ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

OPTIMUM STORAGE SCHEDULING IN DISTRIBUTION GRIDS TO MINIMIZE THE NET LOAD CURVE SLOPE

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

DAĞITIM ŞEBEKELERİNDE NET YÜK EĞRİSİ EĞİMİNİ MİNİMİZE ETMEYE YÖNELİK OPTİMUM DEPOLAMA ZAMANLAMASI

YÜKSEK LİSANS TEZİ

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HAZIRAN 2025

Fatemeh MOHAMMADI BEHBAHANI, a M.Sc. student of ITU Graduate School student ID 504211062 successfully defended the thesis entitled “OPTIMUM STORAGE SCHEDULING IN DISTRIBUTION GRIDS TO MINIMIZE THE NET LOAD CURVE SLOPE”, which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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		....

Date of Submission : **30 May 2025**
Date of Defense : **23 June 2025**

To my wonderful family,

FOREWORD

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Finally, I want to say how much I appreciate all of your constant encouragement and support during these extremely challenging academic years.

June 2025
Fatemeh MOHAMMADI BEHBAHANI
(Electrical Engineer)

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ABBREVIATIONS

BESS : Battery Energy Storage System
CAISO : California Independent System Operator
DCSI : Duck Curve Severity Index
DER : Distributed Energy Resources
DG : Distributed Generation
DNs : Distribution networks
ESS : Energy Storage System
BFSW : Backwards-Forward Sweep
GA : Genetic Algorithms
GWO : Grey Wolf Optimizer
MILP : Mixed-Integer Linear Programming
MIQP : Mixed-Integer Quadratic Programming
PSO : Particle Swarm Optimization
PV : Photovoltaic
SoC : State of Charge
WOA : Whale Optimization Algorithm
WT : wind turbines

SYMBOLS

$\mathbf{f}$: Objective function
$\vec{X}$: Position of search agent
t : Time
S : Net load slope
α, β, and δ : Wolves type
$\max\_it$: Maximum number of iteration

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OPTIMUM STORAGE SCHEDULING IN DISTRIBUTION GRIDS TO MINIMIZE THE NET LOAD CURVE SLOPE

SUMMARY

The demand for electrical power is increasing rapidly due to developments in modern technology. Consequently, the availability and affordability of electricity have become essential for users. To address this, power distributors are now exploring more cost-effective and accessible alternative energy sources. In addition, we are investing more in renewable energy sources, which release less carbon dioxide (CO_2), as a result of the problems caused by climate change. However, because they depend on the weather, these renewable energy sources aren't always accessible. In order to guarantee a steady supply of energy, energy storage will be required. A thorough understanding of the problems associated with energy production and consumption is essential for managing this energy storage effectively and preventing the generation of excess energy.

Renewable energy includes all forms of energy that are abundant and infinite, at least from a human perspective. Geothermal, biomass, hydraulic, wind, and solar energy are the five primary forms of renewable energy. In California, the Independent System Operator Corporation (ISO), which is in charge of most of the state's electrical grid, has seen a significant rise in solar photovoltaic energy. The ISO grid operator in California has multiple challenges as it looks to the future with more renewable energy. The Duck Curve problem, which is depicted by a widely used figure in the energy communities, is the most significant of these challenges. This graph illustrates the difference between the overall load that a public utility serves and how this load appears after some of it has been serviced by wind and solar energy. This graphical representation looks like a sitting duck. During the day, the demand for electricity from the grid dropped as solar generation grew (the duck belly). The surplus photovoltaic energy is the reason for this. The network then undergoes a peak in demand when the sun sets and people start going home in the evening (the duck's neck). It seems that the grid demand decreases during the day and then rises once more in the evening. These load patterns put traditional generating units under operational stress, threaten system stability, and necessitate flexible, fast-ramping resources to keep the power balance. These rapid fluctuations in net load frequently require expensive and ineffective ramping of peaking units in conventional grid operation. Insufficient utilization of clean energy investments and a reduction in renewable energy can potentially result from the duck curve if it is not adequately mitigated. Thus, new strategies are required to increase the flexibility of distribution systems, reduce ramping needs, and smooth the net load curve. Current strategies, including tariff reforms, advanced ancillary services, improved inverter capabilities, and enhanced control systems, primarily aim to flatten the load curve and tackle minimum system load issues. However, the hourly scheduling of battery energy storage systems remains largely overlooked, despite the introduction of various proposed solutions.

This thesis addresses the duck curve problem by proposing an optimization-based battery dispatching strategy using Battery Energy Storage Systems (BESS) to flatten the net load curve during the daytime. The idea is to optimally control when and how much of a specific BESS unit will charge or discharge as a function of predicted system load and PV output profile. By storing surplus solar energy during the day and releasing it during high demand in the evening, BESS can significantly flatten the duck curve. A modified IEEE 33-bus radial distribution grid with six PV generators and six BESS units is considered in this study. The goal of the optimization problem is to minimize the net load curve's sum squared slope over 24 hours. The ramping issue is specifically taken into account by the slope technique, which minimizes the change between two successive hourly net load values.

To solve the optimization problem, two nature-inspired metaheuristic algorithms—Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO)—were implemented and compared. Each algorithm was used to determine the hourly dispatch power of each BESS unit and the initial State of Charge (SoC) of each unit, which is crucial for maintaining energy balance over the day. The optimization was subject to several constraints, including SoC boundaries, charge/discharge power limits, SoC continuity (initial SoC equals final SoC), and energy conservation across time steps.

The findings of this thesis offer valuable insights for distribution grid operators, planners, and researchers seeking to deploy energy storage as a flexible resource in high-renewable environments. The proposed method supports the reliable integration of solar energy, reduces the reliance on fast-ramping thermal units, and contributes to the broader goal of decarbonizing the electric power sector.

DAĞITIM ŞEBEKELERİNDE NET YÜK EĞRİSİ EĞİMİNİ MİNİMİZE ETMEYE YÖNELİK OPTİMUM DEPOLAMA ZAMANLAMASI

ÖZET

Modern teknolojideki gelişmelerle birlikte elektrik enerjisine olan talep hızla artmaktadır. Bu nedenle, elektriğin erişilebilirliği ve uygun maliyetli olması kullanıcılar için hayati önem taşımaktadır. Bu durumu karşılamak amacıyla elektrik dağıtım şirketleri, daha ucuz ve erişilebilir alternatif enerji kaynaklarını araştırmaktadır. Ayrıca, iklim değişikliğinin yol açtığı sorunlar nedeniyle daha az karbon dioksit (CO_2) salan yenilenebilir enerji kaynaklarına yapılan yatırımlar artmaktadır. Ancak, bu yenilenebilir enerji kaynakları hava koşullarına bağlı oldukları için her zaman erişilebilir değildir. Bu nedenle, sürekli bir enerji arzı sağlamak için enerji depolama sistemleri gereklidir. Bu enerji depolamanın etkin şekilde yönetilmesi ve fazla enerji üretiminin önlenmesi için enerji üretimi ve tüketimi ile ilgili sorunların doğru anlaşılması büyük önem taşımaktadır.

Yenilenebilir enerji, insan ölçeğinde tükenmez ve bol miktarda bulunan tüm enerji türlerini kapsar. Jeotermal, biyokütle, hidroelektrik, rüzgar ve güneş enerjisi, beş ana yenilenebilir enerji türüdür. Kaliforniya'da, eyaletin elektrik şebekesinin büyük bölümünden sorumlu olan Bağımsız Sistem Operatörü (ISO), güneş enerjisinin önemli ölçüde arttığını bildirmektedir. ISO'nun gelecekte daha yüksek yenilenebilir enerji oranlarını hedeflemesi, çeşitli zorlukları beraberinde getirmektedir. Bu zorlukların en önemlisi, enerji topluluklarında sıkça kullanılan bir grafikle temsil edilen "Duck Curve (Ördek Eğrisi)" problemidir. Bu grafik, kamu hizmeti sağlayıcısı tarafından karşılanan toplam yük ile rüzgar ve güneş üretimi sonrası kalan yük arasındaki farkı göstermektedir. Grafiksel olarak bu eğri, oturan bir ördeğe benzetilmektedir.

Gün boyunca güneş üretimi arttıkça, şebekeden çekilen elektrik talebi azalır (ördeğin gövdesi). Bu durum, güneşten kaynaklanan fazla enerjiden kaynaklanmaktadır. Güneşin batması ve insanların akşam evlerine dönmesiyle birlikte talep tekrar artar (ördeğin boynu). Bu yük profili, geleneksel üretim birimlerini zorlar, sistem kararlılığını tehdit eder ve şebeke dengelemesi için hızlı tepki verebilen esnek kaynaklara ihtiyaç duyulmasına neden olur. Geleneksel sistemlerde bu hızlı değişimler genellikle verimsiz ve maliyetli pik üretim birimlerinin kullanımıyla karşılanmaktadır. Duck Curve yeterince azaltılmazsa, yenilenebilir enerji yatırımlarının verimsiz kullanımı ve kesintiye uğraması riski de artar. Bu nedenle, dağıtım sistemlerinin esnekliğini artıracak, rampalama ihtiyaçlarını azaltacak ve net yük eğrisini düzleştirecek yeni stratejilere ihtiyaç duyulmaktadır.

Mevcut stratejiler, tarife reformları, gelişmiş yardımcı hizmetler, inverter işlevselliğinin artırılması ve kontrol sistemleri gibi yöntemlerle yük eğrisini düzleştirmeye odaklanmaktadır. Ancak, saatlik bazda Batarya Enerji Depolama Sistemleri (BESS) planlaması genellikle göz ardı edilmektedir.

Bu tez, Duck Curve sorununu çözmek için, BESS sistemlerinin gün içindeki şarj ve deşarj zamanlarını ve miktarlarını, tahmin edilen yük ve güneş üretim profiline göre optimum şekilde planlayan bir optimizasyon temelli strateji önermektedir. Amaç, gündüz saatlerinde fazla güneş enerjisini depolayıp, akşam saatlerindeki yüksek talep dönemlerinde bu enerjiyi kullanarak net yük eğrisini düzleştirmektir. Bu çalışma kapsamında, altı PV jeneratörü ve altı BESS ünitesi içeren modifiye edilmiş bir IEEE 33 düğümlü dağıtım sistemi kullanılmıştır. Optimizasyon probleminin hedefi, 24 saatlik süre boyunca net yük eğrisinin ardışık saatler arasındaki farkların karelerinin toplamını en aza indirmektir.

Bu optimizasyon problemi, Parçacık Sürü Optimizasyonu (PSO) ve Gri Kurt Optimizasyonu (GWO) olmak üzere iki doğadan esinlenen meta-sezgisel algoritma kullanılarak çözülmüştür. Her algoritma, her BESS ünitesinin saatlik şarj/deşarj gücünü ve gün başındaki SoC (şarj durumu) değerlerini belirlemek için kullanılmıştır. Optimizasyon, SoC sınırları, güç kısıtlamaları, SoC sürekliliği (başlangıç ve bitiş SoC eşitliği) ve enerji korunumu gibi çeşitli kısıtlarla gerçekleştirilmiştir.

Tezin bulguları, enerji depolamanın yüksek yenilenebilir entegrasyona sahip ortamlarda esnek bir kaynak olarak nasıl kullanılabileceği konusunda dağıtım şebekesi işletmecileri, planlamacılar ve araştırmacılar için önemli bilgiler sunmaktadır. Önerilen yöntem, güneş enerjisinin güvenilir bir şekilde entegre edilmesini desteklemekte, hızlı tepki veren termik üretim birimlerine olan bağımlılığı azaltmakta ve elektrik sektörünün karbon emisyonlarını düşürmeye yönelik daha geniş hedefine katkı sağlamaktadır.

1. INTRODUCTION

1.1 Background

Investments in renewable energy sources, which release low amounts of carbon dioxide (CO_2), are growing in response to the difficulties posed by climate change. However, because they depend on the weather, these renewable energy sources aren't always accessible. Therefore, energy storage will be required to guarantee a steady energy supply. Effective management of energy storage requires an extensive awareness of the problems associated with the generation and use of energy to prevent the development of excess energy.

Solar, wind, hydraulic, biomass, and geothermal energy are the five primary forms of renewable energy [1]. A portion of the sunlight that reaches photovoltaic (PV) cells can be transformed into electrical power. In California, where the Independent System Operator Corporation (CAISO), which oversees most of the state's electrical grid, released a graph showing the net load and its possible future appearance, solar photovoltaic energy has been expanding extremely quickly [2]. This graph, which illustrates the difference between the variable electricity production coming into the system from solar panels and the load predicted by the grid operators, is called the Duck curve. California's ISO grid operator is anticipating a future with 33% renewable energy thanks to solar PV, which presents several difficulties. The most significant of these issues is the Duck Curve problem, which is depicted by a widely used image in the energy industry. The graph in Fig. 1.1 illustrates the difference between the overall load that a public utility serves and how this load appears after some of it has been serviced by wind and solar energy [2]. This scenario's graphical representation appears to be a sitting duck. The CAISO, which is in charge of managing the state's electrical transmission and generation infrastructure, released this well-known plot in 2013. This graph, which is depicted in Fig. 1.1, shows the energy demand on a spring day across time. As seen, grid demand decreases during the day and subsequently rises once more in the evening.

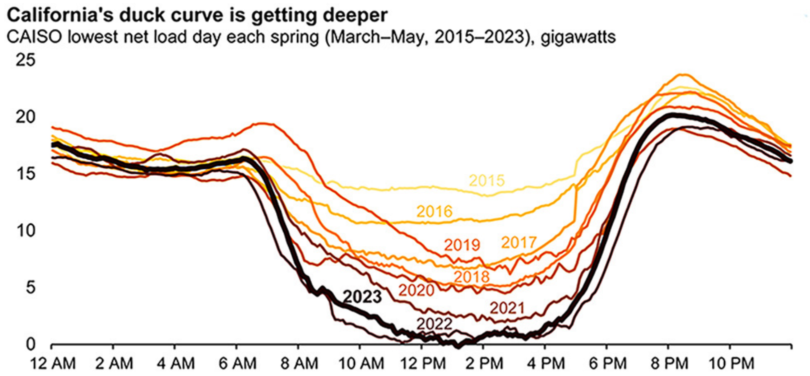

Figure 1.1: Duck Curve problem.

The growing adoption of solar energy is transforming the future of electrical systems. Reliance on natural gas and other baseload power stations reduces as the amount of electricity produced by PV power plants increases. The total net power demand is determined by subtracting the solar electricity from the total energy demand. As sun penetration increases, natural gas power plants must rapidly ramp up during certain hours of the day, as seen by this "Duck Curve" [3,4]. Distribution networks (DNs) have seen a growth in distributed energy resources (DERs) like wind, solar, etc., in recent years. However, it is anticipated that distributed generation (DG)—such as PVs, wind turbines (WT), and energy storage systems (ESS)—will be crucial in meeting the network's load, producing inexpensive energy, being readily available, being near customers, requiring less installation time, and posing little risk to investment [5].

The benefits of DGs and ESSs primarily depend on their sizes and placements, which is a challenging issue to resolve [6,7]. As already mentioned, one of the problems is the Duck curve, wherein the extra energy from solar PV and wind segments has to be curtailed. Before adding large amounts of solar PV electricity to the grid, both short-term and long-term load predictions are required to ensure power supply stability and sustainability. Consequently, a number of strategies have been put forth to address the ramping and surplus generation issues that define the duck curve. These remedies could involve demand-side control like peak shaving and valley filling [8]–[10], reorienting the solar panels [11], and using energy storage technology to increase the power system's overall flexibility [12,13].

This study focuses on optimizing the scheduling of Battery Energy Storage Systems (BESSs) to minimize the slope of the Duck curve. Duck curve slope reduction is crucial for a number of reasons, most notably grid stability, operational effectiveness, and economic impact. The evening's steep ramp-up encourages power plants to speed up their production ramp-up as demand peaks and solar output declines. Conventional power facilities—particularly coal and nuclear—cannot react rapidly, and gas plants with ramp-up capabilities are costly to run. By balancing supply and demand and reducing reliance on costly fast-ramping plants, it is simpler to make the slope softer. A BESS stores excess solar energy throughout the day and releases it at night. BESSs can charge during noon when there is surplus solar energy and discharge at night to reduce the ramp-up. Moreover, flattening the curve maximizes battery efficiency and prolongs their lifespan by avoiding excessive charge-discharge cycles. However, sizing and scheduling a BESS properly are critical to ensuring grid stability, economic efficiency, and the optimization of the use of renewable energy. If a BESS is too small, it will not be able to accumulate sufficient energy to operate optimally, leading to less peak shaving and grid instability. On the other hand, if a BESS is oversized, the cost of investment is more than required, leading to economic inefficiencies.

The optimal sizing compromises between cost and performance at the appropriate level. Without storage, there is a chance that solar or wind energy would be curtailed in excess. With optimal BESS scheduling, we can shift this energy to where it is most needed. It reduces fossil fuel use and increases the penetration of renewables. Additionally, optimal scheduling ensures that BESS is in its optimum state-of-charge (SoC) rate. This improves battery performance and delays degradation, so it is a more worthwhile long-term investment. Poor scheduling (deep discharging or high-rate cycling) reduces battery life.

1.2 Literature Review

Numerous investigations regarding the Duck curve problem have been carried out throughout the literature. Various optimization strategies have been explored to mitigate these issues, with a particular focus on energy storage scheduling, demand-side management, and market-based incentives.

The Duck Curve's greater ramping demand for traditional power plants is one of its main effects. In order to satisfy the increasing demand, dispatchable power sources like gas-fired power plants must quickly ramp up as solar energy declines in the late afternoon. Many of these conventional generators are not built to withstand such abrupt output variations, which results in decreased efficiency, more wear and tear, and greater maintenance expenses [14]. The possibility of overgeneration during noon, when solar energy production is strong but demand is relatively low, is another operational worry. Grid congestion, negative electricity pricing, and a reduction in renewable energy can result from improper management of this extra electricity [15].

Consumers and utilities are also significantly impacted financially by the Duck Curve. During peak demand hours, electricity prices rise due to greater dependence on peaking power facilities, which are generally less efficient and more expensive [16]. Customers may pay more for energy as a result of the steep evening ramp-up since it raises fuel consumption and operating expenses. The financial and green advantages of renewable energy sources may be limited if grid operators are compelled to turn off or limit solar power.

In addition, the Duck Curve has an impact on frequency regulation and grid stability. Advanced grid management strategies, including demand management, flexible generation, and improved energy storage integration, are necessary due to the voltage and frequency changes caused by the unpredictability of solar power [17]. BESSs are widely recognized as a key tool for mitigating the Duck Curve. Optimal scheduling and sizing of BESSs is the most promising solution to address the Duck Curve. By storing excess solar energy during peak generation and discharging it during the evening ramp, BESS helps smooth out fluctuations in net demand [18].Numerous studies have examined the efficiency of various optimization techniques for BESS scheduling, including rule-based control [17], model predictive control [19], and artificial intelligence-based techniques [20].

Different optimization methods, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA),Grey Wolf Optimizer (GWO), and Mixed-Integer Linear Programming (MILP), have been studied by scholars to determine the most suitable operation strategy for deploying BESS. PSO and GA have been widely applied to balance economic and technical constraints in energy storage management [16]. [21] proposes a method to determine the optimal location and size of BESS to minimize system losses in distribution networks, specifically addressing the Duck Curve. The study utilizes the Whale Optimization Algorithm (WOA) and highlights that appropriately optimized BESS can mitigate the steep ramps associated with the Duck Curve, making the solution economically viable. Further, an approach for improving BESS location and capacity in distribution networks with integrated solar and wind generation is presented in [22]. The Duck Curve problem in grids with high solar energy integration is addressed by this study's introduction of Mixed-Integer Quadratic Programming (MIQP) models. According to the study, putting BESS into practice can lower the Duck Curve's ramp rate by as much as 57.6% [23]. However, determining the optimal capacity and the best charging/discharge schedules remains a challenging task due to uncertainty in renewable generation, market prices, and load variations.

The second important aspect of BESS optimization is SoC management. Discharging and charging cycles affecting the life of batteries need to be accounted for using lifetime-aware optimization strategies. A unique SoC estimate technique combining dual extended Kalman filtering, backpropagation neural networks, and particle swarm optimization is proposed by Lu Chen et al. [24]. High SoC estimation accuracy is attained by the method in a range of dynamic operating temperatures and situations. By concentrating on SoC and temperature balance, Amir Farakhor et al. offer a scalable method for optimal power management in large-scale BESS [25]. The suggested clustering technique makes large-scale applications possible by drastically lowering processing costs.

For electricity systems, the Duck Curve poses serious operational and financial difficulties, especially in grids with a high solar penetration rate. Demand-side management, energy storage technologies, better forecasting, and grid flexibility are all necessary to meet these difficulties. For instance, a properly scaled and operated BESS offers a workable answer by reducing ramping problems, boosting grid stability, and increasing economic efficiency. In order to further improve its efficiency in addressing the Duck Curve problem, ongoing research keeps improving optimization strategies for

BESS deployment by integrating elements like SOC management, cost reduction, and renewable energy forecasting.

1.3 Contributions

The thesis's key contribution is the development of appropriate goal functions for optimal integration of PV and ESS units into distribution networks. This study introduces a novel performance metric, the *Duck Curve Severity Index (DCSI)*, to quantitatively assess the severity of net load variability and the effectiveness of mitigation strategies. Two metaheuristic optimization methodologies—PSO and GWO—were utilized and compared to determine the optimal hourly dispatch of ESS units along with their initial SoC. The objective was to minimize the slope of the net load curve, thereby reducing grid ramping stress and improving operational flexibility.

Results demonstrated that both algorithms effectively reduced the DCSI, with PSO yielding comparatively better performance in terms of ramp rate reduction, net load flattening, and overall duck curve mitigation. This work contributes a comprehensive methodology combining mathematical modeling, optimization, and a meaningful performance index for evaluating and comparing advanced grid flexibility solutions.

1.4 Dissertation Layout

This thesis consists of six chapters. The first chapter introduces the main subject, literature review, and general contributions. The second chapter is devoted to defining the problem formulation, including the objective function and constraints. Chapter 3 introduces the structure of the test network together with the PVs and ESSs. Chapter 4 defines the optimization algorithm. Finally, in chapter 5, the simulation results for the single objective optimization are discussed, and then the last chapter is devoted to the conclusion.

2. PROBLEM FORMULATION

The formulation of the optimization issue will be covered in this section. Objective functions, equality and inequality constraints, and state variables will all be part of this.

2.1 Objectives of Operation of Distribution System Integration

The following is an expression for an n-dimensional optimization problem:

$$\begin{aligned} &\underset{\text{w.r.t } \vec{x}}{\text{minimize}} \{f_1(\vec{x}), f_2(\vec{x}), \ldots, f_n(\vec{x})\} \\ &\text{subject to} \begin{cases} h_n(\vec{x}) = 0, & n = 1, 2, \ldots, q \\ g_n(\vec{x}) \geq 0, & n = 1, 2, \ldots, p \end{cases} \end{aligned} \tag{2.1}$$

where **x** is a vector of the solution variables, $f_n(\mathbf{x})$ is the n^{th} objective function, and $g_n(\mathbf{x})$ and $h_n(\mathbf{x})$ represent the inequality and equality constraints, respectively. This research uses the PSO and GWO algorithms to optimize a single-objective problem to find the optimal solution. Mathematically, this objective formulation can be stated as:

$$\begin{aligned} &\underset{\text{w.r.t. } \mathbf{P}_{\text{BESS}}, \mathbf{SoC}_0}{\text{minimize}} \quad \{F\} \\ &\text{subject to} \quad \begin{cases} h_n(x) = 0, & n = 1, 2, \ldots, q \\ g_n(x) \geq 0, & n = 1, 2, \ldots, p \end{cases} \end{aligned} \tag{2.2}$$

where P_{BESS} and SoC_0 denote the hourly power of BESS and its initial SoC, respectively. The terms h_n and g_n indicate the equality and inequality constraints, respectively. F is a single-objective function that has the following description.

2.2 Objective Function

For the MG operation, optimal sizing and scheduling of BESS are two pillars of utmost significance, whose direct impacts are on system cost and reliability. Adequate BESS sizing reduces capital and operating expenses and enhances system stability; it is by optimal scheduling that the microgrid can respond to generation and load effectively, foremost during the intermittency of renewable resources.

2.2.1 Definition of Net-Load Curve

The net load in a power distribution network is the power flow measured at the feeder head substation. The power that is monitored at the feeder's head is determined by two factors: i) the power needed by the downstream loads, and ii) the power generated by the feeder's distributed energy resources (DER) (PV, WT, and BESS).

$$P_{nl} = P_l - P_{PV} - P_{\text{BESS}} \tag{2.3}$$

wherein P_{BESS} is the power sent by energy storage, P_l is the total load, P_{PV} is the total PV generation, and P_{nl} is the net load. To quickly and effectively adjust downstream PV, and load variations, the energy storage is presumed to be deployed at the net-load bus. The P_{BESS} is positive when BESS is discharging, and the opposite is negative when charging.

2.2.2 Mathematical Formulation

To mathematically model the objective function, the optimization problem is to minimize the sum of squared differences in net load between each set of consecutive periods. This is formulated as follows:

$$\text{Minimize} \quad \sum_{t \in \mathscr{T}_0} S_t^2 \tag{2.4}$$

Here, the slope variable S_t is the net load difference between two adjacent time steps and can be calculated as:

$$S_t = [P_l(t) - P_{PV}(t) - P_{BESS}(t)] - [P_l(t-1) - P_{PV}(t-1) - P_{BESS}(t-1)], \quad t \in \mathscr{T}_0 \tag{2.5}$$

Where:

$\mathscr{T}_0$ shows the interval of [1,24]

$P_l(t)$ is the total demand load at time t,

$P_{PV}(t)$ is the sum of the power supplied by PVs at time t,

$P_{BESS}(t)$ is the net power charged or discharged from the BESS at time t.

To avoid abrupt slopes in the net load curve, the quadratic S_t^2 is employed in place of the absolute value of the terms S_t. The utilization of the squared slope S_t^2 as opposed to the absolute slope $|S_t|$ places larger weights on bigger deviations, and therefore supports smoother net load curves. It should be noted that limiting the maximum change in total demand between two successive periods is frequently used to simulate the goal of minimizing ramping-up needs [26]. By minimizing the total of squared net load changes, the optimization discourages steep ramps and improves the operational balance of the MG with the main grid—particularly at peak and off-peak switching hours. This improves grid stability and energy efficiency.

2.2.3 Demand-Side Management

Peak shaving and valley filling are two common demand-side management strategies. Peak shaving involves shaving the peak power demand hours by offloading energy from BESS during peak hours, which reduces the load on generation assets and prevents grid overloading. Valley filling involves charging batteries during periods of low electricity demand. This approach smoothens the overall electricity consumption pattern and improves the efficiency of power generation assets.

In the present study, the optimal hourly dispatch of BESS units was optimized with a metaheuristic optimization algorithm to achieve peak shaving and valley filling. The net load curve was smoothed by minimizing its hourly slope. The optimization considered operational constraints such as battery power ratings, SoC behavior, and power flow feasibility through MATPOWER [27]. To quantify the effectiveness of the optimization, we calculated the percentage decrease of the peak load and the percentage increase of the valley load by using equation Eq.(2.6), where $P_{\text{peak, before}}$ and $P_{\text{peak, after}}$ indicate the peak of net load, while $P_{\text{valley, before}}$ and $P_{\text{valley, after}}$ show the minimum value of net load before and after the near-optimal scheduling of BESSs, respectively.

$$\begin{aligned} \text{Peak Reduction } (\%) &= \frac{P_{\text{peak, before}} - P_{\text{peak, after}}}{P_{\text{peak, before}}} \times 100 \\ \text{Valley Filling } (\%) &= \frac{P_{\text{valley, after}} - P_{\text{valley, before}}}{\left|P_{\text{valley, before}}\right|} \times 100 \end{aligned} \tag{2.6}$$

2.2.3.1 DCSI Index

In addition, this work introduces a novel performance indicator, DCSI, to quantify how well strategies for optimization decrease the net load fluctuation. The ratio of the highest ramp rate to the mean ramp rate of the net load curve during 24 hours is known as DCSI:

$$\mathrm{DCSI} = \frac{\text{Maximum Ramp Rate } (\mathrm{kW/h})}{\text{Average Ramp Rate } (\mathrm{kW/h})} \tag{2.7}$$

This unitless measure is a compact indicator of steepness and fluctuation in the net load curve, with larger values indicating a more extreme "duck curve" with steeper ramps. DCSI normalizes peak ramp to average, allowing for an accurate comparison of scenarios regardless of system size or total demand. This rating is especially useful for assessing the role of DERs and ESS in reducing grid stress caused by sudden load fluctuations. Although DCSI is not a common metric in the literature, its derivation is consistent with similar analytical approaches used in current research that account for ramp rate measurements and net load fluctuation. As a result, this is presented as a novel, quite useful method for assessing duck curve mitigation performance.

2.3 Equality Constraints

In the optimization model presented, several equality constraints are imposed to ensure the physical feasibility and consistency of the solution in power system operations. These constraints reflect basic system-level constraints and the operational logic of energy storage systems.

2.3.1 Energy Neutrality of BESS ($\sum P_{\mathrm{BESS}} = 0$)

Charge and discharge must equal zero for each BESS to have an energy balance over 24 hours. This restriction guarantees that during the scheduling period, the BESS units neither supply nor consume net energy:

$$\sum_{t=1}^{24} P_{\mathrm{BESS},i}(t) = 0 \quad \forall i \in \{1, 2, ..., N_{\mathrm{BESS}}\} \tag{2.8}$$

This equivalence supports daily cyclic operation and prevents energy drift by ensuring that each BESS returns to its initial energy level at the end of the cycle.

2.3.2 Initial and Final SoC Equality

The initial and final SoC of every BESS must be equal to meet the previous restriction and provide daily energy stability. The mathematical expression for this is:

$$\mathrm{SoC}_i(t=1) = \mathrm{SoC}_i(t=24) \quad \forall i \tag{2.9}$$

This requirement is crucial for sustainable and repeatable dispatch cycles, especially in systems where storage devices are expected to operate in a daily cycle.

2.3.3 Power Balance at Each Bus (Load Flow Constraint)

One of the basic equality constraints of optimal scheduling BESS is the nodal power balance that ensures that, for every bus i and at each time step t, the power injected is equal to the power consumed. It balances all power sources and sinks, such as distributed generation (e.g., PV), BESS units, local loads, power losses, and power exchanged with the grid. The power balance equation is:

$$P_{\mathrm{grid},i}(t) + P_{\mathrm{PV},i}(t) + P_{\mathrm{BESS},i}(t) - P_{\mathrm{load},i}(t) - P_{\mathrm{loss},i}(t) = 0 \quad \forall i, \forall t \tag{2.10}$$

In this equation:

$P_{\mathrm{grid},i}(t)$ is Power exchanged with the main grid at bus i,

$P_{\mathrm{PV},i}(t)$ is the active power generated by photovoltaic (PV) systems at bus i,

$P_{\mathrm{BESS},i}(t)$ is the power charged (< 0) or discharged (> 0) from the BESS at bus i,

$P_{\mathrm{load},i}(t)$ is the active load demand at bus i,

$P_{\mathrm{loss},i}(t)$ is the active power losses in the lines connected to bus i.

Every hour of the scheduling horizon is covered by this equivalence, which guarantees that the power flow at every node in the 33-bus distribution system is physically feasible. The iterative forward-backwards sweep approach (FBSW) is

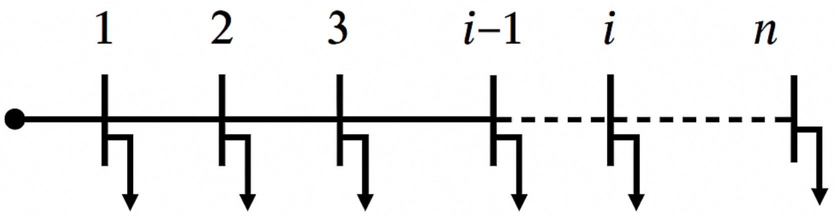

Figure 2.1: Single-phase example of a radial feeder.

employed throughout this study to solve the power flow of the balanced network. Let's take a closer look at the partial radial feeder shown in Fig.2.1 to better understand the use of FBSM. From the initial node 1 to the final bus *n*, the radial feeder's nodes are listed. Only one phase of the radial feeder is represented by the single line. Assume that the radial feeder's spot loads and line impedances are known. The forward-backward sweep method is implemented by first selecting a voltage value to correspond to node n (the far-right node-end node). The currents at *n* are then determined by applying Kirchhoff's current law. Eq. (2.11) is used to express Kirchhoff's current law.

$$\dot{I}_n = \frac{\dot{V}_n}{\dot{Z}_n} \tag{2.11}$$

where i and (i-1) are consecutive node voltages of the same phase, and $\dot{V}_n$, $\dot{I}_n$, and $\dot{Z}_n$ are the node voltages, branch currents, and branch impedance in phasor form. The node voltage at node (n-1) is then determined by applying Kirchoff's voltage law, which is stated in Eq.(2.12). The node current at node (n-1) is determined using Eq. (2.13).

$$\dot{V}_{n-1} = \dot{V}_n + \dot{Z}_{n-1,n} * \dot{I}_{n-1,n} \tag{2.12}$$

$$\dot{I}_{n,n-1} = \dot{I}_n + \dot{I}_{n+1,n} \tag{2.13}$$

The process keeps going until the initial node's voltage and node current are determined. After that, Eq.(2.14) is used to verify the stopping criterion. If the requirement is met—that is, the reference voltage and calculated voltage fall within the designated tolerance—the process comes to an end. If not, the procedure continues in reverse order, assigning the reference value to node 1 before beginning anew using equations (2.12) and (2.13) to get the voltage magnitude at node (2). Keep in mind that this line current will be identical to the one discovered in the reverse process.

$$\left|\dot{\dot{V}}_{1\ \text{calc}} - \dot{V}_{1ref}\right| \leq \varepsilon \tag{2.14}$$

The forward process continues until node (n) is reached, after which the backward process begins for the second time from node (n) to node (1). It is also important to note that in (2.12),$\dot{V}_{n-1}$ is known and $\dot{V}_n$ is unknown, while in (2.13), $\dot{I}_{n,n-1}$ is known and $\dot{I}_{n+1,n}$ is unknown.

2.4 Inequality Constraints

For BESS scheduling optimization in a distribution network, inequality constraints play a crucial role in maintaining the operational feasibility and security of the network. Equality constraints enforce fundamental physical laws like energy balance, while inequality constraints enforce equipment's safe operating limits as well as electrical parameters. These constraints define acceptable operating parameters for the state of charge, BESS power dispatch, and bus voltage magnitudes, hence preventing technical violations and extending asset life. Properly integrating these constraints into the optimization model ensures that the BESS can effectively respond to fluctuations in energy demand and supply. By adhering to these guidelines, operators can maximize the efficiency of the system while minimizing risks associated with overloading or underutilization of the storage resources.

2.4.1 SoC Boundaries

All BESSs possess a specific energy storage capacity, and it's essential to maintain the SoC within safe limits to maximize both the lifespan and safety of the battery. Excessive charging, resulting in a high SoC, or deep discharging, leading to a low SoC, can cause significant harm or even irreversible damage to the battery. To prevent this, the SoC at any given hour t must remain within established minimum and maximum limits, which are usually expressed as a percentage of the battery's nominal energy capacity.

$$0.2 \times E_{\text{ESS}} \leq \text{SoC}(t) \leq 0.9 \times E_{\text{ESS}} \tag{2.15}$$

where E_{ESS} represents the energy capacity (in kWh) of the BESS, and $\text{SoC}(t)$ is the state of charge at time t. These 20% and 90% boundaries are practical engineering standards used to balance energy availability with cell health.

2.4.2 BESS Charging/Discharging Power Limits

The rate at which a BESS can charge or discharge is limited by the design of its inverter and associated power electronics. Dispatching power beyond these ratings could result in thermal issues or inverter protection trips. Therefore, for each time step, the power injected to or drawn from the grid by the BESS must stay within its allowable power range:

$$P_{\text{BESS}}^{\min} \leq P_{\text{BESS}}(t) \leq P_{\text{BESS}}^{\max} \tag{2.16}$$

Here, $P_{\text{BESS}}^{\min}$ typically takes a negative value indicating the maximum charging power, and $P_{\text{BESS}}^{\max}$ is the maximum discharging power. These limits are determined by the inverter capacity and are essential for preventing overloading of BESS equipment.

2.4.3 Voltage Magnitude Limits at Each Bus

Voltage levels being within acceptable levels at all buses is a necessary power quality and equipment protection specification. In medium-voltage and low-voltage distribution systems, standard limits for voltage magnitude in normal operation are between 0.95 p.u. and 1.05 p.u. of nominal voltage. Deviation outside this can lead to inefficient operation, increased losses, or failure of sensitive loads.

$$0.95 \leq V_i(t) \leq 1.05 \quad \text{(p.u.)} \tag{2.17}$$

where $V_i(t)$ denotes the voltage magnitude at the bus i during hour t. These voltage constraints are enforced for every bus and every time step of the scheduling horizon to ensure grid reliability.

These constraints of inequality are built into the optimization framework such that the proposed dispatch schedules are not only economically optimal but also technically viable. In addition to the equality constraints, they define the feasible solution space of the optimization problem. Adhering to these limits ensures the system operates within its designated parameters for all scheduling decisions, thereby maintaining grid stability, protecting equipment, and optimizing energy efficiency.

2.5 Decision Variables

The best set of values for the state variables under consideration is selected using programming techniques to get the objective function's minimized values, which is equivalent to the flattened net load curve. Two categories of choice variables are taken into consideration in this study. These key decision variables are those that directly influence the behavior of the BESS over the scheduling horizon.

2.5.1 Hourly Power of BESS

For each BESS unit i and for each hour t out of the 24-hour scheduling horizon, active power dispatch $P_{\text{BESS},i}(t)$ represents the amount of power the battery supplies to (delivers) or takes away from (recovers from) the grid. Delivery is indicated by positive values of $P_{\text{BESS},i}(t)$, while recovery is indicated by negative values. Dispatch volumes are optimized to synchronize the operation of the BESS with the grid's overall dynamics, renewable generation, and load.

$$P_{\text{BESS},i}(t) \in \left[P_{\text{BESS},i}^{\min}, P_{\text{BESS},i}^{\max}\right] \quad \forall t \in \{1,2,\ldots,24\} \tag{2.18}$$

The hourly dispatch vector for each BESS is a crucial component of the optimization problem, determining how energy is shifted temporally to balance the grid and reduce fluctuations in net load.

2.5.2 Initial SoC

The initial SoC, denoted $\text{SoC}_i(0)$, represents the energy level stored in BESS unit i at the beginning of the scheduling horizon. This variable is critical because it determines the available flexibility for charging or discharging operations throughout the day. In this study, a $\text{SoC}_i(0)$ is taken as a decision variable to allow the optimization algorithm to explore the optimal initial energy level for every BESS, thereby improving the quality of the dispatch solution and system performance.

3. TEST SYSTEM

3.1 IEEE-33 Node Test Feeder

The IEEE-33 Node Test Feeder is a standard system commonly used to study and analyze power distribution systems. It is a convenient system with a radial structure and typical load distribution. It is a perfect testbed for studying new methodologies related to DG, ESS integration, voltage regulation, loss minimization, and power flow optimization. The single-line diagram of the IEEE 33-bus feeder is shown in Fig.3.1 [28]. The system data is illustrated in the Table.A.1 [29].

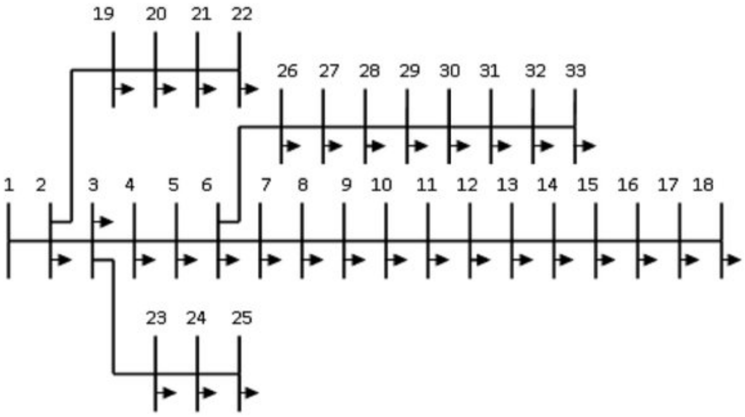

Figure 3.1: IEEE 33-node test feeder.

The base system has 33 buses, 32 feeder lines, and a substation at Bus 1 at 12.66 kV. The system load is approximately 3.715 MW of real power and 2.3 MVAR of reactive power. The radial configuration of the feeder is typical of the general operational behaviour of medium-voltage distribution systems and, therefore, highly suitable for time-series simulation and development of real-world control strategies. For this study, the IEEE-33 Node Test Feeder is extended to include several DGs, such as solar panels and a few BESSs. All of these turn the system into a hybrid distribution network, allowing for complete examination of energy dispatch, system flexibility, and the impact of intermittent renewables. The IEEE 33-bus test system is particularly well-suited for this analysis due to:

- Its realistic topology and load distribution.
- The presence of voltage drop issues, which challenge the control of DERs.
- Its flexibility for integrating additional components such as PV, wind, and BESS.
- Extensive reference data, which allows for meaningful comparison with prior studies.

3.2 Load Profile

At this level of the study, it is considered that all nodes adapt to the same load pattern, as depicted in Fig.3.2. We utilized the data from references [30,31] for the residential load type on a summer day in the load curve calculations.

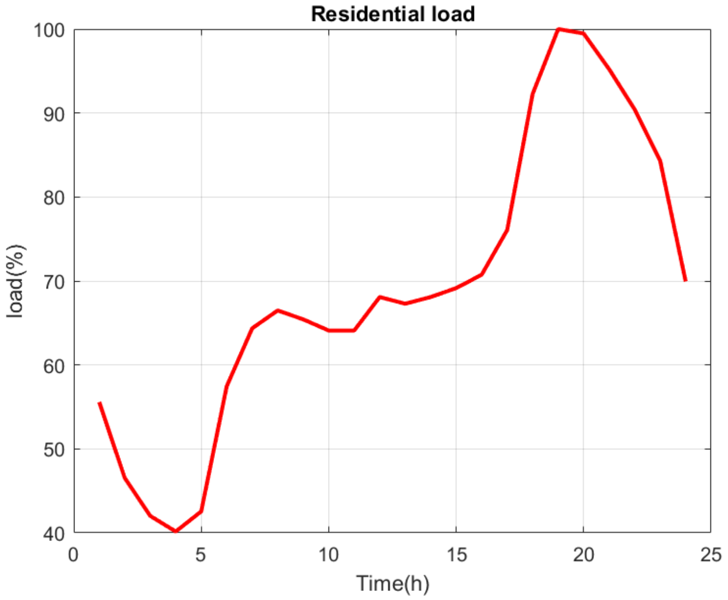

Figure 3.2: Scaled hourly residential load profile.

3.3 Photovoltaic Units

Actual annual solar irradiation from the Karaman region in Turkey is utilized to determine the generation profiles of PV units accurately [32]. Based on these local measurements, the capacity factor of 34% for PV systems is adopted. In the simulation environment, PV units are modelled as negative P-Q loads with a unity power factor, indicating pure active power injection into the distribution network. This is a realistic technique to simulate renewable energy contributions, allowing for the exact evaluation of their effects on the net load curve, especially when duck curve mitigation is used. The assumption for PVs outputs is shown in Fig.3.3. In this study, the 6 PV units integrated into the DNs have varying capacities of 1 MW, 780 kW, 640 and 500 kW. These units are located on buses 14, 17, 25, 29, 25, 29, 31, and 32 [32].

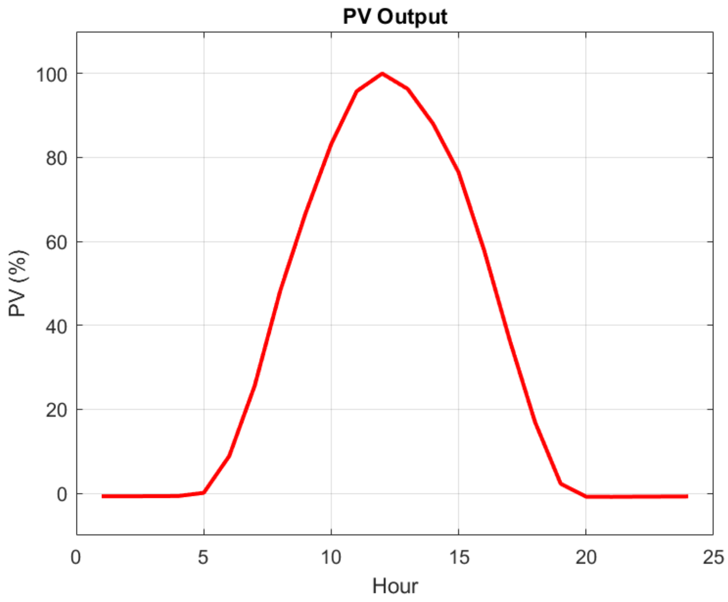

Figure 3.3: Scaled hourly PV output.

3.4 ESS Units

In this study, ESSs are strategically placed in the distribution grid with the primary goal of flattening the slope of the net load curve. By optimizing day-ahead ESS unit charging and discharging schedules, the volatility of the net load caused by uncertain generation and demand profiles is mitigated. The operation mode and role of ESS in this optimization problem are as follows:

- Objective-Driven Scheduling:

  ESS units will charge and discharge during the day over several hours, depending on the optimization goal—in this example, it is to minimize the slope of the net load curve by smoothing rapid fluctuations. Scheduling will be adaptable and dynamically calculated to ensure the most balanced load profile.

- Daily Charge/Discharge Cycles for Slope Minimization:

  Compared to traditional peak shaving methods that only account for peak and off-peak periods, the proposed method allows the ESS to charge and discharge throughout the day. The ESS can thus store energy during low-demand or high-distributed generation intervals (e.g., solar) and dispatch it during high load increase intervals, thereby smoothing out steep transitions in the net load profile.

- Utilization of PV Surplus:

  ESS units have priority over local DG charging, especially at times when PV production exceeds local consumption, typically in midday or overnight. In the event further charging is necessary and the ESS has remaining capacity, it may draw energy from the central grid.

- Modelling in Optimization: In the optimization model, the ESS units are represented as negative loads when discharging (injecting electricity into the grid) and as positive loads when charging (absorbing power). Such a representation is useful in allowing the algorithm to directly improve the net load profile by modulating ESS dispatch.

This ESS integration system guarantees a more stable and predictable load profile in grid distribution, promoting operational efficiency, minimizing stress on grid components, and improving alignment between demand and production. Table 3.1 shows the locations and sizes of the used ESS units in this study [32]. Fig. 3.4 illustrates the configuration of the 33-bus system with integrated PV and BESS units.

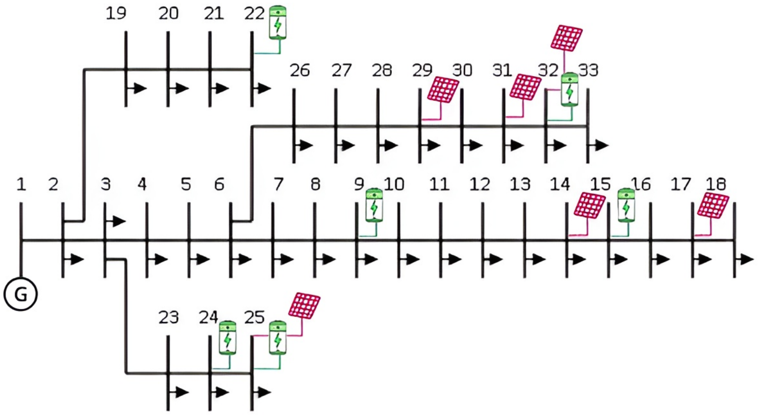

Figure 3.4: Schematic of the 33-bus distribution system with PV and BESS integration.

Table 3.1: Location and capacity of ESS units.

BESS Unit	Location	Energy(kWh)	Power (kW)
BESS 1	9	680	200
BESS 2	15	800	200
BESS 3	22	860	200
BESS 4	24	190	100
BESS 5	25	340	200
BESS 6	32	390	200

4. OPTIMIZATION ALGORITHM

Meta-heuristic algorithms are flexible, derivative-free techniques applicable to both convex and non-convex optimization. These methods work by iteratively generating and assessing potential solutions based on the objective function until a suitable one is found. Their benefits include fast convergence and reliable identification of robust optimal solutions, though the risk of becoming stuck in local minima remains a key challenge.

4.1 Introduction

To optimize problems for single or multi-objectives, meta-heuristic methods are employed. Researchers have developed various optimization algorithms in recent decades, drawing inspiration from physics, social behavior, natural events, animal hunting behavior, and biological activity. Several well-known evolutionary optimization techniques include Differential Evolution [33], Cuckoo Search (CS) [34], GA [35], the Non-dominated Sorting Genetic Algorithm (NSGA) [36], the single and multi-objective versions of the PSO algorithm [27,37], and GWO [38].

GA [39] was the first evolutionary-based method presented, building on the concept of reproduction-based evolution. GA may solve any nonlinear and difficult problem by minimizing or maximizing a cost function. However, if the number of iterations is insufficient for convergence, the algorithm may become stuck in local optimums [40]. PSO is a commonly utilized swarm-based technique in which each possible solution is treated as a particle with certain features that dictate the particle's direction of movement [41].GWO [38] is the other metaheuristic algorithm that mimics grey wolf hunting behavior. GWO has shown competitive efficiency in numerous optimization challenges owing to its simplicity, rapid convergence, and robust global search capability.

For our BESS dispatch optimization problem, PSO and GWO were chosen as the most promising techniques because of their complementary capabilities and previous performance in comparable energy optimization situations [42,43]. Despite the high dimensionality (150 variables), PSO was chosen because the problem structure—optimizing battery dispatch across discrete time intervals—takes advantage of PSO's effective exploration of continuous solution spaces and flexibility to satisfy equality constraints for energy balancing. Although PSO requires additional parameters (inertia weight and acceleration coefficients), its behaviour is well understood, and default values are frequently effective in practice. Though, especially for complicated issues, proper tuning is still essential for convergence and preventing undesirable solutions despite having these advantages. However, because GWO contains fewer parameters, it is easier to implement and might be more reliable in situations where parameter adjustment is difficult or time-consuming. Since there may be numerous feasible dispatch strategies, GWO's demonstrated effectiveness of avoiding local optimal in complex optimization landscapes makes it a suitable comparison approach for duck curve reduction. When addressing complicated constraint limits in BESS optimization problems, the hierarchical hunting strategy offers an organized method for striking a balance between exploration and exploitation. This study offers important insight into the relative performance of the two algorithms by applying them to high-dimensional energy dispatch optimization issues.

4.1.1 PSO

Kennedy and Eberhart created PSO in 1995 [44]. This population-based stochastic optimization technique is inspired by the social behaviour of bird flocks and fish schools. Unlike evolutionary algorithms, PSO depends on the collective intelligence of a swarm of particles, each of which represents a possible solution in the search space. In PSO, a swarm of particles flies around the search space, changing their routes based on their own experience and that of their neighbours. The key concepts of PSO are as follows:

- Particle: An individual agent moving over the search space is called a particle. It has a current velocity and a position.
- Swarm: the population of particles that collaborate to find the optimal solution.

- Position: the particle's current location in the search space, representing a potential solution.

- Velocity: the rate and direction at which a particle moves. It's influenced by the particle's own experience and the experience of its neighbors.

- Fitness Function: the function being optimized, which evaluates the quality of each particle's position.

The pseudo-code shown in algorithm 1 provides a step-by-step description of single-objective PSO. PSO seeks to find near-optimal solutions to complex optimization problems by updating the positions of candidate solutions, called particles, based on the best solution that the particle has found so far (P_{best}) and the best solution found by the entire swarm across all iterations (G_{best}). PSO updates each particle's position and velocity using Eq. (4.1). If a particle finds a better solution than the current global best, it becomes the new global best. The process continues until the maximum number of iterations (*max_it*) is reached. The final global best gives the near-optimal fitness.

$$\begin{gathered} v_{i+1} = v_i + c_1 r_1 \left(P_{\text{best}} - x_i\right) + c_2 r_2 \left(G_{\text{best}} - x_i\right) \\ x_{i+1} = v_{i+1} + x_i \end{gathered} \tag{4.1}$$

where i^{th} is the iteration numbers, v_i is the velocity of a particle at iteration i^{th}, x_i is the position of a particle at iteration i^{th}, P_{best} is the best solution at iteration i^{th}, G_{best} is the best global solution at iteration i^{th}. Note that r_1 and r_2 are the random numbers between 0 and 1, and c_1, c_2 are the learning factors.

Algorithm 1 PSO

```
Initialize a population of particles with random positions and velocities;
Evaluate the fitness value of each particle;
Identify the personal best position ($P_{Best}$) of each particle;
Identify the global best position ($G_{Best}$) among all particles;
while $it < \max\_it$ do
    for each particle do
        Update the velocity using Eq. 4.1;
        Update the position;
        Apply boundary conditions;
        Evaluate the new fitness;
        Update $P_{Best}$ if current fitness is better;
    end for
    Update $G_{Best}$ if any $P_{Best}$ is better than current $G_{Best}$;
    $it = it + 1$;
end while
Return the fitness ($G_{Best}$);
```

For this study, the PSO parameters were chosen based on practical adjustments and previous research. A swarm size of 300 was used to ensure enough diversity for the 150-dimensional search space, helping to avoid premature convergence. The maximum number of iterations was set to 20,000 to give the algorithm enough time to find a near-optimal solution without excessive computation. Learning factors $c_1 = 1.49$ and $c_2 = 1.5$ follow the recommendation of [45] for balancing exploration and exploitation. The inertia weight $w = 0.75$ is based on [46], providing stable particle movement and good convergence. These settings were confirmed through test runs showing stable and effective results. The flowchart shown in Fig.4.1 depicts the implementation of PSO in this study.

4.1.2 GWO

Mirjalili *et al.* presented the nature-based metaheuristic algorithm known as GWO [38]. GWO simulates the hunting habits and social structure of grey wolves in nature. With a balanced exploration and exploitation process, the algorithm can effectively solve both continuous and discrete optimization problems.

According to their dominance hierarchy, wolves in the GWO algorithm are divided into four groups: alpha (α), beta (β), delta (δ), and omega (ω). Beta and delta

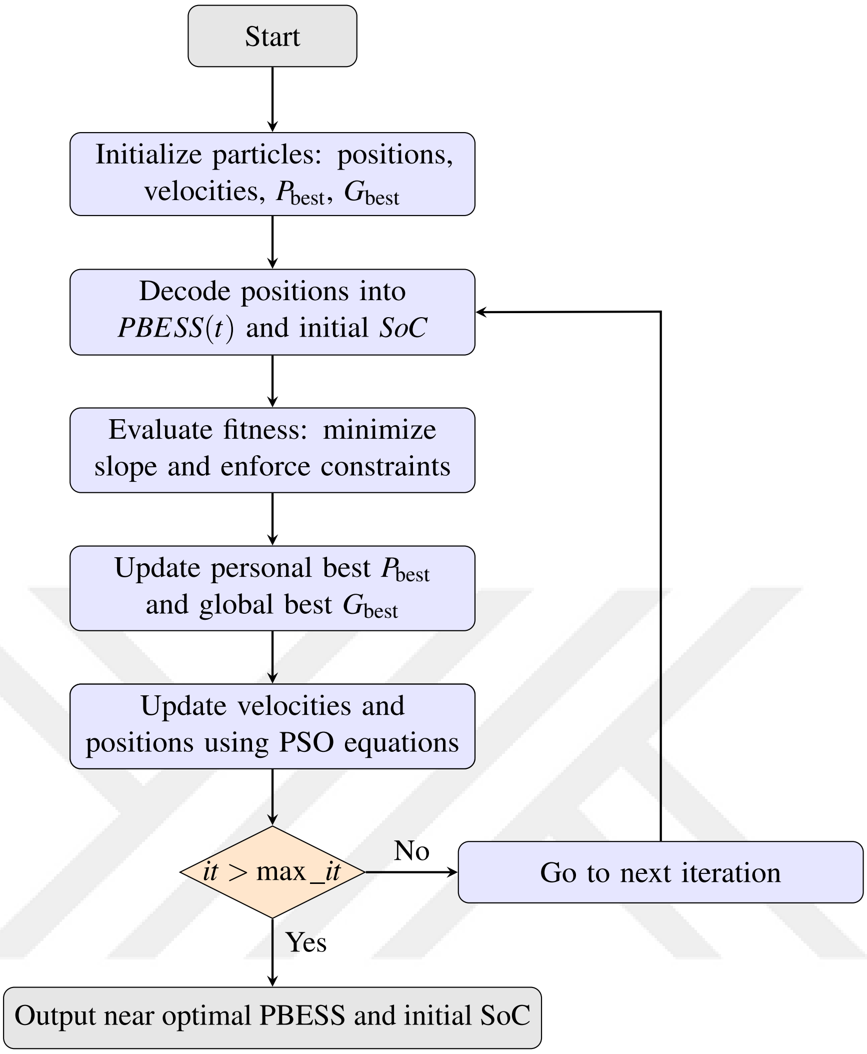

Figure 4.1: Flowchart of the PSO-based optimization process to determine the near optimal PBESS and SoC.

are entrusted with directing the search based on the second and third best solutions, respectively, while the remaining wolves (omega) represent the alpha wolf, which is used to symbolize the best solution at the moment.

4.1.2.1 Mathematical Modeling

The three main steps of the hunting mechanism are: surrounding the prey, hunting, and attacking. The positions of (α), (β), and (δ) wolves are used to update the position of a search agent (wolf). The following equations are used to update the position. In Eq. 4.2, $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ represent the distance of the i^{th} omega wolf from the alpha, beta, and delta wolves, respectively. $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the position vectors of the alpha, beta, and delta wolves, respectively. $\vec{X}_i$ shows the position vector of the i^{th} omega wolf.

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}_i\right|, \quad \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}_i\right|, \quad \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}_i\right| \tag{4.2}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \tag{4.3}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{4.4}$$

The coefficient vectors $\vec{A}$ and $\vec{C}$ are defined as follows:

$$\vec{A} = 2 \cdot a \cdot \vec{r}_1 - a, \quad \vec{C} = 2 \cdot \vec{r}_2 \tag{4.5}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors uniformly distributed in the range $[0,1]$, and a is a parameter that decreases linearly from 2 to 0 over the course of iterations. This linear decrease helps balance the exploration and exploitation capabilities of the algorithm. Vector $\vec{A}$ influences how much leaders affect the position updates of other wolves, while $\vec{C}$ introduces randomness to ensure sufficient diversity in the search. Together, these parameters allow the algorithm to effectively explore the solution space and prevent premature convergence. The pseudo-code shown in algorithm 2 provides a step-by-step description of single-objective GWO. In the implementation of GWO, the number of search agents was set as 300, and we used a maximum of 20000 iterations.

Algorithm 2 GWO

```
Initialize the population of grey wolves (search agents) randomly;
while $it < \max\_it$ do
    Check the boundaries of search agent positions;
    Evaluate the fitness of all search agents;
    Update the positions of $\alpha$, $\beta$, and $\delta$ wolves;
    for each search agent do
        Update position using Eqs. 4.2 to 4.5;
    end for
    $it = it + 1$;
end while
Return the fitness ($X_\alpha$);
```

GWO has several advantages that make it a great way for optimization problem solving. It is very good at exploring the search space and finding the best exploration and exploitation balance during the optimization phase. GWO is also straightforward to implement, with fewer control parameters than most other metaheuristic algorithms, making it both robust and easy to use. However, in addition to its advantages, GWO has several drawbacks. Premature convergence can occur in certain complex or high-dimensional problems, resulting in low-quality solutions. Furthermore, the algorithm's performance might be significantly problem-dependent, requiring careful fine-tuning or a hybrid design with other algorithms to improve its performance. The flowchart shown in Fig. 4.2 describes the implementation of GWO in this study.

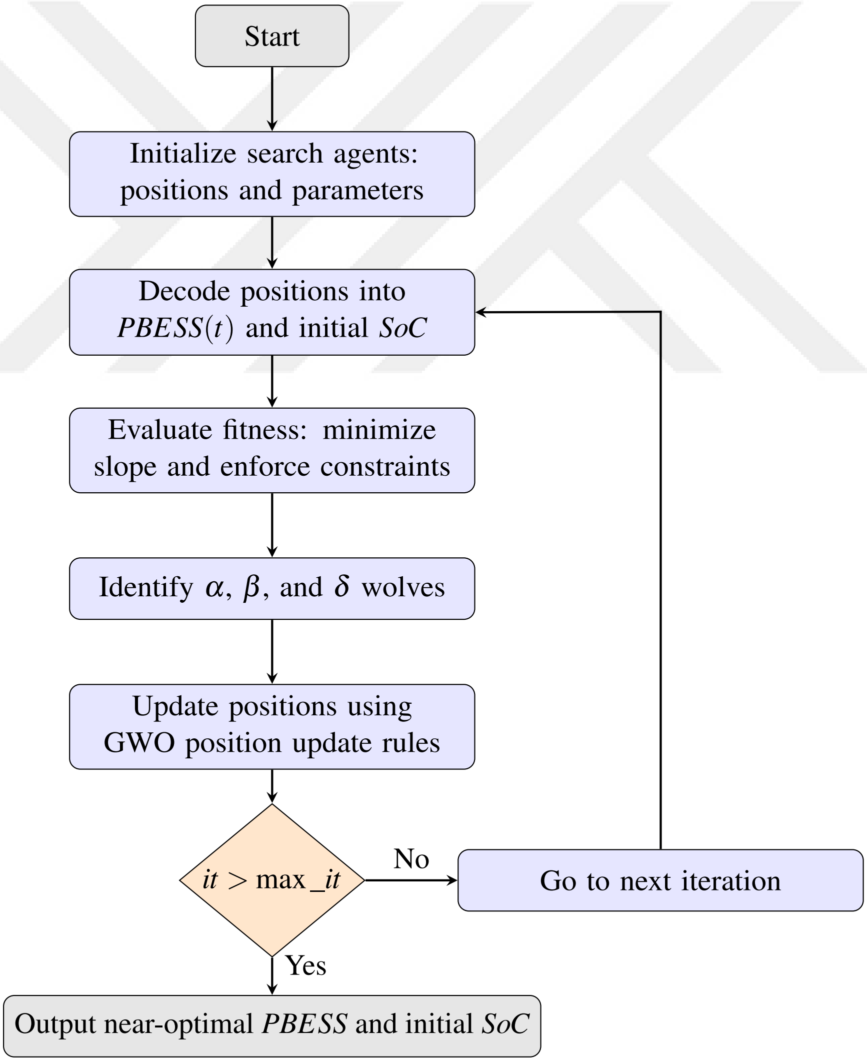

Figure 4.2: Flowchart of the GWO-based optimization process to determine the near-optimal $PBESS$ and SoC.

5. SIMULATION RESULTS

This chapter presents the experimental results of applying the GWO and PSO algorithms to two important energy management objectives: demand-side management and duck curve slope minimization. This chapter provides an exhaustive analysis of the algorithms' performance, the quality of the solutions, and the practical application of the optimized BESS dispatch strategies. We used a personal computer with 16 GB of RAM, an AMD Ryzen 7 6800HS, 8 cores, and a 3201 MHz process configuration.

5.1 Objective Function

We use a specially designed MATLAB-based optimization tool to implement and evaluate the optimal dispatch of six BESS units in a 33-bus distribution system. Simulations were run for 24 hours to evaluate the system's ability to mitigate the Duck curve by scheduling BESS charging and discharging using PSO and GWO algorithms. These time-series power flow simulations are executed in MATPOWER [27], incorporating real power injections from BESS and DG units.

Moreover, operational constraints such as SoC limits, power capacity constraints, and energy balance (to ensure that 24-hour total BESS net discharge is equal to zero) are enforced to ensure realistic dispatch solutions. This enhanced IEEE-33 bus system thus presents a good testbed for evaluating the effectiveness of slope minimization and demand-side management in a modern distribution network environment.

5.1.1 Slope Minimization

The main performance metric in this study is the 24-hour total of the squared net load slopes, which reflects load fluctuations throughout the day. Reducing this metric is the primary objective of the optimization. Without BESS integration, the value of this metric was 7,396,732.92. After optimal BESS scheduling using the PSO algorithm, it was reduced to 1,621,378.28, corresponding to a 78% reduction. Similarly, optimization with another configuration yielded a value of 2,797,268.8480, representing an approximate 62.18% reduction. The optimized net load profiles generated by the PSO and GWO algorithms are presented in Fig.5.1a and Fig.5.1b, respectively, in comparison to the original duck curve. Both approaches significantly mitigated the duck curve effect, particularly during the morning ramp-down (7:00–10:00) and the evening ramp-up (16:00–20:00) periods, as illustrated in Fig.5.1.

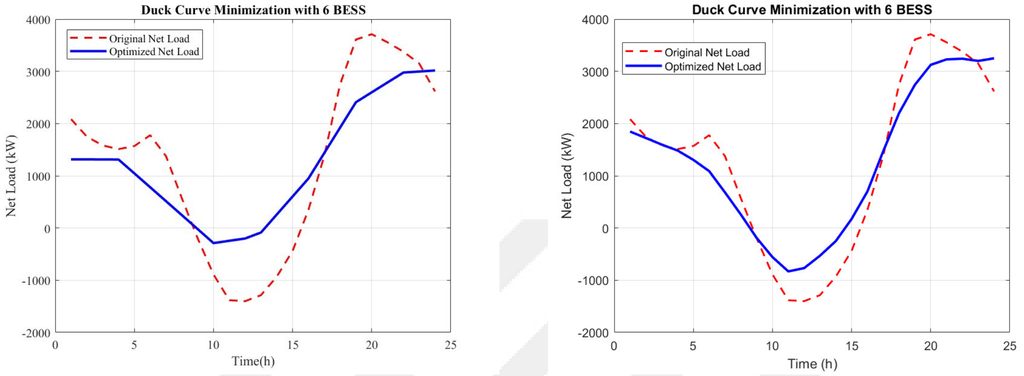

Figure 5.1a: PSO-optimized net load. **Figure 5.1b:** GWO-optimized net load.

Figure 5.1: Comparison of net load profiles optimized using PSO and GWO.

5.1.2 Demand-side managment

Although the primary objective of the optimization was to minimize the slope of the net load for smoother transitions, peak shaving and valley filling were achieved as beneficial by-products. The numerical results demonstrate a measurable reduction in peak demand and an improvement in valley depth, contributing to a more balanced and grid-friendly load profile. As shown in Table 5.1, the PSO-based optimization in this study resulted in significant peak shaving and valley filling effects of 18.73% and 84.29%, respectively, while the GWO-based optimization achieved 12.75% and 57.12% for these metrics.

These results indicate that both optimization strategies successfully improved the shape of the duck curve by lowering peaks and raising valleys. However, PSO demonstrated better performance, suggesting it is a more effective approach for the real-time dispatch of BESS units to enhance grid flexibility and support renewable energy integration.

5.1.2.1 DCSI index

The Table 5.1 shows that PSO performed better, reducing the maximum ramp rate by 47% (from 978.4 kW/h to 520.3 kW/h). Moreover, PSO produced a value of 0.40 for the DCSI index, which is 60% better than the initial baseline of 1.00. While GWO also showed significant improvements—reducing maximum ramp rates by 38.6% and improving the DCSI index to 0.63. These results demonstrate that optimized BESS operation can substantially mitigate the technical challenges associated with steep ramping requirements and extreme load variations in systems with high renewable energy penetration.

Table 5.1: Duck Curve Slope Minimization Performance Metrics

Metric	**Original Duck Curve**	**GWO Optimized**	**PSO Optimized**
Maximum ramp rate (kW/h)	978.4	600.5	520.3
Average ramp rate (kW/h)	324.7	215	180.6
Standard deviation of ramp rates (kW/h)	401.3	267.8	210.4
Peak net load (kW)	3724.6	3250	3040
Minimum net load (kW)	-1435.2	-850	-225
Duck curve severity index*	1.00	0.63	0.40

5.1.3 Near-Optimal BESS Scheduling and Initial SoC

The near-optimal initial SoC values for six BESS units, determined by PSO and GWO algorithms relative to each unit's rated energy capacity (as detailed in Table 5.2), directly influence the operational flexibility of these storage units in responding to net load fluctuations. In addition to comparing initial SoC values, it is vital to examine how these values influence the dispatch behavior of each BESS unit over the optimization period. A higher initial SoC allows the BESS unit to discharge more energy during peak demand periods. However, lower initial SoC values offer greater charging flexibility during periods of excess solar generation, thereby supporting valley filling operations.

The PSO-derived initial SoC values typically assign a greater stored energy level at the beginning of the scheduling period. For instance, BESS 5 begins at 226.52 kWh out of 340 kWh ($\sim$ 67%) and BESS 1 at 455.88 kWh out of 680 kWh ($\sim$ 67%). This suggests that PSO prioritizes a higher initial energy reserve, thereby maximizing the BESS units' discharge capability during peak demand. This strategy offers increased flexibility for mitigating over-generation by down-ramping during midday and enables more effective peak shaving, contributing to a smoother and more stable net load profile. Conversely, GWO initialized BESS 5 and BESS 6 with significantly lower SoC values, 119.23 kWh and 88.85 kWh, respectively. This lower initial energy level means their discharge capability is more reliant on prior charging from midday solar surplus. Consequently, GWO's approach appears more conservative and less aggressive in peak shaving compared to PSO's higher initial SoC strategy. Interestingly, despite initializing BESS with relatively higher SoC values, PSO demonstrated superior valley filling performance compared to GWO. This indicates that PSO more effectively coordinated the BESS dispatch schedule, strategically managing charging during periods of excess renewable generation while respecting operational constraints. This result underscores that optimal valley filling is not solely a function of available initial SoC headroom but is significantly influenced by the dynamic scheduling efficiency of the optimization algorithm.

Table 5.2: Comparison of BESS capacities and near-optimal initial SoC values obtained by PSO and GWO.

BESS Unit	PSO-Derived Initial SoC (kWh)	GWO-Derived Initial SoC (kWh)	Capacity (kWh)
BESS 1	455.88	449.88	680
BESS 2	386.05	419.60	800
BESS 3	250	260.78	860
BESS 4	75.48	72.00	190
BESS 5	226.52	119.23	340
BESS 6	200	88.85	390

Notably, all SoC values remained within the safe operating range of their respective energy capacities, ensuring adherence to BESS limitations. The algorithms showed different optimization objectives and exploration patterns: GWO focuses on achieving a balanced energy distribution across units, while PSO prioritizes system flexibility and smoothing of net load. According to these results, the initial SoC selection significantly impacts the effectiveness of BESS units in reducing duck curve problems and facilitating the integration of renewable energy sources by providing sufficient charge and discharge capacity.

Figures 5.2a and 5.2b depict the hourly SoC profiles of six BESS units over a 24-hour period, utilizing PSO and GWO methods, respectively. The SoC profiles describe the scheduling of energy storage dispatch by each algorithm to mitigate the duck curve through net load slope minimization while adhering to operational constraints.

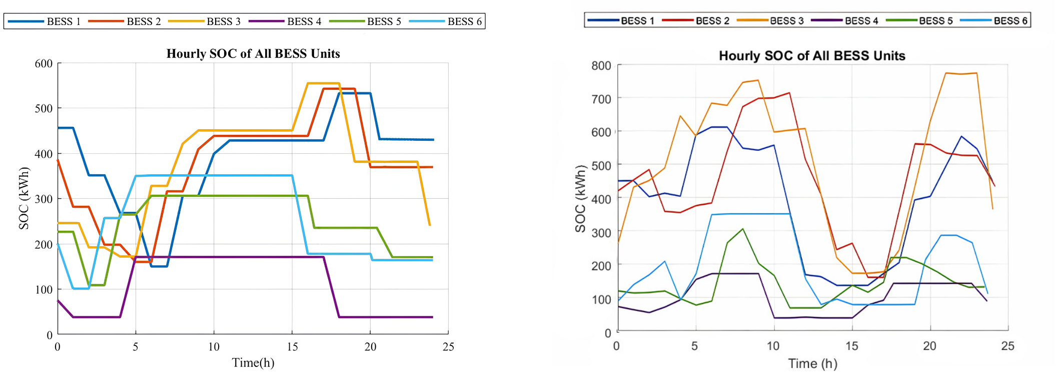

Figure 5.2a: Hourly SoC profile for ESS units under PSO

Figure 5.2b: Hourly SoC profile for ESS units under GWO

Figure 5.2: Comparison of hourly SoC profiles for ESS units under PSO and GWO optimization.

5.1.3.1 PSO-Optimized BESS Operation

The PSO optimization results indicate an organized and coordinated dispatch method among all BESS units. BESS 1, 2, and 3, as the greater capacity units, show early morning discharging (hours 0–5), indicating their active utilization to mitigate the significant decrease in net load resulting from solar PV ramp-up. This early discharge mitigates the morning ramp-down feature of the duck curve. The SOC values demonstrate conservative depth-of-discharge limits that ensure battery longevity by maintaining relatively narrow operational bounds between 100 and 450 kWh. A noticeable and coordinated charging phase is seen in practically all BESS units, especially BESS 1 through 3, between hours 6 and 14. This suggests that PSO efficiently captures and stores excess energy during low net load hours, since it corresponds with times of midday solar overgeneration. The enforcement of SoC upper boundaries, which avoids overcharging and maintains capacity for possible frequency response or later discharge, is reflected in the afternoon SoC flat. Most units have a steady discharge in the evening, with BESS 1 and BESS 2 supporting peak shaving throughout the evening demand ramp. The SoC profiles under PSO are well-organized, indicating optimal scheduling that effectively reduces net load fluctuations while adhering to power and energy constraints.

5.1.3.2 GWO-Optimized BESS Operation

The result of the GWO optimization indicates more unpredictable and less coordinated SoC dynamics. Multiple SoC peaks occur in the 24-hour time horizon for some BESS units, specifically BESS 3 and BESS 2, showing that the algorithm determines several charge/discharge cycles without creating a dominating daily cycle. BESS 5 and 6's small SoC bands imply that their dispatch power is underutilized relative to capacity. An imperfect balance between maximizing energy storage and preserving discharge flexibility might explain the unpredictable fluctuations observed in BESS 1 and BESS 3 near their high SoC limits. These patterns suggest that GWO may not be utilizing the full dynamic range of the BESS units, which could result in less effective slope minimization and load balancing. GWO might overlook ramp rate reduction during critical periods.

In summary, PSO makes it possible for all BESS units to switch between charging and discharging in a more coordinated and regulated manner, which improves load-following performance and lessens the grid's ramping stress. Conversely, GWO promotes more localized dispatch actions that are less successful in reducing net load fluctuations over time and show less system-wide cooperation. Utilizing energy and power capacity more efficiently is demonstrated by PSO's ability to strategically discharge at periods of peak demand and maintain flatter SoC profiles throughout the noon hours. PSO's enhanced performance in important metrics, such as valley filling, peak shaving, and overall slope minimization, is directly attributed to these operational improvements.

6. CONCLUSIONS and RECOMMENDATION

6.1 Conclusions

This thesis examined the strategic optimization of BESS as an effective solution to mitigate the duck curve phenomenon in contemporary distribution networks. The study simulated actual grid operations under high renewable penetration scenarios using a thorough 33-bus radial test feeder model with integrated PV generation and strategically positioned BESS units. The main goal was to reduce the net load curve's slope characteristics to solve one of the most important operational issues that utilities are currently dealing with: the quick ramping demands placed on traditional generating resources.

PSO and GWO, two sophisticated metaheuristic optimization algorithms, were used in the study to identify the best hourly BESS dispatch schedules and initial SoC values. Both algorithms represent a significant reduction in slope-related performance indicators.

6.2 Innovation

The formulation and implementation of the innovative Duck Curve Severity Index (DCSI), which offers a consistent quantitative framework for evaluating the smoothness of net load profiles across various optimization techniques, was a significant contribution of this study. This index fills a major gap in the literature by allowing more impartial and consistent evaluations of duck curve mitigation techniques. According to the DCSI research, GWO solutions tended toward more localized optimization with lower overall grid advantages, whereas PSO-derived charging and discharging profiles enabled more coordinated and systemically beneficial load-following behavior.

The results clearly show that the challenging duck curve profile may be changed into a more controllable load pattern through properly tuned BESS processes. This change allows for greater penetrations of renewable energy resources without affecting system reliability, and lessens operating load on conventional generation systems. For this case, the PSO technique in particular worked quite well, indicating that it could be used for other grid optimization problems.

This research created a strong foundation for mitigating the duck curve using BESS, revealing various intriguing directions for future exploration. Besides slope minimization, future studies should focus on other important goals, such as minimizing network energy loss, optimizing operating costs, and improving voltage profiles. This comprehensive approach would better reflect the complex requirements of real-world utility operations.

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APPENDICES

APPENDIX A : System Data

Table A.1: 33-Bus System Data (Simplified)

Branch No.	**Sending Node**	**Receiving Node**	**R(Ω)**	**X(Ω)**	λ_l	λ_d	**Active Load (kW)**	**Reactive Load (kVar)**
1	1	2	0.092	0.047	0.06	0.05	100	60
2	2	3	0.493	0.251	0.18	0.15	90	40
3	3	4	0.366	0.186	0.20	0.15	120	80
4	4	5	0.381	0.194	0.12	0.10	60	30
5	5	6	0.819	0.707	0.08	0.05	60	20
6	6	7	0.187	0.618	0.15	0.10	200	100
7	7	8	0.711	0.235	0.24	0.20	200	100
8	8	9	1.030	0.740	0.36	0.30	60	20
9	9	10	1.044	0.740	0.36	0.30	60	20
10	10	11	0.196	0.065	0.18	0.10	60	35
11	11	12	0.374	0.123	0.18	0.12	60	35
12	12	13	1.468	1.155	0.24	0.15	120	80
13	13	14	0.542	0.713	0.18	0.15	120	80
14	14	15	0.591	0.526	0.18	0.15	60	10
15	15	16	0.746	0.545	0.24	0.05	60	10
16	16	17	1.289	1.721	0.42	0.35	90	40
17	17	18	0.732	0.574	0.36	0.30	90	40
18	2	19	0.164	0.157	0.06	0.05	90	40
19	19	20	1.504	1.355	0.42	0.30	90	40
20	20	21	0.409	0.478	0.18	0.15	90	40
21	21	22	0.708	0.937	0.18	0.15	90	40
22	3	23	0.451	0.308	0.18	0.15	90	50
23	23	24	0.898	0.709	0.30	0.25	420	200
24	24	25	0.896	0.701	0.30	0.25	420	200
25	6	26	0.203	0.103	0.12	0.10	60	25

Continued on next page

Branch No.	**Sending Node**	**Receiving Node**	**R(Ω)**	**X(Ω)**	λ_l	λ_d	**Active Load (kW)**	**Reactive Load (kVar)**
26	26	27	0.284	0.145	0.12	0.10	60	25
27	27	28	1.059	0.934	0.36	0.30	60	20
28	28	29	0.804	0.701	0.30	0.25	120	70
29	29	30	0.507	0.258	0.18	0.15	210	100
30	30	31	0.974	0.963	0.30	0.25	150	70
31	31	32	0.310	0.361	0.18	0.15	210	100
32	32	33	0.341	0.530	0.12	0.10	60	20

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- F. M. Behbahani, O. Ceylan, and A. Ozdemir, "Optimum Scheduling of Energy Storage Systems in Distribution Grids to Minimize the Duck Curve Slope," in Proc. 60th Int. Universities Power Engineering Conf. (UPEC 2025), London, UK, 2025.

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