České vysoké učení technické v Praze
Fakulta elektrotechnická

Katedra kybernetiky

ZADÁNÍ DIPLOMOVÉ PRÁCE

Student: Bc. Petr K ö r n e r

Studijní program: Otevřená informatika (magisterský)

Obor: Umělá inteligence

Název tématu: Metaheuristická optimalizace rozvrhu nabíjení a vybíjení elektromobilů

Pokyny pro vypracování:

1. Prostudujte existující metody rozvrhování nabíjení a vybíjení elektromobilů v síti smart grid.
2. Identifikujte nedostatky, slabá místa v existujících implementacích a zdůrazněte důležité aspekty, které je třeba uvažovat při dobíjení a vybíjení elektromobilů.
3. Navrhněte a implementujte algoritmus využívající vybranou metaheuristickou optimalizační techniku pro toto rozvrhování, uvažující i některé z důležitých aspektů z bodu 2.
4. Funkci systému demonstrujte a porovnejte s jiným vybraným přístupem.

Seznam odborné literatury: Dodá vedoucí práce.

Vedoucí diplomové práce: Ing. Martin Macaš, Ph.D.

Platnost zadání: do konce letního semestru 2013/2014

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V Praze dne 10. 1. 2013

Czech Technical University in Prague
Faculty of Electrical Engineering

Department of Cybernetics

DIPLOMA THESIS ASSIGNMENT

Student: Bc. Petr K ö r n e r

Study programme: Open Informatics

Specialisation: Artificial Intelligence

Title of Diploma Thesis: Metaheuristic Optimization of Charging/Discharging Schedules for Electric Vehicles

Guidelines:

1. Make a survey on existing method for charging/discharging scheduling for electric vehicles in smart grid.
2. Identify drawbacks and disadvantages of existing implementations and emphasize crucial aspects, that must be considered in charging and discharging of electric vehicles.
3. Propose and implement algorithm, which uses a selected metaheuristical optimization technique for the scheduling and considers some of the crucial aspects mentioned in task 2.
4. Demonstrate and validate the functionality of the system and compare it with another approach.

Bibliography/Sources: Will be provided by the supervisor.

Diploma Thesis Supervisor: Ing. Martin Macaš, Ph.D.

Valid until: the end of the summer semester of academic year 2013/2014

L.S.

prof. Ing. Vladimír Mařík, DrSc.
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Dean

Prague, January 10, 2013

Czech Technical University in Prague
Faculty of Electrical Engineering
Department of Cybernetics

Diploma Thesis

Metaheuristic Optimisation of Charging and Discharging Schedules for Electric Vehicles

Bc. Petr Körner

Supervisor: Ing. Martin Macaš, Ph.D.

Study Programme: Open Informatics

Specialisation: Artificial Intelligence

May 12, 2014

Poděkování

Rád bych poděkoval vedoucímu mé diplomové práce, Ing. Martinu Macašovi, Ph.D., za spolupráci, a dále také Ing. Jiřímu Kubalíkovi, Ph.D., za cenné rady.

Velké poděkování ovšem taktéž náleží celé mojí rodině a blízkým, kteří mi byli při mých studiích nesmírnou oporou, za níž jsem velmi vděčen.

Prohlášení

Prohlašuji, že jsem předloženou práci vypracoval samostatně a že jsem uvedl veškeré použité informační zdroje v souladu s metodickým pokynem o dodržování etických principů při přípravě vysokoškolských závěrečných prací.

V Jablonci nad Nisou dne 12. 5. 2014 ....

Abstract

This diploma thesis investigates the topic of intelligent optimisation of schedules for charging and discharging of *electric vehicles* (EVs). At first, we carry out a research on related topics of *Smart Grids* and *vehicle-to-grid* transactions, and then, we examine existing studies solving the problem, including an application of a *binary particle swarm optimisation* (BPSO). Subsequently, disadvantages and weaknesses of the investigated methods are identified.

We then reformulate the problem definition and its representation to dispose of the major drawbacks identified before. The modified formulation emerges a continuous optimisation problem, which for we propose a *particle swarm optimisation* (PSO) application. To eliminate remaining drawbacks, the algorithm implements a penalty function for penalising inconsistent solutions, and an alternative fitness function reflecting the battery degradation costs.

Finally, the implemented algorithm is confronted with the BPSO method, and it is verified that the proposed PSO implementation significantly outperforms the other algorithm in terms of quality of the best found solutions, and in terms of time efficiency as well.

Abstrakt

Tato diplomová práce zkoumá téma inteligentní optimalizace rozvrhů pro nabíjení a vybíjení *elektromobilů* (EV). Nejprve je proveden průzkum v souvisejících oblastech *inteligentních sítí* a *vehicle-to-grid* transakcí, a posléze jsou prostudovány existující prace zabývající se řešením daného problému, včetně aplikace metody *binární optimalizace rojem částic* (BPSO). Následně jsou pak identifikovány nevýhody a slabiny dříve zkoumaných metod.

Definice problému včetně jeho reprezentace je poté přeformulována za účelem odstranění hlavních ze zmíněných nedostatků. Upravená formulace utváří spojitý optimalizační problém, pro který je následně navržena aplikace *optimalizace rojem částic* (PSO). Za účelem eliminace zbývajících nedostatků navržený algoritmus zahrnuje funkci pro penalizaci nekonzistentních řešení a také alternativní objektivní funkci reflektující výdaje spojené s degradací baterie.

Na závěr je implementovaný algoritmus porovnán s metodou BPSO, výsledkem čehož je ověřeno, že navržená implementace PSO výrazně překonává druhý algoritmus, a to jak ve smyslu kvality nejlepších nalezených řešení, tak i z pohledu časové efektivity.

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Chapter 1

Introduction

Although transportation and electricity infrastructure have generally much in common, for a long time the transportation industry has been dominated by a dependence on oil products, leaving electric vehicles only a tight segment of use, such as public transport vehicles, airport vehicles, or forklifts in industrial facilities. Historically there has only been a little chance of the two industries converging when it comes to personal transportation [1].

However, extensive progress over the past decade in technology, design, and development of a commercially viable electric vehicle has changed that, together with recent advances in rechargeable battery materials, leading to an explosion of interest in electric vehicles. Convergence of these two industries is now a foregone conclusion, and the automotive industry is intensively investing in *plug-in hybrid electric vehicles* (PHEVs) and fully *electric vehicles* (EVs), mainly in order to reduce the CO_2 emissions and cut down the oil dependency of the current automotive technology.

1.1 Electric Vehicle Adoption

Since electricity is an exclusive source of energy in EVs—and partially in PHEVs—the vehicle electrification will have significant impact on the power grid due to the increase in electricity consumption. The overall load profile of electric system will change due to the introduction of electric vehicle charging, and electric utilities will have to reconsider the potential impact related to a massive EV adoption.

On the other hand, besides charging, electric vehicles can produce an interesting new potential to the operation of the electric system through providing energy to the power grid by discharging the battery. This type of transaction is known as *vehicle-to-grid* (V2G) [2]. Considering the potential extensive EV adoption with all the obstructions and opportunities it will give rise to at the same time, it is very important to provide the means of intelligent scheduling for charging and discharging of electric vehicles.

1.2 Objectives

The study documented in this thesis, sets up a target of making a survey on existing methods for optimisation of charging and discharging schedules for electric vehicles, identifying their drawbacks and weaknesses, and addressing the most crucial aspects that should be considered in optimisation of the given problem.

Then, the goal is to propose and implement an algorithm utilising a selected metaheuristic optimisation technique to solve the problem, while concurrently reflecting and resolving some of the crucial issues suggested afore. Lastly, it is required to demonstrate and validate the functionality of the proposed system, and match its performance with some of the other previously discussed methods.

1.3 Navigation

This diploma thesis is divided into *seven* chapters. Chapter 1 provides introduction to the study by discussing *electric vehicles*, their potential massive adoption, and by defining the objectives of this study. A detailed insight to the closely related topics of *Smart Grids* and *vehicle-to-grid* transactions is presented in Chapter 2 along with potential motivation for charging and discharging of electric vehicles. Chapter 3 then finally introduces the problem of schedule optimisation for charging and discharging of electric vehicles, which this study is the most concerned with. Subsequently, the existing works attempting to solve the given problem are introduced, and their drawbacks are identified and explained. Chapter 4 presents the proposal of reformulated problem definition and solution representation, which is the main outcome of the study. Additional considered aspects like *charging voltage* and *battery degradation* are introduced as well. In Chapter 5, this is followed by description of the *particle swarm optimisation* (PSO) algorithm, which is implemented to solve the optimisation problem. Initially, a general scheme for the PSO algorithm is introduced, and then employed problem-related components are explained as well. In Chapter 6, the implemented PSO algorithm is extensively tested against a BPSO implementation in order to demonstrate and validate its functionality. Additional experiments are conducted to further examine the performance of the algorithm, followed by analysis of effects of various aspects concerning the problem. Finally, Chapter 7 concludes the thesis by summarising the course of the study, evaluating its accomplishment, and discussing potential future work.

Chapter 2

Motivation

The current electric power grid in most countries is almost entirely a mechanical system, with only limited use of sensors, minimal electronic communication and almost no electronic control. It is based on and developed from a distribution grid established more than a hundred years ago, when the energy demand was much smaller and straightforward than in the modern day. The grid was designed for utilities to deliver electric power to consumers' homes and bill them monthly. This limited one-way interaction makes it difficult for the grid to react to the ever-changing and growing energy demands of the 21st century [3].

The insufficiency of the current electric grid will become increasingly apparent along with the growing market penetration of electric vehicles. It has been estimated that the total charging load of EVs can reach 18% of summer peak electricity demand in the United States already at the electric vehicle penetration level of 30% [4]. The associated increase in electricity demand will call for a radical change in electricity distribution. Especially if intelligent scheduling for charging and discharging of EVs is required, the electric grid must provide more flexibility and develop the ability to perform optimisation.

2.1 Smart Grid

As an evolutionary step towards improvement of the electric grid and its adaptation to the increasing electric energy requirements significantly affected by the potential EV adoption, a *Smart Grid* introduces a two-way communication dialogue, where both electricity and information can be exchanged between utility and its customers.

Smart grid is a modernised electricity distribution grid that expands capabilities of the electricity system by the use of information and communications technology to collect information about behaviour of suppliers and consumers, and use it in an automated manner to improve the efficiency, flexibility, reliability, economics, and the environmental impact of the production and distribution of electric energy.

Research and development of the novelty smart grid concept is being taken by various organisations and research groups simultaneously, and the actual practical application of the smart grid is tested within so-called *smart cities* and *smart villages.* Since the research proceeds independently and to a certain extent separately, a variety of broad definitions have arisen, describing what the smart grid actually is and what characteristics should it have.

Having various industrial, scientific, governmental, and academic subjects involved, each focusing on different aspects of the smart grid, many studies relevant to the topic emerged. The visions of the smart grid presented in the studies share many common aspects, yet to a certain degree they are distinct from each other. This situation of having all the complement studies around, initiated few attempts to summarise all these individual definitions and provide a universal description of the smart grid concept.

One of such efforts, called "What is the Smart Grid?," [5] managed to gather all the available information and express the common shared characteristics by listing a set of the ultimate goals that *Smart Grid* would have to accomplish:

- Enhance the electric power system infrastructure by employment of sensors, smart meters, communication channels, computational facilities, and so forth;
- Improve reliability, availability, quality, efficiency and security of the power system;
- Enable various entities to share benefits of smart grid;
- Establish more competitive electricity market with open access;
- Create new business opportunities;
- Mitigate emissions and reduce the human footprint on the environment.

2.2 Consumer Participation

Additionally, there is a feature worth highlighting that has been frequently echoing through a number of *smart grid*-related articles and books – the *consumer participation.*

For example, *European Union* stated it sees smart grid as an active network "to enable demand-side participation" and "to engage consumers' interest," [6] while similarly, the *Department of Energy* of the United States identified ability to "enable active participation by consumers" as one of the defining traits of a smart grid [7]. This has as well been supported by the *ABB* corporation, under which model of, the smart grid is supposed to be "interactive between customers and markets" [8].

Hydro-Québec, a public electric utility of Canada, went slightly further with their vision of smart grid "providing customer with the means to optimise consumption and reduce electricity bills" [9]. In a similar way, Ofgem—the UK's energy regulator—defined that a smart grid employs technologies to "enable demand side to play a part in optimising the operation of the system" [10].

All these statements go hand in hand with what has become more than apparent – regardless of how will the actual *Smart Grid* turn up, it will be desirable for it to let consumers participate on its operation, either by means of generating electric energy or providing support in optimisation of its performance.

2.3 Vehicle-to-Grid

Assuming it is inevitable that a certain sort of *Smart Grid* is adopted in the foreseeable future, many new opportunities would emerge, including the potential of technologies making use of the large scale integration of electric vehicles.

In the wake of statements emphasising the opportunity of *consumer participation*, the aforementioned *vehicle-to-grid* scheme becomes a perfect example of such occasion.

Vehicle-to-grid (V2G) is a system which allows plug-in electric vehicles to communicate with the power grid and deliver electricity into the grid by either discharging the car battery in case of a pure *electric vehicle* (EV) or even by generating energy from fossil fuel, biofuel, or hydrogen in case of a *plug-in hybrid electric vehicle* (PHEV).

2.3.1 Gridable Vehicles

Vehicle-to-grid transactions can be practised with so-called *gridable* vehicles, that is, plug-in electric vehicles (either EVs or PHEVs) with grid capacity.

The original plans for electric vehicles only allowed for their battery storage to extract power *from* the grid through charging, known as *grid-to-vehicle* (G2V). But, since EVs and PHEVs already have the necessary electronics to drive their electric motors, programming and wiring adjustments can be made to turn their power electronics into inverters suitable for V2G transactions as well [11] [12].

In fact, this has already been put into practise as for example, the Californian *PG&E* utility company has been taking V2G trials with a number of *Toyota Prius* converted into V2G PHEVs, or another American utility *Xcel Energy* have converted several *Ford Escape Hybrids* to V2G-capable PHEVs [13].

2.3.2 Motivation for V2G

Considering a V2G-capable EV plugged into the electric grid, there are various reasons to perform a V2G transaction. The motivation may be a combination of the following:

- To discharge excess battery capacity to the grid when electricity demand is high in order to gain profit;
- To provide power to the electric grid in response to peak load demands, resulting in so-called *peak load levelling*;
- To serve as a storage device capable of providing electric power to homes during black-outs and other emergency situations.

2.3.3 New Opportunities

As consumer adoption of EVs progresses, the collective storage capacity of fleet vehicles will grow as well, giving promise for a new clean-tech resource for *peak load levelling.*

Perhaps the most fascinating proposition regarding EVs is that they could be used to store renewable energy production, particularly power from wind farms, which produce most proficiently during off-peak hours—at the night—when both energy demand, and energy prices are the lowest. Using EVs to store wind power during off-peak periods could provide significant value arbitrage if that stored energy could be discharged to the grid during peak periods, when both demand, and prices are far higher [1].

As the prices of batteries decrease and the amount of personal distributed generation increases, consumers are likely to be interested in selling power obtained from either nightly charging at cheap prices, or their own electric power generation such as small wind turbines or solar panels. And in such situation, EV batteries could provide the necessary storage to accumulate the power charge in them and discharge it to the grid at peak price later.

Considering that EVs and PHEVs—like other personal vehicles—are parked most of the time, the potential of using their batteries to perform optimisation could really create an interesting new business opportunity. However, having a large population of electric vehicles performing charging and discharging would require intelligent planning and a third party to take control and arrange for it.

2.3.4 Scepticism

Since the battery is considered one of the most crucial components of an electric vehicle and is very expensive at the same time, it appears to be the most limiting factor speaking against the use of the V2G transactions.

Any excess transfer beyond the required charging to a desired state of charge and discharging through driving reduces the battery life and might thus as a result appear to be an additional hidden cost, which would have to be reflected in any research concerned with V2G transactions and electric vehicle discharging.

Chapter 3

Research and Analysis

In the wake of the motivation discussed in the previous parts of the thesis, from here onwards, this study is concerned with developing an optimisation algorithm which would intelligently schedule charging and discharging of EVs and PHEVs.

3.1 Problem Definition

The essential problem studied, analysed, and solved in this work assumes a situation of a *Smard Grid*-connected parking lot capable of accommodating large number of *gridable* vehicles (either EVs or PHEVs) with a target to perform intelligent scheduling for charging and discharging of their batteries. An example of such situation is depicted in Figure 3.1.

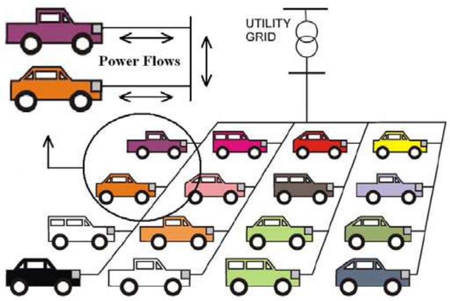

Figure 3.1: Example of a parking lot diagram[1]

The parking lot system is a scalable set of vehicles, each with its own system parameters like the battery capacity kWh_{Max} in kilowatt-hours, the current battery state of charge (SoC), battery charging and discharging efficiency, and the expected time of departure from the parking lot n. In a real life situation, the target battery SoC at the departure time n would be defined by the EV owner at the moment of arrival, however this is not considered in this study to allow subsequent comparison with related research methods. Instead, the

[1]The parking lot image borrowed from [14].

target state of charge SoC_{Target} is fixed to 60%. Additionally, the arrival time m would be detected automatically upon the vehicle arrival at the parking lot.

During charging, a vehicle buys electricity from the grid through grid-to-vehicle (G2V) transactions, while when discharging, it sells power to the grid by performing vehicle-to-grid (V2G) transactions. To help determine the optimal times of charging and discharging, a price curve $P \in \mathbb{R}^{1\times 24}$ is obtained, defining electricity price in \$/kWh for each hour of the day. It is assumed that the electricity price always holds for the whole length of any hour and gets changed always at the beginning of an hour. An example of price curve showing electricity price fluctuation for 7 August 2008, is shown in Figure 3.2.

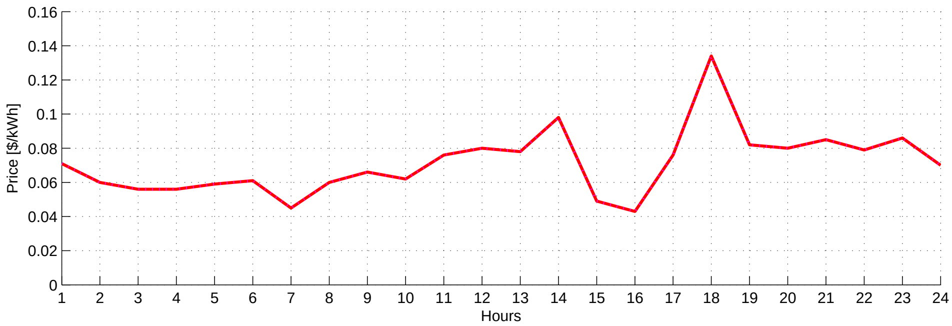

Figure 3.2: Example of curve showing electricity price fluctuation over a day

For a given day and for each vehicle at the parking lot, the main task is to find a sequence of 24 actions consisting of *charging*, *hold*, and *discharging*, such that the profit made by difference in *revenues* from selling energy and *costs* from buying it is *maximised*. The optimisation process is restricted by the required final SoC_{Target}, which must hold at the time of vehicle departure from the parking lot. By maximising the profit for every individual vehicle, the total profit for the whole vehicle lot is maximised as well.

The entire parking lot is controlled by an operator, which performs the optimisation and controls the individual EV charging slots based on the schedules produced by an optimisation algorithm. The operator can be either the utility itself, or a third party organisation acting as a mediator between the utility and the vehicle owners.

3.2 State of the Art

The idea of utilising an electric vehicle parking lot to generate profit through optimisation has been researched by many, thus a number of articles and studies emerged, examining this scheduling problem and solving it using various intelligent optimisation methods.

3.2.1 Binary Particle Swarm Optimisation

One of the most fundamental works dealing with the use of *vehicle-to-grid* transaction to generate profit, called *"Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity* *in a Parking Lot for Profit Maximization in Grid Power Transactions,"* was published by C. Hutson, G. Venayagamoorthy, and K. Corzine in 2008 [14].

In the article, authors presented two case studies for charging and discharging of EVs and PHEVs parked in a parking lot disposing of the ability to perform V2G transactions. The goal to the optimisation problem was to maximise the overall profit obtained by selling energy from vehicles at peak price and buying it back, or vice versa. To provide realistic price fluctuations, price curves for 3 different days were obtained from the California Independent System Operators (CAISO) database. For scheduling purposes, a given day is split up into 24 intervals to coincide with the hourly prices provided by CAISO. The electricity price is considered to remain the same for any whole given hour.

As there are no constraints among the individual vehicles, the charging and discharging schedule is determined for each vehicle separately. A solution to a single vehicle scheduling problem is established as 24 pairs of bits, each pair representing an action scheduled for a certain hour of the day. These actions include *buying* represented by '11', *selling* by '00', and *hold* by either '01' or '10'. The arrival and departure time together define a time window where transactions are allowed, therefore, any information outside the defined time window is ignored when evaluating the quality of a schedule.

Three different parking lot sizes, accommodating vehicle sets of 50, 500, and 5000, were subject to testing. For each given vehicle, a set of parameters was randomly generated from within the ranges given by minimum and maximum values in Table 3.1.

Parameter	Minimum	Maximum
Battery Capacity [kWh]	10	25
Available Capacity [%]	50	100
Arrive Time	1^{st} hour	23^{rd} hour
Departure Time	2^{nd} hour	24^{th} hour
Inverter Discharge Eff. [%]	80	95
Batter Charge Eff. [%]	80	95

Table 3.1: Vehicle parameters

As seen in the table, each vehicle has a defined maximum battery capacity in kilowatt-hours, its arrival time and expected time of departure, as well as efficiency of inverter during discharging, and the battery charging efficiency. Moreover, each vehicle has its own state of charge (SoC) at the moment of arrival to the parking lot, while the desired departure state of charge was set to 60% for all of them globally.

In *Case Study 1*, the algorithm to find a schedule for each vehicle is very simple. In the given price curve, the best (maximum) selling price is found for each vehicle *over* the desired departure SoC of 60%, and the best (minimum) buying price for each vehicle *under* the desired departure SoC. As a result, only one transaction (either charging or discharging) occurs for each vehicle in a given day. This leads to lower profit potential, but the schedule for each vehicle is very easy to determine.

Opposed to this, in *Case Study 2*, multiple transactions are allowed to occur for each vehicle throughout the day. Multiple transactions allow for higher profits but greatly increase the problem complexity. The authors implemented a *binary particle swarm optimisation* algorithm (BPSO), which generates a population of random schedules and improves them iteratively based on a profit-based fitness function.

To calculate the fitness function, first the revenues made by selling energy from the vehicle, and costs of charging the vehicle battery from the grid must be determined. The hourly revenues $R(k)$ and costs $C(k)$ for any time instant k are calculated as

$$R(k) = P(k) \cdot (kWh_{Available} - SoC \cdot kWh_{Max}) \cdot \mathit{Eff}_{Discharge} \tag{3.1}$$

and

$$C(k) = \frac{P(k) \cdot (SoC \cdot kWh_{Max} - kWh_{Available})}{\mathit{Eff}_{Charge}}, \tag{3.2}$$

respectively, where $P(k)$ is electricity price at time k, SoC is the desired battery state of charge, $kWh_{Available}$ is the current available energy stored in the battery (in kilowatt-hours), kWh_{Max} is the maximum battery capacity in kilowatt-hours, while Eff_{Charge} and $\mathit{Eff}_{Discharge}$ are charging and discharging efficiency, respectively.

Having the hourly revenues and costs defined, the fitness function f to be maximised for each separate vehicle is described as a difference between the revenues and costs summed over the whole day, i.e.

$$f = \sum_{k=1}^{Hours} \big(R(k) - C(k)\big). \tag{3.3}$$

In the process, the two case studies were compared against each other using randomly generated sets of 50, 500, and 5000 vehicles. The results shown in Table 3.2 indicate that the BPSO algorithm described in *Case Study 2* easily outperformed the simpler algorithm from *Case Study 1* in terms of profit. As the table suggests, the amount of energy discharged from vehicles *(power out of lot)*, and especially the amount of energy charged back *(power into lot)*, are significantly increased in *Case Study 2* scenario compared to *Case Study 1.* This is not surprising as the schedules produced by the BPSO algorithm contain more *charge* and *discharge* actions leading to greater amounts of energy transferred within the vehicle set.

Number of Vehicles	Case Study	Power into Lot [MWh]	Power out of Lot [MWh]	Net Power Out [MW]	Total Profit
50	CS1	0.0089	0.1131	0.1042	$11.41
	CS2	0.3492	0.3421	-0.0072	$19.09
500	CS1	0.0984	1.2533	1.1549	$128.42
	CS2	3.5167	3.8271	0.3104	$234.22
5000	CS1	1.0359	12.1769	11.1401	$1223.49
	CS2	31.9632	35.2408	3.2777	$2200.40

Table 3.2: Results of three different sized sets of vehicles on August 7, 2008

Every time a vehicle buys power from the grid and sells later, there are two efficiency drops, one for the charger and one for the inverter. However, even considering these not insignificant efficiency drops, the increased amount of charging and discharging actions in *Case Study 2* proves to be beneficial, leading to almost twice as much profit compared to the simple and straightforward approach from the *Case Study 1.*

3.2.2 Social Impact Theory Based Optimisation

In 2013, I contributed to a paper by M. Macaš and L. Lhotská entitled *"Scheduling of Hybrid and Electric Vehicle Storage Capacity using Social Impact Theory based Optimization"* [15]. In this study, we applied *Simplified Social Impact Theory based Optimisation* (SSITO) proposed by Macaš [16] to the problem of intelligent optimisation of charging and discharging schedules for electric vehicles, utilising the exact same problem definition, vehicle parameters, and the fitness function to be maximised as in the paper published by Hutson and collective [14]. The study shows experimentally, that the novel SSITO method, although being simple and parameter-less, reasonably outperforms the BPSO algorithm in profit maximisation.

Number of Vehicles	Optimisation Method	Power into Lot [MWh]	Power out of Lot [MWh]	Net Power Out [MW]	Total Profit
5000	Simple	0.694	10.468	9.501	$1243
	BPSO	23.356	29.012	4.933	$2061
	SSITO	23.592	29.283	5.030	$2129

Table 3.3: Results for 5000 vehicles averaged over 30 independent runs

As seen in the Table 3.3, the SSITO method provided better results on the same set of 5000 vehicles, but it outperformed the BPSO algorithm by only a little more than 3% of the total profit. This observation of two completely different algorithms providing a relatively close best solution seems to indicate limitation of the problem definition and solution representation, leading to infeasibility of improving the best solution regardless of the used algorithm.

3.2.3 Convex Optimisation

Another notable work, one of the more recent ones, called *"Optimal Scheduling for Charging and Discharging of Electric Vehicles"* was presented by Y. He, B. Venkatesh, and L. Guan in 2012 [17]. In the article, the problem of charging and discharging electric vehicles is formulated using a convex objective function and a set of linear constraints, which together form a convex optimisation problem allowing to be solved efficiently using the method of interior points.

In the paper, a globally optimal scheduling scheme is proposed at first, but then, its several drawbacks are identified. The globally optimal scheduling scheme requires information on future base loads and future arrival times of EVs. To overcome this, a local scheduling optimisation problem is formulated instead, which aims to optimise schedules only for short intervals of a day belonging to the current sliding time window, and the base load is approximated using regression of historic data from similar days, in the same way this was done in another study concerning optimisation in electric power systems [18].

Additionally, the global network of all EVs connected to charging stations is separated into smaller groups clustering EVs in one location or multiple nearby locations. Each group is then operated by a local controller which communicates with the individual charging stations and with a central controller. The local controller then performs the optimisation of schedules for the assigned group of EVs. This approach, compared to the global scheme is significantly more practical, and it is demonstrated through simulations that it can achieve a close performance to the globally optimal scheduling scheme.

3.3 Drawbacks and Weaknesses

As this thesis is primarily inspired by the study of Hutson et al. [14], the following section is mainly oriented towards drawbacks found in the BPSO study. Disadvantages of the other implementations are subsequently discussed as well.

3.3.1 Binary Particle Swarm Optimisation

The article of Hutson documented one of the pioneering works regarding the problem of charging and discharging of EVs. Although the implemented BPSO algorithm provided fairly good results, it relaxed on many topics:

- **Battery degradation** – One of the most significant drawbacks of the vehicle-to-grid transmissions is that they accelerate battery degradation. Each electric vehicle battery has a limited number of life cycles which it can be put through, and if additional charging and discharging occurs beyond the regular usage of the vehicle, the battery degradation accelerates and its lifetime gets reduced.

  Thus, even though this aspect was not considered in the study, a more practical-oriented implementation should reflect the battery degradation to help reduce the number of operations per vehicle to a reasonable amount.

- **Instant operations** – The implementation considers infinitely fast charging and discharging operations. Basically, whatever is the battery state of charge at the start of any hour of the day, it can be charged or discharged to an arbitrary SoC percentage in just an hour, no matter how many kilowatt-hours of energy does that include.

  Moreover, as the authors allow charging and discharging at the beginning of any hour between arrival and departure, any operation can be performed even at the moment of the vehicle departure, which indicates instant charging and discharging. Such approach, of course, would be certainly unrealistic in a real-life application and an adequate amount of time spent on each operation should be considered.

- **Algorithm overkill** – Using a relatively complicated BPSO algorithm seems to be a slight overkill considering the given problem definition and solution representation. For example, if the schedule representation was converted from binary to integer values where selling would be represented by ‘1’, buying by ‘2’, and hold by ‘3’, we would end up with a vector of n numbers, where n is the amount of hours the car is parked for, connected to the grid. Given the arrival and departure times for each vehicle being uniformly distributed within the intervals given in Table 3.1, an average n is roughly equal to 8, leading to total number of possible scheduling solutions for an average vehicle being only $3^8 = 6561$. Problem of such complexity could be easily solved by an exhaustive search or a simple heuristic.

Naturally, finding the best schedule for vehicles staying at the parking lot for more than 10 hours would become increasingly more difficult eliminating the potential of using the exhaustive search, but still the problem definition as it is seems overly simplified for the PSO algorithm to be used.

- **Discharging restriction** – Once a vehicle reaches the desired departure state of charge of 60%, it can never be discharged below this level again. Such regulation eliminates the opportunity of accumulating more profit by discharging at a peak price, charging after the price drops, and then repeating the same cycle again if another price peak occurs within the day. On one hand, this restriction is said to prevent from low charge levels occurring in case of unexpected early departure from the parking lot, but on the other hand, it reduces the profit potential which the whole optimisation is driven by.

- **Desired SoC verification** – According to the information the article provides, there is no check at the end of a vehicle schedule optimisation process to verify if the desired final state of charge is actually achieved by the given schedule or not. In a situation when a vehicle arrives at the parking lot with its battery SoC less than 60%, there is a great chance that a schedule consisting only of *hold* actions would survive throughout the whole run of the algorithm and will be returned as the best solution from the profit point of view.

  Due to the restriction forbidding discharging below 60% of the battery capacity, any other solution would necessarily contain at least one *charge* action to achieve the desired departure SoC target of 60%, while the remaining 40% of manipulable battery capacity might not allow producing enough profit to overcome the loss caused by charging in the first place. As a result of this, the only solution ensuring a non-negative outcome would be the empty schedule, which would end up being accepted as the best solution despite the fact the desired departure state of charge is not accomplished. Though driven by maximisation of profit, the optimisation algorithm should not produce invalid solutions on its output, providing results which violate given constraints.

3.3.2 Social Impact Theory Based Optimisation

Given the fact that our application of the SSITO algorithm to the vehicle charging and discharging problem [15] shared the exact same problem definition and solution representation with the above analysed BPSO implementation, the list of drawbacks would be more or less the same as in the previous section. This is due to the fact that the majority of the drawbacks is induced by the problem representation itself.

On the other hand, the SSITO method, being parameter-less, did not require any extensive empirical parameter settings optimisation, and still provided better solutions to the problem.

3.3.3 Convex Optimisation

The study presented by He [17], same as those mentioned above, splits each day into 24 hourly intervals. If a charging or discharging action takes place within a given interval, it persists for the whole hour as well. But, in order to allow achieving a given target SoC precisely, the nominal value of charging voltage alternates through the course of the hour. Although this resolves the problem associated with the fixed hourly length of actions, employing this approach in a real life application could not only be complicated in terms of equipment and technology, but the frequent voltage alterations could also cause harm to the battery.

On the contrary, it is favourable that the authors of the study incorporated a model of battery degradation into the fitness function of their locally optimal scheduling scheme.

Chapter 4

Solution Proposal

Inspired by the BPSO application to the EV charging and discharging scheduling problem with all its pros and cons, the work described in this thesis sets a target of implementing an optimisation algorithm to solve the problem more efficiently, while at the same time putting emphasis on a more realistic approach reducing the amount of relaxations and reflecting a number of additional important aspects to push the boundaries closer towards a practical implementation viable for use in a real *smart grid*-powered parking lot application.

4.1 Problem Definition

To accomplish the established goals, the problem definition has to be altered in the first place. Same as in the aforementioned BPSO implementation, in this work each day is split into 24 one-hour intervals to correspond with the hourly electricity prices provided by CAISO. Each interval allows only for one type of action to occur within, however, the instancy of actions is not assumed anymore, and only a definite reasonable amount of kilowatt-hours of battery capacity can be charged to or discharged from a battery within 1 hour. Given this assumption, it is very likely that charging a half-empty vehicle battery up to the state of full charge would take up few hours to accomplish.

Additionally, this reworked problem definition assumes a constant charging voltage, thus reflecting a real-life situation. However, with constant voltage it becomes difficult to achieve a specific given battery charge percentage precisely, because charging or discharging a battery in hourly steps can lead only to a limited amount of SoC states. In a drastic majority of cases, the final actual battery SoC would end up being either *below* or *above* the target SoC which leads to either not accomplishing a user-defined target SoC (when finishing below), or not utilising the excess energy to maximise the profit (when finishing above).

To overcome this obstacle, a certain amount of granularity of battery charging and discharging needs to be achieved. As described in the article researched above [17], the granularity can be obtained by altering the charging/discharging voltage during the course of a given hour to secure a precise SoC percentage at the end of the hour. The problem is that such approach can be cost-inefficient and harmful to the battery as stated above. Instead, this work suggests a much more straightforward solution, where the charging/discharging voltage remains the same throughout the process, but each action can last an arbitrary fragment of an hour. This way, a charging or discharging action still has to start at the beginning of a given hour, but it can be terminated at any time before the hour ends which allows for an arbitrary final state of charge to be achieved.

As an additional restriction, if an action starting at the beginning of the i-th hour ends before the hour does, no other action can start earlier than at the beginning of the $(i+1)$-th hour. Simply put, each hour of a day can still see only a single action.

4.2 Solution Representation

Allowing for an action to take an arbitrary portion of an hour requires an essential change in the solution representation as the binary matrix used in BPSO algorithm cannot be used to formulate such information easily.

Therefore, for the algorithm implemented in this work, we propose a different approach with a schedule represented by a vector $\mathbf{x} \in \mathbb{R}^{1\times(n-m)}$ consisting of $(n-m)$ real numbers, where m is time of arrival and n is departure time of a certain vehicle. Then, each real value $x_i, \forall i \in \{m, m+1, \dots, n-2, n-1\}$ of the schedule vector $\mathbf{x} = (x_m, x_{m+1}, \dots, x_{n-1}, x_{n-1})$ describes, which operation will take place at i-th hour of the day and how long will the action take. Naturally, the last action has to be completed before the vehicle departs from the parking lot at hour n and thus, the last action can start at $(n-1)$-th hour.

A lower bound LB and an upper bound UB such that $0 < LB < UB$ are then defined for all x_i, while $\forall i : x_i \in [-UB, +UB]$. Subsequently, for each hour i, a corresponding type of action $OP(i)$ is specified as

$$OP(i) = \begin{cases} \textit{discharge} & \text{if } x_i \in [-UB, -LB) \\ \textit{hold} & \text{if } x_i \in [-LB, +LB] \\ \textit{charge} & \text{if } x_i \in (+LB, +UB]. \end{cases} \tag{4.1}$$

This way, each real number x_i in the solution vector $\mathbf{x}$ represents both the action *type*, and its *duration* at the same time. The distribution of all available actions (discharge, hold, charge) within x_i is depicted in Figure 4.1.

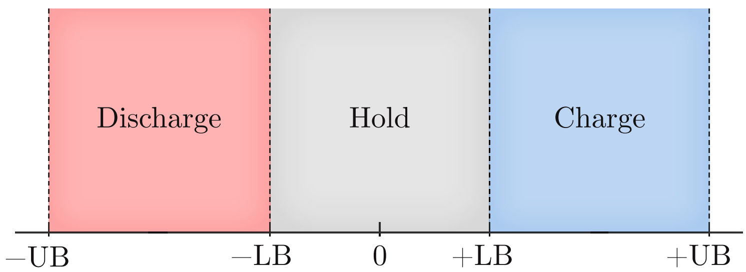

Figure 4.1: Distribution of available actions within a value of x_i

Now that the action type is identified, it is important to determine its length as well. This step is not required for *hold* actions, but for a *charge* or a *discharge* actions, the duration is determined by scaling the x_i value to the range of $(0, 1]$. For the x_i lying between $-UB$ and $-LB$ (discharging), or between LB and UB (charging), the action length $time_{OP}(i)$ is calculated as

$$time_{OP}(i) = \frac{x_i - LB}{UB - LB}. \tag{4.2}$$

This calculation returns a value $time_{OP}(i) \in (0, 1]$ defining what fraction off the i-th hour of the day will the action $OP(i)$ take. For example, if $time_{OP}(i) = 1$, the action $OP(i)$ will last for the entire hour, whilst $time_{OP}(i) = 0.5$ defines an action spanning only half an hour, and finally, if the value $time_{OP}(i) = 0.33$, the given action will be terminated after the first 20 minutes of the i-th hour.

4.3 Charging Voltage

The speed of EV charging is measured by the voltage used over time by an EV charging station. Since the discussed concept of instant charging operations suggesting unlimited connection to the source of electric current is unrealistic, in this study we utilise a constant electric voltage level of a rational nominal value to perform charging and discharging.

As described in *The Advanced Smart Grid* book, there are three different levels of EV charging, varying in the charging voltage. *Level I* charging occurs at the standard voltage of a typical electrical outlet in the United States: 110 to 120 volts, which can result in a charge period of between 8 and 16 hours. *Level II* charging is more suited to overnight charging, taking 4 to 6 hours at 220 to 240 volts. In case of need for a more rapid charge, *Level III* charging uses 440 volts, providing an 80% charge in as little as 30 minutes. [1]

Inspired by the system of charging voltage *Levels I*, *II*, and *III*, this work as well examines three different charging voltage U_{CHG} levels of 110 V, 220 V, and 440 V. The charging voltage U_{CHG} determines the value kWh_{Hourly}, which specifies how much electric energy in kilowatt-hours can be transmitted from the grid to vehicle battery, or vice versa, in just 1 hour.

Based on the information from *The Advanced Smart Grid* book on charging voltage and corresponding charge periods, we define an adequate mapping of U_{CHG} to kWh_{Hourly} as

$$kWh_{Hourly} = \begin{cases} 1.5\,\text{kWh/hour} & \text{if } U_{CHG} = 110\,\text{V} \\ 4.0\,\text{kWh/hour} & \text{if } U_{CHG} = 220\,\text{V} \\ 12.0\,\text{kWh/hour} & \text{if } U_{CHG} = 440\,\text{V}. \end{cases} \tag{4.3}$$

The charging voltage remains the same for any run of the optimisation process, and since the charging and discharging voltage are assumed to be of the same potential, only the charging voltage U_{CHG} will be discussed henceforward. Furthermore, since the selection of kWh_{Hourly} value based on the charging voltage U_{CHG} is done upon initialisation of the algorithm, all further calculations are done based only on the kWh_{Hourly} value.

4.4 Battery Degradation

There is an important aspect to the idea of charging and discharging vehicle batteries to make a profit which notably affects the whole concept and might actually prove it unfavourable on the whole despite the seeming impression of profitability.

As each battery can be put through only a limited number of life cycles, each consisting of completely discharging down and charging back up, any additional battery charge transfer beyond necessary charging, and discharging through driving, exploits the battery and reduces its life time. The battery life time depends on the used technology, but in most batteries these days, it spans a few thousands of cycles. The standard *lithium-ion* batteries, for example, can withstand around 3,000 cycles before the loss of capacity starts to occur.

To take the battery degradation caused by its excessive use into account, we propose a simple battery degradation model adding an additional cost to the problem, representing the drop that the extra transactions cause to the battery life time. In the algorithm, it is assumed that all vehicles have the same battery type, only varying in its size kWh_{Max} in kilowatt-hours. Thereby, identical for all the cars in the parking lot is the battery price P_{Bat} in \$/kWh, and the battery life time LT_{Bat} expressed in the maximum number of cycles.

For each vehicle schedule i and the k-th hour of a day, a degradation coefficient $DG'_i(k)$ defining a battery size proportion charged or discharged during the hour k is calculated as

$$DG'_i(k) = \frac{load_{OP_i}(k)}{kWh_{Max}}, \tag{4.4}$$

where $load_{OP_i}(k)$ is the amount of charge in kWh transferred from or into the vehicle during the hour k, calculated according to equation 5.3, as described later.

Then, for the given vehicle, the amount of charge necessarily required to transfer in order to accomplish the vehicle's final SoC_{Target}, depicted as NDG_i, is expressed by

$$NDG_i = |SoC_{Init} - SoC_{Target}|, \tag{4.5}$$

where SoC_{Init} is the initial state of charge at the time of vehicle arrival. Since SoC_{Init} and SoC_{Target} are both expressed as a fraction of the EV's total battery capacity kWh_{Max}, the value NDG_i belongs to interval $[0, 1]$.

Now having the required components explained, the final degradation cost DG_i for a vehicle schedule i can be determined using

$$DG_i = \frac{1}{2} \left(\sum_{k=m}^{n-1} DG'_i(k) - NDG_i \right) \cdot \frac{kWh_{Max} \cdot P_{Bat}}{LT_{Bat}}, \tag{4.6}$$

which expresses the price of additional charging and discharging beyond necessity, scaled to the price of battery P_{Bat} and its life time LT_{Bat}.

By subtracting the necessary charge transfer NDG_i from the sum of all charge transfers $DG'_i(k)$ between the vehicle arrival m and its departure n, and finally dividing the difference by 2, we get a number of cycles that the battery has been put through in excess of the necessary charging or discharging. The division by 2 is related to the fact that a single cycle indicates transferring the whole battery capacity twice – once by charging it all up, and then discharging it all down. Then, the fraction on the far right of the equation 4.6 indicates the price of 1 cycle in relationship to the total battery price and its life time.

Finally, to allow reflecting the influence of the battery degradation in the porposed optimisation algorithm, the calculated degradation cost DG_i value can be used to reformulate a fitness function f. This will be explained later in the following chapter.

Chapter 5

Implementation

Although the reformulation of the problem together with the redefined solution representation are promising steps towards a more realistic model of the charging and discharging scheduling problem, they significantly increase the problem complexity, as the binary solution space of finite number of solutions, as used in the BPSO implementation, is this way replaced by a continuous space of indefinite number of solutions.

5.1 Particle Swarm Optimisation

Continuous optimisation problems of such complexity are difficult to be solved within a reasonable amount of computational time using conventional mathematical optimisation methods, giving a way to alternative metaheuristic optimisation techniques which do not guarantee a globally optimal solution to be found, but provide a sufficiently good solution within a reasonable calculation time. *Artificial intelligence*, as a sub-field of computer science, gave birth to many metaheuristic optimisation methods inspired by nature, one of such being the aforementioned *particle swarm optimisation* (PSO) technique utilising a population of candidate solutions known as *particles* to explore the search-space of a given problem.

This study implements the original *particle swarm optimisation* algorithm, which the BPSO is derived from through reduction from continuous to binary domain. The PSO algorithm, first introduced by Eberhart and Kennedy [19], is inspired by social behaviour of animals seen in bird flocks, fish schools or swarms of insects. It maintains a population of particles called *swarm*, where each particle represents a potential problem solution, and these particles move around in a search-space driven by experience of their own and experience of their neighbours.

Each particle i is characterised by *position* vector $\mathbf{x}_i$ and *velocity* vector $\mathbf{v}_i$, and moves around the search space in discrete time steps. The position of the particle is updated by adding a velocity $\mathbf{v}_i(t)$ to its current position, i.e.

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1). \tag{5.1}$$

The velocity drives the optimisation process, and reflects both personal experience of the particle (called *cognitive component*), and global experience of the whole swarm (called *social component*). The velocity vector $\mathbf{v}_i$ is updated according to the equation

$$\mathbf{v}_i(t+1) = \omega \mathbf{v}_i(t) + C_1\varphi_1\big(P_{best_i}(t) - \mathbf{x}_i(t)\big) + C_2\varphi_2\big(G_{best}(t) - \mathbf{x}_i(t)\big), \tag{5.2}$$

where ω is inertia weight defining how much is the particle resistant to change of velocity, P_{best_i} is a position with the best fitness reached by the particle i itself starting from the algorithm initialisation up until the current iteration, and G_{best} is the best global position reached so far by any particle of the swarm. Furthermore, C_1 and C_2 are a *cognitive* and a *social* constant, used to scale and prioritise significance of the best personal and global solution, respectively. Finally, φ_1 and φ_2 are diagonal matrices of uniformly distributed random values $\sim U(0,1)$, that as well regulate contribution of the P_{best_i} and G_{best} solutions. These random values introduce a stochastic element to the algorithm [20].

Having the most fundamental formulae defined, and considering a fitness function f to be maximised, where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a projection which returns a real number for a vector of particle position, a basic *particle swarm optimisation algorithm* follows the pseudocode procedure described in Figure 5.1.

Particle swarm optimisation scheme

create and initialise an n-dimensional swarm S;
repeat
    for *each particle* $i = 1 \ldots |S|$ **do**
        if $f(\mathbf{x}_i) > f(P_{best_i})$ **then**
            $P_{best_i} := \mathbf{x}_i$
        end if
        if $f(\mathbf{x}_i) > f(G_{best})$ **then**
            $G_{best} := \mathbf{x}_i$
        end if
    end for
    for *each particle* $i = 1 \ldots |S|$ **do**
        update the particle velocity according to equation (5.2);
        update the particle position according to equation (5.1);
    end for
until *stopping condition is true*;

Figure 5.1: Particle swarm optimisation algorithm pseudocode

In the PSO scheme above, the stopping condition can be either a number of iterations performed, or a target objective function value. In the PSO algorithm implemented in this work, the number of iterations was used as the stopping criterion.

5.2 Fitness Function

The crucial component of the PSO algorithm is the fitness function, which models the solution space that is being searched by the optimisation algorithm. In each iteration of the algorithm, all particles in the swarm need to be evaluated in order to determine quality of individual solutions and allow for their comparison with each other.

The quality of each solution in this case where a solution represents a schedule for given vehicle, is determined as a profit that the given schedule leads to, i.e., the amount of money that can be achieved by performing a set of charging and discharging actions with the vehicle battery. The higher the profit for a given schedule, the better fitness the particle that represents it has.

To determine the fitness value $f(\mathbf{x}_i)$ of any particle $\mathbf{x}_i$ of the swarm S, each value $x_{i,k} \in \mathbf{x}_i$ must be first mapped to a corresponding action it represents. Given that $k \in [m, n-1]$ is the k-th hour of a day between the vehicle arrival time m, and its departure n, the action length $time_{OP_i}(k)$ is calculated according to the equation 4.2, assuming that in the given equation, $x_i := x_{i,k}$.

Having the value $time_{OP_i}(k)$ established, the next step is to calculate the amount of charge load in kilowatt-hours transferred within the hour k by the action $OP_i(k)$ as

$$load_{OP_i}(k) = time_{OP_i}(k) \cdot kWh_{Hourly}, \tag{5.3}$$

where kWh_{Hourly} is the maximum amount of charge that can be transferred within an hour, defined in equation 4.3.

The next step in calculation of the fitness value is then retrieving the amount of costs and revenues, expressed in dollars. For a particle i, the costs $C_i(k)$ arisen by charging, and revenues $R_i(k)$ acquired by discharging, are for any hour k computed as

$$C_i(k) = \frac{P(k) \cdot load_{OP_i}(k)}{Eff_{Charge}}, \tag{5.4}$$

and

$$R_i(k) = P(k) \cdot load_{OP_i}(k) \cdot Eff_{Discharge}, \tag{5.5}$$

where $P(k)$ is electricity price at time k, while Eff_{Charge}, and $Eff_{Discharge}$ are charging, and discharging efficiency, respectively.

Finally, as the costs and revenues are known for all actions occurring during the vehicle's stay at the parking lot, the fitness value $f(\mathbf{x}_i)$ for the particle $\mathbf{x}_i$ can be simply calculated by summing the difference of these values over interval of the whole stay $k \in [m, n-1]$ as

$$f(\mathbf{x}_i) = \sum_{k=m}^{n-1} (R_i(k) - C_i(k)). \tag{5.6}$$

Additionally, to reflect the influence of the battery degradation explained earlier, the degradation cost DG_i, calculated according to equation 4.6, can be used to reformulate the original fitness function as

$$f'(\mathbf{x}_i) = \sum_{k=m}^{n-1} \big(R_i(k) - C_i(k)\big) - DG_i \tag{5.7}$$

by simply subtracting the DG_i value as an additional cost from the total profit for a particle i representing the schedule for the given vehicle.

It should be noted that by default, throughout the whole work, the simpler fitness function f is used instead of f', unless stated otherwise.

5.3 Fitness Penalisation

In the problem of profit maximisation where profit is produced by revenues generated through discharging, securing the final desired state of charge SoC_{Target} to be met is very important. Considering that the SoC_{Target} is the problem constraint, the optimisation algorithm must ensure that this target is met by any solution returned upon its output. To achieve this in the implemented PSO algorithm, we propose a penalty function that penalises any potential solutions not meeting SoC_{Target} by an adequate reduction of their fitness value.

In each iteration, after having all particles in the swarm evaluated using the fitness function f, a SoC_{Final} value can be determined for each particle. The SoC_{Final} expresses the actual SoC at the time of departure, which in a generative algorithm like PSO does not necessarily need to be equal to the SoC_{Target}. Thus, each particle not meeting the desired SoC_{Target} is penalised.

For each particle, for which $SoC_{Final} < SoC_{Target}$, the amount of charge lacking to meet the SoC_{Target}, indicated by $Diff_{Charge}$, is expressed as

$$Diff_{Charge} = \left|SoC_{Final} - SoC_{Target}\right| \cdot kWh_{Max}. \tag{5.8}$$

Then, for interval between the vehicle arrival m, and its departure n, the maximum electricity price P_{Max} is found as

$$P_{Max} = \max_{m \leq k \leq n-1} P(k). \tag{5.9}$$

Finally, a new penalised value $g(\mathbf{x}_i)$ for each particle $\mathbf{x}_i$ not meeting the target is calculated according to equation

$$g(\mathbf{x}_i) = f(\mathbf{x}_i) - \frac{Diff_{Charge} \cdot (P_{Max} + 0.001)}{Eff_{Charge}}. \tag{5.10}$$

The function g subtracts from the actual particle fitness value $f(\mathbf{x}_i)$ a value that is supposed to represent a financial penalty only slightly higher than the alleged cost of charging the battery up to the SoC_{Target} at the highest electricity price within the interval of the vehicles's stay at the parking lot.

Chapter 6

Experiments

This chapter describes a set of various experiments performed to verify the performance of the implemented PSO algorithm to solve the optimisation problem of EV charging and discharging.

Due to the stochastic nature of the PSO algorithm leading to instability of the output values which differ in each run of the algorithm, it is important to re-run the algorithm few times to provide stable results. To retrieve steady results allowing further comparison and analysis, upon each experiment the presented values are averaged from either 30, or 10 independent runs of the algorithm, depending on the situation.

6.1 Comparison of PSO with BPSO

The main goal for this work was to demonstrate and validate functionality of the proposed PSO algorithm. Since the problem definition, although modified, is based upon the definition as described in the BPSO-concerned study including the vehicle parameters and used price curves, it is *this* exact BPSO algorithm, the PSO is confronted with in the following section.

6.1.1 Verification of Reference Algorithm

To demonstrate functionality of the PSO algorithm, a comparison of its performance against the original BPSO, as described by Hutson [14], is performed. At first, an identical copy of the BPSO algorithm is programmed according to all the information available in the original article. Additionally, to extend the opportunity for further comparison, the simple heuristic approach described in *Case Study 1* of the article is implemented as well.

Both algorithms were tested using the same input data consisting of 10 different sets of 500 vehicles, and an electricity price curve from August 7, 2008 was used to establish equal conditions for comparison with the corresponding numbers extracted from the Hutson's article. All these results are then put together in Table 6.1.

As seen in the table showing average values of all runs, despite the effort to reproduce the identical implementation of BPSO method, output of the two versions slightly differ in the maximum profit as well as in the amount of power into and out of the EV lot. This has been rather expected because the original vehicle data, retrieved through random generation,

Optimisation Method	Power into Lot [MWh]	Power out of Lot [MWh]	Total Profit
Simple (Hutson)	0.0984	1.2533	\$128.42
Simple (Körner)	0.1067	1.2372	\$125.06
BPSO (Hutson)	3.5164	3.8271	\$234.22
BPSO (Körner)	3.6831	4.0274	\$233.74

Table 6.1: Comparison of two different implementations of identical algorithms

could not be reproduced precisely. The deviation in results thus might be partly the work of non-identical input data, and partially induced by possible minor differences in the algorithm implementation and its settings. The latter one is relatively likely, considering that a BPSO, in general, employs several settings and parameters, of those only the number of iterations, being 100, was revealed in the original article.

The simple heuristic scheduling algorithm shall provide some clarification to the situation thanks to its straightforwardness. By examining results of the simple heuristic scheduling algorithm, a very similar trend in difference of the values can be observed between the two implementations as well. However, considering explicitness of the method description and the simplicity of the method itself, it is almost impossible for it to be implemented differently on any occasion, therefore this suggest that the deviation in results is a consequence of the usage of non-identical input data rather than anything else.

Finally, as the Table 6.1 above suggests, difference between the results is merely subtle, indicating that we have established a matching BPSO implementation ready to be compared with the PSO algorithm proposed in this study.

6.1.2 Comparison of Performance

Having a reference BPSO algorithm prepared, the PSO can be tested against it in terms of performance. The main part of testing consisted of maximising total profit for 10 diverse sets of 500 vehicles parked in a parking lot in various intervals over a single day, again utilising the price curve of August 7, 2008. Both the BPSO and the PSO algorithm shared the same parameters, values of which were determined experimentally and based on experience to ensure the best performance. The actual parameter values are documented in Table 6.2.

Parameter	Value
Number of iterations	200
Number of particles $\|S\|$	75
Initial inertia weight ω	0.9
Cognitive acceleration constant C_1	2
Social acceleration constant C_2	2
Maximum velocity v_{max}	7

Table 6.2: Parameter settings used in BPSO and PSO

Due to the increased complexity of the redefined problem definition proposed in this study, the maximum number of iterations was increased to 200 in order to discover the point of fitness saturation even in the PSO algorithm, and to find the best feasible solutions. The resultant curves showing the best fitness growth over the run of both algorithms are shown in the graph in Figure 6.1. Note that each pictured fitness curve is a sum of optimised fitness development for all 500 vehicles in a given vehicle set, thus denoting the total profit for the whole vehicle set.

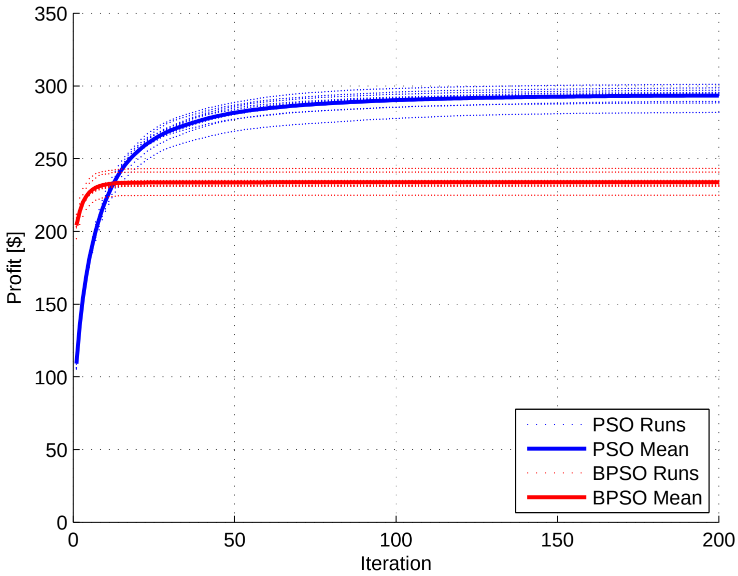

Figure 6.1: Comparison of BPSO and PSO on 10 different sets of 500 vehicles

The graph clearly shows how significantly the proposed PSO algorithm outperforms the BPSO as it finds a fitter solution already after approximately 10 iterations of its run. The fitness curves demonstrate that although BPSO saturates sharply and rapidly, after only roughly 25 iterations, it is unable to improve the best found solution anymore, which is very likely the effect of the limiting binary representation of the problem. The PSO, as opposed to that, converges gradually and slowly—which is due to its continuous nature—but it shortly achieves better solutions and manages to keep improving the best fitness until approximately 150^{th} iteration when it more or less reaches saturation.

The Table 6.3 summarises the same results seen in the figure above, showing amounts of power into and out of vehicle lot, and total profit for all 500 vehicles together. The data is averaged over all 10 runs with different vehicle sets.

This summary shows that the PSO algorithm outperformed its binary version by more than 25%. To achieve such profit increase with the identical vehicle sets, much more power had to be transferred out of EV batteries and back in – specifically, 65% more power in discharging, and over 93% more in charging. The radical disproportional increase of power charged into the electric vehicle lot in the PSO algorithm is a result of the strict requirement to meet the target SoC at the time of vehicle departure, which—on the contrary—is not

Optimisation Method	Power into Lot [MWh]	Power out of Lot [MWh]	Total Profit
BPSO	3.6706	4.0185	$233.75
PSO	7.1012	6.6332	$293.44
Difference	3.4306 (93.46%)	2.6147 (65.07%)	$59.69 (25.54%)

Table 6.3: Comparsion of BPSO and PSO on 10 different sets of 500 vehicles

handled in the binary algorithm. If the BPSO implementation incorporated this restriction as well, more power would have to be charged back into vehicle batteries, which would have led to lower total profit and even larger gap in its performance compared to the PSO.

6.1.3 Impact of Initialisation

It is not without significance that the initial best fitness in the 1st iteration, as pictured in zoomed-in graph in Figure 6.2, is fairly lower in the PSO algorithm than it is in the BPSO. This is induced by initialisation of the swarm of particles and broadly the solution representation itself.

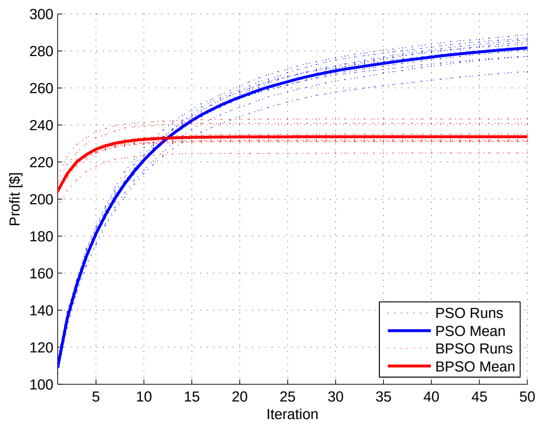

Figure 6.2: Comparison of initial behaviour of BPSO and PSO

In BPSO, a schedule for any day is represented by binary matrix $\mathbf{X} \in \{0,1\}^{2\times 24}$, where each pair of bits in a matrix column j denotes an action for the j-th hour of the day. Considering random generation of the particles from uniform distribution, the probability of any bit $x_{i,j} \in \mathbf{X}$ becoming '0' or '1' is equal, that is $P(x_{i,j} = 0) = P(x_{i,j} = 1) = 0.5$.

As a consequence of this, a probability of any action in the schedule $\mathbf{X}$ being *charging* is determined as conjoined probability of 2 bits in the same column j becoming both '1'. This can be formulated to calculate the probability $P(charge)$ as

$$P(x_{1,j} = 1, x_{2,j} = 1) = P(x_{1,j} = 1) \cdot P(x_{2,j} = 1) = 0.5 \cdot 0.5 = 0.25 \tag{6.1}$$

and analogically, $P(discharge)$ is calculated as conjoined probability of 2 bits in one column becoming both '0', delivering the same result.

Adding up these two probabilities together, there is a 50% chance that either charging or discharging action will take place in any hour of a newly initialised schedule, which means that roughly 50% of the schedule will lead to selling and buying power and thus generating profit. Besides, owing to the instant unlimited operations allowed in the relaxed BPSO problem definition, a lot of power can be transferred within these hourly intervals, developing potential for more profit at the start of optimisation.

Although the initial swarm in PSO method is as well generated randomly from uniform distribution, the situation here is quite different due to the continuity of the problem. The values comprising the particle vector $\mathbf{x}$ are restricted by the lower and upper bound, in this study experimentally determined to be $LB = 5$ and $UB = 40$, respectively. Given the UB, it is ensured that all values $x_i \in \mathbf{x}$ belong to interval $[-40, +40]$, and by excluding its inner interval $[-10, +10]$ denoting a *hold* action, we are left with 75% probability of any action in the initial schedule being either *charging* or *discharging*.

While this is more than the 50% chance seen in the BPSO, as soon as these uniformly distributed x_i values get scaled to interval $(0, 1]$ transforming the action length to proportion of an hour, there is only a very little chance left that an initial solution would comprise a full-hour action. Unlike in BPSO, a typical initial schedule would contain actions of various lengths spanning only minutes or tens of minutes, rarely getting close to the whole hour.

This represents a low profit potential at the beginning of optimisation, but as the PSO progresses through its iterations, it manages to improve the best solution by extending duration of actions where profitable and by connecting neighbouring actions into lengthy intervals, thus shortly outperforming the BPSO despite the initial disadvantage.

6.1.4 Consistency of Solutions

When optimising, it is desirable to obtain a stable algorithm which would, for the same input data, always return the same result. This is obviously not the case in metaheuristic algorithms, because these are unable to produce the same result on any occasion due to their stochastic nature. On the other hand, it is appropriate even for metaheuristic methods to always provide at least very similar output when the same input data are submitted.

Since PSO is a stochastic algorithm, it was tested, together with BPSO, on 10 runs for the same single set of 500 vehicles to determine their ability to provide consistent results throughout all trials. The results are to be found in zoomed-in graph in Figure 6.3.

As the curves suggest, the individual runs of the PSO algorithm are not identical, but considerably alike. The progress of improving the best found solution is very close especially at the beginning of optimisation, then it starts to differentiate across the runs, but the best result found after saturation show a very small deviation in the end.

In BPSO, the curves for individual runs display only a subtle difference among themselves being almost identical, but this is mainly due to the binary representation of the solution, making the optimised problem much more simple than it is in the redefined formulation for the proposed PSO method.

Detailed results for the individual PSO runs are further summarised in Table 6.4 showing that the standard deviation of maximised profit for all 10 runs is only \$0.63, which makes

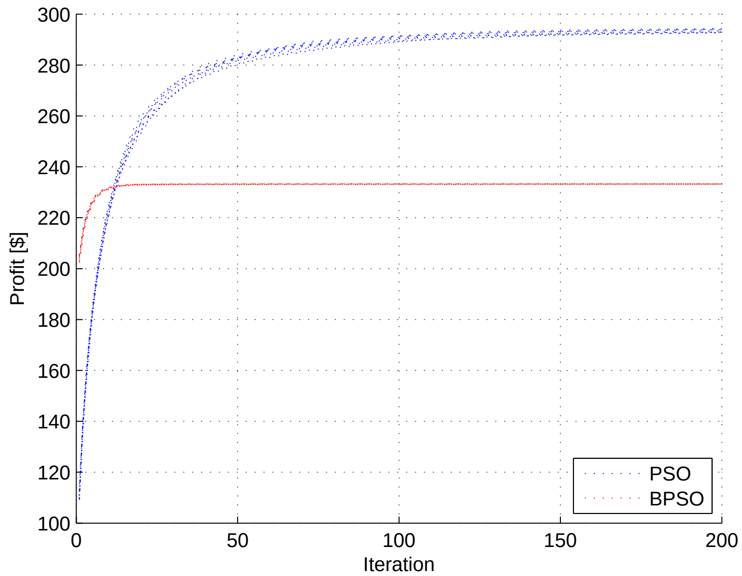

Figure 6.3: Comparison of 10 runs of BPSO and PSO with same set of 500 vehicles

it 0.21% of the total profit. Similarly to that, the standard deviations in values of power into and out of vehicle lot are also less than 0.5%, which demonstrates a very reasonable accuracy for a stochastic algorithm solving a continuous problem.

6.1.5 Comparison of Efficiency

One last step in the comparison between the pair of algorithms involves competing in computational efficiency. To compare the efficiency, both algorithms were tested with 10 separate sets of 50 vehicles and the time spent by optimisation was measured. Again, the algorithm parameters used were the same as in previous experiments, but this time, the number of iterations was decreased to 100. Table 6.5 sums up the results for both algorithms.

As the table suggests, the PSO algorithm not only provided better overall results in terms of objective function maximisation, but it also spent less time optimising the schedules for each vehicle set. The computing time for a single set in PSO spanned only 13.9 seconds in average, whereas in BPSO it took as much as 44.3 seconds, making its average duration more than 3 times worse compared to PSO.

Considering that the PSO implementation, although sharing the overall scheme with BPSO, incorporates additional computational burden—such as schedule consistency check, solution fitness penalisation, or solution vector transformation—the massive reduction of computing time cannot be achieved by anything else than the reduced solution representation.

In PSO, each solution particle $\mathbf{x} \in \mathbb{R}^{1\times(n-m)}$ is a vector of length defined by the vehicle arrival time m and departure time n, whereas in the BPSO implementation, each solution is a matrix $\mathbf{X} \in \{0,1\}^{2\times 24}$ of fixed size. Then, if we consider an average car staying in the parking lot for 8 hours a day, an average particle size for PSO is $|\mathbf{x}| = 1 \times 8$, whereas in

Run Number	Power into Lot [MWh]	Power out of Lot [MWh]	Total Profit
1	6.9243	6.5299	$293.90
2	6.8981	6.5155	$293.91
3	6.9316	6.5439	$294.26
4	6.8665	6.4892	$292.95
5	6.9066	6.5187	$292.66
6	6.9486	6.5519	$292.93
7	6.9018	6.5244	$293.44
8	6.9059	6.5250	$292.71
9	6.8548	6.4813	$292.85
10	6.9385	6.5441	$294.15
Average	6.91 ± 0.030 ($\pm 0.43\%$)	6.52 ± 0.023 ($\pm 0.35\%$)	\$293.38 $\pm$ 0.63 ($\pm 0.21\%$)

Table 6.4: Results for 10 runs of PSO with the same set of 500 vehicles

Vehicle Set	Total Profit (BPSO)	Run Time (BPSO)	Total Profit (PSO)	Run Time (PSO)
1	$19.87	41.7 s	$24.69	14.0 s
2	$22.17	43.2 s	$27.17	13.8 s
3	$19.65	39.6 s	$23.70	13.8 s
4	$24.35	45.6 s	$32.36	14.1 s
5	$24.11	44.5 s	$30.52	14.1 s
6	$24.25	43.2 s	$29.74	14.0 s
7	$24.17	44.6 s	$29.44	13.2 s
8	$28.87	50.2 s	$36.47	14.3 s
9	$21.26	42.8 s	$25.18	13.6 s
10	$24.49	46.1 s	$29.78	13.9 s
Average	$23.32	44.2 s	$28.90	13.9 s

Table 6.5: Results for 10 runs of BPSO and PSO with the same set of 500 vehicles

BPSO it is fixed to $|\mathbf{X}| = 2 \times 24$. By a naive assumption that the used data type is irrelevant in computation, this smart particle size reduction would in average case require 6 times less computing power speaking in favour of PSO, thanks to which the PSO is more time-efficient.

6.2 Schedule Consistency

Although the PSO implementation outperformed the BPSO method significantly, it is hard to determine, how close are the PSO's best solutions to the global optimum. However, it can be at least approximately verified by visual inspection of the actual schedules.

In regard to a given price curve, the charging and discharging operations scheduled by the PSO must appear to be rational and must not show any evident signs of non-optimality. To verify this, a number of schedules are visually observed in this section.

The first example of a solution for a vehicle arriving at 3 PM and departing at 12 PM is shown in Figure 6.4. In the figure, the upper sub-plot depicts the price curve, the middle one shows the change in SoC over time, and the lower one represents the schedule. Charging is marked with blue lines, discharging with red ones, and the vertical dotted lines in the colour of magenta symbolize the time of vehicle arrival m and departure n.

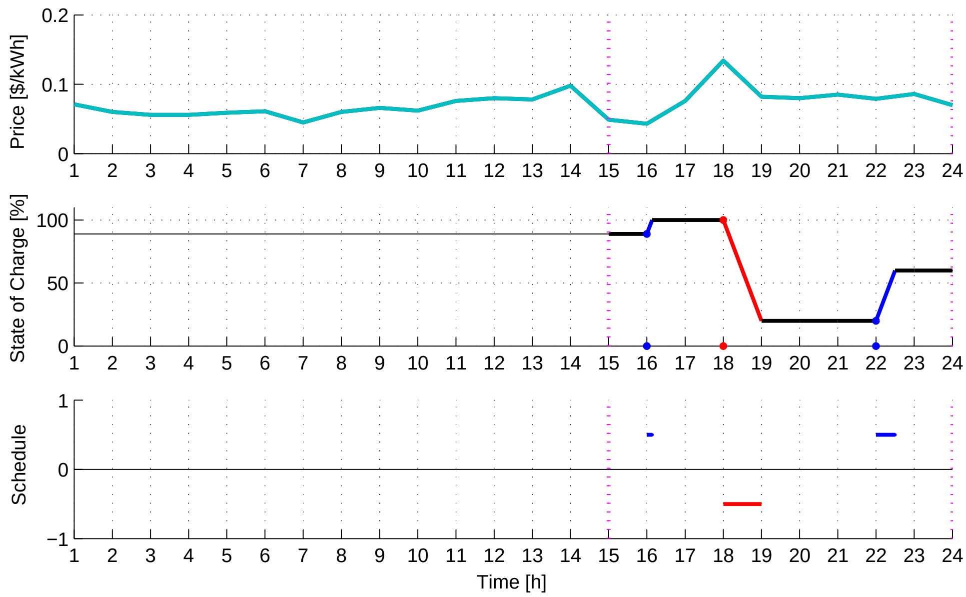

Figure 6.4: Example 1 of a solution to the scheduling problem for one vehicle

As the figure shows, this solution contains 3 actions – charging twice, and discharging once. At first, the vehicle charges its battery at the lowest price for something close to 10 minutes to achieve 100% SoC. Then, it waits for the peak price at 6 PM, when it discharges as much power as possible within the hour. Given that within the next couple of hours, the price stagnates and charging plus discharging efficiency would not allow for a profit to be achieved, the vehicle waits until a minimum price within the remaining interval occurs and it charges at that time only as much to meet the target of $SoC_{Target} = 60\%$, and leave at 12 PM. This behaviour appears to be perfectly reasonable.

The next example, shown in Figure 6.5, depicts an EV that arrives at the parking lot and starts charging immediately up to 100% SoC again to utilise the most capacity potential of its battery. The vehicle then keeps its full battery charge until the maximum price within its stay interval occurs, but because, due to the realistic charging/discharging speed, it cannot discharge all capacity within only one hour, it discharges a small portion of it already before the peek price, when the price is the second highest. Then, within the last hour prior to departure, when the price is the lowest, the vehicle battery is charged to the desired target SoC level of 60%.

The last example, showing a situation with a completely different price curve, is depicted in Figure 6.6. In this situation, the vehicle completely discharges its battery at the time of the first small price peak, and then utilises the price decrease to gain full battery charge prior to the greatest price peak of the day. At the peak price, it sells as much energy as

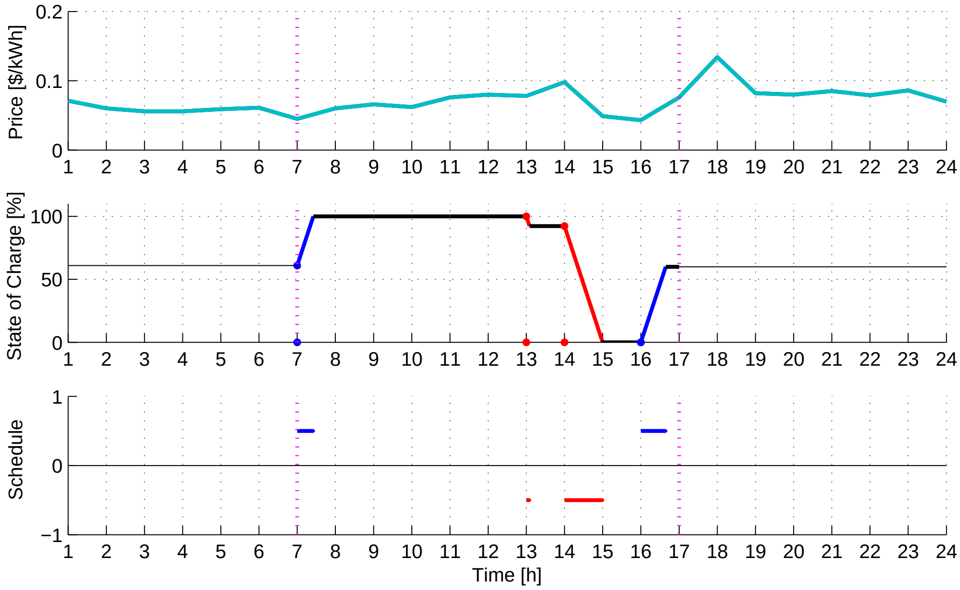

Figure 6.5: Example 2 of a solution to the scheduling problem for one vehicle

possible, and again uses the last hour before departure to gain the necessary target SoC.

The presented graphs revealed a new information, which was not apparent from the results in previous sections. With the problem definition as it is, the PSO algorithm creates schedules, which very often lead to charging vehicle batteries up to the full charge, as well as discharging down to the completely empty state. From the profit point of view, this is perfectly rational and leads to high profits, therefore we verified that the implemented method creates reasonable schedules that maximise profit.

However, in a real life situation, where the excessive amounts of extra charging and discharging would decrease battery life time, the profits generated by this technique might not be high enough to even compensate the arising costs associated with the harm to the battery leading to the potential need of its expensive replacement.

6.3 Effect of Voltage

Up to this point, every previous experiment was conducted while considering the charging voltage U_{CHG} of 440 V. Such high voltage, as explained earlier (Section 4.3), allows to charge or discharge as much as 12 kWh of the battery capacity within just an hour. For most of the vehicles, according to the Table 3.1 of vehicle parameters, kWh_{Hourly} rate this high allows transferring more than a half of their battery capacity within an hour. This should ensure sufficient flexibility of the system and good potential for considerable profit.

It is clearly supposable that the level of used charging voltage U_{CHG} will have a direct impact on the fitness of the best found solutions. To verify this, a set of tests was conducted,

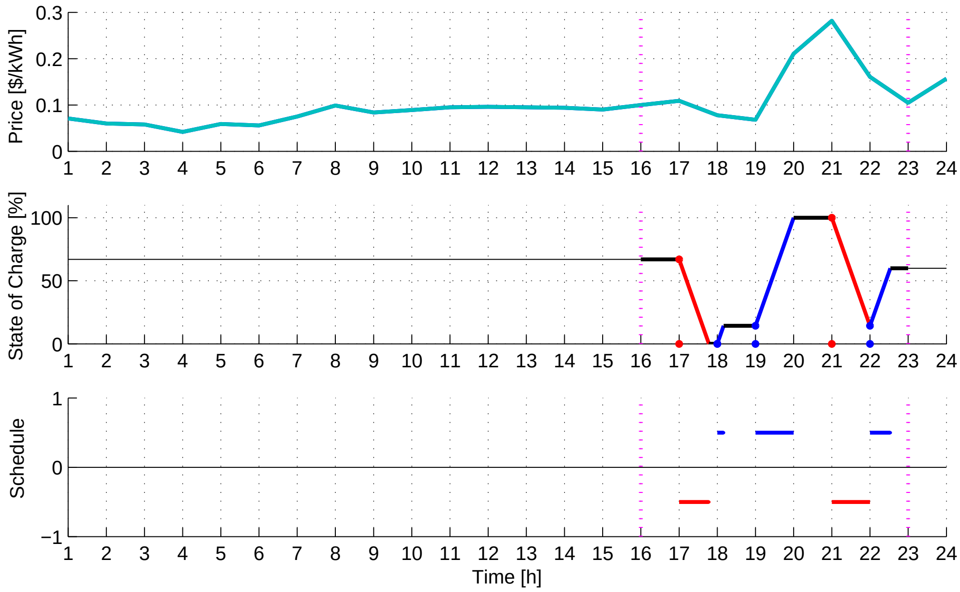

Figure 6.6: Example 3 of a solution to the scheduling problem for one vehicle

comparing the influence of various voltage levels on the profit function growth. The voltage levels used were 110 V, 220 V, and 440 V. The results comparing impact of the use of different voltage levels, given a price curve for 7 August 2008, is shown in the Figure 6.7. The experiment was conducted for 10 different vehicle sets of size 500.

As the figure shows, the used charging voltage U_{CHG} has a direct impact on the system performance, which is entirely in accordance with the presumptions. Interestingly, the fitness curves appear to be almost perfectly proportional to the level of voltage used, suggesting that there might be approximately linear relation between the charging voltage and the profit.

The lower is the charging voltage U_{CHG}, the lower is the kWh_{Hourly} rate, leading to reduction of the EV ability to use its battery capacity to generate profit. This is due to the reduced amounts of energy that can be transferred within the same time, which is clearly shown in Table 6.6. The low charging voltage leads to smaller amounts of power into and out of the vehicle lot, allowing only for smaller amounts of profit to be achieved.

Charging Voltage	Power into Lot [MWh]	Power out of Lot [MWh]	Total Profit
110 V	1.2048	1.9571	$109.71
220 V	3.0386	3.4745	$176.51
440 V	7.1012	6.6332	$293.44

Table 6.6: Comparison of influence of charging voltage

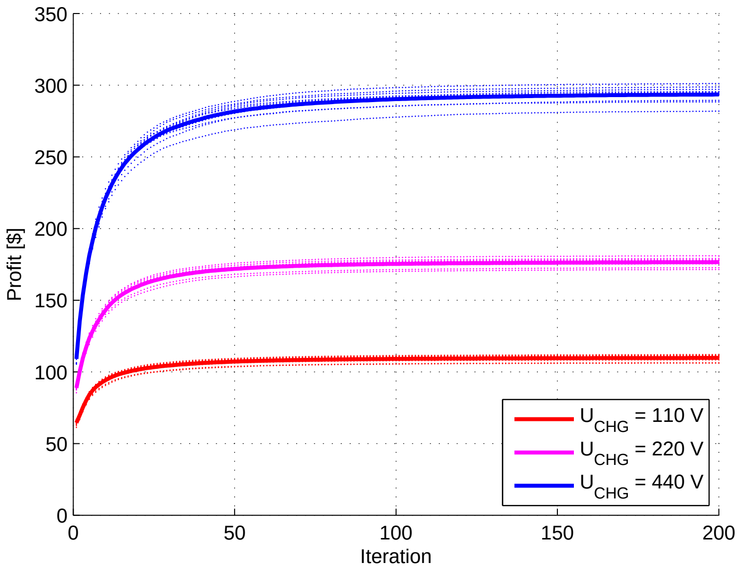

Figure 6.7: Comparison of influence of charging voltage on profit

6.4 Impact of Battery Degradation

Due to the presumed significant negative effect of battery degradation on the proposed system, this section examines the extent of the awaited effect. It is worth noting that the previous tests did not assume the battery degradation in the process, and maximised the fitness function only based on the revenues and costs.

The following experiments are performed with the modified objective function $f'(\mathbf{x}_i)$, which incorporates battery degradation costs DG_i. For the purposes of battery degradation cost calculation, it was at first required to define the battery price P_{Bat} and the battery life time LT_{Bat}. Since the commonly indicated number of cycles in EV *lithium-ion* batteries is around 3000, we adopted the value for the battery life time $LT_{Bat} = 3000$ cycles.

According to the report by NADA organisation [21], the current cost of a complete automotive *lithium-ion* battery system ranges from \$500 to \$600 per kilowatt-hour. Also, according to estimations, the lithium-ion battery prices are likely to drop down to only around \$150 per kWh by 2030. Given that observation, we conducted experiments with various different battery prices, those being $P_{Bat} = \{50, 150, 500\}$, all expressed in \$/kWh.

Having various battery prices defined, the testing of the PSO algorithm was taken, again with a set of 10 different sets of 500 vehicles. The results retrieved from the testing are shown in Figure 6.8.

The bold red curve shows averaged results for multiple PSO runs *without* the degradation costs considered. Naturally, with relaxation on the degradation costs, the best performance in terms of profit is achieved.

The remaining curves all represent runs of the algorithm with the battery degradation employed. With the battery price P_{Bat} = \$500/kWh, which corresponds to the current

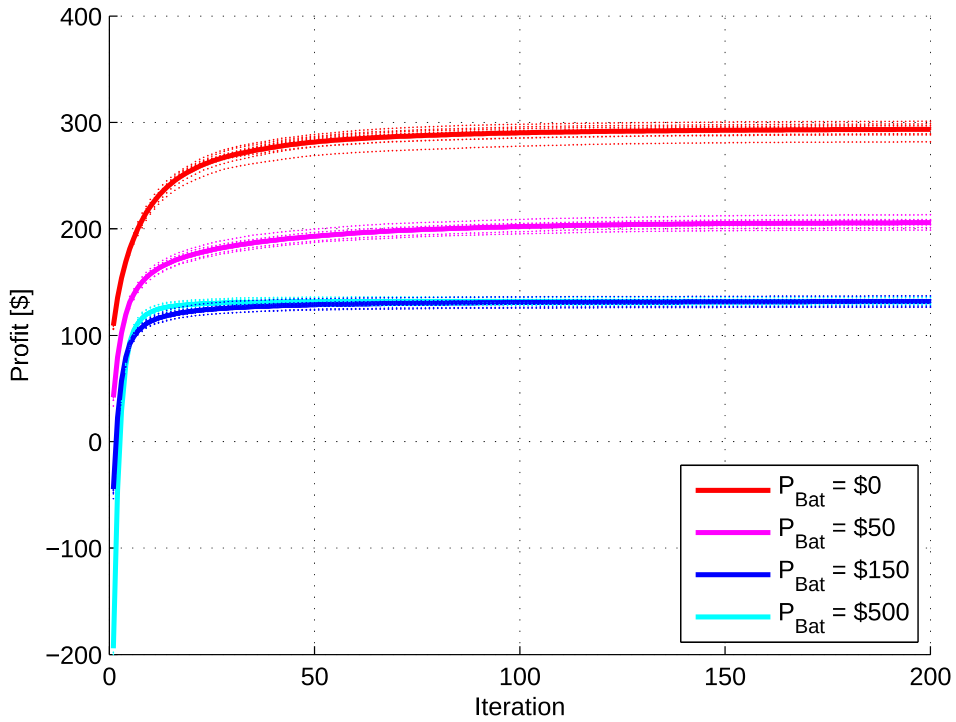

Figure 6.8: Comparison of influence of battery degradation to profit

situation in automotive industry, the initial fitness of the whole vehicle lot starts profoundly from negative values, which is the result of the additional degradation costs over-riding the revenues. Possibly with the assistance of the penalty function penalising solutions that do not meet the target SoC, the algorithm within only few iterations manages to push fitness value across the zero line to area of positive profit by reducing the number of actions in vehicle schedules and their lengths.

Even with the battery price set to P_{Bat} = \$150/kWh to simulate the battery price decrease likely to happen within 15 years from today, the situation is still quite alike. Regardless of the decreased battery price, the algorithm seems to schedule only the extent of charging and discharging needed to meet the target SoC requirement, omitting any additional power flow due to its unprofitability induced by battery degradation costs.

Despite the similarity in the final best achieved values, shared in both cases when the battery price is \$150/kWh, and when it is \$500/kWh, it is observable that in each of the two cases, the PSO algorithm behaves quite differently around approximately the 10$^{\text{th}}$ iteration. It appears that when the battery price is higher and thus incurring worse initial fitness, the penalty function stimulates the whole swarm of particles to gain higher velocity and keep improving the best solution more briskly, producing a sharper knee on the fitness curve compared to the situation of the lower battery price.

The Table 6.7 provides further insight and clarification to this situation showing that at the battery price of $150 per kilowatt-hour, although the average number of *charge* and *discharge* actions per vehicle is higher leading to larger amounts of power transferred, all the consequent revenues get disguised by the resulting degradation costs, providing the same final profit as if those additional actions did not occur in the end.

Battery Price	Power into Lot [MWh]	Power out of Lot [MWh]	Number of Charging Actions	Number of Discharging Actions	Total Profit
$0/kWh	7.0852	6.6219	1.90	1.87	$293.33
$50/kWh	4.6234	4.7335	1.44	1.34	$205.73
$150/kWh	0.8980	1.8450	0.54	0.86	$131.51
$500/kWh	0.1069	0.6405	0.21	0.40	$131.99

Table 6.7: Comparison of influence of battery degradation to performance

Finally, as the Figure 6.8 and Table 6.7 suggest, at the battery price of only $50 per kilowatt-hour, the degradation costs for the proposed model get reduced to such an acceptable amount, which allows for the extra charging and discharging to occur and generate reasonable profit considerably outmatching the associated degradation costs.

Based upon that, a conclusion can be made such that somewhere in the course of battery price decrease from $150 to $50 per kilowatt-hour, there is a breaking-point when it actually becomes profitable to use the electric vehicle batteries as a grid electricity storage device.

Chapter 7

Conclusions

This diploma thesis thoroughly investigates the topic of intelligent optimisation of schedules for charging and discharging of *electric vehicles* and *plug-in hybrid electric vehicles*.

7.1 Summary

First of all, a comprehensive research was done to explore the closely related topics of *Smart Grids* and *vehicle-to-grid* transactions, discovering the key aspects such as *charging efficiency* and *battery degradation* likely to affect the concerned optimisation problem.

Following to this, we investigated various existing studies that solved the EV charging and discharging scheduling problem by utilising metaheuristic methods like *binary particle swarm optimisation* (BPSO), *simplified social impact theory based optimisation* (SSITO), or even mathematical methods like *convex optimisation*. Owing to its straightforwardness, the published vehicle parameters, and the presented detailed results allowing potential comparison, the BPSO implementation became the most inspiring source for this work.

Having the related research done, we identified disadvantages and weaknesses of the existing methods, and presented the resulting drawbacks in a detailed list. We then proposed a reformulated problem definition and solution representation providing a new outsight to the given optimisation problem, removing some of the major drawbacks identified before.

The proposed formulation emerged as a problem of continuous search space, which for we then proposed and implemented a *particle swarm optimisation* (PSO) method tailored to the needs of the study. To eliminate remaining drawbacks, the implementation incorporated a penalty function to penalise inconsistent solutions for not meeting requirement on target battery state of charge, and an alternative fitness function comprising battery degradation costs to outline a model of a practical real-life situation.

Finally, the implemented PSO algorithm was confronted with the BPSO implementation in order to determine its performance. In the testing, it was verified that the proposed PSO implementation significantly outperforms the other algorithm in terms of the quality of the best found solutions (by more than 25%), and in terms of time and memory efficiency as well. The superior performance of the PSO algorithm, observed despite the fact that it incorporates more restrictions allowing to simulate a more realistic situation compared to the BPSO, was proved to be substantially the work of the proposed solution representation.

7.2 Eliminated Drawbacks

Besides the very good overall performance, the implemented PSO algorithm managed to eliminate the following drawbacks off the designated list:

- **instant operations** – this unrealistic assumption was eradicated by the use of constant level of charging voltage requiring a realistic amount of time for each operation;
- **battery degradation** – through the proposal of a simple battery degradation model, the effect of battery price was taken into account;
- **desired SoC verification** – the engagement of the penalty function helps to prevent inconsistent solutions from occurring within the final stages of optimisation;
- **discharging restriction** – the removal of restriction disabling discharging bellow the target SoC could be done owing to the penalty function, which watches over the accomplishment of the target SoC;
- **algorithm overkill** – by the transformation from binary to continuous search space, in favour of the problem practicability, its complexity increased as well, thus making the used algorithm adequate to the situation.

7.3 Battery Degradation

The experiments with the PSO offered an interesting outlook to the problem of battery degradation. Based on the assumption that the proposed battery degradation model is at least approximately accurate and relevant, it appears that the current automotive battery prices, ranging from \$500/kWh to \$600/kWh, completely put the whole idea of making profit by charging and discharging off the table.

Given a situation of similar electricity prices and vehicle parameters to those in this study, it might require the battery prices to drop down to somewhere between \$50–\$150/kWh before this approach becomes profitable.

On the other hand, subtracting the battery degradation costs from the profit is necessary only by the assumption that the extra charging and discharging accelerates the degradation of the EV battery to such degree that its replacement would be inevitable. In case that the life time of the battery would outlast the life span of the EV itself, this penalisation would need not to be done. Considering the rapid automotive battery technology development in recent years, this situation could in the future be accomplished by combining increase of the battery life time with decrease of its price.

7.4 Future Work

Although not necessarily economically viable at the conditions of today, the concept of optimisation of EV charging and discharging schedules remain very interesting, and would deserve further attention. The future works concerning this topic could take additional aspects in consideration to provide even more realistic model of the situation. Investigating the effect of realistic battery charging characteristics, or influence of error in electricity price prediction could prove as a great example of such aspects.

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Appendix A

List of Abbreviations

EV Electric Vehicle

PHEV Plug-in Hybrid Electric Vehicle

G2V Grid-to-Vehicle

V2G Vehicle-to-Grid

SoC State of Charge

LB Lower Bound

UB Upper Bound

PSO Particle Swarm Optimisation

BPSO Binary Particle Swarm Optimisation

SSITO Simplified Social Impact Theory based Optimisation

CAISO California Independent System Operators

Appendix B

CD Contents

Since the character of this work is rather research-oriented than implementation-oriented, all programming was done in MATLAB, a computing environment and a programming language, supporting easy manipulation with matrices and plotting of various types of data.

The programmed source codes, included on the CD enclosed with this diploma thesis, consist of MATLAB scripts and functions in `*.m` files.

On the attached CD, there is a `MATLAB` directory containing subdirectories `Data`, `BPSO`, and `PSO`, which the contents of are following:

- **Data** – Contains 10 randomly generated sets of 500 vehicles;
- **BPSO** – Contains own implementation of BPSO algorithm;
- **PSO** – Contains own implementation of PSO algorithm.

In each directory containing source codes for an algorithm, use the `main_script.m` file to run the algorithm.