Charge scheduling of plug-in hybrid electric vehicles (PHEVs) for minimized Li-ion battery degradation

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A Thesis

entitled

Charge Scheduling of Plug-in Hybrid Electric Vehicles (PHEVs) for Minimized Li-ion Battery Degradation

by

Anik Bandyopadhyay

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the Master of Science Degree in Electrical Engineering

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December 2012
An Abstract of

Charge Scheduling of Plug-in Hybrid Electric Vehicles (PHEVs) for Minimized Li-ion Battery Degradation

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Plug-in Hybrid Electric Vehicles (PHEVs) are being touted as one of the most important technological advancements that will help make the smart grid a reality. The Vehicle to Grid (V2G) feature of PHEVs has the potential to help both the PHEV user as well as the electric utilities. However, overuse of V2G for profit will result in the accelerated degradation of the Li-ion batteries of the PHEVs. Thus, it is necessary to have charging schedules that would meet the requirements of all parties. Swarm intelligence techniques are used in this thesis in order to devise strategies that would help in preventing the unnecessary degradation of Li-ion batteries. These optimization techniques are employed for specific scenarios for a future smart grid environment involving PHEVs. Various studies have been carried out to simulate the effect of aggregated PHEV loads. Simulations were also performed to simulate PHEVs in a fast charging scheme. All simulations have been performed with the aim to obtain a balance between profit margins and battery health degradation.
Dedicated to my Parents for always being there for me.
Acknowledgements

Doing my research here in the EECS Department at The University of Toledo has been one of the most enriching experiences of my life. The work presented here in this thesis would not have been possible without the help of several people and I would like to take this opportunity to thank them.

I have to thank Dr. Wang for being the chair of my committee. I would like to thank Dr. Devabhaktuni for his guidance in my research as well as for being a pillar of support emotionally. Many thanks to Dr. Alam for taking time out of his busy schedule to be a member of my committee and his timely comments which helped improve the thesis.

My lab mates are the most encouraging, knowledgeable, patient and wonderful people I have had the fortune to meet. I would like to thank Sreenadh, Rob, Rui, Yichi and Zhu for being the perfect lab mates. To me, you guys are simply the best. One page is simply not enough for me to express the admiration that I have for you.

Perhaps the most important thing that I have learned during my Masters study is that there will be good times and periods of difficulty. The strength to go through the tough times would be impossible without gratitude for the blessings we have already received. My parents, teachers and friends have helped me learn this very important lesson and for that I would like to thank all of them from the bottom of my heart.
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List of Abbreviations

ACO ......................... Ant Colony Optimization
AEM ......................... All Electric Mode
AER ......................... All Electric Range
BMS ......................... Battery Management System
BPSO ......................... Binary Particle Swarm Optimization
CD .......................... Charge Depleting
CS .......................... Charge Sustaining
DDP ......................... Deterministic Dynamic Programming
DP .......................... Dynamic Programming
DVFS ........................ Dynamic Voltage and Frequency Scaling
ECMS ......................... Equivalent Consumption Management System
EKF ......................... Extended Kalman Filter
EOL ......................... End of Life
EV .......................... Electric Vehicle
FACTS ....................... Flexible AC Transmission System
G2V .......................... Grid to Vehicle
HEV .......................... Hybrid Electric Vehicle
HPSO ......................... Hybrid Particle Swarm Optimization
HWFET ....................... Highway Fuel Economy Driving Schedule
IPSO ........................ Integer Particle Swarm Optimization
ISO .......................... Independent System Operator
MFR ......................... Mandatory Frequency Response
MOPSO ....................... Multi Objective Particle Swarm Optimization
NSGA ......................... Non Dominated Sorting Genetic Algorithm
PHEV ......................... Plug-in Hybrid Electric Vehicle
PMU .......................... Phasor Measurement Unit
QBPSO ....................... Quantum Inspired Binary Particle Swarm Optimization
RBPF ......................... Rap-Blackwell Particle Filter
RC ......................... Remaining Capacity
RVM .......................... Relevance Vector Machine
SIR ......................... Sampling Importance Resampling
SMC ......................... Sequential Monte Carlo
SOC ......................... State of Charge
SOH .......................... State of Health
STOR ........................ Short Term Operating Reserve
UDDDS ....................... Urban Dynamometer Drive Schedule
V2G .......................... Vehicle to Grid
VEPSO ....................... Vector Evaluated Particle Swarm Optimization
List of Symbols

$\alpha_a$ ................................Transfer coefficient of anode
$\alpha_b$ ................................Transfer coefficient of cathode
$\phi_1$ ................................Solid phase
$\phi_2$ ................................Solution phase
$\rho$ ................................Density of side reaction product
$\eta_{mr}$ ..............................Overpotential of main reaction
$\eta_{sr}$ ................................Overpotential of side reaction
$\eta_{charge}$ .......................Charging efficiency
$\eta_{discharge}$ ......................Discharging efficiency
$\eta_{inverter}$ ........................Efficiency of DC-AC inverter
$\eta_{PHEV}$ ........................ Efficiency of the PHEV
$\delta_{FILM}$ ..........................Thickness of the resistive film
$C_{available}$ ......................Available battery capacity
$C_p$ .............................Peukert capacity
$c_1$ ..............................Cognitive acceleration constant
$c_2$ ..............................Social acceleration constant
$c_{1_m}^{\text{max}}$ ................Maximum value of concentration of Li in solid phase
$c_{1_m}^{\text{max}}$ ................Maximum value of concentration of Li in solid phase
$C_N$ ...............................Nominal capacity
$d_d$ ..............................Distance driven
$d_{rb}$ ...............................Minimum distance driven
$E_s$ ...............................Energy stored in the battery
$F$ .................................Faradays constant
$G_{BEST}$ ........................Global best
$i_{0,mr}$ ............................Exchange current density of the main reaction
$i_{0,sr}$ ............................Exchange current density of the side reaction
$i$ ..................................Particle number
$j$ ..................................Dimension
$J_T$ .................................Total intercalation current density
$J_{mr}$ ..............................Current density of the main reaction
$J_{sr}$ ..............................Current density of the side reaction
$k$ ..................................Peukert exponent
$k_1$ ...............................Rate constant of electrochemical reaction
$K_p$ ...............................Conductivity of the side product
$kWh_{available}$ ..................Energy available in the battery
$kWh_{MAX}$ ........................Maximum energy that can be stored in the battery
$P(t)$ ...............................RMCP at the particular hour
$P_{BEST}$ ...........................Personal best
$r_1$ .................................Random number
$r_2$ .................................Random number
t₁ ......................................Plug-in time

Tₐ .......................................Absolute temperature

t₃ ........................................Time for which the energy is dispatched

Uₘr .......................................Equilibrium potential of the main reaction

Uₘr .......................................Equilibrium potential of the side reaction

vᵢj ........................................Velocity of the particle

Xᵢj .........................................Position of the particle
Chapter 1

Introduction

1.1. Research Motivation

The present electric power grid is undergoing a major overhaul for the first time since its inception over a hundred years back. These changes are aimed at not only improving its overall functionality but also positively impact the lives of the millions of people who are in one way or another dependent on it. The term coined to denote this mass collaborative effort is the smart grid.

Making the smart grid a reality will involve the improvement of the existing power related infrastructure, as well as the introduction of new technology to work in conjunction with the existing infrastructure. Flexible AC Transmission System (FACTS) devices, extensive use of sensors, phasor measurement units (PMUs) and Plug-in Hybrid Electric Vehicles (PHEVs) are just a few examples of the new technologies that will be introduced for the realization of the smart grid. It is widely believed that PHEVs will be the most vital component to make the smart grid a reality.

PHEVs possess a number of features that make it an attractive option to both the smart grid and the PHEV user as well. The defining characteristic of PHEVs that has
placed them in the spotlight is the Vehicle to Grid (V2G) feature. PHEVs need to charge and draw power from the grid when the State of Charge (SOC) of its battery reaches low levels. The V2G property of PHEVs would also allow PHEVs to deliver power back to the grid.

The PHEV features that would be beneficial to the smart grid are:

i. Bidirectional power flow between PHEV and the grid would help meet power requirements during periods of peak load demand.

ii. Similarly, the bidirectional property could be used in order to charge the PHEVs when the grid is at off peak hours.

iii. Aggregated loads of PHEVs could serve as means of energy storage and help the grid by providing ancillary services.

iv. Help in improving power quality by providing reactive power when necessary.

Similarly, PHEVs are beneficial to the users in the following ways:

i. They are a source of revenue for the user via the V2G feature.

ii. PHEVs have superior fuel efficiency as compared to regular vehicles. This would further reduce the vehicle related expenditure for the users.

1.1. Research Problem

The fact that the PHEV is actually a source of income for the user poses a rather unique problem. Overusing the battery for V2G transactions in order to earn high amounts of money is a definite possibility. However, utilizing the battery excessively, purely for profit would result in unnecessary battery degradation.

The drawbacks of adopting this profit based strategy are namely:
i. Reduction in the overall lifetime of the battery.

ii. Additional battery degradation will also lead to a reduced all electric range (AER) of the PHEV.

This necessitates the need to have strategies in place which would prevent the unnecessary degradation of the Li-ion batteries. The independent system operator (ISO) would be responsible to make the decision on whether a V2G, G2V or no transaction takes place. In order to make these decisions, the ISO would not only have to take grid conditions at any given time into consideration but also the relevant PHEV parameters.

A principal step in developing said strategies would be to devise certain rules that form the basis for certain charge schedules. PHEV charging and discharging has to be governed by a number of rules. Lack of any definitive policy could result in PHEVs doing more harm than good. For example, it is in the benefit of the user to have the PHEV charged at an hour when the rate of charging is low. These periods occur when the overall load demand of the grid is low.

Similarly, periods having high rates of charging are due to the high load demand of the grid. Thus, another objective would be to perform V2G during periods with high rates of charging. This would increase the profit margin for the PHEV user and also benefit the grid at a period of high load demand.

Balancing the power grid requirements, the PHEV and PHEV battery health is the main concern. Fulfilling all the objectives is a legitimate concern for automakers and electric utilities alike if the smart grid is to be a reality someday. The enthusiasm around the smart grid along with the popularity of PHEVs may wane if these problems are not properly addressed.
Having multiple objectives increases the complexity as far as reaching a solution is concerned. Each objective will have its own set of constraints and decision variables. Based on this, the dimensionality of the problem will vary from situation to situation. Thus, in addition to actually achieving these objectives, it is also required that these operations take place quickly.

Depending on the scenario it may not be possible to achieve all the objectives. However, tradeoffs will need to be made between the objectives. Optimization of these objectives will be necessary for the benefit of the electric utilities, PHEV users and also consider the Li-ion battery health of the PHEVs. Swarm intelligence techniques were used in this thesis because they have shown the fastest computational times among the optimization algorithms. This would be in conjunction with the expected future requirements of the smart grid that decisions on charging/discharging be made quickly.

It has been well established that Li-ion batteries will be the battery of choice for all future PHEV applications. If the Li-ion battery health is an objective that is in need to be optimized, it will be necessary to have a thorough understanding of Li-ion battery chemistry. Without knowing the chemical processes that take place within a Li-ion battery pack, it is not possible to know how the degradation actually transpires.

1.3. Thesis Organization

This thesis is organized as follows. Chapter II reviews the literature related to PHEV technology and Li-ion battery health. In Chapter III the involvement of PHEVs in the smart grid is discussed and the various functions it could serve to perform are highlighted. Chapter IV discusses the Li-ion battery model that is used for running the
simulations. Chapter V introduces the concept of swarm intelligence and its use in this study. Chapter VI deals with an aggregator model of PHEVs and how they can help in maximizing profit for the user without causing unnecessary Li-ion battery degradation. Chapter VII discusses charging topologies of PHEVs and focuses specifically on the effect fast charging on the Li-ion battery. Chapter VIII recapitulates the results from all the simulations and discusses the potential impact of having charging schedules for PHEVs.
Chapter 2

Review of Li-ion Battery Health

The maximum amount of charge depletion in a PHEV occurs when the vehicle is traveling. Most of the research done in order to optimize the SOC of the PHEV involves schemes that aid in optimizing the fuel efficiency of the vehicle. There is extensive literature regarding battery characteristics, modeling and optimal power management strategies. In this section a literature survey is carried out in order to examine the various factors, constraints, methodologies, computational techniques, and final results of various papers that deal with the importance of SOC management.

Energy management strategy options are explored in [1]. A parallel Hybrid Electric Vehicle (HEV) configuration is utilized for the study. The authors demonstrate the results of optimizing the fuel efficiency. Particle Swarm Optimization (PSO) is the algorithm that is used to optimize the fuel efficiency of the vehicle. The optimization process is carried out on two driving cycles, the Urban Dynamometer Driving Schedule (UDDS) and the Highway Fuel Economy Driving Schedule (HWFET) [2]. The optimization is carried out for the Charge Depleting (CD) mode so as to enhance the fuel economy. The results demonstrate that selecting a set of parameters for investigation
depends on average driving distances. Thus it can very well be imagined that the fuel economy will vary between PHEVs.

Vehicle performance and fuel economy are simulated in [3]. It utilizes several mechanical PHEV parameters in order to estimate the wheel torque needed to achieve the desired speed of driving. A parallel HEV configuration is used with a multi-gear transmission. This is done to model a driver who follows a pre-defined speed cycle. The complexities involved in this analysis are increased because of the stochastic nature of parameters such as the length of driving cycles and SOC. The Bellman Principle is utilized in this study to map the optimal path of the SOC. This algorithm aims at minimizing the total energy loss throughout one cycle.

This study also carries out a comparison between blended and electric only control strategy. The SOC is examined in the case when only the battery is used to power the vehicle and also in the case when the battery is used in conjunction with the engine. It is shown that the algorithm gives better results in the case of blended strategy. The algorithm only uses the engine when the efficiency area is the best. It is demonstrated that the final SOC is reached only at the end of the final drive cycle. This is explained due to increased battery losses at low SOC which are a result of increased current because of lower voltage. Thus, it is necessary to know the length of the driving cycle when the SOC is low. It is concluded that for optimal control, the first part of the trip should be completed in electric-only mode and the engine should be used during periods of high acceleration.

The potential benefits of using Li-ion batteries of PHEVs as a power source for grid operations is explored in [4]. Battery requirements for different PHEV
configurations are carried out. Models for the various components are developed along with control strategies in order to characterize PHEVs. The impact of AER on fuel efficiency is analyzed to provide direction on the best sizing strategy. Equations are derived for calculating the impedance of the battery. This is done in order to simulate the battery under driving conditions. It is more difficult to carry this out for PHEVs as compared to HEVs because PHEVs may be charged or discharged for certain duration of time.

This study is carried out keeping an upper limit of 90% and lower limit of 30% for SOC. Thus, only 60% of the stored battery energy is utilized in propelling the vehicle. This is called the SOC window and establishes a relationship between the total energy of the battery and its usable energy. If the value of the SOC window is changed while the battery remains unchanged, it is noted that the usable energy increases along with the AER. However, there is a very small difference in energy consumption by the engine. Decreasing the SOC window also results in a longer battery life, but conversely increases costs as a larger number of cells need to be incorporated.

The effects of different control strategies for PHEVs are examined in [5]. This paper studies two categories for PHEV control: EV mode and blended mode. In EV mode, the vehicle operates in CD condition as long as the electric motor can supply the power and the SOC is greater than the threshold value. Once the SOC is about to go below the set value, the controller switches to charge sustaining (CS) mode. In blended mode the engine is used with the electric motor during the entire driving trip. The SOC decreases during the entire trip and reaches its minimum value at the end of the trip.
This control strategy was designed using a modified Equivalent Consumption Minimization Strategy (ECMS) algorithm. The ECMS algorithm solves the problem considering the total energy consumption, keeping the SOC and the fuel efficiency constant. The basis of the ECMS algorithm is that the energy consumption of the battery of the PHEV is supplied by running the engine. Thus, the discharge of the battery will be equivalent to fuel consumption in the future.

The electricity needed to charge a PHEV battery may come from sources like coal, gas, wind etc [5]. This makes the analysis even more complex because there are factors that are not of the vehicle. Driving cycles of one year are analyzed. This battery energy considers the final and initial SOC but also the energy that is exchanged during the CS mode. It is shown that PHEVs with series configuration have better fuel economy but the usage of the battery is higher. Thus it is necessary to obtain a trade-off between the cost of operation and battery life.

Control models are developed to calculate the SOC for different schemes in [6]. Dynamic programming (DP) is used to obtain a global optimizing solution for CD operation. A CD strategy is implemented for PHEV power management. SOC values for DP based CD control and rule-based control is calculated and the SOC has a higher value in the former. Historical traffic data is used for modeling and simulation purposes as well. Using this data the SOC for the rule based control algorithm and depletion control is calculated. From the analysis it is shown that the SOC will have a higher value in the former case.
Using this globally optimized SOC profile the real-time operation tries to make
the SOC change follow the global optimum through trip-segmentation. Even though DP
is a computationally intensive process, it is highly efficient in this regard.

A V2G aggregator is developed for frequency regulation in [7]. Again, DP is used
to obtain the optimal charging control sequence. The factors that determine the regulation
service provided by the PHEV depend on the adjustable power level, response time, and
energy constraints. The SOC is the most important factor that limits the power. The
charge and discharge are not allowed at the highest and the lowest SOC respectively. The
battery management system (BMS) decreases the power capacity to protect the battery.
This represents one of the design considerations that go into the designing of an optimal
aggregator.

All experiments carried out in this study were only for charging mode. Provisions
were made to adjust the relative importance between the final SOC control and the
revenue generated. Using DP, the optimal control sequences are derived from an initial
SOC of 0% to a maximum final SOC of 100%. A proportionality factor, $\alpha$, is introduced
which accounts for the importance of the level of SOC. When $\alpha$ is decreased it is seen
that the final requested SOC is not met exactly. This happens in the case when the
aggregator judges that the importance of the expected revenue is too high as compared to
the exact control of SOC.

In [8] the fuel efficiency is optimized using different algorithms and a different
methodology. The two methods that are used are the DP algorithm and Pontryagin’s
Minimum Principle (PMP). The DP method approaches the optimization problem using
the Bellman Principle of optimality and the PMP approaches the optimization problem by
improving the charge trajectory. Thus, DP calculates the optimal field and produces a global optimum and PMP produces the necessary conditions that optimal trajectories must satisfy. This means that there is no guarantee of an optimal solution. DP needs to perform more calculations to check for all possible trajectories and PMP checks for optimality only on the optimal trajectory. Thus, DP generates a superior solution whereas PMP requires less computational time. The only advantage that PMP holds over DP is that, a solution can be generated instantly if the appropriate co-state is known.

It is shown that SOC does not impact the time-derivative of SOC, $d(SOC)/dt$, in the primary operating region of the battery in [9]. This is because the resistance and the voltage of the battery are negligibly influenced by the SOC. It is important to select the co-state carefully in PMP to determine how quickly the electric energy is used up during a driving cycle. It has been shown that the optimal co-state is found to be closely related to the patterns of a driving cycle that are represented by the effective SOC drop rate and the effective mean power over the duration of traction.

A battery degradation map is formed in [10]. A high fidelity Li-ion battery is used for the simulations. It shows that at higher SOCs and higher charge rates the battery tends to degrade faster. Even when no current is flowing in the battery, degradation can take place. It is proposed that the PHEV battery should receive the required charge right before the time of use. This essentially decreases the amount of time that the battery has to spend at high SOC resulting in lowered battery degradation.

The optimizing objectives in this study aim to minimize the total energy cost of the PHEV for a given daily drive cycle and to reduce the amount of resistive film growth in order to improve the State of Health (SOH) of the battery. A genetic algorithm, the
Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is utilized in order to optimize the two objectives. This study considers the drive cycles over a 24 hour time frame. The measure of battery degradation is obtained through a reduced order representation of the electrochemistry-based battery model. However, carrying out this optimization problem suffers from a couple of conflicting objectives. Minimizing the total energy cost requires high SOC at the beginning of the trips, but the battery tends to degrade faster at higher SOCs. Therefore a single optimal point does not exist. As a result an optimal Pareto front has to be obtained in order to perform the analysis.

The impact of battery size on optimal power management in PHEVs is studied in [11]. It is shown that with an increase in battery size, the operating costs and energy efficiency reach an asymptotic value. This shows that the daily pay-off for purchasing large batteries for PHEVs does not justify the high acquisition cost at the time of purchase. For very large batteries it is unlikely that the battery will fully deplete its charge because the duration of most trips is less than 35 minutes. It is, however, necessary to have large batteries to minimize performance degradation over the lifetime of the vehicle. Using a small battery may result a small payment initially, but the resulting degradation from the deep discharge cycles will eventually increase the cost of payments.

In this study, the daily drive cycles are examined in great detail because the basic validity of choosing a certain battery size has direct correlation with the daily driving distance. It is shown that 10-16% of PHEV daily trips would result in full CD of a 320 module battery. This percentage is relatively small as compared to the rest. Thus it was
concluded that the benefit of large battery sizes diminishes as the number of modules increases.

The prediction of SOH for Li-ion batteries is not as straightforward as that of other important battery parameters such as the SOC. The SOH of a battery depends on a number of factors as opposed to a single factor. As a result of which there are a number of ways to approach SOH prediction of Li-ion batteries.

Dual-Sliding mode observers were utilized by Kim in [12] to estimate the SOH. As opposed to examining the SOH using an electrochemical model, the author opted to use an electric circuit model for the study. Capacity fade and resistance deterioration are calculated using the dual-sliding mode observer in order to estimate the SOC. The Lyapunov equation is used so as to enable the observer to converge.

This method eliminates several key problems that are raised by conventional methods such as the Kalman Filters and AC Impedance measurement method. These two problems are not dynamic in nature and as a result cannot be implemented on-board a PHEV. To this end, the dual-sliding mode approach eliminates this problem as it is an electric circuit model driven approach. To further illustrate the dynamic nature of the said observer, its effectiveness is tested on the UDDS drive cycle.

The difficulty in monitoring the internal state conditions of Li-ion battery packs without sensors is identified by Saha et al. in [13]. In this study the electrochemical processes are modeled in terms of the equivalent electrical circuit. Furthermore these parameters are coupled with statistical models that help in capturing the aging process of the cells.
In this study a comparison is made of the various particle filters that could be utilized. The Extended Kalman Filter (EKF) approach utilizes a Gaussian function to approximate the probability density function (pdf). Thus, it is highly probable that there might be large deviations. The Sequential Monte Carlo (SMC) method on the other hand implements a recursive Bayesian filter. The sampling importance resampling (SIR) algorithm approximates the filter distribution using a set of weighted particles. This algorithm eliminates the problem of degeneracy of the particle filter algorithm. The Rao-Blackwell particle filter (RBPF) divides the state space into deterministic and probabilistic parts. The deterministic part is solved analytically and the probabilistic part is solved using a particle filter. As a result of this the variance is reduced in the state estimate.

Relevance vector machines (RVMs) are combined with RBPFs in order to predict the End-of-Life (EOL) of the cell. The difference between the RVM and support vector machine (SVM) is that the RVM uses less kernel functions. Previously collected data is used to perform the RVM regression and the kernel functions help in reducing the variance in the number of data points.

The power and thermal characteristics of a Li-ion battery pack are examined by Smith and Wang in [14]. A mathematical and an electrochemical model of a Li-ion battery are considered. A Butler-Volmer kinetic equation is used to calculate the rate of the side reaction at the anode. The Arrhenius equation is used to establish the temperature sensitivity of the general physiochemical property at 25°C. The heat generated in the battery pack is due to the Ohmic heat and the heat generated due to the contact resistance. The Ohmic heat is represented in terms of the heat generated due to the solid phase and
the electrolyte phase. The heat due to the contact resistance is an extra amount of heat and this quantity increases as the number of cycles increase because of the electrochemical reactions that are taking place.

The electrochemical and mathematical models are tested out on the US06, FUDS and HWFET drive cycles keeping a reference temperature of 25°C. The amount of heat generated due to the FUDS and HWFET cycles are 6-12 times less than the heat generated due to the US06 dive cycle.

Extensive laboratory testing has been done in [15] to determine the degradation index. The battery pack was subjected to temperatures of -20°C, -8°C, 12°C, 30°C and 50°C. It is shown that the temperature, SOC, and magnitude of current affect the internal resistance. The significance of these parameters varies from battery pack to battery pack and their respective battery chemistries.

The model under consideration has been adapted for onboard applications using an identification signal which is characterized by a low duration of current measurement and terminal voltage at the start of ignition. Using the model parameters the internal resistance is calculated and the degradation index is computed.

Fuzzy logic was utilized by Singh and Reisner in [16] for SOH determination. The fuzzy membership function uses temperature as a metric. Three categories of temperatures are taken: HOT, WARM and COLD. Electrochemical impedance spectroscopy (EIS) results of defibrillator batteries are taken at constant current discharge. A 3-input, 1-output model was developed to predict the SOC using the cell impedance data.
The advantage of the fuzzy logic approach is that even if there are several related or unrelated measures having partial information, they can be used to predict the state of the system and in this case it can be used to predict the SOH. In this study however, lead-acid batteries were used for analysis, however, the fuzzy logic approach could be extended to other battery types including Li-ion.

Ng et al. estimate the SOH as a percentage of the maximum releasable capacity to the rated capacity in [17]. The SOC is represented as a function of the constant current and constant voltage during the discharging stage. Similarly the SOC has been represented as a function of the open circuit voltage in the open circuit stage. The operating efficiency is evaluated as the Coulombic efficiency.

The calculated estimation errors are shown to increase with each operating cycle. The error increases to 8.93% (21st cycle) from 2.43% (6th cycle). After correction of the operating efficiency, the estimation error is reduced to 1.08% (28th cycle).

A model is developed with the objective to control the film growth in Li-ion battery packs in [18]. Two cells are connected in parallel via relay switches. The switches are controlled using deterministic dynamic programming (DDP) inspired algorithms. The algorithm used in this case is the fall enumeration algorithm. In this a family of optimal trajectories is computed for a set of fixed initial conditions.

It is shown that the DDP and heuristic controller manage to reduce the film growth by over 50%. It is shown that the majority of the film growth reduction takes place by delaying the charging process towards the end of the duration of study. Perhaps the most important conclusion is that the reduction of film growth takes place at the cost of compromising the power efficiency. It was found that the optimization resulted in the
power efficiency being reduced by over 1%. Thus it is necessary to strike a balance between long-term battery degradation and short-term power efficiency.

Rong and Pedram use an analytical model to predict the remaining battery capacity of Li-ion batteries in [19]. The most significant contribution of this study is in coming up with a completely new expression for the remaining capacity (RC). The authors prove that RC can be represented as the product of the SOC, SOH and Design Capacity (DC).

Dynamic voltage and frequency scaling (DVFS) is a method to reduce energy consumption in real-time applications. The RC of the battery is used to calculate the optimal supply voltage. It was found that the difference between the optimal values and calculated values was very low.

Business models and possible implementation of V2G architecture in the current electricity grid is discussed in [20]. The most detailed study on how V2G transactions could be carried out is explained in [21] by proposing a conceptual framework. Intelligent techniques like particle swarm optimization (PSO), binary PSO (BPSO) and ant colony optimization (ACO) are used to solve the unit commitment problem considering that V2G transactions take place in [22]. Aggregated PHEV loads are used to perform demand side management in [23]. The authors use this in conjunction with the energy hub concept which reduces the computational complexity of the entire process. A coordinated charging approach is proposed in [24] for residential areas. Stochastic programming is utilized to minimize power losses and thus obtain the optimal charging profile. The feasibility of implementing V2G for large fleets of PHEVs was shown to be
possible in [25]. The study concluded that PHEVs could be considered as a good source of regulation.
Chapter 3

PHEV Involvement in The Smart Grid

The most significant contribution of PHEVs will be to the future smart grid as opposed to the automotive industry. The future smart grid environment will feature PHEVs as an integral component. Some of the major goals of the smart grid include, bidirectional flow of power between customers and electric utilities, greater integration of renewable energy sources, and make the grid self healing. PHEVs will have a direct impact on the realization of these goals.

The growth of PHEVs will be taking place at a steady rate over the next couple of years. For example in Japan there is a very optimistic outlook on the growth of PHEVs in the market [26]. In Table 3.1 a comparison is shown between the expected growth of PHEVs along with wind power and solar power in Japan.

<table>
<thead>
<tr>
<th></th>
<th>2005</th>
<th>2020</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar Power</td>
<td>1.42 GW</td>
<td>14.32 GW</td>
<td>53.21 GW</td>
</tr>
<tr>
<td>Wind Power</td>
<td>1.08 GW</td>
<td>4.91 GW</td>
<td>6.61 GW</td>
</tr>
<tr>
<td>PHEVs</td>
<td>0%</td>
<td>20% total penetration</td>
<td>40% total penetration</td>
</tr>
</tbody>
</table>
3.1. PHEVs and the bidirectional flow of power

PHEVs can be used as Distributed Energy Resources (DERs) when plugged-in to the electric grid. Bidirectional flow of power is the feature that helps distinguish the smart grid from the current electric grid. The consumption of power is taking place in many avenues. Households for example constitute a large energy consuming group. It is easy to imagine that the energy consumption will peak during the mornings and evenings. The opposite is true for office complexes which will have minimum consumption of energy during the morning period and maximized use during the afternoon and evenings [25].

This results in a few scenarios which make PHEV involvement a benefit. V2G would result in additional income for the PHEV user and V2G would serve help during periods of peak load demand. Also, the V2G taking place during periods of peak load demand would result in the lowering of the RMCP. Table 3.2 summarizes the residential requirements [27].

<table>
<thead>
<tr>
<th>TABLE 3.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>RESIDENTIAL REQUIREMENTS</td>
</tr>
<tr>
<td>Min</td>
</tr>
<tr>
<td>Peak Power</td>
</tr>
<tr>
<td>AC Voltage</td>
</tr>
<tr>
<td>DC Voltage</td>
</tr>
<tr>
<td>Efficiency</td>
</tr>
</tbody>
</table>

Facilitating the bidirectional flow of power by the use of PHEVs is only possible because aggregated loads of PHEVs can serve as an effective means of energy storage. This is the same feature that will help in the greater integration of renewable energy. The
most prominent problem that is impeding the widespread integration of renewable energy is its intermittency. Renewable energy sources like wind and solar are time varying quantities. In the case of wind power, not only does the wind have to be present, it actually has to be above a value called the cut-in velocity so as to enable its production. It can be imagined that with an effective form of energy storage the problem of intermittency can be solved to a very large degree.

3.2. PHEVs and Wind Power

PHEV charging through conventional power sources like coal will result in an increase of harmful emissions. Harmful emissions include: (i) Oxides of Nitrogen which are comprised of Nitrogen monoxide (NO) and Nitrogen dioxide (NO$_2$). (ii) Non-Methane Organic Gases group which has hydrocarbons and Carbon monoxide (CO) (iii) Volatile Organic Compounds (VOCs) and (iv) Particulate matter. Thus, keeping environmental considerations in mind, future charging schemes for PHEVs should ensure that PHEVs charge from renewable energy sources when possible [28].

Wind power is the fastest growing form of renewable energy in the world. With increasing fuel prices and heightened pollution levels throughout the world production of wind power is an attractive option of bulk power production because wind power leads to zero emissions. This increased penetration of wind power has resulted in a marked reduction in wind energy costs since its introduction.

In the case of wind, when the wind velocity is excessive the turbines are made to shut down so as not cross the Betz limit. If that excessive wind is used to charge a battery, then that stored energy could later be used to power the wind turbines when the
wind velocity is below the cut-in velocity. To this end, the battery of PHEVs could be utilized. Aggregated loads of PHEVs could be used to achieve this. This relation is demonstrated in Fig. 3-1.

![Wind Farm - PHEVs - Electric Grid Diagram](image)

**Fig. 3-1** Relationship between wind farm, aggregated PHEVs and electric grid.

It has been noted that wind speeds are higher and steadier during the night-time as compared to the day-time. Also, the overall load demand is lower at night as compared to the day-time. This results in lower RMCP values. Thus, it can be concluded that an ideal situation would be the night-time charging of PHEVs, provided that wind power is the source of power. These PHEVs would in-turn transfer power back to the grid via V2G during the day-time when the load demand is much higher. This would essentially result in the greater integration of wind power into the grid.

Using PHEVs as the primary means of energy storage will require the understanding of several models. Dutta and Overbye used dynamic programming, stochastic dynamic programming and a rule based algorithm for efficient scheduling of wind power deviations with the energy storage medium [29] and [30]. The complexity in implementing the same methodology in our work lies in the fact that PHEVs are not a
constant source of spinning reserve. They have their own schedule and thus may not be available when regulation is required.

The lack of a viable means of energy storage is a glaring flaw that is detrimental to the realization of the smart grid. There are many conceptual ideas which in theory are excellent choices for energy storage. Some of the examples of energy storage options are lead acid battery banks, flywheels, and compressed air energy storage. However, each of these options is not without their flaws, which prevent them from easy integration into the existing system.

In theory the integration of PHEVs and wind power in a symbiotic relationship seems very convenient and idealistic. However, it is worth taking note of the fact there will be significant infrastructure requirements to make this relationship a reality. A fully functioning SCADA/EMS system will be required which will track aggregated PHEV data and information from the ISO’s [31].

A robust communication network will be required that is able to manage the data traffic during periods having large number of transactions. This is especially important because the PHEV user would not be looking for an extended delay in determining when there would be an optimal hour of charging. PHEV parking lots or SmartParks would have to ensure that the routers which are facilitating this communication are secured physically so that they are not harmed physically. In the eventuality that they are compromised, it has to be ensured that it would not result in a domino effect and result in other communication network nodes to cease functioning [31].

Another requirement of the said network will be to securely the data back and forth between the PHEV and the ISO. The encryption/decryption methodology will not
be as straightforward as other instances owing to the randomness of the PHEVs. Furthermore, the PHEVs will be treated as an aggregated unit and this will lead to batch authentication protocols as opposed to a simplistic authentication [31].

The cyber part of this whole system will also include several large databases. These databases should keep an accurate account of several parameters. These parameters will include plug-in, plug-out times, the energy consumed, energy transferred to the grid, number of V2G and G2V transactions. Maintaining an accurate record of these parameters is essential towards ensuring that the PHEV user gets billed accurately [31].

3.3. PHEVs and Smart Grid Health

A study conducted by Mitra et al. [32] indicates that aggregated PHEV loads in the form of parking lots could be used as STATCOMs. The ability of aggregated PHEV loads to be used as STATCOMs would directly influence the power quality of the smart grid. This unique use of PHEVs would help in preventing outages and also help in injecting reactive power into the grid when the voltage is low.

Voltage stability is the ability of the electric grid to return to its original bus voltages after some disturbance. In [27] it is shown how PHEVs help in the short term voltage stability of the electric grid. The simulations for the study were carried out on the IEEE RTS 96, which is a 24 bus system designed to originally test the reliability of the given system. The study was carried out for various penetration levels of aggregated PHEVs in order to determine the stability. It was demonstrated that PHEVs would be suitable for resolving short term voltage issues with the grid. Table 3.3 shows the battery charger requirements that will be needed.
In [25] the effect of PHEVs in various markets was studied. Perhaps the most significant contribution of the paper was stating the fact that the impact of PHEVs would also depend on the market where it was deployed. According to the studies it was shown that the California, Pennsylvania, New Jersey and Maryland markets were favorable for PHEV deployment. The markets in California and New York were deemed to be unsuitable for PHEVs.

In [33] simulation studies were carried out using 120 PHEVs. The results from the study showed PHEVs to be excellent energy storage medium. It was shown that the PHEVs could perform well when required to perform mandatory frequency response (MFR) and also when required to act as a short term operating reserve (STOR). It was shown that using the PHEVs for these services was advantageous from an economic point of view.
Chapter 4

Li-ion Battery Degradation Model

The Li-ion battery is one of the most critical components in the PHEV. The specific properties of the battery vary with the vehicle category, size, and whether the vehicle is an Electric Vehicle (EV), Hybrid Electric Vehicle (HEV) or PHEV. Along with being one of the most important parts of the PHEV, it also represents one of the most expensive parts to replace. Overusing the PHEV for V2G transactions would result in accelerated degradation of the Li-ion batteries. In the long term this could result in becoming a major deterrent to potential buyers.

Li-metal has high electrochemical reduction potential and the lowest atomic mass. The main advantages of Li-ion batteries are the higher specific energy, energy density, lifetime, potentially lower cost in large volumes. The Li-ion battery system is the only battery system that is being considered to be incorporated into PHEVs. The disadvantages are cost, cycle life in All-Electric mode and energy density for long range PHEVs [34] and [35].
In Fig. 4-1 we can see the schematic of a Li-ion cell. During the charging process, the charging current forces the Li-ions to be transferred from the negative electrode to the positive electrode. Conversely, during the discharging period the Li-ions move from the positive electrode to the negative electrode.

The storage of energy in Li-ion batteries is brought about by the transfer of Li-ions between low and high potential energy states. This movement is controlled by two diffusion processes and two electrochemical reactions which are in turn driven by cell overpotentials.

The SOC can be calculated according to Eq.’s (4-1) to (4-3) [37].

\[
\Delta SOC(t) = 1 - \frac{\left( \int_{0}^{t} idt \right)}{C_{available}} \quad (4-1)
\]

where \( i \) is the charging/discharging current, \( C_{available} \) is the available battery capacity in Ampere-hour (Ah). The available battery capacity is expressed as:

\[
\text{Available Capacity} = \int_{0}^{t} idt
\]
\[ C_{available} = i \frac{C_p}{(i)^k} \]  

(4-2)

where \( C_p \) is the Peukert Capacity of the battery in Ah; \( k \) is the Peukert exponent which ranges between 1.1~1.3. These parameters are fixed for each Li-ion battery for a given PHEV.

The Peukert Capacity is expressed as:

\[ C_p = t\left(\frac{C_N}{t}\right)^k \]  

(4-3)

where \( C_N \) is the nominal capacity and \( t \) is the rated charge/discharge time in hours; \((C_N/t)\) is the nominal discharging current in Amperes (A).

When the decision is made that regulation will take place the SOC is updated accordingly. When regulation-up is taking place Eq. (4-4) is followed and Eq. (4-5) is followed in the case of regulation-down.

\[
SOC(t+1) = SOC(t) - \Delta SOC(t) \\
SOC(t+1) = SOC(t) + \Delta SOC(t)
\]

(4-4)  

(4-5)

where \( SOC(t) \) is the current SOC, \( SOC(t+1) \) is the SOC for the next hour and \( \Delta SOC(t) \) is the change in SOC due to transactions with the grid.

The Li-ion battery model used in this study is represented by Eq.’s (4-6) to (4-13) and was developed in [36]. The total intercalation current density, \( J \) is calculated as the sum of the current density of the main reaction and the side reaction and is given by:

\[ J = J_{mr} + J_{sr} \]  

(4-6)
The current density of the main reaction, \( J_{mr} \) and that of the side reaction, \( J_{sr} \) can be given according to Eq.’ (4-7) and (4-8):

\[
J_{mr} = i_{0,mr} A \left[ \exp \left( \frac{\alpha_a F}{RT_A} \eta_{mr} \right) - \exp \left( \frac{\alpha_c F}{RT_A} \eta_{mr} \right) \right]
\]

\[
J_{sr} = -i_{0,sr} A \exp \left( -\frac{\alpha_c F}{RT_A} \eta_{sr} \right)
\]

where \( A \) is the specific area of the electrode, \( i_{0,mr} \) and \( i_{0,sr} \) are the exchange current density of the main reaction and side reaction respectively, \( \alpha_a \) and \( \alpha_c \) are the transfer coefficients of the anode and cathode respectively, \( F \) is Faraday’s constant, \( R \) is the universal gas constant, \( T_A \) is the absolute temperature, \( \eta_{mr} \) and \( \eta_{sr} \) are the overpotentials of the main reaction and side reaction respectively.

The exchange current density, \( i_{0,mr} \) is given by the following expression:

\[
i_{0,mr} = k_1 (c_1^{max} - c_1)^{\alpha_c} (c_1)^{\alpha_a} \]

(4-9)

where \( k_1 \) is the rate constant of the electrochemical reaction taking place, \( c_1^{o} \) and \( c_1^{max} \) are the concentration of Lithium in the solid phase and its maximum value respectively.

The overpotentials of the main reaction and side reaction, \( \eta_{mr} \) and \( \eta_{sr} \) are calculated according to:

\[
\eta_{mr} = \phi_1 - \phi_2 - U_{mr} - \frac{J}{A} R_{FILM}
\]

(4-10)

\[
\eta_{sr} = \phi_1 - \phi_2 - U_{sr} - \frac{J}{A} R_{FILM}
\]

(4-11)

where \( U_{mr} \) and \( U_{sr} \) are the equilibrium potentials of the main reaction and side reaction respectively, \( \phi_1 \) and \( \phi_2 \) are the solid and solution phase potentials respectively.
During the charging/discharging process a resistive film builds up in the anode due to a side reaction at the following rate:

\[
\frac{\partial \delta_{\text{FILM}}}{\partial t} = \frac{J_{\text{SR}} M_p}{A \rho_p F}
\]  

(4-12)

where \(\delta_{\text{FILM}}\) is the thickness of the resistive film, \(M_p\) is the molecular weight and \(\rho_p\) density of the side reaction product. This results in an increase in the resistance of the side film. This resistance, \(R_{\text{FILM}}\) is expressed as:

\[
R_{\text{FILM}} = R_{\text{SEI}} + \frac{\delta_{\text{FILM}}}{K_p}
\]  

(4-13)

where \(R_{\text{SEI}}\) is the initial solid electrolyte interphase resistance and \(K_p\) is the conductivity of the side reaction. The values of the various battery parameters can be found in Table 4.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_1^{\text{max}})</td>
<td>mol/m³</td>
<td>30555</td>
</tr>
<tr>
<td>(\alpha_a)</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>(\alpha_c)</td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>(R_{\text{SEI}})</td>
<td>Ωm⁻¹</td>
<td>0.01</td>
</tr>
<tr>
<td>(F)</td>
<td>C/mol</td>
<td>96485.33</td>
</tr>
<tr>
<td>(R)</td>
<td>J/mol/K</td>
<td>8.314</td>
</tr>
<tr>
<td>(T_a)</td>
<td>K</td>
<td>298</td>
</tr>
<tr>
<td>(M_p)</td>
<td>mol/kg</td>
<td>7.3x10⁴</td>
</tr>
<tr>
<td>(\rho_p)</td>
<td>kg/m³</td>
<td>2100</td>
</tr>
<tr>
<td>(K_p)</td>
<td>S/m</td>
<td>1</td>
</tr>
<tr>
<td>(i_{\text{os}})</td>
<td>A/m²</td>
<td>1.5x10⁶</td>
</tr>
</tbody>
</table>

Based on Eq.’s (4-6) to (4-13) the increase in \(R_{\text{FILM}}\) can be demonstrated according to Fig. 4-1. It can be seen that \(R_{\text{FILM}}\) increases by 0.0025 mΩ over 50 cycles.
Fig. 4-2 Increase in Resistance (mΩ).

This increase in $R_{FILM}$ will lead to increased temperatures in the battery pack during charging as well as when the PHEV is traveling. The increased temperature will lead to greater thermal degradation within the battery pack.

The maximum power available from the PHEV is expressed as:

$$P_{PHEV} = \frac{(E_s - \frac{d_d + d_{rb}}{\eta_{PHEV}})}{t_{disp} \eta_{inverter}}$$

where $E_s$ is the stored energy available to the inverter; $d_d$ is the distance driven in miles since the energy storage was full; $d_{rb}$ is the minimum distance that maybe required to be driven by the driver; $\eta_{PHEV}$ is the vehicle efficiency represented in miles/kWh; $\eta_{inverter}$ is the efficiency of the DC to AC inverter; and $t_{disp}$ is the time the vehicles energy is dispatched in hours [38].
Chapter 5

Swarm Intelligence

5.1. Introduction

Since its introduction in 1995 [39], Particle Swarm Optimization (PSO) and its many variants have been used extensively in power system studies. PSO is a form of nature inspired computing that draws its inspiration from the flocking behavior of birds [40]. Any problem which can have a mathematical formulation has variables which are bound by a set of constraints. As a result of which this problem will have a well defined solution space. PSO involves the releasing of a number of particles that search the given solution space for the global optimum value of the function. A few examples of the various forms of PSO are: Binary PSO (BPSO), Evolutionary PSO (EPSO), Multi-objective PSO (MOPSO), Quantum-inspired BPSO (QBPSO), Integer PSO (IPSO), Vector evaluated PSO (VEPSO), Hybrid PSO (HPSO) etc [40].

One of the factors that has lead to widespread acceptance of PSO as the algorithm of choice for optimization is because the computational times remain low even though the dimensionality of the problem increases. This is due to the fact that, PSO is modeled using linear equations.
The word “swarm” comes from the irregular movements of the particles in the problem space, now more similar to a swarm of mosquitoes rather than a flock of birds or a school of fish. The movement of each particle naturally evolves to an optimal or near-optimal solution. PSO is not largely affected by the size and nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge.

The pseudo code for PSO can be given by [41]:

```
Begin
  Initialize swarm
  Locate gbest
  generation = 0
  While generation < gmax
    For each particle
      Update velocity and position
      Evaluate fitness function
      Update pbest
    End For
    Update gbest
    g++
  End While
End
```

The velocity of the particles is updated according to the following expression in [39]:

\[
v_{ij}(n) = w \cdot v_{ij}(n-1) + c_1 \cdot rand_1 \cdot (P_{BEST}(n) - X_{ij}(n-1)) + c_2 \cdot rand_2 \cdot (G_{BEST}(n) - X_{ij}(n-1))
\]  \hspace{1cm} (5-1)

The position of the particles is updated according to the following expression:

\[
X_{ij} = X_{ij} + v_{ij}
\]  \hspace{1cm} (5-2)

where
The terms $c_1$ and $c_2$ are the cognitive acceleration and social acceleration constants respectively. $c_1$ is a user defined term which helps the particle in accelerating towards the position of $P_{BEST}$. Essentially, it scales $rand_1$ and helps in storing the $P_{BEST}$ position. Similarly, $c_2$ is a user defined term which helps the particle in accelerating towards the position of $G_{BEST}$. Just like $c_1$, $c_2$ helps in scaling $rand_2$ and in this case it helps in storing the $G_{BEST}$ position [40].

5.2. Binary Particle Swarm Optimization

The BPSO is a binary variant of PSO [42]. A modified BPSO developed in [43] is used in this thesis. One of the primary differences between PSO and BPSO is that the BPSO algorithm utilizes discrete variables as opposed to continuous variables in PSO. In this thesis, BPSO has been used for certain simulations because of its ability to find optimal solutions in a multi-dimensional solution space at quicker times as compared to the algorithms highlighted in Chapter 2.

A new normalized velocity term is then calculated by using the sigmoid function as shown in Eq. (5-3). The new velocity term lies in the range of [0-1].
Finally, the new position is calculated using Eq. (5-4) with the new velocity.

\[ X_{ij}(n) = 1, \text{ if } \text{rand} < v_{ij} \]
\[ X_{ij}(n) = 0, \text{ for all other cases.} \]  

\[ (5-4) \]

5.3. Multi-objective Particle Swarm Optimization

Multi-objective problems generally involves the optimization of functions which maybe conflicting with each other. To this end, the solution of such a problem includes a set of tradeoff solutions between the optimized parameters as opposed to a single unique solution. MOPSO was developed by Coello and Lechuga in 2002 [44].

In a single objective PSO, the values of \( P_{\text{BEST}} \) and \( G_{\text{BEST}} \) reach their optimal values based on the corresponding values of the leader. In MOPSO, each particle has a different number of leaders from which a leader is selected for the position to be updated. These leaders are then compiled in an archive or repository [41].

The \( P_{\text{BEST}} \) of a particle is updated only when the new fitness value is non-dominated or when both cannot be compared. In the case when both the particles cannot be compared one of the particles is selected randomly as one of the leaders. This process leads to improvement in the search for optimal value in the solution space [41].

A kernel density estimator is used in order to select a leader from the archive/repository [45]. This is used in order to determine the congestion degree of the particle. As such, a particle which is less crowded manages to get selected. Also, a niche is defined which keeps a track of the number of comparable particles. The number of
particles in the niche helps in determining the degree of congestion of the said particle. The roulette-wheel selection method is employed in order to select the particle that becomes the leader.

One of the methods of selecting the non-dominated solutions from the archive/repository is to retain all the non-dominant solutions with respect to the previous populations of particles. As a result of which, a particle can only be added to the archive if the following situations take place: (i) It is non-dominated to all the solutions in the archive (ii) It is dominant over just any one of the solutions. In this case the dominated solution has to be deleted from the archive.

Since the archive size is limited there has to be a mechanism which increases the diversity of solutions while maintaining the size. The ε-dominance approach has been used for our study [46]. According to this method a set of boxes is defined and each box keeps only one non-dominated solution. If the box has more than one solution the box which is closer to the non-dominated vertex of the box will be selected. When this method is used the size of the archive is dependent on the user defined parameter ε.

The MOPSO algorithm is executed according to the following steps:

**STEP 1:** A population of particles is initialized.

**STEP 2:** The leaders are initialized in an archive.

**STEP 3:** A leader is selected.

**STEP 4:** Velocity and position are updated according to Eq.’s (5-1) and (5-2).
**STEP 5**: The fitness functions are evaluated according to the relevant equations.

**STEP 6**: The value of $P_{BEST}$ is updated.

**STEP 7**: STEP’s (3)-(6) are repeated for every particle.

**STEP 8**: The leaders are updated in the archive.

**STEP 9**: STEP’s (3)-(8) are repeated till the maximum number of generations are reached.

**STEP 10**: The non-dominant solutions that are stored in the archive are plotted in the form of a Pareto optimal front.
Chapter 6

Using Swarm Intelligence for Developing an Optimal Charging Profile of PHEVs

6.1. Introduction

The introduction of PHEVs is an important step for both the automotive industry as well as the power industry. Smart grid implementation has been one of the most talked about research topics in recent times. This is a major challenge from many aspects, namely: infrastructure, policy planning, technology development and availability of capital. The goal in the US is to achieve a market penetration of 1 million PHEVs by 2015 [47]. In Belgium the target is to reach a penetration of 30% by 2030 [48].

A vital advantage that the smart grid will have over the current electricity grid is that it will be bidirectional i.e. not only will the grid provide power to the customers like before but it will also have the ability receive power from the users. A few of the sources that will enable this to take place are: PHEVs, intelligent buildings and intelligently coordinated energy storage banks. The ability of the PHEV to give power to the grid is an advantage to the grid because if it is done at a period of high load demand, this could lead to load curtailment.
The individual energy available in the PHEV battery is not a quantity that is large enough to make any significant change to the grid in terms of power injected. For example, the Chevy Volt has a maximum available energy capacity of 16 kWh [49]. Thus, it is necessary to take a number of PHEVs together so that they represent a large kW load and have the ability to make a significant contribution to the grid when the need arises. This particular action can be facilitated with the help of the aggregator concept. The aggregator is the interface between the PHEV and the ISO. The aggregator keeps a track of the total aggregated load of the PHEVs and the grid demand as given by the ISO at any given time. These parameters combined with the electricity rates at any particular hour help the aggregator determine whether or not a transaction (V2G/G2V) will take place. This relationship between the aggregator, PHEVs and ISO has been illustrated in Fig. 6-1.

![Fig. 6-1 Framework for V2G transactions for aggregated PHEV loads.](image-url)
In the future smart grid environment the PHEV user preferences should have a bearing on aggregator behavior. For example, the PHEV user will have the option of whether or not to allow their vehicle to participate in aggregation. The PHEV user could reserve the right to use their PHEV in only a dumb charging scenario i.e. the PHEV will automatically start to charge when it is plugged in.

It has already been mentioned that a major attraction of V2G technology is that it could be used by the PHEV user to earn revenue. This revenue could be maximized by having multiple V2G transactions with the grid [50]. However, the frequent change in SOC of the battery will result in battery degradation and reduce battery storage capability [38]. While it is economically sensible to maintain a profit margin, measures must be taken to prevent the unnecessary degradation of battery health. A balance has to be achieved when it comes to the number of V2G transactions taking place and preventing unnecessary battery degradation. It has been mentioned earlier in Chapter 4 that the cost of the battery is a major part of the overall cost of the PHEV. This is also a disadvantage for PHEVs with parallel drive-trains as the battery is the main energy source that is powering the engine.

It is proposed that the PHEV should be subjected to an intelligent charging/discharging schedule. The aggregator would be following this schedule in order to accomplish the following objectives: (i) Maintaining a profit margin for the PHEV user (ii) Preventing unnecessary battery degradation in the PHEV (iii) Meeting grid requirements. The aggregated load of PHEVs should not be excessive especially at a time
of peak load demand as this could lead to additional power losses and affect overall power quality.

Vehicles are generally parked for an overwhelming majority of the time in a day. It was shown in [51] that vehicles are parked for 23 hours in a day. The bulk of this time is spent in being parked at home or at the work place. This optimized charging/discharging schedule would serve two primary objectives: (i) Profit maximization and (ii) Prevention of unnecessary battery health degradation.

In order to analyze this aspect of PHEV aggregator behavior the MOPSO algorithm has been used. This is done in order to obtain a balance when it comes to profit maximization and prevention of battery degradation. Two charging/discharging profiles have been defined which represent both the objectives being pursued in this study.

6.2. Problem Formulation

6.2.1. With Fixed Plug-in and Plug-out Times

One aspect of PHEV aggregator behavior that is explored is when the plug-in and plug-out times of the PHEVs are fixed between 9 AM and 5 PM. The significance of studying PHEV charging/discharging patterns for this specific time slot is significant because in a future smart grid scenario aggregated PHEV loads could be used for load curtailment during the peak load demand which takes place during the said time-frame. In the future smart grid environment it can be expected that aggregated loads of PHEVs in office spaces will be used for regulation.
We consider whether transactions will take place using the Regulation Market Clearing Price (RMCP) data in Table 6.1, SOC and \( k\text{Wh}_{\text{available}} \) of the PHEV. Furthermore, the following three possibilities may take place: (i) Charging (ii) Discharging and (iii) No transaction with the grid. The BPSO algorithm is used to generate a charging/discharging profile which would be applicable to every PHEV that is plugged-in. Cost and revenue functions as shown in Eq.’s (6-1) and (6-2) [50] are used.

\[
C(t) = \frac{P(t) \times (SOC \times k\text{Wh}_{\text{MAX}} - k\text{Wh}_{\text{available}})}{\eta_{\text{charge}}} \tag{6-1}
\]

\[
REV(t) = P(t) \times (k\text{Wh}_{\text{available}} - SOC \times k\text{Wh}_{\text{MAX}}) \times \eta_{\text{discharge}} \tag{6-2}
\]

where

\[
C(t) = \text{Resulting cost of charging that vehicle.}
\]

\[
REV(t) = \text{Revenue made by selling from that vehicle.}
\]

\[
P(t) = \text{Price at hour } t.
\]

\[
t = \text{Optimal buy/sell time hour.}
\]

\[
k\text{Wh}_{\text{available}} = \text{Kilowatt-Hour energy in the battery.}
\]

\[
k\text{Wh}_{\text{MAX}} = \text{Maximum battery capacity.}
\]

\[
SOC = \text{Departure SOC.}
\]

\[
\eta_{\text{charge}} = \text{Charging Efficiency.}
\]

\[
\eta_{\text{discharge}} = \text{Inverter Efficiency.}
\]

| TABLE 6.1 |
|---|---|
| RMCP FOR 07/01/2011 from PJM [52] |

<table>
<thead>
<tr>
<th>Hour</th>
<th>Price ($/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 AM</td>
<td>0.0141</td>
</tr>
<tr>
<td>1 AM</td>
<td>0.0120</td>
</tr>
<tr>
<td>2 AM</td>
<td>0.0124</td>
</tr>
<tr>
<td>3 AM</td>
<td>0.0127</td>
</tr>
<tr>
<td>4 AM</td>
<td>0.0119</td>
</tr>
<tr>
<td>5 AM</td>
<td>0.0078</td>
</tr>
<tr>
<td>6 AM</td>
<td>0.0076</td>
</tr>
<tr>
<td>7 AM</td>
<td>0.0075</td>
</tr>
<tr>
<td>8 AM</td>
<td>0.0112</td>
</tr>
<tr>
<td>9 AM</td>
<td>0.0113</td>
</tr>
<tr>
<td>10 AM</td>
<td>0.0100</td>
</tr>
</tbody>
</table>
6.2.2 With Variable Plug-in and Plug-out Times

It is also necessary to study charging/discharging behaviors of PHEVs over an extended period of study with flexible plug-in and plug-out times as this is a more practical representation of a real-time scenario. A primary difficulty arises in this case because the number of possible profiles varies according to the duration for which the PHEV is plugged in. As a result of which it becomes more complex to determine a balance between the need for profit maximization for the PHEV user and the need to prevent unnecessary battery degradation.

Two profiles are considered for the purpose of our simulations. The first profile is the one that was introduced in [53] and will be referred to as the battery health optimizing profile. In this profile the transactions with the grid are limited to only two. There will be one V2G transaction at the hour with the highest regulation market clearing price (RMCP), one G2V transaction at the hour with the lowest RMCP and the remainder of the period is spent in CS mode. The objective of the second profile is that of profit maximization. In this profile a G2V transaction takes place at the hour with the lowest
RMCP, CS takes place at the hour with the second lowest RMCP and the remainder of the period is spent in V2G transactions.

When the plug-in \((t_1)\) and plug-out times \((t_2)\) of the PHEVs is not fixed, it is not possible to have uniform aggregator action keeping a fixed objective. It can be imagined that for shorter durations of charging/discharging, the revenue will be lower and the battery degradation characterized by \(R_{FILM}\) build-up will also be lower. Similarly, for longer durations of charging/discharging the revenue will be higher and \(R_{FILM}\) build-up will also be correspondingly higher. As \(\Delta t = t_2 - t_1\) varies between the period of study, profit maximization for the PHEV user should be obtained at reduced \(R_{FILM}\) build-up. This \(R_{FILM}\) build-up can be controlled by the SOC at \(t_1\). This is not an inherently user controlled quantity but it can be manipulated by the PHEV user to reach the optimal SOC value. This concept will be further explained later in this chapter.

Thus, this could be classified as a bi-objective problem where the two objectives are: (i) Profit maximization, (ii) Reduction in \(R_{FILM}\). Profit maximization through transactions with the grid can be achieved in the following ways: (i) Many transactions with the grid should take place. Ideally there should be a high number of V2G transactions and a comparatively low number of G2V (ii) When the number of V2G transactions is equal to the number of G2V transactions the profit formulation should be given as \((REV_{MAX} - COST_{MIN})\). Battery degradation can be reduced by: (i) Having a large number of periods in CS mode. (ii) Having a minimum of only one V2G and G2V transaction and keeping the PHEV in CS mode for the rest of the period.

The problem formulation can be given as:
Maximize Profit = \sum_{t=1}^{T} [REV(t) - C(t)]

where \( t = 1, 2, \ldots 24 \)

Minimize Resistive film = \( R_{FILM} \)

subject to,

\( t_2 > t_1 \)

\( \Delta t = (t_2 - t_1) > 2 \)

\( 1 \leq t \leq 24 \)

\( SOC_{MIN} \leq SOC(t) \leq SOC_{MAX} \)

\( COST_{MIN} \leq C(t) \leq COST_{MAX} \)

\( REV_{MIN} \leq REV(t) \leq REV_{MAX} \)

6.3. Methodology

It has been assumed in these simulations that the PHEV does not leave the aggregation unit during the period of study. Another assumption that has been made is that the basic PHEV and Li-ion battery characteristics of the battery are assumed to be the same for each PHEV.

**STEP 1:** The MOPSO algorithm takes the number of PHEVs taking part in the aggregation as input from the user.

**STEP 2:** The MOPSO algorithm generates a random value for \( t_1 \) and \( t_2 \) time constrained by Eq.’s (6-5) to (6-7). The SOC at \( t_1 \) is a necessary parameter because this value directly determines how much power the PHEV can provide to the grid. Alternately, it will also help determine how much power the PHEV would need to draw from the grid. This in-turn helps in computing the cost of charging as well as the revenue that could be earned via V2G transactions. As such, the lower the value of the initial SOC the higher the cost of charging and the
longer the PHEV battery will be used. Since $t_1$, $t_2$ and the SOC at $t_1$ are the quantities that are being optimized, the dimensionality of the problem for $n$-number of PHEVs will be given as $3n$.

**STEP 3:** The period for which the PHEV will remain in aggregation is calculated as $\Delta t = t_2 - t_1$. This is constrained according to Eq. (6-6).

**STEP 4:** The charging profile is generated. The profile that ensures the minimization of battery health degradation by curtailing the number of transactions with the grid is as follows: For $t_1 \leq t \leq t_2$ the PHEV takes part in G2V at the hour with the lowest RMCP value and V2G at the hour with the highest RMCP. The second profile that we consider ensures a high profit margin by ensuring that a large number of transactions take place with the grid and is as follows: For $t_1 \leq t \leq t_2$ the PHEV takes part in G2V at the hour with the lowest RMCP. The PHEV is kept in CS mode at the hour with the second lowest RMCP. The rest of the period the PHEV takes part in V2G. MOPSO simulations are run for both profiles separately.

**STEP 5:** The SOC for the PHEVs is calculated according to Eq.’s (4-1) to (4-3) and the corresponding profile generated in **STEP 4**.

**STEP 6:** The cost and revenue is calculated using Eq.’s (6-1) and (6-2), the RMCP values in Table 6.1, the calculated SOC values from **STEP 5** and the profile that was obtained in **STEP 4**.
STEP 7: The increase in $R_{FILM}$ is calculated according to Eq.’s (4-6) to (4-13) for the charging/discharging profile.

6.4. Results and Discussions

The Li-ion battery being considered for simulations is assumed to have a rated capacity of 6 Ah, a nominal voltage of 276 V and nominal capacity of 4.5 Ah. The simulations were run on MATLAB and executed on a PC with 3.33 GHz Core i7 Processor and 12 GB RAM.

6.4.1. For Fixed Plug-in and Plug-out Times

The optimal charging profile obtained by using BPSO has been utilized for mapping the SOC with the V2G transactions in this case. The result is demonstrated in Fig. 6-2. It can be seen that the PHEV charging takes place in the hour before the time of departure. Keeping in mind the results found in [10], this is extremely beneficial for battery health parameters. It can also be seen that the vehicle is able to successfully supply power to the grid between 9-10 AM. The remainder of the times the PHEV is seen to be operating in CS mode.

Following the methodology that we have implemented, we have limited the transactions with the grid to only 2. It was found that the increase in $R_{FILM}$ is only 0.000007 mΩ which is significantly less than the increase in $R_{FILM}$ when BPSO is not used. The profit that the PHEV user will earn will be the maximum revenue that could be earned when two transactions with the grid are carried out.
6.4.2. For Variable Plug-in and Plug-out Times

In Table 6.2 the optimal values of $t_1$, $t_2$ and the SOC at $t_1$ are listed. These have been obtained from MOPSO when a profit maximizing charging/discharging profile was used.

**TABLE 6.2**
**POSSIBLE SOLUTIONS OF OPTIMAL $T_1$ AND $T_2$ FOR PROFIT MAXIMIZATION**

<table>
<thead>
<tr>
<th>PHEV</th>
<th>Plug-in time ($t_1$)</th>
<th>Plug-out time ($t_2$)</th>
<th>Plug-in duration (Hours)</th>
<th>SOC at $t_1$(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10 AM</td>
<td>3 PM</td>
<td>5</td>
<td>45.79</td>
</tr>
<tr>
<td>2</td>
<td>11 AM</td>
<td>3 PM</td>
<td>4</td>
<td>63.70</td>
</tr>
<tr>
<td>3</td>
<td>1 PM</td>
<td>6 PM</td>
<td>5</td>
<td>45.72</td>
</tr>
<tr>
<td>4</td>
<td>7 AM</td>
<td>10 AM</td>
<td>3</td>
<td>66.15</td>
</tr>
<tr>
<td>5</td>
<td>11 AM</td>
<td>5 PM</td>
<td>6</td>
<td>57.58</td>
</tr>
<tr>
<td>6</td>
<td>10 AM</td>
<td>4 PM</td>
<td>6</td>
<td>55.54</td>
</tr>
<tr>
<td>7</td>
<td>9 AM</td>
<td>2 PM</td>
<td>5</td>
<td>59.83</td>
</tr>
<tr>
<td>8</td>
<td>8 AM</td>
<td>10 AM</td>
<td>2</td>
<td>54.87</td>
</tr>
<tr>
<td>9</td>
<td>1 PM</td>
<td>3 PM</td>
<td>2</td>
<td>83.73</td>
</tr>
<tr>
<td>10</td>
<td>5 AM</td>
<td>9 AM</td>
<td>4</td>
<td>58.83</td>
</tr>
</tbody>
</table>
In Table 6.3 the optimal values of $t_1$, $t_2$ and the SOC at $t_1$ have been listed when the alternate charging/discharging profile which helps in preventing battery health degradation is used. The key value to be noted in Tables 6.2 and 6.3 are the values of the SOC at $t_1$ and the plugged in duration. On studying these solutions it can be seen that the plugged in duration in Table 6.2 is lower as compared to Table 6.3. The values of plugged in duration may be higher in Table 6.3 but the point to be noted is that in the second case the number of transactions are only limited to two.

The values in Table 6.2 indicate that the strategy in a profit maximizing mode should have the following characteristics: (i) The SOC at $t_1$ should not be too high or too low. The only exception to this rule is PHEV 9 in Table 6.2 which has an initial SOC of 83.73%. However, this is an acceptable value as it can be seen that the duration for which it is plugged-in is only 2 hours. (ii) The plugged in duration cannot be too high or too low. As was demonstrated in the previous point, if the duration is too low the corresponding initial SOC should be high. This gives an indication of the nature of trade-off that must be made by the aggregator in the future if the PHEV user opts for a profit maximizing profile.

The profile that was adopted to obtain the results in Table 6.3 will undoubtedly be a superior profile when it comes to preventing battery health degradation. However, it suffers in comparison to the profile in Table 6.2. This is because not only does it give higher profits, it ensures that it is achieved in the shortest plugged-in duration.
### TABLE 6.3
**Possible Solutions of Optimal \( t_1 \) and \( t_2 \) to Prevent Battery Health Degradation**

| PHEV | Plug-in time \( (t_i) \) | Plug-out time \( (t_o) \) | Plug-in duration (Hours) | SOC at \( t_i \)(%)
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8 AM</td>
<td>7 PM</td>
<td>11</td>
<td>51.29</td>
</tr>
<tr>
<td>2</td>
<td>3 AM</td>
<td>1 PM</td>
<td>10</td>
<td>68.04</td>
</tr>
<tr>
<td>3</td>
<td>5 AM</td>
<td>1 PM</td>
<td>8</td>
<td>53.52</td>
</tr>
<tr>
<td>4</td>
<td>3 AM</td>
<td>11 AM</td>
<td>8</td>
<td>65.66</td>
</tr>
<tr>
<td>5</td>
<td>10 AM</td>
<td>3 PM</td>
<td>5</td>
<td>59.16</td>
</tr>
<tr>
<td>6</td>
<td>10 AM</td>
<td>2 PM</td>
<td>4</td>
<td>54.71</td>
</tr>
<tr>
<td>7</td>
<td>10 AM</td>
<td>10 PM</td>
<td>12</td>
<td>60.45</td>
</tr>
<tr>
<td>8</td>
<td>5 AM</td>
<td>2 PM</td>
<td>9</td>
<td>42.68</td>
</tr>
<tr>
<td>9</td>
<td>9 AM</td>
<td>4 PM</td>
<td>7</td>
<td>47.22</td>
</tr>
<tr>
<td>10</td>
<td>4 PM</td>
<td>11 PM</td>
<td>7</td>
<td>51.94</td>
</tr>
</tbody>
</table>

In Table 6.4, the computational times have been listed for different combinations of number of generations and number of particles. It was seen that the increase in time takes place more significantly with the increase in number of particles.

### TABLE 6.4
**Computational Times for MOPSO**

<table>
<thead>
<tr>
<th>No. of Generations</th>
<th>No. of Particles</th>
<th>Time (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>14</td>
</tr>
<tr>
<td>300</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>22</td>
</tr>
<tr>
<td>400</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>30</td>
</tr>
</tbody>
</table>
Fig.'s 6-3 to 6-5 demonstrates the Pareto optimal front that was obtained for resistance vs. cost for a profit maximizing profile for 10, 20 and 30 PHEVs respectively. The plots indicate increasing profit margins for an increase in resistance which is inevitable while charging/discharging. Fig. 6-6 demonstrates the Pareto optimal front that was obtained for resistance vs. cost in a battery health optimizing profile.

Fig. 6-3 Pareto optimal front for Resistance vs. Cost for profit maximization profile for 10 PHEVs.
Fig. 6-4 Pareto optimal front for Resistance vs. Cost for profit maximization profile for 20 PHEVs.

Fig. 6-5 Pareto optimal front for Resistance vs. Cost for profit maximization profile for 30 PHEVs.
Fig. 6-6 Pareto optimal front for Resistance vs. Cost for battery health optimization profile.
Chapter 7

Assessing the Effect of Fast Charging on Overall PHEV Battery Health

7.1. Introduction

PHEVs produce lower emissions and have superior fuel efficiency and these characteristics are advantageous for both the environment and the end-user. An important problem plaguing PHEVs is range anxiety. It may be very difficult for the customer to predict how many miles the PHEV can operate with one full charge. To this end, the best possible solution could be the easy availability of charging stations. For maximum benefit to the users, charging stations should be within easy reach, i.e. both within city limits and at regular intervals on highways [54].

The charging methodology of PHEVs is well documented in [55]-[57]. There are three primary methods of charging: Dumb charging, dual-tariff charging, and smart charging. Under the dumb charging scheme a PHEV starts to charge as soon as it is plugged in. Regarding the dual-tariff charging methodology, the tariff is the variable that determines whether charging should take place keeping in mind the needs of the customer. Smart charging attains the balance between user needs and grid demands by taking into account real-time electricity rates without compromising on individual PHEV
requirements.

In addition to the above three methods of charging, another way to classify PHEV charging is as follows. Three levels that have been identified are shown in Table 7.1.

<table>
<thead>
<tr>
<th>Level</th>
<th>Location</th>
<th>V and I</th>
<th>Power (kW)</th>
<th>Approx. time to charge</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Residential</td>
<td>110V, 15 A</td>
<td>1.4</td>
<td>18 Hours</td>
</tr>
<tr>
<td>2</td>
<td>Residential/Public</td>
<td>220V, 15-30 A</td>
<td>3.3</td>
<td>4-8 Hours</td>
</tr>
<tr>
<td>3</td>
<td>Commercial</td>
<td>480V, 167 A</td>
<td>50-70</td>
<td>20-50 minutes</td>
</tr>
</tbody>
</table>

LEVEL 3 or fast charging is the quickest form of charging among the three levels. This fast form of charging is only possible due to the high voltage, current and power ratings. As a result of which fast charging has no feasibility to be implemented in a residential neighborhood due to the excess load it will incur on the grid. Fast charging can be identified as the gas station equivalent of PHEV charging stations. This form of charging could be implemented in commercial enterprises such as malls and highway rest-stops. In short this could be used in locations where PHEV users are not expected to spend a long duration of time.

A clear advantage of fast charging over the other two charging schemes is that the charging period is by far the shortest. The battery of choice in PHEVs is the Li-ion batteries. Since the battery is subjected to such high voltage and current it will experience greater thermal degradation as a result of the comparatively higher temperatures generated during charging. As a result, it can be expected that the overall health of the batteries will deteriorate over time depending on the number of times the PHEV user
decides to opt for this form of charging.

This paper uses a Li-ion battery model to simulate the effect that fast charging has on the various factors that affect the health of the battery. MOPSO is used to device strategies that will help in reducing battery degradation and also make fast charging cost effective.

7.2. Problem Formulation

The time at which the PHEV charging takes place would seem to be an inflexible quantity. Time of charging for PHEVs in fast charging mode varies between 30-50 minutes, thus there is very little room for an effective strategy within such a limited constraint. The decision variable for the first fitness function given by Eq. (7-1) is the hour of charging and the decision variable for the second fitness function given by Eq. (7-2) is the SOC at the time of plug-in.

Problem formulation:

\[
\begin{align*}
\text{Minimize Cost} &= C(t) \\
\text{Minimize Resistive film} &= R_{\text{FILM}}
\end{align*}
\]

subject to,

\[
\begin{align*}
SO_{\text{MIN}} &\leq SOC(t) \leq SO_{\text{MAX}} \\
COST_{\text{MIN}} &\leq C(t) \leq COST_{\text{MAX}}
\end{align*}
\]

RMCP values are taken from the PJM website. Since RMCP values vary from season to season, the values are taken over a 24 hour period during the summer, fall and winter. The RMCP values that have been taken are for the following dates 05/02/2010, 09/01/2010, and 02/01/2011. It has already been shown in Table 7.1, that fast charging utilizes higher voltage and current values. That along with the exclusively commercial nature of this form of charging, it can be imagined that the cost of charging will be higher.
than the actual RMCP value at any given hour. As such, for the purpose of our simulations the RMCP values are assumed to be 3 times ($3x$) the actual value. The RMCP value distribution over the summer, fall and winter are shown in Fig. 7-1.

![Fig. 7-1 RMCP Values for summer, fall and winter.](image)

### 7.3. Results and Discussions

Charging and discharging characteristics have been analyzed in this section. In addition the optimization results obtained from MOPSO are also presented. The simulations were run on MATLAB and AUTONOMIE [58].

#### 7.3.1. Discharge Characteristics

Based on the battery characteristics that have been stated, the discharging characteristics of the battery were simulated. The simulations were carried out for the discharging currents of the following values: $C/3$, $C/2$ and $C$ and the corresponding relationship is shown in Fig. 7-2.
Fig. 7-2 Discharge Characteristics of Li-ion Battery.

The relationship between the OCV and the DOD has been shown in Fig. 7-3. It can be clearly seen that with increase in the DOD the OCV decreases almost linearly but experiences a sharp drop as the DOD approaches zero.

Fig. 7-3 DOD vs. OCV.
7.3.2. Charging Characteristics

The effectiveness of fast charging is demonstrated in Fig. 7-4. The simulations have been carried out with the aim to show that the time required to charge a PHEV for SOC window values between 75-100% is very low. For an almost discharged PHEV the amount of time required to fully charge will be ~31 minutes. This is clearly demonstrated in Fig. 7-4. Thus, it follows that for lower values of SOC window, the time will decrease. In this scenario it can be seen that the time decreases linearly. A discharging current of 167 A is used for the purpose of our simulations.

![Fig. 7-4 SOC Window vs. Time.](image)

7.3.3. Optimization Results

Table 7.2 summarizes a list of trade-off solutions between SOC and time of charging for summer, fall and winter. Thus the trade-off solutions obtained using MOPSO can be beneficial to the PHEV user in the following two ways: (i) If the user finds that the SOC is at an optimal value, but the time of charging is not suitable due to high RMCP values, the user could make the decision to wait for some time until a more
cost-effective hour. (ii) If the user finds that the hour of charging is ideal to his needs but
the PHEV SOC will result in greater battery degradation, the user could make the
decision to drive for some extra time so as to deplete the SOC to a more desirable level.
Since a fast charging ensures that a PHEV with near zero SOC is charged fully within an
hour, the user might make it within the hour of opportunity although it is highly probable
that the PHEV may not charge fully.

Observing the optimal tradeoff solutions in Table 7.2 it can be seen that the
optimal times of charging in summer are more convenient as compared to fall and winter.
The inference that could be made is that, the optimal times of charging calculated for fall
and winter maybe beneficial for PHEV users who are making long distance trips by
driving on highway.

Potential PHEV customers will not be bothered with technical term like the
resistive film of the Li-ion battery. However, embedding this methodology on the on-
board vehicle management system would help the user get an understanding as to when
the PHEV battery health will get lowered. Since the RMCP will play an important role in
the optimization, the PHEV customers will also be aware of a daily RMCP values in the
future just like almost everyone has an estimated idea of the daily gas prices [59].

Swarm intelligence algorithms demonstrate much superior performance times as
compared to other multi-objective optimization techniques. Embedding the software
which would help in implementing this methodology would definitely be feasible if the
MOPSO running times can be reduced further. Widespread adoption and acceptance of
PHEV charging stations with fast charging feature will surely help in decreasing costs in
the future. Coupled with advertising on the charging stations [55], the cost of charging
can be expected to decrease in the future.

**Table 7.2**
**Selected Optimal Tradeoff Solutions**

<table>
<thead>
<tr>
<th>SUMMER</th>
<th>FALL</th>
<th>WINTER</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOC (%)</td>
<td>Time</td>
<td>SOC (%)</td>
</tr>
<tr>
<td>0</td>
<td>9:00 AM</td>
<td>2.76</td>
</tr>
<tr>
<td>2.14</td>
<td>1:00 AM</td>
<td>6.82</td>
</tr>
<tr>
<td>10.0</td>
<td>3:00 PM</td>
<td>10.90</td>
</tr>
<tr>
<td>16.0</td>
<td>2:00 PM</td>
<td>14.81</td>
</tr>
<tr>
<td>23.37</td>
<td>3:00 PM</td>
<td>17.27</td>
</tr>
</tbody>
</table>

Fig.'s 7-5 to 7-7 show the Pareto optimal front obtained for $R_{FILM}$ vs. Cost for fall, summer and winter respectively. Fig. 3-1 shows that there will be a definite increase in resistance due to high voltage-high current nature of fast charging. Thus, it can be concluded that the increase in resistance due to fast charging is inevitable. Thus, using the MOPSO algorithm will result in a decrease in cost with the increase in resistance. This is demonstrated by the Pareto fronts in Fig.’s 7-5 to 7-7.

![Fig. 7-5 Pareto optimal front for increase in Resistance vs. Cost for fall.](image)

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7.3.4. Computational Times

The computational times for running the MOPSO algorithm for 500 iterations are shown in Table 7.3. As can be expected, the computational time increases with the number of
particles. The tradeoff solutions in Table 7.3 and the Pareto optimal fronts that were demonstrated in Fig.’s 7-5 to 7-7 were obtained as a result of using 20 to 40 particles.

Table 7.3
Computational Times

<table>
<thead>
<tr>
<th>Particles</th>
<th>Computational Time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>3.2</td>
</tr>
<tr>
<td>40</td>
<td>6.3</td>
</tr>
<tr>
<td>60</td>
<td>7.7</td>
</tr>
<tr>
<td>80</td>
<td>10.2</td>
</tr>
<tr>
<td>100</td>
<td>16.1</td>
</tr>
</tbody>
</table>
Chapter 8

Conclusions and Future Work

It has been shown that optimal battery conditioning involves the optimization of several factors as opposed to focusing on a particular aspect of PHEVs. A literature review is conducted which analyzes the various factors that affect the SOC of the PHEV.

A Li-ion battery model is examined and the simulation methodology is explained. The SOC is mapped for various charging scenarios during V2G transactions. BPSO is utilized to obtain the optimal charging profile which would lead to the least amount of $R_{FILM}$ buildup. MOPSO was used to develop aggregator strategies when the plug-in and plug-out times of the PHEV were flexible and not constrained between 9 AM-5 PM.

Discharge characteristics are demonstrated and the relationship between the OCV and DOD is established. Fast charging simulations are carried out on the Li-ion battery model. It is shown that it takes ~31 minutes to fully charge a PHEV which is at near zero SOC. Tradeoff solution between the SOC at plug-in time and time of charging are presented and the significance of the values are discussed. Pareto fronts which were obtained from a MOPSO algorithm are presented depicting reduced PHEV charging cost at minimized resistive film growth.
An important point to be noted is that, PHEVs are able to function even when the SOC is 0. When the SOC is 0, the PHEV will operate on its internal combustion engine (ICE) as a result of which it is apparent that a PHEV is not wholly dependent on the charge of the battery. However, keeping in mind the global environmental concerns, it makes more sense to maximize the duration that PHEVs operate in all-electric mode. This analysis shows how important it will be for fast charging stations to be an integral part of the smart grid infrastructure. The presence of these stations coupled with the use of the methodology presented in this paper will be able to successfully eliminate range anxiety without compromising greatly on the overall health of the battery and being cost-effective at the same time.

Future work in this area may include exploratory analysis into other possible causes of battery degradation which would directly influence the SOC and overall lifetime of the battery. Possible causes may include the component stress of the bi-directional charging units. Stochastic programming may be utilized to account for the uncertain nature of aggregated loads with the objective to improve the SOC. Also, further analysis of traffic data using software packages like MATSim [60] may lead to a more intelligent assignment of $SOC_{MIN}$ and thus give more flexibility to the user.
References


[58] AUTONOMIE: [Online], Available: http://www.autonomie.net/
