Southern part		
	Art	İst	Çan	Esk	Yoz	Den	Van	Ada	Ant
Initial capital cost ($)					-6350				
Net present cost ($)	-4210	-3584	-2681	-2072	-1144	-602	-270	95	517
Cost of grid-only ($)					-5968				
Net present value ($)	1758	2384	3287	3896	4824	5366	5698	6063	6485
Energy demand of household (kWh/year)					4113				
Electricity produced by PV (kWh/year)	6455	6760	7231	7559	8048	8313	8511	8664	8881
Electricity purchased from grid (kWh/year)	2257	2171	2128	2127	2145	2071	2127	2121	2062
Renew. electricity sold to grid (kWh/year)	4391	4605	5021	5341	5839	6026	6265	6412	6572
Discounted payback period (year)	14.43	13.13	11.65	10.85	9.27	8.59	8.33	8.04	**7.75**
Internal rate of return (%)	6.87	7.86	9.21	10.09	11.39	12.16	12.59	**13.12**	**13.68**
Profitability index	1.28	1.38	1.52	1.61	1.76	1.85	1.90	1.96	**2.02**

The feasibility results are discussed through DPBP, IRR, and PI. The projects with DPBP less than 8 years [37], IRR greater than the discount rate (13.12%), and PI greater than 2 [6] were considered as favorable investments in the study (highlighted in bold in Table 2.2). The results show that, under current conditions, DPBP of the systems in Türkiye is in the range of 7.75 – 8.33 years in the southern part, 8.59 – 10.85 in the central part, and 11.65 – 14.43 years in the northern part. IRR of the systems is in the range of 13.68% – 12.59% in the southern part, 12.16% – 10.09% in the central part, and 9.21% – 6.87% years in the northern part. And, PI of the systems are in the range of 2.02 – 1.90 in the southern part, 1.85 – 1.61 in the central part, and 1.52 – 1.28 in the northern part. Only, province of Antalya in the southern part meets the all of three viability criteria under the current FiT.

As of 2017, there are 9.1 million buildings in Türkiye, 87% of which are residential [56]. Despite the high rooftop area potential, the share of rooftop PV is only 5.84% (200 MW) of the total installed PV capacity (3.42 GW). The attractiveness of rooftop PV systems is noticeably higher in the rest of the world, that is the share of rooftop PV in total installed PV capacity are 21.5% in China (2017), 70% in Germany (2017) and 76.5% in Australia (2018) [57–59]. Thus, a sensitivity analysis was carried out to discuss how to make rooftop PV systems viable in Türkiye.

2.6 Sensitivity Analysis

In order to make future projections and analyze the effect of varying FiT and PV system initial cost on the feasibility of the systems, scenarios of decrease and increase in FiT (-30%, -20%, -10%, +10%, +20%, +30%) and decrease in initial PV initial cost (-30%, -20%, -10%) were evaluated.

The reasons for the increase in FiT can be listed as follows:

- Policymakers increase the amount of FiT to promote rooftop PV investments.
- PV cells and modules begin to be produced in Türkiye and investors who prefer Turkish cells and modules earn higher amount of FiT.

The reasons for the decrease in FiT can be listed as:

- PV deployment rate reaches to a desired level and policymakers decrease FiT.
- Payback period and profitability of the systems reach to a desired level and policymakers decide to decrease FiT.
- PV initial costs drop and policymakers decide to decrease FiT.

And, the reasons for the decrease in PV initial costs can be listed as follows:

- PV module prices continue to fall.
- Policymakers decide to enable tax allowance, tax reduction or capital subsidies to promote rooftop PV systems.

Moreover, for the provinces where 5 kW rooftop PV investments are not favorable, it was calculated how much PV capacity is needed for an attractive investment.

2.6.1 Sensitivity analysis results for the DPBP of 5 kW rooftop PV systems

The results show that under current PV initial cost (Figure 2.7a):

- 10% increase in FiT makes DPBP viable in four of nine provinces.
- 20% increase in FiT makes DPBP viable in five of nine provinces.
- 30% increase in FiT makes DPBP viable in six of nine provinces.

If PV initial costs drop by 10% (Figure 2.7b):

- DPBP in four of nine provinces becomes viable under the current FiT.
- 10% increase in FiT makes DPBP viable in five of nine provinces.

- 20% increase in FiT makes DPBP viable in six of nine provinces.
- 30% increase in FiT makes DPBP viable in seven of nine provinces.

If PV initial costs drop by 20% (Figure 2.7c):

- DPBP in six of nine provinces becomes viable under the current FiT.
- 10% and 20% increase in FiT makes DPBP viable in seven of nine provinces.
- 30% increase in FiT makes DPBP viable in eight of nine provinces.

If PV initial costs drop by 30% (Figure 2.7d):

- DPBP in seven of nine provinces becomes viable under the current FiT.
- 10% increase in FiT makes DPBP viable in eight of nine provinces.
- 20% increase in FiT makes DPBP viable in all nine provinces.

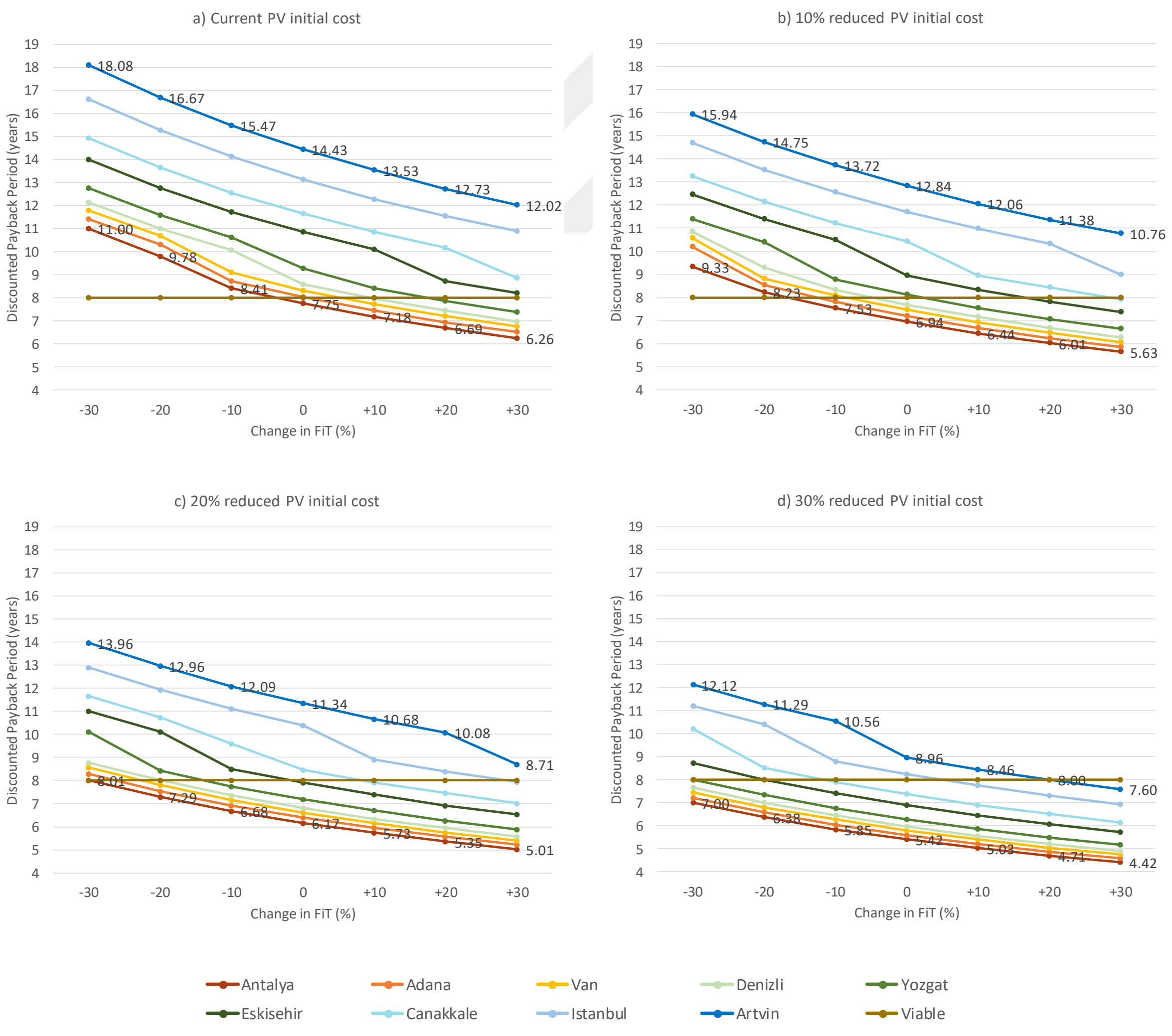

Figure 2.7 : DPBP of 5 kW rooftop systems under varying PV initial cost and FiT.

Note that, after some extent, decrease in PV initial costs makes DPBP of the systems drop a lot more than the desired level in some provinces. Such that, FiT can be decreased in these provinces gradually. And the required increased FiT of northern Türkiye can be compensated with the decreased FiT of the southern provinces.

For instance, as above-mentioned, a 20% reduction in PV costs causes DPBP of the systems to drop below 8 years in six out of nine provinces. In this case, if the amount of FiT is decreased by 10% in five of these six provinces, their DPBP of these systems still stay below 8 years. Moreover, in three of these six provinces, the FiT can be decreased by 20%.

Similarly, a 30% reduction in PV initial costs makes DPBP of the systems drop below 8 years in seven provinces. In this case, the FiT can be decreased by 10% in seven, 20% in six and 30% in five provinces and DPBP of the systems still meet the viability criteria.

2.6.2 Sensitivity analysis results for the IRR of 5 kW rooftop PV systems

The results of the sensitivity analysis show that under current PV initial cost (Figure 2.8a):

- 10% increase in FiT makes IRR viable in four of nine provinces.
- 20% and 30% increase in FiT makes IRR viable in five of nine provinces.

If PV initial costs drop by 10% (Figure 2.8b):

- IRR in four of nine provinces becomes viable under the current FiT.
- 10% increase in FiT makes IRR viable in five of nine provinces.
- 20% increase in FiT makes IRR viable in six of nine provinces.
- 30% increase in FiT makes IRR viable in seven of nine provinces.

If PV initial costs drop by 20% (Figure 2.8c):

- IRR in six of nine provinces becomes viable under the current FiT.
- 10% and 20% increase in FiT makes IRR viable in seven of nine provinces.
- 30% increase in FiT makes IRR viable in eight of nine provinces.

If PV initial costs drop by 30% (Figure 2.8d):

- IRR in seven of nine provinces becomes viable under the current FiT.
- 10% and 20% increase in FiT makes IRR viable in eight of nine provinces.

- 30% increase in FiT makes IRR viable in all nine provinces.

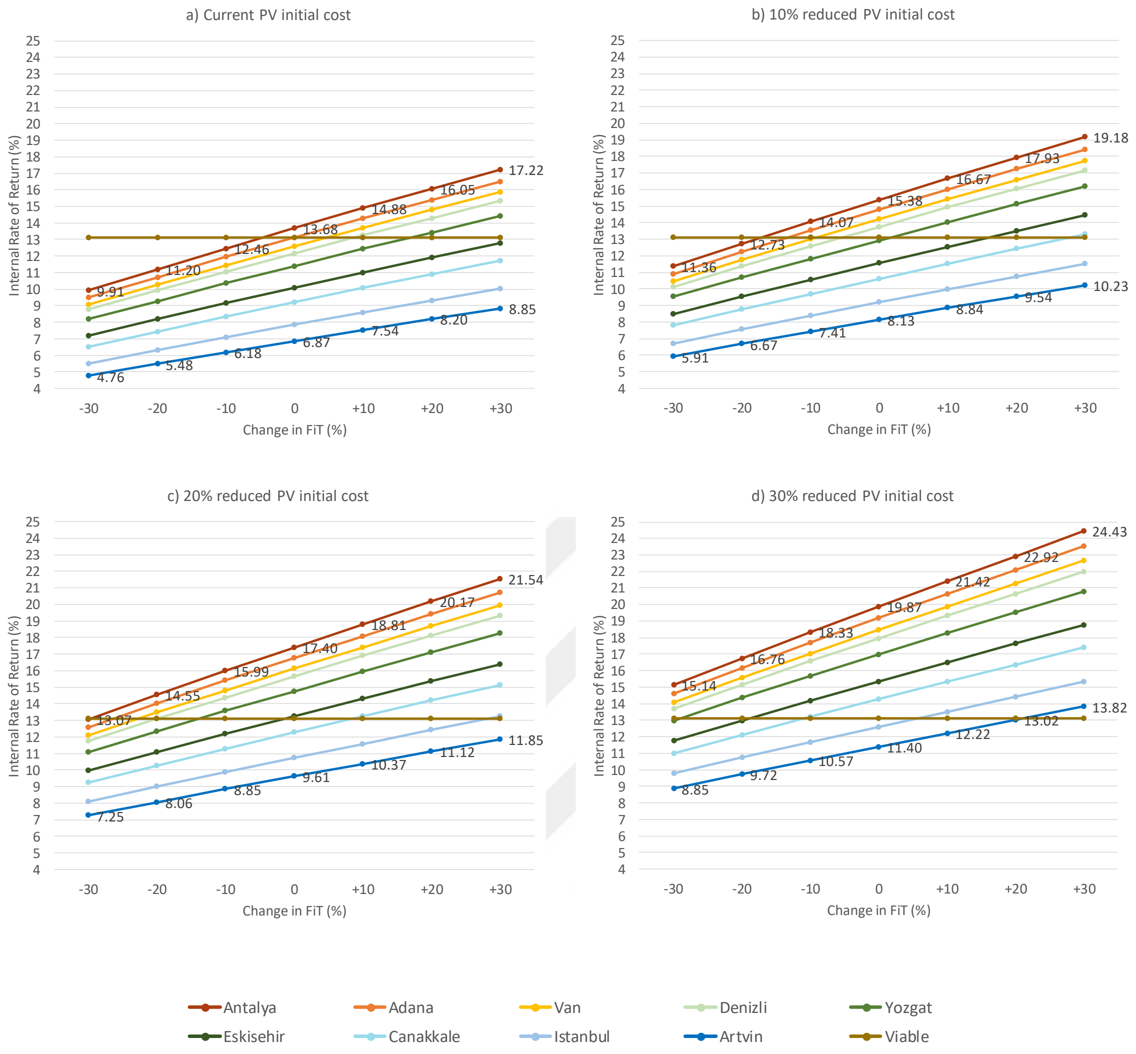

Figure 2.8 : IRR of 5 kW rooftop systems under varying PV initial cost and FiT.

2.6.3 Sensitivity analysis results for the PI of 5 kW rooftop PV systems

The results of the sensitivity analysis show that under current PV initial cost (Figure 2.9a):

- 10% increase in FiT makes PI viable in three of nine provinces.
- 20% increase in FiT makes PI viable in four of nine provinces.
- 30% increase in FiT makes PI viable in five of nine provinces.

If PV initial costs drop by 10% (Figure 2.9b):

- PI in two of nine provinces becomes viable under the current FiT.
- 10% increase in FiT makes PI viable in four of nine provinces.

- 20% increase in FiT makes PI viable in five of nine provinces.
- 30% increase in FiT makes PI viable in six of nine provinces.

If PV initial costs drop by 20% (Figure 2.9c):

- PI in four of nine provinces becomes viable under the current FiT.
- 10% increase in FiT makes PI viable in five of nine provinces.
- 20% and 30% increase in FiT makes PI viable in six of nine provinces.

If PV initial costs drop by 30% (Figure 2.9d):

- PI in five of nine provinces becomes viable under the current FiT.
- 10% and 20% increase in FiT makes PI viable in six of nine provinces.
- 30% increase in FiT makes PI viable in seven of nine provinces.

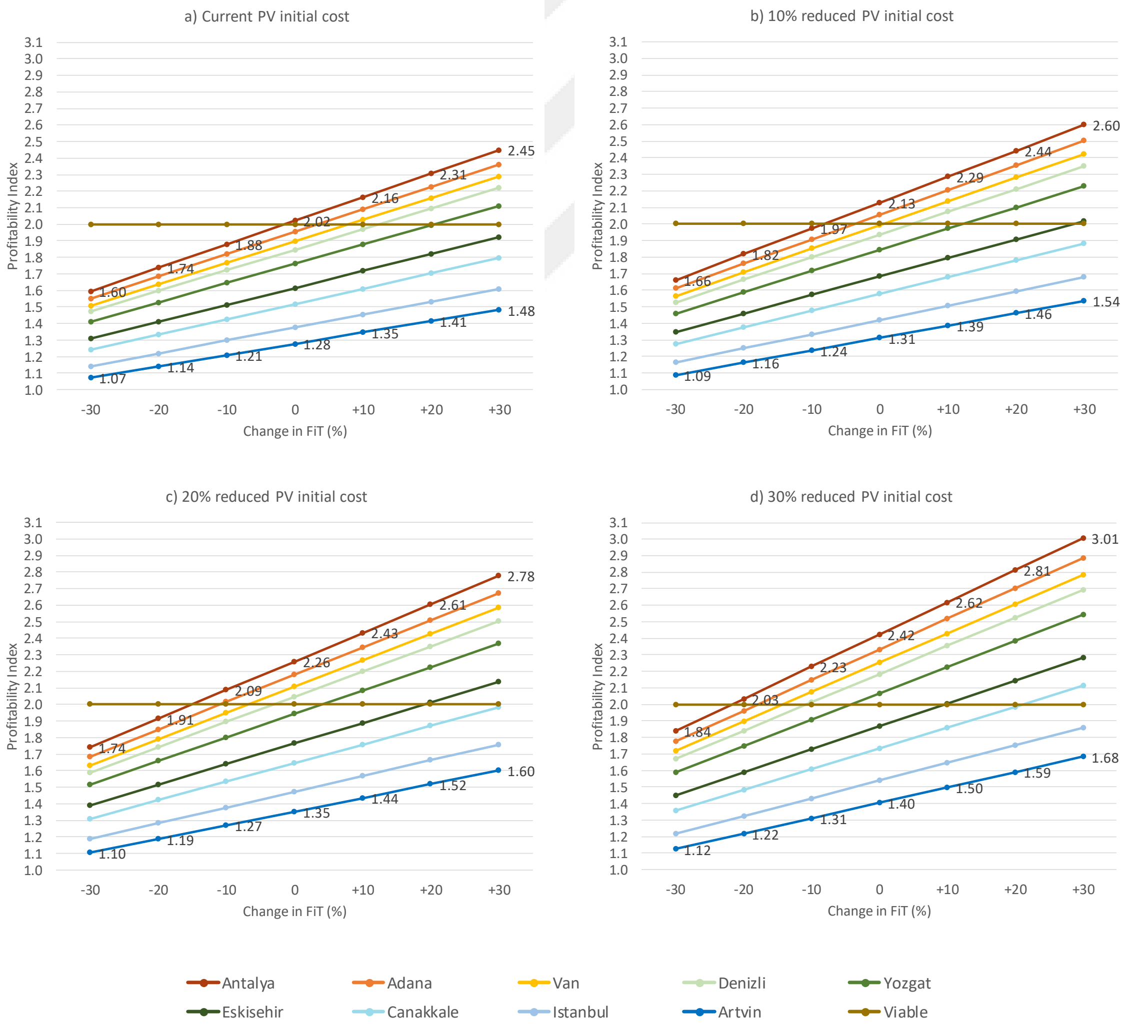

Figure 2.9 : PI of 5 kW rooftop systems under varying PV initial cost and FiT.

2.6.4 Overall results of the sensitivity analysis

The scenarios that make rooftop PV investments viable in each pilot province are given in Table 2.3. Indices I, II, and III represent the southern, central and northern parts of Türkiye, respectively. The given provinces in the table meet all of three viability criteria (DPBP less than 8 years, IRR greater than the discount rate of 13.12%, and PI greater than 2). It is seen that in none of the scenarios Artvin and Istanbul in the northern part can meet the defined criteria.

Table 2.3 : The scenarios that make rooftop PV investments viable.

		PV initial cost			
		Current	10% reduced	20% reduced	30% reduced
Feed-in tariff	30% reduced	None	None	None	None
	20% reduced	None	None	None	Antalya^{I}
	10% reduced	None	None	Antalya^{I}, Adana^{I}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}
	Current	Antalya^{I}	Antalya^{I}, Adana^{I}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}
	10% increased	Antalya^{I}, Adana^{I}, Van^{I}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}
	20% increased	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}
	30% increased	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}	Antalya^{I}, Adana^{I}, Van^{I}, Denizli^{II}, Yozgat^{II}, E.sehir^{II}, Canakkale^{III}

2.6.5 Required PV capacity on the rooftops in each pilot province

The results showed that, under current conditions, 5 kW rooftop PV systems can meet the defined viability criteria only in one province (Antalya) in the southern part. Since the FiT is available in Türkiye up to 10 kW, a sensitivity analysis was conducted up to 10 kW to find out the required PV capacity in provinces in which 5 kW is insufficient. The effect of PV capacity on DPBP, IRR, and PI of the systems are given in Figure 2.10. Table 2.4 demonstrates the PV capacities which meet the defined viability criteria in each province under current conditions. Indices I, II, and III represent the southern, central and northern parts of Türkiye, respectively. It is seen that, in addition to Antalya, the systems can meet the all of three viability criteria, only in three provinces, namely Adana, Van and Denizli by increasing the PV capacity to at least 5.5 kW, 6 kW and 7.5 kW, respectively. After 7.5 kW (up to 10 kW) not any other province can enter this list. To summarize, under current FiT and PV initial cost, by increasing the PV capacity, three of provinces from part I, one province from part II and none of the provinces from part III can meet the viability criteria.

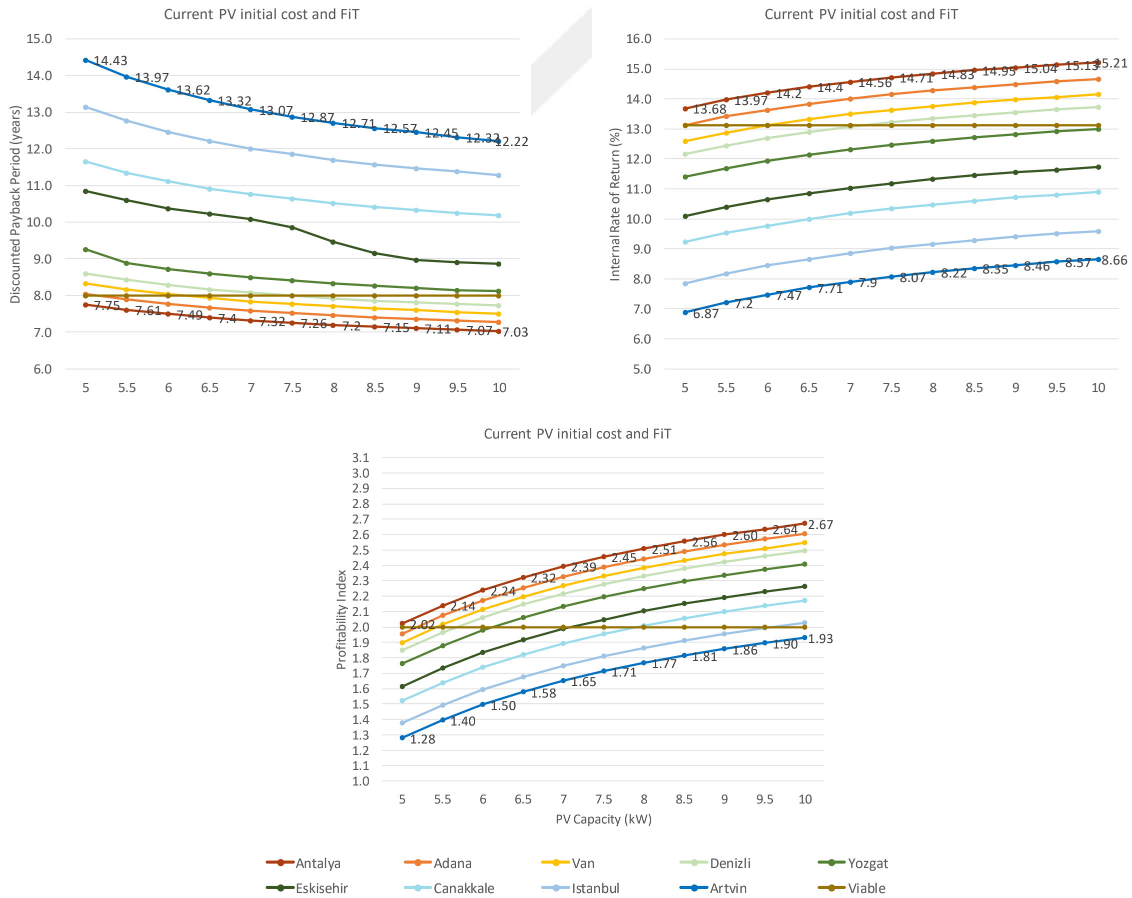

Figure 2.10 : Effect of PV capacity on DPBP, IRR and PI of rooftop PV systems under current PV initial cost and FiT.

Table 2.4 : PV capacities which meet the defined viability criteria under current conditions.

PV capacity (kW)	Province
5	Antalya[I]
5.5	Antalya[I], Adana[I]
6	Antalya[I], Adana[I], Van[I]
6.5	Antalya[I], Adana[I], Van[I]
7	Antalya[I], Adana[I], Van[I]
7.5	Antalya[I], Adana[I], Van[I], Denizli[II]
8	Antalya[I], Adana[I], Van[I], Denizli[II]
8.5	Antalya[I], Adana[I], Van[I], Denizli[II]
9	Antalya[I], Adana[I], Van[I], Denizli[II]
9.5	Antalya[I], Adana[I], Van[I], Denizli[II]
10	Antalya[I], Adana[I], Van[I], Denizli[II]

2.7 Conclusion and Policy Implications

Rooftop PV systems have not become widespread in Türkiye despite the country's relatively high solar radiation, and there is a lack of studies in the literature discussing the efficiency of the current PV support mechanism in the country. Thus, this study presents an economic analysis of grid-connected rooftop PV systems in Türkiye under the current FiT scheme.

In Türkiye, there are large solar radiation differences between regions. In such a country, using a single nationwide support mechanism for grid-connected residential rooftop PVs can become an obstacle for widespread adoption of the systems. Therefore, the need for different PV support schemes for different solar parts in the country was discussed. Three solar parts were formed on the solar potential map of Türkiye in the north-south direction, and three provinces from each part were selected for a comparative feasibility analysis.

To investigate the feasibility of grid-connected residential 5 kW rooftop PV systems, simulations were performed using HOMER Grid software. The results were examined through three different economic indicators, namely DPBP, IRR, and PI, to ensure the viability of the systems from all aspects.

A sensitivity analysis was needed for future projections and policy implications. The analysis was made to investigate the effect of varying PV initial cost, FiT and solar radiation on the feasibility of the systems. In addition to the varying solar radiation of the selected nine provinces, the parameters considered in the sensitivity analysis were:

- 30%, 20%, 10% decrease and increase in FiT.
- 30%, 20%, 10% decrease in initial PV cost.

Here, the instruments to decrease PV initial cost can be capital subsidies or tax incentives. It should be noted that the scenario for decreased PV initial cost also corresponds to the future projections in which PV module prices fall.

Results showed that under current conditions in Türkiye;

- DPBP of 5 kW rooftop PV systems is in the range of 7.75 – 14.43 years.
- IRR of 5 kW rooftop PV systems is in the range of 13.68% – 6.87%.
- PI of 5 kW rooftop PV systems is in the range of 2.02 – 1.28.

These results indicate the insufficiency of the current FiT scheme. Among nine provinces, only Antalya in the southern region can meet the viability criteria with DPBP below 8 years, IRR more than 13.68%, and PI more than 2. Profitability decreases from South to North in the country as expected. Antalya is the best location among the nine provinces in Türkiye to invest in rooftop PVs, whereas Artvin presents the least viable results.

According to the results of the sensitivity analysis, the support schemes given below make the systems meet all the defined economic criteria (DPBP below 8 years, IRR above 13.12%, and PI above 2) in all three solar parts:

Southern part

- 10% increased FiT or,
- 20% reduced PV initial cost or,
- 10% reduced FiT with 30% reduced PV initial cost

Central part

- 30% increased FiT with 10% reduced PV initial cost or,
- 20% increased FiT with 20% reduced PV initial cost or,
- 10% increased FiT with 30% reduced PV initial cost

Northern part

- 30% increased FiT and 30% reduced PV initial cost (In this case, all three criteria are met in the province of Canakkale. However, in provinces of Istanbul and Artvin although DPBP and IRR criteria are met, PI slightly stays under the defined limit.)

The study was conducted for an average open gable roof in Türkiye which is suitable for 5 kW rooftop PV systems. Nevertheless, FiT for residential users is available up to 10 kW in Türkiye. If there is enough space, users can also invest in higher capacity PV systems. The required PV capacities in each province were also calculated as summarized as follows:

- 5 kW – Antalya
- 5.5 kW – Antalya, Adana
- 6 kW – Antalya, Adana, Van
- 7.5 kW – Antalya Adana, Van, Denizli

The other findings and insights of the study are listed as follows:

- Despite Türkiye's high solar potential, relatively low electricity prices prevent widespread adoption of rooftop PV systems in Türkiye. The prices have remained almost stable in the last ten years, and at a low level. This causes rooftop PV investors to achieve low electricity bill savings. The profitability is low and this makes payback period of the systems to increase.
- Province of Istanbul (which alone contains 18.75% of Türkiye's entire population), the capital Ankara and many other populated and industrialized provinces are located in the northern part and contain the highest rooftop potential in Türkiye. Therefore, increasing the attractiveness of rooftop PVs in the northern part of Türkiye has vital importance.
  In many countries, the authorities have begun to reduce the amount of FiT due to falling PV module prices and PV supply exceeding the demand during midday. Nevertheless, possible high penetration of electric vehicles to the grid in the near future should be taken into account, and FiT should be sustained as high as possible. Since the number of electric vehicles in Türkiye will be greater in the populated and developed northern part, the requirement of the regional incentive mechanisms is much of greater significance.
- Türkiye's first integrated solar module, cell, and panel production factory was inaugurated at the beginning of 2018. Since the amount of FiT in Türkiye can rise up to 0.20 $/kWh depending on the local content of the PV components,

residential users who prefer products manufactured in Türkiye may benefit from increased FiT. In this case, rooftop PV investments can become viable not only in the southern provinces but also in the central provinces of the country. The scenario of increased FiT in the sensitivity analysis also corresponds to this case.

The main limitation of this study was the interest rate fluctuation at the time of the study. We decided to use the historical average of the last 10 years. Also, the change in retail electricity prices which can be an important parameter in the sensitivity analysis was neglected. This was due to the stable retail electricity prices in Türkiye in the last 10 years. Consideration of one more dimension in the sensitivity analysis could have made it difficult to interpret and explain the results.

The profitability of the residential PV systems can be further increased by the application of demand-side management (DSM) through storage systems and self-consumption. For this reason, promotional campaigns should also be developed to encourage DSM. DSM will also constitute the subject of future studies.

The proposed model in this study can be adapted in countries where there are large solar radiation differences between different regions, such as in Türkiye. Instead of using nationwide support models, regional support models can be considered.

3. A HOME ENERGY MANAGEMENT SYSTEM WITH AN INTEGRATED SMART THERMOSTAT FOR DEMAND RESPONSE IN SMART GRIDS

Smart thermostats and home energy management systems (HEMSs) are generally studied separately. However, their joint use can provide a greater benefit. Therefore, this chapter aims to combine a smart thermostat with a HEMS. The mixed-integer linear programming (MILP)-based HEMS performs day-ahead load scheduling for cost-minimization and provides optimal demand response (DR) and photovoltaic (PV) self-consumption, and the fuzzy logic-based thermostat aims efficient DR of air-conditioning and maintenance of thermal comfort. In the first stage, unlike conventional fixed set-point thermostats, the proposed thermostat defines different set-points for each time interval, by fuzzifying input parameters of electricity prices, solar radiation, and occupant presence, to be used by HEMS. In the second stage, the HEMS schedules the operation of time-shiftable, thermostatically controlled, and power-shiftable (battery energy storage system (BESS), electric vehicle (EV)) loads. The HEMS considers bi-directional power flow between home, BESS, EV, and grid, as well as battery degradation to avoid unnecessary energy arbitrage. The simulation results show that a daily cost reduction of 53.2% is achieved under time-of-use (TOU) and feed-in tariff rates of Türkiye. AC cost is reduced by 24% compared to conventional thermostats. In a future scenario of real-time pricing (RTP) and dynamic feed-in tariff, vehicle-to-grid (V2G) becomes possible.

3.1 Introduction

The rise in global electrical energy consumption and production, along with the rapid integration of intermittent renewable sources to the electricity network required improvement and modernization of the aging grid infrastructure to obtain safe, reliable, and clean energy. Consequently, the smart grid concept has emerged, in which all players in the grid network connect and interact with each other through information and communication technologies (ICTs) to improve stability, resource efficiency, and sustainability in energy production, transmission, and distribution fields [1]. Residential demand-side management (DSM), associated with the smart grid concept, aims to address these challenges by managing electrical energy usage of residential end-users which are responsible for 26.9% of world electricity final consumption [60].

Demand response (DR), which is a tool for DSM, can be defined as all the short-term activities, aiming to modify consumption patterns of end-users in the form of peak clipping, valley filling, or load shifting to meet a load shape demanded by the electricity grid [61]. To implement residential DR, load-serving entities (LSEs) offer time-dependent pricing or financial incentives to end-users to perform direct load control (DLC) or indirect load control (ILC) with the help of advanced metering infrastructure (AMI).

In DLC programs, end-users permit LSEs to remotely control their appliances mainly for peak shaving or frequency regulation in return for incentives [62]. Yet, DLC may lead to unwillingness due to a sense of losing control [63,64] and privacy concerns [65].

In ILC programs (also known as price-based programs) end-users are motivated to change their consumption patterns according to time-based electricity rates such as time-of-use (TOU) [66], critical peak pricing (CPP) [67], inclining block rates (IBR) [68] and real-time pricing (RTP) [69] in a penalty-reward manner [70]. However, ILC brings along a challenge of energy management as a number of electrical appliances increases in a household [71].

On the other hand, as distributed generation units are becoming more widespread, especially rooftop photovoltaics (PVs), a paradigm shift has occurred in the structure of the traditional electricity grid. Traditionally passive residential consumers are turned into active market players and assume the role of prosumers. Since the generous feed-in tariff rates introduced at the beginning have reduced today [72], residential load management gains importance not only to respond to time-based prices for DR but also to benefit from a distributed generation at the maximum level by increasing self-consumption.

In addition, the residential users earned the opportunity to become active participants in the electricity market environment by means of energy arbitrage practiced by battery energy storage systems (BESSs) to buy energy from the grid at a low price or store on-site generated energy for free and to sell it to the grid at a higher price [73].

Moreover, the emergence of electric vehicles (EVs) introduced new technologies such as vehicle-to-grid (V2G) and vehicle-to-home (V2H) [74], or in short, vehicle-to-everything (V2X) [75] to overcome the problems which will be caused by the substantial impact of EVs on the electricity grid in the near future.

Consequently, in recent years, researchers have been primarily focused on home energy management systems (HEMSs) that can respond to all the above-mentioned challenges and innovations. This study, too, aims to develop a HEMS for their subsequent use in residential buildings, by enabling DR and increased self-consumption together.

Today, space heating and cooling accounts for a share of more than 50% in total residential electricity consumption [76]. Therefore, maintaining thermal comfort gains more importance since thermal discomfort is one of the main barriers in adopting DR programs [77]. To that end, the study also proposes to integrate a smart thermostat into a HEMS for efficient DR of air-conditioning and higher thermal comfort of residents.

3.2 Literature Summary

3.2.1 Smart home appliances in residential DR

In the literature, smart home appliances compatible with residential DR fall into three categories as follows:

1) Time-shiftable appliances (TSAs) like washing machines, dishwashers, clothes dryers, which have fixed power consumption patterns and are uninterruptible once they are launched [78].

2) Thermostatically controlled appliances (TCAs) like air conditioners (ACs), electric water heaters (EWHs), and refrigerators, which are capable of storing thermal energy in a storage medium by pre-cooling or pre-heating and providing set-point temperature modification within the limits of thermal boundaries [79].

3) Power-shiftable appliances (PSAs) like BESSs and EVs, which have flexible power consumption patterns and can operate between the minimum and maximum power limits [78].

TSAs generally have lower power consumption in households compared to TCAs and PSAs. [80] studied DR options of a dishwasher in a home with an integrated wind turbine. [81] investigated the DSM of dishwashers and washing machines through the management of hot water supply. Several studies demonstrated the measured data of load profiles of TSAs to be used in DR studies [82,83].

TCAs offer wider DR possibilities with their higher energy consumption and thermal energy storage capability, yet thermal comfort boundaries limit them. [84] and [85] studied DR possibilities of refrigerators with set-point adjustment and pre-cooling control. [86] developed a partial differential equation (PDE) based model for EWHs as a benchmark in DR studies. [87] applied cost-comfort oriented EWH management under dynamic pricing. [88] enabled model predictive control (MPC) of ACs for DR considering pre-defined set-point values of inhabitants and real-time electricity prices. The DR possibilities of fixed-speed and inverter ACs are studied in [89] and [90], respectively.

The DR possibility of PSAs have recently aroused interest due to the emergence of EVs and the wide distribution of energy storage systems combined with distributed generation units. [91] studied a PV–BESS based energy management system to increase residential self-consumption. [92] developed an optimal EV charging/discharging strategy to provide DR and prevent adverse effects of EVs on low voltage distribution systems.

Residential DR can be enabled through individual smart appliances as in the above examples. Also, following a holistic approach, several smart appliances can be controlled simultaneously utilizing a HEMS.

3.2.2 Home energy management systems (HEMSs)

A HEMS allows users to monitor, control, and automate an ever-increasing number of their smart appliances efficiently by spending the least effort and time without human intervention [93]. It can maximize electricity bill savings by DR and self-consumption as well as can provide energy arbitrage. The holistic approach exemplified by HEMS allows to avoid demand charges or to comply with peak limits.

In recent years, there has been a growing body of research about HEMSs for DR. [94] studied scheduling of shiftable appliances in a smart home, which alone provided low bill savings. [95] optimized load scheduling of dishwasher, washing machine, clothes dryer, and plug-in hybrid EV under RTP. A peak limiting strategy to prevent the occurrence of further peaks was neglected. [96] developed an algorithm-based HEMS considering load priority and users' comfort preferences based on the use of AC, EWH, EV, and clothes dryer. A peak limit was considered to be imposed on household energy consumption. Demand curtailment was guaranteed during peak hours, but pre-cooling/heating was not considered for AC and EWH. [97] dealt with the uncertainties of EV arrival and departure times in a stochastic framework. However, in [94–97], V2G and V2H possibilities of EVs were neglected in HEMS operation. Also, these studies did not include the presence of distributed generation units and BESSs in smart homes.

[98] studied operation of TSAs, TCAs and considered presence of PV-BESS units. [99] evaluated operation of TSAs, EV, and PV-BESS taking into account V2H, but the management of TCAs is neglected. [100] considered battery-to-grid (B2G), battery-to-home (B2H), V2G, and V2H operations in a household comprising EV, PV–BESS, and EWH. The operation of TSAs and ACs were not considered. The model proposed by [101] combined all the above-mentioned types of operational possibilities of TSAs, TCAs, and PSAs together in a single HEMS structure as well as considered a presence of an integrated distributed generation unit. V2H and B2H operations were taken into account, yet selling energy back to the grid was not considered. In [100,101] a PV model was not embedded in HEMSs, and estimation of PV production was based on pre-measured values. [102] and [103] included a simplified solar model for a fixed-tilt PV array that could turn a received solar radiation data into a PV power output, but a model for a tilted PV array was neglected. [104] used a location-based regression model for PV output, which may be hard to implement in a commercially available HEMS in real life. None of the mentioned studies considered a solar model for a tilted PV array. Also, in all the studies (except in [102]) battery degradation was neglected or batteries were assumed to be replaced free-of-charge due to pre-made agreements. In [102] self-consumption with BESS is proved to be not always preferable to a PV-only system when battery degradation is taken into account.

Self-consumption can be increased by shifting loads to a PV generation period. In [91], self-consumption was managed, however, performing DR to benefit from time-based prices was neglected. [105] proposed a detailed HEMS framework based on DR, however, the proposed algorithm did not aim to increase self-consumption. [102], [106], and [107] considered DR and self-consumption together and took into account battery degradation, but did not focus on load management.

3.2.3 Smart thermostats

DR may not be adopted to a desired level due to possible end-user comfort violations. One of the most repulsive of these is thermal comfort violation. Therefore, the studies regarding DR-related thermostats are examined under a subtitle in the literature summary.

[94], [108] and [109] handled ACs as curtailable loads and the curtailment was enabled through kW reduction. Yet, without a thermal model that allows to make an accurate prediction of the thermal behaviour of a household, this method is likely to cause a thermal comfort violation due to not being able to capture temperature changes.

[110] obtained a detailed thermal model of a house using OpenStudio and Energyplus and applied set-point modification under RTP. [111] developed a detailed lumped-capacitance model for HVAC operation in a household considering occupants' comfort level. Although highly-complex thermal models reduce the percentage of error, they are hard to implement in real-life applications due to a lack of knowledge about physical properties of buildings [112]. [113] examined various thermal models for buildings and a detailed 8R3C thermal model and a simplified 1R1C model are found to have closer Root Mean Square Errors (RMSEs), whereas the best result is obtained with a 4R2C model. 1R1C thermal model is widely preferred in HEMS studies due to its linear form, simplicity, and fast response [101,105,114–116].

Various studies focused on smart thermostats to respond to changing conditions. [114,117,118] proposed a fuzzy logic-based smart thermostat for residential heating, ventilation, and air conditioning (HVAC) systems. Unlike conventional thermostats, the proposed model uses a fuzzy inference system (FIS) to adjust set-point temperature according to the changes in electricity prices, occupant presence and outdoor temperature. Nevertheless, the possible availability of a small-scale PV or a BESS in the household was not evaluated in the decision-making process. [119] designed a controller to coordinate PV, BESS, and HVAC in a building to reduce peak electrical demand in response to fluctuations in dry-bulb air temperature, electricity prices, energy demand, and comfort conditions, taking into account PV generation and battery state-of-charge (SoC) in decision-making. In [114,117–119] only set-point modification was considered in a real-time control manner and pre-cooling/heating were not available.

In [101,103,120] benefiting from thermal inertia inside was considered. [120] proposed a MATLAB-TRNSYS based model that could provide pre-cooling/heating and also switch between an electrical Air Source Heat Pump (ASHP) and a natural gas mini boiler depending on the thermal demand of a house and electricity/gas prices. [79] considered comfort violation minimization in DLC based DR programs for AC control. Fairness of allocation of comfort violation was considered as well as the impact of humidity on dry-bulb temperature.

A few number of studies considered smart AC operation under a HEMS framework, in which both varying outer and inner conditions and status of other appliances in a household can be taken into account in decision-making. [121] proposed a hardware design of a HEMS and considered thermal comfort in AC operation. However, the HEMS handled each electrical load individually which limits to respond to demand charges/peak limits and does not allow to optimally distribute a generated energy in presence of a PV unit. [122] developed a detailed HEMS comprising a smart thermostat that adjusts set-point considering varying conditions including occupancy level. Battery degradation was neglected both in [121,122]. [123] considered all the above-mentioned deficiencies except occupant presence in a thermostat integrated HEMS. AC set-point temperature was adjusted based on the dissatisfaction of homeowners. [124] combined an adaptive AC with a HEMS considering indoor temperature, humidity, and clothing condition.

3.3 Content and Contributions

Based on the literature review and the above discussions, the specific contribution of this study is twofold:

(1) The main contribution is to combine a HEMS with a smart thermostat to provide efficient demand response (DR) of the air conditioner (AC) with a higher thermal comfort of end-users.

- Instead of using a conventional thermostat with a fixed set-point, we introduce a smart thermostat that regulates an initialized set-point according to the changing conditions (electricity prices, solar radiation, and occupant presence), as specified in Table 3.2. Therefore, DR for AC is provided flexibly. For instance, the thermostat sets a higher set-point within the ASHRAE limits for AC in on-peak hours to reduce the electricity costs; however, the set-point will not be the same for different occupancy levels. In the case of high occupancy, the smart thermostat places more emphasis on thermal comfort, and the set-point becomes lower than in the case of less or no occupancy. The changes in the AC set-point also differ depending on the state of PV generation at home. Ultimately, fuzzy logic is preferred for considering several factors.

- Since the smart thermostat is not handled as a separate device but a part of a HEMS, all the electrical loads, including AC, are considered in the day-ahead optimization and it is ensured that a stored solar energy is optimally distributed among all household appliances, peak power limits are met and demand charges are avoided. When necessary, the HEMS can provide pre-heating/cooling as well.

(2) To the best of our knowledge, this is one of the most comprehensive HEMSs in the literature when all the relevant aspects are considered. After examination of the publications, it became apparent that on the basis of HEMSs:

- integration of a smart thermostat into a HEMS
- controlling of all type of residential loads (TSA, TCA, PSA)
- consideration of increased PV self-consumption and DR at the same time
- consideration of vehicle-to-grid (V2G), vehicle-to-home (V2H), vehicle-to-battery (V2B), battery-to-grid (B2G), battery-to-home (B2H), battery-to-vehicle (B2V), home-to-grid (H2G) operations together
- consideration of battery degradation to prevent unnecessary energy arbitrage
- consideration of a solar model for a tilted PV array, that considers installed capacity, tilt angle of array and the impact of temperature on PV power output

are not evaluated together in a single HEMS framework. Therefore, a load scheduling optimization-based HEMS which combines all the above-mentioned features within is proposed in this study.

Istanbul is chosen as the case study location. Cost savings provided by the HEMS varies according to different types of households. Thus, daily utility bills of six types of households with different load profiles are analyzed under TOU and feed-in tariff rates of Türkiye, and solar radiation and temperature conditions of Istanbul. Afterward, the HEMS is tested for different days of the same month to examine the smart thermostat operation under different weather conditions. Lastly, since Turkish residents cannot benefit from residential RTP, which can enhance the efficiency of HEMSs, the static TOU rates of Türkiye are modified into hourly varying RTP rates and the performance of the HEMS is evaluated under dynamic pricing.

The proposed HEMS includes two stages: set-point adjustment of AC and day-ahead scheduling of all electrical loads. The workflow of the HEMS is given in Figure 3.1. Homeowners enter occupant presence information, their preferred initial set-point temperature for AC, their preferred times of operation ranges for TSAs (if any), hot water usage times for EWH, and preferred charging times of EV. → LSE forwards energy price, DR information, and weather forecast to the household. → The embedded smart thermostat uses the received solar radiation forecast and electricity price data and user-defined occupant presence information (which can either be measured by sensors or be entered by users) and defines different AC set-point values for each time interval to be used in the optimization. → The optimization algorithm of the HEMS performs day-ahead load scheduling to provide DR and self-consumption. Bi-directional power flow between home, BESS, EV, and grid are considered as well as battery degradation to avoid unnecessary energy arbitrage. The framework of the HEMS architecture and the present electrical loads in the household are presented in Figure 3.2.

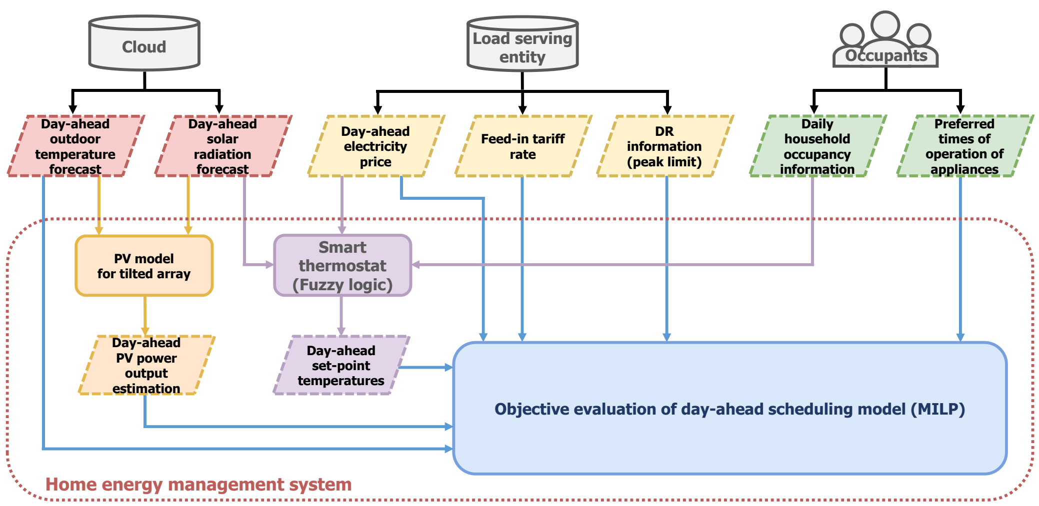

Figure 3.1 : The workflow of the HEMS.

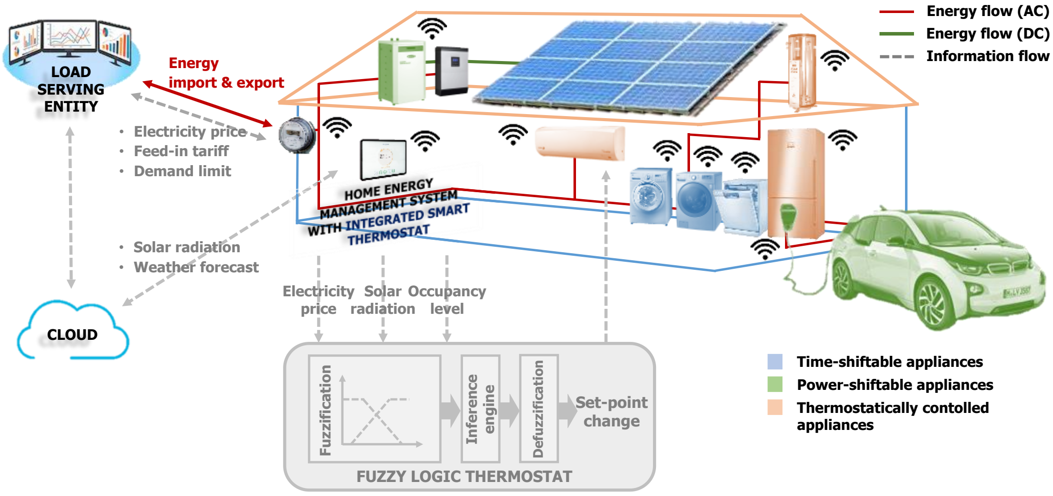

Figure 3.2 : The framework of the HEMS architecture.

3.4 Methodology and Formulation

The HEMS is formulated in the form of a MILP problem as the appliance models are linear and MILP ensures a global optimum solution with a fast convergence rate. MATLAB's branch-and-bound based "intlinprog" solver is used. The objective of the HEMS optimization problem is to minimize the daily electricity cost of the household:

$$\min f = \sum_{t} \left\{ \begin{matrix} P_t^{G} \cdot \Delta t \cdot \lambda_t^{buy} + P_t^{V,G} \cdot \Delta t \cdot \lambda_t^{V,buy} + P_t^{B,G} \cdot \Delta t \cdot \lambda_t^{B,buy} \\ -P_t^{PV,2G} \cdot \Delta t \cdot \lambda_t^{sell} - P_t^{V,2G} \cdot \Delta t \cdot \lambda_t^{V,sell} - P_t^{B,2G} \cdot \Delta t \cdot \lambda_t^{B,sell} \end{matrix} \right\} \tag{3.1}$$

$$\begin{aligned} \lambda_t^{V,buy} &= \lambda_t^{buy} + \lambda^{V,deg} \\ \lambda_t^{V,sell} &= \lambda_t^{sell} + \lambda^{V,deg} \\ \lambda^{V,deg} &= \frac{Rep^V}{(L^V \cdot \eta^{V,rt})} \\ L^V &= Cyc^V \cdot Cap^V \cdot DoD^V \end{aligned} \tag{3.2}$$

$$\begin{aligned} \lambda_t^{B,buy} &= \lambda_t^{buy} + \lambda^{B,deg} \\ \lambda_t^{B,sell} &= \lambda_t^{sell} + \lambda^{B,deg} \\ \lambda^{B,deg} &= \frac{Rep^B}{(L^B \cdot \eta^{B,rt})} \\ L^B &= Cyc^B \cdot Cap^B \cdot DoD^B \end{aligned} \tag{3.3}$$

Here, the bought energy expressed by P_t^G is the sum of the power purchased from the grid by all appliances (TCAs, TSAs) excluding the PSAs. The PSAs are differentiated here to prevent unnecessary energy arbitrage by including battery degradation costs in their buying and selling prices [125]. Therefore, $\lambda_t^{V,buy}$ and $\lambda_t^{B,buy}$ are the sum of buying price λ_t^{buy} and battery degradation prices $\lambda^{V,deg}$, $\lambda^{B,deg}$. Similarly, $\lambda_t^{V,sell}$ and $\lambda_t^{B,sell}$ are the sum of the selling price λ_t^{sell} and battery degradation prices $\lambda^{V,deg}$, $\lambda^{B,deg}$. Thus;

- V2G or B2G are considered if only the benefit of selling energy to the grid is higher than the battery degradation cost.
- V2H and B2H are considered if only the benefit of buying energy to use at a later time at home is higher than the battery degradation cost.

It should be noted that the degradation cost is not included in the electricity bill. The buying and selling prices of the PSAs above are artificial prices to optimally schedule loads and prevent batteries from unnecessary energy arbitrage. Therefore, after the load scheduling, EV and BESS buying and selling costs are calculated once again by removing the degradation cost.

3.4.1 Time-shiftable appliances (TSAs)

TSAs have fixed power consumption patterns and uninterruptible once they are launched. TSAs are modeled as follows [126,127]:

$$P_a^{TSA} = \begin{bmatrix} p_{a,1}^{TSA} & p_{a,t}^{TSA} & \cdots & p_{a,3}^{TSA} & p_{a,2}^{TSA} \\ p_{a,2}^{TSA} & p_{a,1}^{TSA} & \cdots & p_{a,4}^{TSA} & p_{a,3}^{TSA} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{a,t}^{TSA} & p_{a,t-1}^{TSA} & \cdots & p_{a,2}^{TSA} & p_{a,1}^{TSA} \end{bmatrix}, \forall t \in \ [t_a^{min}, t_a^{max}] \tag{3.4}$$

$$X_a^{TSA} = [x_{a,1}^{TSA}, x_{a,2}^{TSA}, \dots, x_{a,t}^{TSA}]', \forall t \in \ [t_a^{min}, t_a^{max}] \tag{3.5}$$

$$X_a^{TSA} = \sum_{t=1}^{T} x_{a,t}^{TSA} = 1,\ X^{TSA} \in \{0,1\}, \forall t \in \ [t_a^{min}, t_a^{max}] \tag{3.6}$$

$$run_a \leq |t_a^{max} - t_a^{min}| \tag{3.7}$$

$$P^{TSA} = \sum_{a=1}^{A} P_a^{TSA} X_a^{TSA} \tag{3.8}$$

Power consumption of a TSA cannot be interfered during its operation. Fixed power consumption of a TSA can be given by $\boldsymbol{P_a^{TSA}} = \begin{bmatrix} \boldsymbol{p_{a,1}^{TSA}} & \boldsymbol{p_{a,2}^{TSA}} & \cdots & \boldsymbol{p_{a,T}^{TSA}} \end{bmatrix}'$. Then, all possible combinations of power consumption of a TSA can be expressed as in Eq. (3.4). Since only one of the combinations gives the optimal result, to select the optimal one, a switch vector of $\boldsymbol{X_a^{TSA}}$ is used as in Eq. (3.5). There can be only one non-zero element in $\boldsymbol{X_a^{TSA}}$ as expressed in Eq. (3.6). Vector $\boldsymbol{X_a^{TSA}}$ is an optimization parameter to choose the optimal column in $\boldsymbol{P_a^{TSA}}$. Users may have preferred times of operation for TSAs. Therefore, $\boldsymbol{t_a^{min}}$ and $\boldsymbol{t_a^{max}}$ denote the beginning and ending of the preferred times of operation range of a TSA. The length of a preferred time interval (the difference between $\boldsymbol{t_a^{min}}$ and $\boldsymbol{t_a^{max}}$) cannot be lower than a running time of a TSA as stated in Eq. (3.7). The power consumption of a TSA is given in Eq. (3.8).

3.4.2 Power-shiftable appliances (PSAs)

3.4.2.1 Battery energy storage system (BESS)

BESS is modeled as follows [128]:

$$P_t^{B,2H} + P_t^{B,2V} + P_t^{B,2G} = \eta^{B,dis} \cdot P_t^{B,dis}, \qquad \forall t \tag{3.9}$$

$$0 \leq P_t^{B,ch} \leq R^{B,ch} \cdot x_t^B, \qquad \forall t \tag{3.10}$$

$$0 \leq P_t^{B,dis} \leq R^{B,dis} \cdot (1 - x_t^B), \qquad \forall t \tag{3.11}$$

$$SoE_t^B = SoE_{t-1}^B + \eta^{B,ch} \cdot P^{B,ch} \cdot \Delta t - P^{B,dis} \cdot \Delta t\,, \qquad \forall t > 1 \tag{3.12}$$

$$SoE_t^B = SoE^{B,ini}, if\ t = 1 \tag{3.13}$$

$$SoE^{B,max} \cdot (1 - DoD^B) \leq SoE_t^B \leq SoE^{B,max}, \qquad \forall t \tag{3.14}$$

Eq. (3.9) describes that the discharged power of the BESS is the sum of the power used in the household and injected to the grid. Eq. (3.10) and (3.11) state that the charging and discharging power of the BESS at a particular time cannot exceed the charging and discharging rate of the battery. Eq. (3.12) and (3.13) define the state of energy

(SoE) of the BESS. Eq. (3.14) states that SoE of the BESS cannot exceed the maximum battery capacity and the minimum allowed SoE is limited by the permissible depth of discharge (DoD).

3.4.2.2 Electric vehicle (EV)

The operation of the EV, so are the Eq. (3.15-3.20) are similar to the BESS except that, while BESS is in operation all day long, charging and discharging of the EV are constrained by the EV arrival and departure time (or preferred charging times). Besides, the EV battery should be fully charged before its departure as expressed in Eq. (3.21). EV is modeled as follows [128]:

$$P_t^{V,2H} + P_t^{V,2B} + P_t^{V,2G} = \eta^{V,dis} \cdot P_t^{V,dis}, \qquad \forall t \in [t^{arr}, \quad t^{dep}] \tag{3.15}$$

$$0 \leq P_t^{V,ch} \leq R^{V,ch} \cdot x_t^V, \qquad \forall t \in [t^{arr}, \quad t^{dep}] \tag{3.16}$$

$$0 \leq P_t^{V,dis} \leq R^{V,dis} \cdot (1 - x_t^V), \qquad \forall t \in [t^{arr}, \quad t^{dep}] \tag{3.17}$$

$$SoE_t^V = SoE^{V,ini} + \eta^{V,ch} \cdot P^{V,ch} \cdot \Delta t - P^{V,dis} \cdot \Delta t, \qquad \forall t \in t^{arr} \tag{3.18}$$

$$SoE_t^V = SoE_{t-1}^V + \eta^{V,ch} \cdot P^{V,ch} \cdot \Delta t - P^{V,dis} \cdot \Delta t, \ \forall t \in [t^{arr}, \ t^{dep}] \tag{3.19}$$

$$SoE^{V,max} \cdot (1 - DoD^V) \leq SoE_t^V \leq SoE^{V,max}, \qquad \forall t \in [t^{arr}, \quad t^{dep}] \tag{3.20}$$

$$SoE_t^V = SoE^{V,max}, \ t = t^{dep} \tag{3.21}$$

3.4.3 Thermostatically controlled appliances (TCAs)

Three TCAs are considered in the HEMS operation, namely, AC, EWH, and refrigerator. A first-order lumped capacitance 1R1C gray-box model is used, which is reported in several studies to be sufficiently reliable to capture thermal behaviour of house, EWH tank, and refrigerator cabinet [129–131].

3.4.3.1 Electric water heater (EWH)

Eq. (3.22) formulates the EWH model. Here, the EWH tank is assumed to be located in a part of the house that is under the effect of AC operation, thus T_t^{amb} represents the day-ahead ambient set-point temperatures imposed by the smart AC thermostat. uc vector defines the hot water usage times. When hot water is used, it is replaced by inlet water. EWH does not allow the water temperature to drop below the minimum allowed temperature. Eq. (3.23) denotes the allowed hot water temperature limits inside the EWH tank. Eq. (3.24) gives the electrical power consumption of the EWH.

$$T_t^{hw} = \frac{\left(T_t^{amb} + \dot{c}^{EWH} \cdot R^{EWH} \cdot T_t^c \cdot uc_t + R^{EWH} \cdot COP^{EWH} \cdot P^{EWH} \cdot x_t^{EWH}\right)}{(1 + \dot{c}^{EWH} \cdot R^{EWH} \cdot uc_t)} + \left(T_{t-1}^{hw} - \left(\frac{\left(T_t^{amb} + \dot{c}^{EWH} \cdot R^{EWH} \cdot T_t^c \cdot uc_t + R^{EWH} \cdot COP^{EWH} \cdot P^{EWH} \cdot x_t^{EWH}\right)}{(1 + \dot{c}^{EWH} \cdot R^{EWH} \cdot uc_t)}\right)\right) \cdot e^{\frac{-(1+\dot{c}^{EWH} \cdot R^{EWH} \cdot uc_t) \cdot \Delta t}{R^{EWH} \cdot C^{EWH}}}, \quad \forall t \tag{3.22}$$

$$T^{hw,min} \leq T_t^{hw} \leq T^{hw,max}, \forall t \tag{3.23}$$

$$P_t^{EWH} = P^{EWH} \cdot x_t^{EWH}, \forall t \tag{3.24}$$

3.4.3.2 Refrigerator

The refrigerator's thermal model is similar to the EWH's. Except that, the decision variable changes sign and becomes negative for the cooling operation. Also, the effect of door openings on cabinet temperature is neglected. The latter is excluded from the model due to its low effect on temperature and power consumption [82,83].

$$T_t^{in} = \left(T_t^{amb} - R^R \cdot COP^R \cdot P^R \cdot x_t^R\right) + \left(T_{t-1}^{in} - \left(T_t^{amb} - R^R \cdot COP^R \cdot P^R \cdot x_t^R\right)\right) \cdot e^{-\frac{\Delta t}{R^R \cdot C^R}}, \forall t \tag{3.25}$$

$$T^{R,min} \leq T_t^R \leq T^{R,max}, \forall t \tag{3.26}$$

$$P_t^R = P^R \cdot x_t^R, \forall t \tag{3.27}$$

3.4.3.3 Air conditioner (AC)

AC's model is similar to the refrigerator's. Here, Eq. (3.28) accounts only for the cooling operation of the AC (for the heating, which is not considered here, x_t^{AC} changes sign and becomes negative). The used COP value belongs to cooling. The effect of air ventilation on the inside temperature is neglected. Eq. (3.29) denotes that the AC operates within a dead band of the set-point temperatures defined by the FIS

(Fuzzy logic set-point adjustment is detailed in Section 4.5). Eq. (3.30) stands for the electrical power consumption of the AC.

$$T_t^{AC} = T_t^{out} - R^{AC} \cdot COP^{AC} \cdot P^{AC} \cdot x_t^{AC} \\ +\left(T_{t-1}^{AC} - (T_t^{out} - R^{AC} \cdot COP^{AC} \cdot P^{AC} \cdot x_t^{AC})\right) \cdot e^{-\frac{\Delta t}{R^{AC} \cdot C^{AC}}}, \forall t \tag{3.28}$$

$$SP_t^{min} \leq T_t^{AC} \leq SP_t^{max}, \forall t \tag{3.29}$$

$$P_t^{AC} = P^{AC} \cdot x_t^{AC}, \forall t \tag{3.30}$$

3.4.4 PV model

The proposed HEMS uses Liu and Jordan's isotropic solar model, which is widely used to calculate total solar radiation and PV array output on a tilted surface [132,133].

In this approach, LSE or a system operator forwards not only a price signal but also a day-ahead solar forecast of a city or a location to the household [134]. Then, the HEMS turns the solar data input into a PV power output according to the specific parameters such as tilt angle and array capacity. Eq. (3.31-3.39) gives the calculation of solar radiation. Eq. (3.40) calculates the cell temperature to consider the effect of temperature on PV power output and Eq. (3.41) stands for the power calculation of the PV array. The study assumes that the PV array always operates at its maximum power point.

$$\delta = 23.45 \sin\left[\frac{360(n + 284)}{365}\right] \tag{3.31}$$

$$\omega = \arccos[-\tan(\delta)\tan(\varphi)] \tag{3.32}$$

$$\omega' = min\{\omega, \arccos[-\tan(\delta)\tan(\varphi - s)]\} \tag{3.33}$$

$$Ho = \frac{24}{\pi} Isc\left(1 + 0.033\cos\left(\frac{360n}{365}\right)\right)\left(\cos(\varphi)\cos(\delta)\sin(\omega) \\ + \frac{\pi\omega}{180}\sin(\varphi)\sin(\delta)\right) \tag{3.34}$$

$$K = H/Ho \tag{3.35}$$

$$Hd = H(1 - 1.13K) \tag{3.36}$$

$$Rb = \frac{\cos(\varphi - s)\cos(\delta)\sin(\omega') + \frac{\pi\omega'}{180}\sin(\varphi - s)\sin(\delta)}{\cos(\varphi)\cos(\delta)\sin(\omega) + \frac{\pi\omega'}{180}\sin(\varphi)\sin(\delta)} \tag{3.37}$$

$$R = Rb\left(1 - \frac{Hd}{H}\right) + Hd\left(\frac{1 + \cos(s)}{2H}\right) + \rho\left(\frac{1 - \cos(s)}{2}\right) \tag{3.38}$$

$$Ht = RH \tag{3.39}$$

$$T_t^{cell} = T_t^{out} + \frac{Ht}{Ht^{NOCT}}\left(T^{cell,NOCT} - T^{amb,NOCT}\right) \tag{3.40}$$

$$P_t^{PV,prod} = Y^{PV} d^{PV}\left(\frac{Ht}{Ht^{STC}}\right)\left[1 + \alpha^P \cdot \left(T_t^{cell} - T^{cell,STC}\right)\right] \tag{3.41}$$

3.4.5 Fuzzy logic-based smart thermostat for AC

In this study, a fuzzy logic rule-based algorithm is proposed to define day-ahead set-point temperatures in response to time-based electricity prices, solar radiation, and occupancy level. In the fuzzy logic approach, instead of complicated mathematical models, various input parameters are fuzzified into linguistic IF-THEN rules by using Mamdani fuzzy inference system (FIS).

Then the appropriate fuzzy rules are aggregated and the defuzzification process is performed to transfer fuzzy inference results into a crisp "set-point change" output. The defuzzification method chosen for the study is the center of area (COA), as described in Eq. (3.42), where K is the number of items in the fuzzy set and $\mu_A(x)$ is the membership function of fuzzy set A [114]. MATLAB fuzzy logic toolbox is used to implement FIS.

$$COA = \frac{\sum_{i=1}^{K}\mu_A(x)\cdot x}{\sum_{i=1}^{K}\mu_A(x)} \tag{3.42}$$

The thermostat adds the "set-point change" of each time interval (which can be either "positive big (PB)", "positive small (PS)", "zero (Z)", "negative small (NS)", or "negative big (NB)") to the initialized set-point temperature. Membership functions of input and output parameters of the smart thermostat are given in Figure 3.3.

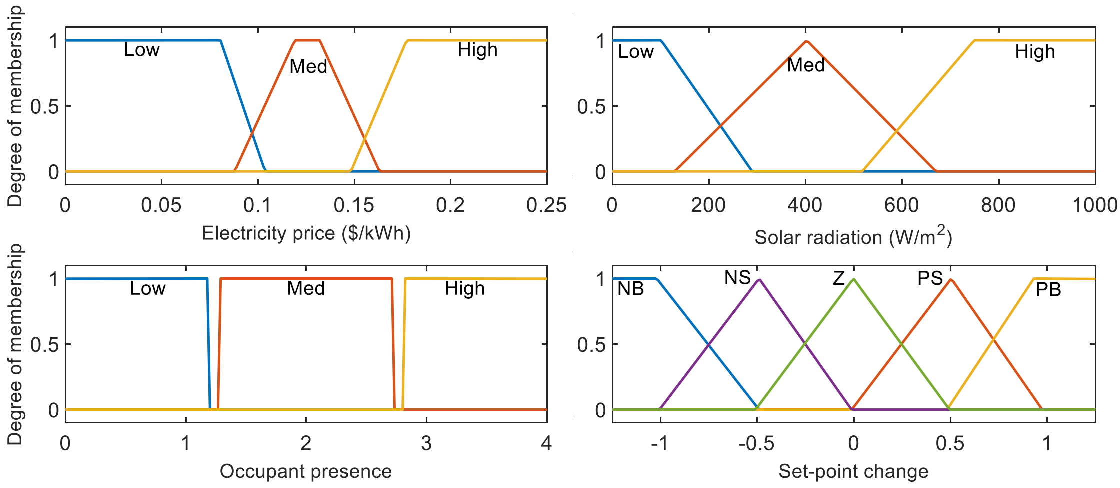

Figure 3.3 : Membership functions of input (electricity price, solar radiation, occupant presence) and output (set-point change) parameters of the fuzzy logic-based smart thermostat.

The HEMS increases or decreases the user-defined set-point without exceeding the thermal comfort conditions defined by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE). Table 3.1 shows acceptable inner temperature levels according to the ASHRAE Standard 55 [135]. As seen, a thermostat set-point can vary within the range of 4 ºC in the course of a day, still staying inside the ASHRAE comfort level and allowing consumers to benefit from DR programs.

Table 3.1 : Acceptable temperature ranges according to ASHRAE Standard 55.

Condition	Relative humidity	Temperature range (ºC)
Summer season	30%	23-27
(Clothing insulation = 0.5 clo)	60%	22-26
Winter season	30%	18-22
(Clothing insulation = 1.0 clo)	60%	19-23

The thermostat can increase set-point within ASHRAE limits to pay less during on-peak period or to cover the loss caused by low PV production when solar radiation is low. Furthermore, the occupancy level of the residents can be considered in the evaluation process and thermostat can make different decisions for different occupancy levels. By considering occupancy level and solar radiation in the decision-making process, the proposed smart thermostat also indirectly takes into account the human presence and solar radiation as heat sources which are not considered in the 1R1C model.

- Considering the mentioned varying conditions, a typical fuzzy rule can be decided in the most favorable case as follows: IF electricity price is "low", solar radiation is "high" and occupant presence is "high", THEN set-point change is "negative big" to provide the highest thermal comfort.
- Or, in the most unfavorable case: IF electricity price is "high", solar radiation is "low" and occupant presence is "low", THEN set-point change is "positive big" to sacrifice the thermal comfort.

All the fuzzy rules defined in a linguistic form are demonstrated in Table 3.2. Unlike the wider dead band of conventional thermostats (±0.5), the inverter AC used in the study has a narrower dead band of ±0.25 ºC. The set-point change is limited to ±1.25 ºC, and therefore it is ensured that the smart thermostat operates between ASHRAE thermal comfort limits.

Table 3.2 : Rules (#) table for FIS in the smart thermostat.

#	Elec. price	Solar rad.	Occ. presence	Set-point change	#	Elec. price	Solar rad.	Occ. presence	Set-point change	#	Elec. price	Solar rad.	Occ. presence	Set-point change
1	High	Low	Low	PB	**10**	Med.	Low	Low	PS	**19**	Low	Low	Low	Z
2	High	Low	Med.	PB	**11**	Med.	Low	Med.	Z	**20**	Low	Low	Med.	NS
3	High	Low	High	PS	**12**	Med.	Low	High	NS	**21**	Low	Low	High	NB
4	High	Med.	Low	PB	**13**	Med.	Med.	Low	PS	**22**	Low	Med.	Low	Z
5	High	Med.	Med.	Z	**14**	Med.	Med.	Med.	Z	**23**	Low	Med.	Med.	NS
6	High	Med.	High	NS	**15**	Med.	Med.	High	NS	**24**	Low	Med.	High	NB
7	High	High	Low	PB	**16**	Med.	High	Low	Z	**25**	Low	High	Low	NS
8	High	High	Med.	Z	**17**	Med.	High	Med.	NS	**26**	Low	High	Med.	NB
9	High	High	High	NS	**18**	Med.	High	High	NB	**27**	Low	High	High	NB

PB: positive big, PS: positive small, Z: zero, NS: negative small, NB: negative big.

3.4.6 Power balance

The power balance in the smart household provided by the HEMS is described by Eq. (3.43).

$$P_t^G + P_t^{PV,used} + P_t^{V,used} + P_t^{B,used} = P_t^H + P_t^{V,ch} + P_t^{B,ch}, \forall t \qquad (3.43)$$

P_t^H includes the power consumption of flexible and inflexible appliances except of PSAs (3.44).

$$P_t^{H} = P_t^{other} + \sum_{a=1}^{A} P_{a,t}^{TSA} + P_t^{EWH} + P_t^{AC} + P_t^{ref}, \forall t \tag{3.44}$$

$P_t^{PV,used}$ is PV power used to supply the energy demand of flexible and inflexible appliances and charging of PSAs (3.45). Similarly, $P_t^{V,used}$ and $P_t^{B,used}$ are powers used to supply energy demand of flexible and inflexible appliances and charging of PSAs due to V2H, V2B, B2H, and B2V operations (3.46-3.47).

$$P_t^{PV,used} = P_t^{PV,2H} + P_t^{PV,2B} + P_t^{PV,2V}, \forall t \tag{3.45}$$

$$P_t^{V,used} = P_t^{V,2H} + P_t^{V,2B}, \forall t \tag{3.46}$$

$$P_t^{B,used} = P_t^{B,2H} + P_t^{B,2V}, \forall t \tag{3.47}$$

PV production is used both for energy storage and self-consumption. The surplus production is sold to the grid (3.48).

$$P_t^{PV,prod} = P_t^{PV,used} + P_t^{PV,2G} \tag{3.48}$$

Power sold to the grid through surplus PV production, and V2G and B2G operations are given in Eq. (3.49).

$$P_t^{2G} = P_t^{PV,2G} + P_t^{V,2G} + P_t^{B,2G}, \forall t \tag{3.49}$$

The system operator may impose a power limit for the power imported to the grid or exported from the grid as shown by (3.50-3.51) [128].

$$P_t^{G} + P_t^{PV,used} + P_t^{V,used} + P_t^{B,used} \leq PL_t^{G}, \forall t \tag{3.50}$$

$$P_t^{2G} \leq PL_t^{2G}, \forall t \tag{3.51}$$

3.5 Input Data

3.5.1 Solar radiation and temperature data and specifications of the PV modules

The selected time window for the optimization is 5 minutes (0.0833 h). The reason for choosing high resolution is to better capture the load profiles of electrical devices. The global solar radiation and temperature data of Istanbul are extracted from [136] (Figure

3.4 and Figure 3.5). The data belongs to the year 2016. The rated capacity of the rooftop PV array is 5 kW. The technical specifications of the PV array are given in Table 3.3.

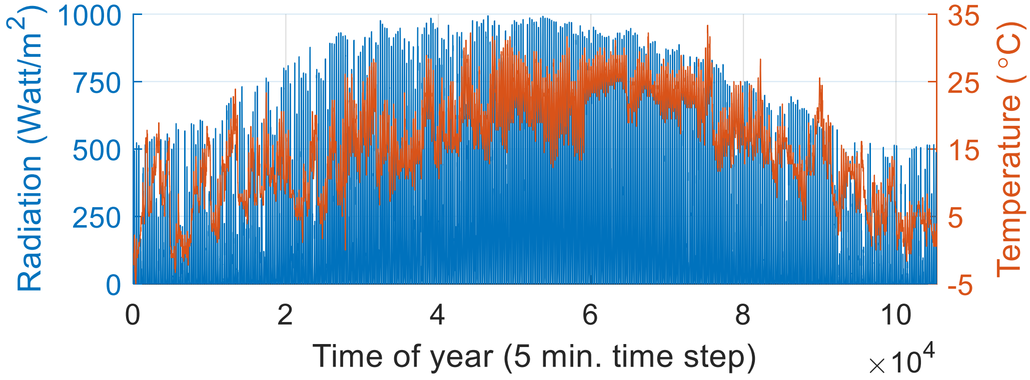

Figure 3.4 : Annual global solar radiation and dry bulb temperature data of Istanbul (2016).

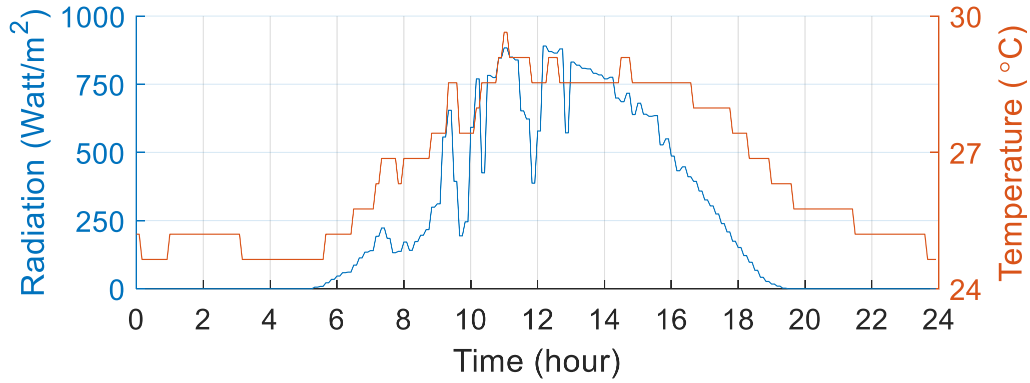

Figure 3.5 : Global solar radiation and dry bulb temperature data of Istanbul, August 4, 2016.

Table 3.3 : Technical specifications of the 5 kW PV array [137].

Model	Canadian-Solar-CS6P-230P
Rated capacity (W)	230
Temperature coefficient of power (%/ºC)	-0.38
Nominal operating cell temperature (ºC)	45
PV derating factor (%)	95
Number of panels	22
Latitude of the region (º)	41.01
Optimal tilt angle (º)	29

3.5.2 Specifications of the batteries (EV and BESS)

PSAs, namely EV and BESS, comprise lithium-ion and lead-acid batteries, respectively. The technical specifications of the batteries are given in Table 3.4. Here, battery replacement cost, lifetime throughput in kWh, and lifetime in cycles are given to calculate the battery degradation cost of the batteries. The BESS operates all day long in the household. It consists of five Trojan T-105 RE Solar batteries, of which technical specifications and price information are taken from [138,139] and [140]. The residents own a Nissan Leaf, of which technical specifications are given in [141]. It is assumed that the residents prefer EV charging to be performed at any time between EV arrival and departure times. The battery replacement cost of the EV is half the price of a brand new battery pack. This is due to the refabricated battery replacement offer of the EV manufacturer [142].

Table 3.4 : Technical specifications of the batteries used in EV and BESS.

Model	5 x Trojan T-105 RE Solar (lead-acid)	Nissan LEAF EV battery (lithium-ion)
Nominal capacity (kWh)	7.65	24
Charging rate (kW)	2.0	3.3
Discharging rate (kW)	2.0	3.3
Charging efficiency (%)	89	95
Discharging efficiency (%)	89	95
DoD (%)	70	80
Round-trip efficiency (%)	89	95
Battery lifetime in cycles	1250	2000
Lifetime throughput measured for specific DoD (kWh)	6694	38400
Battery replacement cost ($)	695	2850
Calculated battery degradation cost ($/kWh)	0.117	0.078
Operating time interval	All-day long	18 pm (arrival) – 8 am (departure)
Initial SoC (%)	0	68.75
Final SoC (%)	0	100

3.5.3 Thermal properties of the smart home and thermal loads

For the thermal properties of the household, measured parameter values of a 125 m² one-storey house are used [143], of which thermal capacitance C^{AC} and thermal resistance R^{AC} are 12,312 kJ/ºC and 4.87 ºC/kW, respectively. The selected values are compatible with other studies in the literature, like [144], which uses measured data of another 120 m² house, or [145] and [146] which scales R and C values per square meter of floor space. It should be noted that, instead of using a first-order thermal model, a second-order model can be used and more accurate results can be achieved. However, this study concentrates on describing the lumped thermal capacity of a household rather than a detailed description of the temperature transients, as stated in [147]. The inverter AC with a rated power P^{AC} of 2.21 kW provides cooling capacity Q^{AC} of 7.1 kW with COP of 3.21 [148].

Thermal properties measured in [149] are used in the EWH model. Thermal capacitance C^{EWH} and thermal resistance R^{EWH} are stated as 1770 kJ/ºC and 223 ºC/kW, respectively. Q^{EWH} is given as 3.0 kW. Although EWH size is not given, the size of a 3 kW EWH can be estimated as 200 liters [150]. COP value of a standard EWH can be taken as 1.0 [151]. Hot water usage is assumed to be 2.5 gallons per minute and the constant amount of water heat flow capacity in single time-step $\dot{c}^{EWH}$ is calculated as 0.6594 kW/K. Since bacterias such as legionella can proliferate up to 45 ºC and temperature above 60 ºC may cause scalding, allowed minimum and maximum hot water temperature inside the EWH tank is limited between these temperatures [152]. Hot water is assumed to be used only for bathing and showering. Inlet water temperature T_t^c is assumed to have a daily constant temperature at 21 ºC.

Thermal properties of a large inverter refrigerator which is more suitable for DR due to its higher thermal inertia, was not found in the literature. Thus, values of a small 60 liters refrigerator [153] are scaled considering a 600 liters one. Thermal resistance is scaled according to surface area, and thermal capacitance is scaled according to volume. Accordingly, thermal capacitance C^{Ref} and thermal resistance R^{Ref} values are estimated as 89.34 kJ/ºC and 297.15 ºC/kW, with a power rating P^{Ref} of 0.29 kW and cooling capacity Q^{Ref} of 0.381 kW. A typical refrigerator consumes daily 1-2 kWh, and our assumptions give a result in between (1.4 kWh) [154]. Technical specifications, thermal parameters, and user preferences are presented in Table 3.5.

Table 3.5 : Technical specifications and user preferences regarding TCAs.

	Inverter AC/House	EWH/Tank	Refrigerator/Cabinet
Heating/Cooling capacity (kW)	7.1 (24,225 BTU/h)	3.0	0.29
COP	3.21	1	0.76
Power consumption (kW)	2.21	3.0	0.381
Size	125 m²	200 liters	600 liters
Thermal resistance (ºC/kW)	4.87	223	89.34
Thermal capacitance (kJ/ºC)	12312	1770	297.15
Constant amount of water heat flow capacity in a single time-step (kW/K)	-	0.6594	-
Hot water usage times	-	06:10 – 06:20 14:00 – 14:05 18:30 – 18:40	-
Inlet water temperature (ºC)	-	21	-
Min. set-point temperature (ºC)	Defined by smart thermostat for each time step	45.0	-1.0
Max. set-point temperature (ºC)		60.0	4.5

3.5.4 Operating phases and load profiles of the appliances

The operating phases of the TSAs are given in Table 3.6. The load profiles of dishwasher and washing machine rely on our former measurements [155]. The load profile of the clothes dryer is derived from [82]. The users can enter their preferred operating times for their TSAs as stated in Eq. (3.4-3.7). Here, for the sake of simplicity, it is assumed that the users agree that their TSAs can start to operate at any time of day. While the refrigerator is categorized as a TCA, here, the defrost cycle of the refrigerator is also taken into account and handled as a TSA. The defrost timer sets the defrost cycle to run automatically every 12 hours a day, and the defrosting lasts approximately 35 minutes [156,157].

Table 3.6 : Operating phases of the TSAs.

TSA	Phase	1	2	3	4	5	6
Washing machine	Power (kW)	0.15	2.1	0.15	2.1	0.15	0.3
	Duration (periods)	1	2	2	4	4	2
Dishwasher	Power (kW)	2.1	0.15	2.1	-	-	-
	Duration (periods)	4	3	6	-	-	-
Clothes dryer	Power (kW)	3	0.15	3	0.15	3	0.15
	Duration (periods)	3	1	1	1	1	3
Automatic defrost	Power (kW)	0.48	0	0.48	0	-	-
	Duration (periods)	7	137	7	137	-	-

The load profile of the inflexible loads (Table 3.7) is based on load profile and usage data extracted from various studies in the literature and our own experience on daily usage of appliances [134,158–160].

Table 3.7 : Load profile of the inflexible loads.

Inflexible appliance	Rated power (kW)	Periods (5 min.)	Operating time interval
Iron	1.1	6	21:00-21:30
Toaster	1.2	4	06:45-06:55, 09:30-09:40
Kettle	2.1	3	07:00-07:05, 09:30-09:35, 19:30-19:35
Coffee maker	0.6	6	08:00-08:10, 17:30-17:40, 19:00-19:10
Hairdryer	1.8	2	06:30-06:35, 22:00-22:05
TV1	0.091	96	08:00-10:30, 18:30-00:00
TV2	0.091	36	19:00-22:00
PC1	0.11	90	10:30-12:30, 17:00-20:00, 21:00-23:30
PC2	0.09	30	18:00-20:00
Electric stove	2.4	8	19:30-20:10
Cooker hood	0.225	12	19:30-20:30
Lighting	0.24	102	06:00-06:30, 17:00-01:00
Microwave	1.5	2	07:00-07:05, 10:30-10:35
Other (fixed)	0.1	288	00:00-00:00

3.5.5 Electricity prices

The residential TOU rates of Türkiye (April 2020) are given in Figure 3.6 [161]. The rates are 0.077 $/kWh (off-peak), 0.122 $/kWh (mid-peak), and 0.178 $/kWh (on-peak). The PV sells the excess energy to the grid through a feed-in tariff rate (0.061 $/kWh). The BESS and EV are also assumed to sell energy at the same price. Here, it should be noted again that the buying and selling prices of the BESS and EV are used only for load scheduling in the objective function as an artificial penalty to prevent batteries from unwanted energy arbitrage. The battery degradation cost is included in the optimization but not included in the daily bill calculation which is made after the optimization.

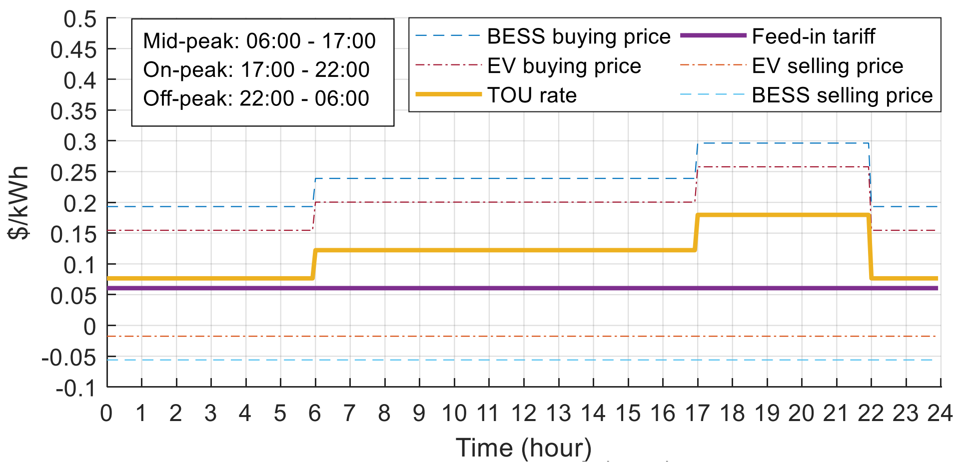

Figure 3.6 : TOU and feed-in tariff rates of Türkiye (EV and BESS prices indicate degradation cost included artificial prices to be used in load scheduling).

The HEMS is assumed to receive a peak demand limit signal from the LSE, which is set at 6.0 kW to prevent further peaks. In addition, in many countries, the power export rate of recently-built residential PVs is limited by LSEs to promote self-consumption. Therefore, it is also assumed that the LSE limits the power injection of the 5 kW array by 70% [162]. And accordingly, the HEMS allows power export to the grid up to 3.5 kW.

3.5.6 Occupancy level

The occupant presence information, which is used by the smart thermostat in fuzzy decision-making, can either be entered into the HEMS by the residents or measured by occupancy sensors. In the study, an assumed occupant presence data of a typical Turkish family is used, consisting of two working parents (A and B) and two children (C and D); one school-aged (age 6-11) and one adolescent (age 12-18), as applied in [122]. Although a real occupant presence data of Turkish families is not found in the literature, the assumed profile shows similarity to a typical American family [163]. The daily presence of occupants A, B, C, and D is explained in Figure 3.7. Since residents prefer slightly higher set-point temperatures during sleep hours, the HEMS multiplies the occupancy level by 0.5 between 00:00 and 06:00. Therefore, although smart thermostat enforces a higher set-point decrease during high occupancy, during sleep hours it does not decrease set-point as high as in a daytime.

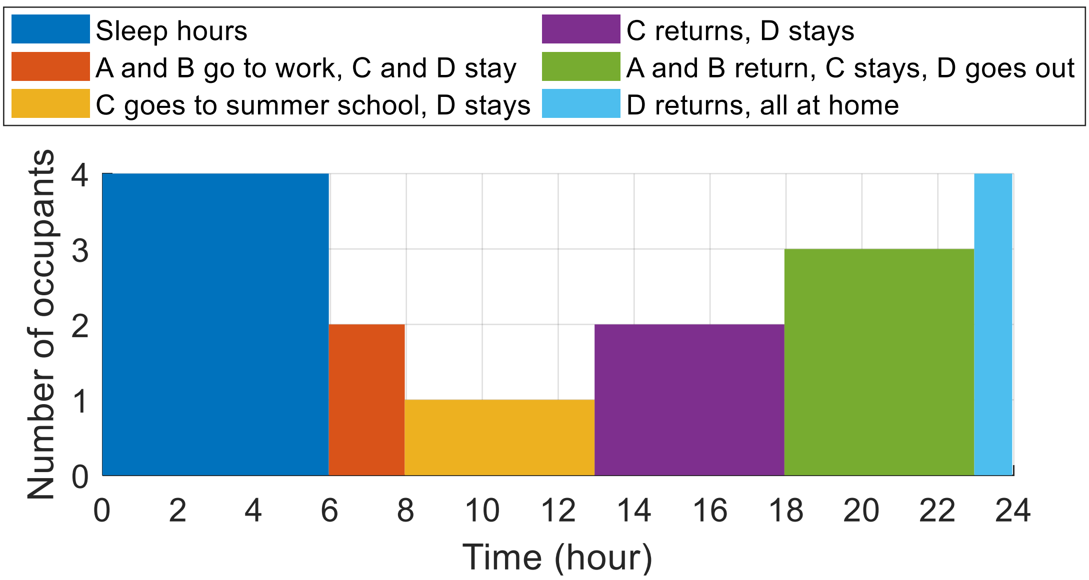

Figure 3.7 : Daily occupant presence in the household.

3.5.7 AC set-point temperatures due to fuzzy decision-making

The input variables of the smart thermostat and the adjusted set-point temperatures are shown in Figure 3.8. Firstly, the defuzzification defines the set-point change (which varies between ±1.25 ºC) for each time interval. Then, the smart thermostat adds the defined set-point change values to the initialized set-point of 23.6 ºC and obtains the set-point of each time interval (Figure 3.8). Lastly, the HEMS uses the obtained set-point values in the day-ahead optimization considering the dead band of ±0.25 ºC for the AC (Eq. (3.29)).

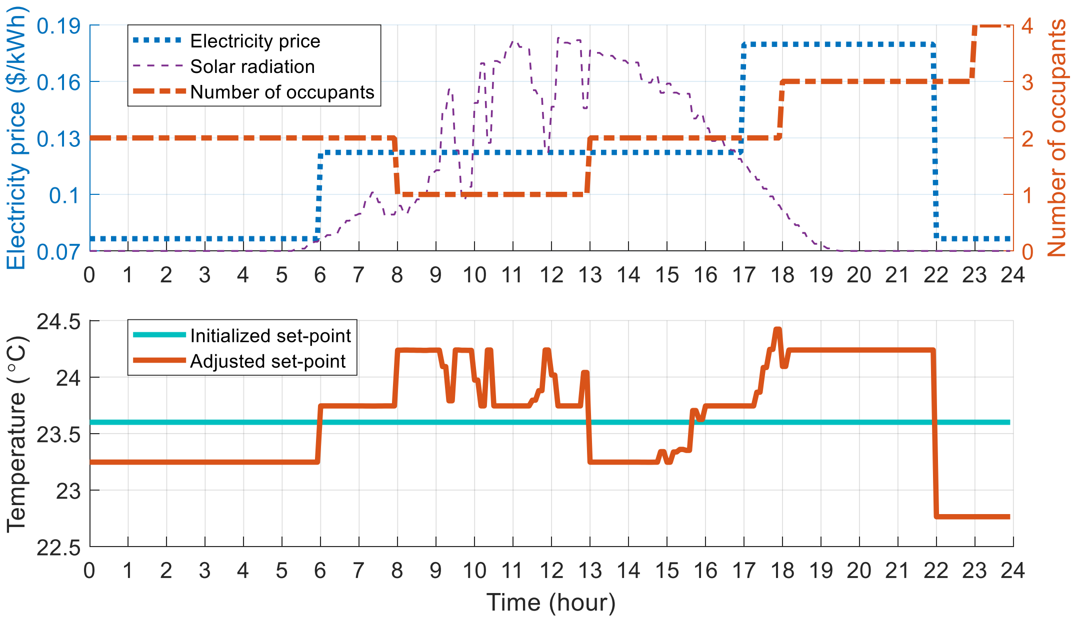

Figure 3.8 : "Electricity price", "solar radiation", and "number of occupants" as smart thermostat input parameters (top), and the adjusted set-point temperatures due to output parameter of "set-point change" (bottom).

As a result, the lowest and highest set-point values become 22.76 ºC and 24.42 ºC, respectively in the household in Istanbul on August 4. Taking into account the dead band of the AC (±0.25 ºC), the maximum and minimum daily inside temperature in the household can reach 22.51 ºC and 24.67 ºC, respectively. These values, as previously stated in Table 3.1, stay within the minimum and maximum limits (22 – 26 ºC) defined by the ASHRAE for a humid region in summer season (Table 3.1), which matches the conditions of Istanbul.

Although, the smart thermostat sacrifices the thermal comfort during on-peak period by defining a higher set-point, it provides a lower set-point temperature when the prices are lower and the occupancy level is high. At the end of the day, whereas the initialized set-point temperature was 23.6 ºC, the daily average of the adjusted set-points becomes nearly the same (23.7 ºC).

3.6 Simulation Results and Discussions

The base-load profile of the household without battery storage, load scheduling, and self-consumption is shown in Figure 3.9 to demonstrate all the loads within the household before an energy management. In the formation of the base-load, the most probable times of use of TSAs are used [164,165]. The EWH operates only when the temperature comfort band is exceeded. The AC and refrigerator operate at their set-point. EV charging immediately begins as it arrives home and is plugged-in. A simple energy management system can store the surplus PV energy to be used later during the on-peak period, however, it cannot enable load scheduling and does not hold a smart thermostat.

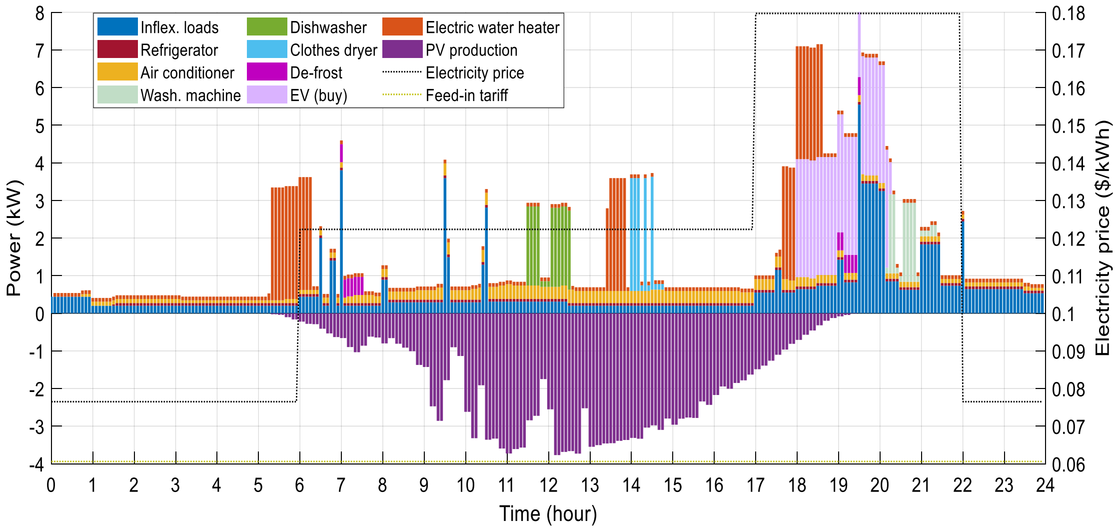

Figure 3.9 : The daily base-load profile of the household without battery storage, load scheduling, and self-consumption.

The load profile of the smart home under HEMS operation is shown in Figure 3.10 (top). The HEMS provides both DR and self-consumption by shifting all the possible loads from the on-peak period to the off-peak or PV production period. Only a little portion (1.73 kWh) of the total PV production (26.03 kWh) is sold to the grid and 93.37% of the PV production is self-consumed either directly or due to energy storage. The charge/discharge scheduling of the batteries is shown in Figure 3.10 (bottom).

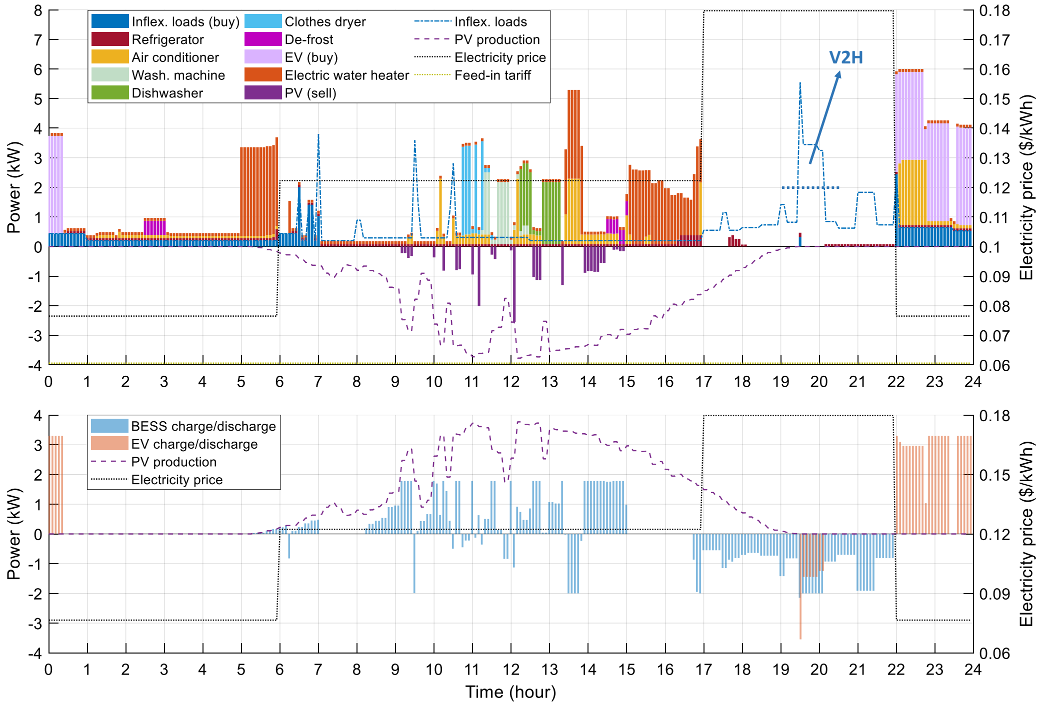

Figure 3.10 : The daily load profile of the smart home under HEMS operation (top), The charge/discharge scheduling of the BESS, and EV (bottom).

All the TSAs are shifted to the midday to benefit from the PV production, and one of the de-frost cycles of the refrigerator is shifted to the PV production period, whereas the other to the off-peak.

All the TCAs enable pre-cooling or pre-heating before the on-peak period within the upper and lower temperature bounds. Likewise, the least energy consumption of the TCAs occurs within the on-peak period. The temperature level and usage of the TCAs are detailed in Section 6.1.

The EV arrives home at 18:00 but the charging is postponed to the end of the on-peak period, but before, between 18:00 and 22:00, the charge rate of BESS (2 kW) cannot cover the demand of inflexible loads and the remaining part is covered by EV battery due to V2H. B2G and V2G operations do not occur in the smart home under the current battery degradation costs and electricity prices of Türkiye.

3.6.1 Results for AC

In Figure 3.11, the inverter AC operates at set-point temperatures defined by the smart thermostat and within the lower and upper bounds of the dead band. It also performs pre-cooling when necessary.

The set-point is at its lowest during the period when all the residents are at home and the electricity prices are cheaper. The highest set-point level is between 17:00 and 18:00 where the occupancy is at the lowest, electricity prices are at the highest, and solar radiation is low. The average defined set-point temperature is relatively high (24.5 ºC) during the on-peak period due to the high electricity price and low solar radiation. The set-point adjustment and the pre-cooling performed before the beginning of the on-peak period provides the AC not to operate during the whole on-peak period of 5 hours (between 17:00 – 22:00).

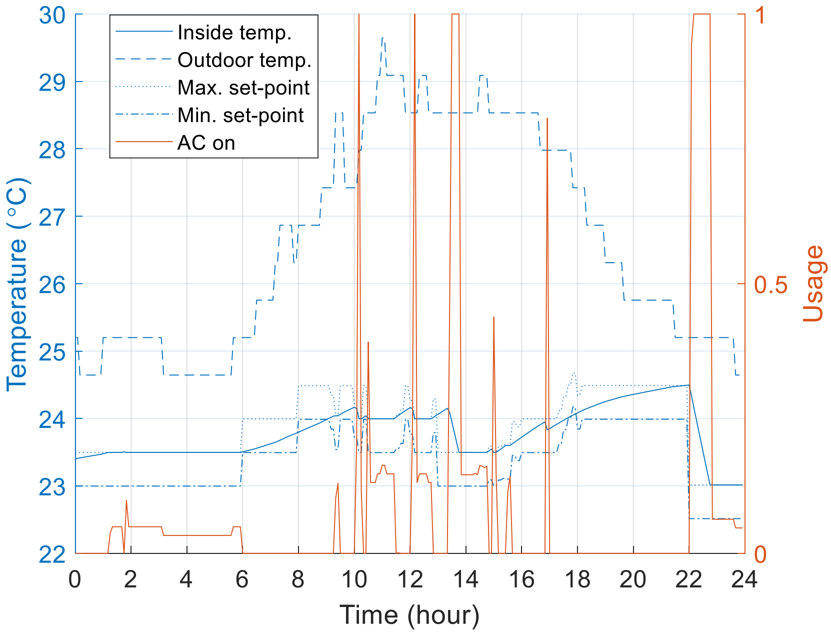

Figure 3.11 : AC operation due to set-point adjustment and pre-cooling/heating and the temperature change inside the smart home, August 4.

The thermostat set-point can sharply increase or decrease after some time steps. For instance, at 22:00, the maximum set-point sharply decreases and becomes lower than the minimum set-point of the previous time step. In such occurrences, the smart thermostat is allowed to behave flexibly and violate boundaries until the inside temperature reaches the defined set-point.

3.6.2 Results for EWH

In Figure 3.12, the sharp temperature drops indicate the hot water usages. The EWH enables pre-heating before the first hot water usage which occurs between 06:10 and 06:20. The heater starts working just before 05:00 within the off-peak period and stops before the end of the off-peak period at 06:00. The second hot water usage occurs between 14:00 and 14:05. Before the hot water usage, the EWH does not enable pre-heating and uses the free PV power directly for heating. The HEMS does not allow the tank temperature to drop below the minimum limit of 45 °C during hot water use. The third hot water usage occurs between 18:30 and 18:40, which is within the on-peak period. To avoid high electricity prices during the on-peak period, the EWH provides pre-heating using the PV power (as seen in Figure 3.10) until the end of the mid-peak period, which ends at 17:00.

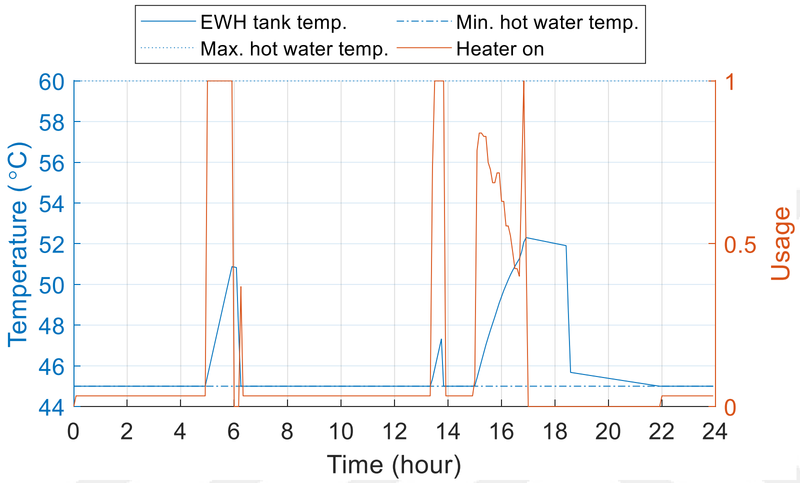

Figure 3.12 : Temperature change inside the EWH tank.

3.6.3 Results for refrigerator

In Figure 3.13, the refrigerator starts pre-cooling before the beginning of the on-peak period. This allows the refrigerator not to consume energy for 2 hours during the on-peak period (which lasts for 5 hours).

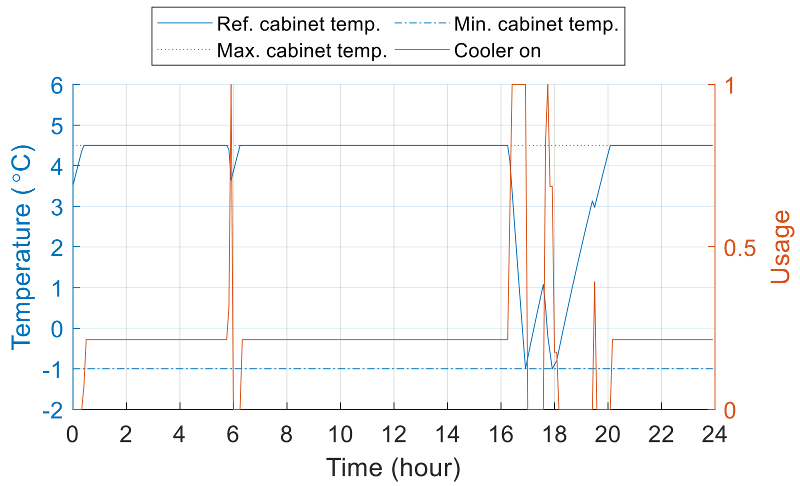

Figure 3.13 : Temperature change inside the refrigerator cabinet.

3.6.4 Case studies

3.6.4.1 HEMS operation in different types of households

The main purpose of the proposed HEMS is to reduce the daily bill of the smart household. Thus, cost comparison with and without HEMS usage is made for different types of households. The first case is the main case detailed in Section 6, in which all the TSA, TCA, PSA type of loads, as well as a PV array, are present. In all other cases, inflexible loads, TSAs, and TCAs are considered to be present, and the presence of PSAs and PV are variable. In the evaluation of "without HEMS" cases which contains BESS, it is assumed that a simple energy management system can store the surplus PV energy to be used later during the on-peak period. However, this simple energy management system cannot enable load scheduling and does not hold a smart thermostat.

Not every rooftop might be suitable for PV installation or and not everybody may want to invest in PV and BESS, Also, not everybody wants to have a car or replace their gasoline cars with EVs. Thus, the absence of these loads is considered in the case studies. Table 3.8 demonstrates daily energy purchases, self-consumption ratios, and utility bills of six types of households, as well as their cost reduction comparison, with and without HEMS usage.

Table 3.8 : Daily cost and power consumption comparison of different types of households with and without HEMS usage.

Case	PV prod. (kWh)	Without HEMS				With HEMS				Cost reduction (%)
		Energy bought from grid (kWh)	PV energy used in household (kWh)	PV self-consumption (%)	Daily cost ($)	Energy bought from grid (kWh)	PV energy used in household (kWh)	PV self-consumption (%)	Daily cost ($)	
1	26.03	21.46	19.22	74.83	2.69	17.29	24.30	93.37	1.26	53.2
2	26.03	28.09	12.59	49.08	3.41	22.84	18.79	72.16	1.89	44.6
3	-	40.74	-	-	5.79	42.33	-	-	4.44	23.3
4	26.03	14.34	19.22	74.83	1.41	10.31	24.26	93.18	0.84	40.4
5	26.03	20.96	12.59	49.08	2.13	15.72	18.87	72.50	1.35	36.6
6	-	33.61	-	-	4.51	35.30	-	-	3.90	13.5

The considered household types (cases) in Table 3.8 are as follows,

1) TSAs+TCAs+PV+BESS+EV
2) TSAs+TCAs+PV+EV,
3) TSAs+TCAs+EV (only DR),
4) TSAs+TCAs+PV+BESS,
5) TSAs+TCAs+PV
6) TSAs+TCAs (only DR).

In Case 2 (44.6%) and Case 4 (40.4%) considerably high cost reduction is obtained due to the presence of EV in the former (high DR capability) and of BESS in the latter (energy storage). The highest cost reduction is obtained in Case 1 (53.2%), which contains both EV and BESS. In Case 2 and Case 5, PV exists, but without a BESS, the self-consumption is applied only by shifting the adequate loads to the PV production period, and the excess energy is sold to the grid. The households without PV (Case 3 and Case 6) cannot enable self-consumption but only DR. The cost reduction in these two cases (23.3% and 13.5%, respectively) is lower compared to the others.

Under HEMS operation, a smart home that holds TSAs and TCAs (Case 6) receives a daily bill of $3.90. When a 5 kW PV is installed (Case 5), the daily cost decreases to $1.35, and with an inclusion of a BESS (Case 4), it decreases even to $0.84. If the household also has an EV (Case 3), then the daily bill becomes $4.44, which decreases to $1.89 by installing a PV (Case 2) and to $1.26 by including a BESS (Case 1).

The proposed HEMS significantly increases the self-consumption by shifting the loads to the PV production period, such that, the self-consumption increases from 74% to 93% in Case 1 and Case 4, and from 49% to 72% in Case 2 and Case 6.

For Case 3 and Case 6, the AC cost reduction is calculable due to not having a free PV power. According to the results, the smart HEMS thermostat provides an AC cost reduction of 24.2% compared to a conventional fixed set-point thermostat. The cost reduction of 24.2% is enabled with relatively low thermal comfort violation, such that, the average daily inside temperature increase is only 0.1 ºC (23.6 ºC in case of use of a conventional thermostat, and 23.7 ºC in case of use of the proposed thermostat).

The load profiles of the households under HEMS operation in all cases are given in Figure 3.14.

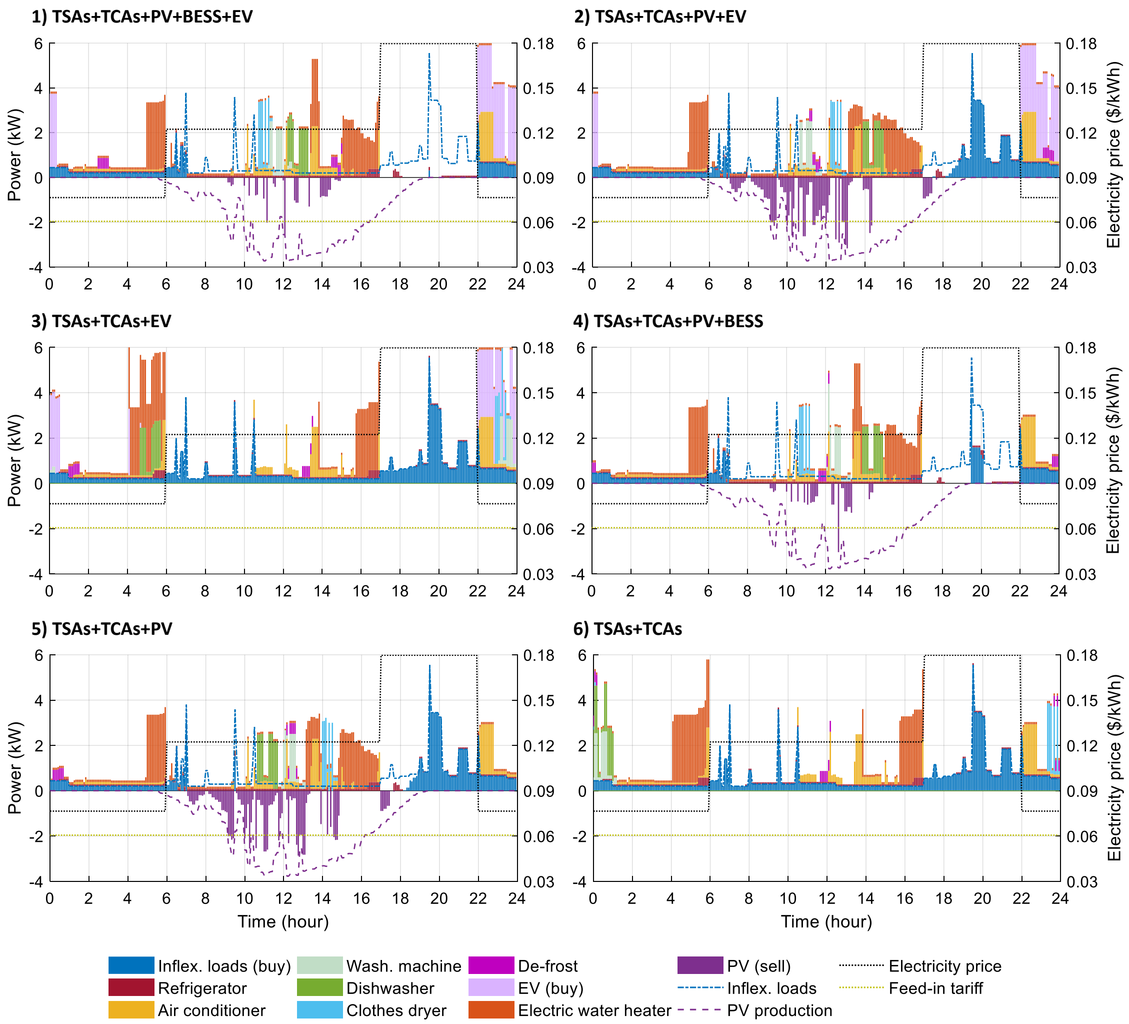

Figure 3.14 : The load profiles of different types of households under HEMS operation (Cases 1 – 6).

3.6.4.2 Behaviour of the smart HEMS thermostat under different solar radiation and temperature levels

The simulations above are carried out for a day (August 4) representing the monthly average outdoor temperature of August. In this section, the simulations are conducted for the coolest and warmest day of the month.

In Table 3.9, the cost comparison of ACs with and without HEMS is presented under different temperature levels. The cost reduction of 24% remains the same on a cooler day, however, it comes down to 15% on the warmest day of the month. This is because, while on an average and a cooler day the thermal storage can last for 5 hours during the on-peak period (covers all the on-peak period), on the warmest day, it lasts for 2 hours 45 minutes (Figure 3.15). The average outdoor temperature during the on-peak period is higher on this warmest day, and consequently, AC is forced to operate during the on-peak period. Yet, although the thermal storage lasts for a shorter duration, it is still remarkable.

Table 3.9 : Daily cost and energy consumption comparison of AC under different solar radiation and temperature values.

Case	Day	Average outdoor temp. (ºC)	Without HEMS (fixed set-point)			With HEMS (adjusted set-point)			AC cost reduction (%)
			Average inside temp. (ºC)	AC consump. (kWh)	AC cost ($)	Average inside temp. (ºC)	AC consump. (kWh)	AC cost ($)	
3 and 6	Coolest (August 12)	24.9	23.6	3.09	0.41	23.7	3.01	0.31	24.4
	Average (August 4)	26.6		4.93	0.62	23.7	4.82	0.47	24.2
	Warmest (August 21)	28.3		7.46	0.98	23.8	6.91	0.83	15.3

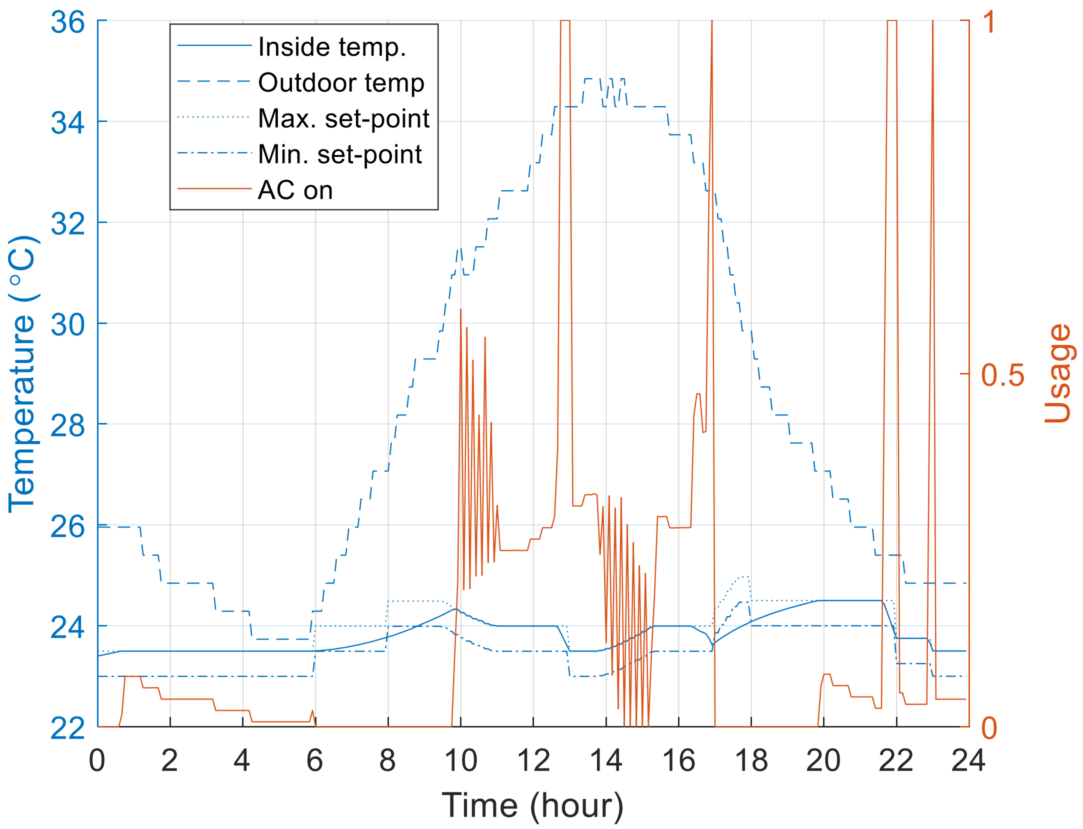

Figure 3.15 : Behaviour of the AC on the warmest day of the month, August 21.

Still, it should be noted that, here, the DR capability of the thermostat is not tried to be exploited. While the set-point could be increased up to 26 ℃ according to the ASHRAE limits, considering all the parameters, the smart thermostat does not let the set-point exceed 25 ℃. Besides, in all cases, the average daily temperature stays close to the initialized set-point of 23.6 ℃. Thus, the cost reduction in Table 9 is achieved with a relatively low sacrifice of thermal comfort. The users who want higher cost reduction can still increase the initialized set-point temperature.

3.6.4.3 Behaviour of the HEMS under RTP and dynamic feed-in tariff

Although not in use in Türkiye, RTP which is already in use in several countries [166], can increase the efficiency of the HEMS. To investigate the effect of a possible RTP, the TOU rate of Türkiye is modified into RTP (Figure 3.16) as applied in [100]. To be fair, it is ensured that the modified RTP gives quite the same daily cost as the TOU without a use of a HEMS, but if there is a HEMS, it provides a higher demand-side flexibility.

V2G and B2G are stated to be not viable in various studies due to the current high battery degradation costs, and new market designs and pricing structures are recommended to be developed to promote these technologies [102,167]. Thus, here in this future scenario, one of the alternative pricing schemes; hourly dynamic feed-in tariff is considered as discussed in [168,169], and the selling price is assumed to be 90% of the buying price as applied in [170].

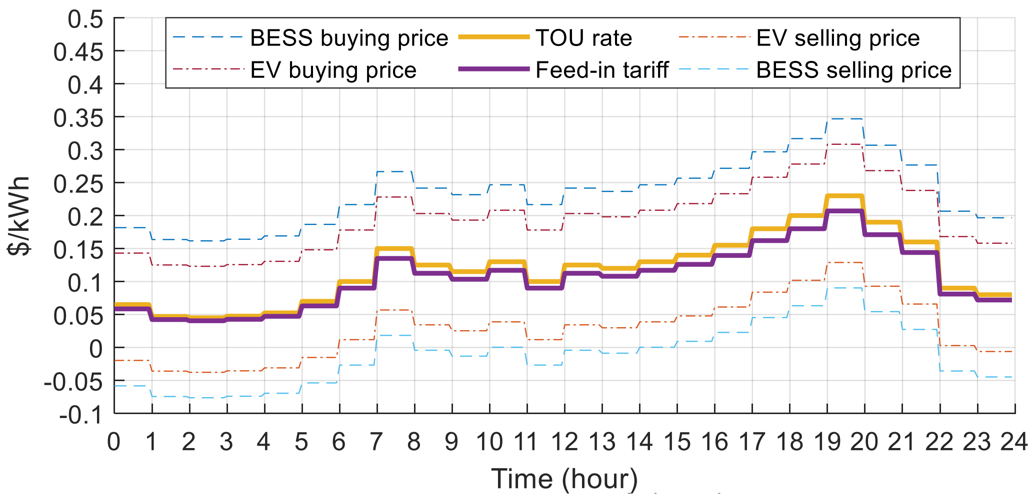

Figure 3.16 : Modified RTP and dynamic feed-in tariff rates of Türkiye (EV and BESS prices indicate degradation cost included artificial prices to be used in load scheduling).

The load profile of the smart household in Istanbul under a possible future RTP scenario is given in Figure 3.17. The first notable change is that V2G which was not available under the current TOU rate becomes available under RTP and dynamic feed-in tariff rates. From Figure 3.16, it can be seen that the EV selling price between 19:00-20:00 is higher than the EV buying price between 02:00-03:00, which makes V2G available in the smart household only for a short amount of time (an hour), but at the highest peak period which can be crucial for the grid. The self-consumption in the household decreases because the electricity prices during the night time decrease considerably and DR is performed instead.

In Table 3.10, the cost comparison of HEMS operation under TOU and RTP pricing is made. It can be seen that the RTP provides a higher DR capability to the HEMS. Higher cost reduction in Cases 1 – 3 than Cases 4 – 6 is caused by the existence of EV and V2G operation.

The behaviour of the TCAs under RTP is shown in Figure 3.18. The smart thermostat behaves more flexible in terms of the defined set-points due to the varying prices of RTP than TOU. The AC operates with a daily average temperature of 23.7 ºC. During the high price period, the AC pre-cooling provides energy storage that lasts for 6 hours from 15:00 to 21:00.

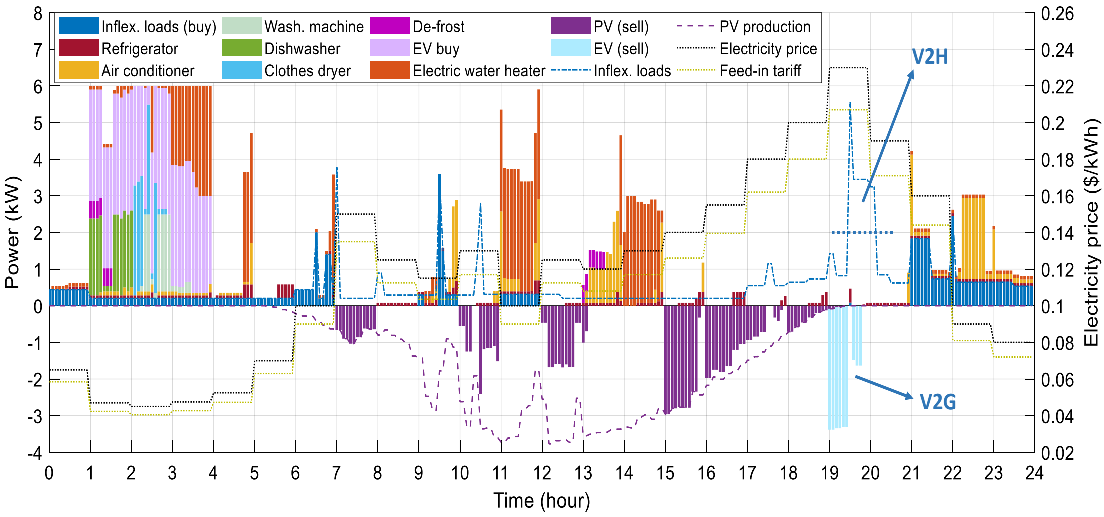

Figure 3.17 : The load profile of the smart home under the modified RTP and dynamic feed-in tariff rates (TSAs+TCAs+PV+BESS+EV).

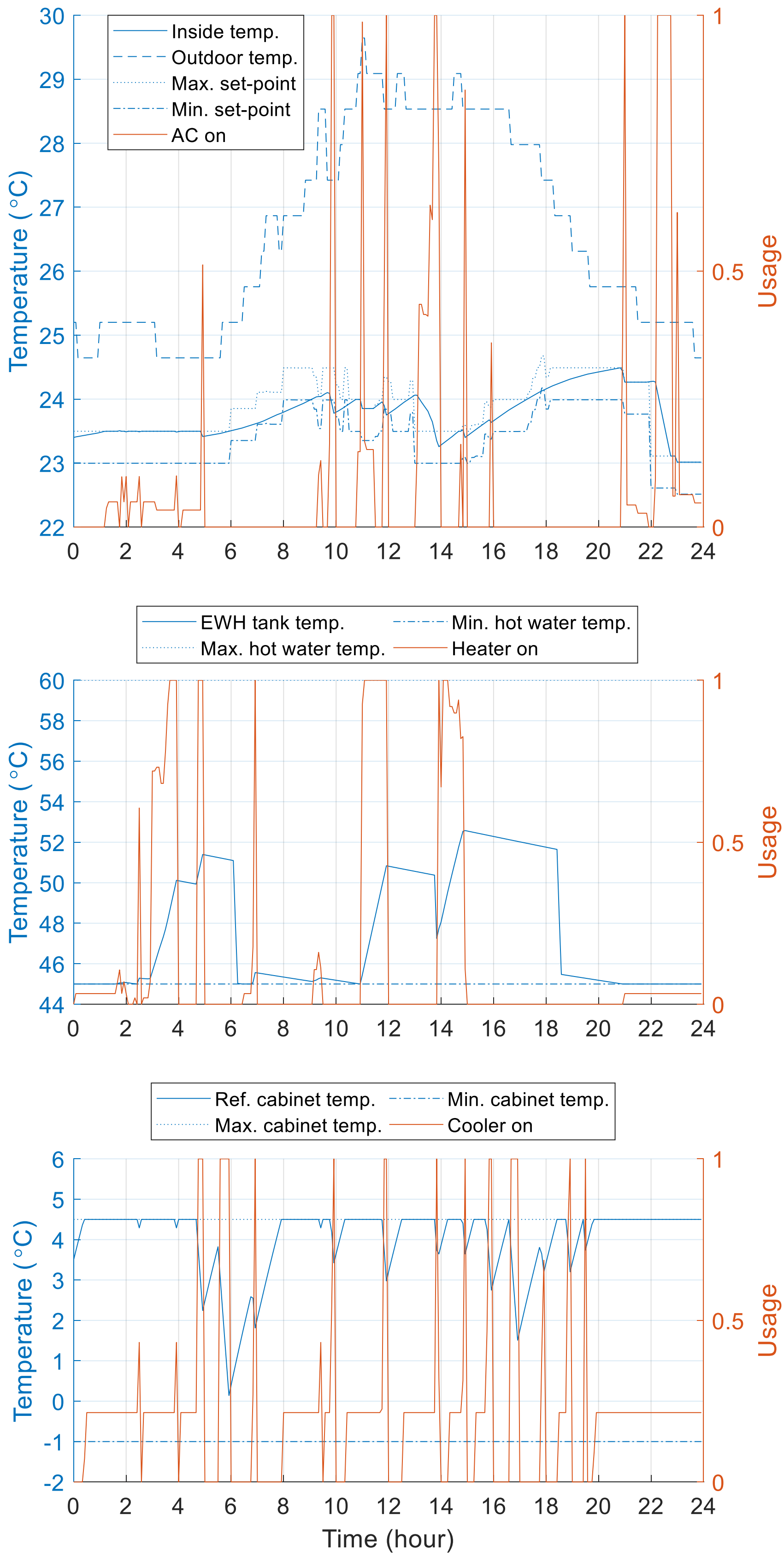

Figure 3.18 : Temperature change inside the household (top), EWH tank (middle), and refrigerator cabinet (bottom) under RTP and dynamic feed-in tariff rates.

Table 3.10 : Cost comparison of HEMS operation for different types of households under RTP and dynamic feed-in tariff rates.

Case	Household type	Daily cost ($)		
		Without HEMS (TOU and flat feed-in tariff)	With HEMS (TOU and flat feed-in tariff)	With HEMS (RTP and dynamic feed-in tariff)
1	TSAs+TCAs+PV+BESS+EV	2.69	1.26	0.10
2	TSAs+TCAs+PV+EV	3.41	1.89	0.66
3	TSAs+TCAs+EV (only DR)	5.79	4.44	3.91
4	TSAs+TCAs+PV+BESS	1.41	0.84	0.27
5	TSAs+TCAs+PV	2.13	1.35	0.55
6	TSAs+TCAs (only DR)	4.51	3.90	3.57

3.6.4.4 Other findings and limitations

The other findings and insights of the study are listed as follows:

- The proposed model can be implemented in other countries as well and the results may differ primarily depending on electricity prices, climatic conditions, and electrical appliance use patterns. In general, the efficiency of the HEMS is expected to be higher in developed countries considering the availability of dynamic electricity pricing schemes and higher income levels of residents. People with higher income levels are more likely to own a higher number of smart home appliances and EVs, and to afford detached houses where rooftop PV systems can be invested and EV home charging can be performed.
- In particular, the integrated smart thermostat can provide a higher benefit in warmer countries where the average temperature is higher and the cooling operation is repeated more frequently during a year. Furthermore, in countries where electricity prices are high, the HEMS provides higher savings, and the higher the savings are, the higher the NPV of the PV-BESS investment becomes. This is important because a PV-BESS investment may not always be feasible considering the reduced feed-in tariff rates today, and the feasibility primarily depends on savings and solar radiation.

- Currently, the price differential between on-peak and off-peak hours is not enough to offset battery degradation costs to perform energy arbitrage. Yet, as lithium-ion battery costs are decreasing, battery degradation costs can reach favorable levels and energy arbitrage can become possible in the near future.

Lastly, the limitations of the study can be listed as follows:

- Here, the HEMS requires that users input the EV arrival and departure times and occupancy status. In the case of integrating an artificial intelligence-based algorithm, the HEMS can learn these inputs on its own, which was beyond the scope of our study. In addition, the uncertainty of such inputs can be taken into account in simulations. The study ignored the above-mentioned topics due to its main focus.
- The 1R1C model was used in the thermal modeling of the house. Although this model is applicable for well-insulated, detached, and low-rise houses, it may not be suitable for multi-storey buildings due to the heat transfer between floors, which are not taken into account in the 1R1C model.
- As widely applied in the literature, we assumed that battery cycles at specific DoDs and then degradation are linear, which are in fact non-linear and can slightly change the results.
- Not in the TOU, but in the RTP case, the cost-reduction is calculated based on day-ahead prices. In reality, the results may slightly differ since there might be a difference between the estimated day-ahead prices and intraday prices on which the bill is calculated.

3.7 Conclusions

In this chapter, a MILP-based HEMS architecture is proposed to minimize total daily electricity costs in households by facilitating optimal DR and self-consumption. The proposed algorithm handles the control of all types of electrical loads (TSAs, TCAs, and PSAs) and responds to all types of battery-to-everything (B2X) and V2X technologies taking into account battery degradation. A solar model for a tilted PV array (Liu and Jordan's) is embedded into the HEMS to turn a solar radiation forecast into a PV power output. Therefore, the tilt angle of array and the impact of outdoor temperature are taken into account in the estimation of PV power output.

As its main contribution, the study combines a smart thermostat with a HEMS. Instead of using a conventional thermostat with a fixed-set point, the proposed fuzzy logic-based smart thermostat adjusts an initialized set-point in response to changing conditions (electricity prices, solar radiation, and occupant presence) and defines different set-points for each time interval. Therefore, DR for AC is provided flexibly. By not considering the smart thermostat as a separate device but as part of a HEMS, the AC is included in day-ahead optimization with other electrical loads at home and it is ensured that a stored solar energy is optimally distributed among all household appliances and peak power limits are met. The proposed method is compatible to use with both fixed-speed and inverter ACs.

The effectiveness of the HEMS is investigated through six types of households in Istanbul, Türkiye. The highest daily cost reduction of 53.2% (from $2.69 to $1.26) is observed in the household with TSAs, TCAs, PSAs, and PV, whereas the least daily cost reduction of 13.5% (from $4.51 to $3.90) is obtained in the household that comprises only TSAs and TCAs. The inclusion of PV, EV, and BESS remarkably increases the effectiveness of the HEMS with higher DR and self-consumption potential. Unlike B2H and V2H, B2G and V2G cannot be performed under the current TOU and feed-in tariff rates due to currently high battery replacement costs.

The impact of the proposed smart HEMS thermostat is examined under different solar radiation and temperature levels as well, and a daily AC cost reduction between 15% and 24% is achieved in August, depending on the day of the month.

The effectiveness of HEMSs can be increased by introducing dynamic pricing schemes. In the case of a future RTP and dynamic feed-in tariff in Türkiye, the proposed HEMS shows a significantly higher cost-benefit than in the case of static TOU pricing and static feed-in tariff. Moreover, unlike in TOU pricing, V2G becomes possible in dynamic pricing due to the larger gap between electricity buying and selling prices that can surpass the battery degradation cost. Although the results are evaluated through daily electricity cost reduction, the flexibility in prices benefits not only the demand-side but also the grid-side by flattening the peak demand and offsetting the need for additional generation capacity and operational costs. In this regard, the results of the study may guide and help policymakers working on DR.

Even though the inclusion of PV and BESS decreases the daily electricity bill, in fact, these units have initial investment, operation, maintenance, and replacement costs. Thus, an analysis just based on a daily cost reduction may be misleading since the savings due to cost reduction may not return the investment for distributed generation and energy storage units. Therefore, a detailed techno-economic and life cycle cost analysis (LCCA) and optimal system design for HEMS-operated households are going to constitute the subject of future research.

4. OPTIMAL SIZING OF PV-BESS UNITS FOR HOME ENERGY MANAGEMENT SYSTEM-EQUIPPED HOUSEHOLDS CONSIDERING DAY-AHEAD LOAD SCHEDULING FOR DEMAND RESPONSE AND SELF-CONSUMPTION

Today, selling electricity to the grid has lost its former profitability with reduced feed-in tariff (FiT) rates. This makes it crucial for prosumers to increase self-consumption and size their photovoltaic (PV) and battery energy storage system (BESS) units accordingly. Self-consumption can be increased through demand-side management (DSM) and an efficient DSM can be achieved using home energy management systems (HEMSs). Therefore, as its main contribution, this chapter proposes an optimal PV-BESS sizing model for HEMS-equipped prosumers considering day-ahead load scheduling-based DSM. Unlike other studies in the literature, the proposed model takes into account the determination of optimal PV tilt angle, load scheduling of all types of controllable appliances (time-shiftable, thermostatically controllable, power-shiftable), consideration of battery degradation, and vehicle-to-home (V2H) availability in the sizing procedure. First, the mixed-integer linear programming (MILP)-based model performs demand response (DR) and increased self-consumption to minimize the daily bill. Second, it simulates one year of HEMS operation and determines the net present value (NPV) of a PV-BESS configuration over the system lifetime. Finally, it repeats the same process for each combination of PV capacity-PV tilt angle-battery number and chooses the combination with the highest NPV as the optimal design.

The simulations were conducted to find the required PV-BESS capacity for a HEMS-equipped household with average daily electricity consumption of 37.5 kWh in Istanbul, Türkiye. The optimal configuration was found to be 3 kW PV without BESS at the tilt angle of 10°. A techno-economic sizing comparison was made between households using and not using HEMS. The NPV of PV-BESS was found to be significantly higher with HEMS use ($2273) compared with that without HEMS use ($920). Lastly, a sensitivity analysis was performed based on rising electricity prices

(+25%, +50%, +75%, +100%) and declining battery prices (-25%). The use of BESS became viable in Türkiye even with +25% electricity prices or -25% battery prices.

4.1 Introduction

In recent years, with the growing adoption of photovoltaic (PV) systems and falling PV module costs, countries have begun to phase out feed-in tariffs (FiTs) or reduce FiT rates [171]. Consequently, the sale of on-site generated renewable energy to the grid has lost its previously high economic appeal. The decrease in FiT rates has also had an impact on how PV systems should be sized. Previously, the larger the system size, the higher the profit from electricity sold to the grid. However, today, reduced FiT rates make it necessary to increase self-consumption, in which generated electricity is primarily used to cover domestic demand [6]. In the case of self-consumption, PV and battery energy storage system (BESS) units should be optimally sized, and oversizing should be avoided.

To increase self-consumption, prosumers can perform demand-side management (DSM) by shifting available electrical loads to distributed generation (DG) period [172]. They can also perform DSM to implement demand response (DR) to take advantage of time-based rates to pay less for electricity [173]. Taking into account both features, as well as an ever-increasing number of electrical appliances, the inclusion of solar batteries, and the widespread use of electric vehicles (EVs), the management of loads brings a challenge that can be surmounted by the implementation of home energy management systems (HEMSs) [174].

Today, electricity consumption in buildings accounts for about 40% of the total energy consumption [119] and the residential sector is responsible for 26.6% of the total electricity consumption [175]. In this respect, HEMSs not only provide economic benefits to their users but also contribute to the environment and climate change mitigation.

DR and increased self-consumption provided by HEMS in a household can significantly increase NPV of PV-BESS units and reduce component size and installation cost during sizing. Ultimately, this study aims to develop an optimal PV-BESS sizing model for HEMS-equipped households to achieve the highest net present value (NPV) over the life of a system.

4.1.1 Literature review

In the literature, there are a vast number of studies regarding the sizing of DG and BESS units for residential applications [176–179]. These studies do not consider the presence of HEMSs capable of performing DSM for controllable electrical loads, which can reduce the size of DG-BESS units and increase NPV.

Recently, HEMS studies aiming to lower household electricity bills by providing load scheduling for demand response and increased renewable self-consumption have received a lot of attention. Golmohammadi et al. [98] studied load scheduling of time-shiftable appliances (TSAs) and thermostatically controlled appliances (TCAs) in a smart home. Ghavzini et al. [100] examined the energy management of electric water heaters (EWHs) as TCAs and EVs as power-shiftable appliances (PSAs) in a household taking into account vehicle-to-grid (V2G) and vehicle-to-home (V2H) capabilities. Paterakis et al. [101] developed a HEMS capable of energy management of all types of home appliances (TCAs, TSAs, and EVs). Although all these studies included PV-BESS units, they neglected battery degradation. Shafie-khah and Siano [123] considered the operation of all types of loads, as well as battery degradation and thermal comfort in a household. These HEMS studies, with the majority not covered here, do not address the sizing procedure. The HEMSs mentioned above are tested in homes with pre-sized DG-BESS units installed. A HEMS of course reduces the daily bill, but when the HEMS installation in a household is considered from the ground up, then DG-BESS sizing can be reduced from the very beginning.

There are only a few studies that address the optimal sizing and total life cycle cost (LCC) assessment of DG-BESS units for households that are equipped with HEMSs capable of electrical load scheduling for DSM. Hemmati and Saboori [180] evaluated the presence of HEMS in PV-BESS sizing, which ensures optimal charging/discharging of batteries. Korjani et al. [181] developed an offline energy management tool to be used in PV-BESS sizing considering the energy consumption habits of prosumer households. Zhou et al. [182] investigated the capacity allocation of PV-BESS units in HEMS operation considering different pricing schemes. Yaldız et al. [183] studied the optimal sizing of PV-BESS units considering peer-to-peer (P2P) energy trading. Khezri et al. [184] determined the optimal capacity of a small-scale wind turbine (WT)-BESS system for a rule-based HEMS taking into account the uncertainties of EV, household load, and wind generation. Despite the presence of

HEMS, electrical load management and scheduling of appliances are not considered in [180–184]. Erdinç et al. [185] conducted techno-economic sizing of PV-BESS units for EV-owner households that are under HEMS operation. Load management of PSAs is considered but that of TSAs and TCAs is neglected. Tostado-Veliz et al. [186] performed optimal PV-BESS sizing for smart homes considering the energy management of TSAs and reliability against DR and grid outages. Bhamidi and Sivasubramani [187] proposed a two-stage optimization for the sizing of WT-PV-BESS and the electrical load management of TSAs and EVs in a household. Yet, the presence of TCAs is neglected. It should be noted that [180–187] did not take into account battery degradation, which is crucial to the total LCC of the systems. Mulleriyawage and Shen [188] considered the load management of TSAs and TCAs and the impact of battery degradation in BESS sizing for households but PV array sizing is not considered. In all the above-mentioned sizing studies, the optimal PV tilt angle determination was neglected. It is a crucial element in PV-BESS sizing, which can vary according to house location, electrical load profile, and DSM. In these studies, either PVs were not sized, pre-measured array data were used or panels were assumed to be flat. The summary of the shortcomings of the studies regarding DG-BESS sizing considering DSM/the presence of HEMS is demonstrated in Table 4.1.

Table 4.1 : Summary of studies on optimal sizing of DG-BESS units considering DSM/the presence of HEMS.

Ref.	Load scheduling			Sizing				Battery degradation
	TSA	TCA	EV	PV	WT	BESS	Tilt angle	
[180]	–	–	–	✓	–	✓	–	–
[181]	–	–	–	✓	–	✓	–	–
[182]	–	–	–	✓	–	✓	–	–
[183]	–	–	–	✓	–	✓	–	–
[184]	–	–	✓	–	✓	✓	–	–
[185]	–	–	✓	✓	–	✓	–	–
[186]	✓	–	✓	✓	–	✓	–	–
[187]	✓	–	✓	✓	✓	✓	–	–
[188]	✓	✓	–	–	–	✓	–	✓
This study	✓	✓	✓	✓	–	✓	✓	✓

4.1.2 Contribution

In the light of the reviewed studies, it is seen that, although there are many HEMS- or PV-BESS sizing-related studies in the literature, only very few of them combine the two and consider the impact of HEMS-based load scheduling on PV-BESS sizing. Among them; none consider the modeling and management of all three types of loads (TSAs, TCAs, PSAs). None addresses optimal PV tilt angle determination in the presence of a load scheduling-based HEMS. They generally neglect battery degradation or assume batteries to be replaced after a fixed time duration.

Therefore, the main contributions of this study are as follows:

(1) A comprehensive PV-BESS sizing model is developed for HEMS-equipped households, which takes into account day-ahead load scheduling-based DR and self-consumption in the sizing procedure. Unlike the few available studies in the literature, the proposed model takes into account the scheduling of all types of electrical loads, the impact of battery degradation, the V2H availability, and the determination of optimal PV tilt angle in component sizing.

(2) A techno-economic comparison is made between PV-BESS-equipped households using and not using HEMS. By this means, the effect of using HEMS on the NPV of PV-BESS systems is investigated.

(3) A sensitivity analysis is performed and the impact of rising electricity prices and falling battery prices on the PV-BESS sizing of HEMS-equipped households is investigated.

(4) Optimal PV-BESS configurations in European countries at the same latitude as Türkiye (case location) but with different electricity prices are determined and the local results are extended to the general.

4.2 Methodology

The main steps of the procedure are summarized in a flowchart as shown in Figure 4.1. The sizing optimization consists of two stages:

In the first stage,

- With the optimal load scheduling carried out by HEMS, the daily electricity bill of the smart home is minimized.

In the second stage,

- The daily bill minimization is performed for each day of the year and the total annual electricity bill is calculated.
- The net cash inflow is calculated by finding the difference between the annual bill with and without PV-BESS-HEMS.
- The NPV is calculated by taking the difference between discounted cash inflows and outflows.
- The procedure is repeated for all possible configuration combinations of PV array capacity-battery number-tilt angle.
- The NPVs of all possible configurations are determined and then ranked from highest to lowest. The configuration with the highest NPV is chosen as the optimal system design.

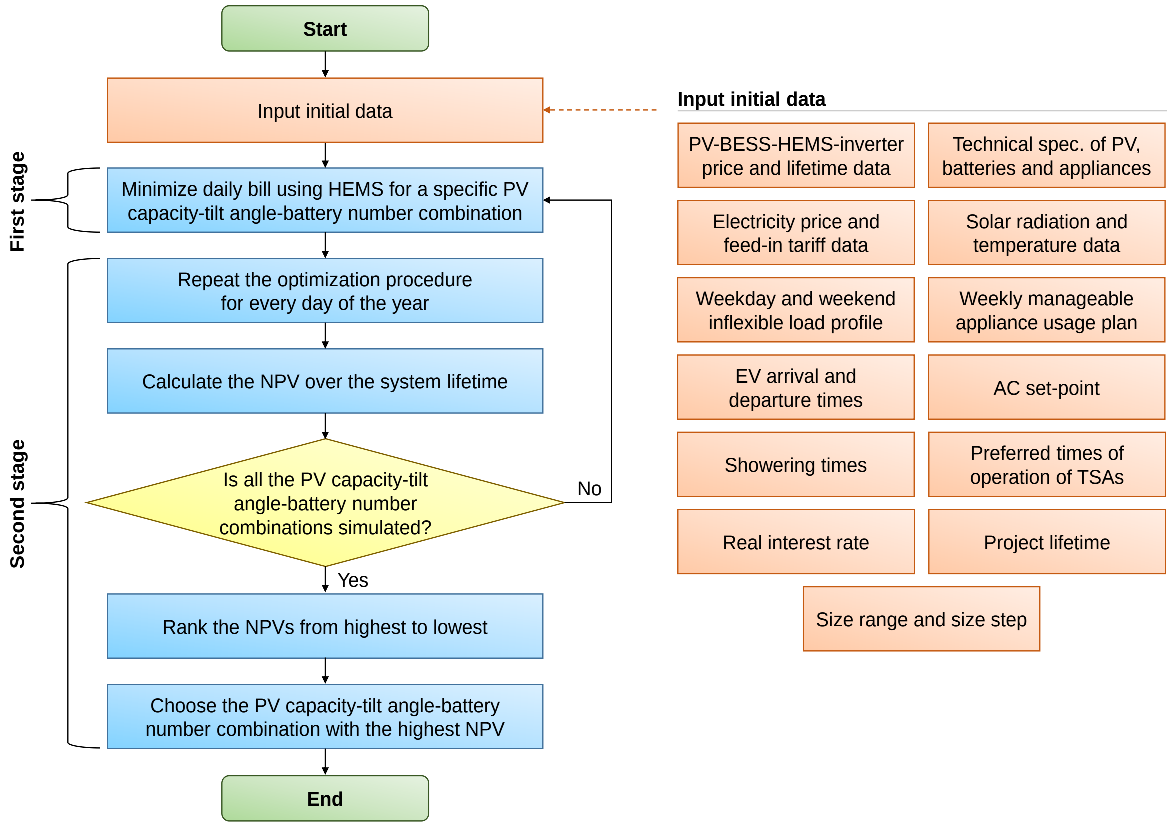

Figure 4.1 : Flowchart of the optimal PV-BESS sizing model for HEMS-equipped households.

4.2.1 First stage – Daily load scheduling

The mixed-integer linear programming (MILP) problem is solved by “intlingprog” solver of MATLAB. The objective function in the first stage is annual electricity bill minimization performed by HEMS [14]:

$$C_{c,y,d} = \min \sum_{t} \{P_{c,d,t}^{G} \cdot \Delta t \cdot \lambda_{t}^{buy} + P_{c,d,t}^{V,G} \cdot \Delta t \cdot \lambda_{t}^{V,buy} + P_{c,d,t}^{B,G} \cdot \Delta t \cdot \lambda_{t}^{B,buy} - P_{c,d,t}^{PV,2G} \cdot \Delta t \cdot \lambda_{t}^{sell}\} \tag{4.1}$$

Daily bill minimization for a specific PV-BESS-PV tilt angle combination of c in year y and on day d is given in Eq. (4.1). $P_{c,d,t}^{G}$ is the total power bought from the grid by all household appliances (inflexible loads, TCAs and TSAs). $P_{c,d,t}^{PV,2G}$ is the power sold to the grid by PV. $P_{c,d,t}^{V,G}$ and $P_{c,d,t}^{B,G}$ are the power bought from the grid by EV and BESS, respectively. EV and BESS are assumed to buy electricity at a higher, battery degradation cost included artificial price (λ_{t}^{buy}+$\lambda^{k,deg}$) to prevent unnecessary battery cycles (Eq. (4.2)). That is, V2H and battery-to-home (B2H) should occur if only the profit from buying power to utilize in household is greater than the degradation cost of batteries [125].

$$\begin{gathered} \lambda_{t}^{k,buy} = \lambda_{t}^{buy} + \lambda^{k,deg} \\ \lambda^{k,deg} = \frac{Rep^{k}}{(L^{k} \cdot \eta^{k,rt})} \\ L^{k} = Cyc^{k} \cdot Cap^{k} \cdot DoD^{k} \end{gathered} \tag{4.2}$$

For example, if a household needs to buy electricity at on-peak period from 0.25 \$/kWh, their EV can perform V2H if later the EV will be able to buy electricity at a cheap price from 0.12 \$/kWh at off-peak period. Considering that this process degrades EV battery, and the calculated degradation cost for EV battery is 0.08 \$/kWh, the cost of V2H becomes 0.20 \$/kWh, which is lower than 0.25 \$/kWh. If this cost was higher than 0.25 \$/kWh, then the optimization model would not permit HEMS to perform V2H.

Here, the battery degradation cost is also used to calculate battery replacement cost (as detailed in Eq. (4.11)). So, instead of periodic replacement, a replacement cost is calculated over battery usage which is more accurate than the periodic replacement method.

Artificial battery degradation cost added buying prices for BESS and EV ($\lambda_t^{V,buy}, \lambda_t^{B,buy}$) are only used in optimization and should be discluded from the optimization result later. Therefore, the real bill is recalculated using real buying prices ($\lambda_t^{B,buy}$):

$$C'_{c,y,d} = P^{G}_{d,c,t} \cdot \Delta t \cdot \lambda_t^{buy} + P^{V,G}_{d,c,t} \cdot \Delta t \cdot \lambda_t^{buy} + P^{B,G}_{d,c,t} \cdot \Delta t \cdot \lambda_t^{buy} - P^{PV,2G}_{d,c,t} \cdot \Delta t \cdot \lambda_t^{sell} \tag{4.3}$$

$C^{ann}_{c,y}$ gives the total annual electricity bill of a specific PV-BESS-tilt angle combination:

$$C^{ann}_{c,y} = \sum_{d=1}^{365} C'_{c,y,d} \tag{4.4}$$

4.2.2 Second stage – Calculation of NPV and ranking of system combinations

The objective function in the second stage is to find the project with the highest NPV among all possible combinations of PV array capacity, battery number, and PV tilt angle. NPV is calculated by taking the difference between discounted cash inflows and outflows over a period of time. An investor most of the time chooses a project with the highest NPV. NPV is calculated as follows:

$$NPV_c = C_c^{in} - C_c^{out} \tag{4.5}$$

And the objective function is to find the optimal PV-BESS-tilt angle combination with the highest NPV:

$$max \sum_{c=1} NPV_c \tag{4.6}$$

In Eq. (4.7), C_c^{in} denotes cash inflows resulting from monetary savings over the life of the project. Monetary savings refers to the difference in the total electricity bill when PV-BESS-HEMS is used and not used. Here, the bill difference is due to DR, self-consumption, and electricity sales to the grid in case of PV-BESS-HEMS use.

Therefore, $C_{c,y}^{ann}$ in Eq. (4.4) is calculated two times as $C_{c,y}^{ann,without}$ and $C_{c,y}^{ann,with}$ to be used in Eq. (4.7).

$$C_c^{in} = \sum_{y=1}^{20} \left(\frac{C_{c,y}^{ann,without}}{(1+r)^y} - \frac{C_{c,y}^{ann,with}}{(1+r)^y} \right) \tag{4.7}$$

Yet, the savings are the result of investments and related expenses. C_{out} indicates the cash outflows as shown in Eq. (4.8).

$$C_c^{out} = C_c^{initial} + C_c^{O\&M} + C_c^{replacement} \tag{4.8}$$

Cash outflows include initial investment, O&M, and replacement cost of components as shown in Eq. (4.9-4.11). In Eq. (4.9), for a residential application, installation labor cost is assumed to be fixed regardless of its size. The initial cost of PV depends on its size. The initial cost of BESS is not included here and is calculated over BESS usage in Eq. (4.11). It is assumed that inverter size depends on PV size. As a general rule of thumb, the inverter-to-array size ratio is taken as 0.8 [189]. The novelty of the study is the consideration of the HEMS operation in the sizing optimization. Therefore, the initial cost of HEMS is also added.

$$C_c^{initial} = C^{labor} + n_c^{PV} \cdot \left(C^{PV,ini} + 0.8 \cdot C^{inv,ini} \right) + C^{HEMS,ini} \tag{4.9}$$

In Eq. (4.10), O&M costs are considered only for PV and BESS. HEMS is assumed to have no O&M cost and the O&M cost of the inverter is assumed to be joint with that of the PV.

$$C_c^{O\&M} = \sum_{y=1}^{20} \left(\frac{n_c^{PV} \cdot C^{PV,O\&M}}{(1+r)^y} + \frac{n_c^{B} \cdot C^{B,O\&M}}{(1+r)^y} \right) \tag{4.10}$$

In Eq. (4.11), the replacement cost of the PV array is neglected since project lifetime and PV lifetime are equal. BESS replacement is handled through BESS use. Inverter replacement is treated as periodic replacement (10 years due to standard warranty).

$$C_c^{replacement} = \sum_{y=1}^{20} \left(\frac{use_{c,y}^{B} \cdot \lambda^{B,deg}}{(1+r)^y} \right) + \sum_{y=1}^{\frac{20}{L^{inv}}-1} \left(\frac{n_c^{PV} \cdot 0.8 \cdot C^{inv,rep}}{(1+r)^{y \cdot L^{inv}}} \right) \tag{4.11}$$

4.2.3 Modeling of appliances

4.2.3.1 TSAs

TSAs (clothes dryer, dishwasher, and washing machine) have fixed consumption patterns and their operation cannot be interrupted once they run [126]. If the vector of $P^i = [p_1^i \quad p_2^i \quad \cdots \quad p_T^i]'$ shows the fixed power consumption of a TSA, then all possible scheduling combinations of P^i can be represented in a matrix as in Eq. (4.12).

$$P^i = \begin{bmatrix} p_1^i & p_T^i & \cdots & p_3^i & p_2^i \\ p_2^i & p_1^i & \cdots & p_4^i & p_3^i \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_T^i & p_{T-1}^i & \cdots & p_2^i & p_1^i \end{bmatrix}, \forall t \in [t^{i,min}, t^{i,max}] \tag{4.12}$$

Among the combinations, only one of them gives the optimal result and the binary integer vector X^i defined in Eq. (4.13) functions as switch control to choose that optimal column.

$$X^i = [x_1^i, x_2^i, \ldots, x_T^i]', \forall t \in [t^{i,min}, t^{i,max}] \tag{4.13}$$

Eq. (4.14) expresses that only one of the elements can be non-zero in X^i.

$$X^i = \sum_{t=1}^{T} x_t^i = 1,\ X^i \in \{0,1\}, \forall t \in [t^{i,min}, t^{i,max}] \tag{4.14}$$

Residents may set a preferred time of operation for a TSA. $t^{i,min}, t^{i,max}$ represent the start and end of the time range, respectively, in which TSA is allowed to operate. The length of this interval (the difference between $t^{i,min}$ and $t^{i,max}$) cannot be lower than the running duration of a TSA (Eq. (4.15)).

$$run^i \leq |t^{i,min}, t^{i,max}| \tag{4.15}$$

Eq. (4.16) gives the power consumption of a TSA.

$$P_t^i = P^i \cdot X^i, \forall t \in [t^{i,min}, t^{i,max}] \tag{4.16}$$

4.2.3.2 TCAs

Two TCAs are assumed to be present in the household, AC, and EWH. For the sake of simplicity and due to its lower flexibility and low energy consumption, the refrigerator is categorized as an inflexible load. A simple 1R1C thermal model is used in the modeling of the EWH tank and house [129–131]. EWH and AC can perform pre-heating and pre-cooling, respectively, for DR and increased self-consumption. Also, HEMS can increase AC set point during DR event to perform DR [14].

Eq. (4.17) models the inside hot water/indoor air temperature ($T_t^{i,j}$) in the EWH tank or house. Here, the outside temperature $T_t^{o,j}$ stands for the ambient temperature where the EWH tank is located or the outdoor temperature outside the house. Thermal resistance (R^j) and thermal capacitance (C^j) are specific to the EWH tank/house envelope. Constant heat flow capacity per time interval ($\dot{c}^j$) belongs to the entering water due to water replacement or the fresh air due to air ventilation. uc_t defines the times of water replacement/air ventilation.

It should be noted that, in the study, air ventilation is assumed to not affect the indoor air temperature and is therefore excluded for AC operation. Thus, the expressions of $T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j$ and $\dot{c}^j \cdot R^j \cdot uc_t^j$ takes the value 0 in Eq. (4.17) for AC operation. Besides, the sign of the decision variable is negative in AC operation to perform cooling.

$$\begin{aligned} T_t^{i,j} = & \frac{\left(T_t^{o,j} + T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j + R^j \cdot COP^j \cdot P^j \cdot x_t^j\right)}{\left(1 + \dot{c}^j \cdot R^j \cdot uc_t^j\right)} \\ & + \left(T_t^{o,j} - \left(\frac{\left(T_t^{o,j} + T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j + R^j \cdot COP^j \cdot P^j \cdot\right)}{\left(1 + \dot{c}^j \cdot R^j \cdot uc_t^j\right)}\right)\right) \\ & \cdot e^{\left(\frac{-\left(1+\dot{c}^j \cdot R^j \cdot uc_t^j\right) \cdot \Delta t}{R^j \cdot C^j}\right)}, \qquad \forall t \end{aligned} \tag{4.17}$$

Eq. (4.18) expresses the upper and lower limits of hot water/indoor temperature within the EWH tank/house.

$$T^{i,min,j} \leq T_{j,t}^{i} \leq T^{i,max,j}, \forall t \tag{4.18}$$

Eq. (4.19) indicates the power consumption of a TCA.

$$P_t^j = P^j \cdot x_t^j, \forall t \tag{4.19}$$

4.2.3.3 PSAs

The PSAs in the household are BESS and EV which are rechargeable and operate between certain power limits. BESS and EV have similar operations and their models are constructed as in [128]. Eq. (4.20) implies that the BESS or EV can discharge power in the form of B2H ($P_t^{B,2H}$) or V2H ($P_t^{V,2H}$).

$$P_t^{k,2H} = \eta^{k,dis} \cdot P_t^{k,dis},\ \forall t \tag{4.20}$$

Eq. (4.21-4.22) denote that the charging ($P_t^{B,ch}$ and $P_t^{V,ch}$) and discharging ($P_t^{B,dis}$ and $P_t^{V,dis}$) power of BESS and EV cannot exceed their specific charging ($R^{B,ch}$ and $R^{V,ch}$) and discharging ($R^{B,dis}$ and $R^{V,dis}$) rates.

$$0 \leq P_t^{k,ch} \leq R^{k,ch} \cdot x_t^k,\ \forall t \tag{4.21}$$

$$0 \leq P_t^{k,dis} \leq R^{k,dis} \cdot (1 - x_t^k),\ \forall t \tag{4.22}$$

Eq. (4.23) stands for the state of energy (SoE) of BESS and EV. Eq. (4.24) indicates that the SoE of batteries is limited between maximum battery capacity and allowed depth of discharge (DoD).

$$SoE_t^k = SoE_{t-1}^k + \eta^{k,ch} \cdot P_t^{k,ch} \cdot \Delta t - P_t^{k,dis} \cdot \Delta t\ , \forall t \tag{4.23}$$

$$SoE^{k,max} \cdot (1 - DoD^k) \leq SoE_t^k \leq SoE^{k,max},\ \forall t \tag{4.24}$$

The operation of EV is similar to BESS, except that, while BESS can operate for 24 hours, EV can operate only when it is home. The charge and discharge of EV are limited between arrival and departure times. Therefore, t (time interval) index between Eq. (4.20-4.24) is defined as in Eq. (4.25).

$$t = \begin{cases} k = B \longrightarrow \forall t > 1 \\ k = V \longrightarrow \forall t \in [t^{arr}, t^{dep}] \end{cases} \quad (4.25)$$

The initial SoE assignment of BESS and the SoE update on the arrival of EV are specified in Eq. (4.26-4.27). Also, as stated in Eq. (4.28), the SoE of the EV battery should be 100% of the battery capacity before the departure.

$$SoE_t^B = SoE^{B,ini}, if\ t = 1 \quad (4.26)$$

$$SoE_t^V = SoE^{V,ini} + \eta^{V,ch} \cdot P_t^{V,ch} \cdot \Delta t - P_t^{V dis} \cdot \Delta t\ ,\ \forall t \in t^{arr} \quad (4.27)$$

$$SoE_t^V = SoE^{V,max},\ t = t^{dep} \quad (4.28)$$

4.2.4 Tilted PV array model

In the reviewed HEMS-related studies, it was seen that the use of a solar radiation estimation model for tilted PV arrays was not considered. Either arrays were considered flat, which did not allow determination of the optimal tilt angle, or pre-measured data from pre-installed arrays were used, which is a difficult method to implement in real life due to its site-specific nature.

Therefore, this study uses an isotropic solar radiation estimation model (Liu and Jordan) to estimate total global solar radiation on a tilted PV panel [132]. By using a solar model, the proposed PV-BESS sizing model can be used in every part of the world by entering solar radiation, latitude, and temperature information of a location that can be accessed easily. After estimating the solar radiation on a tilted panel, the estimation data can be converted into a useful PV power output based on the specifications of a PV system.

Eq. (4.29-4.37) describe the estimation of solar radiation on a tilted plane using the Liu and Jordan model.

$$\delta = 23.45 \sin\left[\frac{360(n + 284)}{365}\right] \quad (4.29)$$

$$\omega = \arccos[-\tan(\delta)\tan(\varphi)] \quad (4.30)$$

$$\omega' = min\{\omega, \arccos[-\tan(\delta)\tan(\varphi - s)]\} \quad (4.31)$$

$$H_o = \frac{24}{\pi} I_{SC} \left(1 + 0.033 \cos\left(\frac{360n}{365}\right)\right) \left(\cos(\varphi)\cos(\delta)\sin(\omega) + \frac{\pi\omega}{180}\sin(\varphi)\sin(\delta)\right) \tag{4.32}$$

$$Kt = H/H_o \tag{4.33}$$

$$H_d = H(1 - 1.13K) \tag{4.34}$$

$$R_b = \frac{\cos(\varphi - s)\cos(\delta)\sin(\omega') + \frac{\pi\omega'}{180}\sin(\varphi - s)\sin(\delta)}{\cos(\varphi)\cos(\delta)\sin(\omega) + \frac{\pi\omega'}{180}\sin(\varphi)\sin(\delta)} \tag{4.35}$$

$$R = R_b\left(1 - \frac{H_d}{H}\right) + H_d\left(\frac{1 + \cos(s)}{2H}\right) + \rho\left(\frac{1 - \cos(s)}{2}\right) \tag{4.36}$$

$$H_t = RH \tag{4.37}$$

Eq. (4.38) describes the estimation of the cell temperature which has a direct influence on the array power output.

$$T_t^{cell} = T_t^{out} + \frac{H_t}{H_t^{NOCT}}\left(T^{cell,NOCT} - T^{amb,NOCT}\right) \tag{4.38}$$

Eq. (4.39) gives the power output calculation of the PV array. It should be noted that the PV system is assumed to be always operating at its maximum power point.

$$P_t^{PV,prod} = Y^{PV} d^{PV}\left(\frac{Ht}{H_t^{STC}}\right)\left[1 + \alpha^P \cdot \left(T_t^{cell} - T^{cell,STC}\right)\right] \tag{4.39}$$

4.2.5 Power balance

The power balance in the HEMS-operated household is summarized in Figure 4.2 (without showing the AC to DC and DC to AC conversion). Eq. (4.40) describes the power balance of HEMS. The power drawn from the grid, used PV power, and power transferred from PSAs to home in the form of B2H and V2H is equal to the power consumption of the household appliances and charging power of PSAs at time t.

$$P_t^G + P_t^{V,G} + P_t^{B,G} + P_t^{PV,used} = P_t^H + \sum_{k=1}^{K} P_t^{k,ch}, \forall t \quad (4.40)$$

In Eq. (4.41), P_t^H is the power consumption of household appliances at time t (TSAs, TCAs and inflexible loads) except BESS and EV (PSAs).

$$P_t^H = P_t^{inf} + \sum_{i=1}^{I} P_t^i + \sum_{j=1}^{J} P_t^j, \forall t \quad (4.41)$$

In Eq. (4.42), $P_t^{PV,used}$ is the PV power supplying power to household appliances, BESS and EV at time t.

$$P_t^{PV,used} = P_t^{PV,2H} + P_t^{PV,2B} + P_t^{PV,2V}, \forall t \quad (4.42)$$

Eq. (4.43) states that PV production at time t is used for self-consumption and energy storage. The excess PV power is exported to the grid.

$$P_t^{PV,prod} = P_t^{PV,used} + P_t^{PV,2G} \quad (4.43)$$

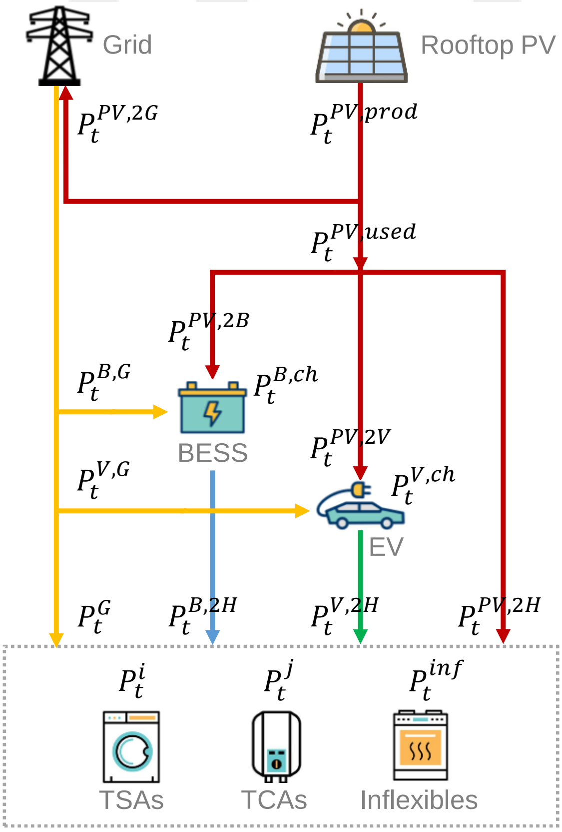

Figure 4.2 : Representation of the power balance in the HEMS-equipped household.

4.3 Input Data

A day is discretized into 144 time slots and the time-window for the daily load scheduling optimization is 10 minutes (0.167 h). The hypothetical house is located in Istanbul, Türkiye, at the latitude of 41.01º. The climatic data in 10 minutes resolution of the case study location (Figure 4.3) are obtained from *TARBIL* [136]. 250 W Canadian-Solar-CS6P-250P polycrystalline panels of which temperature coefficient of power is -0.424 %/ºC and average nominal operating cell temperature is 43.6 ºC are used in the simulations [137]. PV derating factor is assumed to be 90%. The default ground reflectance is 0.2. Türkiye stays in the Northern Hemisphere and therefore the panels are oriented towards the south.

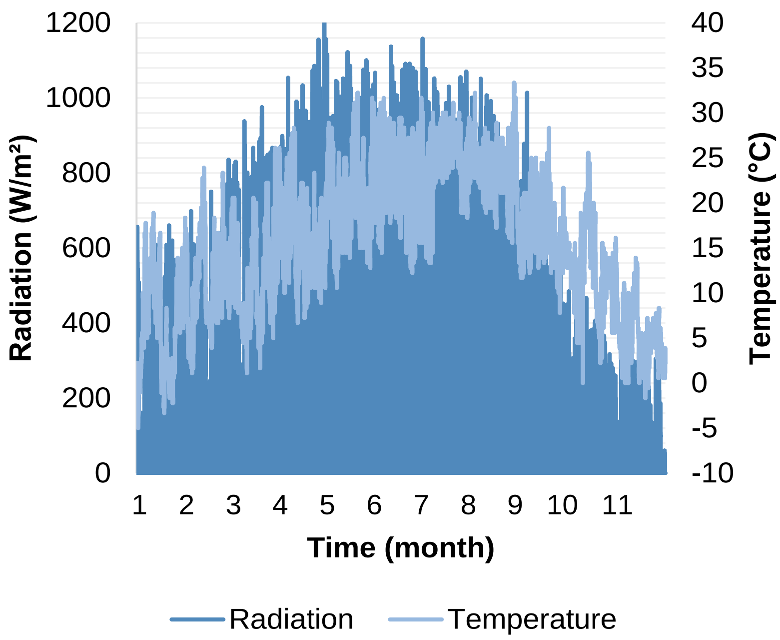

Figure 4.3 : Climatic data of the case study location (Istanbul, Türkiye).

Thermal properties and technical specifications regarding AC and EWH are given in Table 4.2. Thermal properties of a 125 m² one-story household are used [143]. An inverter AC is considered of which rated power is 2.21 kW [148]. The initialized thermostat set point is 22.0 ºC and inverter AC works within a dead band of ±0.1 ºC. During on-peak hours (between 17:00 and 22:00) HEMS increases the set point by 1.0 ºC and it becomes 23.0 ºC to provide DR. Thermal properties of EWH are adopted from [149]. EWH size is not stated in [149] and is estimated as 200 liters for a 3 kW EWH [150]. A default COP is used as 1.0 [151]. Residents are assumed to take a shower approximately three times a day and each shower is assumed to last for 10 minutes. Residents shower daily at 06:10, 14:00 and 18:30. The temperature inside the EWH tank is constrained between 45 and 60 ºC to avoid bacterial growth and scalding [152]. The monthly inlet water temperature values of Istanbul are given in Table 4.3 [190]. It is assumed that inlet water temperature is constant throughout the month.

Table 4.2 : Thermal properties and technical specifications regarding AC and EWH.

Parameter	House	EWH tank
Size	125 m²	200 liters
Thermal capacitance (kJ/ºC)	12312	1770
Thermal resistance (ºC/kW)	4.87	223
	AC	EWH
Rated power (kW)	2.21	3.0
Coefficient of performance (COP)	3.21	1
Heat flow capacity per time interval (kW/K)	-	0.659
Minimum inside temp. (ºC)	21.9*	45
Maximum inside temp. (ºC)	22.1*	60

*The HEMS increases AC set point from 22 ºC to 23 ºC during DR event (between 17:00 and 22:00).

Table 4.3 : Monthly inlet water temperatures in Istanbul.

Month	Temp. (ºC)	Month	Temp. (ºC)
January	10.2	July	21.9
February	9.0	August	22.9
March	9.5	September	22.4
April	11.8	October	19.8
May	15.4	November	16.9
June	19.2	December	13.2

The BESS and EV use lithium-ion batteries (Table 4.4). Lifetime throughput of batteries in kWh are measured for specific DoD, capacity, and lifetime in cycle. Then, battery degradation cost is calculated through lifetime throughput, round-trip efficiency, and battery replacement cost as shown in Eq. (2) [142,191,192]. The BESS is in operation all day long. The initial and final SoE of the BESS are 0. The batteries are charged and discharged during the day according to the daily bill minimization. After a full day’s operation, the BESS starts the next day with empty batteries. The maximum SoE that BESS can reach depends on the number of batteries and the nominal capacity. The EV is in operation between 18:00 (EV arrival) and 08:00 (EV departure). The initial SoE of the EV on arrival is assumed to be 16.5 kWh (68.75%) after a daily 50 km of travel which roughly equates to 7.5 kWh of consumption (31.25%) [193]. The SoE should be 24 kWh (100%) again before departure.

Table 4.4 : Technical specifications of BESS (KiloVault) and EV (Nissan LEAF) batteries [141,142,192–194].

Parameter	BESS	EV
Nominal capacity (kWh)	2.5	24
Charging rate (kW)	2.0	3.3
Discharging rate (kW)	2.0	3.3
Charging efficiency (%)	95	95
Discharging efficiency (%)	95	95
Round-trip efficiency (%)	90	90
DoD (%)	80	80
Battery lifetime in cycles	5000	2000
Lifetime throughput (kWh)	10000	38400
Battery replacement cost ($)	2500	3800
Bat. degradation cost ($/kWh)	0.105	0.104
Initial SoE (kWh)	0	16.5
Final SoE (kWh)	0	24
Operating time interval	00:00 – 00:00	18:00 – 08:00

The daily electricity consumption of the household is 37.5 kWh on average, depending on the use of different appliances on different days of the week. Load profiles of TSAs (clothes dryer, washing machine, and dishwasher) are demonstrated in Table 4.5. Once initialized, the dishwasher, washing machine, and clothes dryer run for 50 minutes, 70 minutes, and 60 minutes, respectively. The data are derived from [82,155]. The residents can set their preferred operating times of TSAs on the HEMS interface as previously expressed in Eq. 15. In this study, it is assumed that residents allow HEMS to shift the operation of TSAs to any moment of the day.

Table 4.5 : Operating stages of TSA cycles.

	Power (kW)		
Time step	Dishwasher	Wash. machine	Clothes dryer
1	2.1	1.8	3
2	2.1	1.8	3
3	0.15	0.3	0.15
4	2.1	1.8	3
5	2.1	1.8	0.15
6	–	0.15	0.15
7	–	0.15	–

Inflexible load demand consists of a kettle, coffee maker, two PCs, two televisions, iron, toaster, hairdryer, microwave, refrigerator, lights, electric stove, cooker hood, and refrigerator. The inflexible load profile is based on both the data collected from references [134,158–160] and the authors' usage habits. Users can specify separate inflexible load profiles for weekdays and weekends, or different load profiles according to the seasons. In this study, it is assumed that the inflexible load profile of the household remains the same throughout the year. The weekly use of flexible appliances in the household is demonstrated in Table 4.6. It is assumed that the weekly pattern applies to the whole year. The dishwasher runs five and the washing machine and clothes dryer run two times a week. The EV is charged every day except Sunday. The EWH and AC operate every day. Yet, since AC operation depends on outdoor temperature, it does not operate on cold days.

Table 4.6 : Residents' weekly manageable appliance usage plan.

Appliance	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Dishwasher	✓	✓	✓	✓	–	–	✓
Wash. machine	–	✓	–	–	✓	–	–
Clothes dryer	–	✓	–	–	✓	–	–
EV	✓	✓	✓	✓	✓	✓	–
AC*	✓	✓	✓	✓	✓	✓	✓
EWH	✓	✓	✓	✓	✓	✓	✓

*depending on the outdoor temperature.

Residential TOU rates consists of three tiers in Türkiye as off-peak (0.076 $/kWh from 22:00 to 06:00), shoulder (0.122 $/kWh from 06:00 to 17:00) and on-peak (0.179 $/kWh from 17:00 to 22:00). Turkish residents can sell surplus electricity at the price of 0.061 $/kWh. The prices are presented in Table 4.7 [195].

Table 4.7 : Residential electricity prices.

Rate	Duration	Price ($/kWh)
Flat	All-day	0.120
TOU – Shoulder	06:00 – 17:00	0.122
TOU – On-peak	17:00 – 22:00	0.179
TOU – Off-peak	22:00 – 06:00	0.076
FiT	All-day	0.061

Component price data are collected through market research. Relevant price and lifetime values of system components are given in Table 4.8. Since HEMSs have not been commercialized enough yet, existing smart thermostats and energy monitoring systems have been considered to set the HEMS price. The O&M cost for PV and inverter is selected to be 2% of their initial cost as a rule of thumb. The O&M cost for BESS is assumed to be 1% of its initial cost [196]. Battery lifetime throughput is measured for a specific DoD of 80% as shown in Eq. (2). Soft costs include the cost of all associated permits and all overheads including marketing, sales, and administrative costs associated with the system.

Table 4.8 : Price and lifetime values of PV, BESS and inverter.

Parameter	Value
Installation and soft costs ($)	800
PV array ($/kW)	600
Inverter ($/kW)	500
Li-ion battery - 2.5 kWh ($)	1000
HEMS ($)	200
PV array lifetime (yr)	20
Inverter lifetime (yr)	10
Battery lifetime throughput (kWh)	10000
Project lifetime (yr)	20
O&M of PV+inverter ($/kW-year)	2% of PV+inverter price
O&M of battery ($/year)	1% of battery pack price
Real interest rate (%)	2

In the simulations PV array size ranges from 1 to 7 kW with 1 kW increments, the number of 2.5 kWh batteries ranges from 0 to 4, and the PV tilt angle ranges from 0 to 70° with 10° increments (Table 4.9). The sizing model, therefore, simulates a total of 280 combinations, determines the NPV of each system combination, and ranks them from the highest to the lowest. It should be noted that the size range can be increased and the size step can be reduced even more. Here, the resolution is kept low to facilitate the interpretation of the results and to demonstrate the capabilities of the model.

Table 4.9 : Sizing range of PV-BESS systems for HEMS-equipped households.

	Size range	Size step
PV	1-7 kW	1 kW
BESS	0-10 kWh	2.5 kWh
PV tilt angle	0-70°	10°

4.4 Simulation Results

4.4.1 Optimal configuration at current electricity and battery prices

The NPVs of all the PV-BESS combinations are calculated by taking into account the savings before and after installing PV, BESS and HEMS, and considering the associated initial investment, O&M, and replacement costs. As a result, the optimal configuration is found as 3 kW PV – no BESS – 10° tilt angle for the HEMS-operated household at the current electricity and battery prices in Türkiye (Table 4.10).

As seen in Table 4.10, increasing PV size increases NPV, but only to some extent. After a specific array size, the self-consumption rate starts to drop. And since the selling price is very low today, the surplus electricity which is sold to the grid does not provide enough revenue to cover the investment that can be made for increased PV capacity.

Table 4.10 also shows that the inclusion of batteries reduces the NPV of systems in Türkiye. This is due to the currently high battery prices and low electricity prices in the country. The bill savings provided by BESS cannot exceed the investment made in it. Therefore, battery storage is found to be not profitable in Türkiye as of today.

Table 4.10 : NPV ($) of PV-BESS systems for the HEMS-equipped household (current electricity and battery prices).

	Number of batteries (x2.5 kWh)				
PV (kW)	0	1	2	3	4
1	1425	991	489	-35	-1078
2	1999	1660	1156	620	-465
3	**2273**	2022	1527	963	-237
4	2248	2057	1598	999	-250
5	2065	1895	1482	871	-431
6	1809	1642	1241	625	-687
7	1514	1344	951	315	-1008

The daily bill of the smart home with and without using the optimal configuration is shown in Figure 4.4. The annual average of the daily bill is \$4.10 without any configuration (base case) and \$2.78 with 3 kW PV – no battery – HEMS configuration (optimal case), with a reduction of 33%. The increased daily bill on summer days, which reaches a maximum of \$5.25, is due to AC usage. The minimum daily bill is \$3.18 and is for winter Sundays when there is no air conditioning and the EV does not leave the house. In the optimal case, the daily bill varies between \$4.08 and \$1.20. The annual electricity bill of the household is found to be \$1510 without any configuration. When the household is equipped with PV and HEMS (no BESS due to low feasibility), the annual electricity bill reduces to \$1008.

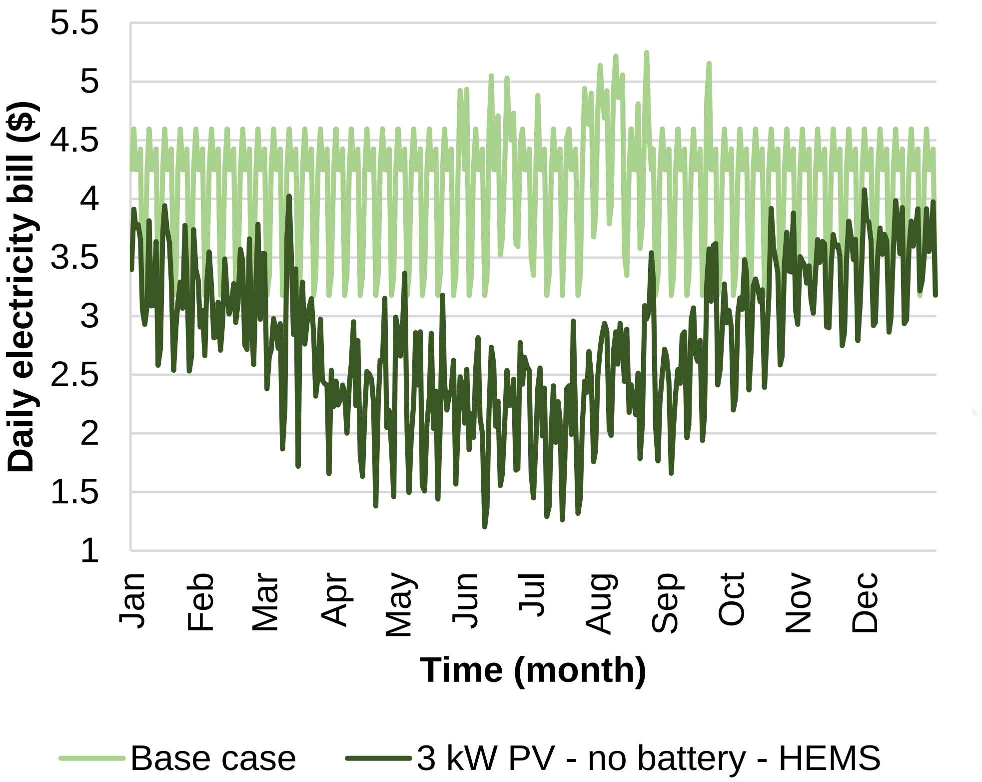

Figure 4.4 : The daily electricity bill for one-year period with and without PV-HEMS installation.

The net and cumulative cash flows are presented in Figure 4.5. Cash inflow consists of savings, which is the difference (\$502) in the annual bill before (\$1510) and after (\$1008) using PV – HEMS. And the cash outflow consists of the initial investment of a PV system, which is \$4000 (\$1800 PV array + \$1200 inverter + \$800 labor and soft costs + \$200 HEMS) and O&M costs (\$66) and replacement cost of the inverter. The cash inflows and outflows are susceptible to the real interest rate of 2%.

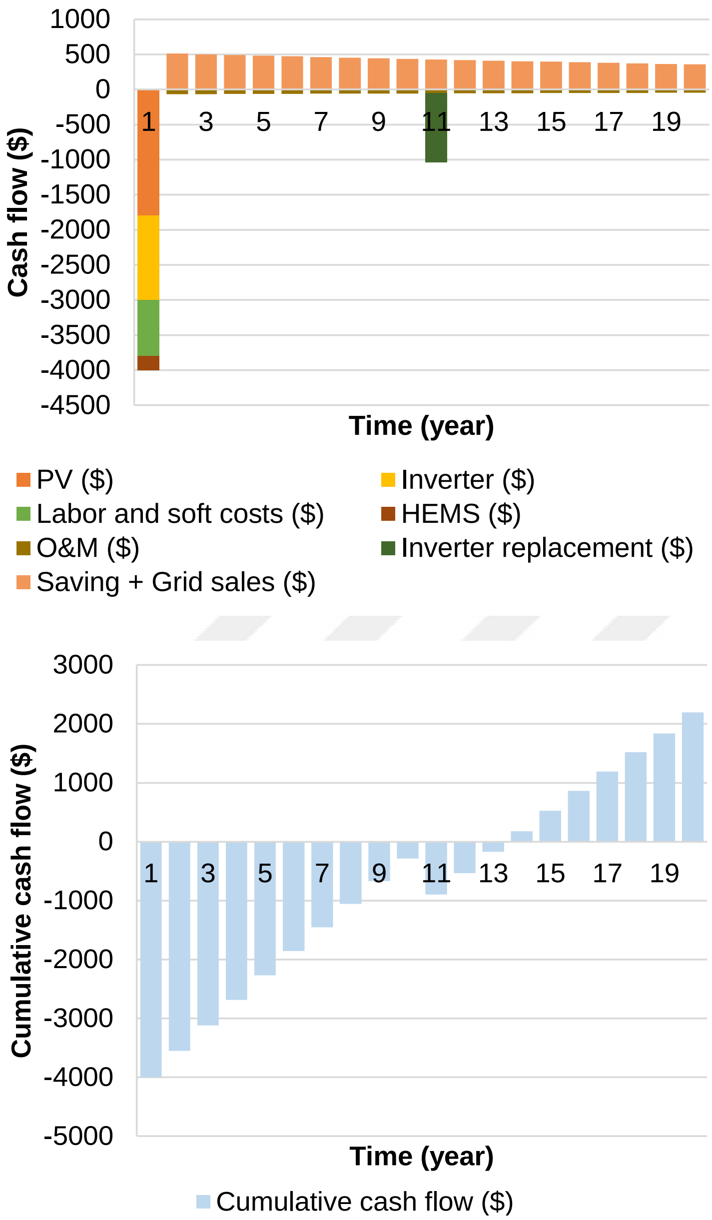

Figure 4.5 : The net (top figure) and cumulative (bottom figure) cash flow for the optimal configuration for the HEMS-equipped household (3 kW PV – no BESS).

The load profile of the HEMS-equipped household for the optimal configuration (3 kW PV – no BESS) in winter and summer periods is shown in Figure 4.6. January 9 and July 24 are chosen as sample days. Both these days coincide with Tuesday, when all devices are operational, as stated in Table 4.6. In this way, it can be seen how the HEMS schedules all manageable appliances.

HEMS shifts EV charging to off-peak hours on both days. On January 9, the PV generation is very low and all the generated energy is self-consumed without any injection into the grid. Part of the EWH heating demand is covered by this generation. TSAs are shifted to the off-peak period.

On July 24, self-consumption is maximized by EWH pre-heating, AC pre-cooling, and dishwasher running during the PV generation period. Clothes dryer and washing machine operation are not shifted to the PV generation period as the surplus generation can only cover a very small fraction of their power consumption. Instead, they benefit from lower electricity prices of the off-peak period and provide DR.

Residents shower daily at 06:10, 14:00, and 18:30. For the first shower, on both days, EWH pre-heats before 6:00 while it is still an off-peak period. For the second shower, on both days, EWH uses PV power before 14:00. For the third shower, on July 24, the energy for the use of EWH is supplied from PV via pre-heating. And on January 9 the energy is supplied by the grid, taking advantage of lower electricity prices the shoulder period which are cheaper than the prices of the on-peak period which starts at 17:00.

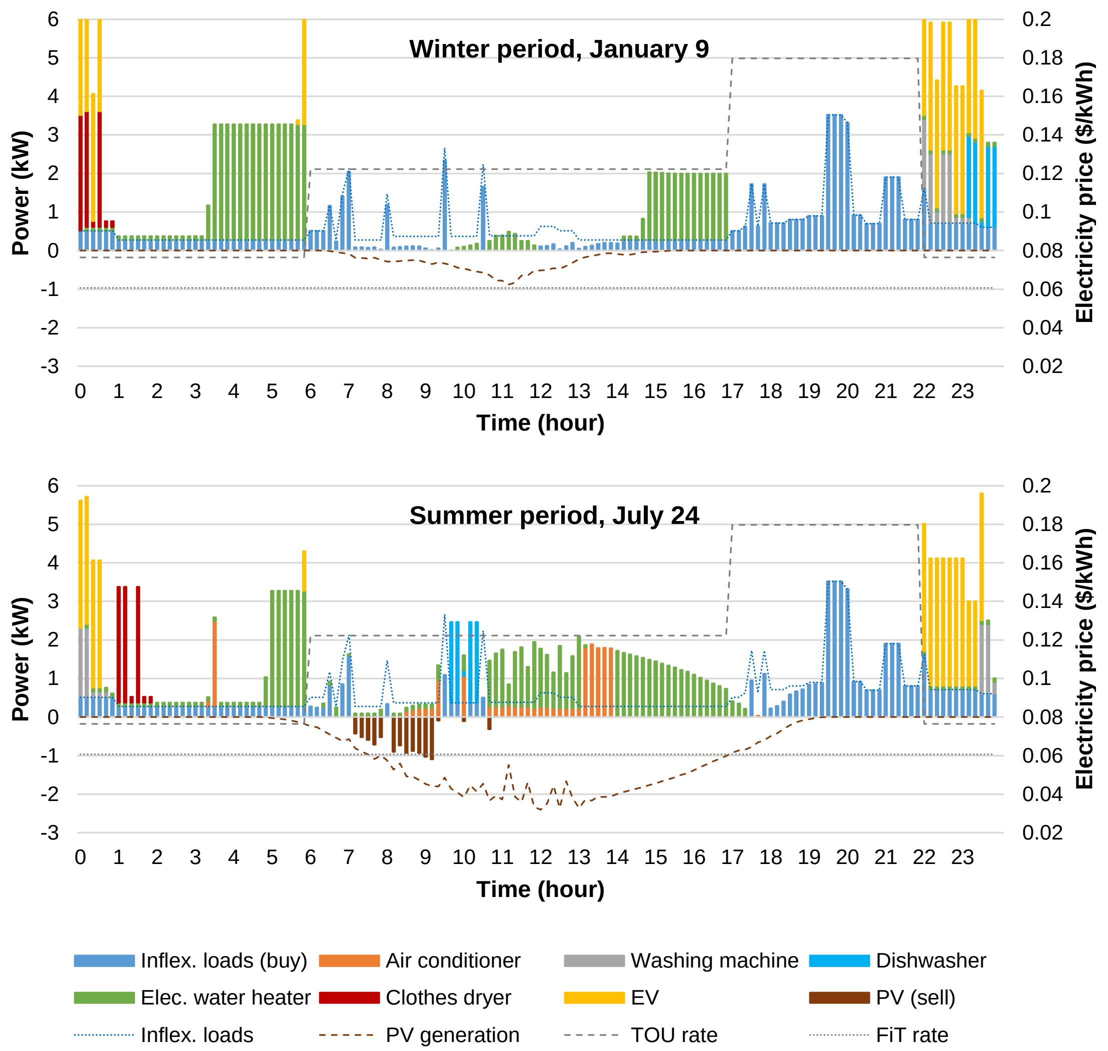

Figure 4.6. The load profile of the HEMS-operated household with the optimal configuration (3 kW PV – no BESS – 10° tilt angle).

4.4.2 Impact of tilt angle on PV-BESS sizing for HEMS-equipped households

The sizing model not only sizes the required PV-BESS capacity but also determines the optimal tilt angle. The optimal angle for the entire annual period was found to be 10° for the 3 kW – no BESS configuration.

The change in the monthly bill of the HEMS-equipped house according to different tilt angles is shown in Figure 4.7. In winter, the highest power output and therefore the lowest bill is achieved at the angle of 20°. In summer, the highest output and the highest bill are achieved at the angle of 0°. It can be seen that the changes in tilt angle significantly affect the PV power output on summer days, but have a minor effect on winter days.

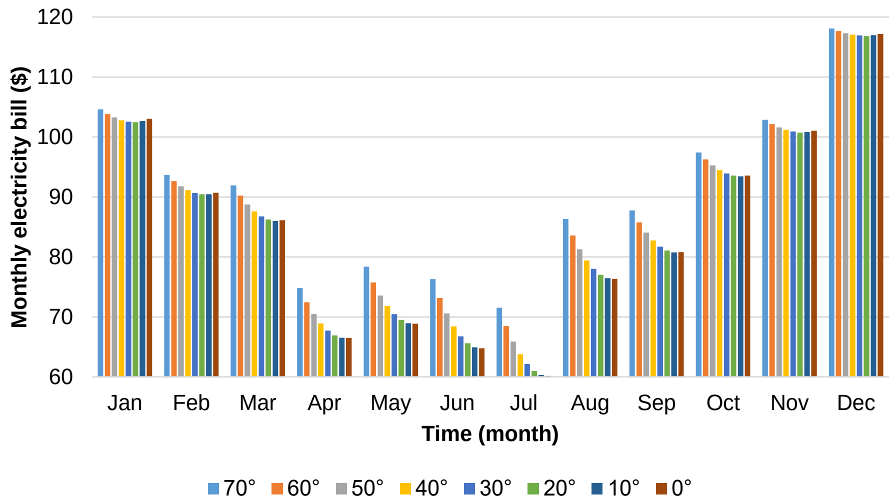

Figure 4.7 : The monthly electricity bill of the HEMS-equipped household with the optimal configuration (3 kW PV – no BESS) for different PV tilt angles.

The annual PV generation and annual electricity bill are shown in Table 4.11. As seen, the lowest annual electricity bill is achieved at the angle of 10°. The annual bill change is very low between 0° and 20°, and therefore, it can be concluded that there is no need to be very sensitive in the selection of the tilt angle for HEMS-operated prosumer households. If this was a PV power plant and all the produced energy was injected into the grid, then the sensitivity in the tilt angle could have a higher impact.

Table 4.11 : Annual electricity bill and PV production of the HEMS-equipped household for different tilt angles (3 kW PV – no BESS).

Tilt angle (°)	0	10	20	30	40	50	60	70
Annual PV prod. (kWh)	3529	3537	3502	3424	3305	3148	2957	2737
Annual electricity bill ($)	1009	1008	1012	1019	1029	1044	1062	1083

4.4.3 Techno-economic comparison of PV-BESS with and without HEMS

The impact of HEMS use on the NPV of PV-BESS units can be better understood when a comparison is made between households using and not using HEMS. Therefore, different case scenarios are created.

Case A represents a household with HEMS (examined in detail in Sections 4.2 and 4.3) and Cases B, C and D represent households without HEMS. The residents in each case have different levels of DSM awareness, decreasing from A to D. The residents in Case A have the highest DSM awareness since they use HEMS. The residents in Case B do not use HEMS but still have high DSM awareness and try to maximize PV self-consumption by running appliances during the solar generation period. On the other hand, the residents in Case C and D do not care much about DSM and run most of their electrical appliances outside of the solar generation period despite having rooftop PV. The DSM awareness level of the users is explained in detail in Table 4.12. ✓✓* indicates that the relevant appliance in the household is shifted optimally by HEMS. ✓✓ indicates that the appliance is shifted manually by users either to the solar generation period or to the low price period. ✓ indicates that the appliance is manually shifted by users but partially, which means, the appliance either operates during the shoulder period or some part of it operates at advantageous hours and some at disadvantageous hours. For AC, ✓✓ and ✓ indicate that the residents manually decrease the set point level during on-peak hours. − indicates that the appliance is not shifted at all and operates during on-peak hours.

Table 4.12 : Hypothetical DSM awareness level of households based on load shifting status of manageable loads.

DSM awareness (Case)	Very high (A)	High (B)	Medium (C)	Low (D)
Dishwasher	✓✓*	✓✓	✓✓	✓✓
Washing machine	✓✓*	✓✓	✓	✓
EV	✓✓*	✓	✓	✓
AC	✓✓*	✓	✓	−
EWH	✓✓*	✓✓	✓	−
Clothes dryer	✓✓*	✓✓	−	−

✓✓*: Shifted by HEMS, ✓✓: Shifted manually, ✓: Partially shifted manually, −: Not shifted

The cases examined and their results are given in Table 4.13. The load profiles of the households of all cases are shown in Fig. 8 over a sample day (Tuesday, March 1). It should be noted that many different cases can be formed. Nevertheless, the cases reviewed here are sufficient to demonstrate the impact of HEMS use.

Table 4.13 : Techno-economic comparison of PV-BESS systems for households with and without HEMS.

Case	A	B	C	D
HEMS use	Yes	No	No	No
DSM awareness	Very high	High	Medium	Low
Optimal configuration	3 kW PV – no BESS	4 kW PV – no BESS	4 kW PV – no BESS	2 kW PV – no BESS
Viable tariff	TOU	TOU	Flat	Flat
Self-consumption rate (%)	93	68	63	69
Cash outflow ($)	-6064	-7551	-7551	-4176
Cash inflow ($)	8336	8472	6796	3006
NPV ($)	2273	920	-755	-1167

As seen in Figure 4.8, in Case A, the HEMS maximizes the PV self-consumption. It shifts the TSAs to the off-peak period to take advantage of low electricity prices and uses nearly all solar generation to cover the load demand of water heating and inflexible loads during midday. Just a very little portion of the generated electricity is sold to the grid. On the other hand, in Case B, C, and D, a larger portion of solar generation is sold to the grid. As can be seen in Table 4.13, this causes the NPV to decrease because the FiT rate is low, that is, it is not very profitable to sell power to the grid and the PV investment cannot pay itself back. In addition, the ability of HEMS to heat water in accordance with the form of solar production significantly increases the self-consumption in Case A. In the absence of HEMS, solar generation can only meet a certain portion of the EWH demand.

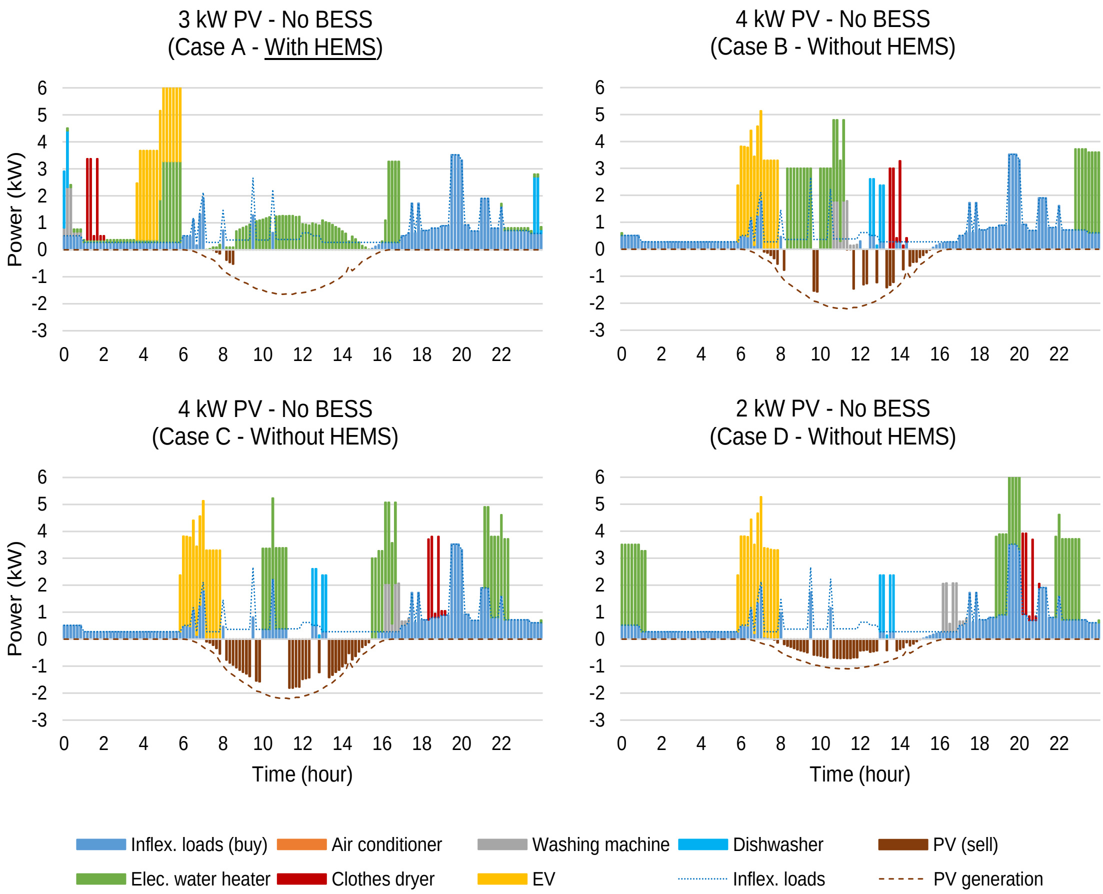

Figure 4.8 : The load profile of households with and without HEMS use on March 1 (DSM awareness decreases from A to D).

The simulations showed that the residents in cases C and D should use flat tariff instead of TOU, as their electricity consumption during the on-peak period is too high and they do not shift enough loads to the off-peak period or the solar generation period. For Cases C and D, the higher electricity price of the TOU scheme during the on-peak period is a disadvantage. For the non-HEMS case, PV-BESS sizing was performed for both TOU and flat tariff, and the NPV values for the two tariff cases were compared. It was found that it would not be economically viable to switch from flat tariff to TOU for these residents unless a more efficient DSM is implemented, as in Cases B and A. The economically viable tariff schemes for different DSM awareness levels are shown in Table 4.13.

The use of HEMS reduced the required PV size by increasing self-consumption and shifting available loads to the off-peak period. In Case A, the optimal configuration was found to be 3 kW PV, while in Case B and C, the optimal configurations were found to be 4 kW PV as more devices were running during the solar generation period in these households. In Case D, the optimal configuration was 2 kW PV as the load demand is very low during the solar generation period in the household.

Today, with the reduced FiT rates negative NPV for PV systems is not rare. For example, in the USA, in 33 of 50 states break-even point cannot be reached and the NPV of PV systems stays negative [34]. In Cases C and D, the NPVs are found to be negative (Table 4.13), meaning that the savings from the PV installation cannot meet the initial investment. The low savings are due to cheap electricity prices and low FiT rates in Türkiye. Yet, in Case A, it is seen that the use of HEMS makes PV-BESS investments more feasible and NPV increases significantly as it maximizes the savings due to optimal load scheduling. This is one of the main findings of the study. The savings are greater when HEMS is used as it significantly increases self-consumption and shifts required loads to the cheap electricity period.

4.5 Sensitivity Analysis

4.5.1 Optimal configurations at varying electricity and battery prices

In the previous section, it was determined that it is not possible to include BESS in a rooftop PV system at current electricity and battery prices in Türkiye, and the optimal configuration was obtained with a PV-only system. Yet, BESSs can become applicable in different conditions. For this reason, a sensitivity analysis is performed for taking into account the rising electricity prices and falling battery prices in PV-BESS sizing. The reasons for choosing these two parameters and neglecting others are listed as follows:

- ✓ Today, especially after the commercialization of EVs, lithium-ion battery prices have entered a downward trend and are expected to decrease further in the future [196,197]. In addition, purchase subsidies and tax deductions can be applied for these units to encourage battery storage, as is already practiced in some countries such as Australia [176].
- ✓ Residential electricity prices have increased in the last decade (more than 25% in the EU) [198]. Therefore, the scenario of an increase in electricity prices is included in the sensitivity analysis. Another reason is that electricity prices in Türkiye are low (one of the lowest in Europe), so the results in Section 4 based on these prices may not reflect the situation in countries with higher electricity

prices. Therefore, this case gives an idea about the possible PV-BESS sizing that can be implemented in countries such as Greece, Croatia, Romania, Portugal, Spain, Italy, and France (southern part) that have similar solar radiation to Türkiye but have higher electricity prices. In these countries, unlike in Türkiye, BESSs can become viable due to the increased bill savings which can cover the battery investment.

- Although the change in the initial investment cost of PV is generally taken into account in sensitivity analysis in such studies, the initial investment cost of rooftop PV systems has become quite stable in recent years [199]. Thus, the change in PV initial investment cost is not considered in the sensitivity analysis.
- The change in the electricity sales price to the grid was not taken into account as well, since selling prices/FiT rates have decreased significantly today and lost their previously high impact and instead, increasing the self-consumption has gained importance [72].

The cases examined in the sensitivity analysis are +25%, +50%, +75% and +100% electricity prices and -25% battery prices. The NPV results are shown in a heatmap in Table 4.14. As seen, the use of BESS becomes viable with reduced battery prices and increased electricity prices. Even +25% electricity prices or -25% battery prices make the use of BESS viable in Türkiye.

- In the case of -25% battery prices, the optimal configuration becomes 4 kW PV – 2.5 kWh BESS.
- In the case of +25% electricity prices, the optimal configuration becomes 5 kW PV – 5 kWh BESS.
- In the case of -25% battery prices with +25% electricity prices, the optimal configuration becomes 5 kW PV – 7.5 kWh BESS.
- In the cases of +50% electricity prices, +50% electricity prices with -25% battery prices, +75% electricity prices, and +75% electricity prices with -25% battery prices, the optimal configuration becomes 6 kW PV – 7.5 kWh BESS.
- In the cases of +100% electricity prices and +100% electricity prices with -25% battery prices, the optimal configuration becomes 7 kW PV – 7.5 kWh BESS.

Table 4.14 : NPV ($) of PV-BESS systems for the HEMS-equipped household at different electricity and battery prices.

	Number of batteries (x2.5 kWh)						Number of batteries (x2.5 kWh)				
PV (kW)	0	1	2	3	4	**PV (kW)**	0	1	2	3	4
Case 1: Current electricity prices and current battery prices						**Case 2:** Current electricity prices and -25% battery prices					
1	1425	991	489	-35	-1078	1	1425	1425	1356	1267	658
2	1999	1660	1156	620	-465	2	1999	2093	2024	1921	1270
3	**2273**	2022	1527	963	-237	3	2273	2456	2395	2264	1498
4	2248	2057	1598	999	-250	4	2248	**2491**	2465	2300	1485
5	2065	1895	1482	871	-431	5	2065	2329	2349	2172	1304
6	1809	1642	1241	625	-687	6	1809	2075	2109	1927	1048
7	1514	1344	951	315	-1008	7	1514	1777	1819	1616	727
Case 3: +25% electricity prices and current battery prices						**Case 4:** +25% electricity prices and -25% battery prices					
1	2454	2345	2151	1930	1060	1	2454	2779	3018	3231	2795
2	3616	3602	3407	3170	2247	2	3616	4036	4274	4471	3982
3	4282	4425	4271	4016	2954	3	4282	4859	5138	5317	4689
4	4472	4731	4655	4388	3301	4	4472	5165	5523	5689	5036
5	4401	4726	**4741**	4483	3344	5	4401	5160	5609	**5784**	5079
6	4238	4577	4620	4381	3248	6	4238	5011	5487	5682	4983
7	4018	4358	4420	4166	2279	7	4018	4792	5287	5467	4766
Case 5: +50% electricity prices and current battery prices						**Case 6:** +50% electricity prices and -25% battery prices					
1	3482	3698	3812	3895	3198	1	3482	4132	4680	5196	4933
2	5212	5545	5657	5720	4960	2	5212	5977	6524	7021	6695
3	6268	6829	7015	7070	6146	3	6268	7262	7882	8371	7881
4	6672	7403	7712	7778	6852	4	6672	7837	8580	9079	8588
5	6723	7556	7999	8094	7119	5	6723	7990	8866	9395	8854
6	6652	7510	7996	**8134**	7181	6	6652	7944	8863	**9435**	8916
7	6506	7370	7886	8013	7068	7	6506	7804	8754	9314	8803
Case 7: +75% electricity prices and current battery prices						**Case 8:** +75% electricity prices and -25% battery prices					
1	4510	5052	5474	5859	5335	1	4510	5486	6341	7160	7070
2	6809	7487	7907	8269	7672	2	6809	7921	8774	9570	9407
3	8254	9231	9757	10121	9335	3	8254	9665	10625	11422	11070
4	8871	10074	10767	11165	10402	4	8871	10508	11635	12466	12137
5	9044	10384	11255	11703	10892	5	9044	10818	12122	13005	12627
6	9065	10441	11370	**11885**	11112	6	9065	10875	12238	**13186**	12847
7	8993	10380	11350	11859	11102	7	8993	10814	12218	13160	12837
Case 9: +100% electricity prices and current battery prices						**Case 10:** +100% electricity prices and -25% battery prices					
1	5539	6405	7136	7824	7473	1	5539	6839	8003	9125	9208
2	8407	9427	10157	10819	10385	2	8407	9863	11025	12120	12120
3	10280	11749	12568	13174	12526	3	10280	12183	13435	14475	14261
4	11252	13043	14070	14736	14070	4	11252	13476	14918	16038	15803
5	11752	13697	14915	15613	14903	5	11752	14130	15783	16915	16637
6	11936	13984	15316	16082	15405	6	11936	14418	16184	17383	17140
7	12035	14068	15465	**16283**	15611	7	12035	14502	16333	**17584**	17335

The load profiles of the HEMS-equipped households for all electricity and battery price cases are demonstrated in Figure 4.9 over a sample summer Tuesday. As seen, BESS is present in all cases except for Case 1. In Case 1, the power is drawn from the grid during the entire on-peak period. In Case 2 and 3, a part of the on-peak demand is met from the grid. In Cases 4-10 all the on-peak demand is covered by the battery. The use of BESS becomes more and more viable as electricity prices increase or battery prices decrease. It is seen that as electricity price increases, PV size increases. This is to be expected because when the electricity price is high, the most important thing is to buy as little electricity from the grid as possible.

In Case 1 and 2, where there is no battery and the electricity price is low, the optimal tilt angle is 10° whereas in Cases 2-10, where a battery exists and the electricity price increases, the optimal tilt angle is 20°. This is because the PV output is maximized in winter at the tilt angle of 20° and it is more beneficial that this maximized production is stored in BESS to meet load demand during the on-peak period.

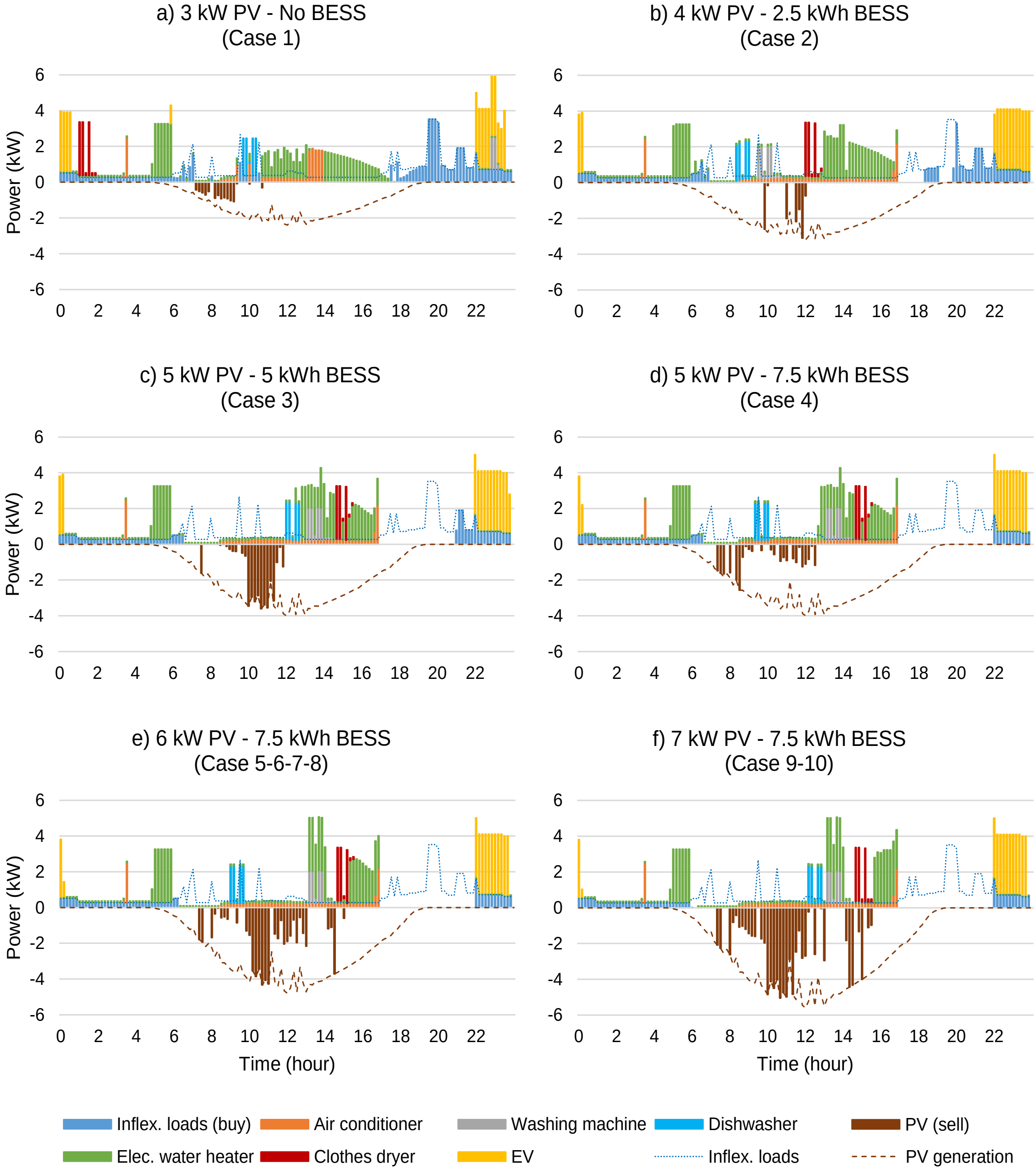

Figure 4.9 : Load profile of HEMS-equipped household for optimal configuration for all electricity and battery price cases (Summer period, July 24).

V2H occurs in all cases except Case 1. The reason for the availability of V2H in other cases is the decrease in the battery price for Case 2, and the decrease in both the battery price and the increase in the electricity prices for Cases 3-10. In cases where V2H occurs, the household does not buy electricity at a high price. Instead, the EV injects power to the household at on-peak hours and then recharges the battery at off-peak hours. When V2H occurs, the sum of the off-peak electricity price and battery degradation cost of EV is lower than the on-peak electricity price.

The charge and discharge scheduling of BESS and EV batteries is explained in detail in Figure 4.10 over a sample graph, which belongs to Case 3 (5 kW – 5 kWh BESS) where BESS exists. During the day, BESS is charged by the PV to be discharged during the on-peak period. The reason for the intermittent discharges during the day is that the consumption at these moments is higher than the PV production. As can be seen, part of the household load demand during on-peak hours is supplied by the EV battery in the form of V2H. This is because the discharge rate of the BESS battery is 2 kW, which cannot cover the whole demand. Therefore, EV supplies the rest of the on-peak demand.

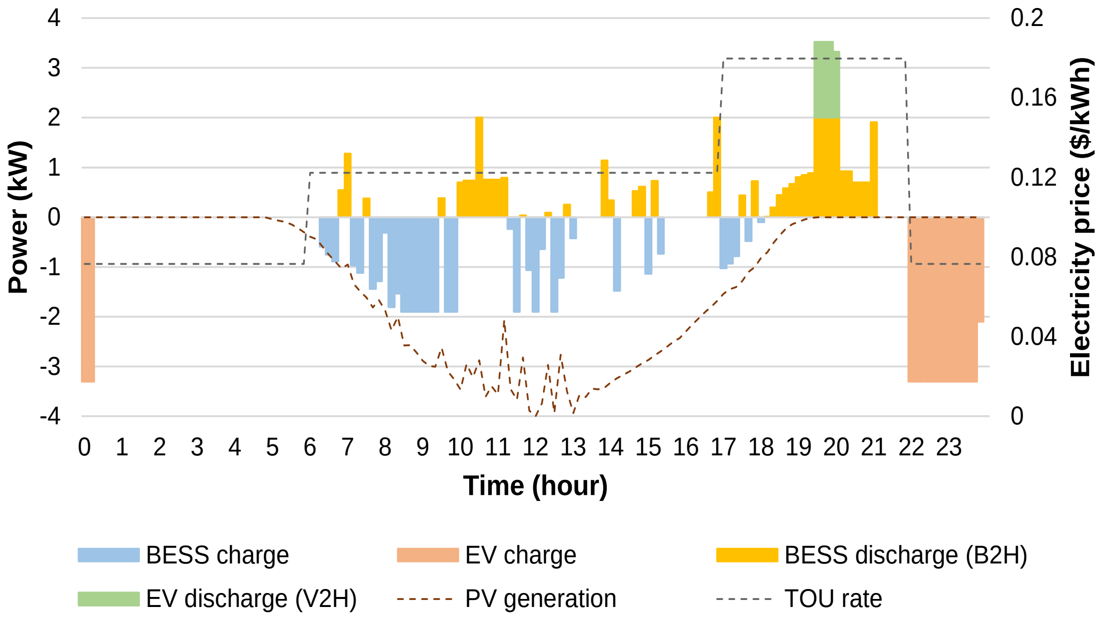

Figure 4.10 : Charge/discharge scheduling of BESS and EV batteries as a sample (Summer period, July 24, Case 3 (5 kW PV – 5 kWh BESS).

The detailed economic results of the optimal configurations for all electricity and battery price cases are presented in Table 4.15. As seen, the NPV of PV-BESS units increases as the electricity price, and therefore the bill savings that PV-BESS investment can provide increases. This also means that the use of HEMS can provide a higher NPV increase when electricity prices are high.

Table 4.15 : Detailed results of optimal PV-BESS configurations for HEMS-equipped households for all electricity and battery price cases.

Case	Elec. price	Battery price	PV (kW)	BESS (kWh)	Tilt (°)	Initial cost ($)	O&M cost ($)	Replace. cost ($)	Cash outflow ($)	Cash inflow ($)	NPV ($)
1	Current	Current	3	-	10	-4000	-1079	-984	-6064	8336	2273
2	Current	-25%	4	2.5	10	-5750	-1562	-1741	-9053	11544	2491
3	+25%	Current	5	5	20	-8000	-2126	-2784	-12909	17651	4741
4	+25%	-25%	5	7.5	20	-8250	-2167	-2927	-13343	19127	5784
5	+50%	Current	6	7.5	20	-10000	-2649	-3682	-16332	24466	8134
6	+50%	-25%	6	7.5	20	-9250	-2526	-3255	-15031	24466	9435
7	+75%	Current	6	7.5	20	-10000	-2649	-3683	-16332	28217	11885
8	+75%	-25%	6	7.5	20	-9250	-2526	-3255	-15031	28217	13186
9	+100%	Current	7	7.5	20	-11000	-3009	-4011	-18020	34303	16283
10	+100%	-25%	7	7.5	20	-10250	-2886	-3583	-16719	34303	17584

4.5.2 Comparison of examined cases with other countries

The cases examined in Section 5.1 can give an idea about the required PV-BESS configurations for HEMS-equipped households in several major European cities that are located in the same solar belt as Istanbul (Türkiye), such as Porto (Portugal), Barcelona (Spain), Marseille (France), Rome (Italy), Thessaloniki (Greece), Split (Croatia) and Bucharest (Romania).

The household electricity prices and sell-back prices in these countries are given in Table 4.16. Increasing electricity price cases for Türkiye in Section 5.1 coincide with the current electricity prices of these countries. The form of the TOU scheme can slightly differ, but in principle, on-peak and off-peak hours are quite the same in each country. A few years ago sell-back rates could make a difference, but today they have fallen in most countries, and instead, self-consumption has gained importance. Here, Bulgaria does not match any of the cases due to the currently favorable FiT rates in the country (0.13 – 0.15 $/kWh) [200,201].

The cities located in the same solar belt with the selected location and the corresponding cases are highlighted on the Global Solar Atlas [202] in Figure 4.11. According to the results, 7 kWh PV – 7.5 kWh BESS configurations for HEMS-equipped households can become viable in Spain, Italy and Portugal, 6 kWh PV – 7.5

kWh configurations in France and Greece, and 5 kW PV – 5 kWh BESS configurations in Romania and Croatia.

Table 4.16 : The household electricity prices and sell-back prices in the countries that are located in the same solar belt as Türkiye.

Country	Electricity price ($/kWh) [198]	Sell-back price ($/kWh)	Corresponding case
Türkiye	0.12	0.06	Base
Bulgaria	0.12	0.13 – 0.15 [201]	None*
Croatia	0.15	0.09 [203]	+25% elec. price
Romania	0.16	0.06 [204]	+25% elec. price
Greece	0.18	0.09 [205]	+50% elec. price
France	0.22	0.07 – 0.12 [206]	+75% elec. price
Italy	0.24	0.06 – 0.07 [207]	+100% elec. price
Portugal	0.24	0.05 [208]	+100% elec. price
Spain	0.25	0.06 [209]	+100% elec. price

*Due to the high FiT rate that does not promote self-consumption.

Sign	Corresponding case	Elec. price ($/kWh)	Optimal configuration
O	Current elec. prices	~0.12	3 kW PV – No BESS
O	+25% elec. prices	~0.15	5 kW PV – 5 kWh BESS
O	+50% elec. prices	~0.18	6 kW PV – 7.5 kWh BESS
O	+75% elec. prices	~0.21	6 kW PV – 7.5 kWh BESS
O	+100% elec. prices	~0.24	7 kW PV – 7.5 kWh BESS

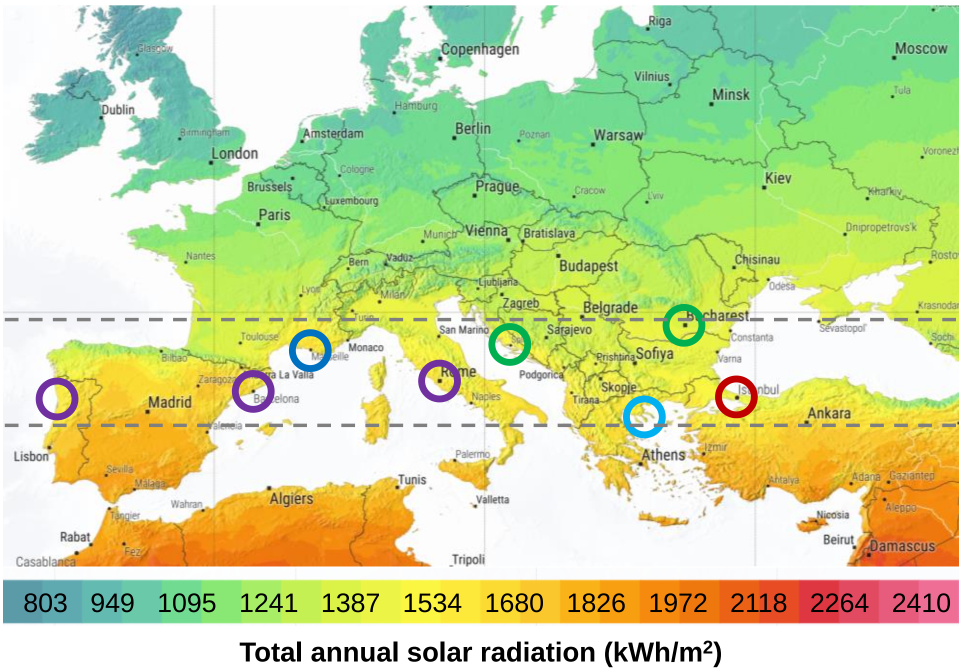

Figure 4.11 : The cities (Porto, Barcelona, Marseille, Rome, Split, Thessaloniki, Bucharest) located in the same solar belt as the selected location (Istanbul) and the corresponding cases.

4.6 Discussion

As a result of the study, the highest NPV in Türkiye was obtained with the configuration of 3 kW PV without BESS. The main reason why the use of batteries is not viable is low electricity prices in the country and high battery prices globally. For this reason, a sensitivity analysis was performed for increasing electricity prices and decreasing battery prices. Among the scenarios considered in the sensitivity analysis, possible ones for Türkiye in the short term are -25% battery prices and +25% electricity prices.

Currently, residential electricity prices in Türkiye are subsidized and kept low. Commercial and industrial electricity prices are 21% and 16% higher than residential electricity prices, respectively [210]. On the contrary, residential electricity prices are higher than commercial and industrial electricity prices in Europe and the USA [211,212]. Considering that the price gap between residential and other end-user groups can be eliminated in Türkiye, as in Europe and the USA, it can be said that the +25% electricity price scenario is quite likely for Türkiye in the short term. In addition, the electricity prices have already increased by 15% in the country in 2021. Yet, increases of 50% or more do not seem possible in the short term.

The decrease in battery price may result from improvements in manufacturing technology, as well as subsidies or value-added tax (VAT) reductions to be applied by the government to encourage battery storage. Presumably, Türkiye will soon offer incentives to promote battery storage as in other countries. For instance, Germany offers generous incentives for battery installation such as battery rebates (covering around 30% of the cost) and 40% of rooftop PV applications in the country are with batteries. The country expects 150,000 new battery installations in 2021 [213,214]. Australia provides favorable purchase subsidies for battery storage and aims to reach one million battery installations by 2025 for behind-the-meter applications [213]. So far, the prevalence of battery systems for on-grid applications in Türkiye has remained almost non-existent. One reason is that until the end of 2020, the FiT rates were very high which did not require battery installation. Another reason is that the regulations on battery storage have just begun in the country and there are no incentive schemes yet.

4.7 Conclusion

This study proposes a method to optimally size residential PV-BESS units considering HEMS capable of performing DSM of controllable electrical loads. In this way, automated DR by taking advantage of time-based electricity tariffs and increased self-consumption are taken into account in component sizing. Unlike other studies in the literature, the proposed model can determine the optimal PV tilt angle according to the climatic conditions of the location. Moreover, it can perform load scheduling of all types of electrical loads (TCA, TSA, and PSA), consider battery degradation to avoid unnecessary battery cycles, and respond to V2H technology.

The case location is selected as Istanbul, Türkiye, and simulations are conducted for a HEMS-equipped household with average daily electricity consumption of 37.5 kWh. The sizing model simulates HEMS operation over one year and repeats the simulations for each PV array capacity-tilt angle-battery number combination. The model determines the NPV of each combination over the system lifetime and then ranks them from highest to lowest.

The optimal configuration is found to be 3 kW PV – no BESS – 10° tilt angle for a HEMS-equipped household in Istanbul at the current battery and electricity prices. A sensitivity analysis is performed based on rising electricity prices (+25%, +50%, +75%, +100%) and falling battery prices (-25%) to make future projections. The BESS use becomes viable even with +25% electricity prices or -%25 battery prices in Türkiye. The optimal system configurations are found as follows:

- 4 kW PV – 2.5 kWh BESS – 20° tilt angle in the case of -25% battery prices
- 5 kW PV – 5 kWh BESS – 20° tilt angle in the case of +25% electricity prices
- 5 kW PV – 7.5 kWh BESS – 20° tilt angle in the case of -25% battery prices with +25% electricity prices
- 6 kW PV – 7.5 kWh BESS – 20° tilt angle in the cases of +50% electricity prices, +50% electricity prices with -25% battery prices, +75% electricity prices, and +75% electricity prices with -25% battery prices
- 7 kW PV – 7.5 kWh BESS – 20° tilt angle in the cases of +100% electricity prices and +100% electricity prices with -25% battery prices

Lastly, a techno-economic comparison is made. PV-BESS units are sized with and without HEMS use and the impact of HEMS use on the NPV of the systems is investigated. In three hypothetical cases where residents have different levels of DSM awareness, the NPV values are found to be $920, $-755, and $-1167. When HEMS is used, the NPV increases drastically and becomes $2273. This is an important finding, as PV projects in many countries suffer from low feasibility today in the absence of incentives.

The proposed optimal PV-BESS sizing model is applied for a HEMS-equipped household in Istanbul, Türkiye. This model can also be applied to different types of households in various regions of the world with different electricity prices and different solar energy characteristics. The decentralized model developed in this study for individual households can be reconsidered with a centralized approach. The model can be modified for use in grid-connected microgrids, increasing self-consumption through shared use of PV, and considering P2P energy trading in component sizing.

5. SURVEY- AND SIMULATION-BASED ANALYSIS OF RESIDENTIAL DEMAND RESPONSE: APPLIANCE USE BEHAVIOR, ELECTRICITY TARIFFS, HOME ENERGY MANAGEMENT SYSTEMS

Residential demand response (DR) aims to stabilize the electricity grid by utilizing the flexibility of end-users. To this end, end-users are offered time-varying electricity prices and incentivized for load shifting. End-users can maximize bill reduction through automated load shifting using home energy management systems (HEMSs). Since HEMS is a new technology, the future DR potential of its mass use is unknown. Here, surveys can be very useful for gaining insight into future behavior and preferences in using HEMS. Therefore, the objective of this study is twofold: (1) to understand appliance use behavior, electricity tariff perception, and tendency towards HEMS-based DR participation, through a survey. And then, (2) to simulate the DR potential by entering survey responses into a HEMS optimization tool. The results show that 78% of the respondents are willing to engage in HEMS-based DR. This provides the potential to reduce the peak period consumption by 33%. However, the average bill savings achieved by HEMS owners is only 6.7%, which can hinder reaching this potential. Still, 21% of the HEMS owners save more than 10% on their bills. 8% save over 15%, and 3% over 20%. These can be the target audience of the future HEMS market and DR campaigns.

5.1 Introduction

In the last decades, the modernization of the traditional grid has become a necessity, both to ensure reliable, sustainable, and cost-effective transmission and distribution of electricity and to integrate renewable sources into the power grid to mitigate global warming [215]. To this end, the concept of the smart grid has emerged to provide better measurement, monitoring, and control of the grid infrastructure through information and communication technologies (ICTs) [216].

Two-way communication provided by ICT led to the utilization of advanced metering systems (AMIs). In this way, traditionally static electricity consumers became flexible participants of the grid. The grid-side earned the opportunity to change the power consumption pattern of the demand side to stabilize the grid by offering time-based electricity tariffs and incentives, which is defined as demand response (DR) [217]. Today, residential buildings are responsible for a large portion (26.6%) of total electricity consumption, and therefore residential DR gains absolute importance [175].

Residential DR can be implemented in two ways: Direct load control (DLC) and Indirect load control (ILC). In DLC, users, in return for incentives, allow a system operator to remotely control home appliances during critical conditions to meet grid needs such as frequency regulation, peak shaving, or ancillary services [218]. DLC can provide higher DR than ILC in terms of load reduction but with lower customer participation [219]. Reasons such as the sense of losing control over appliances or the lack of an override option hinder its adoption [64]. Besides, DLC can raise privacy concerns due to the collection of energy usage data that may be processed in the hands of third parties [65,220]. In ILC, on the other hand, users are motivated to perform DR to take advantage of time-based electricity tariffs with their consent, without involving any remote operator. Therefore, they gain more control over their electrical appliances and do not have privacy concerns. They either change their electrical appliance usage habits on their own or through automation devices such as programmable home appliances, smart plugs, or smart thermostats [221].

The individual home automation devices mentioned above can also be centrally managed using home energy management systems (HEMSs). Users can set their scheduling priorities via a HEMS interface for each smart home appliance and can optimally schedule their loads considering price and DR signals or (if it exists) photovoltaic (PV) generation. In this way, users both reduce their electricity bills and indirectly balance electricity supply and demand at the grid end [222]. To use HEMS, households require to have smart meters to receive price or DR signals, and appliances require to have the "smart" feature. Once installed, HEMSs can optimally schedule running hours of time-shiftable loads such as washing machines, dishwashers, and clothes dryers. It can also perform set-point adjustment or pre-cooling/heating for thermostatically controlled loads such as air conditioners, refrigerators, and electric water heaters [223]. The increasing use of smart home appliances and rooftop PV/battery energy storage systems (BESSs), as well as increasing electricity prices make the use of HEMSs more viable than ever before.

5.1.1 Objective

HEMS is a new technology that has not yet become widespread and future HEMS usage preferences (and their load mitigationewwe potential) are not yet known. Therefore, simulation studies on HEMS-based DR are often performed for non-standardized situations with uncertain user preferences. Whereas, initial research into HEMS usage preferences can be conducted through surveys using small or incomplete sample sets, and then enabling larger-scale, more complete testing can help validate real-world HEMS usage preferences, ideally in a field setting [224].

Therefore, the objective of this study is twofold: (1) to understand electrical appliance use behavior, perceptions of DR and time-based electricity tariffs, and tendency towards HEMS use, through a survey study. And then, (2) to simulate survey responses of participants using a HEMS optimization tool to explore to what extent their electrical load demand could be changed by HEMS-based DR.

The motivation in (2) emerged during our previous works on developing a load scheduling-based HEMS tool and sizing PV-BESS for households using this tool [14,15]. When we wanted to simulate the HEMS model and perform PV-BESS sizing using it, we needed to rely on many assumptions regarding energy use behavior. Modeling the unmanageable load profile in the household was not a problem since there were available data in the literature, but modeling the manageable load profile was. What would be the HEMS preferences of users? For instance, what percentage of people who install HEMS would allow load shifting for their dishwashers? Would they allow its run to be shifted to any time of day or a certain time interval? How many times a week would they run their dishwashers? And what would be the answers to these questions for other manageable home appliances? This study tried to give answers to these, or at least, to get an idea to be used in future simulation studies.

5.2 Related Studies

In the literature, many studies have been carried out on residential demand-side management (DSM), DR, and HEMS. A vast amount of these is survey studies to understand electrical home appliances usage behavior and to what extent it can be modified through DR [225].

[226] used time-use survey data of Swedish households to construct load profiles of home appliances using a deterministic conversion model and then validated the results with measurement data. The study showed that time-use data could be an alternative to energy monitoring and measurement. [227] showed the practicality of the same approach for load profiling in the absence of smart meters in developing countries to design targeted DSM strategies. [228] modeled electrical and thermal load profiles of private households in Germany as the electrification of these two sectors will place a large burden on the grid infrastructure soon. [229] examined DR and DR-based gamification preferences and expectations of Turkish households. The conducted gamification trial provided a significant change in the dishwasher and washing machine usage habits during the peak period. [230] conducted a survey on energy use behavior (space cooling behavior, lighting behavior, etc.), energy-saving awareness, and consumer reaction to energy-saving policies for residential end-users in China. [231] surveyed 146 people on the island of Mayotte to assess the preferences of the population on DLC-based DR and electricity tariffs. [232] used a multi-criteria decision-making method using survey data of 1023 participants for identifying user preferences for residential DR. Appliance use types were ranked in terms of willingness to give up for DR. Participants were more willing to sacrifice showering needs and less willing for laundry and dishwashing. Load shifting can be performed not only to perform DR but also, with a similar motivation, to increase PV self-consumption. [233] surveyed 2505 prosumers in Denmark and showed that 67% of Danish prosumers often or always try to shift their loads to the solar generation period.

The survey-based studies on residential buildings in the literature can be classified as; energy consumption, resident behavior, comfort, resident preferences, time use, and simulation [234]. Almost all simulation studies are directed toward generating load profiles using survey responses. The same approach can be used to generate load profiles of DR-performing households as well [235], but only very few studies in the literature attempt this. [236] investigated the demand-side flexibility of washing machines and dishwashers in 12 European countries. Washing machines and dishwashers were found to be available in the grid as flexible loads of 5 MW and 10 MW, respectively if 100,000 households agreed to load shifting. [237] analyzed the bidding behavior of air conditioner users for DR participation with a survey study and then simulated the survey results of 552 participants using an optimization tool. [238]

conducted a survey to identify the flexible load use pattern of households in rural Guanzhong, China. Then, the optimal scheduling of flexible loads was made according to the survey results. [239] surveyed DR preferences of 200 households in Italy. Participants' preferred set-points for air conditioners and desired operating time intervals for washing machines and dishwashers were learned, and then the results were translated into a simulation. [240] surveyed 80 households in Ghana and then calibrated the survey data using the measurements from monitoring of households. The study provided information on end-users' responsiveness and financial benefits which are crucial in evaluating the cost-effectiveness of different DR programs. [241] surveyed 141 EV owners from two different cities in China to understand EV use behavior, charging demand, and charging service quality. Next, a survey-based simulation platform was developed which was capable of implementing optimized charging/discharging strategies based on survey results. [242] et al. surveyed the operating hours of dishwashers, washing machines, clothes dryers, ovens, and ranges in 564 households in the Midwest region of the US. The results were then aggregated to the grid level and the maximum load reduction potential of each appliance was simulated. The taxonomy of studies simulating electrical load profiles of buildings that perform DR, based on survey responses, is given in Table 5.1.

Table 5.1 : Taxonomy of studies simulating electrical load profile of DR-performing buildings, based on survey responses.

Reference	Survey	DR type	Simulated behavior of appliance							Location
			DW	WM	CD	Ref.	AC	EWH	EV	
[236]	Online	ILC	✓	✓	×	×	×	×	×	Europe
[237]	Field	DLC	×	×	×	×	✓	×	×	China
[238]	Field	ILC	×	✓	×	×	✓	×	✓	China
[239]	Online	DLC	✓	✓	×	×	✓	×	×	Italy
[240]	Field	ILC	×	✓	×	✓	✓	✓	×	Ghana
[241]	Field	DLC	×	×	×	×	×	×	✓	China
[242]	Online	ILC	✓	✓	✓	×	×	×	×	USA
This study	Online	ILC	✓	✓	✓	✓	✓	✓	×	Türkiye

DW: Dishwasher, WM: Washing machine, CD: Clothes dryer, AC: Air conditioner, EWH: Electric water heater

The above-mentioned studies can help utilities and aggregators to comprehensively benefit from the shifting potential of manageable electrical appliances. Yet, the adoption of DR or HEMS depends not only on technical issues but also on social plausibility. Financial opportunities are linked to social motivators. The main concerns of the public about smart homes are loss of control, affordability, trustworthiness, privacy, and data security [243]. Strengthening the concept of HEMS raises an important issue as technology anxiety stands out as a big obstacle [244].

Bill reduction seems to be the biggest motivator, yet the social groups most concerned with their energy bills are those most resistant to performing DR [220]. HEMSs are more appealing to the upper-middle income group, in fact, those who suffer from energy poverty are the ones who need HEMS the most [245]. Nevertheless, the social injustice regarding availability and affordability between different consumer groups can be overcome with appropriate designs and policies, which also enhances the effectiveness of DR programs [246]. It is also worth noting that while consuming electricity was previously a background activity, consuming it with a HEMS requires an “effort”, which creates a paradigm shift. This effort to control the HEMS interface should be somewhat compensated, but trials show that bill discounts are much lower than users’ initial expectations [247]. Therefore, additional motivational factors come to the fore to boost HEMS use. 75% of people in New York were willing to pay at least $1 per month for HEMS features to support the environment, control their home appliances, and visualize and monitor their electricity consumption [248]. In a resource-rich country, Qatar, people did not seem to be interested in price-based DR as a concept but were interested in adopting smart, modern, and new infrastructures in households, including smart thermostats and smart water heaters which provide DR [249]. Prosumers in Germany enjoyed the technical side of monitoring their electrical energy production and consumption. With a deepening environmental awareness, they set energy-saving targets and tried to achieve them [250].

Regardless of social factors, the adoption of DR also depends on the adequacy of electricity tariffs [251]. The most common time-based tariff in a significant part of the world is time-of-use (TOU), which divides the day into parts with different prices for electricity. A less-used alternative is dynamic pricing, where prices change hourly throughout the day according to the supply-demand balance [252]. Two major barriers to the adoption of time-based electricity tariffs stand out as the low consumer confidence in electricity suppliers and the complexity of the pricing systems [253]. Residential users are more likely to adopt less complex static TOU compared to dynamic pricing. Nevertheless, dynamic pricing has been shown to be as acceptable as static pricing in the case of automation that can be provided by HEMSs [254].

5.2.1 Contribution

Before a large-scale deployment of technology, it is required to do extensive field trials, tests, and simulations [255]. Survey questionnaires can be very insightful in this respect. Although many studies in the literature make electrical load profiling using time-use survey data, only very few use the same method for load profiling in the case of home energy management. One reason for this is that the latter is a more complex process due to automation.

Therefore, this study aims to fill a gap. As its main contribution, it combines information gathered in a survey with an optimization tool to simulate the load mitigation potential of future mass adoption of HEMSs for DR. The study contributes to the existing literature in the following ways:

(1) It collects information on residential electrical energy use behavior, such as ownership rate of appliances, running hours of time-shiftable appliances (dishwashers, washing machines, dryers, etc.), weekly operating frequency of appliances, preferred temperature set-points of refrigerators and air conditioners, frequency of use of electric water heaters (shower times, shower duration, etc.).

(2) It investigates the consumer perception of electricity tariffs,

(3) It investigates the residential demand-side flexibility through the willingness to participate in DR and defining operational priorities and limitations of HEMS use, such as willingness to use HEMS (if yes, which appliances do users allow HEMS to control), time intervals users prefer HEMS to shift electrical loads, expectations, concerns, motivational factors, etc.

(4) It investigates to what extent HEMS-based DR can change the initial load profile. To this end, survey responses are entered into a load scheduling-based HEMS tool to simulate the load profiles of DR-performing households.

(5) The study is comprehensive in scope and includes DR participation of all major manageable home appliances (Table 5.1).

5.2.2 Methodology

The study consists of two parts. In Part 1, the results of the survey are presented and analyzed, and in Part 2, the before and after of the HEMS use are simulated based on the survey responses.

Part 1 (Survey) consists of three subparts; a) Ownership rate of electrical home appliances and energy use behavior, b) Electricity tariffs, c) HEMS use behavior for DR purposes. “a” investigates the present residential energy use behavior. “b” is important as electricity tariffs are a major instrument to implement DR, and “c” explores the willingness to use HEMS and the preferences and priorities regarding its use (e.g. to what extent people would leave the control of their appliances to HEMS).

Part 2 (Simulations) investigates the impact of HEMS use on total load demand and electricity bills. The information collected in “a” allows creating the electrical load profile before HEMS use, and the information collected in “c” allows creating the load profile after HEMS use. These data are entered into a HEMS tool, and the before and after of the survey participants' load profiles are simulated, and then the change is compared. An optimization-based HEMS tool that was previously developed (as introduced and detailed in [14,15]) is used in the simulations. The flowchart of the study is presented in Figure 5.1.

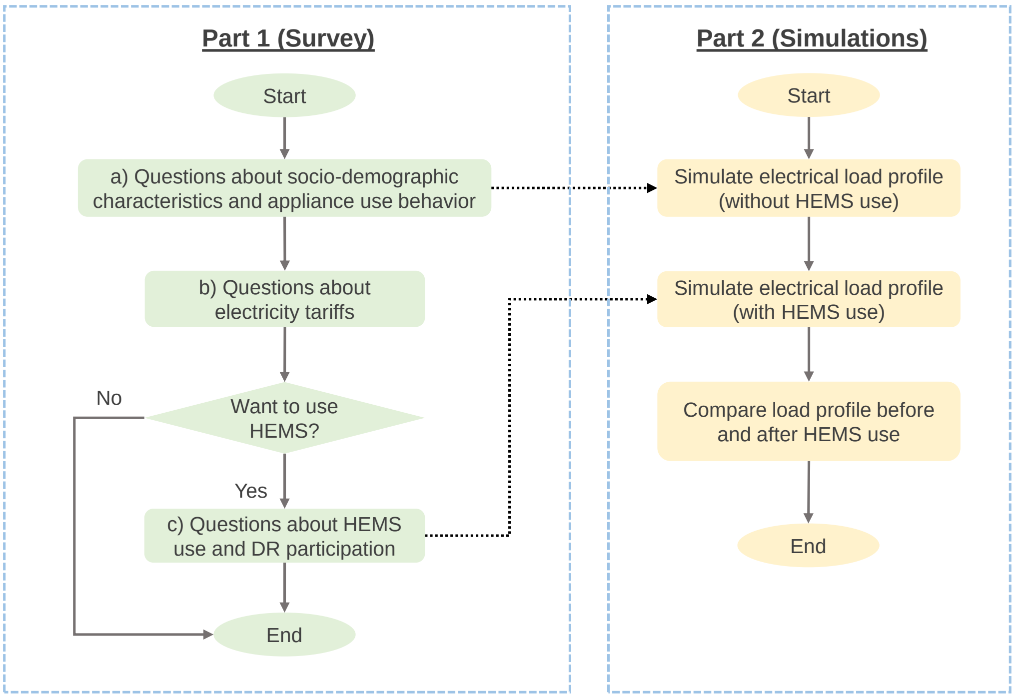

Figure 5.1 : Flowchart of the study.

5.3 Sociodemographic Characteristics and Household Electricity Consumption Behavior of the Participants

5.3.1 Participants and surveyed households

The survey was conducted across Türkiye. A web-based online questionnaire was structured and distributed through a professional online survey company. Gift vouchers were used as incentives. The minimum sample size was calculated as 384 with a confidence level of 95% using Krejcie and Morgan's formula [256]. Following the initial filtering of the survey company, 460 complete results were received, 18 results were excluded due to inconsistent information, and 442 results were considered valid. The survey company aimed to target those responsible for the management of household appliances. The proportion of older participants were lower than average which is expected in online surveys [257]. For these reasons, the sample is considered slightly biased. Yet, there are also important consistencies, as will be explained. Each participant represented a household. Different people from the same household did not participate in the survey. Answering the questionnaire took an average of 20 minutes. The majority (56%) were between the ages of 25 and 34 (the average of the survey sample is 34.3 and the average of Türkiye is 33.5 according to the Turkish Statistical Institute (TURKSTAT) [258]). Half of the participants had 2- or 4-year (vocational or bachelor's) degrees (not reflecting the average of Türkiye). Most of the participants were from Istanbul, followed by Ankara, Antalya, Bursa, and Izmir, in line with [258] with slight differences. The participant profile is summarized in Table 5.2.

Table 5.2 : Socio-economic character of the survey participants.

Age	Frequency (%)
18-24	5.2
25-34	55.9
35-44	27.4
45-54	7.5
55-64	3.6
65+	0.5
Education level	Frequency (%)
Primary school	12.2
High school	28.7
2-year/4-year degree	50.2
Master's degree	6.1
Doctoral degree	2.7

Half of the households belonged to the low-income group. Household income distribution showed a quite high similarity with [259]. The vast majority (88%) stated that they live in apartments. Although there is no data on this, 11.7% of the Turkish population live in 1-storey, 17.3% in 2-storey and the rest in higher-floor buildings [260]. The average size of the residential dwellings of the participants was 116 m^2 (114 m^2 according to TURKSTAT [261]. Family size distribution did not match with TURKSTAT data, yet the average family size was close (3.50 people in our sample and 3.35 people in TURKSTAT data [261]). 42% of the participants were landlords which is 60.7% according to [260]. The monthly electricity consumption of participants was calculated as 211 kWh based on the bills they declared and the residential electricity price of the period (4th quarter, 2021). Although there is no TURKSTAT data on this subject, the average monthly bill of the respondents (195 ₺) at that time exactly coincides with the figure given in the Energy Consumption and Economy Survey, conducted by [262]. According to [262], 58% of Turkish households use combi boilers for heating, 22% use stoves, 10% use central heating, 7% use air conditioners, and 2% use electric heaters [262]. These rates are close to the survey results, except for combi boilers and stoves. The detailed profile of the surveyed households is presented in Table 5.3. The household size and monthly electricity consumption is demonstrated in Figure 5.2.

Table 5.3 : Detailed profile of the surveyed households.

Tenure	Frequency (%)
Tenant	57.9
Landlord	42.1
Family size	Frequency (%)
1 person	0.9
2 persons	16.5
3 persons	32.8
4 persons	35.1
5 or more persons	14.7
Household type	Frequency (%)
Apartment	88.0
Detached	12.0
Household heating	Frequency (%)
Combi boiler	70.8
Central heating	14.0
Heating stove	7.2
Air conditioner	6.1
Electric heater	1.6
Heat pump	0.3
Household income	Frequency (%)
Low	49.9
Lower-middle	27.5
Middle	15.5
Upper-middle	4.7
High	2.5
Average household size	116 m^2
Average electricity use	211 kWh/month

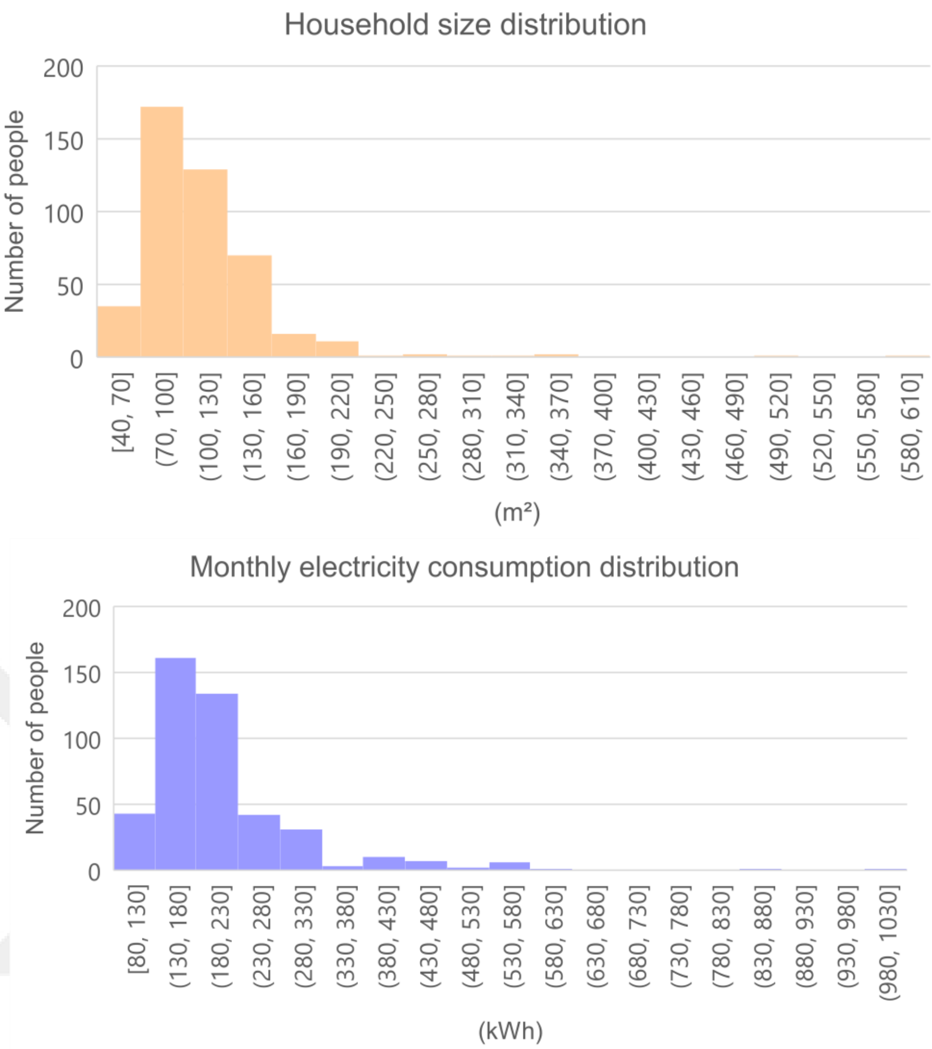

Figure 5.2 : Household size and monthly electricity consumption distribution of 442 participants.

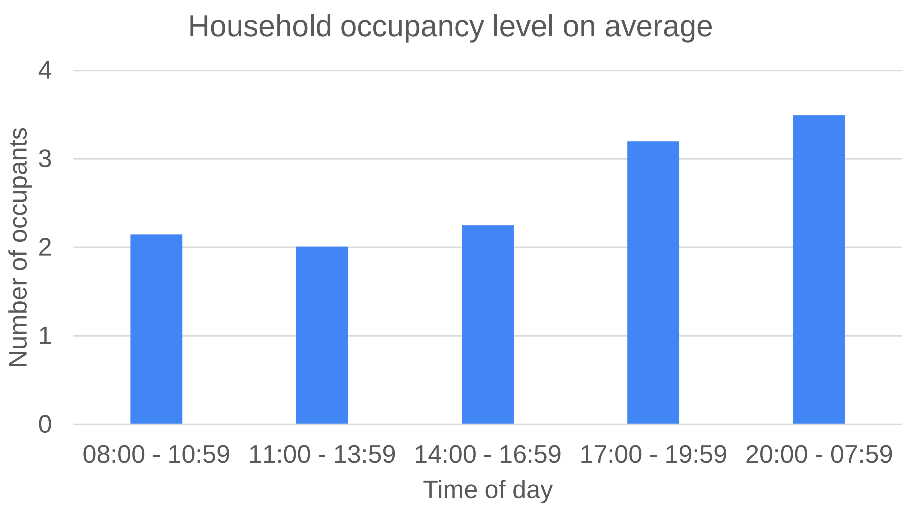

Figure 5.3 : Occupancy level in households on average.

The average occupancy level of households according to the time of day is demonstrated in Figure 5.3. Most of the households consisted of 3 to 4 people (68%). The average number of residents from 08:00 to 17:00 was quite similar, between 2.0 and 2.3. The number increased to 3.2 between 17:00 and 19:00 when parents and children come home from work and school. The average number of residents present at home from after 20:00 to the morning was 3.5.

5.3.2 Electrical load profile of the households

Electrical home appliances can be divided into two as manageable and unmanageable in terms of automation. The ownership rate of unmanageable and manageable appliances in the surveyed households is given in Table 5.4 and Table 5.5, respectively.

[263] shares the ownership rates of the unmanageable appliances in Türkiye as 94% for vacuum cleaner, 92% for cooker/oven, 81% for blender/food processor, 54% for microwave, and 34% for toaster. As seen from Table 5.4, vacuum cleaner, oven and blender/food processor ownership rates show great similarity but microwave and toaster do not. The incompatibility in the toaster may be because panini grills are also called toasters in Türkiye. [264] shares the ownership rate of laptop as 50% which is 56% in our sample. [262] shares the kettle ownership rate as 69% which is 74% in our sample.

Despite the slight bias in the sample, refrigerator, washing machine, and air conditioner ownership rates are in line with the data of [259,265]. The ownership rate of dishwasher is 94% in our survey, whereas it is 78% according to TURKSTAT and 91% according to [263]. There is no source on the dryer and electric water heater ownership rates. It can be said that the ownership rate of refrigerators and washing machines is similar in European countries [266,267]. The ownership rate of electric water heaters is low as the majority live in natural gas-heated apartments and the number of detached households is low. The ownership of solar collectors (these may also belong to the whole building) is 7.5%. The participants have an average of 4 compact fluorescent lamps (CFL) and 6.34 light-emitting diode (LED) lights in their homes.

Table 5.4 : Ownership rate of unmanageable household appliances.

Appliance	Ownership rate (%)	Appliance	Ownership rate (%)
Oven	97.3	LED TV	24.4
Microwave oven	31.2	LCD TV	64.3
Electric stove	37.6	CRT TV	11.8
Electric grill	11.5	Iron	93.7
Stove hood	67.9	Vacuum cleaner	97.1
Toaster	85.3	Hair dryer	90.5
Kettle	73.8	Laptop computer	56.1
Blender/Food processor	83.7	Desktop computer	17.0
Electric fryer	10.2	Scanner	15.6
Air purifier	4.8	Printer	5.0
Fan/Ceiling fan	26.0	Solar collector	7.5

Table 5.5 : Ownership rate of manageable household appliances.

Manageable appliance	Ownership rate (%)
Time-shiftable	
Dishwasher	94.1
Washing machine	99.1
Clothes dryer	13.8
Washer dryer	8.1
Rice cooker	0.0
Bread maker	2.3
Robotic vacuum	12.7
Electric bike/scooter	2.5
Thermostatically controlled	
Air conditioner	22.6
Refrigerator	99.3
Electric water heater	9.9

In Figure 5.4, the most preferred usage times of time-shiftable appliances (dishwashers, washing machines, clothes dryers, washer dryers) on weekdays and weekends are presented (bread makers, rice cookers, robot vacuums, and electric bikes/scooters are excluded due to their low ownership rates and low energy demand). Users usually run their appliances when they come home from work on weekdays. Dishwashers are usually run after dinner time while washing machines and dryers are run both in the middle of the day and during peak hours. This pattern complies with the results obtained by [268]. Washing machines are usually run in the middle of the day (peak at 10-11 am), showing a similar pattern to that of [269,270]. On weekdays

33% of dishwasher, 29% of washing machine, 22% of clothes dryer and 21% of washer dryer operation occurs during the on-peak period when electricity is expensive. The time of use of appliances on weekends and weekdays are quite the same except for dishwashers. On weekends, dishwashers work significantly more during midday. On weekends 23% of dishwasher, 17% of washing machine, 25% of clothes dryer, and 15% of washer dryer operation occurs during on-peak period.

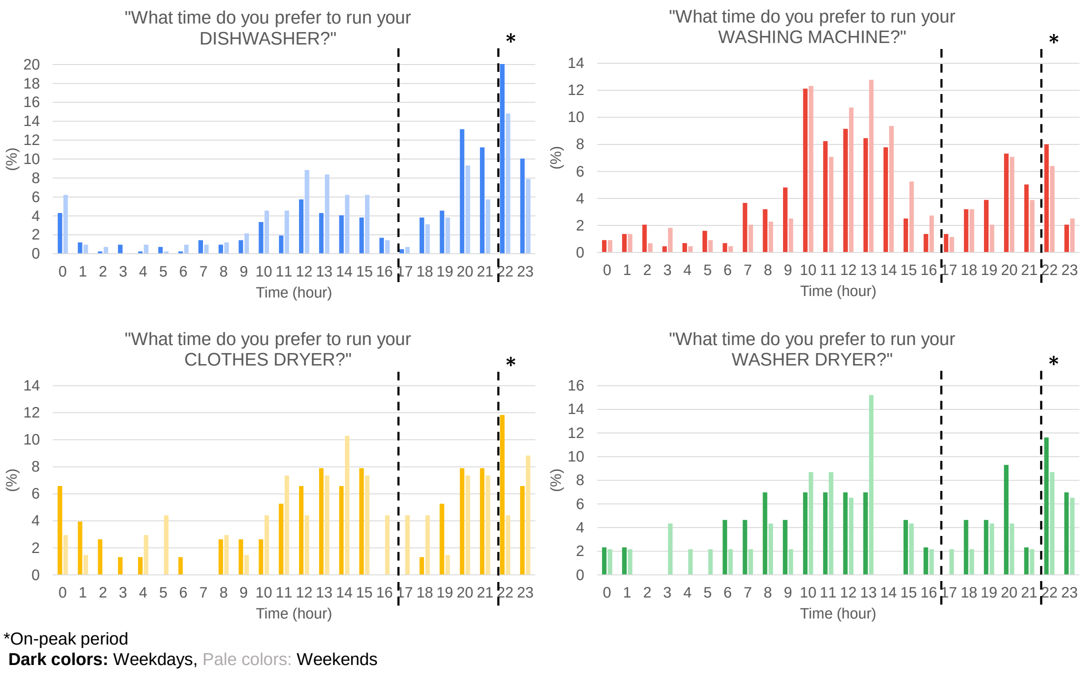

Figure 5.4 : Most preferred time of use of time-shiftable appliances (dishwashers, washing machines, clothes dryers, and washer dryers).

Time-shiftable appliances do not operate every day of the week. Therefore, when creating a survey-based load profile, it is important to know how many times a week these appliances run. Users were asked about this. The results are shared in Figure 5.5. Among time-shiftables, dishwashers are the most frequently operated. For instance, on Monday, while 71% of the dishwashers run, the number is lower for washing machines as 47%. On Tuesdays and Thursdays, clothes dryers run more often than washing machines. This may be due to the urgent need for hand washing followed by sudden drying (e.g. drying hand-washed baby clothes, school uniforms, or work clothes). On average, users run their dishwashers, washing machines, clothes dryers, and washer dryers 63%, 46%, 43%, and 40% of a week, respectively (100%, when an appliance runs once every day). The average operation ratio is lower on weekdays (62%, 40%, 39%, and 32%, respectively) and gets higher on weekends (67%, 61%, 54%, and 61%, respectively).

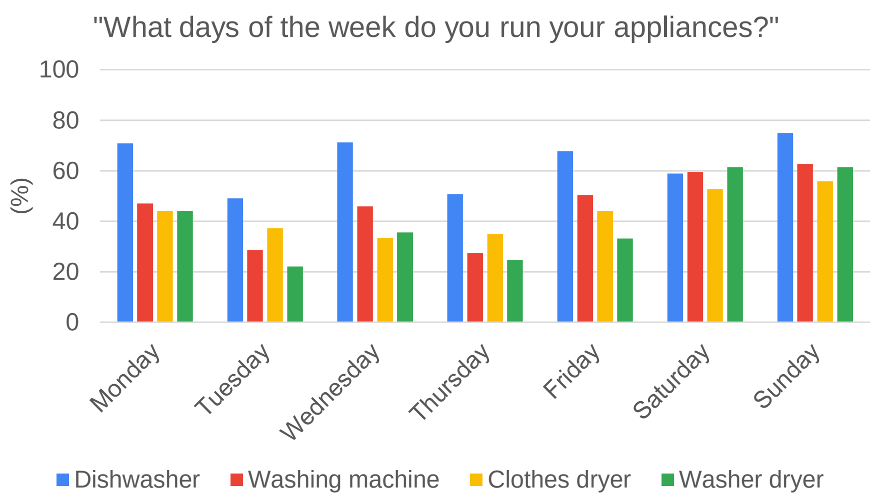

Figure 5.5 : Frequency of running time-shiftable appliances.

Participants were asked about the use habits of their thermostatically controlled appliances (air conditioner, refrigerator, electric water heater). On average, they set refrigerator temperature to 3.9°C. This is important because especially during the peak period this temperature can be increased even further and offer a DR potential of up to 7°C. Or, pre-cooling can be applied before electricity gets expensive. Refrigerators can be cooled down to 1°C before the peak period and the stored energy can be benefited during peak hours [271].

On average, the participants set their air conditioner temperature to 21.7°C on summer days during the daytime. This temperature can be increased even further, especially during the peak period, and offers a DR potential of up to 26°C (high humidity) or 27°C (low humidity) in summer according to the ASHRAE standard [114]. Or, similarly, pre-cooling can be performed and the relevant zone can be cooled to a certain temperature before expensive hours. Nearly 20% of the users stated that they operate their air conditioners at 18°C. These might be intermittent users turning on and off their devices due to air conditioning disturbances such as lethargy, headaches, irritated skin, etc. The average air conditioner set-point temperature during sleep hours is higher than that during the daytime as 22.5°C. 44% of air conditioner users turn off their air conditioners during sleep hours.

The use of electric water heaters is not common in Türkiye, as the vast majority live in multi-storey apartment buildings heated by natural gas. The ownership rate of electric water heaters among the participants was 9.9%. Most of them (43%) use 65-liter water heaters (77 liters on average). People usually shower 4 times a week in winter and 7.5 times a week in summer. On average, they spend 16 minutes a day in the shower. The majority take showers between 20:00 and 22:00 (within peak hours). The rate of taking a shower is high between 07:00 and 09:00 as well on weekdays. The majority take showers between 20:00 and 22:00 (within peak hours). The rate of taking a shower is high between 07:00 and 09:00 as well on weekdays. Showering is done more often in the middle of the day on weekends than on weekdays. This pattern shows similarity to the measured values in [226]. The distribution of the refrigerator and air conditioner set-point temperatures and showering hours of participants are shared in Figure 5.6.

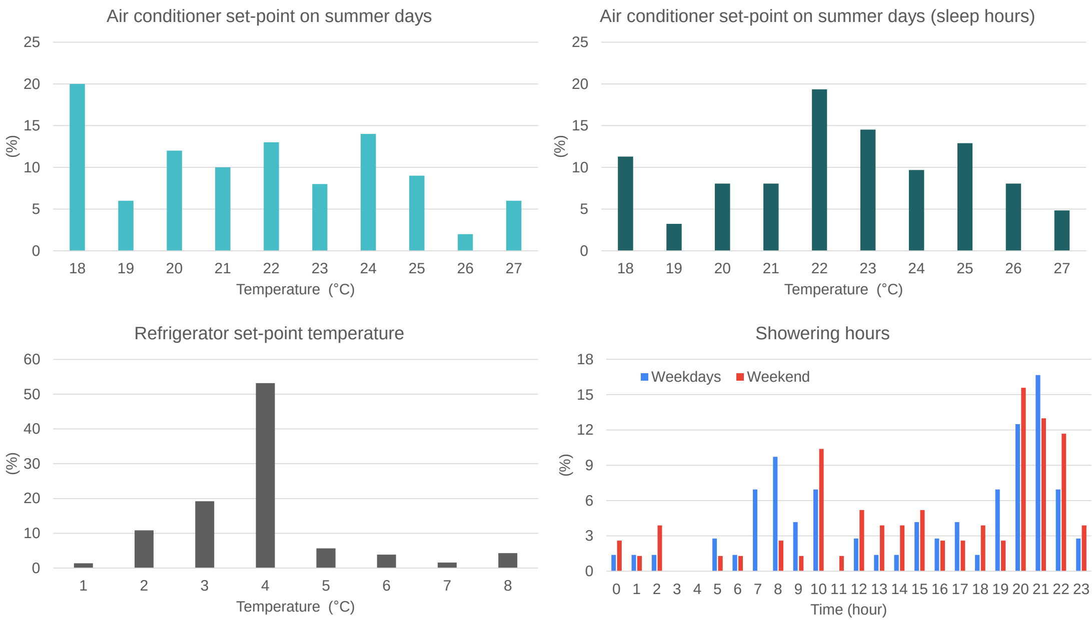

Figure 5.6. Distribution of air conditioner set-point temperature, refrigerator set-point temperature, and showering hours.

5.4 Perception of Electricity Tariffs

Residential customers in Türkiye can subscribe to three types of electricity tariffs; fixed tariff, TOU tariff, and green tariff (which guarantees that all the electricity supplied is produced from environmentally friendly renewable energy sources). Turkish TOU divides the day into three and does not differ for weekdays and weekends. Options such as critical peak pricing (CPP) or real-time pricing (RTP) have not been available for the residential group so far. This part of the survey aims to understand residents’ perception of electricity tariffs in Türkiye.

According to the survey results, 59.9% of the participants do not know which tariff they are subscribed to. As switching to TOU and green tariff are a result of choice and awareness, these participants can be assumed as fixed tariff subscribers. Then, with this assumption, 91% of the participants use fixed tariff, 8.4% use TOU, and 0.6% use green tariff. The detailed results of electricity tariff awareness are presented in Table 5.6.

Table 5.6 : Awareness of the participants about electricity tariffs.

Do you know which tariff you are subscribed to?	Frequency (%)
Yes	40.1
No	59.9
Tariff distribution	Frequency (%)
Fixed tariff	91.0
TOU	8.4
Green tariff	0.6
TOU awareness	Frequency (%)
I do not know about the TOU scheme.	73.8
I know about the TOU scheme.*	26.2
*I know expensive/cheap hours.	44.8
*I approximately know expensive/cheap hours.	35.3
*I have no idea when it gets expensive/cheap.	19.8
TOU misconception	Frequency (%)
Fixed tariff subscriber but tries to run appliances at night, thinking that electricity will be cheaper.	51.6
Green tariff awareness	Frequency (%)
I heard about the green tariff.	8.4
I have not heard about the green tariff.	91.6
(After informed) Would you be willing to switch to the green tariff?	Frequency (%)
Yes	76.2
No	23.8
Green tariff is 60% more expensive. Still willing to switch?	Frequency (%)
Yes	14.2
No	85.8

When all participants were informed about the green tariff and asked if they would like to switch to it, 76.2% showed willingness. However, there was a big change in their views when they were later informed that the green tariff was 60% more expensive than the fixed tariff. After updated, 81.4% changed their minds about their willingness to pay for green electricity.

5.4.1 Perception of TOU

Only 26.2% of the respondents stated that they have heard about TOU. Among them, 44.8% stated they know when electricity gets cheaper or more expensive, 35.3% stated they approximately know the cheap and expensive hours and 19.8% stated they do not know the cheap and expensive hours (Table 5.6).

In Türkiye, many people suffer from a misconception: "*Electricity is cheap at night for everyone*". Although they are not TOU subscribers and cannot benefit from cheap electricity prices, many fixed tariff subscribers try to run their electrical devices after 10 pm. 51.6% of the fixed-rate subscribers were found to be suffering from this misconception from time to time, thinking that electricity will be cheaper for them as well at night (Table 5.6). Although this unexpected load shifting contributes to reducing the peak load, it is a big misconception for consumers. It is also a sign that many fixed tariff subscribers are potential TOU subscribers and can be guided in this direction.

5.4.2 Expectations, concerns, and motivational factors associated with TOU

The results of participants' monetary and comfort-related concerns and expectations, and their social motivations regarding the TOU tariff are demonstrated in Figure 5.7. The two biggest concerns are similar: TOU does not provide sufficient bill discount or it is hard to estimate what kind of bill discount TOU can provide. The difficulty of keeping track of when electricity gets cheaper or more expensive seems to be an important obstacle as well. As seen, 47% of respondents do not want to track the times when electricity prices get cheap/expensive. Here, HEMS might be a solution for these people. Although these people do not want to follow cheap/expensive times, it does not mean they do not want to perform DR. HEMS can enable these individuals to shift their loads automatically and therefore effortlessly.

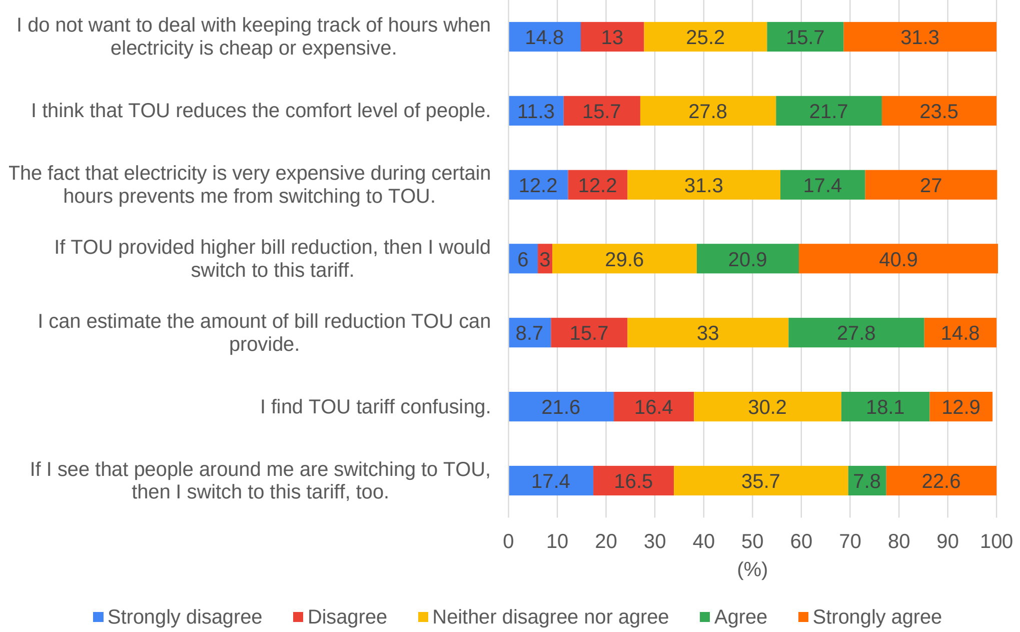

Figure 5.7 : Perception of time-based electricity tariffs.

5.5 Perception of HEMS Use and DR

In the last part of the questionnaire, detailed information about the concept of HEMS (how it works, functions, benefits, etc.) was presented to the participants and then they were asked about their willingness to use HEMS and HEMS usage preferences. A majority of 78% showed a willingness to install a HEMS. The willingness to participate in DR was found to be 50% in Tokyo and 70% in New York [272], 81.5 in the island of Mayotte [231], 74.7% in China [273], 50% in US Midwest [274] and 78% in another study conducted in Türkiye [275].

After the initial interest in HEMS use was learned, the respondents who said they wanted to use HEMS were asked which manageable appliances they would like to leave control of to HEMS. 72% of dishwasher, 69% of washing machine, 59% of clothes dryer, 67% of washer dryer, 81% of refrigerator, 93% of air conditioner, and 95% of electric water heater users agreed to leave control of their appliances to HEMS. This is in line with the results obtained by [232], in terms of the priority order of appliances for DR participation. The results are presented in Figure 5.8. Overall, participants were willing to install HEMS for DR.

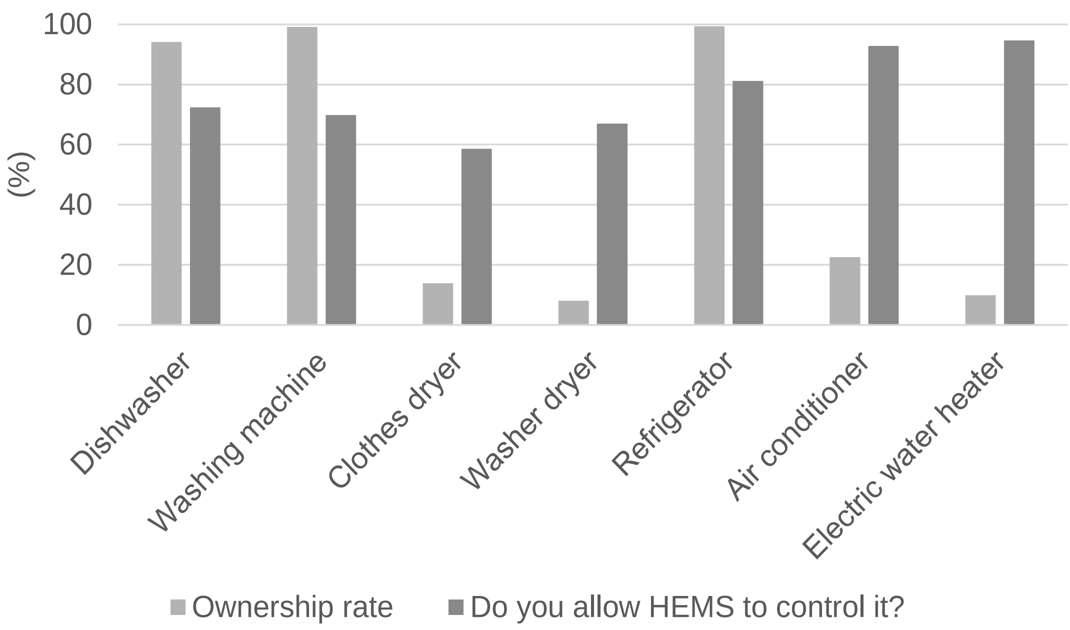

Figure 5.8 : Ownership rate of manageable appliances and answer to “Do you allow HEMS to control this device?”.

After learning how many participants want to use HEMS and what appliances they leave control of to HEMS, they were asked about the time intervals they want HEMS to shift time-shiftable appliances. Then, the following questions were asked regarding thermostatically controlled appliances:

- "*Would you allow HEMS to interfere with the temperature of your air conditioner? So that, within thermal comfort standards, you can compromise your comfort level a little for the benefit of your bill and electricity grid.*"
- "*Would you allow HEMS to interfere with your refrigerator temperature without spoiling your food?*"
- "*Would you allow HEMS to interfere with your electric water heater temperature by performing pre-heating before electricity gets expensive?*".

According to the answers, the highest HEMS participation was for electric water heaters, where users were expected to feel the least loss of comfort. 95% of electric water heater users let HEMS pre-heat water during cheap hours before shower time. Although this is a very high rate, only 9.9% of the total participants use electric water heaters. In other words, the DR participation potential of the electric water heater in the total population is 9.4%. Still, it should be noted that electric water heaters offer a great DR possibility due to their significantly high energy consumption.

A significant portion (81.2%) of refrigerator users allowed HEMS to intervene in refrigerator temperature when necessary. Although the individual DR potential of refrigerators is low due to their low instantaneous power, the widespread use of refrigerators (99.3%) makes the DR associated with the refrigerator important when their collective participation is considered. The DR participation of refrigerators in the total population is very high as 80.6%.

The DR potential of air conditioners is also high. 22.6% of the participants have air conditioners and 92.8% of them allowed HEMS to intervene in the set-point temperature when necessary, making the ratio of the DR potential of air conditioners to the general population 21%.

Among time-shiftable appliances, the appliance with the highest demand-side flexibility belonged to dishwashers. Most respondents chose to leave control of their dishwashers (72%) and washing machines (69%) to HEMS. The lowest HEMS participation was for the clothes dryers (59%) among all manageable appliances, probably because their operation depends on a previous wash cycle or washing clothes by hand. Since washer dryers do not have that problem, the share of washer dryers (67%) showed a similar pattern to washing machines. The DR participation potentials of these appliances in the total population are 68%, 68%, 8%, and 5% for dishwasher, washing machine, clothes dryer, and washer dryer, respectively.

5.5.1 Operational priorities regarding time-shiftable appliances

In the literature, in the simulation of HEMS tools, it is either assumed that time-shiftable appliances can be shifted to any time of the day or to preferred time intervals. These preferred intervals reflect the authors' own preferences, daily experiences, or opinions. Various preferred load shifting intervals for time-shiftable appliances can be found in [101,276–284]. Although they individually give an idea, they do not reflect the actual preferences of the average population.

This shortcoming in the literature led us to search for the average preferred time intervals for time-shiftable appliances to be shifted, which is among the contributions of the study. Hereby, the participants were asked; "*What time slots would you prefer HEMS to shift your dishwasher, washing machine, clothes dryer, and washer dryer*?". A day was divided into seven time slots in the questionnaire, and the participants were asked to choose the appropriate slots (could be multiple choice) for load shifting.

The results are shared in Figure 5.9. Participants who are willing to use HEMS are highly fond of their appliances being shifted to off-peak periods, especially to 22:00 and 00:00, where both electricity is cheap and it is not sleep time yet (where the noise of appliances cannot wake anyone up). 00:00 – 02:00 seemed to be a very desirable period as well. The least favorable time slot was 06:00 – 09:00 for all appliances. Presumably, this time slot is the most suitable to unload laundry and dishes for users who prefer to run appliances at night.

To summarize, 74% of dishwasher, 58% of washing machine, 61% of clothes dryer and 51% of washer dryer users who are willing to use HEMS agreed their electrical appliances to be shifted to off-peak periods.

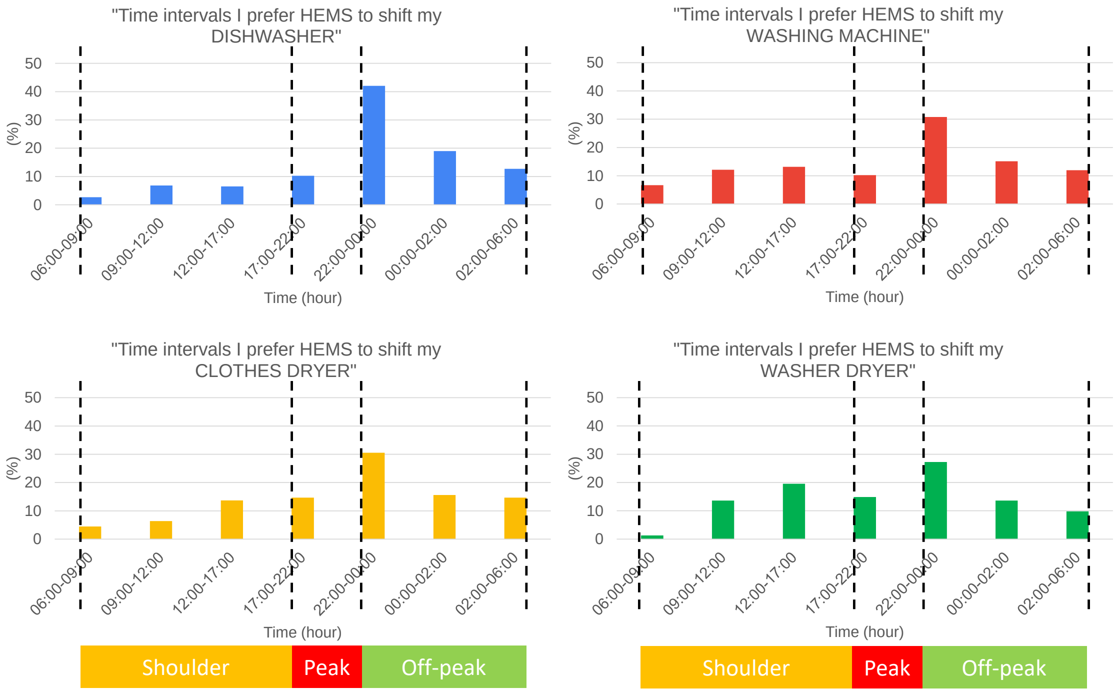

Figure 5.9 : "What time slots do you prefer HEMS to shift your dishwasher, washing machine, clothes dryer, and washer dryer?".

5.5.2 Expectations, concerns and motivational factors for HEMSs

The participants were asked about their expectations, concerns, and motivational factors regarding HEMSs. The results are demonstrated in Figure 5.10 and Figure 5.11. The influence of the social environment seems to be quite effective in the acceptance of HEMS. People who see that people around them start using HEMS are likely to adopt this technology. Among the concerns, the biggest seems to be the waiting of the clothes in the washing machine and the related odor problem. The least of the concerns is an unwanted decrease/increase in the air conditioner set-point.

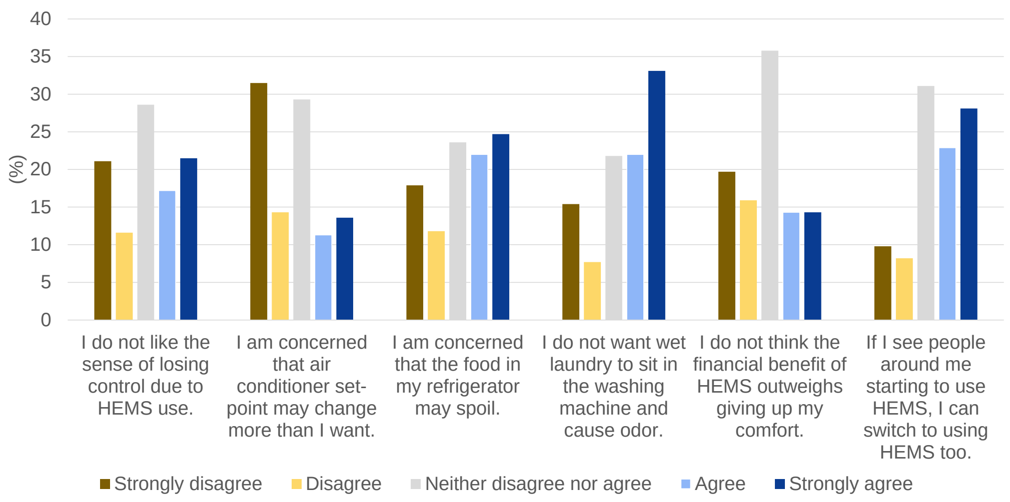

Figure 5.10 : Perception of HEMS.

Participants were asked about factors that could motivate them to use HEMS. The results are presented in Fig. 5.11. The biggest motivation was financial factors such as the free installation of the systems and electricity bill reduction. Technological factors such as following a technological innovation and visualized monitoring of electricity consumption in the household received slightly less attention.

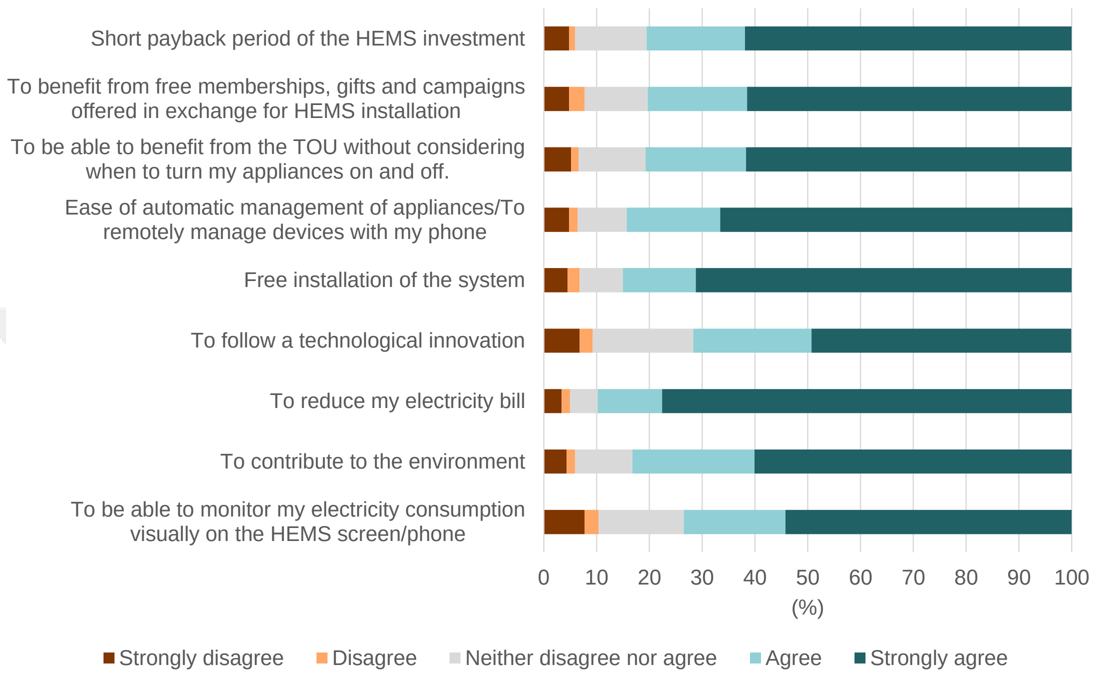

Figure 5.11 : "What does motivate you for a HEMS installation?".

5.6 Simulations: Methodology and Input Data

5.6.1 Methodology

Most of the data presented in the previous sections are not available in the literature or are only partially available. These data can be very useful in HEMS/DR-based simulation studies which often use assumed input parameters in simulations (e.g. the preferred time intervals for load shifting). In this section, these data will be used as input and entered into a HEMS-optimization tool. So, the changes in the electricity load profiles and electricity bills of the 442 participants will be simulated based on their responses.

5.6.1.1 Objective function

A previously developed mixed-integer linear programming (MILP)-based HEMS tool is simplified to be used in this study [14,15]. The objective of this model is to minimize the daily electricity bill by shifting time-shiftable appliances to the cheap electricity period, and pre-cooling or pre-heating the zones (water heater tank, household, and refrigerator cabinet) of thermostatically controlled appliances for thermal storage before electricity gets expensive.

The MILP problem is solved using "intlingprog" solver of MATLAB. The objective function is daily electricity bill minimization performed by HEMS as shown in Eq. (5.1).

$$f_c = min \sum_t P_t \cdot \Delta t \cdot \lambda_t \tag{5.1}$$

where, P_t is the power drawn from the grid at time t [kW], Δt is the time interval and λ_t is electricity price at time t [$/kWh].

P_t consists of the sum of the power consumption of all available home appliances in the household as in Eq. (5.2).

$$P_t = P_t^{un} + \sum_{i=1}^{I} P_t^i + \sum_{j=1}^{J} P_t^j \,, \forall t \tag{5.2}$$

where, P_t^{un}, P_t^i and P_t^j are the power drawn from the grid by unmanageable appliances, time-shiftable appliances, and thermostatically controlled appliances at time t, respectively [kW].

5.6.1.2 Time-shiftable appliance model

The optimization model can shift time-shiftable appliances (dishwasher, washing machine, clothes dryer or washer dryer) to cheap electricity period to perform DR. These appliances are modeled as in Eq. (5.3-5.7) [126]. A time-shiftable appliance has an uninterruptible operation which means it cannot be interfered with once started. The fixed consumption of a time-shiftable appliance can be represented as in Eq. (5.3).

$$P^i = [p_1^i \quad p_2^i \quad \cdots \quad p_T^i]' \tag{5.3}$$

where p_t^i is the power consumption of the time-shiftable appliance i at time t [kW], and T is the set of time period. For instance, for a daily operation of the dishwasher, at 1-hour interval, T would be 24 (or at 5-min interval 288). At 1-hour interval, P^i could have been something like $P^i = [1.61 \quad 0.18 \quad 0 \quad 0 \quad \cdots \quad 0\,]'$. In this example, it would mean that the appliance i could draw power for 2 hours over 24 hours, with a total consumption of 1.79 kWh per cycle.

All possible shifting combinations of P^i can be represented in matrix form as in Eq. (5.4).

$$P^i = \begin{bmatrix} p_1^i & p_T^i & \cdots & p_3^i & p_2^i \\ p_2^i & p_1^i & \cdots & p_4^i & p_3^i \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_T^i & p_{T-1}^i & \cdots & p_2^i & p_1^i \end{bmatrix}, \forall t \tag{5.4}$$

Among all shifting combinations, only one of them belongs to the optimal result. Therefore, the binary integer vector X^i defined in Eq. (5.5) functions as a switch control to choose that optimal column.

$$X^i = [x_1^i, x_2^i, \dots, x_T^i]', \forall t \tag{5.5}$$

where, x_t^i is the binary variable at time t (1 if the appliance i starts working at t, else 0).

Eq. (5.6) expresses that only one of the elements can be non-zero in X^i, which is equal to one, to choose the optimal column.

$$\sum_{t^{i,min}}^{t^{i,max}} x_t^i = 1,\ X^i \in \{0,1\}, \forall t \tag{5.6}$$

Users define their preferred operation range for time-shiftable appliances and HEMS shifts appliances only into this range. For example, if a user prefers appliance i to be operated between 12:00 and 17:00, then, among 24 variables (at 1-hour interval), only the ones between 12 and 16 can take the value of "1" and the rest must be "0". $t^{i,min}$ and $t^{i,max}$ represent the start and end times of the preferred operating range, respectively.

The length of the operation range (the difference between $t^{i,min}$ and $t^{i,max}$) cannot be lower than the running duration dur^i of an appliance as shown in Eq. (5.7). So, if an appliance has a two-hour run duration, then users should set a minimum two-hour operation range for load shifting of this appliance.

$$dur^i \leq |t^{i,min} - t^{i,max}| \tag{5.7}$$

Some appliances, such as washing machines and clothes dryers, may require a sequential operation. The related logical constraints are given in Eqs. (5.8-5.11).

$$T^i = \begin{bmatrix} t_1^i & t_T^i & \cdots & t_3^i & t_2^i \\ t_2^i & t_1^i & \cdots & t_4^i & t_3^i \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ t_T^i & t_{T-1}^i & \cdots & t_2^i & t_1^i \end{bmatrix}, \forall\, t_T^i \in \{0,1\} \tag{5.8}$$

$$\max\left(T^{i1} \cdot X^{i1} + T^{i2} \cdot X^{i2}\right) \leq 1 \tag{5.9}$$

$$T_t^i = T^i \cdot X^i, \forall t \tag{5.10}$$

$$\theta^{i1,i2} \delta_t^{i1,1\_0} < \delta_t^{i2,0\_1} \tag{5.11}$$

In Eq. (5.8), T^i represents the possible shifted-operation combinations where all t_T^i are binary variables. Eq. (5.9) expresses that certain two appliances cannot operate at the same time. However, this constraint cannot ensure that the washing machine runs before the clothes dryer. Therefore, the operational array of appliance i is extracted from Eq. (5.10). Then, the priority of appliance $i1$ and $i2$ are put in order by detecting the stopping and starting instances of appliances from Eq. (5.11). Here, $\delta_t^{i1,1\_0}$ represents the instance when the appliance $i1$ stops (the status from 1 to 0) and similarly $\delta_t^{i2,0\_1}$ gives the starting point of appliance $i2$. Also, $\theta^{i1,i2}$ is 1 when both appliances $i1$ and $i2$ are within the time slot t, otherwise 0.

Eq. (5.12) gives the power consumption of time-shiftable appliance i [kW].

$$P_t^i = P^i \cdot X^i, \forall t \tag{5.12}$$

5.6.1.3 Thermostatically controlled appliance model

The optimization model can perform DR for thermostatically controlled appliances by pre-cooling or pre-heating zones before electricity gets expensive or by setting different set-points during expensive hours.

In the study, a simple first-order lumped capacitance (1R1C) model is used in the modeling of the zones (house envelope for air conditioner, cabinet for refrigerator, tank for water heater) [285]. The same thermal model can be used with slight differences for different thermostatically controlled appliances [129–131]. The sign of the decision variable is positive in the heating operation of the electric water heater (as in Eq. (5.13)) and negative in the cooling operation of the air conditioner and refrigerator.

$T_t^{i,j}$ models the inside air/water temperature in a zone as expressed in Eq. (5.13).

$$T_t^{i,j} = \frac{\left(T_t^{o,j} + T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j + R^j \cdot COP^j \cdot P^j \cdot x_t^j\right)}{\left(1 + \dot{c}^j \cdot R^j \cdot uc_t^j\right)} + \left(T_t^{o,j} - \left(\frac{\left(T_t^{o,j} + T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j + R^j \cdot COP^j \cdot P^j \cdot\right)}{\left(1 + \dot{c}^j \cdot R^j \cdot uc_t^j\right)}\right)\right) \cdot e^{\left(\frac{-\left(1+\dot{c}^j \cdot R^j \cdot uc_t^j\right)\cdot \Delta t}{R^j \cdot C^j}\right)}, \quad \forall t \tag{5.13}$$

where, $T_t^{o,j}$ is the ambient temperature (outdoor temperature for air conditioner / ambient temperature for refrigerator and water heater), R^j and C^j are the equivalent thermal resistance and thermal capacitance of the zone (specific to the house envelope/refrigerator cabinet/water tank), $\dot{c}^j$ is the constant amount of air/water heat flow capacity in a single time-step (due to air replacement for air conditioner and refrigerator / due to water replacement for water heater), uc_t is the time when air replacement or hot water replacement occurs, $T_t^{en,j}$ is the temperature of entering inlet water or outside air at time t, COP^j is the coefficient of performance of the relevant appliance, P^j is the input power of the relevant appliance and x_t^j is the decision variable between 0 and 1, defining the running status of the relevant appliance.

It should be noted that, in the study, air ventilation and refrigerator door openings are assumed to not affect the indoor air temperature. Therefore, the expressions of $T_t^{en,j} \cdot \dot{c}^j \cdot R^j \cdot uc_t^j$ and $\dot{c}^j \cdot R^j \cdot uc_t^j$ takes the value 0 in Eq. (5.13) for air conditioner and refrigerator operation.

Eq. (5.14) expresses the upper and lower limits of hot water/indoor temperature within the zone.

$$T^{i,min,j} \leq T_{j,t}^{i} \leq T^{i,max,j}, \forall t \tag{5.14}$$

where $T^{i,min,j}$ and $T^{i,max,j}$ are the minimum and maximum allowed inside temperatures in a zone.

Eq. (5.15) shows the power consumption of thermostatically controlled appliance j at time t.

$$P_t^j = P^j \cdot x_t^j, \forall t \tag{5.15}$$

5.6.2 Input Data

5.6.2.1 Electricity price and temperature

The selected time window for the optimization is 5 min (0.0833 h). Turkish residential electricity prices are used in the simulations, which are 0.12 $/kWh for the flat rate and 0.122 $/kWh (mid-peak period), 0.179 $/kWh (on-peak period), and 0.076 $/kWh (off-peak period) for the TOU rate [195]. The temperature data required to simulate the air conditioning operation are obtained from [136]. The inlet water temperature data to be used for electric water heater operation when hot water is replaced by inlet water during a shower belongs to the province of Istanbul [190].

5.6.2.2 Manageable loads

The manageable load profile of each participant was individually simulated based on their survey response, and then all 442 profiles are aggregated. The ownership rate of all survey participants' manageable appliances is known (Table 5.5). It is known which time-shiftable appliance is operated on which day of the week and at what time (Figures. 5.4-5.5). Or, the set-point temperatures at which participants operate their refrigerators and air conditioners are known (for the 17% who did not know their refrigerator set-points, the average set-point of the respondents is used in the simulations). For participants who have an electric water heater, it is known how long an average shower lasts, at what times and how many times (Figure 5.6 and Section 3.2).

All necessary information for the load shifting was obtained from the survey results as well. It is learned whether the participants wanted to use HEMS, and if yes, for which manageable home appliances they wanted to use it (Figure 5.8). It is known what time intervals participants prefer their time-shiftable appliances to be shifted (Figure 5.9). Load shifting was done by entering these data into the developed HEMS tool.

The data regarding the technical specifications of the thermostatically controlled appliances and the thermal properties of their zones are collected from various studies (Table 5.7) [145,148–150,153]. These data are used in the modeling.

Every household is assumed to be using the same model of air conditioner, refrigerator, and electric water heater. The thermal resistance and thermal capacitance values are scaled according to the floor area (m^2) for houses and are assumed to be the same for all refrigerators and electric water heaters. The water tank temperature is limited between 45 and 60°C for safety [152]. The showering hours and showering duration are based on the survey responses of the participants.

The air conditioner and refrigerator operate within a dead band at the set-point temperature of each respondent. If the respondents are willing to use HEMS and participate in DR with these devices, then just before peak hours air conditioner set-point temperature is increased by 2°C (limited to a maximum of 27°C due to thermal comfort standards), and refrigerator set-point temperature is decreased to 0°C.

Table 5.7 : Technical specifications and thermal properties regarding thermostatically controlled appliances.

Parameter	Unit	Air conditioner	Refrigerator	Water heater
Rated power	kW	2.21	0.15	3.0
COP	-	3.21	0.76	1.0
Flow heat capacity rate	kW/K	-	-	0.659
		House	Cabinet	Tank
Thermal resistance	°C/kW	1/(0.002 x m^2)	89	223
Thermal capacitance	kJ/°C	144 x m^2	416	1770

Since we do not have data on energy consumption profiles of different types of washing and drying appliances and their different operating modes, we assumed that each household had the same model of appliance and operated them for the same duration in the same mode. The electrical load profiles of time-shiftable appliances are given in Figure 5.12 [82,83,155,286]. It was also assumed that every household had the same model air conditioner, refrigerator, and electric water heater. Also, participants who decided to use HEMS were assumed to switch to the TOU tariff.

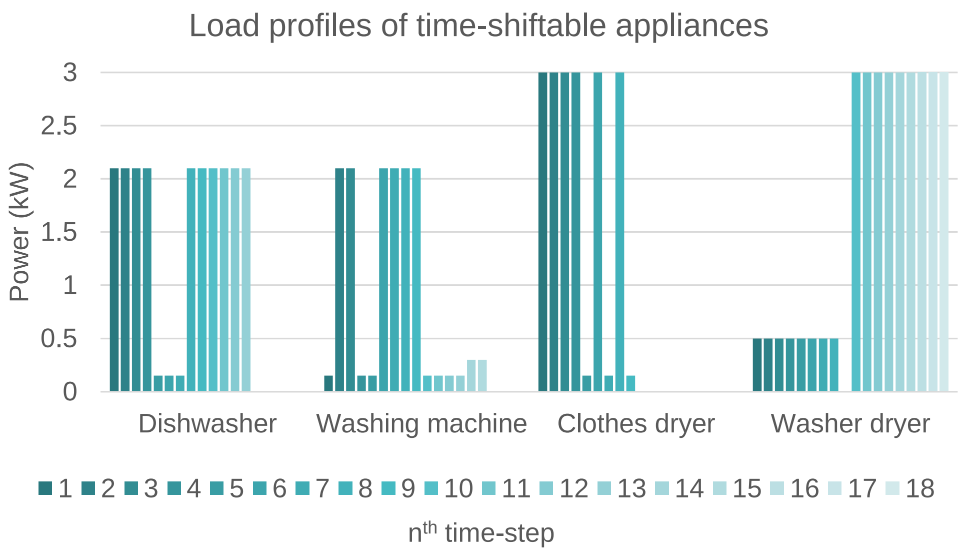

Figure 5.12 : Electrical load profiles of time-shiftable appliances for one cycle (5 min time interval).

5.6.2.3 Unmanageable loads

The survey results are insufficient to generate a load profile of unmanageable home appliances but can help modify profiles that have already been generated. In the generation of unmanageable loads (office equipment, entertainment, cooking, lighting, and others), European Union (EU)'s comprehensive Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE) data was used [287]. REMODECE presents a detailed electrical load profile for an average day for a typical household in Europe. Assuming that the usage pattern remained the same between the date of the project and today, but there would be changes in ownership rate and power consumption of appliances due to technological developments, REMODECE data was slightly modified according to the survey results (e.g. the lighting consumption has been updated according to the number of CFLs and LEDs obtained from the survey results and their power rating). Since the focus of the study is not unmanageable loads, it can be arguably said that such a modification can give a sufficient result in simulations. The modified load consumption was scaled for 442 people. The lighting load demand was also modified by taking into account the lighting pattern (time of use, seasonal changes) in New Zealand, which is symmetrically located at the same latitude as Türkiye [288].

5.7 Simulation Results

In this part of the study, data from the survey results were entered into a HEMS tool and the load profile of 442 survey participants was simulated. Load profiles are differentiated according to seasons, weekdays, and weekends.

5.7.1 Comparison of load profile of participants before and after HEMS use

Survey results reveal that the majority of respondents (78%) are willing to use HEMS. The simulation of this best-case scenario shows what can be technically achieved by HEMS-based DR in practice. It is assumed here that the users do not override their initial preferences or interrupt the scheduled operations of the appliances.

Figure 5.13 shows the electrical load profiles without DR, based on the responses of the survey participants (averages of the weekday and weekend profiles). The differences between the profiles of seasonal profiles are the inclusion of air conditioning, the change in the frequency and amount of hot water use, and the change in the unmanageable load profile. The difference between the weekday and weekend profiles is the running hours of time-shiftable appliances and hot water usage times. The monthly average electricity consumption of a household was found to be 215 kWh, which is very close to the 211 kWh calculated according to the survey responses.

Figure 5.14 demonstrates the electrical load profiles with DR. During the summer period, air conditioning pre-cooling before the price increase provides approximately 1 hour of thermal storage between 06:00 – 07:00. There is just a little air conditioning between 17:00 – 22:00 due to a 2°C increase in set-point temperature for DR. Refrigerators similarly provide thermal storage between 06:00 – 07:00 and 17:00 – 18:00 just before the price increase. Water heaters pre-heat water for thermal storage in cheap hours before showering. This pre-heating results in increased overall electricity consumption to keep water at a certain temperature, but the increase is negligible compared to the benefit of DR. HEMS raises air conditioner set-point during peak hours for DR, so the total electricity consumption in summer after DR is lower than before DR. All possible time-shiftable loads are shifted to participants' preferred time intervals (Figure 5.9).

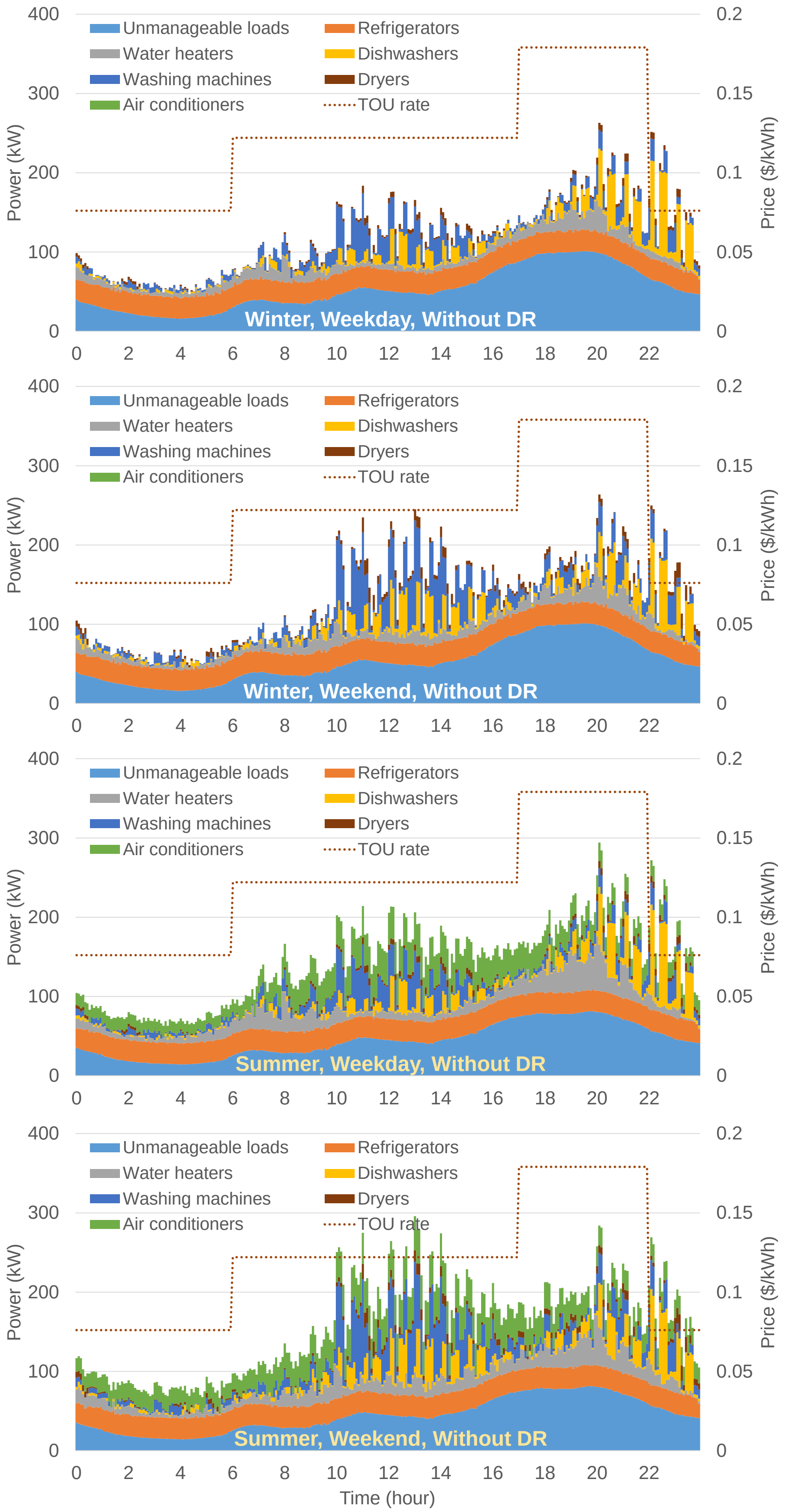

Figure 5.13 : Daily load profile of 442 participants without DR.

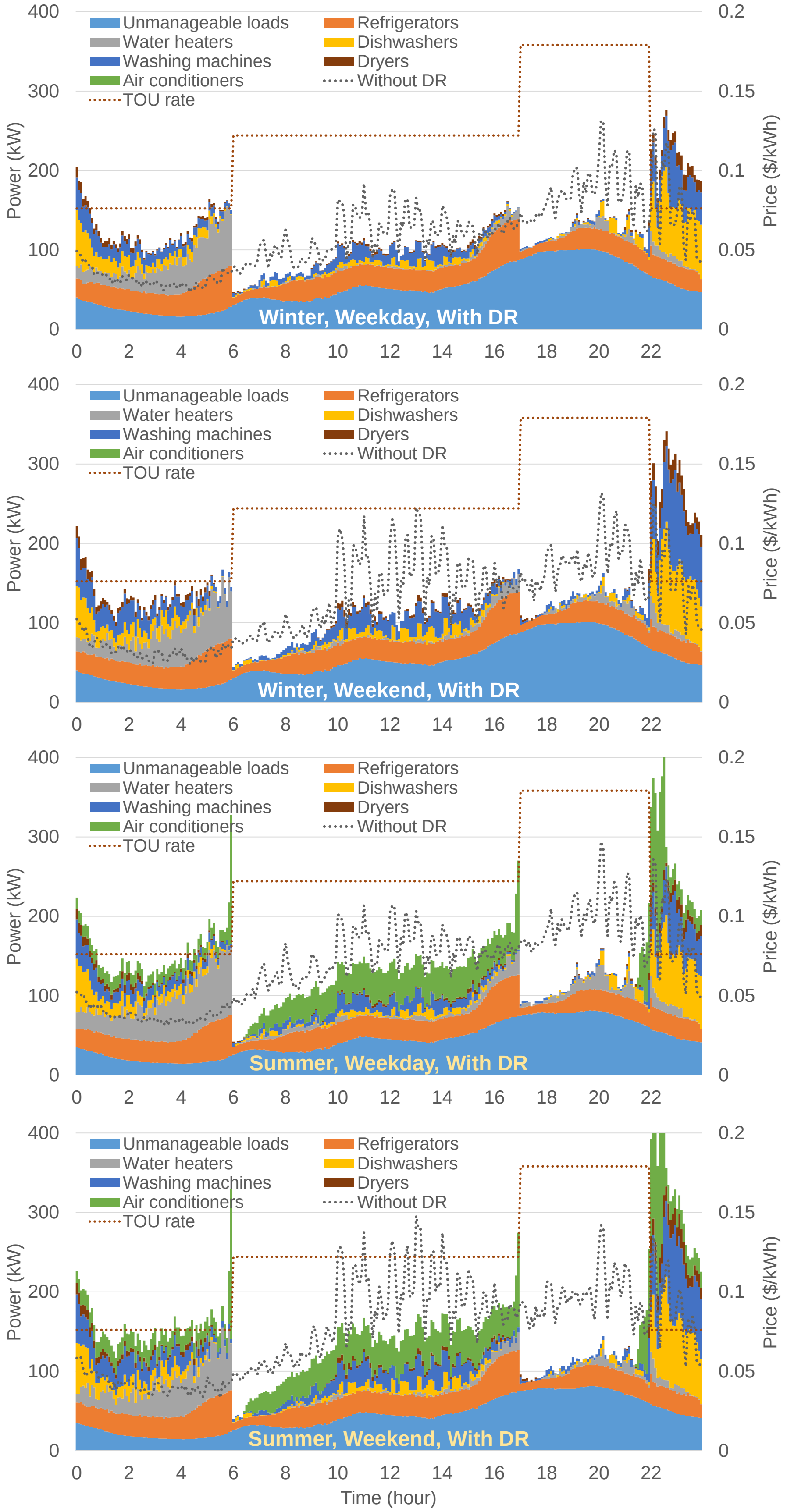

Figure 5.14 : Daily load profile of 442 participants with DR (78% agree to use HEMS).

New peaks occur due to load shifting before 06:00 and 22:00. While this may seem negative, the national load curve is not just about residential loads. These new peaks may provide valley filling in a sense, as pre-6 am and post-22 pm are times when load demand is already very low because of low commercial and industrial load demand (will be examined in the next sections). Also, unwanted new peaks can be limited by grid operators through DR or price signals. Due to its scope, the peak limiting capability of HEMS is not addressed in this study.

The numerical results are summarized in Table 5.8. With DR, on average, the on-peak consumption decreases by 33% from 915 to 614 kWh, which is significantly important. The off-peak consumption increases by 84% from 741 to 1365 kWh and the mid-peak consumption decreases by 19% from 1525 to 1239 kWh. Even though the community achieves a significant amount of load shifting (33% during the on-peak period), the total daily bill reduction is only 5%.

Table 5.8 : The change in total daily electrical energy consumption and bill of 442 participants after HEMS-based DR.

			Before DR		After DR		Change	
Season	Time of week	Time of day	Consumption (kWh)	Bill ($)	Consumption (kWh)	Bill ($)	Consumption (%)	Bill (%)
Winter	Weekday	Off-peak	677	81	1,185	90	+75.0	+11.1
		Mid-peak	1,282	154	1,046	128	-18.4	-16.9
		On-peak	858	103	628	112	-26.8	+8.7
		Total	2,817	338	2,859	330	+1.4	-2.4
	Weekend	Off-peak	685	82	1,350	103	+97	+25.6
		Mid-peak	1,509	181	1,136	139	-24.8	-23.2
		On-peak	875	105	637	114	-27.2	+8.6
		Total	3,070	368	3,123	355	+1.7	-3.6
Summer	Weekday	Off-peak	792	95	1,446	110	+82.6	+15.6
		Mid-peak	1,637	196	1,376	168	-15.9	-14.5
		On-peak	969	116	599	107	-38.1	-7.8
		Total	3,397	408	3,421	385	+0.7	-5.6
	Weekend	Off-peak	831	100	1,629	120	+96.0	+20.0
		Mid-peak	1,875	225	1,484	177	-20.9	-21.3
		On-peak	965	116	596	104	-38.2	-10.3
		Total	3,670	440	3,709	401	-1.0	-8.6
All year		Off-peak	741	89	1,365	103	+84.2	+15.7
		Mid-peak	1,526	183	1,239	151	-18.8	-17.5
		On-peak	915	110	614	109	-32.9	-0.9
		Total	3,182	382	3,219	363	+1.1	-5.0

Here, it should also be calculated how much bill reduction the HEMS users achieve alone, because the reduction they will get is the major factor that will motivate them to install HEMS in the future (Figure 5.11). Unfortunately, on average, the total annual bill reduction of the HEMS users (78% of the participants) is only 6.7% (Table 5.9). This is far from economically attractive and a challenge to surmount. Although users perform automated DR, the unmanageable loads that cannot be shifted still pay high for electricity during the on-peak period. Unfortunately, the TOU scheme in its current form does not make automated DR economically attractive. Yet, bill discounts can be improved where electric vehicle (EV) home charging and manual DSM are performed (e.g. cooking before on-peak period) and PV-battery systems are included. Or, the existing TOU scheme can be redesigned to become economically more attractive.

Table 5.9 : Total daily bill of HEMS users (78% of the survey participants).

Period	Before DR ($)	After DR ($)	Reduction (%)
Winter, Weekday	265	252	-4.9
Winter, Weekend	288	273	-5.2
Summer, Weekday	319	294	-8.1
Summer, Weekend	345	315	-8.6
Average	299	279	-6.7

The average daily running cost of the appliances of HEMS users before and after DR is given in Table 5.10. The total average bill reduction of manageable devices is 13.6%. However, after switching to the TOU, there is a bill increase of 4.8% in unmanageable loads due to the increased prices of the on-peak period. Therefore, the total bill reduction becomes 6.7%.

Table 5.10 : Average daily running cost of the appliances of HEMS users before and after DR.

Appliance	Running cost		Saving	
	Before ($)	After ($)	($)	(%)
Dishwasher	28.5	21.9	6.6	23.2
Wash. machine	32	25.7	6.3	19.5
Dryers	7.1	5.6	1.5	20.9
Refrigerator	60.0	57.6	2.4	3.9
Air conditioner	30.7	26.9	3.8	12.4
Water heater	29.3	24.4	4.9	16.8
Unmanageable	111.5	116.9	-5.4	-4.8
Total	299.1	279.0	20.1	6.7

The daily appliance load profile of the 345 HEMS users before and after DR are shown in Figure 5.15. The average daily consumptions are 243 kWh for dishwashers (9.7%), 269 kWh for washing machines (10.7%), 62 kWh for dryers (2.5%), 507 kWh for refrigerators (20.3%), 250 kWh for air conditioners (10.0%), 264 kWh for electric water heaters (10.6%), and 908 kWh for unmanageable loads (36.3%).

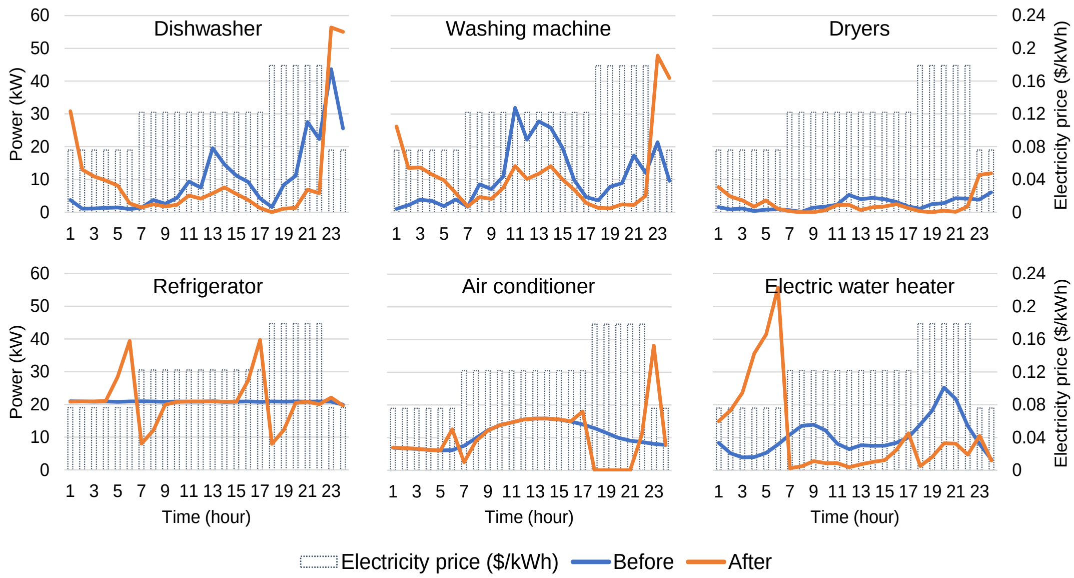

Figure 5.15 : Average daily load profile of the manageable appliances of the HEMS users before and after DR.

In Figure 5.16, the bill reduction of HEMS users is ordered from the highest to the lowest. The rate of those who save more than 20% on their bills is only 3% (the highest bill reduction is 27%). 8% has a bill reduction of above 15%, 13% has a reduction of 10-15%, 39% has a reduction of 5-10%, and 30% has a reduction of 0-5%.

With the current appliance ownership rates, appliance use behaviors and HEMS use preferences, 10% cannot reduce their bills despite owning HEMS. On the contrary, their bills increase after switching to the TOU tariff. These households should not install HEMS unless their main motivation is different from bill saving.

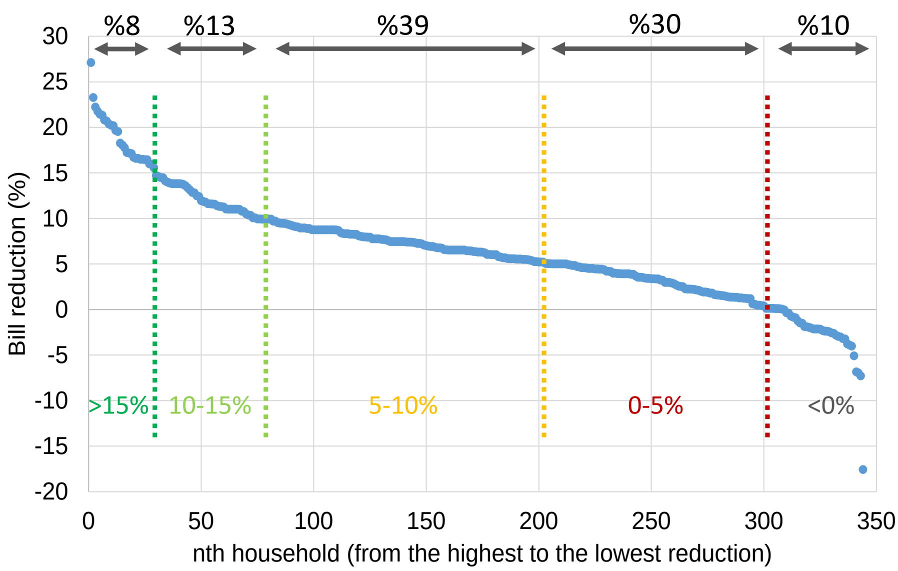

Figure 5.16 : Bill reduction ranking of the HEMS users from the highest to the lowest.

In Table 5.11, the appliance use behavior and HEMS use preferences are given for random sample households each selected from the bill reduction ranges shown in Figure 5.16. The bill reduction increases as the number of manageable household appliances, the participation rate of appliances in DR, the frequency of use of appliances, and the shift of loads from on- to off-peak hours increase.

Table 5.11 : Appliance use behavior and HEMS use preferences of the sample households.

Bill reduction (%)	20.4	13.8	7.7	2.3
Appliance use behavior				
DW run (weekday)	9 pm (Wed, Fri)	7 pm (every day)	-	7 pm (Mon, Wed, Fri)
DW run (weekend)	7 pm (Sun)	8 am (every day)	-	6 pm (Sun)
WM run (weekday)	7 pm (Thu, Fri)	1 pm (Mon, Wed)	8 pm (Wed)	5 pm (Wed)
WM run (weekend)	2 pm (Sat)	10 am (Sat)	2 pm (Sat, Sun)	11 am (Sat, Sun)
CD run (weekday)	9 pm (Thu, Fri)	-	-	-
CD run (weekend)	5 pm (Sat)	-	-	-
WD run (weekday)	-	-	-	-
WD run (weekend)	-	-	-	-
AC set-point (°C)	25 (27 sleep hours)	26	-	-
Ref. set-point (°C)	4	4	4	6
Avg. shower dur. (min)	15	15	-	-
EWH tank (liter)	65	120	-	-
Shower use (weekday)	8 am	8 am	-	-
Shower use (weekend)	9 pm	10 am	-	-
Shower freq. (winter)	3 times	2 times	-	-
Shower freq. (summer)	6 times	4 times	-	-
Number of residents	2	3	4	3
HEMS use preferences				
DW (shifted period)	10 pm – 12 am	12 am – 6 am	-	Shift to anytime
WM (shifted period)	Do not shift	12 am – 6 am	10 pm – 12 am	Do not shift
CD (shifted period)	-	-	-	-
WD (shifted period)	-	-	-	-
AC pre-cooling	Allow	Allow	-	-
Ref. pre-cooling	Allow	Deny	Allow	Allow
EWH pre-heating	Allow	Allow	-	-

DW: Dishwasher, WM: Washing machine, CD: Clothes dryer, WD: Washer dryer, AC: Air conditioner, EWH: Electric water heater

5.7.2 Load profile of the participants for varying HEMS ownership rates

Although 78% of the survey participants wanted to use HEMS, it may not be possible to reach these figures in reality. The bill reduction achieved is very low which may result in less adoption of HEMS than in the survey results. Therefore, in this section, the change in the load curve according to different HEMS ownership rates is examined. Here, the HEMS usage behavior does not change, only the HEMS ownership rates. The load curves of the community for different HEMS ownership rates and DR participation levels are shown in Figure 5.17. As the DR participation rate increases, consumption decreases in on-peak and mid-peak hours and increases in off-peak hours.

Figure 5.17 : Load profile of the community for different HEMS ownership rates (DR participation levels).

Another purpose of DR is to smooth to load curve by reducing the ratio of peak energy demand to average energy demand, in other words, PAR. When the PAR rates are examined (Table 5.12), it is seen that a DR participation of 10% gives the lowest PAR in all periods (winter, summer, weekdays, and weekends). Although most households agreed to shift their loads, they preferred loads to be shifted mostly in between 22:00

and 00:00 (where the prices are cheaper but it is also not sleep hours yet). Therefore, new peaks occur after 22:00 and PAR level starts to increase again after a DR participation of 10%.

These results may be important for residential microgrids. However, assessing PAR alone can be misleading, because the total daily load curve of a country is not only composed of residential but also of commercial, industrial, and other (lighting, agricultural, etc.) loads. For this reason, the effect of DR on the total load curve is examined in the next section.

Table 5.12 : PAR for different HEMS-based DR participation levels of the community (442 participants).

	PAR			
DR participation (%)	Weekday (Winter)	Weekend (Winter)	Weekday (Summer)	Weekend (Summer)
0	1.726	1.666	1.581	1.474
10	1.660	1.592	1.507	1.457
20	1.671	1.625	1.588	1.595
30	1.728	1.733	1.690	1.734
40	1.785	1.841	1.791	1.872
50	1.841	1.949	1.892	2.010
60	1.900	2.056	1.995	2.148
70	1.955	2.163	2.097	2.285
80	2.011	2.270	2.199	2.423

5.7.3 Impact of HEMS-based DR on the total daily load curve

This case scenario seeks to answer the question of how much DR participation would be sufficient to minimize the PAR of Türkiye's total daily load demand if the survey results were representative of all Turkish households. It has been shown in previous studies [226] that the results of time-use surveys can be scaled to the national level after being validated with measurement data. We do not have measurement data and our sample is slightly biased. Nevertheless, it is recommended that the approach we follow here (simulating load profile of DR-performing households using survey results) be applied if a national DR campaign is to be launched in the future or if the impact of mass DR involvement is to be estimated. This section is intended to be a guide for future studies and policymakers.

The impact of different DR participation levels on the national load curve (weekdays) is shown in Figure 5.18 (winter) and Figure 5.19 (summer). The national load curve data (2021-2022) is extracted from Türkiye’s energy exchange company EPIAŞ’s transparency platform [289]. Here, a typical summer and winter weekday represents the six-month average of April-September and October-March, respectively. Weekend load profiles are discluded to avoid redundancy since weekend demand is already below weekday demand both in Türkiye and the rest of the world, which makes weekend DR less important.

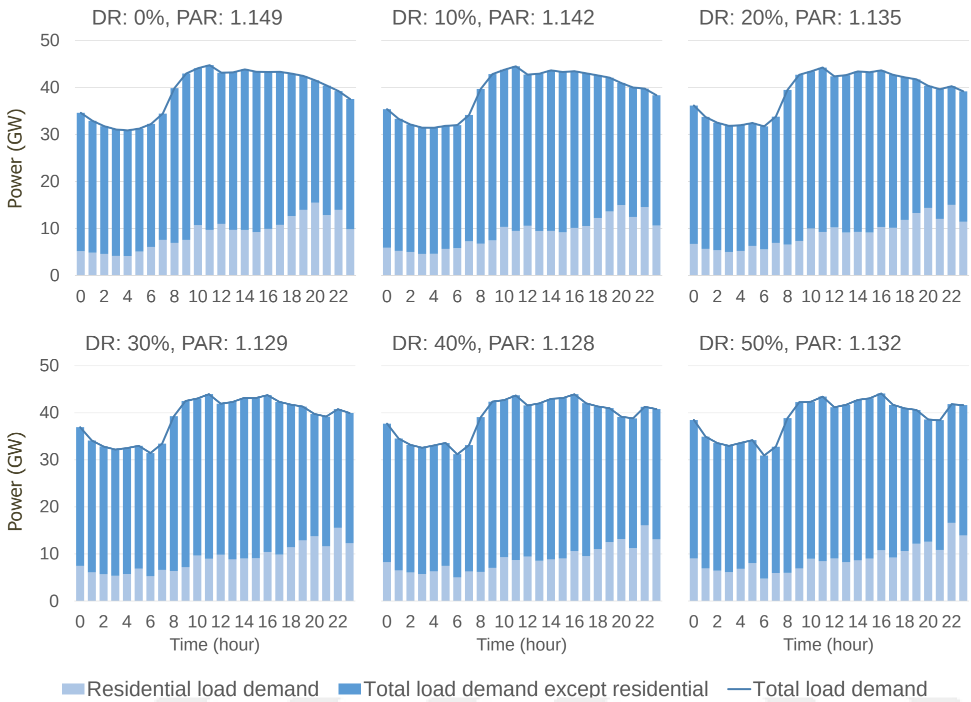

Figure 5.18 : Turkish load curve with different DR participation levels (winter, weekday) – lowest PAR achieved at 40% DR participation level.

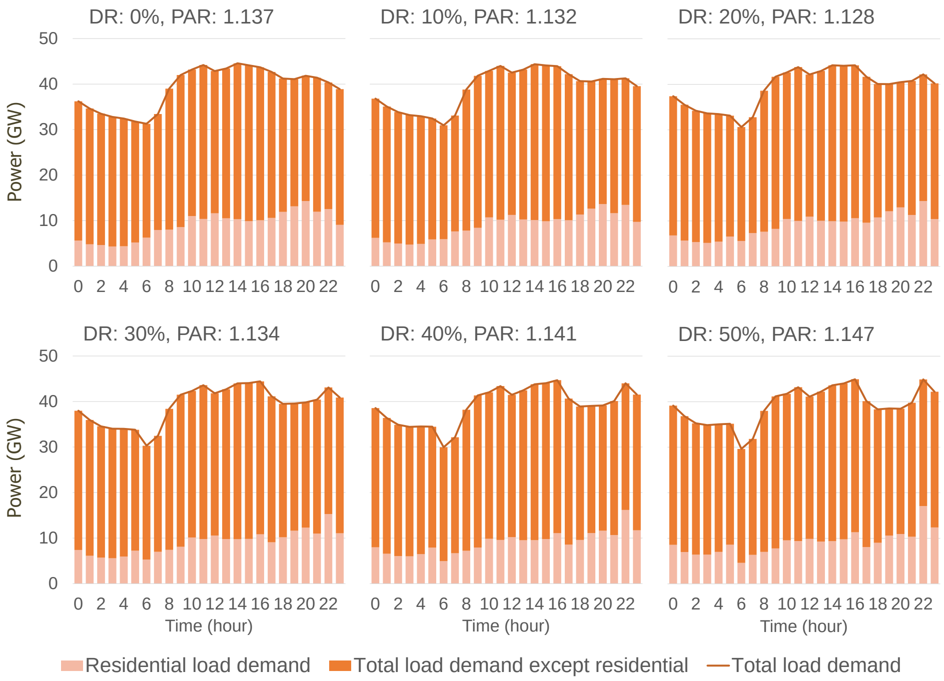

Figure 5.19 : Turkish load curve with different DR participation levels (summer, weekday) – lowest PAR achieved at 20% DR participation level.

According to EPIAŞ, the average daily electricity consumption is 934,553,930 kWh for a typical weekday in winter and 940,422,329 kWh for a typical weekday in summer [289]. Considering that 23.1% of the demand belongs to residential users [54], the average residential daily energy demand is 215,881,958 kWh in winter and 217,237,251 kWh in summer. In the study, the energy demand of 442 households was found to be 2817 kWh for a winter weekday and 3397 kWh for a summer weekend. These numbers were proportioned and the load profiles of 442 households were scaled to represent all the households in Türkiye. The number makes approximately 32 million households which is close to the official number of 39 million [290]. Taking into account the vacant houses and vacation homes that are empty for most of the year, it can be argued that the number is quite acceptable.

The simulations show that if the appliance and HEMS use behavior of the survey participants were representative of the Turkish population, a DR participation of 40% of the total households in winter and 20% in summer would be required to minimize the peak-to-average ratio (PAR) of Türkiye's daily load demand (Figure 5.18 and Figure 5.19).

5.8 Discussions

According to the survey results, the majority of respondents (78%) are willing to install HEMS. This was considered the best-case scenario, and in Section 7.1 the technical potential of the upper limit achievable in practice with HEMS-based DR was simulated. The results showed that there is a potential to reduce peak period consumption by 33%. However, this provides HEMS users only a very low bill reduction of 6.7% on average. Given that the respondents mentioned the "bill reduction" as their biggest motivation for HEMS installation, this is a major barrier to overcome.

Despite the low overall bill savings in total, 3% of the HEMS users achieved bill savings of over 20%, 8% over 15%, and 21% over 10%. These households can be the target customers for the HEMS market and DR programs. The bill reduction increases in the households as the number of manageable household appliances, their participation rate in DR, their frequency of use, and their rate of shift increase. Manual load shifting of unmanageable appliances (ovens, ranges, irons, etc.) was not considered in the study which could further increase the monetary benefit. EV home charging and the use of PV-BESS units were not considered as well, since these are niche applications for Türkiye as of today.

According to the survey results of EU supported “e-balance” project, 12%, 15%, and 12% of the population in Portugal, Poland, and the Netherlands expect 11-20% saving on electricity to convince to make use of HEMS [247]. This is important because our simulation results showed that 13% of the total respondents could also save between 11-20% with HEMS use.

A major factor that affects the ratio of bill savings is the design of a pricing scheme. Turkish TOU seems insufficient for adequate bill savings in its current form. The scheme was introduced in the early 1980s and has not been updated since. Unlike in other countries, the rates are the same throughout the year and do not differ in winter/summer or weekday/weekend periods, and there is no distinction between different customer groups [291]. The Chamber of Electrical Engineers states that the current Turkish TOU scheme, designed to target industrial and commercial groups, is unfair to the residential group. The chamber recommends adjusting the scheme according to seasonal and even geographical features, and simplifying three-tier prices by changing them into two-tier, combining day and night [292].

Apart from improving the TOU scheme, Türkiye can introduce day-ahead dynamic pricing for residential customers. Dynamic pricing is reported to be more cost-effective than TOU in the case of automated energy management [293,294]. Lower off-peak prices in dynamic pricing or RTP can incentivize the adoption of HEMSs as they provide increased savings and save users the hassle of tracking daily and hourly varying cheap prices effortlessly [295]. In the near future, innovations such as peer-to-peer (P2P) energy trading and the community-based local energy markets may further increase the savings HEMSs can provide, but as of today these are small-scale pilot projects [296].

30% of the HEMS users reduced their bills by 0-5% and 10% even increased their bills. This may lead to loss-aversion and prevent the desired levels of DR adoption. For instance, more than 90% of the electricity subscribers in the UK were reported to care more about avoiding financial losses than making savings and therefore are not switching to TOU [297]. In this regard, it may be essential to offer effective, less punitive, and well-designed electricity pricing schemes. For instance, a utility company in Texas offers a residential TOU plan where customers pay a fixed energy rate during the day (with no expensive prices during peak hours) and less at night. The scheme is not only non-punitive but also simple and easy to understand and therefore reported to be more attractive [298].

In addition, customers may be offered additional incentives such as subsidies or rebates for purchasing energy-efficient and DR-capable appliances, or rewards for switching to time-based tariffs. Moreover, tariff switching can be made easy and seamless (by online sign-ups, providing clear instructions, or offering customer service). A marketing move focused on gaining customer support and segmenting customers according to their specific needs can also be vital [299]. Even if an attractive tariff scheme is introduced, customers may not be aware of it. The survey results showed that 59.9% do not even know which tariff they subscribe to. Marketing campaigns and educating consumers and providing clear and accurate information on potential bill savings are critical to reaching the desired PAR reduction levels. The promotion of a design can be just as important as how financially attractive it is.

Although the biggest motivation factor is the bill reduction, HEMSs have additional benefits such as contributing to the environment, following a technological innovation, visually monitoring electricity consumption, managing appliances remotely, improving thermal comfort, and increasing security. These can also motivate users to install HEMS and switch to time-based tariffs.

In the last decade, electricity prices followed an increasing trend [300]. Prices surged especially after the Russian gas crisis, and even if the crisis is resolved, prices are unlikely to fall in the short term as many countries have decided to reduce their reliance on imported (and cheaper) fossil fuels through decarbonization [301]. This may make home energy management more attractive in the very near future. The increased electricity price increases the savings provided by HEMS and the investment made pays back faster as well.

Although this study focused on ILC-based DR, the survey results also provide important information about DLC-based DR. For instance, it was learned which hours users prefer HEMS to shift their loads to (Figure 5.9). These results can be broadly similar for DLC. DLC subscribers will likely prefer a remote system operator to shift their loads to similar hours.

Loss of comfort is a problem in DR. To overcome this problem, some studies propose multi-objective optimization to consider minimizing the discomfort caused by the shifted usage time of appliances [282,302,303]. In the absence of data about preferred time intervals for load shifting, these methods can be very useful. The method we follow in this study asks users the exact times they want to shift their loads, and thus the degree of comfort loss is based on choices.

5.8.1 Limitations

It should be emphasized that, although survey results may provide valuable data on appliance use behavior, these are self-reported and not based on measurements. This is a limitation of the study. Yet, surveys can increase understanding of patterns and provide a key reference for grid operators [304,305]. The way to estimate the mass behavior of users regarding a new technology that is not currently in use but is very likely to be used in the future can be through surveys and questionnaires.

The survey sample used in this study is slightly biased. This factor, combined with the small sample size, may limit the generalizability of research findings. Still, some data such as monthly average electricity consumption and bills, average floor area of households, average family size, distribution of income levels, and ownership rates of many appliances are consistent with data from TURKSTAT and other sources. For a nationwide higher representative conclusion, we recommend the use of the method with a larger dataset with a more detailed time-use survey (for instance, where respondents fill in diaries for designated days and report activities) [306]) and the validation of results with monitoring and measurement data [226]. Following initial research into the performance of different HEMS applications (which can be completed using small or incomplete sample sets), enabling larger scale, more complete testing, ideally in a field setting, can help validate real-world HEMS use preferences [224].

There were several technical limitations. For example, in the simulations, it was assumed that every household had the same model of air conditioner, refrigerator, and electric water heater. These assumptions may not reflect the average. It was possible to find out about this and more through the questionnaire, but it was not possible to include every question. We relied on users' intuition and recall at the determination of set-points of refrigerators and air conditioners or expected them to check their settings. User statements may not match the facts. Older or lower-end refrigerators may not have accurate dials, so actual refrigerator set-point temperatures may differ slightly from what respondents claim.

5.9 Conclusion

The growing use of smart home appliances as well as increasing electricity prices make the use of HEMSs more viable than ever before. Yet, HEMSs have not become widespread so far, and even if they do, we still do not know enough about the future potential of their mass adoption and customer preferences in using them. Understanding this potential is closely related to appliance use behavior, electricity tariff perception, and tendency towards DR participation. Since HEMSs are not widely used today, surveys can be very useful for understanding future behavior and user preferences.

Therefore, in this study, a survey is conducted to understand appliance use behavior and HEMS-based DR preferences. Next, the DR potential is simulated by inputting the survey responses into a HEMS optimization tool. The load profiles with and without HEMS use were simulated and the extent to which the electrical load demand could be changed by DR was investigated. According to the simulation results, there is a technical potential to reduce peak consumption by 33%. The biggest obstacle in achieving this is the low bill reduction (6.7%) that HEMS users get on average from shifting their electrical loads. This obstacle can be overcome by designing more attractive pricing schemes, which will constitute the subject of future work.

Assessing the potential of DR-based HEMS is critical in predicting power reduction and targeting eligible HEMS customers. 21% of the HEMS owners (16.4% of total respondents) reduce their bills by over 10%. 8% reduce by over 15%, and 3% by over 20%. These households can be the target audience of the future HEMS market and DR campaigns.

The survey in this study was conducted in Türkiye. It is recommended to carry out similar studies in other countries. The results will differ according to different load profiles, energy use behavior, and tariff schemes. Such surveys can provide important insights for decision-makers prior to the large-scale deployment of HEMSs and DR programs.

6. CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

Despite Türkiye's abundant solar radiation levels, the adoption of grid-connected residential rooftop PV systems remains limited in the country. A primary reason for this is the lack of economic profitability of the systems. While policy measures, such as financial incentives, can address this issue, a more cost-effective alternative lies in the utilization of technological methods, including automated DSM. However, the lack of instruments like DR programs and dynamic pricing hinders the promotion of automated DSM, making it an uncommon practice in households within the country.

Therefore, in this thesis, a HEMS that can provide optimal DSM in households was developed. The proposed HEMS optimally schedules the running hours of home appliances to increase self-consumption by shifting loads to solar generation period. It also performs DR by shifting loads to cheap electricity period. Next, an optimal sizing tool was developed for users who wish to install HEMS. The sizing tool assists users in determining the required PV-BESS capacity to maximize their NPV. Following that, a nationwide survey was conducted to understand the perception of DSM, DR and HEMS in Türkiye, to find deficiencies and develop policy measures. Finally, the survey results were simulated using the developed HEMS tool and it was examined to what extent the country's daily load curve could change with HEMS-based DR. The research findings and conclusions presented in the thesis are summarized in the following chapters, outlining the key outcomes.

Chapter 2

An economic analysis of residential rooftop PV systems in nine provinces in Türkiye was conducted using HOMER Grid software. Three solar parts were formed on the solar energy potential map of Türkiye and three provinces were selected from each part for a nationwide feasibility analysis.

- The results showed that residential rooftop PV systems were only feasible in the southern part of the country.

- Systems are likely to become more viable in the future as PV installation prices decrease. When this happens, the systems will become even more profitable in the southern part where they are already feasible, while still being unattractive in the northern part. In this case, the FiT rates should be increased in the northern part and this increase should be compensated by reducing the FiT rates in the southern part.
- Therefore, it is recommended to introduce regional FiT rates and purchase subsidies in Türkiye taking into account regional solar radiation differences in the country.
- The FiT rate has remained the same in Türkiye since the unlicensed production law has been amended in 2011. In many countries, including Germany, the United Kingdom, Japan, and Australia, the FiT rate is updated periodically. In Türkiye, the FiT rate can also be updated annually according to rooftop PV targets and the changes in parameters such as PV installation cost, retail electricity price, and grid requirements.

Chapter 3

A MILP-based HEMS architecture was proposed to minimize daily electricity bill by facilitating optimal DR and PV self-consumption. The proposed algorithm schedules tasks of all types of manageable electrical loads (TSAs, TCAs, and PSAs) and responds to all types B2X and V2X technologies taking into account battery degradation. It can provide pre-cooling or pre-heating for TCAs. A an isotropic model for a tilted PV array was embedded into the HEMS to turn a solar radiation forecast into a PV power output. The isotropic model allowed to take into account the tilt angle of array and the impact of outdoor temperature in the estimation of PV power output. The HEMS was combined with a smart thermostat providing a flexible DR for AC users as it can define different AC set-points for different times of the day in response to changing conditions of electricity prices, solar radiation, and occupant presence.

- The HEMS managed to reduce daily electricity bill by between 53.2% (household with TSAs, TCAs, PV, BESS and EV) and 13.5% (household with TSAs and TCAs), depending on household type.

- The embedded smart thermostat of HEMS managed to reduce daily AC bill in Istanbul, Türkiye by between 15% and 24% in August depending on the day of the month.
- The HEMS was tested for the climatic conditions of İstanbul and electricity prices of Türkiye. Since TOU is the only tariff other than flat tariff available for residential users in Türkiye, to explore the effectiveness of the HEMs, Turkish TOU prices were modified into RTP. The HEMS provided higher cost reduction with the use of RTP due to lower electricity prices of off-peak period.
- Under RTP rates, V2G operation became possible because the EV could sell electricity to the grid at a price higher than the cost of battery degradation.
- The use of HEMS provides higher bill reduction when PV and BESS units are available, but it is worth noting that these components have investment and O&M costs, therefore, providing a lower daily bill does not guarantee the highest NPV. Therefore, life cycle cost analysis and optimal PV-BESS sizing become important for smart homes under HEMS operation.

Chapter 4

Renewable energy system sizing becomes more complex in the presence of HEMS due to varying load profile throughout a year. Therefore, an optimal PV-BESS-PV tilt angle sizing tool was developed for HEMS-equipped households. In this way, automated DR by taking advantage of time-based electricity tariffs and increased self-consumption are taken into account in component sizing. The sizing model simulates HEMS operation over one year and repeats the simulations for each PV array capacity-tilt angle-battery number combination. The model determines the NPV of each combination over the system lifetime and then ranks them from highest to lowest.

- The optimal configuration was found to be 3 kW PV – no BESS – 10° tilt angle for a HEMS-equipped household in Istanbul at the current battery and electricity prices. The reason the optimal configuration was without battery is that electricity prices is relatively low in Türkiye as one of the lowest in Europe.
- A sensitivity analysis was performed based on rising electricity and falling battery prices to make future projections. The BESS use became viable when

electricity prices increased by 25% or battery prices fell by 25%. BESS use became viable in other Southern European countries as electricity prices were higher than in Türkiye.

- The NPV of household in case of HEMS use increased from $920 to $2273. This is an important finding, as PV projects in many countries suffer from low feasibility today in the absence of incentives. HEMS use made PV systems economically more attractive and people who want to simulate their load profile for PV-BESS sizing can benefit from this tool.

Chapter 5

The growing use of smart home appliances as well as increasing electricity prices make the use of HEMSs more viable than ever before. Yet, HEMSs have not become widespread so far, and even if they do, we still do not know enough about the future potential of their mass adoption and customer preferences in using them. Understanding this potential is closely related to appliance use behaviour, electricity tariff perception, and tendency towards DR participation. Since HEMSs are not widely used today, surveys can be very useful for understanding future behaviour and user preferences.

- According to the survey results, 78% of the population is willing to use HEMS for DR in Türkiye with different usage preferences.
- 74% of dishwasher, 58% of washing machine, 61% of clothes dryer and 51% of washer dryer users who are willing to use HEMS in Türkiye agree their electrical appliances to be shifted to off-peak periods.
- Simulation of the survey participants' preferences show that, there is a technical potential to reduce peak consumption by 33% with the use of HEMS for DR in Türkiye.
- However, the average bill savings achieved by HEMS owners is only 6.7% in Türkiye, which can hinder reaching this potential.
- This obstacle can be overcome by designing more attractive pricing schemes, which will constitute the subject of future studies. Assessing the potential of HEMS-based DR is critical in predicting power reduction and targeting eligible HEMS customers.

- Still, 21% of the HEMS owners (16.4% of total respondents) reduced their bills by over 10%. 8% reduced by over 15%, and 3% by over 20%. These households can be the target audience of the future HEMS market and DR campaigns.
- The simulations show that if the appliance and HEMS use behaviour of the survey participants were representative of the Turkish population, a DR participation of 40% of the total households in winter and 20% in summer would be required to minimize the peak-to-average ratio (PAR) of Türkiye's daily load demand.
- The survey in this study was conducted in Türkiye. It is recommended to carry out similar studies in other countries. The results will differ according to different load profiles, energy use behaviour, and tariff schemes. Such surveys can provide important insights for decision makers prior to the large-scale deployment of HEMSs and DR programs

6.2 Future Work

The results of the study showed that more effective and flexible electricity pricing schemes should be developed as an alternative to TOU, which has been the only instrument for implementing DR for residential consumers in Türkiye so far. Alternatives such as CPP, peak time rebates or RTP can be offered to residential end-users in Türkiye as applied in other countries.

Innovations such as P2P energy trading and community-based local energy markets are expected to become widespread in the near future. With minor modifications, the proposed HEMS tool can be improved and respond to these technologies. Due to the scope of the thesis, these features have been neglected.

Although the energy management system proposed in this study was developed to be used for individual households, it is possible to modify it to be used for multi-story apartment buildings or other microgrid and neighborhood-based DR applications. These will constitute the subject of the future study.

At the same time, this tool, which is designed for ILC can also be used by system operators for DLC purposes as well as be used in commercial and industrial sites with minor modifications.

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CURRICULUM VITAE

Name Surname : Anıl Can DUMAN

EDUCATION :

- **B.Sc.** : 2010, Yıldız Technical University, Faculty of Electrical and Electronics Engineering, Electrical Engineering Department
- **M.Sc.** : 2016, Istanbul Technical University, Energy Institute, Energy Science and Technology

PROFESSIONAL EXPERIENCE AND AWARDS:

- Research Assistant, Energy Institute, Istanbul Technical University, 2016-2023

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- A.C. Duman, Ö. Güler, Economic analysis of grid-connected residential rooftop PV systems in Turkey, Renew. Energy. (2019). https://doi.org/10.1016/J.RENENE.2019.10.157.
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