ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

REINFORCEMENT LEARNING BASED BATTERY THERMAL MANAGEMENT CONTROLLER FOR ELECTRIC VEHICLE CHARGE TIME OPTIMIZATION USING HORIZON DATA

M.Sc. THESIS

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Department of Electrical Engineering

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

UFUK VERİLERİ KULLANILARAK TAKVİYELİ ÖĞRENME TABANLI BATARYA TERMAL YÖNETİM KONTROLÜ İLE ELEKTRİKLİ ARAÇLARDA ŞARJ SÜRESİNİN İYİLEŞTİRİLMESİ

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Yunus TURHAN, a M.Sc. student of ITU Graduate School student ID 504211040 successfully defended the thesis entitled "REINFORCEMENT LEARNING BASED BATTERY THERMAL MANAGEMENT CONTROLLER FOR ELECTRIC VEHICLE CHARGE TIME OPTIMIZATION USING HORIZON DATA", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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FOREWORD

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Yunus TURHAN
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ABBREVIATIONS

AC : Alternating Current
AGS : Active Grill Shutter
ANN : Artificial Neural Network
BMS : Battery Management System
DC : Direct Current
DDPG : Deep Deterministic Policy Gradient
EV : Electric Vehicle
EXV : Electronic Expansion Valve
HEV : Hybrid Electric Vehicle
HV : High Voltage
ICE : Internal Combustion Engine
LFP : Lithium Iron Phosphate
LV : Low Voltage
LQR : Linear Quadratic Regulator
MPC : Model Predictive Control
NCA : Nickel Cobalt Aluminum
NiCd : Nickel Cadmium
NiMH : Nickel Metal Hydride
NMC : Nickel Manganese Cobalt
OBC : On Board Charger
PCM : Phase Change Material
PMSM : Permanent Magnet Synchronous Motor
PTC : Positive Temperature Coefficient
RL : Reinforcement Learning
SMPC : Stochastic Model Predictive Controller
SOC : State of Charge
SOE : State of Energy
SOH : State of Health
TMS : Thermal Management System

SYMBOLS

$\mathbf{a}$	: Vehicle acceleration
$\mathbf{c_{rr}}$	: Tire rolling resistance coefficient
$\mathbf{c_W}$	: Air resistance coefficient
$\mathbf{C_{Batt}}$	: Heat capacity of battery pack
$\mathbf{C_{coolant}}$	: Specific heat capacity of coolant
$\Delta\,\mathbf{Q_{Total}}$	: Change in the total heat
$\Delta\,\mathbf{T_{Batt}}$	: Temperature difference in the component
$\Delta\,\mathbf{Q_{TotalCoolant}}$	: Change in total heat of coolant
$\Delta\,\mathbf{T_{CoolantOut}}$	: Temperature difference in the coolant
$\eta_{\mathbf{tr}}$	: Transmission efficiency
$\eta_{\mathbf{EDU}}$	: EDU efficiency
$\eta_{\mathbf{dcdc}}$	: DC/DC converter efficiency
$\eta_{\ \mathbf{Chiller}}$	: Chiller efficiency
$\eta_{\ \mathbf{PTC}}$	: PTC heater efficiency
$\mathbf{F_W}$	: Air drag force
$\mathbf{F_a}$	: Acceleration force
$\mathbf{F_{rr}}$	: Tire rolling resistance
$\mathbf{F_{total}}$	: Total force
$\mathbf{g}$	: Gravitational acceleration
$\mathbf{h_{cb}}$, $\mathbf{h_{cc}}$, $\mathbf{h_{cp}}$	: Heat transfer coefficients
$\mathbf{I_{batt}}$	: Battery pack current
$\mathbf{i_{tr}}$	: Transmission gear ratio
$\mathbf{m}$	: Vehicle mass
$\mathbf{m_{coolant}}$	: Mass flow rate of coolant
$\mathbf{n_{motor}}$	: Motor speed
ω	: Angular velocity
$\mathbf{Pm_{MecProp}}$	: Motor propulsion power
$\mathbf{Pm_{MecRegen}}$	: Motor regeneration power
$\mathbf{Pm_{mec}}$	: Motor mechanical power
$\mathbf{Pm_{elec}}$	: Motor electrical power
$\mathbf{P_{dcdc}}$	: DC/DC converter power
$\mathbf{P_{aux}}$	: Auxiliary components power
$\mathbf{P_{comp}}$	: Compressor power
$\mathbf{P_{PTC}}$	: PTC heater power
$\mathbf{P_{therm}}$	: Thermal components power consumption
$\mathbf{Q_{CoolantToBatt}}$	: Heat transfer between coolant and battery pack
$\mathbf{Q_{batt}}$	: Heat loss of battery pack
$\mathbf{Q_{CoolantToChiller}}$	: Heat transfer between coolant and chiller
$\mathbf{Q_{CoolantToPTC}}$	: Heat transfer between coolant and PTC

$\mathbf{Q_{Coolant}}$: Heat loss of coolant
$\mathbf{Q_{Chiller}}$: Heat loss of chiller
$\mathbf{Q_{PTC}}$: Heat loss of the PTC heater
$\mathbf{R_{tire}}$: Tire radius
$\mathbf{R_{int}}$: Battery pack internal resistance
$\rho_{\mathbf{coolant}}$: Coolant density
$\rho_{\mathbf{Air}}$: Air density
$\mathbf{Tq_{motor}}$: Motor torque
$\mathbf{T_{Batt}}$: Battery pack temperature
$\mathbf{T_{CoolantOut}}$: Coolant outlet temperature
$\mathbf{T_{CoolantOut}}$: Coolant outlet temperature
$\mathbf{T_{CoolantIn}}$: Coolant inlet temperature
$\mathbf{T_{Chiller}}$: Chiller temperature
$\mathbf{T_{PTC}}$: PTC heater temperature
$\mathbf{V}$: Vehicle speed
$\mathbf{V_{oc}}$: Battery pack open circuit voltage
$\mathbf{Vol_{CoolantBatt}}$: Coolant volume for battery pack
$\mathbf{Vol_{CoolantChiller}}$: Coolant volume for chiller
$\mathbf{Vol_{CoolantPTC}}$: Coolant volume for PTC heater

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REINFORCEMENT LEARNING BASED BATTERY THERMAL MANAGEMENT CONTROLLER FOR ELECTRIC VEHICLE CHARGE TIME OPTIMIZATION USING HORIZON DATA

SUMMARY

Electric vehicles (EVs) are gaining popularity today due to the shift towards sustainable transportation. They offer significant benefits in terms of reduced emissions when compared to internal combustion engine (ICE) vehicles. Battery is a fundamental component of EVs, playing a critical role in effecting vehicle performance and range, in other words, convenience of the vehicle for users. Today most battery packs in the EVs use lithium-ion based battery cells, because they have higher energy and power density, longer life cycles and higher efficiency when compared to other battery types like lead-acid or nickel-based batteries. Batteries provide the electrical energy by electrochemical reactions that is happening inside them. These reactions are affected by the temperature conditions thus influencing the performance of the battery. Batteries generate heat during charging and discharging due to their internal resistances, extreme temperatures may lead to battery degradation and reduction in life cycle. If the temperature exceeds certain limit, it can lead to thermal runaway, where the battery becomes unstable and may catch fire or explode. That is why EV batteries have a battery management system (BMS), responsible for constantly monitoring the battery pack in order to ensure safe and robust operation. The BMS monitors voltage, current, temperature and state of charge (SOC) of the battery while controlling discharge and charge power limits and also it is responsible for battery pack's temperature management. Thermal management system (TMS) provides the necessary cooling or heating for the battery pack and rest of the vehicle systems. With the algorithm inside the BMS it controls the TMS to ensure the battery temperature remains within the optimal range for every operating condition. Charge performance is also important when it comes to users convenient. Battery packs charge performance usually depends on the cell types that are used, battery pack configuration, SOC and temperature conditions. In order to have advertised maximum charge power of the EV, battery pack temperature has to be in optimum range. That is not always the case where too hot or cold ambient operation conditions thus charge power is usually limited during these conditions. That is why also TMS control is important in order to keep battery pack in optimum operating temperature range to get improved charging performance.

The traditional approach for battery thermal management control is the rule-based control method. The rule-based control method uses battery temperature and ambient temperature as input for look-up tables to create cooling or heating requests. Rule-based control methods are relatively easy to implement which makes them suitable for many applications. However, since this method uses predefined rules, it is not dynamic and limited by the set of rules, so it may not always give the

optimum performance in terms of energy consumption or operating temperature. In order to address these issues of rule-based controller, optimum control methods are also widely used for TMS. Model predictive control (MPC) is the most used method in this area. For using MPC, system has to be modeled in high fidelity in order to predict system behaviour based on operation conditions. After that a cost function is created depending on the application and the MPC algorithm solves the optimum control problem by minimizing the cost function and it controls the heating or cooling actions accordingly. This method requires more computational resources compared to rule-based controllers but results in more efficient control of TMS. Artificial neural networks (ANNs) also widely used to model system behaviour for TMS. When working with real systems, these approach does not require to create a high fidelity system model since ANNs learns from the inputs and outputs of the system to predict its behaviour. ANNs are used in combination with some optimum control methods in order to increase their real time calculation performance and reduce the modeling dependency. Also as a subset of ANNs, reinforcement learning (RL) method is an optimum control method that ANNs are trained by using a reward function that represents goals to achieve in the system. RL aims to learn to react to inputs of the system that maximizing the reward. Reward function must be created in a way that rewards the good actions that aligned with the goal and punishes the actions that are undesired so that RL can learn to optimize its outputs to achieve that goal. As the main goal usually determined as optimized energy consumption for thermal management.

This study focuses on minimizing the charging duration of an EV by using predictive battery thermal management control. A RL based control method is proposed for battery TMS for different environment conditions using horizon data. A drive cycle is used for the use case of driving until charge station and starting to charge in different environment conditions. Vehicle dynamics, propulsion, energy storage, and comprehensive thermal systems are modeled in this study to create a training and testing environment for RL based controller. A cost function is created based on the optimization problem of charge duration and energy consumption for thermal management of the battery. The RL controller is trained with the simulation environment to minimize the cost using the drive cycle as horizon data. Relation between ambient temperatures and charge performances are investigated with RL based TMS method and traditional rule based TMS method. RL controller and the rule-based controller is investigated for the same initial conditions like temperature and SOC for the given test scenario. Based on the results, 14% decrease in charging duration observed using RL controller compared to the rule-based controller.

UFUK VERİLERİ KULLANILARAK TAKVİYELİ ÖĞRENME TABANLI BATARYA TERMAL YÖNETİM KONTROLÜ İLE ELEKTRİKLİ ARAÇLARDA ŞARJ SÜRESİNİN İYİLEŞTİRİLMESİ

ÖZET

Elektrikli araçlar sürdürülebilir ulaşıma geçiş nedeniyle günümüzde popülerlik kazanmaktadır. İçten yanmalı motorlu araçlara kıyasla emisyonların azaltılması açısından önemli faydalar sunmaktadırlar. İçten yanmalı motorlu araçlar petrol türevli fosil kaynaklara bağımlıdırlar. Fosil yakıt kaynakları sınırlı olmaları sebebiyle genellikle elektrik enerjisine göre daha maliyetlidirler. Bu sebeple elektrikli araçlar fosil yakıtlı araçlara göre kullanım açısından daha düşük maliyetlidir. Elektrikli araçların temel bileşenlerinden biri olan batarya, aracın performansını ve menzilini belirleyen en önemli etkenlerden biridir. Diğer bir deyişle aracın kullanıcılara sağladığı deneyimde kritik bir rol oynamaktadır. Günümüzde elektrikli araçlardaki batarya paketlerinin çoğunda lityum-iyon bazlı batarya hücreleri kullanılmaktadır. Lityum-iyon bazlı bataryalar, kurşun-asit veya nikel bazlı batarya türlerine kıyasla daha yüksek enerji ve güç yoğunluğuna, daha uzun yaşam döngüsüne ve daha yüksek verimliliğe sahip oldukları için elektrikli araçlarda yaygın olarak kullanılmaktadır. Elektrikli araçlarda menzile etki eden faktörlerden birisi batarya kapasitesidir. Batarya kapasitesi, bataryanın sahip olduğu elektrik enerjisinin miktarını temsil eder. Çoğunlukla elektrikli binek araçlarda batarya kapasitesi 40 kWh ile 110 kWh arası değişmektedir. Bataryanın kapasitesi arttıkça boyut, ağırlık ve maliyeti de artmaktadır. Araçlarda kullanılabilecek olan maksimum batarya hacmi ve ağırlığı sınırlı olduğundan, bataryaların enerji yoğunluğu araçlarda kullanılabilecek maksimum kapasitesiyi limitleyen önemli faktörlerden biridir. Menzil de aynı şekilde bu limitten etkilenmektedir.

Bataryalar elektrik enerjisini içlerinde gerçekleşen elektrokimyasal reaksiyonlarla sağlar. Bu reaksiyonlar sıcaklık koşullarından etkilenerek bataryanın performansını etkiler. Bataryalar, iç dirençleri nedeniyle şarj ve deşarj sırasında ısı üretir, aşırı sıcaklıklar bataryanın iç yapısını oluşturan materyallerde bozulmalara ve kullanım ömrünün azalmasına neden olabilir. Sıcaklık belirli bir sınırı aşarsa, hücrelerin kararsız bir hale gelip alev alabileceği veya patlayabileceği geri döndürülemez bir olaya yol açabilir. Bu nedenle elektrikli araç bataryalarında, güvenli bir çalışma sağlamak için batarya paketini sürekli izlemekten sorumlu bir batarya yönetim sistemi (BMS) bulunur. BMS, deşarj ve şarj güç limitlerini kontrol ederken bataryanın voltajını, akımını, sıcaklığını ve şarj durumunu izler ve ayrıca batarya paketinin sıcaklık yönetiminden sorumludur. Elektrikli araçlarda termal yönetim sistemi batarya paketi, elektrik motoru, güç elektroniği komponentleri ve araç kabini gibi sistemler için gerekli soğutma veya ısıtmayı sağlar. BMS içindeki algoritma ile batarya sıcaklığının her çalışma koşulu için en uygun aralıkta kalmasını sağlamak amacıyla termal yönetim sistemi ile haberleşerek gerekli ısıtma ve soğutmayı gerçekleştirir. İçten yanmalı

motorlu araçlarda motorun çalışma verimliliği düşük olduğundan çok fazla ısı üretimi olur ve genellikle soğuk havalarda motorun ürettiği ısı kabini ısıtmak için kullanılabilir. Bu da ısının dışarıya atılması yerine kabini ısıtmak için kullanılması sebebiyle verimli bir kullanım biçimidir. Elektrikli araçlarda elektrik motoru içten yanmalı motora kıyasla çok daha verimli çalıştığı için ürettiği ısı miktarı da sınırlıdır. Bu sebeple kabin ve batarya ısıtması için elektrikli araçlarda elektrik enerjisi ile çalışan bir ısıtıcı ünite bulunur. Isıtıcı kullanım ihtiyacı sebebiyle enerji tüketimi soğuk havalarda artar. Aynı şekilde sıcak havalarda da batarya sıcaklığı arttığında batarya paketi soğutma ihtiyacı duyabilir. Isıtma ve soğutma için kullanılan bu enerji, aracın menzilini direkt olarak etkilediği için iyi bir şekilde yönetilmesi gereklidir. Bu sebeple termal yönetim sisteminde kullanılan kontrol yöntemleri elektrikli araçlar için önemlidir.

Elektrikli araçlarda kullanıcıların deneyimini etkileyen diğer bir nokta ise şarj süresidir. Batarya paketlerinin şarj performansı genellikle kullanılan hücre tiplerine, batarya paketi konfigürasyonuna, şarj durumuna ve sıcaklık koşullarına bağlıdır. Maksimum şarj gücünde aracı şarj etmek için batarya paketi sıcaklığının optimum aralıkta olması gerekir. Ortam koşullarının çok sıcak veya soğuk olduğu durumlarda batarya optimum sıcaklıkta olmadığı için aracın şarj performansı kısıtlanır ve şarj süresi uzar. Bu sebeple termal yönetim sistemi batarya paketini optimum çalışma sıcaklığı aralığında tutmak için önem kazanır.

Batarya termal yönetim sisteminin kontrolü için geleneksel yaklaşım kural tabanlı kontrol yöntemidir. Kural tabanlı kontrol yöntemi, soğutma veya ısıtma işlemlerini gerçekleştirmek için bataryanın sıcaklığı, ortam sıcaklığını, şarj durumu gibi koşullara bağlı bir kural seti kullanır. Bu kural setinde tanımlanan şartlar gerçekleştiğinden bu şarta karşılık gelen işlem için gerekli aktüatörler çalıştırılır. Bu şekilde bataryanın belirli sıcaklık aralığında çalışması sağlanabilir. Kural tabanlı kontrol yöntemlerinin uygulanması nispeten kolaydır, bu da onları birçok uygulama için uygun hale getirir. Ancak, bu yöntem önceden tanımlanmış kurallar kullandığından, dinamik değildir ve operasyonları kurallar kümesiyle sınırlıdır, bu nedenle enerji tüketimi veya çalışma sıcaklığı açısından her zaman optimum performansı vermeyebilir. Kural tabanlı kontrolörün bu tip zayıf yönlerini gidermek için, termal yönetim sistemi kontrolü için optimum kontrol yöntemleri de yaygın olarak kullanılmaktadır. Model kestirimli kontrol (MPC) bu alanda en çok kullanılan yöntemdir. MPC, bir sistemin gelecekteki davranışlarını öngörerek, bu davranışlara göre optimum kontrol çıktıları veren bir kontrol yöntemidir. Temel olarak, MPC, bir sistemin matematiksel model kullanarak gelecekteki davranışlarını tahmin eder ve bu davranışlar üzerinden belirli bir performans kriterini optimize eden kontrol sinyalleri üretir. MPC metodu için, çalışma koşullarına dayalı olarak sistem davranışını tahmin etmek amacıyla sistemin yüksek doğrulukta modelinin kurulması gereklidir. Daha sonra amaca bağlı olarak bir maliyet fonksiyonu oluşturulur ve MPC algoritması maliyet fonksiyonunu minimize ederek optimum kontrol problemini çözer. Termal yönetim sistemi için bu maliyet fonksiyonu enerji tüketimini ve istenmeyen diğer sıcaklık değerlerini içerebilir. Bu maliyet fonksiyonunu minimize edecek ısıtma veya soğutma eylemleri MPC tarafından kontrol edilerek optimum kontrol sağlanmış olur. Bu yöntem, kural tabanlı kontrolörlere kıyasla daha fazla işlemci gücü gerektirir daha verimli sonuçlar elde edilir.

Elektrikli araç termal sisteminin davranışını modellemedek amacıyla yapay sinir ağları (YSA) da yaygın olarak kullanılmaktadır. YSA, insan beynindeki sinir ağlarından esinlenerek oluşturulan matematiksel modellerdir. YSA kullanılarak desen tanıma, sınıflandırma, tahmin yapma gibi görevler gerçekleştirilebilir. YSA'lar sistemin giriş çıkışlarına ait gerçek verileri kullanarak sistemin her durumdaki davranışını öğrenebilir. Bu sayede sistemin matematiksel olarak yüksek doğrulukta bir modelinin oluşturulmasına ihtiyaç duyulmaz. YSA'lar, gerçek zamanlı hesaplama performanslarını artırmak ve modelleme bağımlılığını azaltmak için bazı optimum kontrol yöntemleriyle birlikte kullanılabilir. Bu tür yapılar hibrit kontrol yöntemlerine dahildir. Ayrıca YSA'ların bir alt kümesi olarak takviyeli öğrenme (RL) yöntemi de bir optimum kontrol yöntemi olarak kullanılır. RL bir YSA modelinin belirli bir görevi en iyi şekilde gerçekleştirmeyi öğrenmeye çalıştığı bir yöntemdir. RL'in öğrenmesi için bir ödül fonksiyonu tanımlanır ve RL bu ödül fonksiyonunu maksimize edecek şekilde tepki vermeyi öğrenir. Ödül fonksiyonu, sistemde hedeflenen ve ulaşılması istenen parametrelere doğrultusundaki eylemleri ödüllendirirken, istenmeyen eylemleri de cezalandırır. Böylece RL bu hedefe ulaşmak için çıktılarını optimize etmeyi öğrenebilir.

Bu çalışmada, kestirimli batarya termal yönetim kontrolü kullanılarak bir elektrikli aracın şarj süresinin en aza indirilmesi amaçlanmıştır. Öngörülmüş verileri kullanılarak farklı ortam koşulları için batarya termal yönetimi için RL tabanlı bir kontrol yöntemi önerilmiştir. Gerçek kullanım koşuluna benzer bir senaryonun simulasyon ortamında gerçekleştirilmiştir. Bu senaryo, 20 dakikalık bir sürüş ardından aracın şarj edilmesini içerir. Sürüş esnasındaki hız değerleri bir sürüş döngüsünden alınmıştır. Aynı senaryo farklı ortam sıcaklığı koşullarında incelenmiştir. Araç dinamikleri, tahrik, enerji depolama ve termal sistemlerin kapsamlı modeli oluşturulmuştur. Bataryanın termal yönetimi için şarj süresinin optimizasyonuna bağlı bir maliyet fonksiyonu oluşturulmuştur. RL kontrolcü, simülasyon ortamında her bir senaryo için maliyeti en aza indirmeyi amaçlayacak şekilde eğitilmiştir. Ortam sıcaklıkları ve şarj performansları arasındaki ilişki RL tabanlı termal yönetim metodu ve geleneksel kural tabanlı termal yönetim metodu kullanılarak incelenmiştir. Aynı koşullar altında koşturulan simülasyonlara göre RL kontrolcü ve kural tabanlı kontrolcünün sonuçları kıyaslanmıştır. Sonuçlara göre, kural tabanlı kontrolcüye kıyasla RL kontrolcünün, şarj süresinde %14'e kadar bir azalma sağladığı gözlemlenmiştir.

1. INTRODUCTION

Electric vehicles (EVs) are at the forefront of the shift towards sustainable transportation, offering significant benefits in terms of reduced emissions. While the costs are dropping in terms of battery manufacturing, EVs gaining popularity and becoming more available for the customers. Since the beginning of the EVs production, range and charge duration are the most concerning topics in terms of customer expectations. In order to make EVs become feasible for wide population researches and development are continuing on these aspects of EVs.

Recent advancements in battery chemistry, particularly in lithium-ion technology, have significantly enhanced the energy density and longevity of EV batteries. The rapid charging capability of EV batteries is crucial for user convenience and widespread adoption. This requires enabling the fast charging capabilities in the EVs as feature and availability for the users as infrastructure. With fast charge enabled EVs comes significant technical challenges including thermal runaway risks and degradation of battery materials. Since the batteries electrochemical reactions are affected by the temperature, fast charging capability and charge duration depends highly on the conditions of the battery pack. Therefore effective thermal management system (TMS) is critical for maintaining optimal battery temperatures, providing best performance, preventing overheating and ensuring safety and longevity. While improving the battery performance, TMS also effects the range of the EVs. At high ambient temperatures, energy consumption for thermal management can reach to 30% of overall energy consumption of EV [1]. In this sense, development of optimum thermal management features are fundamental to the future of EVs and sustainable transportation.

1.1 Purpose of Thesis

Ambient conditions can change the battery performance significantly including charging power as well. In order to get maximum charging power from the battery

in cold or hot ambient, preconditioning of the battery is crucial. That is why thermal management directly effects the charge duration in these cases. By creating an EV model and simulating different scenarios, this research provides insight into how the environmental conditions affect charging duration. The goal is to improve charge duration of an EV by applying predictive thermal management control that can dynamically adapt to operating conditions and optimize performance in real time. In order to achieve this goal, reinforcement learning (RL) controller is used as a optimum control method and vehicle speed as horizon data to perform predictive thermal management.

1.2 Literature Review

Batteries as the source on energy in EVs, are components that converts chemical energy that stored in the material inside the battery to electrical energy by chemical reactions [2]. These electrochemical reactions influenced by temperature which directly affects the performance and lifespan of the batteries. High temperatures can accelerate the degradation of battery components, leading to a decline in performance and a reduction in the usable life of batteries. Effective TMS is important in terms of increasing both the efficiency and life cycle of the battery [3].

Rule-based methods are commonly used for TMS since they are simple to implement. They rely on set of rules that have been defined to provide the actions needed for cooling and heating in EV. Since they have predefined rules they usually don't give the optimum performance [4]. Since the impact of thermal management can be high on the energy consumption and range most of the researches focuses optimum control strategy in order to improve these aspects.

Optimum control methods have generally highlighted as better performing method compared to rule based. Variety of optimum control algorithms have been used in different researches. Model predictive control (MPC) is the most used method in these category [5-16].

Most of the researches focuses on improving energy consumption by using MPC. In the study by Amini et. al., a thermal management method by using horizon data

with MPC is developed. It focuses on battery cooling and tries to optimize energy consumption with predictive control. Difference between using long term and short term horizon data is also investigated. Research compares the results of optimum control with traditional control and shows 25% improvement in energy consumption [5]. Similar to Amini et al.'s study, an MPC based thermal management control method is implemented by Hu et al., this research focuses on the effect of uncertainties with the horizon data on the MPC performance and efficiency [6]. Similar to these researches, Schaut and Sawodny study uses MPC but for cabin cooling control. In this research, detailed cabin and refrigerant line thermal model is created and validated with real measurements. MPC is used to optimize energy consumption used to keep cabin comfort. Results have been compared with based line strategy which is an on-off control model for cabin temperature, proposed solution reduces energy consumption up to 43% [7]. Glos et al. proposed an MPC to select optimum operation mode of the thermal system in their research. It focuses on the control mode of actuators like valves that requires binary or integer input for control. While MPC deciding the operational modes, traditional control methods used for controlling the heating or cooling power. That way a hybrid control model is developed [8]. In Park and Ahn's research, stochastic model predictive controller (SMPC) is designed to consider future predictions for battery cooling optimization. Heat generations calculated using vehicle speed and acceleration horizon information. SMPC solution have more robust output with the uncertainties taken into consideration when compared to standard MPC but it increases the computational time [9].

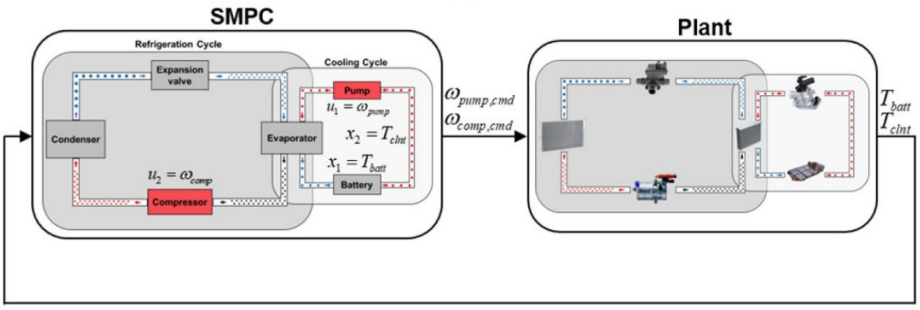

Figure 1.1 : SMPC architecture with plant model [9].

Other than battery and cabin cooling optimization, MPC is also used for powertrain cooling as well in the sense of reducing overall energy consumption. In the study

by Schaut et al., thermal system is modeled for powertrain components and MPC is used for thermal management. Goal is to decrease energy consumption for thermal management and increase the efficiency of electric motors. Suggested method gains 0.3% improvement on the range as an outcome [10]. Similarly Wahl et al., focuses on an experimental setup using chassis dynamometer and climate chamber in order to get electric motor efficiency for different operating temperatures. After that using MPC with a drive cycle input, electric motor efficiency and thermal management energy consumption tried to optimized. According to results, overall 4.2% gain in energy consumption was possible [11]. In Tao et al.'s study, MPC is used to reduce total energy consumption of thermal management and powertrain system by 1.8%. Also with reduced operating temperatures of electric motors, it gives an outcome of increasing the thermal life time of the electric motors [12].

Other than these researches focuses on the energy optimization of thermal management, there are researches related to charging duration optimization using MPC. Study of Hu et al. focuses on charge duration improvement by implementing MPC for optimum control using horizon data. Thermal system model is created in simulation environment and different test scenarios have been investigated. In this research only battery cooling case is investigated and output as 12.3% improvement in charge duration with proposed solution [13]. In a different study by Hu et al. in the same year, charge duration optimization was performed with MPC while including the cabin cooling while charging. It focuses on the interactions between accurately predicting the charging event, charging performance and cabin comfort. In the scenarios where charge event is not predicted correctly, controller output have to comprise from cabin comfort in order to achieve improved charging duration because of system limits [14]. In Hamednia et al.'s researches, charging is tried to optimized by selecting the best possible trip for optimum thermal control and charge duration. They include the trip time for reaching charging station into consideration for optimum control problem. With multiple inputs, road trip time, charge duration and energy consumption, MPC is used to minimize these costs in order to find optimum control strategy [15, 16].

Data driven methods are also used for the optimum thermal management in EV. In the study of Xie et al., an intelligent learning algorithm is proposed for cabin comfort in EV and reducing power consumption. According to users input via air conditioning unit in vehicle, learning algorithm adapts the output to a more suitable desired value for user in order to provide comfort. After that this target used by PID controllers to control thermal management system [17]. Park and Kim's research uses artificial neural networks (ANN) to create the system model using supervised learning. With the ANN models, optimization problem is solved via mixed integer linear programming solver. With the help of ANN, system model doesn't need to be created, ANN learns the system behaviour based on real measurement data and adapt itself accordingly [18]. Research by Bicer et al. uses ANNs to model battery thermal management system. Goal is to create accurate system models without the need of use any complex modeling and showing computational time improvements [19]. In the research by Choi et al., RL is used for the thermal management of cabin cooling for an EV. An accurate model of cabin thermal system is created and RL controller is used to minimize tracking error and power consumption. According to results, RL controller gives better performance and less power consumption compared to rule based controller [20]. Similarly Yuan et al. uses RL for thermal management on cabin and battery cooling performance in EV. Proposed method gives up to 14% less energy consumption compared to rule based controller as result [21].

2. ELECTRIC VEHICLE TECHNOLOGY

2.1 Electric Vehicles

EV's history goes back to the 1830s. They gain popularity with the invention of DC motor. By the end of 19th century more than 30% of the vehicles in US was electric [22]. There was also steam engine and gasoline engine vehicles at that time in the market. EVs were silent, easy to start and simple to drive compared to other vehicle types as gasoline and steam engine vehicles. But EVs were slow, expensive and range was in between 30 km to 60 km at that time. Batteries used in the EVs were costly, heavy and had limited performance [22]. By the time after 1930s, when highways have been build to connect cities and long distance travel with automobile has become popular, EVs were not feasable to be used in these kind of scenarios. And with the series production of Ford Model T, internal combustion engine (ICE) vehicles were much cheaper than the EVs [22].

ICE vehicles have dominated the automobile market until the early 2000s when hybrid electric vehicles (HEVs) started to get into the market. In 2008, more than 2.5% of the vehicles sold in US was HEV [23]. HEVs combines the internal combustion engine and electric motor in a system and allows vehicle to achieve better fuel economy and lowering emissions. HEVs can be categorized according to their hybrid topology as series hybrid, parallel hybrid and series-parallel hybrid. In series hybrid system, electric motor provides the traction torque powered by the battery. ICE is connected to an electric motor that acts as generator to provide power to battery pack. Parallel hybrid system uses both ICE and electric motor as traction. In this system electric motor takes the power from the battery pack only. In series-parallel systems, an additional generator added to parallel system to provide charging power to battery by ICE [24].

With the help of new battery technologies, after 2010s EVs gain interest and many automakers accelerated their EV productions [26]. Also with the need to reduce greenhouse gas emissions, decrease dependency on fossil fuels and improve air

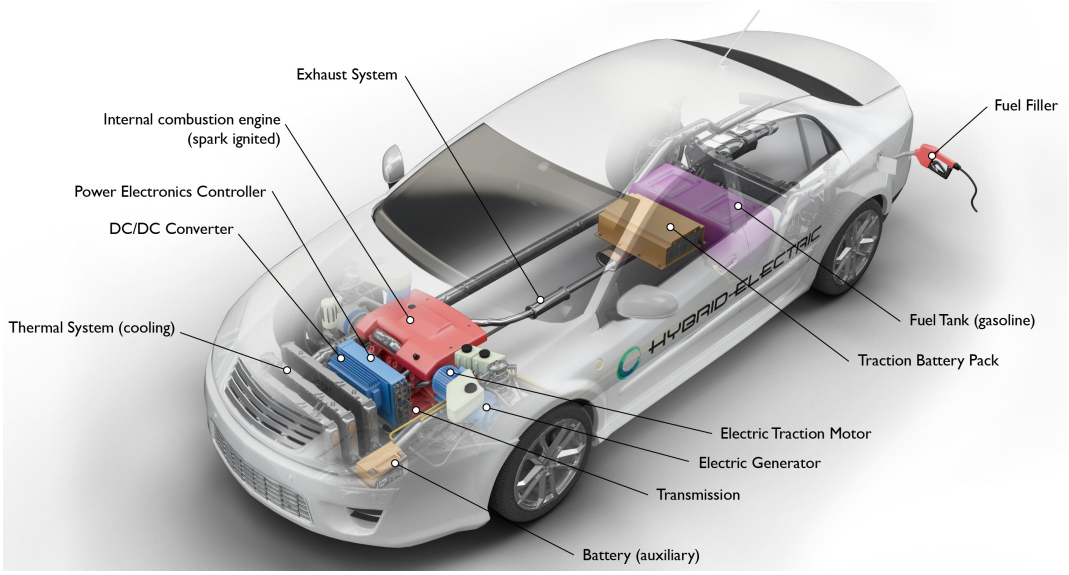

Figure 2.1 : Example HEV architecture [25].

quality, EV technologies offering a cleaner, more efficient alternative to traditional ICE vehicles proposed as solution. In 2023 almost 14 million cars sold was EVs reaching 18% of total cars sold [27].

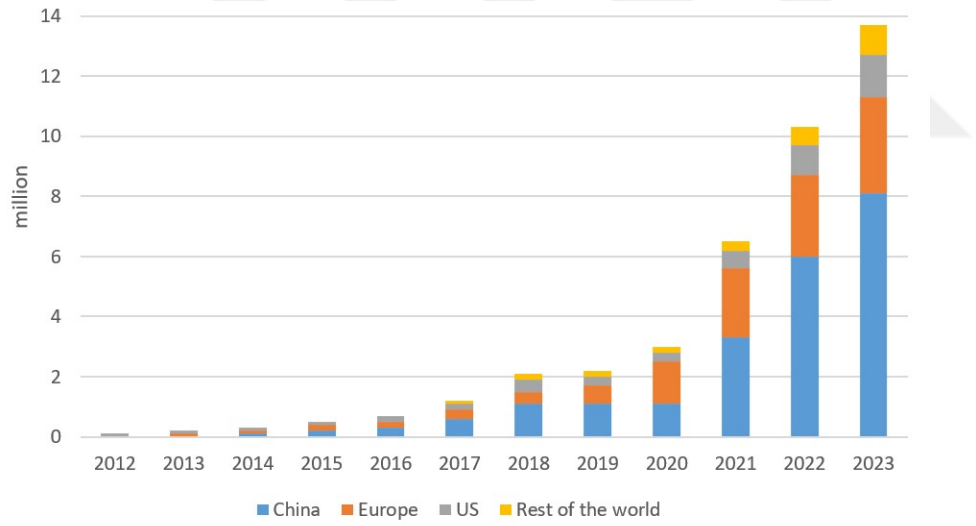

Figure 2.2 : EV sales between 2012-2023 [27].

Most of the EV sales happened in China with 60% of overall EV sales in 2023. According to IEA, the main reason for it that in China over 60% of electric vehicles sold was cheaper than their average internal combustion engine options. But this is not the case yet for Europe and United States [27]. Overall in 2023, best selling 5 EV's have been given in Table 2.1 with some specifications.

Table 2.1 : Top 5 sold EVs in 2023 and specification [28].

Model	Battery Capacity [kWh]	Range [km]	Class
Tesla Model Y	81	533	SUV
BYD Song Plus EV	87	605	SUV
Tesla Model 3	66	554	Sedan
BYD Qin Plus EV EV	72	600	Sedan
BYD ATTO 3	60.5	420	SUV

EVs include the integration of several crucial technological advancements. At the heart of EV technology lies the battery system, which mostly determines the vehicle's range, performance, and overall feasibility. Advances in battery chemistry, energy density, and charging infrastructure are key factors driving the adoption of electric vehicles. In addition to batteries, the power electronics that manage the flow of energy within an electric vehicle are crucial for optimizing efficiency and performance. Innovations in power electronic converters, motor controllers and motors contribute significantly to the overall effectiveness of EVs.

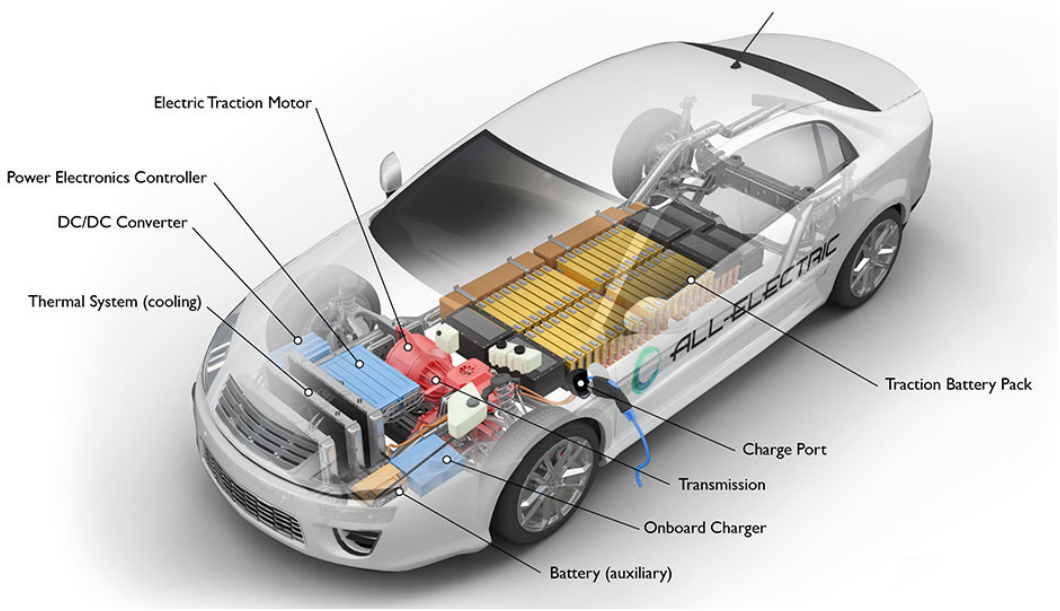

Figure 2.3 : Example EV architecture [29].

EVs uses electric motors as traction motor. Electric motors are electromechanical devices that converts electrical energy into mechanical energy. There is a stationary part called stator and rotating part called rotor in their design. In early stages of EV industry, direct current (DC) motors were used as traction motor [22]. DC motors have windings inside their rotor and they use a commutator ring and brush component

in order to energize these windings while rotating. DC motors have known for their simple control and low costs but since they contain a brush for commutation, they require maintenance and they have lower efficiency compared to brushless type of electric motors and that is why they are generally not used in EVs in recent years [30]. Induction motors have been used by the EVs especially by EV manufacturer Tesla. Induction motors are a brushless type of motors that are known for durability. Since they do not contain any brush or permanent magnets, they are well suitable for diverse operation conditions. They require inverter in order to be controlled effectively, because of their working principle, there are losses in the rotor which makes them less efficient compared to permanent magnet motors [30].

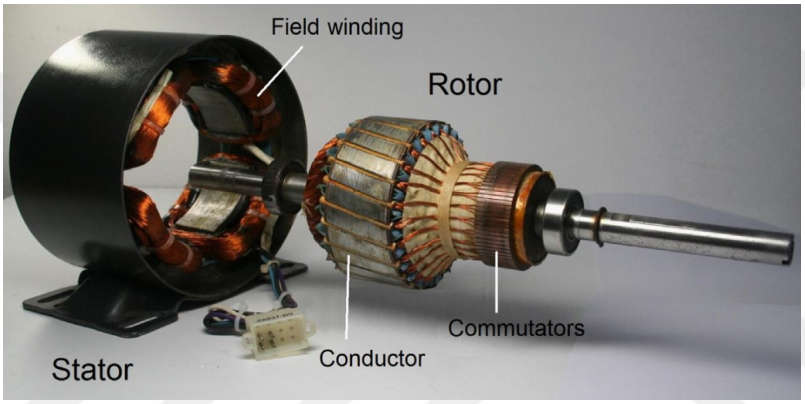

Figure 2.4 : DC motor structure [31].

Synchronous motors are also widely used by EVs. These motors can be categorized as the ones that contains permanent magnet in their rotor and others that contain windings in their rotor. Permanent magnet synchronous motors (PMSMs) have advantages in terms of power density and efficiency compared to other motor types. But since permanent magnets that are used in these motors are made from rare earth materials, it increases their manufacturing costs. Permanent magnets are also effected by temperature so they are less robust compared to other motor types. Synchronous motors on the other hand uses windings instead of permanent magnets in their rotor to create magnetic field. They are more suitable for diverse environments and cheaper because of lacking permanent magnets. Power density and efficiency compared to PMSMs can be lower because they contain windings in the rotor [32]. Synchronous motors, similar to induction machines also requires inverters and controllers in order to operate.

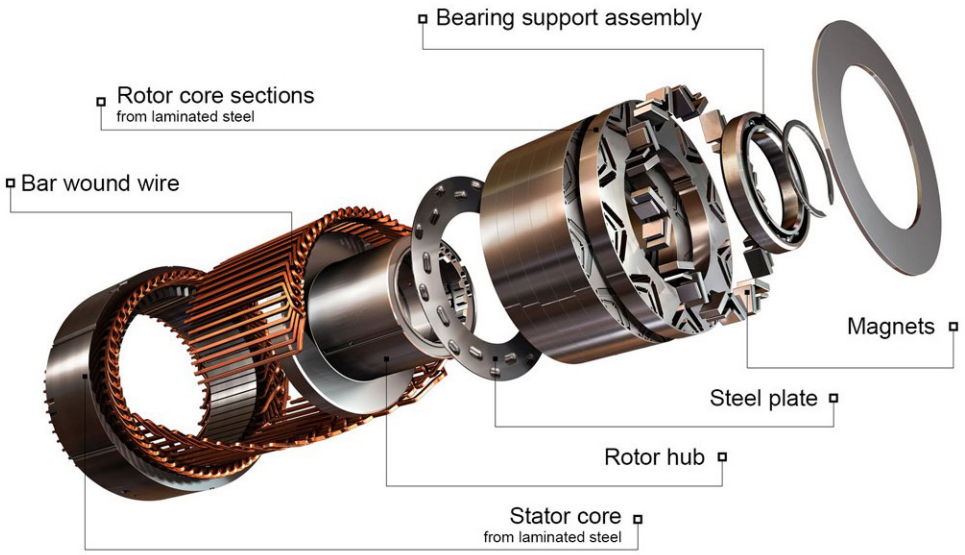

Figure 2.5 : PMSM structure [33].

Inverters are power electronic circuits that transforms DC supply into alternating current (AC). With the inverters, AC voltage output amplitude and frequency can be controlled which is essential for electric motor control. Inverters require a controller that provides the switching inputs in order to get desired output voltage, frequency and current [34].

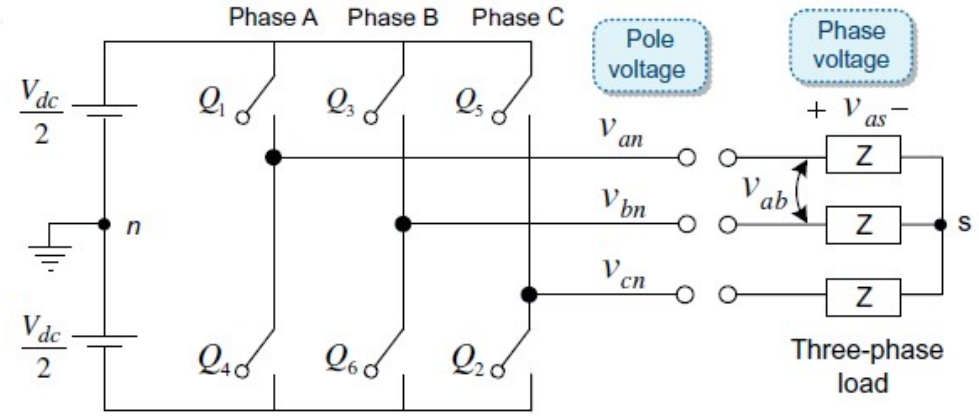

Figure 2.6 : Example inverter topology [34].

For EVs, a transmission is used to convert output torque from the motor shaft into wheel torque for traction. In order to achieve best power and torque density, electric motor, transmission, inverter and controller combined in a same package. These packages are called Electric Drive Unit (EDU) which creates the propulsion torque for EVs [35].

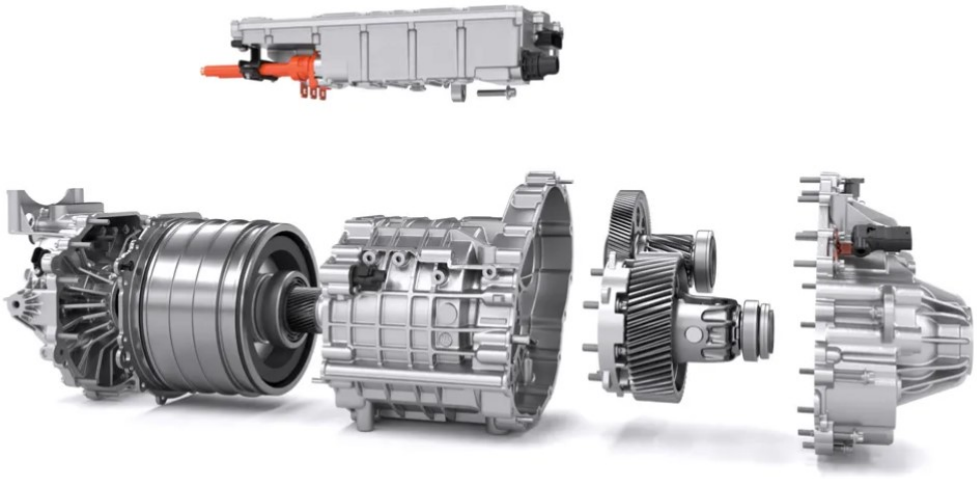

Figure 2.7 : ZF EDU structure [36].

2.2 Battery Technologies

At the core of any EV is its battery system, which serves as the primary source of energy. Batteries transforms chemical energy into electrical energy by electrochemical reactions. They store the energy electrochemically in their main parts as cathode, anode and electrolyte. Cathode is the positively charge electrode and anode is negatively charge electrode. Between these electrodes, electrolyte is used for ions to travel in between [37].

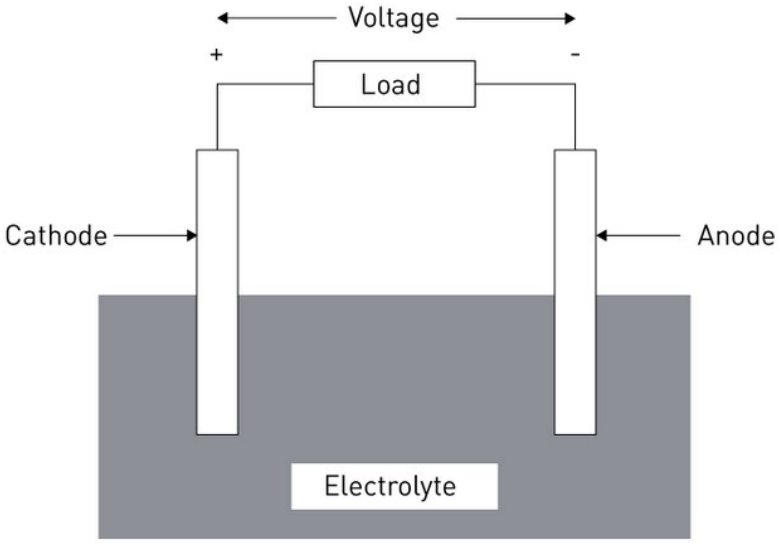

Figure 2.8 : Battery cell structure [37].

2.2.1 History of battery technology

First battery cell is created by the Alessandro Volta in 1800. Volta used copper and zinc as cathode and anode material and he used sulfuric asid or salt water as electrolyte. With compiling these on top of each other he created the so called voltaic pile which known as first battery cell. After that in 1836 John Frederic Daniell followed the research of Volta and improved the design by using zinc, copper and sulfuric acid. This design by Daniell used widely in many area including telegraph and telephone networks. In 1859, Gaston Plante invented the lead-acid battery, the first rechargeable battery, which is still used in automotive applications today. Lead-acid battery can produce high current by using lead dioxide as cathode material, because of this property it has become the starter battery for vehicles [37].

Waldemar Jungner in 1899, invented the nickel cadmium (NiCd) battery, which was a rechargeable battery offering higher energy density and longer life compared to lead acid batteries. This battery was having nickel oxide hydroxide and cadmium as electrodes. Until mid 20th century, consumer devices that required rechargeable batter was using NiCd batteries. But because cadmium is hazardous and toxic heavy metal, it was causing some environmental issues. With introduction of nickel metal hydride (NiMH) batteries in 1960s, NiCd batteries were getting replaced. NiMH batteries was offering higher capacity and more environmentally because the use of metal hydride alloy instead of cadmium. In 1947, invention of the alkaline battery by Lewis Urry was also an important breakthrough because they offer higher energy density and longer shelf life compared to zinc carbon batteries. They were widely used for commercial applications in consumer electronics [37, 38].

In early 1970s and 1980s, development of first rechargeable lithium batteries became commercially available based on the works of John B. Goodenough, M. Stanley Whittingham and Akira Yoshino. The reason for using lithium in battery is that lithium is the lightest metal and has great electrochemical potential. The first attempt for creating lithium batteries was by using lithium metal as anode material. Since lithium was not a stable material it was not a viable option because of safety issues. Yoshino

worked on the issue and used petroleum coke as anode and lithium cobalt oxide as cathode material, which made the cell safe and reliable. Sony in 1991, commercialized the lithium ion based batteries based on Yoshino's work, by deploying it in portable electronics. In early 2000s lithium ion batteries saw rapid improvements in capacity, cost, and safety and still researchers continues to work for improvements [39, 40].

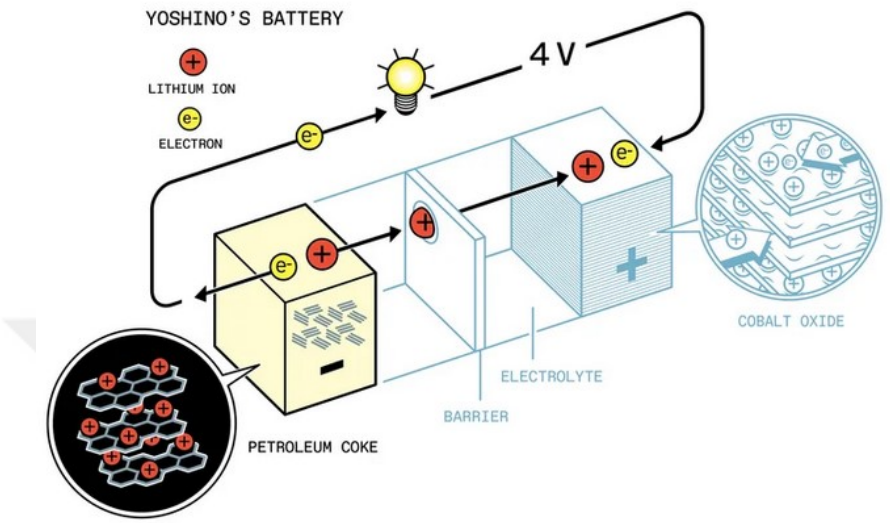

Figure 2.9 : Yoshino's lithium ion based battery [39].

2.2.2 Future of the battery technology

Solid state batteries are in research, they aim to replace the liquid electrolyte with a solid one in lithium ion batteries. Using solid material instead of liquid, can increase energy density and increase the safety by eliminating the risk of leakage and reducing flammability. These type of batteries are still in development phase but it may be seen on the production in few years [41]. Beside from the solid state batteries, there is another research topic using sodium ion instead of lithium in the cells. Sodium is more abundant and cheaper than lithium, offering a cost effective alternative. Performance of these batteries are not matching with the lithium ion batteries as of now but they reduce the cost and can be used for energy storage in grid applications [42]. Another method that is in research is to use silicon in lithium ion based batteries anodes. Silicon bonds with the lithium with respect to carbon atoms in increased numbers. That means lithium density could increase in the same material size using silicon. With

this technique, it is expected to see increase in capacity, charge capability and energy density of the batteries [43].

2.2.3 Battery technologies used in EVs

Since batteries are the main energy sources in EV, properties of the batteries directly affects the usability of the EVs. Because of size and weight constraints, in order to have most range and performance, battery packs that is used in EVs shall have high energy and power density. Even though with the increased ranges, long distance trip still may cause some inconvenience for the users because of the charge durations. That is why battery packs that used by the EVs shall have fast charging capability as well. Today the most commonly used batteries in EVs are lithium ion batteries due to their high energy density, long cycle life, and relatively low self-discharge rates. Comparison between lithium ion and different types of batteries given in Table 2.2, it is clear that the lithium ion based batteries superior to other ones.

Table 2.2 : Comparison of lithium ion batteries with other types [44].

Specifications	Lead Acid	NiCd	NiMH	Lithium Ion
Specific Energy [Wh/kg]	30-50	50-80	60-120	90-250
Power Density [W/kg]	180	150	250-1000	250-680
Self Discharge Rate	Low	Medium	High	Very Low
Charge Temperature [°C]	-20-50	0-45	0-45	0-45
Discharge Temperature [°C]	-20-50	-20-65	-20-65	-20-60
Cycle Life	200 - 300	1000	300 - 500	600-3000

For lithium ion batteries, there are mostly three types have been used in EV batteries, lithium iron phosphate (LFP), nickel manganese cobalt (NMC), nickel cobalt aluminum (NCA). LFP batteries have high thermal stability, longer cycle life compared to traditional lithium ion batteries, and inherently safer chemistry. But they have lower energy density compared to other lithium ion variants, which may result in larger

and heavier battery packs for the same energy capacity. NMC batteries have high energy density and good cycle life. But they have higher cost due to cobalt contain and moderate thermal stability compared to LFP batteries. NCA batteries use nickel, cobalt, and aluminum in the cathode but with a higher proportion of cobalt compared to NMC. They have high energy density and good thermal stability but they have higher cost to due to higher cobalt content [45]. Even tough energy density of LFP batteries cell are lower compared to NMC and NCA batteries, it has been used in 67% of the produced EV's in 2023 in China. Since LFP batteries cost almost 25% less than NMC equivalent batteries, it was still preferable by the EV manufacturers [27]. Battery specifications for different battery types have been given in Table 2.3.

Table 2.3 : Typical LFP, NMC and NCA battery specifications [44, 46].

Specifications	LFP	NMC	NCA
Specific Energy [Wh/kg]	90 - 150	150 - 220	200 - 260
Charge Temperature [°C]	0 - 55	0 - 50	0 - 50
Discharge Temperature [°C]	-20 - 55	-20 - 50	-20 - 50
Cycle Life	1000 - 4000	500 - 2000	500 - 2000
Cost	High	Medium	Medium
Safety	Safest	Good Safety	Safety Concern

2.3 Battery Management System

Lithium ion batteries performance depends on the operational conditions. Temperature, state-of-charge (SOC) and voltage are important factors. SOC is a value that shows the remaining capacity of the battery. Batteries have limited operating voltage, which in case of over voltage or under voltage may result in irreversible cell damage. Electrochemical reactions inside the battery mostly effected by the operating temperature. Low temperatures decreases the chemical reaction rates and increases the batteries internal resistance. Thus leading to limited performance in low temperatures for both discharging and charging. High temperatures create increased reaction speeds but in conclusion internal heat generation is also increases. If the heat inside the battery continuous to rise and cannot dissipate enough heat, it may lead to thermal runaway. Thermal runaway is a case when a temperature threshold exceeded, because of the

reactions inside the battery pack leads to even more increase in temperature may lead to fire or explode [47]. Because of these concerns, lithium ion batteries require battery management system (BMS) to ensure their optimum performance and safety.

BMS constantly monitors the voltage, current, temperature of the battery pack and estimates SOC, state of health (SOH), state of energy (SOE). Because of the limited battery life, batteries maximum capacity degrades over time. SOH represents the degradation inside the battery pack, giving the ratio of actual capacity of the battery and rated capacity. SOE shows the available energy inside the battery. BMS is responsible for calculating the charge and discharge power limits of the battery based on real time measured sensor values and estimations. BMS a feature called balancing, which ensures all cells inside the battery remain in same voltage levels. This is important in terms of cell life cycle equality inside the battery pack. Another critical feature of BMS is thermal management. BMS need to ensure battery pack remains in optimum operation conditions by creating the necessary heating or cooling decisions [44].

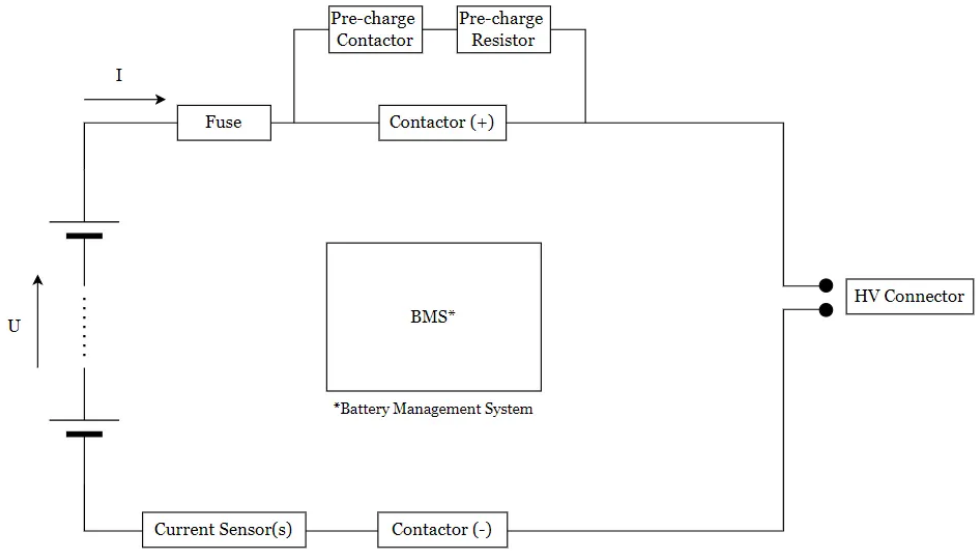

Figure 2.10 : EV Battery pack architecture [48].

BMS controls the contactors inside the battery pack that is used for connecting or disconnecting the high voltage (HV) link from the rest of the components in EV. While BMS constantly monitor cell status, it is also responsible for fault detection like in terms of under voltage, over voltage, over current, over temperature or related to SOC and SOE. Based on the detected fault BMS can take the reaction it self like by reducing

maximum power limits or even disconnecting the contactors. BMS also reports the fault status to rest of the EV's component so that in case of fault necessary actions can be taken by different controllers as well.

2.4 Battery Performance and Charge Duration

EV batteries, typically lithium-ion, are complex systems where electrochemical processes are highly sensitive to temperature variations. Optimal battery performance requires maintaining the battery temperature within a specific range during charging and discharging. Deviations from this optimal temperature range can lead to a variety of issues, including increased charging times, reduced energy efficiency, accelerated battery degradation, and safety risks such as thermal runaway.

Charge duration is an important factor for the users when considering using EVs for long distance travels. Considering a EV with 350 km real range on 600 km travel requires at least one time charging. In order for this situation not to be an inconvenience for the user, charging duration shall be as short as possible. Maximum charging power for electric vehicles directly related to battery pack specifications. Manufacturers list their maximum charging power in the EV's specifications for marketing.

Table 2.4 : Maximum charge power for some electric vehicles.

Model	Maximum Charge Power [kW]	10-80% SOC Charge Power [kW]
Porsche Taycan Plus	320	230
Hyundai IONIQ 6	233	200
Volvo EC40	205	125
Tesla Model Y	175	140
BYD SEAL AWD	150	95

For example a list of EVs and their charge power is given in Table 2.4. One of the key challenges in EV battery technology is managing the thermal environment during high-power charging. Fast charging is essential for improving the convenience and practicality of EVs, but it generates significant heat due to increased current flow. If not properly managed, this heat can lead to elevated battery temperatures. The state-of-charge (SOC) and temperature of the battery are interdependent factors that influence each other during charging.

High temperatures can accelerate the electrochemical reactions, potentially shortening the charge duration but also increasing the risk of degradation and safety hazards like thermal runaway. At low temperatures, the performance of lithium-ion batteries is significantly reduced due to several factors. When the battery is in a low-temperature environment, viscosity in the electrolyte increases and lithium ions mobility slows down thus increasing internal resistance of battery. Because of these phenomena lithium ion batteries works with limited performance in cold ambient temperatures [49].

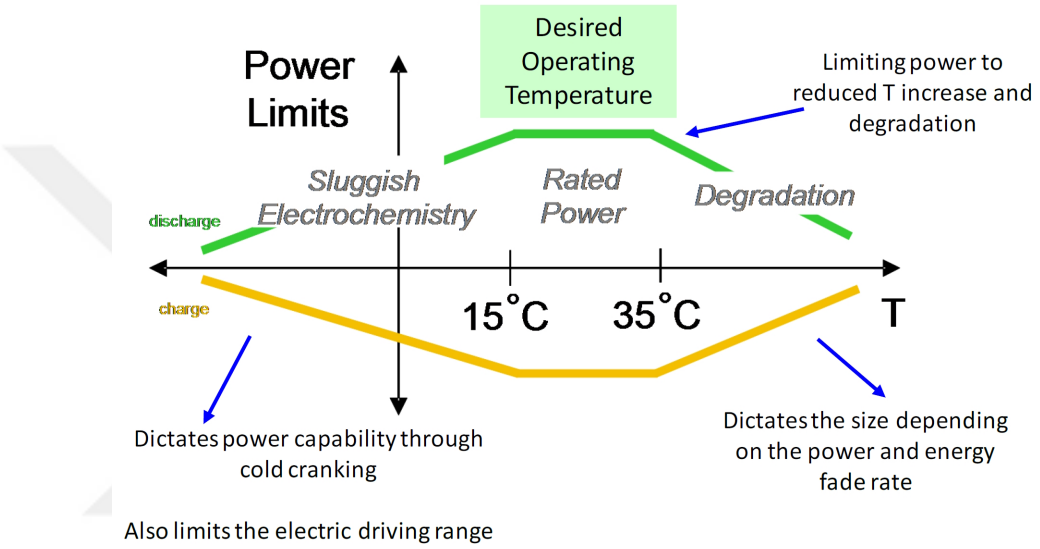

Figure 2.11 : Temperature effect on battery performance [50].

TMS play a crucial role in maintaining battery temperature within the desired range. It is designed to provide needed heating or cooling for battery pack and ensure uniform temperature distribution across the battery pack thus increasing the performance of the vehicle even at extreme ambient conditions.

3. THERMAL MANAGEMENT FOR ELECTRIC VEHICLES

Thermal management is essential for every EV for ensuring the performance, efficiency, and reliability of the system. All powertrain components in the system will require cooling or heating needs during operation according to operating conditions. TMS responsibility is to provide the required heating or cooling to components and also having optimized power consumption at the same time in order to maximize the range of EV.

EVs uses mostly three different approach for thermal management. These are air cooling, liquid cooling and cooling with phase changing materials (PCM). Liquid cooling based method has advantages in terms of performance over the other methods. These can be listed as compactness, better thermal conductivity and bidirectional heat transfer capability [51]. That is the reason for most passenger EVs have liquid cooling based thermal system for the powertrain components.

An example of thermal layout of an EV is given in Figure 3.1. Thermal layout of EVs usually divided into two cooling circuits and one refrigerant line. One cooling circuit for battery and one for the rest of the powertrain components like EDU, DC/DC converter and on board charger (OBC). In some applications these two cooling circuits can be combined with a valve.

3.1 Thermal Management Components

Thermal layout consist of components such as water pumps, valves, radiator, positive temperature coefficient (PTC) heater. On the refrigerant line, there is compressor, expansion valve, shut off valves, condenser, chiller and evaporator. Also for the radiator there is a radiator fan and usually an active grill shutter (AGS) to control air intake in front of the radiator [52].

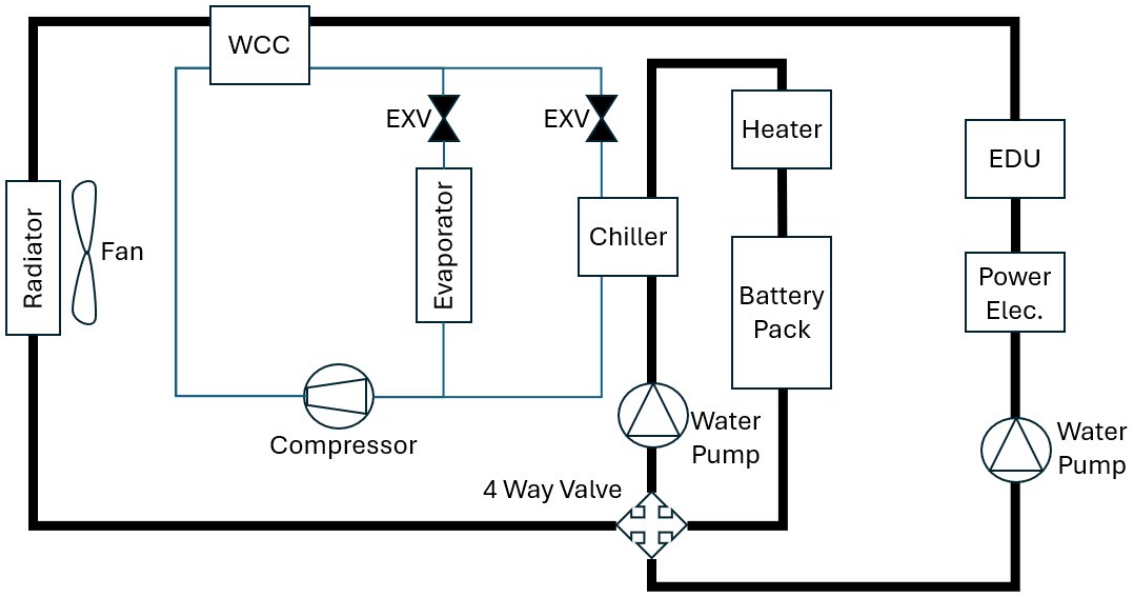

Figure 3.1 : Example thermal layout of an EV.

3.1.1 Valves

Valves are used to direct coolant through desired line or lines. There are different types of valves that is used in thermal system of EVs. For example a 3 way valve can be used as bypass valve for radiator and 4 way valve can be used to select merging or separating the battery circuit and EDU circuits [52].

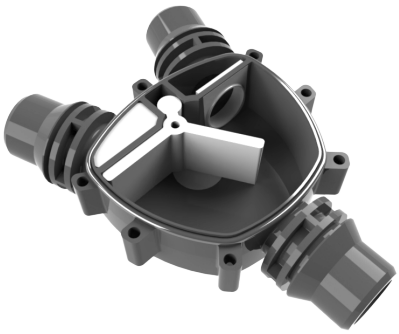

Figure 3.2 : 3 way valve [53].

3.1.2 Radiator and AGS

Radiator, radiator fan and AGS is used to control the heat transfer between coolant line and ambient. AGS position can be controlled according to air mass flow need

for radiator cooling while driving. If the system needs to heated up, AGS can be closed in cold ambient conditions to prevent heat dissipation to environment. If system needs cooling, AGS can be opened to increase heat dissipation. But opening the AGS increases the vehicle drag losses. Therefore while controlling the AGS position, balance between drag losses and air mass flow needs is taken into account [54].

Figure 3.3 : Radiator and AGS [55,56].

3.1.3 Radiator fan

Radiator fan provides forced air through the radiator that increases heat transfer between radiator and the environment. Fan is operated when there is a high demand of cooling required and air mass flow for radiator is insufficient. This can usually happen in standstill conditions where there is no air mass flow from the environment is coming and some components on the vehicle needs cooling. In terms of energy efficiency, it is important to balance cooling power and fan usage. For this purpose, while driving where vehicle speed is higher than some threshold, fan is turned off because air mass flow coming from the environment is usually enough to not operate fan anymore [54].

3.1.4 Water pumps

Water pumps are responsible for circulating the coolant through the cooling circuits. Water pumps are essential part of thermal management system because it supplies the required coolant volume flow in order to cool or heat the component effectively. Volume flow effects the heat transfer between components and coolant liquid. This can be controlled via controlling the water pump speed [52].

Figure 3.4 : Radiator fan [57].

Volume flow needs for the system changes according to operating points of components and environment conditions. In idle conditions when the components are at normal operation temperatures, water pump speeds can be kept at minimum to reduce the power consumption. This shall be taken into account while determining the individual pump speeds in the system.

Figure 3.5 : Water pump [58].

3.1.5 PTC heater

PTC heater consists of resistive elements that heats the coolant. Resistance of the material inside the PTC heater increases with the component temperature. Thus the current or power draw also limited by increasing resistance, this property provides a self regulating safety feature for PTC heaters. PTC heaters are generally used to supply

heated coolant for battery heating and cabin heating. PTC heating power can change in between 5 kW to 10 kW. It is controlled via pulse width modulation so that different heating powers can be supplied according to component needs [59].

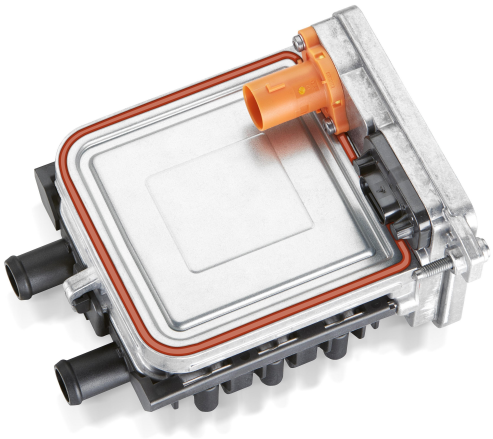

Figure 3.6 : PTC heater [60].

3.1.6 Compressor and chiller

Compressor is used to pressurize refrigerant gas and circulate it throughout the refrigerant line. This refrigerant absorbs warmth from the cabin via evaporator or from battery via chiller, chills it, and after that disperses the accumulated heat outside of the vehicle via air or water cooled condenser.

Battery chiller is responsible for heat exchange between refrigerant line and coolant line. Battery chiller can be activated or deactivated via shut off valve or electronic expansion valve. Electronic expansion valve (EXV) can determine how much refrigerant can pass through the chiller so that heat exchange in the chiller can be controlled. Shut off valve works like an on off valve for refrigerant line. It lets the refrigerant pass through when it is switched on and blocks it when it is off. This provides a flexibility in the system so that battery and cabin cooling can be activated or deactivated separately with using one compressor and refrigerant line.

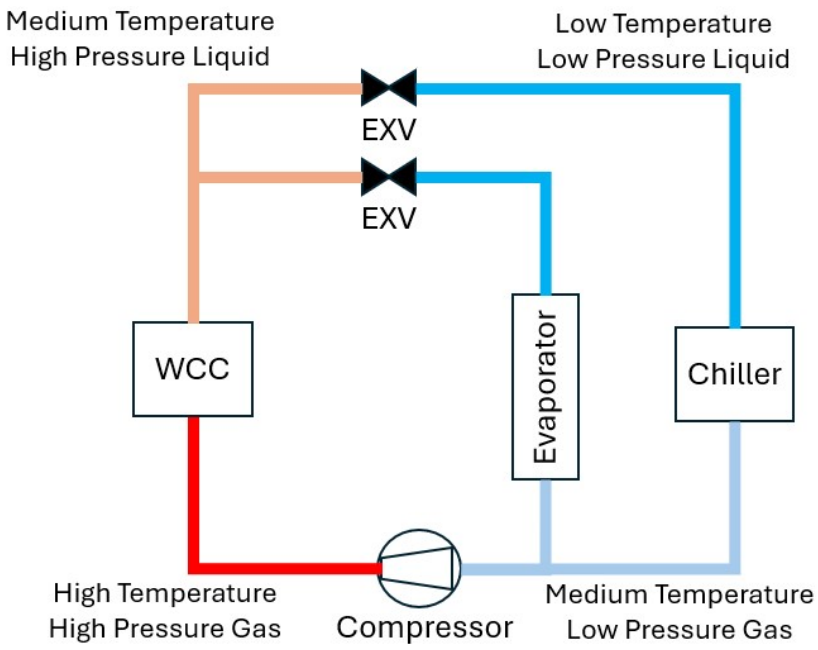

Figure 3.7 : Compressor refrigerant line.

The main goal of the thermal management is to balance the energy consumption and cooling or heating performance of the vehicle by controlling these components in the thermal layout effectively.

3.2 Thermal Management for Electric Drive Unit and Power Electronics

Electric motors for automotive applications are evolving towards higher power and energy density, greater efficiency, reduced mass, compact size, and lower cost. EDU consist of electric motor and motor controller unit in a compact package. Effective thermal management is very important for optimizing EDU's performance and durability of the component. Various loss mechanisms contribute to heat generation in EDU, including copper losses, iron losses and friction losses. Different cooling methods, such as cooling at the stator core, stator winding or end winding, can be selected depending on the motor's design and requirements [59].

Power electronics consist of DC/DC converter and OBC. These components usually combined and packaged in a small form factor. Thus these components require thermal management in order to operate at safely and without creating any hot spots. Coolant temperature requirements of OBC and DC/DC converter are similar to EDUs

as generally around 60 °C. Because of this they can be connected to same cooling loop as series or parallel with the EDUs.

DC/DC converter has lower heat load compared to OBC and EDU so during operation EDU creates more demand for cooling because of higher losses. OBC's on the other hand does not create power losses while vehicle is in driving conditions so it does not affect the cooling system. OBC only works during AC charging, where EDU has no power losses. Cooling system for these components are sized considering these cases.

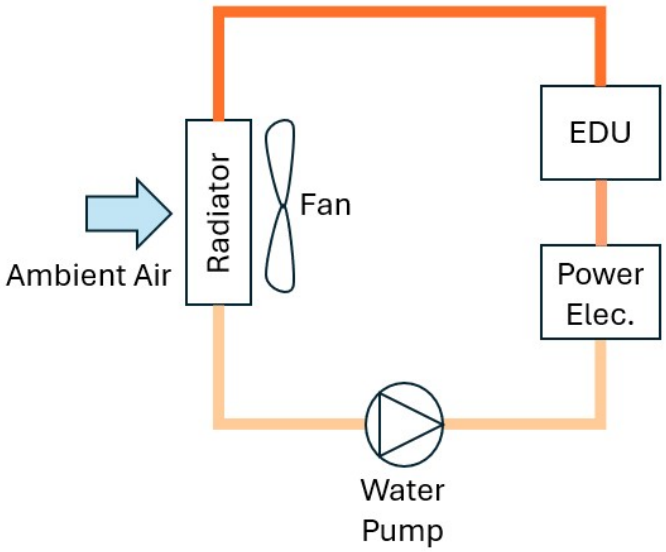

Figure 3.8 : EDU and power electronics cooling circuit.

Cooling circuit for EDU and power electronics consist of a water pump and radiator. Coolant used to take the heat from the components and dissipate the heat to environment through radiator. In order to manage heat in the components, water pump, radiator fan and AGS can be controlled. Stator, rotor, inverter heat sink or junction temperatures, DC/DC converter and OBC component temperatures are considered for controlling these actuators in the cooling circuit.

3.3 Battery Thermal Management System

Non-uniform temperature distribution within a battery pack can cause electrochemical imbalance, accelerating capacity loss and premature aging. Battery thermal management systems are essential for preventing thermal runaway occurrences and increasing the life time of battery packs.

Battery thermal management methods include air cooling, phase change material (PCM) cooling and liquid cooling. Air cooling is advantageous for its simplicity and low cost. Air cooling systems are ideal for small scale battery packs or for battery pack that discharges at lower power rates. For larger battery packs requiring high power output or operating in extreme ambient temperatures, air cooling may not be sufficient to meet desired thermal needs [61].

PCM based cooling enhances cooling capacity by adding a skeleton to paraffin or using highly conductive filler materials. PCMs can achieve great thermal performance but they are not ideal for such cases like high current charging or discharging, or operating in high ambient temperatures [52].

Liquid cooling, using cooling plates to separate coolant from batteries, can be optimized for different battery pack layouts. With liquid cooling of battery pack, cooling circuit is combined with the vehicles air conditioning system so that it can benefit from chilled coolant through the battery. Also for heating same air conditioning system or separate heating elements can be used in the thermal layout to provide heated coolant to battery. This combined solution can decrease the cabin cooling or heating performance according to systems designed capacity and operating conditions while both battery and cabin requests are active at the same time.

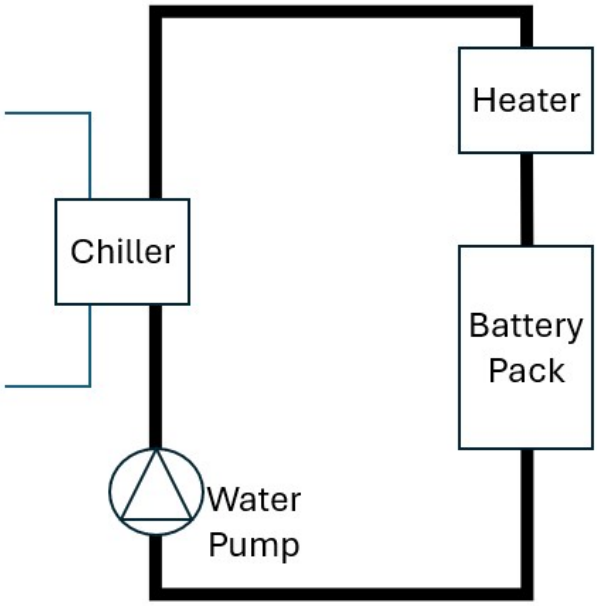

Figure 3.9 : Battery pack parallel operation.

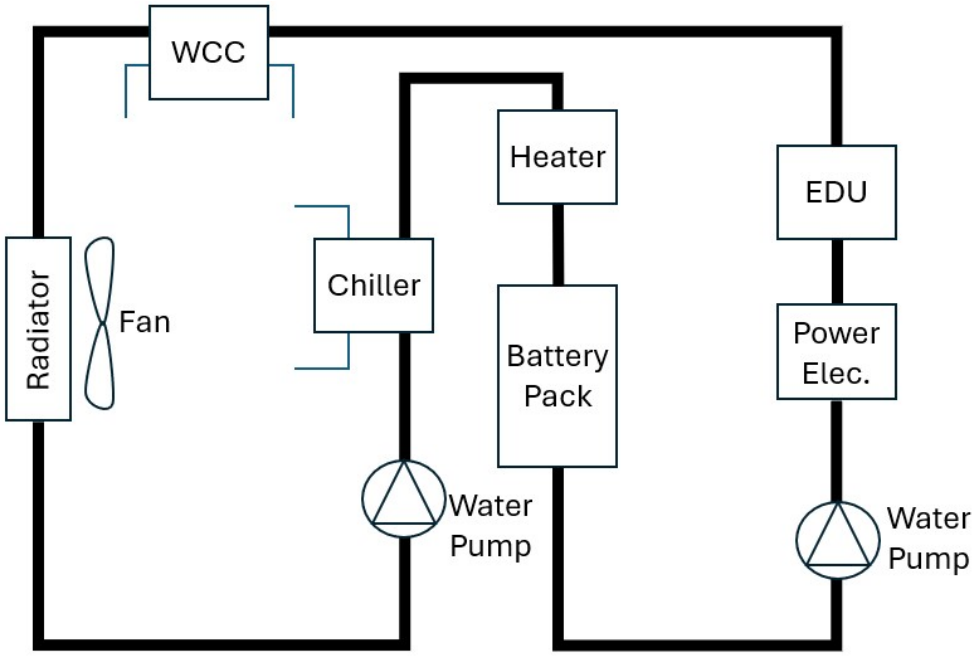

Figure 3.10 : Battery pack series operation.

Battery packs used in electric passenger cars differs in terms of size and cell choices. But generally battery packs are the largest components in the EVs. This also means that in terms of heat capacity they are also the largest in the system. Because of their large heat capacity it takes large amount of heat to increase or decrease the battery packs temperature. Because of this nature, battery cooling circuit can be separate from the EDU and power electronics circuit and can work in idle conditions by only circulating the coolant without the need of any active cooling or heating. But for some systems, it is designed to work in series connection with EDU and power electronics circuit. This is controlled via valve dynamically with respect to operation conditions of battery and temperature of the coolant in EDU and power electronics circuit. While it is increasing the system complexity, when the battery needs heating, it can benefit from EDU and power electronics circuit if the conditions are met. This may help to regulate the heat in both circuits efficiently without the consumption of energy needed for heating.

Since the vehicle's air conditioning system combined with battery circuit, chiller provides the chilled coolant through battery when battery needs cooling. Compressor is controlled according to battery packs cooling power needs in order to provide necessary cooling. For the cases where both battery and cabin requires cooling, compressor can be utilize to provide both cooling powers. But in some cases

compressor power may not be enough to provide sufficient cooling for both cabin and battery pack. This requires some arbitration and prioritization logic to implement in order to control how much cooling will be supplied to which component.

Similarly for heating conditions, PTC heater or heat pump can be utilized. Heat pump is a reverse air conditioning cycle that takes the heat from environment and provides the heated coolant to battery pack or cabin. Heat pumps are more efficient compared to PTC heaters because with less power consumption more heat transfer can be achieved. On the other hand heat pump implementation requires some extra valves in the system to control coolant flow direction and increases system complexity.

3.4 Thermal Management Control Methods

Thermal management system can be complex and have real time impact on the EV safety and performance, thus it requires robust control topology to ensure that system is working efficiently in desired operating conditions. Since components heating and cooling needs also differ from each other, control methods for thermal management can be different for each component.

For EDU and power electronics, heating losses occurs instantaneously and since the components have less heat capacity compared to battery, they can heat up quickly under load. This requires faster more responsive methods in order to dissipate heat and provide necessary cooling for these components.

For battery pack, since the heat capacity is large, component temperature increase and decrease requires large amount of heat energy. Because of this, less dynamic and stable control can be used for battery pack thermal management. Since the heating or cooling characteristic is less dynamic, long term predictive approaches are more suitable for battery pack thermal management.

Thermal management control methods can be categorize as in, rule based control, model based control and optimum control [10].

3.4.1 Rule based control

Rule based controller is a type of control system that operates based on predefined rules or conditions. This method can be used in every part of thermal system because of its simple and adaptable property. In order to provide robust thermal management, rules have to be created based on strong system knowledge. These set of rules usually calibrated based on the tests in various operating conditions. Controller inputs can be temperature of components, coolants and environment, pressure of refrigerant system, vehicle modes like driving or charging, cabin cooling request or heating request. According to such inputs, controller can decide on the thermal components like water pump, fan, valves, compressor, PTC heater. Advantage of this method is simplicity and robustness. Controller can react based on real sensor measurements and adapt its actions based on changing operational conditions. But achieving an efficient or optimum solution with this method requires excessive trial and modification on the rule sets or conditions [20].

Table 3.1 : Example rules for rule based controller.

Conditions	Cooling State	Heating State	Pump Speed
T<5	Off	On	High
5<T<33	Off	Off	Low
33<T	On	Off	High

For battery thermal management, rule based controller can be used to determine when to activate heating or cooling and how much coolant flow rate needed. Rules can be created according to battery pack's optimum operation temperatures while considering the energy consumption for thermal management. Balance of these two parameters are important in terms of EV's performance and range. In order to reduce energy consumption for thermal management, system can compromise on some performance in such cases.

3.4.2 Model based control

Model based control involves using models of the thermal system to predict its behavior or calculate some heating or cooling needs to reach desired operation

conditions. System model can be developed using physical principles such as heat transfer equations, fluid dynamics, and thermal properties of materials. These models can output how the system reacts over time and in response to inputs like heating, cooling and environmental conditions. Other than physical approach, system can be modeled using neural networks. Neural networks can model complex system using real world measurements with training. These models can be used where creating the system model based on mathematical model is hard or requires computing intensive power. Once the model is developed, it can be validated using real world measured data obtained from the thermal system in order to ensure that the model accurately represents the system [10].

By using the system model, thermal control signals can be created such as target inlet coolant temperature or required heating or cooling power. These control signals than can be used as input for a closed loop control system. For example, calculated target inlet coolant temperature can be an input for radiator fan closed loop controller. With this method, models can predict systems behavior under different operating conditions which than be used to achieve efficient thermal management control.

3.4.3 Optimum control

Optimum control methods aim to optimize the performance of a system by determining the control inputs that minimize or maximize a specified objective function. Optimum control is about finding the ideal control inputs over time to achieve desired system behavior while optimizing specific objectives. Optimum control methods use some optimization techniques to find these optimal solutions. Optimum control methods are generally requires system modeling in order to predict its future behaviour. These optimum control methods can be listed such as, gradient based methods, dynamic programming, MPC, linear quadratic regulator (LQR) and RL [62].

MPC is widely used in researches for thermal management in EVs. It uses horizon data to find global optimum for a defined cost function. It requires accurate system model in order to predict system behaviour. Each time step MPC solves an optimum control problem to determine its next action. Any inaccuracy in the system model can lead to sub optimal solutions.

RL is a machine learning technique that an agent makes decisions by interacting with an environment to maximize cumulative reward. Training required for agent to learn from trial and error without knowing any prior information related to system. RL algorithms requires large number of interactions with the environment in order to find an optimal policy. Unlike MPC, RL controller does not need precise model of the system, it can self-learn and optimize strategies by interacting with the environment, which makes it applicable for complex and dynamic problems [21].

RL is a learning based approach where the controller learns optimal behavior through trial and error to maximize a reward metric. It handles complex systems and adapts to dynamic environments but requires extensive training and generally there is no option to set hard constraints directly. In contrast, MPC uses a prediction model to solve an online optimization problem at each time step, providing the flexibility to handle hard constraints and nonlinear dynamics. MPC's runtime optimization makes it computationally intensive, especially for nonlinear systems. While LQR is computationally efficient with in runtime, it lacks the flexibility to handle hard constraints and non-linearities, making it less versatile than MPC but more easy to implement than RL [62].

4. REINFORCEMENT LEARNING FOR OPTIMUM CONTROL

Optimum control strategies ensure that systems operate at maximum efficiency, minimizing waste and energy consumption. This is crucial especially in EV applications like energy management or thermal management, where efficient use of resources can lead to improvements on vehicle's range.

ANNs are widely used in optimal control for their ability to model complex, nonlinear systems and learn from data. ANNs can be trained to model a system especially when the system is too complex for traditional mathematical modeling techniques. ANNs can also be used to predict future states of the system and optimize control inputs over a prediction horizon.

4.1 Artificial Neural Networks

ANNs are computational models created with the inspiration of biological neurons of the human brain. ANNs are well-suited for capturing complex, nonlinear relationships, making them commonly applied to recognize patterns and classify objects vision and control systems.

They consist of input layer, hidden layers and output layer. Input layer receives input data, which could be numerical values, images, text, or any other form of structured data. Hidden layers consists of neurons that process the input data through weighted connections and apply activation functions to produce outputs. Output layer Produces the final output based on the computations performed in the hidden layers. The output could be a classification decision, regression prediction or any other type of computation [63].

ANNs can be trained using a process called supervised learning, where the network learns from labeled input-output pairs provided in a training dataset. At each step of training an algorithm adjust the weighs in the ANN in order to minimize the error between actual labeled output and predicted output [63].

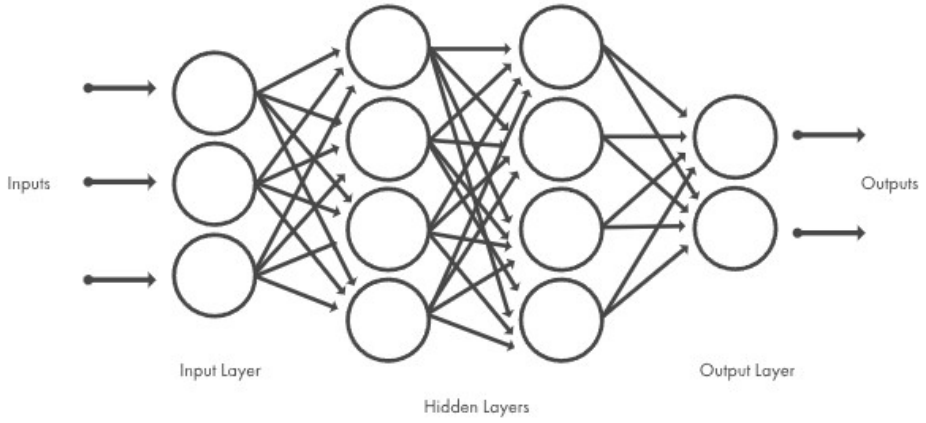

Figure 4.1 : Typical ANN architecture [64].

ANNs can be adapted to used in the fields like aerospace, automotive, robotics and industrial processes. The challenge for the ANNs is that they require large amount of data for training. Training can be computationally intensive especially in case of large neural networks and working with large data. Despite these, the use of artificial neural networks in optimal control is a growing area with great potential to enhance the performance and capabilities of various control systems across different industries.

4.2 Reinforcement Learning Controller

In RL, ANNs are used to create a policy, which maps states to actions. The neural network learns to output the optimal action for a given state based on the experience. The agent explores actions, learns from rewards, and updates its policy to find the optimal control strategy.

The difference in RL compared to other machine learning architectures is that it doesn't require supervisor while training. That means there is no training data that shall be labeled or processed in order to feed into neural network. The training is done by creating a reward function. RL outputs series of decisions in order to get maximized cumulative reward, which makes it suitable for optimum control applications where actions may affect the future state of the system. In the RL training process, actions taken by the RL is also affecting the inputs going into RL because of environment reacts to the actions directly.

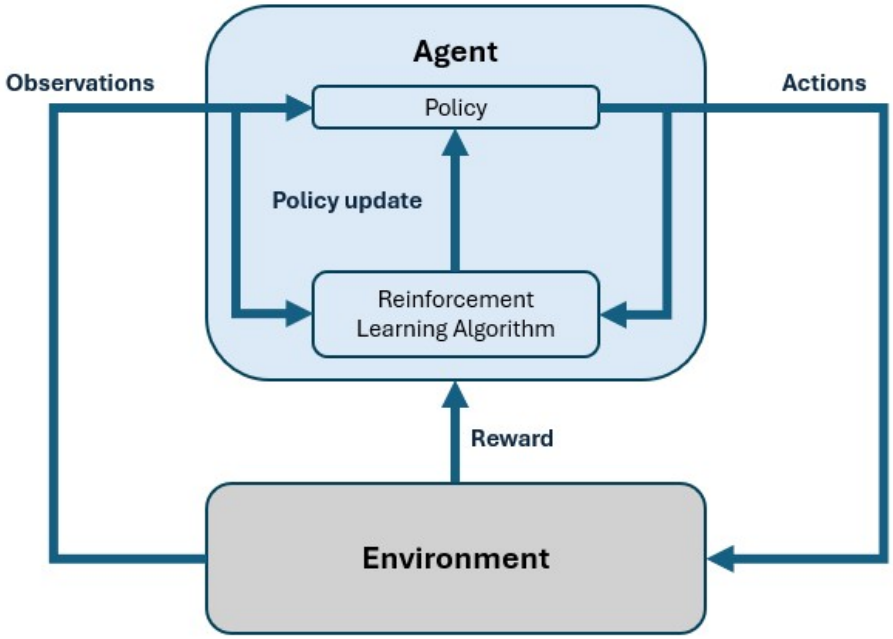

Figure 4.2 : RL architecture [64].

A reinforcement learning agent is part of a reinforcement learning framework that interacts with an environment to learn and make decisions. There are different types of RL agents based on how they learn, complexity and decision making process.

4.2.1 Reinforcement learning agents

Before going into detail with the agent types, two terms must be explained in order to understand agents differences better. These are exploration and exploitation. Exploration involves taking actions that the agent is uncertain about to gather more information about the environment. These actions may not always give the highest immediate reward but are necessary to discover potentially better long term strategies. Exploration is important especially in the early stages of learning or when the agent encounters new states or situations. It helps the agent gather data about the environment, learn about the consequences of its actions, and refine its policy over time. Exploitation is taking actions that the agent believes will give the highest reward based on its current policy or knowledge. These actions are chosen to maximize the agent's performance according to its current understanding of the environment. Exploitation is essential once the agent has gathered sufficient knowledge through exploration. It focuses on maximizing the cumulative reward with the help of learned

policy to make decisions that are expected to give the best outcomes based on past experience [65].

Reinforcement learning agents are categorized as on-policy and off-policy agents related to how they learn and update their policies [66]. On-policy agents learn and improve their policy while interacting with the environment using the current policy. They evaluate and update the policy based on the current behavior and typically use the same policy for exploration and exploitation. Off-policy agents learn and improve their policy based on data collected from a different policy than the one being optimized. They can learn from experiences generated by any policy, not just the current one. Off-policy methods can separate exploration from exploitation, which can lead to more efficient learning [64].

The key differences for on-policy and off-policy agents, off-policy methods can use different experience sources like past experiences generated from any policy, whereas on-policy methods can only use the current policy as source of experience. The decision for choosing between on-policy and off-policy methods may depend on environment model complexity, exploration and exploitation balance. Both type has their advantages and are suited to different reinforcement learning applications.

Another category in the RL agent type is discrete actions space agents and continuous action space agents. In discrete action space, set of actions that agent can take are finite, which agent makes a choice from defined actions in discrete values. For continuous action space, agents can take infinite actions within a defined range rather than discrete values. With the environments that actions can be defined as discrete values, it is viable to use discrete action space agents. Continuous action space agents are suitable for applications where it is required control precision with continuous actions [64]. Comparison for different type of RL agents have been provided in Table 4.1.

4.2.2 Reward function design

In order to RL model to learn something it needs to maximize the cumulative reward that it is getting from the system. That is why reward function is critical when it comes to performance of the RL. Rewards should reflect the desired outcomes and

Table 4.1 : Comparison between different type of RL agents [64].

Agent Name	Agent Type	Action Space	Ease of Tuning	Robustness
PPO	On-Policy	Discrete or Continuous	Hard	Good
DDPG	Off-Policy	Continuous	Easy	Moderate
DQN	Off-Policy	Discrete	Easy	Moderate
SAC	Off-Policy	Continuous	Moderate	Good

aligns with the ultimate goals of the task. While keeping the ultimate goal, reward function should be simple as possible in order for tuning and debugging. In order to reduce training times, rewards shall lead the RL to desired outcomes by encouraging them and it shall penalize the agent for the undesired actions in order to discourage the agent for not repeat them. Ultimate goal can be achieved in the end of simulation but while reaching that goal, reward function shall give some rewards at each intermediate steps in order to guide RL for desired output. If the rewards are given only in the end, it will make learning process very long and difficult. Also reward functions shall not create any possibility for shortcuts. For example it may be penalizing RL for doing certain actions, but doing nothing altogether may lead to better reward. In that case RL will learn to do nothing instead of trying and it will lead to non optimal solutions.

5. SYSTEM MODELING AND SIMULATION

In order to investigate charge performance with reinforcement learning (RL) controller for battery thermal management, system model has to be created in simulation environment. In order to investigate the relation between charge duration and battery temperature, environment temperature selected for this research is between 0°C to 35°C increment by 1 degree. A drive cycle is selected that simulates a driving case for 20 minutes to reach charging station. After reaching the charging station, vehicle directly starts charging and continues to charge until 70% SOC. This SOC value is selected due to battery charge characteristics usually decrease the allowed power after around these SOC values. Along with the RL controller, rule based control approach also implemented for comparison. For this study, Matlab/Simulink environment is used for the modeling and simulations.

System model consists of vehicle dynamics model, components electrical, thermal models and thermal system model. Thermal layout selected for this research is having separated operation for battery coolant circuit and EDU circuit, power electronics cooling circuit. In this layout there are three components to be controlled by the RL controller, compressor for cooling, PTC heater for heating and a water pump for circulating the coolant through the loop.

5.1 Vehicle Dynamics Model

Vehicle dynamics model is needed in order to calculate how much forces are acting on the vehicle for a given speed and road conditions. Based on the goal of vehicle dynamics model, complexity of the model can be determined. Aim with the vehicle dynamics model for this research is to get needed desired wheel torque based on the speed input. Linear single track model is used because of it's simplicity. With this model, vehicle load shifts, rolling and pitching motions are neglected. Since the

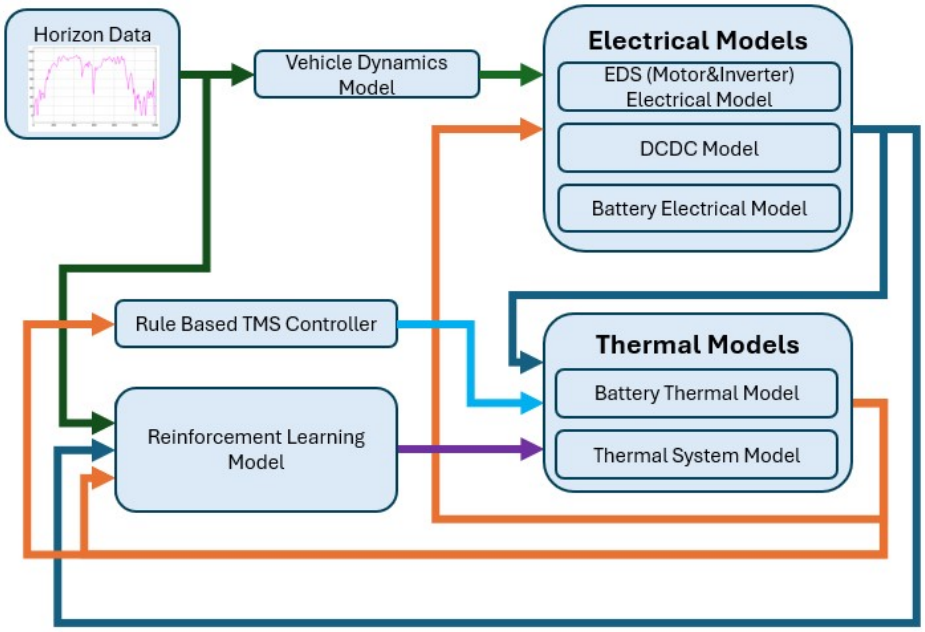

Figure 5.1 : System model in simulation environment.

steering is also not in the spec of this study, only longitudinal forces are taken into consideration [67].

Longitudinal forces includes the air drag forces, tire forces and force caused by acceleration. Since the road slope considered zero for all drive cycles, that calculation also is not included in the model.

$$F_W = \frac{1}{2} c_W A \rho_{Air} V^2 \tag{5.1}$$

In equation 5.1 shows the air drag force F_W is depending on air resistance coefficient of the vehicle c_W, air density ρ_{Air}, front cross sectional area of vehicle A and velocity of the vehicle vehicle V [67].

The rolling resistance force of the tires F_{rr} can be calculated as in equation 5.2. It depends on the tires rolling resistance coefficient cc_{rr}, vehicle mass m and g as gravitational acceleration [67].

$$F_{rr} = c_{rr} m g \tag{5.2}$$

Acceleration force F_a can be calculated as in equation 5.3 based on the vehicle mass m and a as acceleration of vehicle [67].

$$F_a = m\,a \tag{5.3}$$

After calculating the F_W, F_{rr} and F_a, the total longitudinal force F_{total} applied on the vehicle can be calculated as in equation 5.4. Than F_{total} can be converted into electric motor shaft mechanical power using vehicle speed V in m/s and transmission efficiency η_{tr}. While calculating the motor mechanical power, propulsion power $Pm_{MecProp}$ and regeneration power $Pm_{MecRegen}$ shall be separated. Because while EVs are decelerating, they use electric motors for regeneration to create negative force on the wheels. But they use also friction brakes according to their strategy while braking as well. In order to get more realistic regeneration power, during braking, 80% of the power is taken as regeneration by assuming 20% is used by friction brakes. Also during regeneration, because of power flow direction changes, this is taken into consideration by multiplying the transmission efficiency η_{tr} instead of dividing in equation 5.6.

$$F_{total} = F_W + F_{rr} + F_a \tag{5.4}$$

$$Pm_{MecProp} = \frac{F_{total}\,V}{\eta_{tr}} \tag{5.5}$$

$$Pm_{MecRegen} = \frac{80}{100}\,F_{total}\,V\,\eta_{tr} \tag{5.6}$$

Equation 5.5 is only calculated during vehicle acceleration is greater than zero and equation 5.6 is calculated during only vehicle acceleration is less than zero. This way total of these two calculations gives the total mechanical power on electric motor shaft Pm_{mec} as in equation 5.7.

$$Pm_{mec} = Pm_{MecProp} + Pm_{MecRegen} \tag{5.7}$$

In order to calculate the motor shaft torque T_{motor}, angular velocity of motor shaft speed ω needs to be calculated. Angular velocity is directly converted from the vehicle speed using the transmission ratio i_{tr} and tire diameter R_{tire} in equation 5.8. Motor speed calculation is also given in equation 5.9.

$$\omega = \frac{V\, i_{tr}}{R_{tire}} \tag{5.8}$$

$$n_{motor} = \frac{\omega 60}{2\Pi} \tag{5.9}$$

After calculating the angular velocity of the motor shaft, we can convert the mechanical power into motor shaft torque Tq_{motor} as given in equation 5.10

$$Tq_{motor} = \frac{Pm_{mec}}{\omega} \tag{5.10}$$

5.2 Component Electrical Modeling

Components electrical models are needed to calculate power, current, SOC like signals for the system. These models are created according to the needs in the environment.

5.2.1 EDU electrical model

EDU model is needed for the conversion from mechanical power that is used for the axle to consumed electrical power. Mechanical power, motor torque and motor speed are already calculated in the vehicle dynamics model. In order to calculate electrical power consumption, EDU losses must be considered.

Usually supplier or third parties perform bench testing for particular EDU in order to get efficiency maps. These maps can be provided for certain operating conditions like voltage and temperature, by covering all torque and speed region of motor. For this research, supplier data for the efficiency maps have been used for selected EDU. For calculation of consumed electrical power by EDU, these efficiency map is used. It is used as a look-up table to get working efficiency according to torque and motor speed. With the operating efficiency of EDU η_{EDU} taken from the table, mechanical power

can be converted into electrical power Pm_{elec} that EDU consumes in equation 5.11. Efficiency map of the EDU is given in Figure 5.2.

$$Pm_{elec} = \frac{Pm_{mec}}{\eta_{EDU}} \tag{5.11}$$

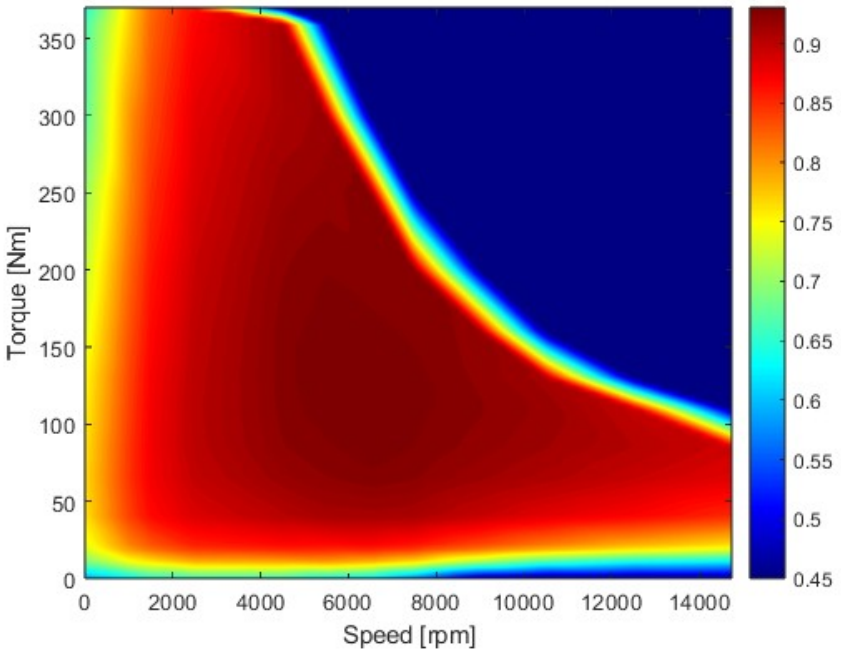

Figure 5.2 : EDU efficiency map.

5.2.2 DC/DC converter electrical model

DC/DC converter is a component responsible for supplying low voltage to system by converting it from HV battery. In order to find DC/DC power consumption from the battery pack, first low voltage (LV) system power consumption needs to be calculated. In the system, there is one EDU circuit pump and battery circuit pump that is operating from LV system as major components. For the electronic controller units and auxiliary electrical consumption like lights and entertainment, a constant power consumption is selected. Radiator fan power taken as zero since vehicle is moving at highway speeds, air mass flow coming to the radiator is assumed to be enough to not operate the fan.

Once the actual LV system power consumption is calculated, it can be converted into HV power consumption using DC/DC converter efficiency factor. This information taken from the component specifications as a constant factor. DC/DC converter's

power drawn from the battery P_{dcdc} is calculated in equation 5.12 using auxiliary power consumption P_{aux}, divided by DC/DC converter efficiency factor η_{dcdc}.

$$P_{dcdc} = \frac{P_{aux}}{\eta_{dcdc}} \tag{5.12}$$

5.2.3 Battery pack electrical model

In order to calculate battery pack temperature and SOC, battery current has to be calculated. That is why battery electrical model is needed. For calculating the battery current Rint model is used. Rint model uses an voltage source and a internal resistance to model the cell behaviour. This model is used due to the reason that less parameters needed in order to create a sufficiently accurate model with Rint [68].

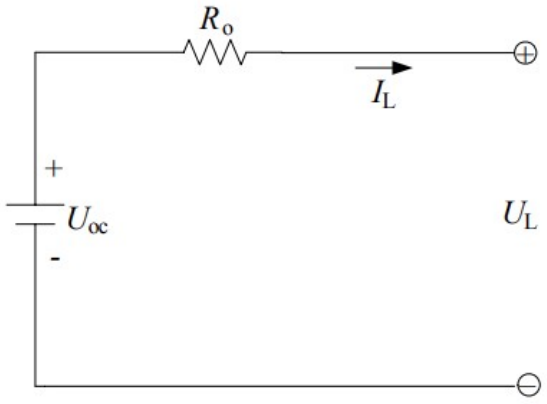

Figure 5.3 : Battery equivalent circuit Rint model [68].

Internal resistance of the battery pack is depending on the temperature and SOC of the battery. Resistance values taken from the battery pack specifications and used as a map with two axis, one is temperature and the other one is SOC. SOC and temperature values are calculated separately and input to this map to get the respective internal resistance value of battery pack. Using the Rint model battery pack current output I_{batt} is calculated as in equation 5.13.

$$I_{batt} = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4\,P_{batt}\,R_{int}}}{2\,R_{int}} \tag{5.13}$$

$$P_{batt} = Pm_{elec} + P_{dcdc} + P_{therm} \tag{5.14}$$

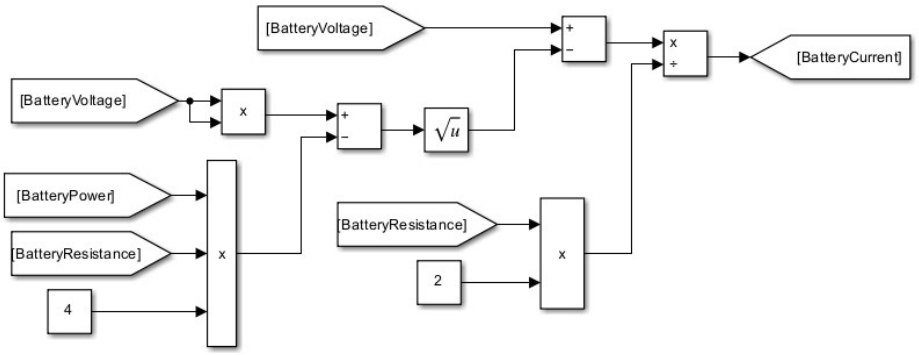

Figure 5.4 : Battery current calculation.

Total power consumption is calculated as in equation 5.14 via other components electrical models and this is used to calculate battery current. For SOC calculation, ampere-hour counting mechanism is used. By calculating how much energy consumed or given to battery and adding it to the last energy calculated, actual available energy can be calculated. Using this actual energy calculation and diving it with the rated capacity of the battery, battery SOC is calculated [68].

In order to simulate charging case, battery charge current shall be determined. A look up table taken from battery supplier data is used for calculating the corresponding charge current based on the calculated battery pack SOC and temperature values. Charge current map of the battery pack depending on the temperature and SOC is given in Figure 5.5.

5.3 Thermal System Modeling

Thermal layout selection is done in order to simplify the system design and RL controller control outputs. Battery system cooling loop is completely separated from the EDU cooling loop, which is not completely foreign, it is used in some vehicles. With this layout there are three possible working conditions for battery like following, heating with PTC heater, cooling with chiller and idle operation. In idle operation no cooling or heating is done, coolant is circulated in closed loop system without providing any heat exchange from outside source. In idle operation flow rate can be kept minimum just enough to balance the heat inside the battery pack equally, thus reduces the pump operation and energy consumption. Since there is no valve in the

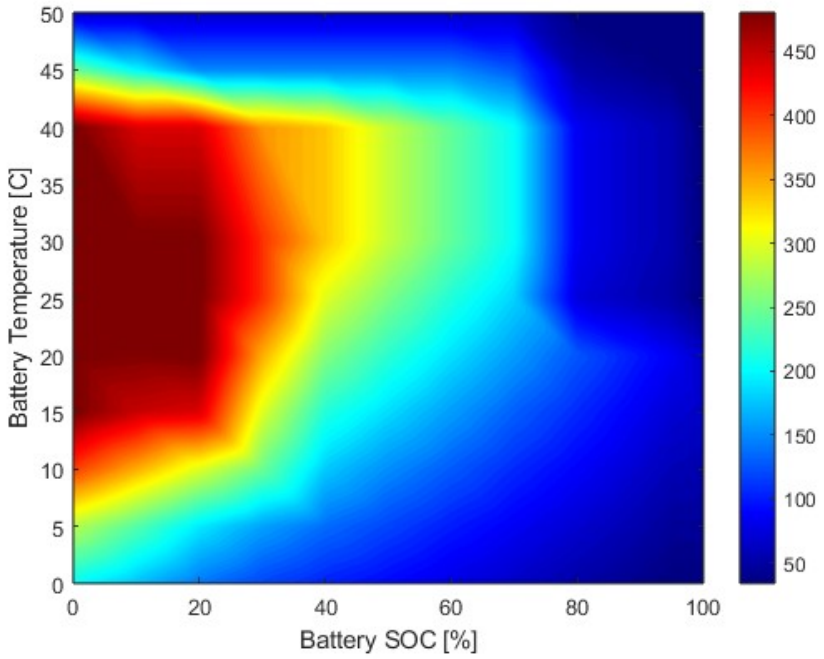

Figure 5.5 : Battery pack charge current map.

battery loop, there is less control parameters which results in simple control mechanism as well.

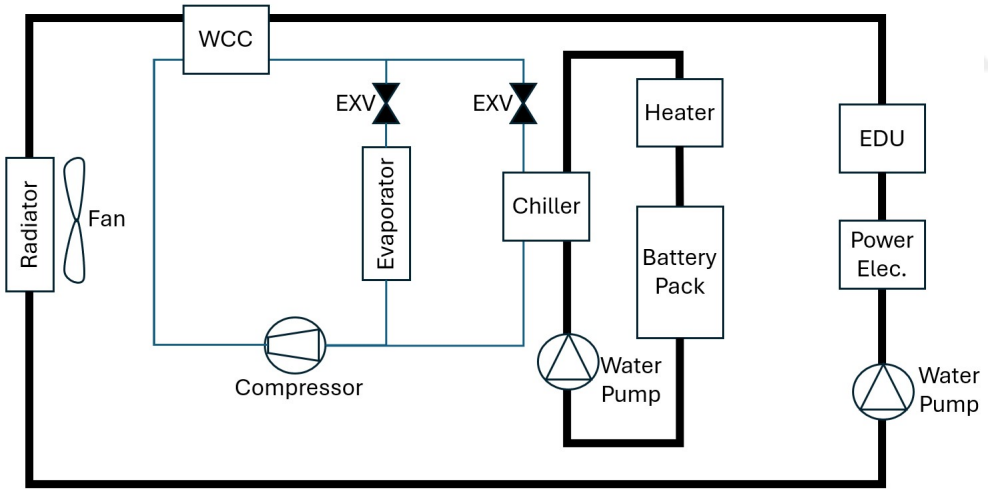

Figure 5.6 : Thermal layout that is used for this study.

The downside of this layout is that battery cannot use any waste heat in the EDU loop for heating or colder ambient air for cooling. Since the dynamics of motor and inverter, EDU loop coolant temperature can heat up quickly even in cold ambient temperatures. There is an opportunity to use that coolant for heating the battery pack without operating the PTC. This requires a valve to connect battery loop with the

EDU loop. This approach reduces the energy consumed to heat up the battery when it is compared to use PTC heater. But this is only providing real benefit in extreme conditions where the ambient temperature is below zero degrees. Because battery packs generally doesn't need heating during driving above zero degrees or close to zero. Since our research only done for temperatures between 0 to 35 °C, using this layout will not provide much benefit from it, that is why more simple layout preferred.

Thermal system model consist of battery pack, chiller, heater and pump thermal models as it is shown in Figure 5.6. Since the EDU and power electronics coolant loop is considered as separate from the battery loop and not interacting with each other, thermal behaviour of EDU and power electronics is not investigated.

5.3.1 Battery pack thermal model

Battery pack temperature calculation is necessary in order to see the effect of overall thermal management system. There is an internal resistance thus power loss inside the battery pack that is affecting the pack temperature. Other than the power losses, heat transfer with the coolant has to be taken into account while calculating the battery pack temperature. For this heat transfer energy balance equation is given in equation 5.15 as ΔQ_{Total} is change in the total heat, $Q_{CoolantToBatt}$ is heat transfer between coolant and battery pack and Q_{batt} is the heat generated inside the battery pack due to power losses.

$$\Delta Q_{Total} = Q_{CoolantToBatt} + Q_{batt} \tag{5.15}$$

Generated heat inside the pack is calculated with the internal resistance of the battery and calculated battery current in equation 5.16.

$$Q_{batt} = I_{batt}^2 R_{int} \tag{5.16}$$

Heat exchange between coolant and battery pack can be calculated according to conduction heat formula as in equation 5.17. It includes the heat transfer coefficient

between coolant and battery pack h_{cb}, coolant outlet temperature $T_{CoolantOut}$ and battery pack temperature T_{Batt} [69].

$$Q_{CoolantToBatt} = h_{cb}\,(T_{Batt} - T_{CoolantOut}) \tag{5.17}$$

Total heat change of the component is expressed as the temperature difference in the component temperature ΔT_{Batt} and specific heat capacity C_{Batt} of the component in equation 5.18 [69].

$$\Delta Q_{Total} = C_{Batt}\,\Delta T_{Batt} \tag{5.18}$$

After defining these equations, we can solve the equation 5.15 for calculating the battery temperature. Battery pack outlet temperature also needs to be calculated in order to calculate further heat exchanges happening on the cooling circuit. For coolant temperature change, equation 5.15 can be written for the coolant heat transfer of coolant calculations where $\Delta Q_{TotalCoolant}$ is change in total heat of coolant and $Q_{Coolant}$ is heat loss of coolant [69].

$$\Delta Q_{TotalCoolant} = Q_{CoolantToBatt} + Q_{Coolant} \tag{5.19}$$

Total heat loss of the coolant can be calculated as in equation 5.20 with the mass flow of coolant $m_{coolant}$, specific heat capacity of coolant $C_{coolant}$ and delta between coolant inlet temperature $T_{CoolantOut}$ and outlet temperature $T_{CoolantIn}$ [69].

$$Q_{Coolant} = m_{coolant}\,C_{coolant}\,(T_{CoolantOut} - T_{CoolantIn}) \tag{5.20}$$

Total heat change in the coolant can be calculated as in equation 5.21 with the coolant density $\rho_{coolant}$, specific heat capacity and coolant volume inside the component $VolCoolantBatt$ as in this case battery.

$$\Delta Q_{TotalCoolant} = \rho_{coolant}\,C_{Coolant}\,Vol_{CoolantBatt}\,\Delta T_{CoolantOut} \tag{5.21}$$

With these equations, we can solve the equation 5.19 for calculating the coolant outlet temperature. These equations are solved in the Matlab Simulink environment in order to calculate battery temperature and coolant outlet temperature.

5.3.2 Chiller thermal model

Chiller is modeled as a heat exchanger that uses the chilled refrigerant to cool down the coolant passing through. In order to create chiller model, single block is used to identify cooling system with an efficiency factor. Efficiency of the cooling system depends on the environment temperature, coolant temperature and compressor power. Look up table is used to get correct efficiency taken from suppliers data. Cabin cooling is considered to be off and effect of cabin cooling is not considered for this research.

Compressor power is taken from the controller output and after efficiency taken into account, cooling power is obtained. Cooling power is given input to chiller heat exchange model in order to calculate chiller outlet temperature. Since battery pack and chiller are connected in series in cooling circuit, battery pack coolant outlet temperature is given as chiller inlet temperature. According to heat exchange happening in chiller model, coolant outlet of the chiller is calculated.

Heat exchange is modeled same for all thermal models as it is explained in battery thermal model section. For using the same model, inputs and parameters need to be changed and adapted according to chiller. Heat balance equation for chiller becomes like given in equation 5.22.

$$\Delta Q_{Total} = Q_{CoolantToChiller} + Q_{Chiller} \tag{5.22}$$

$$Q_{Chiller} = -P_{comp}\,\eta_{Chiller} \tag{5.23}$$

Heat transfer between coolant and chiller is given as $Q_{CoolantToChiller}$ and chiller cooling power is used for heat generated inside the chiller $Q_{Chiller}$. Since chiller is not creating the heat but taking heat from the system, cooling power for chiller is given as negative for $Q_{Chiller}$. Cooling power is calculated in equation 5.23 by electrical

power consumption of compressor P_comp multiplied with the chiller system efficiency $\eta_{Chiller}$.

$$Q_{CoolantToChiller} = h_{cc}\,(T_{Chiller} - T_{CoolantOut}) \tag{5.24}$$

Heat exchange between coolant and chiller is calculated in equation 5.24 similar to equation 5.17, by using heat transfer coefficient between coolant and chiller h_{cc} and delta between coolant temperature and chiller temperature $T_{Chiller}$.

$$\Delta Q_{TotalCoolant} = \rho_{coolant}\, C_{Coolant}\, Vol_{CoolantChiller}\, \Delta T_{CoolantOut} \tag{5.25}$$

In order to calculate the coolant outlet temperature coming from chiller, similar to equation 5.21, same calculations is used but using chiller coolant volume $Vol_{CoolantChiller}$ instead of battery coolant volume in equation 5.25.

5.3.3 Heater thermal model

PTC heater is a component where the coolant heats up while passing through the component with heating materials inside the PTC heater. PTC heater is modeled as a heat exchanger similar to battery and chiller model. There is an internal heat that is produced by the used heating power and it is conducted to the coolant. Formula for the heat exchange balance is given in equation 5.26. Since chiller and heater are connected series in thermal layout, chiller outlet temperature is equal to heater inlet temperature. According to this, heater outlet temperature needs to be calculated in order to provide input to battery pack as inlet coolant.

$$\Delta Q_{Total} = Q_{CoolantToPTC} + Q_{PTC} \tag{5.26}$$

Heat generated inside the PTC heater Q_{PTC} is given in equation 5.27, as P_{PTC} is power used by the PTC heater and η_{PTC} is the component efficiency factor.

$$Q_{PTC} = P_{PTC}\,\eta_{PTC} \tag{5.27}$$

Heat transfer between PTC heater and coolant is calculated in equation 5.28 by using heat transfer coefficient between coolant and PTC heater h_{cp} and difference between coolant temperature and PTC heater temperature T_{PTC}.

$$Q_{CoolantToPTC} = h_{cp}\left(T_{PTC} - T_{CoolantOut}\right) \tag{5.28}$$

PTC heater coolant outlet temperature is calculated similar to the calculations in chiller and battery thermal model only changing the volume parameter to PTC heater coolant volume $Vol_{CoolantPTC}$. It is given in the equation 5.29.

$$\Delta Q_{TotalCoolant} = \rho_{coolant}\, C_{Coolant}\, Vol_{CoolantPTC}\, \Delta T_{CoolantOut} \tag{5.29}$$

5.3.4 Pump thermal model

In order to use in the thermal calculations, flow rate has to be calculated. This can be done according to pump speed characteristics. Pump creates a pressure difference between inlet and outlet of it self to create the flow in the closed loop system. The relation between the flow rate and the pump speed is close to linear while power and flow rate is quadratic [70].

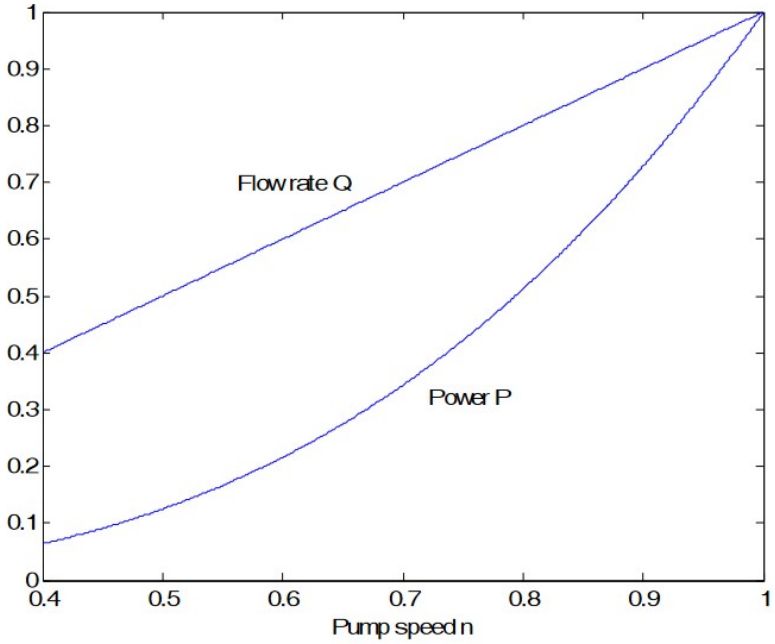

Figure 5.7 : Pump flow rate relation between pump speed and power [70].

Thermal management controller commands the desired flow rate from the pump. According to this power consumption of the pump need to be calculated. This is done with a look up table respective with with flow rate. System flow rate is determined as working in between minimum 0.06 kg/s to maximum 0.25 kg/s. This assumption is made according to literature and flow rate needs of the components [71]. Maximum pump power is determined as 230 W and used quadratic relation to create pump power versus mass flow.

5.4 Rule Based Controller Model

Two types of rule based controller is implemented. One is with preconditioning feature and other one is without preconditioning. Rule based controller with preconditioning is representing a smart feature in the vehicle where user can trigger preconditioning of the battery pack manually before going to charge station. Once the preconditioning is enabled, controller heat up or cool down the battery until reaching target temperature according to rule table than stops. Rule tables are given in Table 5.1 and Table 5.2 for both controllers. Mass flow request for both controller taken as constant 0.2 kg/s.

Table 5.1 : Rules for rule based controller.

Action	Vehicle State	Turn On Condition	Turn Off Condition
Heating	Driving	T < -5 °C	T > 0 °C
Heating	Charging	T < 5 °C	T > 10 °C
Cooling	Driving	T > 36 °C	T < 32 °C
Cooling	Charging	T > 33 °C	T < 29 °C

Table 5.2 : Rules for rule based controller with preconditioning.

Action	Vehicle State	Turn On Condition	Turn Off Condition
Heating	Driving	T < 10 °C	T > 14 °C
Cooling	Driving	T > 29 °C	T < 25 °C

5.5 Reinforcement Learning Controller Model

RL controller is created using Matlab Simulink Reinforcement Learning toolbox. In order to create a RL controller, RL agent type, observations, actions and reward function must be determined. In this application, in order to get best performance from the model, heating and cooling power must be determined in a continuous way rather

than discrete values. From the continuous agent types of RL agents, deep deterministic policy gradient (DDPG) agent is selected for this application. DDPG is a model free agent that uses actor critic approach to maximize long term reward. Since it is model free, it requires less training time compared to model based agents and it has a good balance for training time and tuning capability and robustness. In order to create a DDPG agent, actor and critic neural network sizes must be determined.

Figure 5.8 : RL workflow [64].

Actor and critic neural network sizes are determined based on the different applications found in research. Actor and critic hidden layer sizes can be selected independently. Critic is responsible for learning the system behaviour and estimating rewards, actor on the other responsible for making the decisions that maximizes the reward. So with this understanding actor model can have less complexity compared to critic model. With this way computational times needed for each step for training can be reduced. For starting point, default actor and critic sizes have been used, which consists of 250 hidden layers. Training with these sizes was needing too much computational resources. After some testing 50 hidden layers for critic model and 40 hidden layers for actor model have been decided [72].

Observations for RL controller is selected according to system variables that are important for thermal management. These are vehicle speed, battery pack temperature, inlet and outlet coolant temperature, actual power. Outputs of the RL controller are coolant mass flow request and heating or cooling power. The minimum and maximum values of the outputs of the RL controller are determined as -1 and 1 respectively. As the cooling and heating power maximum power is selected 5000 W, it is directly multiplied in order to convert the RL controller output to power request. Mass flow output is changing between 0.06 kg/s to 0.25 kg/s, so these values are mapped to RL controller output for mass flow request. All the observations that are given to RL controller also linearized since it gives better performance for RL model's training

process. Temperature and speed signals are mapped in between 0 and 1, power signal is mapped in between -1 and 1.

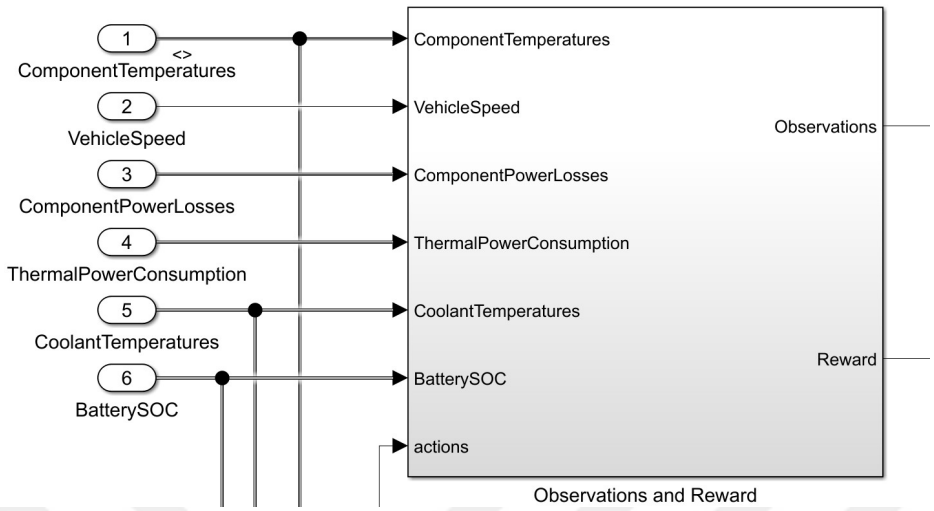

Figure 5.9 : Observations for RL.

Sample time of reinforcement controller for training need to be selected while considering training time and output fidelity of the controller. Since the scenario includes 20 minutes driving and after a charging session, the estimated simulation run time is averaging around 2500 seconds depending on the charge duration. Since the battery thermal system is not very dynamically changing, a long sample time is not considered to be influential on the system. For that 10 second sample time is selected.

Reset function is used to initialize selected variables with different values for every cycle. This is used to create randomized initial temperature, ambient temperature values and vehicle speed shifting in time. This function gives RL controller ability to create optimum policy for all these different conditions and not over fit for a certain condition. Over fitting is a problem where neural network finds the local minimum based on the conditions given, this possibility is very high when the training is done only for small portion of overall expected working conditions.

In order to RL model to learn optimum solution, it needs a well defined reward function. The aim of this research is to find optimum thermal management for achieving best charge duration. These needed to incorporated into reward function for RL model to learn. There have been several different trials done in order to find reward function that gives best results.

The first approach was using the power consumption for thermal components as punishment for RL controller and some reward points if battery temperature converging to target temperature that is set manually. This approach was having the problem of entering the temperature manually or by a rule table. Only part where it was improving is that RL controller was considering the vehicle losses during driving and optimizing it's heating or cooling power controls accordingly. But it was not helping to find the optimal temperature to start the charging process in the first place.

The second approach is created based on the results have been observed from the first approach. Instead of giving rewards based on looking at battery temperature, a reward function is developed by considering the charge duration. For this approach simulation runs for end of charge and during driving, heating and cooling actions are defined as cost to RL controller according to battery temperature condition. After the driving, cost for heating or cooling is decreased because now the power of heating and cooling can be supplied from the charge station not from battery. Cost function in model can be seen in Figure 5.10 for heating and cooling power. Similarly pump usage also creates a cost and different for charging and driving cases as given in Figure 5.11. During charging, every sample adds cost to RL controller as negative reward as given in Figure 5.12. This way RL controller is enforced to use less heating or cooling power during driving and tries to end charge session as soon as possible. Also another consideration is the battery temperature limits. A cost is created for the battery temperatures that are not wanted to be reached as shown in Figure 5.13.

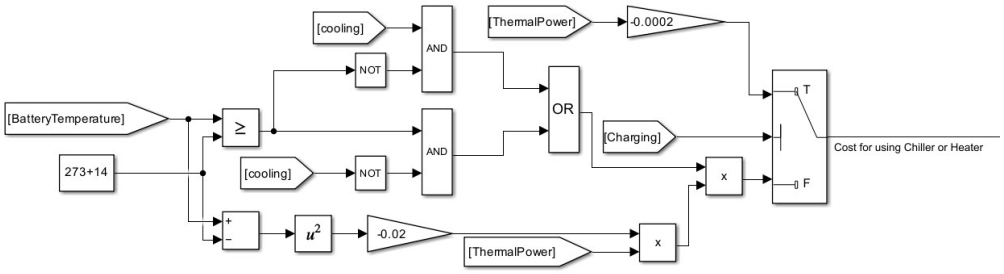

Figure 5.10 : Cost for using chiller or heater.

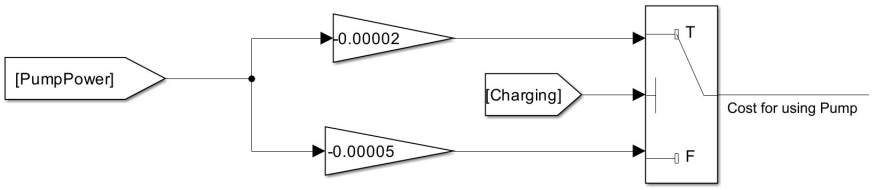

Figure 5.11 : Cost for using water pump.

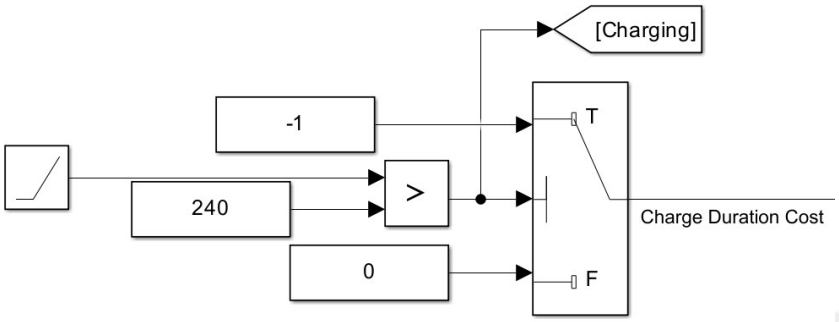

Figure 5.12 : Cost for charge duration.

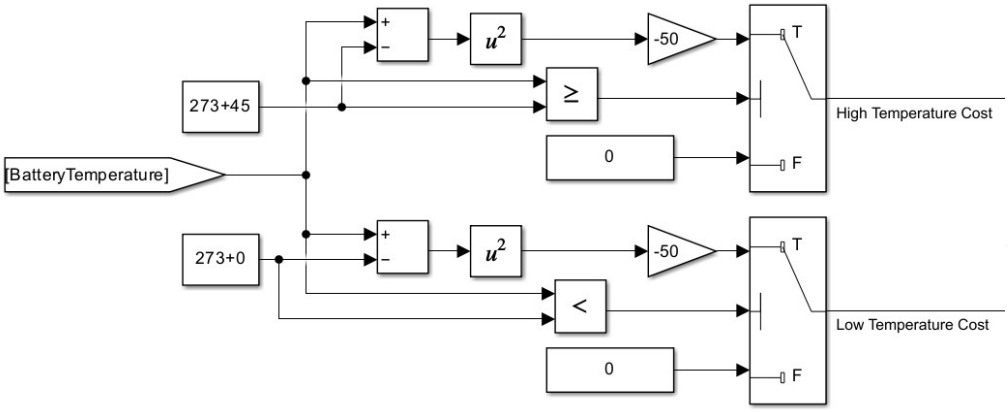

Figure 5.13 : Cost for battery temperature.

Weights for the cost function changes how the RL behaves. Some initial values for weights have been defined and than they are further calibrated according to training results.

5.6 Simulation Results

Three different variables have been defined as initial temperature for simulations. These are ambient temperature, component temperatures and coolant temperature. These initial temperature values starts from 0 °C and goes up to 35 °C creating 36 different testcases for simulation. Three different control methods have been analyzed

for the results. RL controller, rule based controller with preconditioning and without preconditioning. Evaluation is done according to charge duration achieved for each scenario with different controllers. Along with this, SOC gain compared after first 10 minute of charging. This measure can be important for the scenarios where the user does a short break in their trip for coffee and plugs the EV for charging. Any boost in SOC in the short amount of time with thermal management control method is for users benefit for such cases.

Figure 5.14 shows the comparison between RL controller and the other two types in terms of gain charge duration improvement.

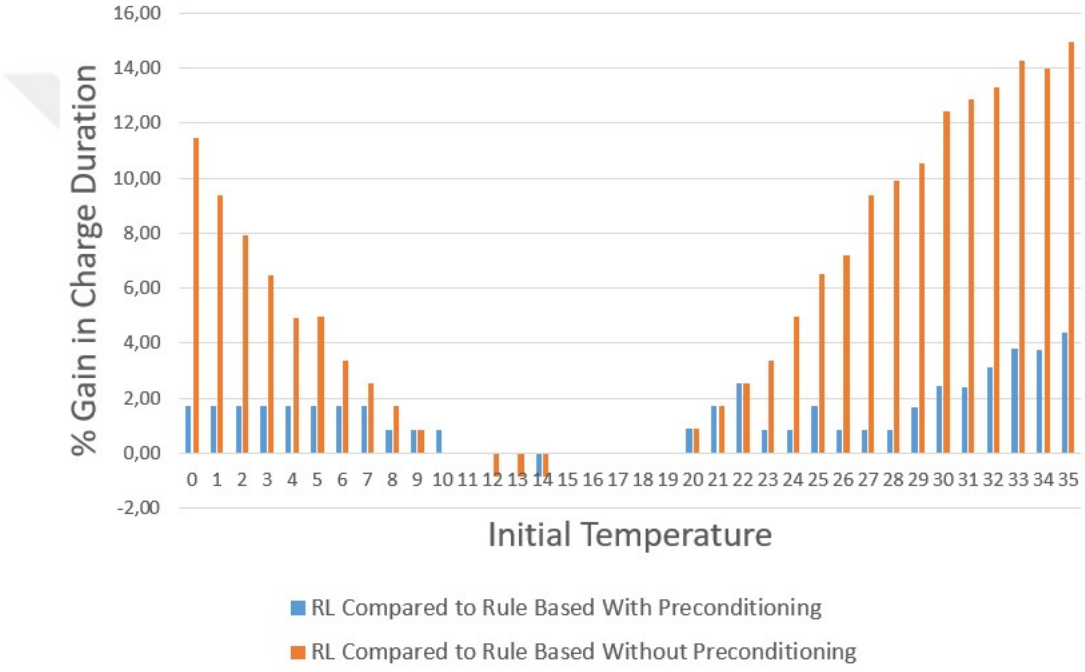

Figure 5.14 : Comparison between RL and other control methods for charge duration.

As it can be seen, RL performance is better when initial temperature closer to the extreme ends of the tested range. At 0 °C initial temperature, RL performs 11.45% better compared to rule based controller without preconditioning. When the behaviour investigated with the rule based controller used, since battery starts from 0 °C, according to the rule table there is no heating demand for battery. After the driving, battery gets heated up around 5 °C and when charging started heating is also started according to rule table. Comparison results are given for temperature in Figure 5.15.

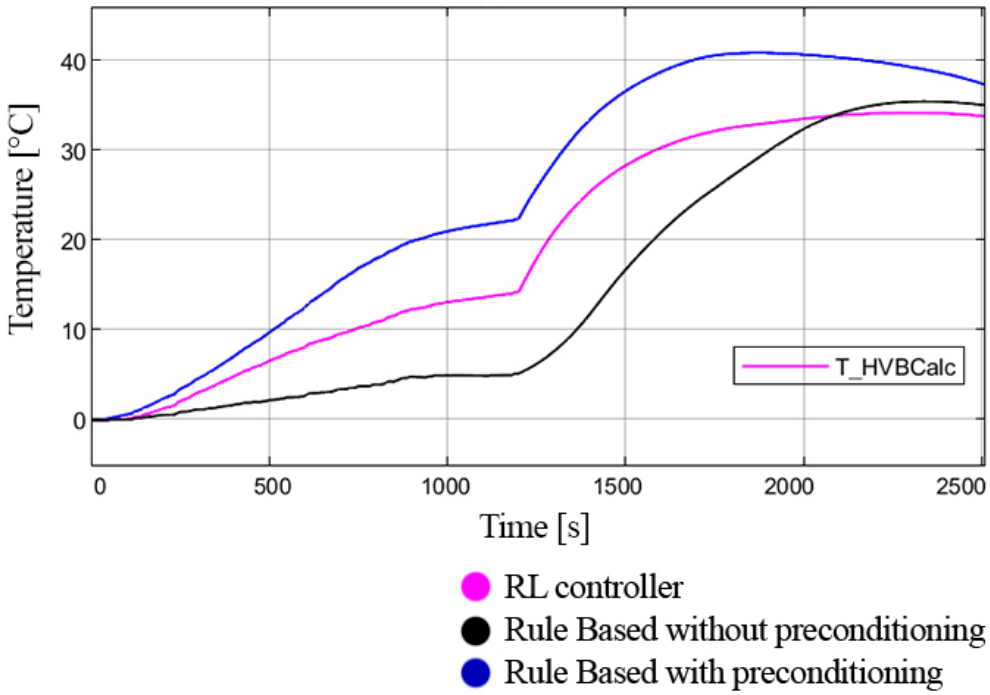

Figure 5.15 : 0 °C initial condition temperature comparison.

In Figure 5.16, negative values corresponds to heating and positive values corresponds to cooling. It is seen that the RL controller applies heating while driving before reaching to charge station in Figure 5.16. That way, when it is reached to charging station, battery temperature was at ideal temperature and can get more charging power. After charging starts, RL controller applies cooling because battery temperature starts to increase. Rule based controller with preconditioning starts to apply heating until reaching the 10 °C threshold. After that when the vehicle reached to charging station, again battery is in optimal range for charging but slightly higher temperature compared to RL controller case. After charge started, due to the higher start temperature, battery gets heat up and ends up in less optimal range. But until then battery SOC is already increased and charge power is getting limited due to that.

SOC can be seen in Figure 5.17 for different controlled cases. For RL controller and rule based controller with preconditioning charge performances are almost same. RL gives 1.68% better compared to preconditioning enabled rule based controller. But it can be seen that RL gives more optimal solution because of it's energy consumption is 40.98% low compared to rule based preconditioning controller during the heating.

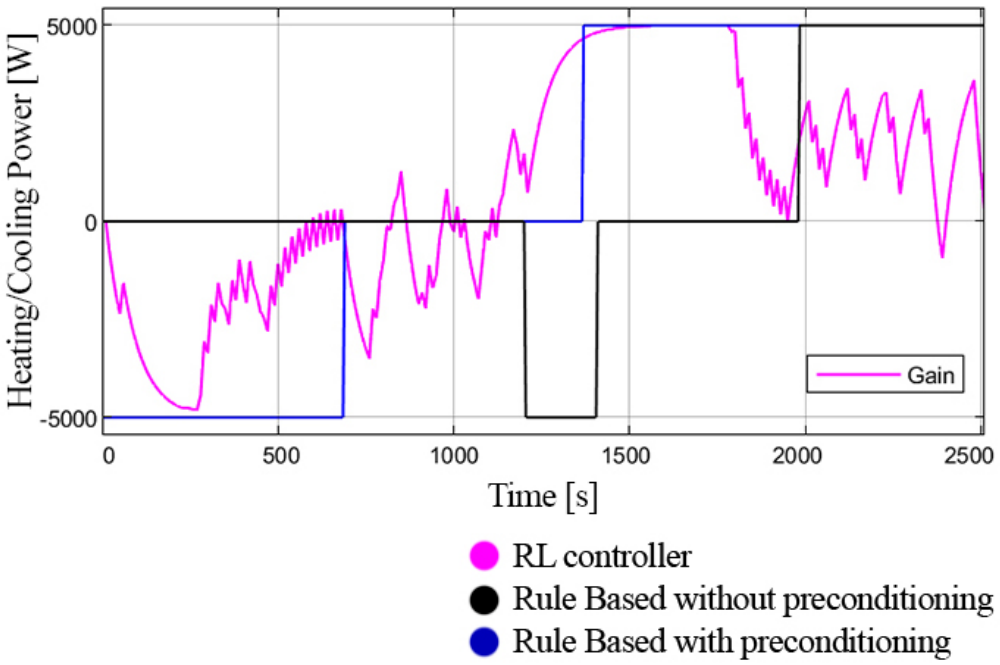

Figure 5.16 : 0 °C initial condition heating and cooling comparison.

Since RL controller looks for the optimum solution considering the vehicle drive cycle as well. This provides RL to estimate the battery heat up due to driving. So that it does not apply full heating like it is the case in rule based with preconditioning controller. Also compared to rule based control RL and rule based with preconditioning gives 6% SOC boost in first 10 minutes of charging due to higher charging powers are achieved.

From the Figure 5.14 it can be seen that in middle of the temperature range, there is no improvement or gained from RL controller. Figure 5.18 shows that without any cooling or heating applied like in rule based controller output, battery temperature reaches to around 15 °C with an initial 11 °C. Due to temperature increase after charging start, battery remains in the optimum range almost all the time during charging.

Figure 5.19 shows that RL controller applies some heating power and cooling power during driving case. It results in a small amount of increase in battery temperature when vehicle reaches to station. After charging started, RL Controller starts to apply cooling as well. After certain amount of time when the charge power gets limited, cooling power is also reduced by RL controller. For the same case, rule based controller with preconditioning activates the heating in the beginning of drive. After reaching to threshold for turning of the heat, battery temperature continues to increase

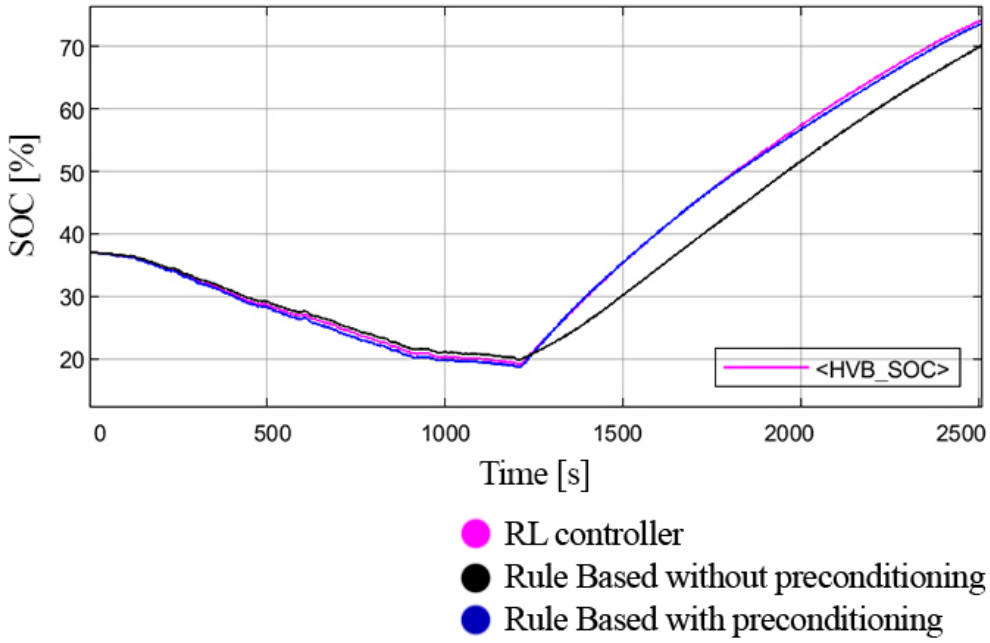

Figure 5.17 : 0 °C initial condition SOC comparison.

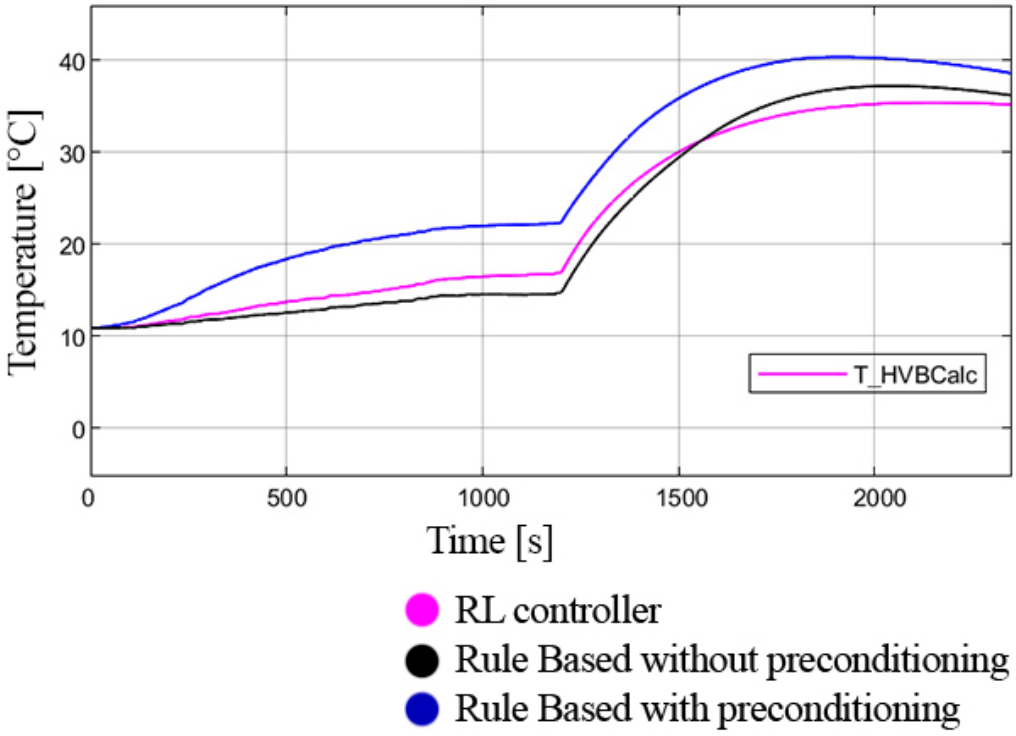

Figure 5.18 : 11 °C initial condition temperature comparison.

due to driving. It ends up in a higher temperature compared to other two controllers and ends with highest temperature after charging as well. This shows that the initial heat up applied by the preconditioning rule set was unnecessary by the controller.

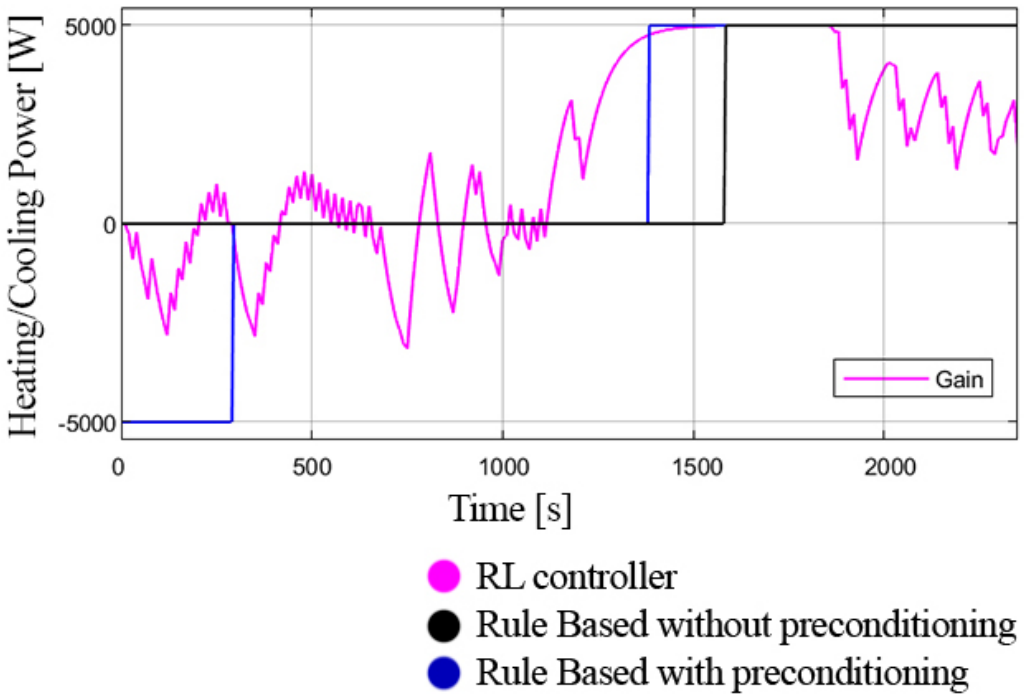

Figure 5.19 : 11 °C initial condition heating and cooling comparison.

Figure 5.20 shows that there is practically no difference in terms of charge duration performance of three different controllers in this case. But in terms of energy consumption, RL controller and rule based controller with preconditioning used more energy due to their heating or cooling actions during driving.

Figure 5.21 shows the results for 25 °C initial temperature. With the rule based control battery reaches to around 27 °C without applying any cooling. Starting the charging with this temperature, it creates the issue for battery to not be in the optimal temperature for charging.

As it can be seen in Figure 5.22 both RL and rule based controller with preconditioning method applies cooling during driving. This decreases the battery temperature until reaching to charge station and ends up in better performance for charging. RL controller performs 6.5% better compared to rule based control without preconditioning in terms of charge duration. Rule based controller with preconditioning enabled is also performing similar only 1.71% worse than RL for charge duration. But RL also uses 45.64% less energy during driving for cooling. This

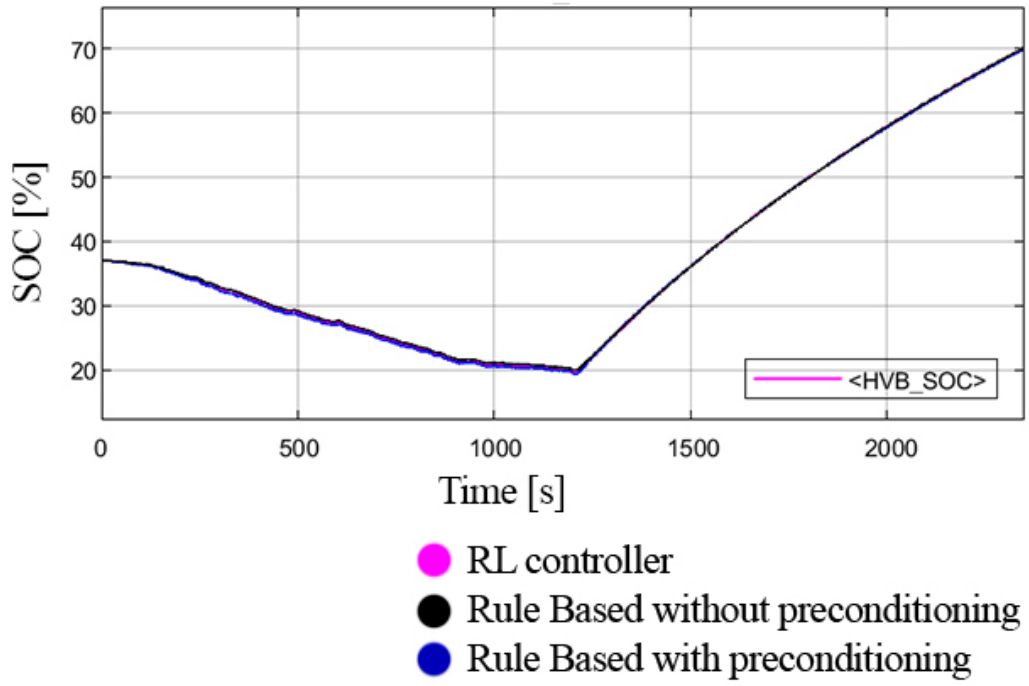

Figure 5.20 : 11 °C initial condition SOC comparison.

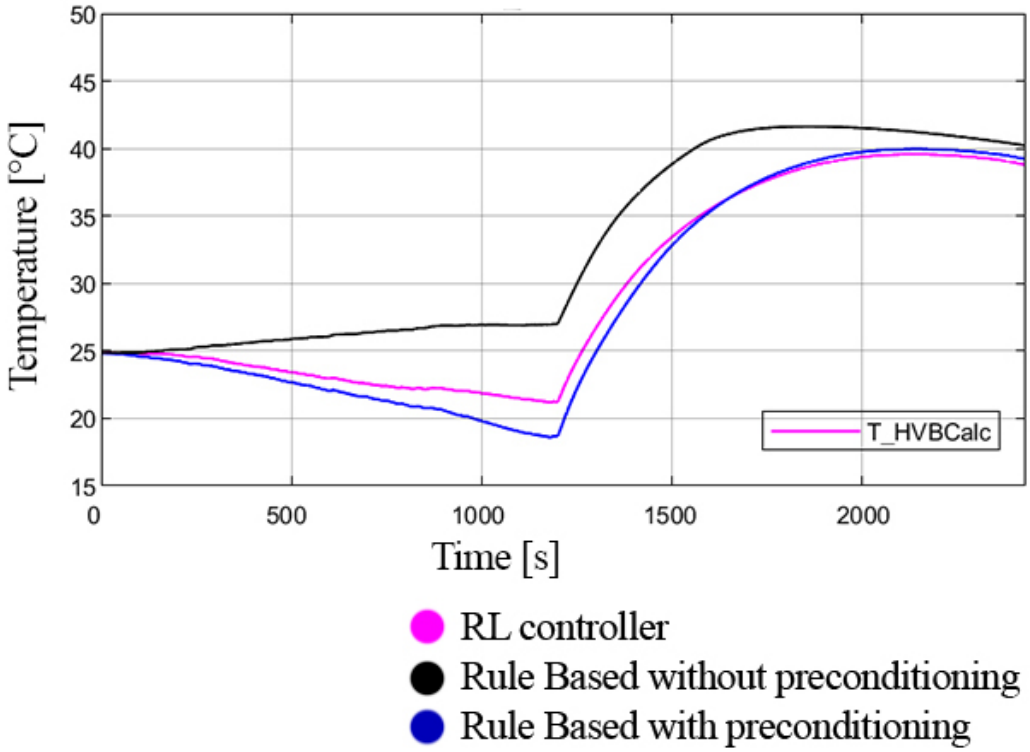

Figure 5.21 : 25 °C initial condition temperature comparison.

again shows the predictive capability of the RL controller which can find the optimum cooling power considering charge performance and also energy consumption.

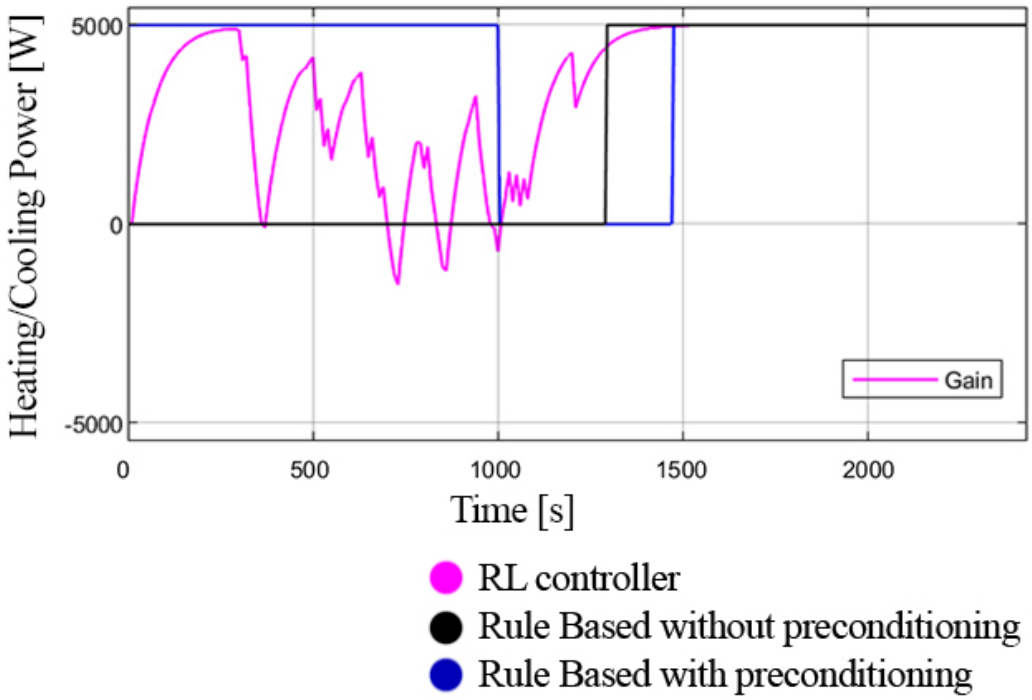

Figure 5.22 : 25 °C initial condition heating and cooling comparison.

Figure 5.23 shows the SOC for all three controller in 25 °C initial temperature. For this scenario there is no boost in SOC achieved in 10 minutes due to SOC drop caused by cooling energy consumption and small difference for charge performance.

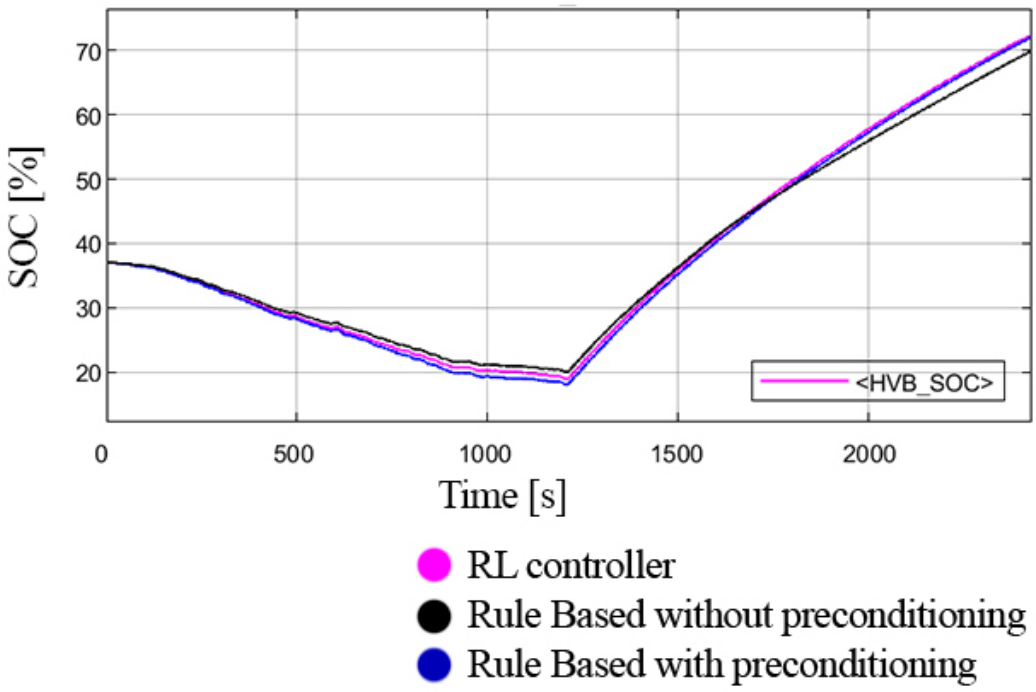

Figure 5.23 : 25 °C initial condition SOC comparison.

As for the extreme end of temperature range tested, 35 °C results given in Figure 5.24 in terms of temperature comparison. When no cooling applied like in rule based controller case, battery temperature goes to 37 °C at the end of drive cycle. Since this is not in the ideal charge temperature range of the battery charge duration increases. For this scenario RL controller provides 14.94% improvement in charge duration compared to rule based controller. When preconditioning enabled with rule based controller, performance is almost identical to RL controller.

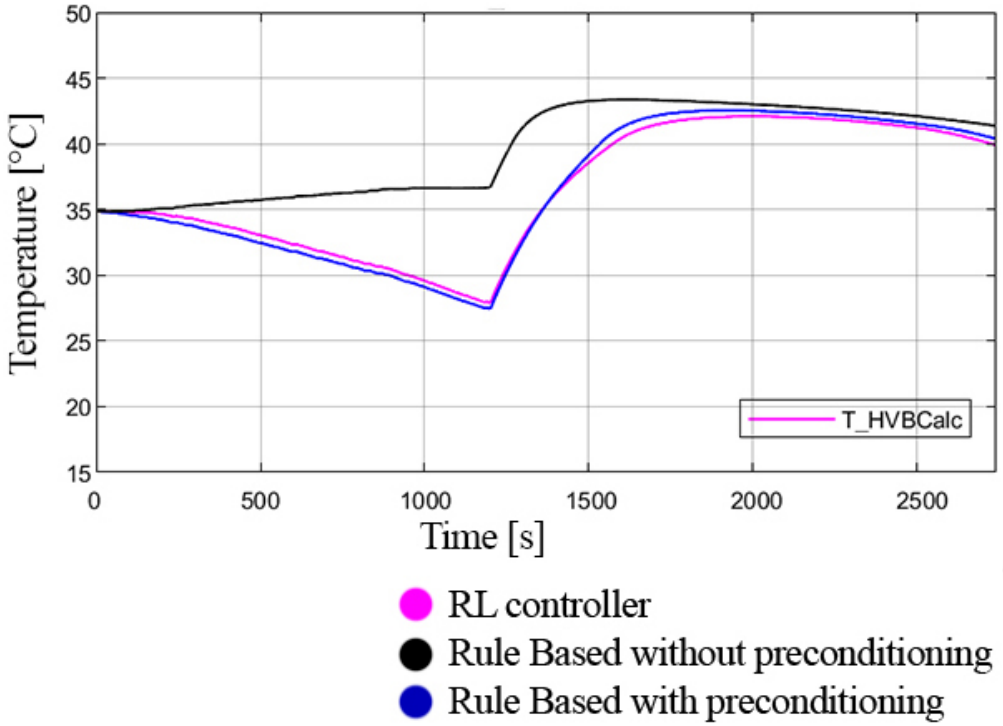

Figure 5.24 : 35 °C initial condition temperature comparison.

Figure 5.25 shows the cooling power applied for each controller. For both RL and rule based with preconditioning enabled controller, cooling starts from the beginning. For RL it continues to apply cooling until the end of measurement. But for rule based controller with preconditioning enabled case, due to battery is cooled down to lower threshold of the rule table, it cuts the cooling. Until battery temperature reaches to upper threshold again, no cooling applied by controller.

SOC comparison is given in Figure 5.26. RL controller and preconditioning enabled rule based controller provides 5.7% boost in SOC after first 10 minutes compared to rule based without preconditioning.

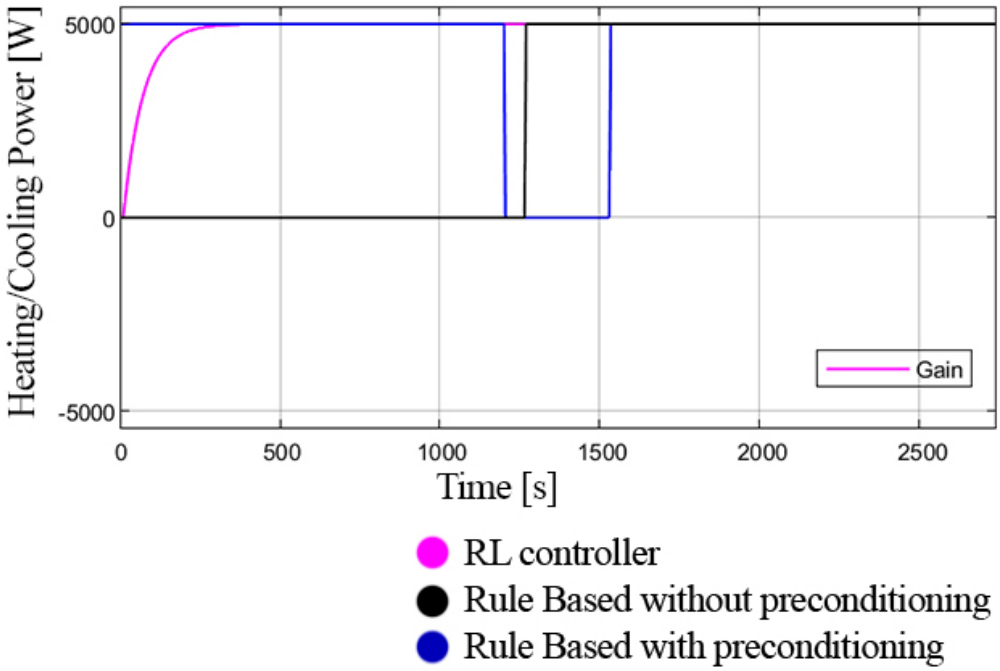

Figure 5.25 : 35 °C initial condition heating and cooling comparison.

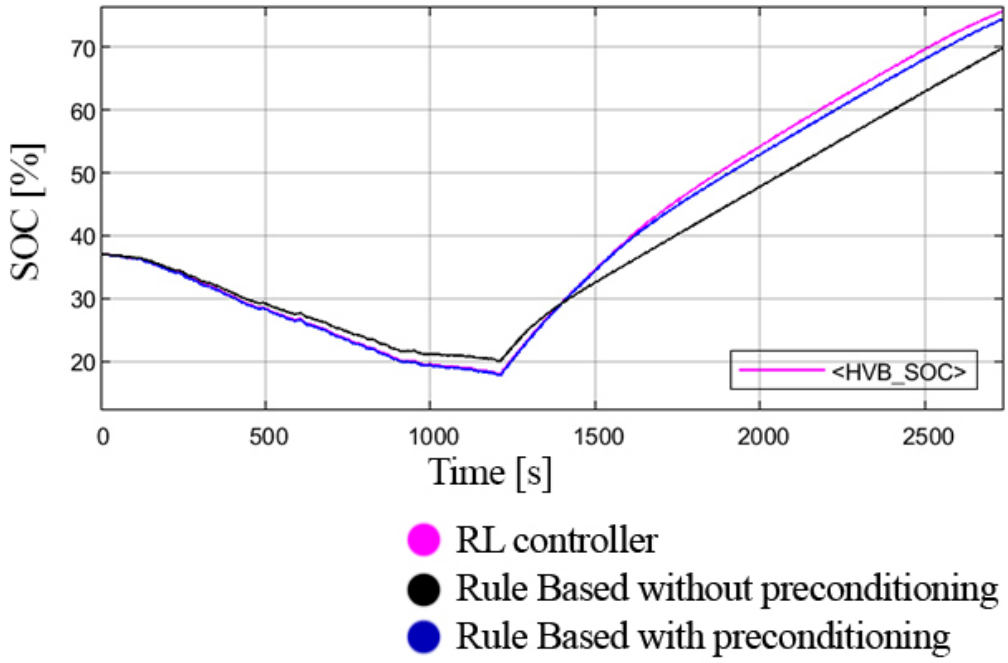

Figure 5.26 : 35 °C initial condition SOC comparison.

According to the results there is a clear advantage of using RL controller for TMS due to it's optimum control capabilities, dynamic behaviour that adapting according to conditions. When it is compared with the more traditional method as rule based controller, it performs better in most of ambient operating conditions that taken into

consideration in this research. With the preconditioning enabled rule based controller, some improvements could be achieved but because of the predefined rules it does not provide the optimum solution for every scenario. RL controller on the other hand, observing the system behaviors, fed with the drive cycle information, takes the advantage of it's predictive nature to provide optimum solutions as shown in this study.

6. CONCLUSION

In this thesis a RL based thermal management control method have been proposed to improve charge duration of the EVs. Since the battery performance and safety deeply connected with the operating temperature an effective TMS is mandatory in order to achieve best performance of the battery pack.

Battery technologies and their different characteristics have been explored. Relationship between the charge duration, battery performance and temperature is mentioned. Due to batteries chemistry's, performance is directly tied to battery temperature. Thus in order to keep batteries in safe and optimum operating conditions, the BMS component have been introduced, it's requirements and importance have been explained.

The effective thermal management of EVs and EV batteries are critical for optimizing performance, safety, and longevity. Throughout this thesis, various thermal management strategies and their impacts have been explored. Thermal management components are defined and their features are mentioned. Difference between the thermal management strategies for powertrain components and batteries have been explored. In order to achieve effective thermal management, control strategies have been given and their advantages and disadvantages mentioned while comparing in between.

Rule based control is the most simple and traditional control method for TMS in different applications. This control method depends depends on the predefined rule set for controlling the actuators like pump, compressor, fan and PTC heater. Because of this feature, even tough it is easy to implement, rule based control methods does not always provide best operation conditions. Thus optimum control methods are widely researched for using in EV TMS, in order to achieve best possible operation conditions with increased energy efficiency. Another widely used control method is MPC which uses system models in order to predict it's behaviour. A cost function

defined to balance energy consumption and MPC algorithm provide necessary actions by minimizing the cost function. Which results in better compared to rule based controller, but computational needs increase significantly.

In order to address computational efficiency and optimum control in this area, data driven solutions are suggested. ANNs can be used from system modeling, parameter optimization to optimum control problems. With the ANNs, while runtime performance increasing, because the system model does not need to be created and it does not include computationally demanding algorithm when it is deployed. RL is one of these methods that learns the system behaviour and tries to maximize a reward function with predicting system behaviour. But data driven methods requires large amount of data in order to train the models.

This research includes a simulation environment in order to train the RL model for different operation scenarios. In order to simulate system behaviour correctly, a comprehensive system model is created that includes vehicle dynamics, thermal and electrical model of an EV. With the defined scenarios, simulation could represent the battery packs temperature changes, power needs and charge characteristics. RL interacts with the system to provide necessary cooling and heating for battery pack according to temperature conditions and system inputs like vehicle speed, power consumption and power losses. A drive cycle is defined for the tested scenario that includes driving the vehicle for a time and starts charging after the driving.

RL controller and rule based control methods have been compared for different operation conditions run in simulation. A preconditioning feature also implemented for rule based controller that creates more narrow operating conditions for battery to optimize charge performance based on set of rules. According to results RL controller performed up to 14.94% gain at 35 °C and 11.45% gain at 0 °C initial temperature in charge duration compared to rule based controller. Rule based controller with preconditioning enabled feature shown that it can decrease the charge duration but not using the optimum energy consumption. When compared to RL, with almost same charge duration achieved at 0 °C RL uses 41% less energy while driving for heating the battery. Similarly for 25 °C initial temperature, RL achieves 1.71% better

charge duration using 45.64% less energy compared to rule based controller with preconditioning.

6.1 Future Work

For future work, RL could be used for different drive cycles while training to contain wider range of data. This way it can learn to optimize wide variety of driving cases. An experimental study can be performed with RL controller deployed TMS in an EV. This way simulation results could be compared with real world measurement in order to see real world performance. This study also can be extended including the extreme hot and extreme cold ambient conditions to see the difference between the control methods. For this work, single thermal layout is investigated. But EVs have variety of thermal layouts and they can have different operation modes using valves. These can be implemented and added as a control output to RL in order to utilize the RL method for different thermal layouts and applications. The constraint handling capability of the RL controller could be explored since in TMS for battery pack application, there shall be hard constraints that should not be exceeded. Another study can be done in experimental hardware to compare the performance and computational needs for using RL controller and MPC method.

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