



HAL
open science

Approches distribuées et adaptatives pour la gestion de l'énergie

Azizbek Ruzmetov

► **To cite this version:**

Azizbek Ruzmetov. Approches distribuées et adaptatives pour la gestion de l'énergie. Autre. Université de Technologie de Belfort-Montbéliard, 2015. Français. NNT : 2015BELF0271 . tel-01875228

HAL Id: tel-01875228

<https://theses.hal.science/tel-01875228>

Submitted on 17 Sep 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

SPIM

Thèse de Doctorat



école doctorale sciences pour l'ingénieur et microtechniques
UNIVERSITÉ DE TECHNOLOGIE BELFORT-MONTBÉLIARD

Thèse présentée par

Azizbek RUZMETOV

pour obtenir le

Grade de Docteur de

l'Université de Technologie de Belfort-Montbéliard

Spécialité : **Informatique**

APPROCHES DISTRIBUEES ET ADAPTATIVES POUR LA GESTION DE L'ENERGIE

Soutenue le 29 octobre 2015 devant le Jury :

Mr. Tarek El-GHAZAWI	Rapporteur	Université de George Washington
Mr. Pascal LORENZ	Rapporteur	Université de Haute Alsace
Mr. Tarek AHMED ALI	Examineur	Université de Caen Normandie
Mr. Chu-Min LI	Examineur	Université de Picardie Jules Verne
Mr. Mohamed BAKHOUYA	Examineur	Université Internationale de Rabat
Mme Marie-Ange MANIER	Directrice de thèse	Université de Technologie de Belfort Montbéliard
Mr. Ahmed NAIT-SIDI-MOH	Co-encadrant	Université de Picardie Jules Verne
Mr. Jaafar GABER	Co-encadrant	Université de Technologie de Belfort Montbéliard

Table of Contents

GENERAL INTRODUCTION	4
I. THE RESEARCH DOMAIN	5
II. THE BACKGROUND	5
III. THE RESEARCH PROBLEM.....	6
IV. THE CONTRIBUTIONS	8
V. ORGANIZATION OF THE DISSERTATION.....	11
V.1. <i>Thesis outline</i>	11
V.2. <i>Chapter Contents</i>	11
VI. CONCLUSIONS AND PERSPECTIVES.....	13
CHAPTER 1	
STATE OF THE ART.....	17
I. INTRODUCTION	18
II. ELECTRIC VEHICLES: AN OVERVIEW	18
II.1. <i>Fully Electric Vehicles</i>	18
II.2. <i>Hybrid Electric Vehicles</i>	19
II.3. <i>Plug-in Hybrid Electric Vehicles</i>	19
III. EV BATTERY.....	20
III.1. <i>Basic terms of battery performances</i>	20
III.2. <i>Battery technologies</i>	23
IV. ELECTRIC VEHICLE CHARGING	26
IV.1. <i>Energy sources</i>	26
IV.2. <i>Charging methods for EV</i>	26
V. SCHEDULING AND OPTIMIZATION FOR EV CHARGING	28
VI. CONCLUSION	31
CHAPTER 2	
OPTIMIZATION BASED APPROACH FOR OPTIMAL SCHEDULING AND ASSIGNMENT OF EVS TO CSS	
I. INTRODUCTION	33

II.	SYSTEM DESCRIPTION	34
II.1.	<i>Charging process architecture</i>	34
II.2.	<i>Communication architecture</i>	36
III.	OPTIMAL ASSIGNMENT OF EVs TO CSS	39
IV.	RESOLUTION AND DISCUSSION.....	46
V.	CONCLUSION	48

CHAPTER 3

MODELLING APPROACH USING (MAX, +) ALGEBRA49

I.	INTRODUCTION	50
II.	GRAPHICAL MODELLING	51
II.1.	<i>Introduction to TEG</i>	51
II.2.	<i>TEG models</i>	52
II.3.	<i>Global TEG model</i>	56
III.	MATHEMATICAL MODELLING	58
III.1.	<i>Basics of (max, +) algebra</i>	58
III.2.	<i>(Max, +) linear model</i>	61
III.3.	<i>Evaluation and analysis</i>	62
IV.	CONCLUSION	64

CHAPTER 4

ADAPTIVE BASED APPROACH65

I.	INTRODUCTION	66
II.	MODELLING WITH TEG	66
III.	(MAX, +) STATE REPRESENTATION	71
IV.	RESOLUTION OF (MAX, +) STATE MODEL	75
V.	PREDICTIVE CHARGING APPROACH	76
V.1.	<i>Numerical and evaluation study</i>	76
V.2.	<i>Improvements: sizing results</i>	82
VI.	CONCLUSION	83

CHAPTER 5

PREDICTIVE AND SCALABLE APPROACH85

I.	INTRODUCTION	86
II.	A TRADE-OFF BASED APPROACH FOR PREDICTIVE CHARGING	86
II.1.	<i>Used predictive function: parameters identification</i>	86
II.2.	<i>Prediction of charging rate and charging time</i>	89
III.	PREDICTION USING (MAX, +) ALGEBRA: EXTENDED CASE STUDY	95
III.1.	<i>Use of one charging point</i>	95
III.2.	<i>Case of multiple charging points</i>	101
III.3.	<i>Analysis and discussions</i>	103
IV.	CONCLUSION	107
CONCLUSIONS AND PERSPECTIVES		109
I.	SUMMARY	110
II.	FUTURE WORKS	113
LIST OF PERSONAL PUBLICATIONS		114
LIST OF TABLES		115
LIST OF FIGURES		116
LITERATURES		118

GENERAL INTRODUCTION

I.	THE RESEARCH DOMAIN	5
II.	THE BACKGROUND	5
III.	THE RESEARCH PROBLEM.....	6
IV.	THE CONTRIBUTIONS	8
V.	ORGANIZATION OF THE DISSERTATION.....	11
VI.	CONCLUSIONS AND PERSPECTIVES.....	13

I. The research domain

General context: Optimization, scheduling and modelling

Specific context: Optimal assignment and scheduling approaches with applications to the Electric Vehicle (EV) charging problem.

II. The background

Recently, the industry is making a great research effort to develop the power engine of electric vehicles and batteries [1]. Three major types of vehicles are available in the market: Fully electric vehicles (FEV), hybrid electric vehicles (HEV), and plug-in hybrid electric vehicles (PHEV). FEV are primarily suited for short journeys with limited ranges. However, the charging process could be time consuming and batteries have to be efficiently used since the propulsion of these vehicles depend on their energy storage capacity. HEV technologies have been developed to overcome the limitations of FEV in order to extend range capability. If the battery reaches its minimum state-of-charge, another source or an engine could be activated to propel and recharge batteries. HEV has an advantage over FEV since recharging the battery at a recharging point is not required. PHEV was introduced and has a large battery pack that can be charged either by an on-board engine, regenerative braking of motor or external electric supply [2]. For example, Opel has developed an energy management system to regulate the interaction between the electric motor, the gasoline engine, the generator and the battery [2].

Currently, the smart grid technology is changing the way the worldviews energy. Such technology aims to deliver sustainable, economic and secure electricity supplies by integrating energy producers and consumers. This allows updating the electricity

utilities around the world and redesigning their power networks. In other words, this is largely in response to growth in user demand and the restructuring of generation capacity to include distributed supply from renewable sources such as wind and solar energy. Consequently, there is a compelling need to incorporate most pervasive communications systems. The resulting “smart grid” is a synthesis of energy and its management, information and communication technologies and infrastructures [3]. Smart grid should ensure that electricity-generating capacity is used efficiently. With a smart grid, one should be able to manage when and how EV charging occurs while still adhering to customer preferences.

In the near future, EVs will play a significant role in the road traffic. However, EVs have a limited driving range between charges, require to be guided charging station (CS) with available slots. This requires novel routing algorithms, since the task is now to determine the most economical route rather than just the shortest one. Thus, the management of electric vehicles charging and adequate assignment to CSs is one of the major challenges facing managers of EV fleet.

III. The research problem

The rise of new modes of electricity production and demands, subject to specific uses and services (e.g. two-way flows of electricity and information, electric vehicles, smart homes...), require new intelligent energy delivery management to ensure reliable operation. Power grid differs from other network systems in that power generation capacity and delivery are statically scheduled and tailored to priori expected demands, besides the fact that electric power is not stored. It is therefore necessary to develop new decentralized control approaches, taking into account infrastructure constraints,

implementation and production capacity to meet fluctuations in demands that could not be entirely predictable.

In the literature, great research efforts have been made to develop the power engine of electric vehicles and batteries. However, little attention has been paid so far to the fact that the charging process for electric vehicles is completely different from the refueling process of vehicles that are powered by conventional power engines. One of the major obstacles to the large deployment of electric vehicles is the uncertainty of drivers to get a suitable and vacant place at a charging station.

Different methods and architectures have been proposed in the literature to tackle the charging problem. The proposed approaches can be classified into four categories: a control based charging systems category, planning and scheduling based methods category, routing guidance based architectures and stations placement category, and energy trading profits oriented category.

The first category of approaches targets the power management of an electric vehicle and its battery life cycle ([4], [5] and [6]). The main objective is to identify the parameters affecting the battery health degradation, such as aging and number of cycles, and optimizing the charge pattern of the EV.

In the second category of approaches, scheduling algorithms are tackled for the charging station in order to decide the service order of multiple requests. The objective is to improve the satisfaction of EVs' drivers by reducing the charge cost and waiting time. Furthermore, the authors compared the reducing imbalance costs by reactive scheduling and proactive scheduling.

The third category tackles routing and vehicle guidance to suitable charging stations, and the location assignment problems of these stations themselves ([7] and [8]). The aim is to guide the EV users to a charging station, and to manage charging system.

The fourth category targets the maximizing energy trading profits and minimizing battery-aging costs. Approaches propose several methods using the battery in an optimized policy under the consideration of battery aging costs and variable electricity prices.

In this work, the framework proposed relies on wireless communication technologies, Web services, and Geo-positioning techniques for information exchange while linear programming and (max, +) algebra are used to develop scheduling algorithms and to model predictive and adaptive based approaches.

IV. The contributions

For driver journeys, selecting not only the nearest charging point, but ones with available slots and additional services are the most important issues. This requires finding the path from the origin (EV actual location) to the destination (a free charging point) with the minimum distance to travel and the shorter time. Finding such paths given that traffic condition and the number of requests could change over time requires an adaptive approach to select the adequate CS for drivers.

The EVs charging management with performance metrics such as follows of drivers to the EVs' queue within charging station, number of vehicles, required charging time, etc. can be seen as a discrete event system. From this point of view, many tools have been developed in the literature to model and analyze systems such as Petri Nets (PN), Discrete Event System Specification (DEVS).

In this work, Timed Event Graphs (TEG), which is a subclass of Petri nets is used with $(\max, +)$ algebra. These tools have been proposed in the literature as powerful tools for modelling and performance analysis issues ([9], [10] and [11]). More precisely, the goal of the proposed approaches is to act on the service times in order to serve a maximum of charging demands while satisfying all EV constraints (e.g. remaining battery energy). The proposed approaches allow defining a predictive function of the charging process by providing ad hoc information and suggesting adequate charging station for each EV.

Particularly, the following contributions have been tackled within the scope of the thesis:

- 1) Optimization based approaches for optimal scheduling and assignment of EVs to charging stations;
- 2) Modelling with $(\max, +)$ algebra of the behavior of the charging systems with all the components: the EVs, the collaborative platform (CPL) and the charging station;
- 3) Adaptive based approaches using $(\max, +)$ algebra;
- 4) Predictive and scalable approaches to support large scale charging systems;

IV.1. Optimization based approaches for optimal scheduling and assignment of EVs to CSs

An integrated platform is introduced with the main objective to increase the synergy between different system entities, such as energy providers, charging stations and electric vehicles. The platform architecture involves communications, Web services and Geo-positioning techniques. Optimization approaches for optimal scheduling and assignment of electric vehicles to charging stations is proposed. The problem is formulated by a linear

program, in which the assignment of all EVs should verify certain constraints such as the status of the charging stations and EVs.

IV.2. Modelling approach using (max, +) algebra

A (max, +) based approaches are described to model the charging processes. Three main components of the system are represented: the EV, the charging stations as energy providers, and a collaborative platform. Each component is modelled and the occurrence date of each event is reported. The objective consists of serving a large number of charging demands, according to the EVs location and their actual needs in terms of energy. The proposed model is given as a sequence of events/states occurring in a chronological order. It is based on an Event Graph model in which the execution of each event requires an amount of time.

IV.3. Adaptive based approach

(Max, +) -equations describing the analytic behavior of the process are derived from the TEG models. A performance tuning based approach is proposed to improve the quality of service offered to EVs by adjusting the charging rate. This tuning method allows a predictive and scalable between the number of charging requests and the number of available charging points, i.e., to charge a maximum of EVs using a minimum number of charging points.

IV.4. Predictive and scalable approaches

The objective here is to mix the adaptive based approaches with the predictive based approaches. The outcome is a trade-off between a large numbers of demands process and an average charging rate acceptable for all to support large-scale systems. Predictive charging approaches are proposed to anticipate and improve the provided services to drivers and to suggest an adequate charging station. Average charging rates and charging

times are calculated according to the predictive and scalable approaches, followed by the adaptive based approaches, which are used to predict charging times and charging rates for each EV individually.

V. Organization of the Dissertation

V.1. Thesis outline

- General introduction
- Chapter 1: State of the art
- Chapter 2: Optimal assignment and scheduling approaches
- Chapter 3: Modelling approaches using (max, +) algebra
- Chapter 4: Adaptive based approaches
- Chapter 5: Predictive and scalable approaches
- Conclusions & Perspectives

V.2. Chapter Contents

V.2.1. General introduction

The General introduction presents the problem statement, the objectives and contributions of the dissertation.

V.2.2. Chapter 1: State of the art

This chapter presents the classification of EVs, their advantages and disadvantages as well as EV batteries and the main concepts of charging process.

V.2.3. Chapter 2: Optimization based approaches for optimal scheduling and assignment of EVs to CSs

In this chapter, a system platform is based on communication technologies is described to manage the charging process and exchange information. Furthermore, an objective

function based linear programming is proposed for optimal scheduling and assignment of EVs to the CSs. The obtained results, which are given selected values and conclusion, generalize this chapter.

V.2.4. Chapter 3: Modelling approaches

This chapter is composed of two main sections: graphical modelling and the mathematical modelling. In the graphical modelling section, the proposed system and its components behavior are described as Time Event Graphs. The mathematical modelling section presents the basics of $(\max, +)$ algebra and the linear model of the system.

V.2.5. Chapter 4: Adaptive based approaches

The system, which is developed with an access control to the charging service and $(\max, +)$ linear system are introduced as a beginning of this chapter. Furthermore, an algorithm is proposed to predict charging times and charging rates for the EV demands. Charging management policy is described to adapt the charging rates of EVs with multiple charging points.

V.2.6. Chapter 5: Predictive and scalable approaches

In this chapter, predictive functions are proposed to determine average charging rates and charging times for received charging requests at a given time interval (i.e., periodically). The average charging rates and charging times are calculated separately for each period. The obtained results and conclusion are presented at the end of the chapter.

VI. Conclusions and perspectives

This section summarizes the contributions of all the chapters further works are also presented in the future work section.

Notations and abbreviations

Notations:

Symbol	Meaning
\mathbb{R}	The set of real numbers
\mathbb{R}^n	The set of all n-tuples of real numbers
$\mathbb{R}^{n \times n}$	The set of all $n \times n$ matrices with real entries
\mathbb{N}	Natural numbers
\oplus	max-algebraic addition
\otimes	max-algebraic multiplication
X	The state vector
x_i	i^{th} component of the vector a
$T_i(k)$	The k^{th} firing of the T, called also <i>dater</i>
a_{ij}	entry of the matrix A on the i^{th} row and the j^{th} column
ε	zero element for (max, +) algebra: $\varepsilon = -\infty$
e	neutral element for (max, +) algebra: $e = 0$
E_n	n by n max-algebraic identity matrix
$\varepsilon_{m \times n}$	m by n max-algebraic zero matrix
$A^{\otimes n}$	nth max-algebraic power of the matrix A
$t_i(j)$	charging time of j^{th} EV within i^{th} received demands
$\lambda_i(j)$	charging rate of j^{th} EV within i^{th} received demands
M_i	the number of EVs within i^{th} EVs set
P_{max}	Maximum proposed charging time
P_{min}	Minimum proposed charging time.
CT_{max}	Required time for a full charging (100%) of the battery
CT_{min}	Required time for minimum acceptable charging rate
TT_i	Trip Time from the i^{th} EV location to the charging station
k	the k^{th} request sent by the EV
$U(k)$	arrival time of the k^{th} request
$X(k)$	execution times of all of the process(connection, waiting, charging, notifying, updating) for the k^{th} request

A_0, A_1, B and C	characteristic matrices
$Y(k)$	notification of ending charging process time of the k^{th}
λ	average charging rate
n_{ev}	number of EVs which are under charging at the same time ($n_{ev} \geq 1$)
n_{cp}	number of available charging points ($n_{cp} \geq 1$)
Δk	inter-arrival between the k^{th} and $(k - 1)^{th}$
P_a	difference between P_{max} and P_{min}
u_1 and u_2	input variables
x_1, x_2, \dots, x_8	input transitions and state variables

Abbreviations:

Symbol	Meaning
EV	Electric Vehicle
PDA	Personal Digital Assistant
CS	Charging Station
CPL	Collaborative Platform
CP	Charging Point
DB	Database
DEVS	Discrete Event System Specification
EG	Event Graphs
FEV	Fully Electric Vehicle
HEV	Hybrid Electric Vehicle
PN	Petri Nets
PHEV	Plug-in Hybrid Electric Vehicle
TEG	Timed Event Graph
BEV	Battery Electric Vehicle
LFP	Lithium Iron Phosphate
Li-poly	Lithium polymer

Li-ion	Lithium-ion
NiMH	Nickel-Metal-Hydride
DES	Discrete Event System
SoC	State of Charge
PTEG	P-Timed Event Graph
DoD	Depth of Discharge
SoH	State of Health
BMS	Battery Management System
TMS	Thermal Management System
NiCD	Nickel Cadmium
NaNiCl	Sodium Nickel Chloride
G2V	Grid to Vehicle
V2G	Vehicle to Grid
AC	Alternating Current
DC	Direct Current
SOA	Service Oriented Architecture
I2V	Infrastructure to Vehicle
V2I	Vehicle to Infrastructure
I2I	Infrastructure to Infrastructure
GPS	Global Positioning System
EGNOS	European Geostationary Navigation Overlay Service
GPRS	General Packet Radio Service
3G	Third Generation (mobile communication system)
FullCh	Full charging
LP	Linear Programming
DDES	Dynamic Discrete Event Systems
FrCS	Free Charging Station
PoI	Points of Interest
H1	Hypothesis 1
H2	Hypothesis 2

CHAPTER 1

STATE OF THE ART

This chapter gives an overview of the main concepts and electric vehicles (EV), some energy sources, charging technologies and tools and some developed optimization methods and algorithms for the management of their charging.

I.	INTRODUCTION	18
II.	ELECTRIC VEHICLES: AN OVERVIEW	18
II.1.	<i>Fully Electric Vehicles</i>	18
II.2.	<i>Hybrid Electric Vehicles</i>	19
II.3.	<i>Plug-in Hybrid Electric Vehicles</i>	19
III.	EV BATTERY.....	20
III.1.	<i>Basic terms of battery performances</i>	20
III.2.	<i>Battery technologies</i>	23
IV.	ELECTRIC VEHICLE CHARGING	26
IV.1.	<i>Energy sources</i>	26
IV.2.	<i>Charging methods for EV</i>	26
V.	SCHEDULING AND OPTIMIZATION FOR EV CHARGING	28
VI.	CONCLUSION	31

I. Introduction

Recently, the industry is making a great research effort to develop the power engine of electric vehicles, their technologies and principally the embedded batteries [1]. An electric vehicle is propelled by an electric engine, which can be charged by a battery, an engine generator, or by a fuel cell. We distinguish three major types of electric vehicles. Fully Electric Vehicles (FEV) are primarily suited for short journeys with limited ranges. However, the charging process takes several hours and batteries have to be efficiently used since the propulsion of these vehicles depends on their energy storage capacity. The second type is Hybrid Electric Vehicles (HEV) whose technologies have been developed to overcome the limitations of FEV in order to extend range capability. If the battery reaches its minimum state-of-charge (SoC), another energy source or an engine could be activated to propel and recharge batteries. HEV has an advantage over FEV since recharging the battery at a recharging point is not required. The third type is Plug-in Hybrid Electric Vehicles (PHEV) were introduced and have large battery pack that can be charged either by an on-board engine, regenerative braking of motor or external electric supply [2]. For example, Opel has developed an energy management system to regulate the interaction between the electric motor, gasoline engine, generator and battery. More details are given hereafter for each of these types.

II. Electric Vehicles: an overview

II.1. Fully Electric Vehicles

Fully Electric Vehicles or Battery Electric Vehicles (BEVs) are powered by electricity supplied by an external source - usually the electric grid and stored in on-board batteries that drive the vehicle's wheels through one or more electric motors. The primary

challenge facing BEVs is the batteries' capacity to hold enough energy to deliver performance comparable to vehicles powered by internal combustion engines. BEVs can draw their power from several types of batteries, each benefiting from their own combination of power and energy densities. The materials that make up their components usually identify the common types of commercial automotive batteries: lead-acid, nickel-metal-hydride (NiMH), lithium polymer (Li-poly), lithium-ion (Li-ion) and lithium iron phosphate (LFP). More details about all these technologies are presented in [12].

II.2. Hybrid Electric Vehicles

Hybrid electric vehicles are powered by a combination of electricity and either petrol or diesel. The electricity is used only as an intermediate energy storage medium to improve the overall efficiency of the vehicle. They therefore do not need to be plugged in to recharge the battery. This cuts down on the amount of fuel needed, producing fewer emissions and lowering overall fuel costs. As with BEVs, most hybrid electric vehicles also use 'regenerative braking', which captures energy from braking to be put back into the battery. This improves energy efficiency and reduces brake wear. Manufacturers are currently developing plug-in hybrid electric vehicles (PHEV) with much bigger batteries, representing a bridge between HEV and BEV technology [13].

II.3. Plug-in Hybrid Electric Vehicles

Plug-in hybrids, sometimes called Plug-in Hybrid-Electric Vehicles, are hybrid vehicles with high-capacity batteries that can be charged by plugging them into an electrical outlet or charging station. They can store enough electricity from the power grid significantly reduce their petroleum consumption under typical driving conditions. Plug-in hybrids also have different battery capacities, allowing some to travel farther on

electricity than others. Their fuel economy, like that of electric vehicles and regular hybrids, can be sensitive to driving style, driving conditions, and accessory use [14].

III. Electric Vehicle battery

The battery is a key element for electric vehicles. The EV differs from other vehicles because it needs to store required energy to ensure a good autonomy and acceptable performances. Storage requirements are not the same for both types of vehicles. Indeed, for an EV, a large storage capacity is required. This type of vehicle requires therefore the use of storage means such as efficient batteries.

III.1. Basic terms of battery performances

Several items exist for describing battery performances. Here, we give commonly used items as a quick reference.

- *Cell, Module, and Pack.* A single cell is a complete battery with two current leads and separate compartment holding electrodes, separator, and electrolyte [43], [44], [45]. A module is composed of a few cells either by physical attachment or by welding in between cells. A pack of batteries is composed of modules and placed in a single containing for thermal management. An EV may have more than one pack of battery situated in a different location in the car [15].
- *Ampere-hour Capacity.* Ampere-hour (Ah) capacity is the total charge that can be discharged from a fully charged battery under specified conditions. The Rated Ah capacity is the nominal capacity of a fully charged new battery under the conditions predefined by the manufacturer.

- *C-rate*. C (nominal C-rate) is used to represent a charge or discharge rate. It equals to the capacity of a battery in one hour.
- *Specific Energy*. Specific energy, also called gravimetric energy density, is used to define how much energy a battery can store per mass unit.
- *Specific Power*. Specific power, also called gravimetric power density of a battery, is the peak power per mass unit.
- *Energy Density*. Energy density, also referred as the volumetric energy density, is the nominal battery energy per volume unit (Wh/l).
- *Power Density*. Power density is the peak power per volume unit of a battery (W/l).
- *Internal Resistance*. Internal resistance is the overall equivalent resistance within the battery. It is different for charging and discharging and may vary as the operating condition changes.
- *Cut-off Voltage*. Cut-off voltage is the minimum allowable voltage defined by the manufacturer. It can be interpreted as the “empty” state of the battery.
- *State of Charge (SoC)*. SoC is defined as the remaining capacity of a battery and it is affected by its operating conditions such as load current and temperature [15].
- *Depth of Discharge (DoD)*. DoD is used to describe how deeply the battery is discharged. If a battery is fully charged (SoC = 100%), it means that the DoD of this battery is 0%. If the battery has delivered 30% of its energy, the SoC of this battery reaches 70% and its DoD is 30%. DoD always can be treated as how much energy that the battery delivered [16].

- *State of Health (SoH)*. SoH can be defined as the ratio of the maximum charge capacity of an aged battery to the maximum charge capacity when the battery was new [17].
- *Cycle Life (number of cycles)*. Cycle life is the number of charge-discharge cycles the battery can handle at a specific DoD (normally 80%) before it fails to meet specific performance criteria. The actual operating life of the battery is affected by the charging and discharging rates, DoD, and other conditions such as temperature. The higher the DoD, the shorter the cycle life. To achieve a higher cycle life, a larger battery can be used for a lower DoD during normal operations.
- *Calendar Life*. Calendar life is the expected life span of the battery under storage or periodic cycling conditions. It can be strongly related to the temperature and SoC during storage.
- *Battery Reversal*. Battery reversal happens when the battery is forced to operate under the negative voltage (voltage of positive electrode is lower than that in the negative electrode). It can happen on a relatively weak cell in a serially connected battery string. As the usable capacity of that particular weak cell runs out, the rest of batteries in the same string will still continue to supply the current and force the weak cell to reverse its voltage. The consequence of battery reversal is either a shortening cycle life or a complete failure.
- *Battery Management System (BMS)*. BMS is a combination of sensors, controller, communication, and computation hardware with software algorithms designed to decide the maximum charge/discharge current and duration from the estimation of SoC and SoH of the battery pack.

- *Thermal Management System (TMS)*. TMS is designed to protect the battery pack from overheating and to extend its calendar life. Simple forced-air cooling TMS is adopted for the NiMH battery, while more sophisticated and powerful liquid cooling is required by most of the Li-ion batteries in EV applications [15].

III.2. Battery technologies

In what follows, we give the most battery technologies used for electric vehicles. A comparative study of the performances of these different technologies, their advantages and disadvantages are given thereafter.

Lead acid (Pb-acid):

Lead-acid batteries are the oldest type of rechargeable battery and have a very low energy-to-weight and energy-to-volume ratio. These factors mean that lead acid batteries take up significant amounts of space within vehicles and add significant amounts of weight. However, they can maintain a relatively large power-to-weight ratio and are low cost making them ideal for use in road vehicles [15].

Nickel Cadmium (NiCd):

Nickel Cadmium give the longest cycle life of any currently available battery (over 1,500 cycles) but has low energy density compared to some other battery types. Cadmium is also toxic – a hazard to both humans and animals, so its use (mainly in domestic applications), is being superseded by Li-ion and NiMH types, in part forced by EU legislation [15].

Nickel-Metal-Hydride (NiMH):

The Nickel Metal Hydride battery technology is similar to a NiCd battery in design, except cadmium is replaced making it less detrimental to the environment. NiMH

batteries can also have 2-3 times the capacity of an equivalent size NiCd, with much less significant memory effect. Compared to lithium-ion batteries, energy capacity is lower and self-discharge is higher. Applications include hybrid vehicles such as the Toyota Prius, the Toyota RAV4-EV all-electric plug-in electric car, and consumer electronics [15].

Lithium-ion (Li-ion):

The relatively modern lithium-ion battery technology has a very high charge density (i.e. a light battery that stores a lot of energy). Current limitations include volatility, the potential for overheating, high cost, and limited shelf and cycle life. The technology currently has widespread use in consumer electronics (e.g. mobile phones) but has only recently begun to be used in transport applications (e.g. the Tesla Roadster electric car and in Prius conversions to a plug-in hybrid). General motors and Toyota are now also moving towards using more Lithium-ion batteries [15].

Li-ion polymer:

This is a similar technology to Li-ion, but typically has slightly lower charge density, greater life cycle degradation rate and an ultra-slim design (as little as 1 mm thick). Disadvantages include the high instability of overcharged batteries and if the battery discharges below a certain voltage it may never be able to hold a charge again [15].

Sodium Nickel Chloride (NaNiCl):

Sodium Nickel Chloride, also known as the Zebra battery, belongs to the class of molten salt batteries. These use molten salts as an electrolyte, offering both a higher energy density, as well as a higher power density making rechargeable molten salt batteries a promising technology for powering electric vehicles. However, the normal operating temperature range is 270–350 °C, which places more stringent requirements on the rest of the battery components and can bring problems of thermal management and

safety. Furthermore, there are also significant thermal losses when the battery is not in use [15].

The Table 1 presents a comparative study for these technologies. More explanations and details can be found in [42], [46] and [47].

	Lead–acid	NI-Cd	NI-MH	NaNiCl (Zebra)	Li-Ion	Li-Ion Polymer
Mass energy (Wh/kg)	30-50	45-80	60-110	120	150-190	150-190
Energy density (Wh/L)	75-120	80-150	220-330	180	220-330	220-330
specific power (W/kg)	Till 700	----	Till 900	200	Till 1500	Till 250
Number of cycles	400-600	2000	1500	800	500-1000	200-300
Self-discharge	5%	20%	30%	12%/day	10%	10%
Nominal voltage (V)	2	1.2	1.2	2.6	3.6	3.7
Operating temperature	-20 to 60°c	-40 to 60°c	-20 to 60°c	-20 to 50°c	20 to 60°c	0 to 60°c
Autonomy (Km)	70-120	70-120	150-200	100-140	150-200	120-200
Advantages	Low cost	performance reliability under low temperatures	Good energy density	Good energy density & cyclability	Excellent energy and power	Small size (thin)
Disadvantages	Low energy, sudden death	Low energy, toxicity	Basic materials costs	Limited power, Self- consumption	Security of big elements, costs	Low performance under low temperatures, costs

Table 1. Comparative study for battery technologies and performances

IV. Electric Vehicle charging

IV.1. Energy sources

Primary energy sources (meaning energy is created directly from the actual resource) can be classified in two groups: non-renewable and renewable energy [48]. Secondary sources are derived from primary sources [18].

Non-Renewable Energy Sources – Energy from the ground that has limited supplies, either in the form of gas, liquid or solid, are called non-renewable resources. They cannot be replenished, or made again, in a short period. Examples include: oil (petroleum), natural gas, coal and uranium (nuclear). Oil, natural gas and coal are called “fossil fuels” because they have been formed from the organic remains of prehistoric plants and animals.

Renewable Energy Sources – Energy that comes from a source that is constantly renewed, such as the sun and wind, can be replenished naturally in a short period. Because of this, we do not have to worry about them running out. Examples include solar, wind, biomass and hydropower. Currently, about 20% of the world’s electricity comes from renewable resources. There is a global debate as to whether geothermal energy is renewable or non-renewable.

Secondary Energy Sources – Energy that is converted from primary sources are called secondary sources of energy. These sources are used to store, move, and deliver energy in an easily usable form. Examples include electricity and hydrogen [18].

IV.2. Charging methods for EV

When talked about an EV charging process, it is also necessary to know about characteristics of charging stations, existence EV battery chargers and charging

technologies and methods. For EV drivers there are two possibilities to charge their EVs. First one is at home overnight in an own garage and second one in public charging stations. According to these locations and specific needs of drivers, slow or fast charging can be used. For example, at home drivers can install slow charging equipment. Public charging stations are often used for fast charging. Furthermore, by power levels we can define charging types. We distinguish three levels of charging. Level 1 is used for home charging, level 2 for public charging stations and finally level 3 for the grid. Usually chargers are divided into two types: on-board and off-board with unidirectional, for G2V (Grid to Vehicle) or V2G (Vehicle to Grid), and bidirectional power flow, for G2V and V2G [19]. More details about energy flows unidirectional and bidirectional can be found in [49], [50] and [51]. If electricity flow is from AC (Alternating current) to DC (Direct current) this kind of charger is known as off-board. The power converter DC/DC is known as on-board charger [42], [46].

In what follows we underline the three charging methods.

a) Standard charging

It just takes one simple step – plug the electric vehicle into a 13A standard socket with dedicated circuit and independent protective device. It is easy and convenient, but takes a longer charging time (8 to 10 hours for a complete charge (SoC = 100%) for an EV with 24kWh as battery capacity) compared to other charging methods. It is suitable to users of EVs who travel regularly between home and office, such that they can park their vehicles overnight at their residential vehicle park to recharge the battery. It can also be used for short time (e.g. 1 to 2 hours) “top-up” purposes at shopping malls or other public vehicle parks to add necessary energy to make 15 to 30 additional kilometers [20].

b) Semi-quick charging

Semi-quick charging could provide up to three-phase 32A current for charging an electric vehicle. It takes much shorter charging time using semi-quick charging compared to standard charging. It takes only just over an hour for a complete charging for an EV with battery capacity of 24 kWh.

c) Quick charging

Uses a specialized fast charger connected to a high-powered electricity source. The high power greatly reduces the charging time. Nevertheless, it requires greater infrastructure investment, space and extra costs from buying specialized equipment. It is suitable for emergency charging purpose, public transportation such as taxis or mini-buses, or corporate fleets where the daily travelling range is long [20].

V. Scheduling and optimization for EV charging

Several methods and optimization algorithms have been developed in the literature regarding the charging management of EVs and their connections with the charging infrastructure. For these issues, several new concepts have been proposed on how to use grid-connected EVs for grid services V2G and energy management [1], [2], [5], [6], [21], [22], [23], [24], [25] and [26]. These concepts usually involve charging of EVs and also discharging in order to support the grid when the demand is superior to the supply. In [27], a multi-agent system has been used to model and control the charging and discharging of PHEVs. Furthermore, authors compared the reducing imbalance costs by reactive scheduling and proactive scheduling. Simulation results show that reactive scheduling is able to reduce imbalance costs by 14%, while proactive scheduling yields the highest imbalance cost reduction of 44%.

The authors examine in [4] the problem of optimizing the charge pattern of a PHEV. The optimization goal is simultaneously to minimize the total cost of fuel and electricity, and the total battery health degradation over a 24 h naturalistic drive cycle. The first objective is calculated using stochastic optimization for power management, whereas the second objective is evaluated through an electrochemistry-based model of anode-side resistive film formation in lithium-ion batteries.

In [28], a genetic optimization algorithm is applied to optimize the charging behavior of a PHEV connected to the grid with the aim to maximize energy-trading profits in a V2G context and minimize battery-aging costs at the same time. The study proposes a method to use the vehicle batteries in an optimized way under the consideration of battery aging costs and variable electricity prices.

In [24] and [29], charging/discharging processes have been formulated as a global scheduling optimization problems, in which powers of charging are considered to minimize the total cost of all EVs. The authors in [5] and [6] focused on developing effective charging algorithms for fast charging and increasing cycle of battery life. In the same context, some approaches for effective planning charging times are proposed in [30] and [31]. All these algorithms and approaches help and serve to organize and build the efficient tools and reliable applications for modern charging infrastructures.

For minimizing the waiting time for EV charging in a large-scale road network, a theoretical study has been conducted in [26] to formulate and analyze the problem. In addition, a distributed scheduling protocol has been proposed for minimizing waiting time in practice.

For driver journeys, finding not only most nearest charging point but free and most relevant (with additional capabilities and suggestions such as shopping, restaurant or other interest points) is one of the most important issues for drivers. This requires finding the path with the minimum distance to travel, time from an origin (the EV location) to a destination (charging station with free charging points). Finding such paths is based on algorithms such as Dijkstra and Bellman [32], [33], and [34]. As the traffic condition changes regularly and increasing number of requests, finding adequate charging stations for drivers is required. In order to reach these objectives, many research works have been developed in the literature. Among the researches, we refer to the contribution presented in [52] and [53]. In [52] the authors proposed an optimization algorithm based on linear programming in order to assign optimally and adequately EVs to charging stations. The proposed approach provides a solution to both minimize the energy consumption by EVs and reaching adequate charging station. Each EV assignment takes into account the constraints of vehicles, charging stations and the traffic situation on the roads. With the proposed solution, the approach keeps the in-vehicle battery SoC to its highest level (maximum level) at its destination. Consequently, this charging method allows reducing the duration of time charging and therefore reducing the time spent within the charging station. The problem addressed by authors in this paper consider the operating of charging system under normal conditions such as normal traffic on the roads, itineraries without severe slopes, without excessive use of electric accessories of the EV. The proposed work in [53] extends the contribution of [52] by studying the same problem of charging management of EVs taking into account many constraints related EVs characteristics, charging infrastructures characteristics and the traffic situation on the roads. In this extended study, the authors addressed one of the most major issues, related to the

uncertainty of the drivers to get suitable charging stations under disturbed situations. The authors are mainly focused on an optimization approach in order to assign optimally and adequately EVs to charging stations under disturbed conditions like traffic jam, misuse of electrical accessories of the vehicle, status of travelled itineraries and roads.

As presented in the introduction, this optimization issue regarding the assignment of EVs to charging stations will be further addressed in the chapter 2 and the assignment results will be reported and analyzed.

VI. Conclusion

In this chapter 1, we gave an overview regarding to EVs classification, EV battery, EV charging and the problems of optimization and scheduling for EV charging. The main aim is to show the difference among the EVs in the subsection Electric vehicles: an overview. FEV, HEV and PHEV are presented and given own properties in this subsection. When talking about the charging process, it is important to give information regarding battery and its properties as well as classification of EV battery. In the subsection EV battery, we gave information regarding basic terms of battery performances and using battery technologies.

Producing energy and energy sources are also important providing to the customers to satisfy needs of them. Thus, information about the energy sources are given in the subsection EV charging. On top of that, the charging methods for EV are presented and counted the several types of charging process. At the end of this chapter, scheduling and optimization problems presented for EV charging.

CHAPTER 2

OPTIMIZATION BASED APPROACH FOR OPTIMAL SCHEDULING AND ASSIGNMENT OF EVs TO CSs

In this chapter, an integrated platform is introduced with the main objective to increase the synergy between different system entities, such as energy providers, charging stations and electric vehicles. The platform architecture is based on communications technologies, Web services and geo-positioning techniques. An optimization approach for optimal scheduling and assignment of electric vehicles to charging stations is proposed. Preliminary results are presented to illustrate this approach and show the usefulness of this integrated solution.

I.	INTRODUCTION	33
II.	SYSTEM DESCRIPTION	34
	<i>II.1. Charging process architecture</i>	34
	<i>II.2. Communication architecture</i>	36
III.	OPTIMAL ASSIGNMENT OF EVs TO CSS	39
IV.	RESOLUTION AND DISCUSSION.....	46

I. Introduction

Currently, the smart grid technology and concepts are changing the way the worldviews energy. Such technology platform delivers sustainable, economic and secure electricity supplies by integrating energy producers and consumers. This allows updating the electricity utilities around the world and redesigning their power networks. In other words, this is largely in response to growth in user demand, regulatory changes, and the restructuring of generation capacity to include distributed supply from renewable sources such as wind and solar energy. Consequently, there is a compelling need to incorporate far more pervasive communications systems. The resulting “smart grid” is a synthesis of energy and its management, information and communication technologies and infrastructures.

The smart grid is a key technology for building charging infrastructures for charging needs of EVs. It provides visibility and control needed to mitigate the load impacts and protect components of the distribution network from being overloaded by EVs. Smart grid ensures also that electricity-generating capacity is used most efficiently. With a smart grid, utilities can manage when and how EV charging occurs while still adhering to customer preferences.

In the near future, EVs will play a significant role in the road traffic. However, original characteristics of EVs are for example limited cruising range, long charging times, and the ability to regain energy during deceleration. This requires novel routing algorithms, since the task is now to determine the most economical itineraries rather than just the shortest one to reach charging stations (CSs). In this chapter, we will bring our contribution by addressing this optimization problem.

II. System description

For this study, we consider a charging system composed of a set of EVs. Each EV is characterized by a specific need in terms of energy and geographic location; a set of CSs proposing the charging service with a given number of charging points, charging power, and characterized by their geographic locations; and an intermediate platform managing the charging operations and ensuring the link between EVs and CSs. This platform can be seen as a service platform in the cloud based on Web services, communication technologies, Service Oriented Architecture (SOA) [54], [55], [56].

II.1. Charging process architecture

In order to illustrate the studied system, the Figure 1 presents its functional architecture. It could integrate all core services such as:

- Identification of EVs with charging needs. This service is made by the intermediate platform, called also a central controller. This platform is used also to collect all information regarding charging stations and their current status (geographic locations, number of charging points, and existence of free charging points, etc.).
- Finding and reserving charging station for each charging request. This service is proposed by the platform according the current information of EVs and additional specific needs of drivers (such as interest points).
- Guidance of EVs to charging stations. The platform suggests an adequate itinerary for each EV to reach the suggested charging station.
- Managing load of charging station groups. The platform manages loading process as well as a list of available and occupied charging stations. All charging stations information are stored in the data base platform.

- Collecting vehicle data for analyzing purposes. These data (location of EV, its SoC etc.) are collected by the platform and stored into its Database(DB).
- Offline operations to ensure reliable charging in the event of connectivity failure of the public network.
- Other services can be provided by the platform such as billing of energy consumption, offline operations ensuring reliable charging in the event of connectivity failure of the public network, etc. These services are not considered in this study since they are not required to reach the fixed objectives.

EVs interactive user interface and the mobile smart phone portal (e.g. iPhone and Android Apps) offer drivers with information about charging station locations, charging process and other required information. Furthermore, it provides battery state-of-charge and distance to carry with remaining energy in the battery. All these information can be displayed on an embedded map.

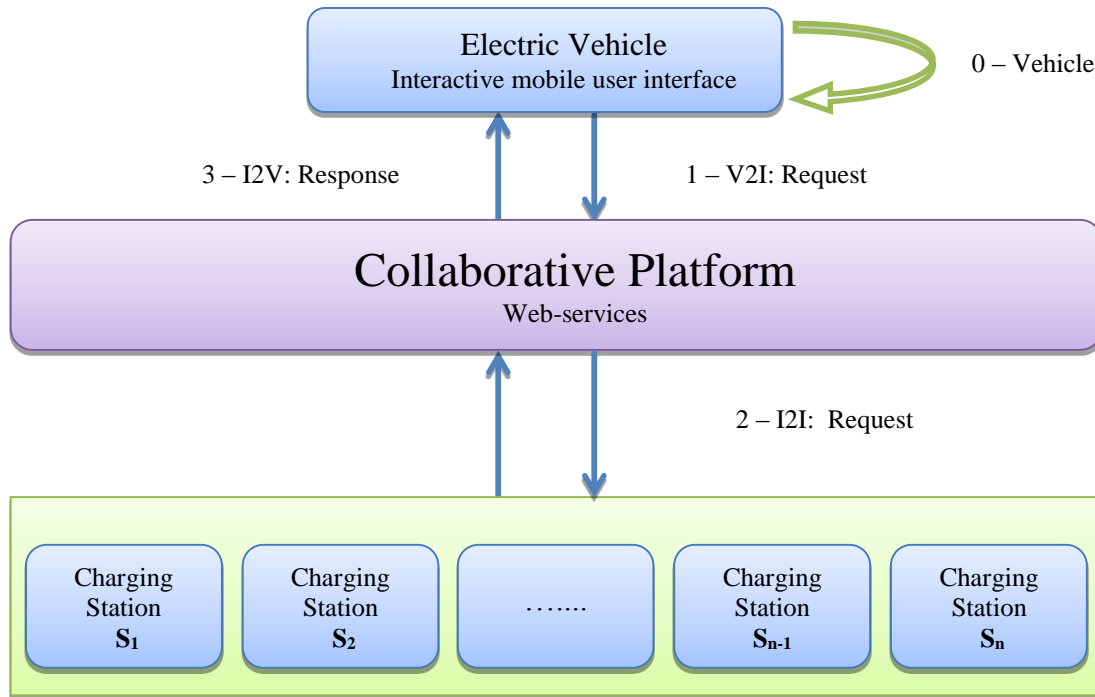


Figure 1. Charging process architecture

As illustrated in the Figure 1, EVs and charging stations are the main entities of the system. Each charging station is composed of many charging places that are connected to the platform. Information about charging stations are saved into the platform Database (DB) for current and future charging requests. For example, free/occupied charging points, charging power of charging points, energy pricing, the location of charging stations, etc... EV drivers connect, via an embedded device (Personal Digital Assistant (PDA, Smartphones, etc.), to the platform. An in-vehicle embedded application sends the charging requests and receives responses from the platform.

II.2. Communication architecture

We recall that each charging station is composed of several charging places (called also charging points). All information regarding a charging station are collected frequently and stored in the platform DB. Furthermore, the platform regularly updates

information about charging processes, such as how many EVs are under charging process, how many EVs are waiting into each charging station, the status of each charging station, etc.. The solution we propose allows to optimally handle requests received from drivers such as finding the nearest charging station and reserving a charging place. On the other hand, the system allows assisting drivers to choose adequate and optimal solutions for EVs charging. To do so, the interaction and communication between all system components are based on the following principles: real-time positioning using ge-positioning techniques (GPS and EGNOS) [57], bidirectional communication between EVs and Collaborative Platform (Vehicle to Infrastructure (V2I) and Infrastructure to Vehicle (I2V)) via wireless technologies (GPRS or 3G) [58], [59], [60]. Based on these technologies and standards, the adopted communication architecture is illustrated in the Figure 2.

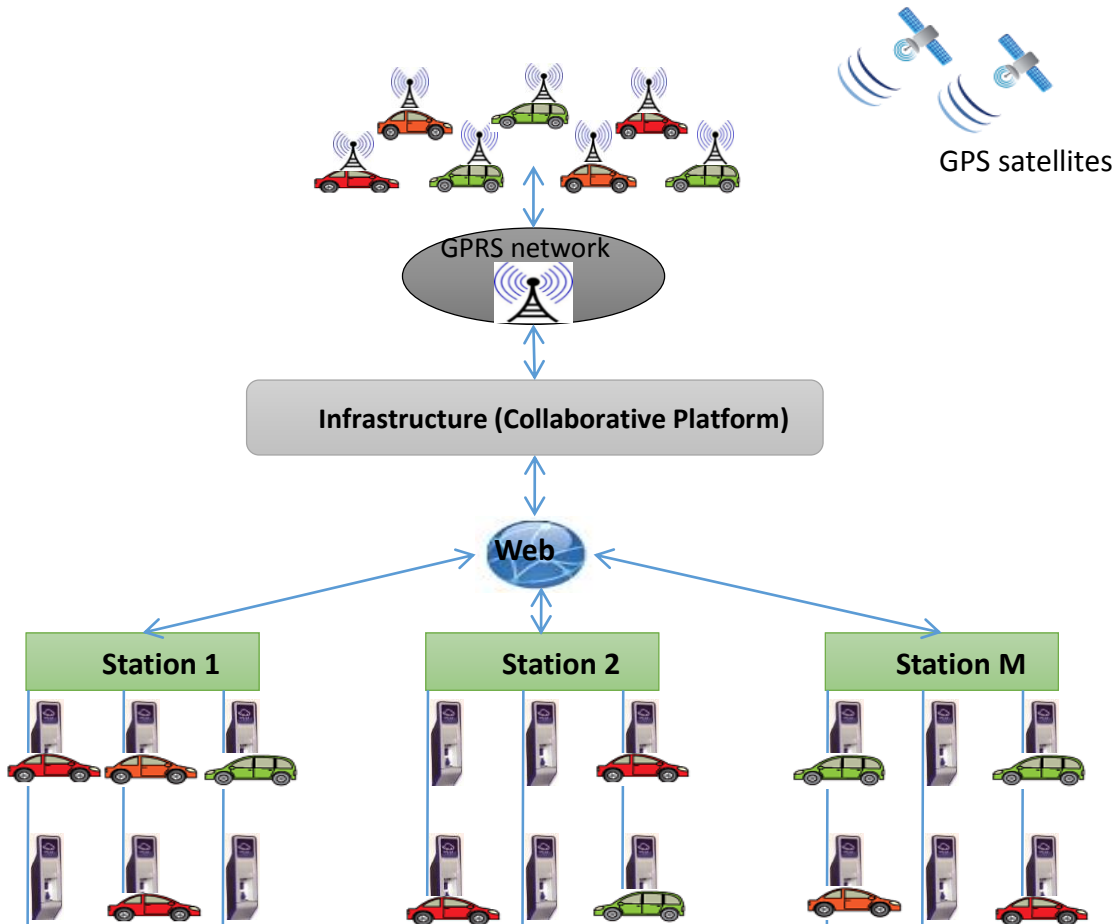


Figure 2. Communications V2G and G2V

The general charging process includes four main steps:

- Warning drivers about battery status. For vehicles equipped with the Battery Management System, this message occurs when the battery's State of Charge has dropped below a predetermined level. The message is intended to inform driver that the battery requires charging to guarantee proper performance under all conditions (propulsion even on itineraries with severe slopes, high electrical system demands, etc.) [35].

- Sending charging request. EV driver sends a charging request to the platform to have an adequate charging station location, the most adequate one according to driver demand.
- Searching the adequate charging station with available charging points according to stored information in the platform database. The platform looks for within all stored information regarding charging station and proposes the adequate charging station taking into account EV' information.
- Make a feedback to the EV. The platform is charged to send the location and other required information, such as the itinerary, distance, of the proposed charging station to the EV.

In fact, after receiving warning information about battery level and distance to be travelled with remaining energy, the embedded application sends a request to the platform, which in turn processes the request and informs the driver about the suitable charging station. Charging process and looking for adequate charging station by the platform is based on the algorithm of the Figure 3.

III. Optimal assignment of EVs to CSs

This subsection presents the optimal assignment of EVs to charging stations. The study is based on the linear programming optimization. The problem formulation is started by a global knowledge of the process context such as information about the status of charging stations, information about EVs such as battery level with possible distances to carry out using the remaining power, GPS coordinates, distance between the EV and nearest charging stations, etc.. All these information can be obtained through exchanges between EVs, the platform and charging stations as shown in Figure 3.

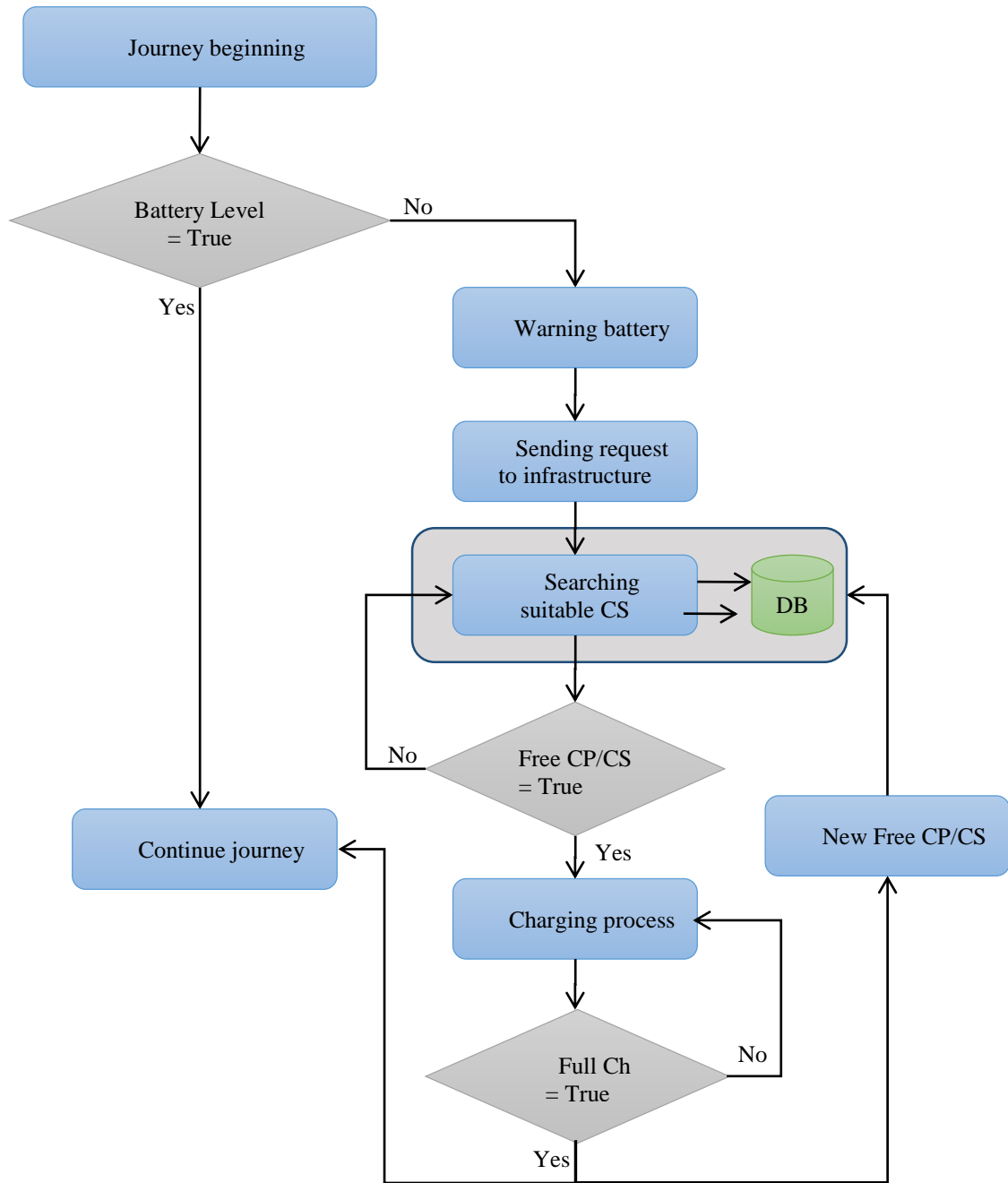


Figure 3. The block diagram of general algorithm of charging process

Legend: CS - Charging station, CP - Charging Point, DB - Database, Full Ch - Full Charging.

Figure 3 describes a journey of an EV. If the battery level or SoC of the battery is enough to carry out desired travel, driver can continue his/her journey. Otherwise, the battery SoC reaches a certain limit, driver get a warning message regarding low energy. In this case, request message for charging is sent (automatically or manually) to the platform by driver. Next step is managed by the platform while searching suitable charging station for the current EV request according its information and status. The platform looks for an available charging station within all collected information which are stored in DB. When an available/free charging point is found, the EV is warned while suggesting a charging station corresponding to the sent criteria. After finishing charging process, used charging point will be free and DB of charging stations is updated. So, the EV driver can continue the journey.

This study consists in selecting the best choice of assignment of EVs to charging stations with minimum waiting times and minimum costs (to avoid overloading stations). Therefore, we assume the following statements:

- There are limited resources (a finite number of charging points available at each charging station).
- There is an explicit objective to reach. This objective is always expressed in linear programming by an objective function formulated with a linear equation.
- The problem is subject to some constraints and conditions to satisfy which are related to the system context. These constraints should be also expressed with linear equations.
- The resources are homogeneous (everything is in one unit of measure) and the characteristics of EVs are same.

- The decision variables are binary (we either make an assignment of an EV to a charging station or not).

The assignment of EVs to charging stations will be carried out according to the assignment matrix of Table 2. Let consider N EVs and M charging stations. N and M are supposed to be non-negative integers with $N \gg M$ meaning that in a real configuration the number of EVs is enough greater than the number of charging station.

	S_1	S_2	S_3	...	S_M
EV_1	$c(1,1)$	$c(1,2)$	$c(1,3)$...	$c(1,M)$
EV_2	$c(2,1)$	$c(2,2)$	$c(2,3)$...	$c(2,M)$
EV_3	$c(3,1)$	$c(3,2)$	$c(3,3)$...	$c(3,M)$
...
EV_N	$c(N,1)$	$c(N,2)$	$c(N,3)$...	$c(N,M)$

Table 2. Assignment coefficients of EVs to Charging Station

For $1 \leq i \leq N$ and $1 \leq j \leq M$, each assignment coefficient $c(i, j)$ in the assignment matrix, should be optimally calculated according to the information exchanged between all components of the system. Considering the dynamic behavior of the studied system, each coefficient $c(i, j)$ depends on time. We consider then in the rest of the chapter $c(i, j, t)$ as the assignment coefficient at the time t .

An electric vehicle EV_i ($1 \leq i \leq N$) is assigned to a charging station S_{j_0} with ($1 \leq j_0 \leq M$) when the associated coefficient $c(i, j, t)$ takes its minimum value $c^*(i, j_0, t)$. The numerical value of the coefficient $c(i, j, t)$ is proportional mainly to the distance separating the EV_i location and the location of the charging station S_j at time t (this distance

varies over the time and according EV displacement). It depends also on other system parameters such as expressed in the equation (2.6). For this reason we assume that the adequate assignment of EV_i to a charging station corresponds to the assignment coefficient $c^*(i, j_0, t)$ as expressed in the equation (2.1).

For $i = 1 \dots N$, there exists j_0 such that:

$$c^*(i, j_0, t) = \min_{1 \leq j \leq M} \{ c(i, j, t) \} \quad (2.1)$$

More details about these coefficients are given hereafter.

In the following, we define all parameters of the system that are required for the problem formulation. For i ($1 \leq i \leq N$), j ($1 \leq j \leq M$) and $t \in IN$ (set of non-negative integers),

- N Set of EVs ($EV_1, EV_2 \dots EV_N$),
- M Set of charging stations ($S_1, S_2 \dots S_M$),
- $c(i, j, t)$ Assignment coefficient of EV_i to a station S_j ,
- $d(i, j, t)$ Distance separating EV_i and S_j at time t ,
- $B_i(t)$ Power level of the battery,
- $dis_i(t)$ Distance to be carried out with the remaining power $B_i(t)$,
- $Sta_j(t)$ State of the charging station S_j at the time t ,
- $Tr(i, j, t)$ Status of road traffic along the shortest path between EV_i and S_j at time t ,
- $x(i, j, t)$ Binary variables where:

$$x(i, j, t) = \begin{cases} 1, & \text{if } EV_i \text{ is assigned to } S_j \text{ at } t \\ 0, & \text{otherwise} \end{cases} \quad (2.2)$$

Mathematically, the assignment optimization problem can be formulated as follows:

$$\text{Minimize } Z(t) = \sum_{i=1}^N \sum_{j=1}^M c(i, j, t)x(i, j, t) \quad (2.3)$$

Subject to:

For $i = 1 \dots N$, and a given time t ,

$$\sum_{j=1}^M x(i, j, t) = 1 \quad (2.4)$$

The constraint (2.4) means that a given EV_i should be assigned to only one charging station at time t .

For $j = 1 \dots M$, and a given time t ,

$$\sum_{i=1}^N x(i, j, t) \leq n_j \quad (2.5)$$

This means that a given charging station S_j may receive until n_j EVs at a given time t .

This constraint is flexible and the number of assigned EVs to a given charging station S_j may change according to its status.

For $i = 1 \dots N, j = 1 \dots M$ and a given time t ,

$$c(i, j, t) = f(d(i, j, t), B_i(t), dis_i(t), Sta_j(t), Tr(i, j, t)) \quad (2.6)$$

As mentioned previously, the coefficient $c(i, j, t)$ in the equation (2.1) depends on several parameters of the system. For example, distance between the EV and the chosen

charging station location, power level of the EV battery, travel time with remaining battery energy, status of the chosen charging station (number of EVs within the queue into the charging station, waiting time, etc.), status of road traffic between EV location and chosen charging station location.

Assuming that the coefficient $c(i, j, t)$ is expressed according to the system parameters, we should verify the feasibility of all system constraints and all received information based on the process architecture of the Figure 1. A coefficient $c(i, j, t)$ can be considered as an assignment score of the EV_i to the station S_j at time t . This score is calculated according to the equation (2.6). In this equation, the high weight is associated to the distance to travel in order to reach the suggested charging station compared with other system parameters. Another strong constraint of the system is given by the equation (2.7) meaning the distance to carry with remaining energy B_i in the EV battery should be bigger the distance separating the EV_i location and the location of charging station S_j candidate for receiving EV_i . This constraint is expressed by:

For $i = 1 \dots N, j \in \{1 \dots M\}$, and at a given time t ,

$$d(i, j, t) \leq dis_i(t) \quad (2.7)$$

Considering all the constraints and the objective function of the system, the linear program (LP) representing the assignment problem is expressed by the system (2.8).

$$\begin{aligned} \text{Minimize } Z(t) &= \sum_{i=1}^N \sum_{j=1}^M c(i, j, t) x(i, j, t) \\ \sum_{j=1}^M x(i, j, t) &= 1, \text{ for } i = 1 \text{ to } N \text{ and any } t \\ \sum_{i=1}^N x(i, j, t) &\leq n_j, \text{ for } j = 1 \text{ to } M \text{ and any } t \\ d(i, j, t) &\leq dis_i(t), \text{ for } i = 1 \text{ to } N \text{ and } j = 1 \text{ to } M \text{ and any } t \\ x(i, j, t) &\in \{0, 1\}, \text{ for } i = 1 \text{ to } N \text{ and } j = 1 \text{ to } M \text{ and any } t \end{aligned} \quad (2.8)$$

IV. Resolution and discussion

The Microsoft Excel solver was used for solving the linear program (2.8). It is more useful and can be handled without having strong mathematics background.

To illustrate the proposed optimization approach, we consider a numerical example. At this stage of our research work, we allocate randomly a numerical value to each assignment coefficient $c(i, j, t)$ representing the assignment value of the EV_i to the station S_j at a given time t . The values expressed by the equation (2.6) are supposed to be chosen according to the system status and the collected information from both EVs and charging stations. In addition the following numerical values were used:

$N = 12$ Electric Vehicles: $EV_1 \dots EV_{12}$,

$M = 5$ Charging Stations: $S_1 \dots S_5$,

$n_1 = 3, n_2 = 2, n_3 = 5, n_4 = 1, n_5 = 2$: number of charging points within each charging station.

The optimal assignment is calculated for $t = t_0$ (t_0 corresponds to a fixed time). For $t \neq t_0$, the system status may be changed, and then the values of the assignment coefficient $c(i, j, t)$ change too. This will affect the assignment of EVs to charging stations.

The obtained optimal solutions corresponding to the optimal values of assignment coefficients $c(i, j, t_0)$ are given by the grey part of the Table 3.

At $t = t_0$	S_1	S_2	S_3	S_4	S_5
EV_1	29	10	29	33	41
EV_2	38	24	30	16	25
EV_3	11	40	33	24	19
EV_4	12	16	19	14	38
EV_5	41	23	37	12	27
EV_6	28	47	13	28	37
EV_7	35	26	10	40	21
EV_8	22	10	28	17	31
EV_9	32	15	39	19	26
EV_{10}	16	33	29	35	44
EV_{11}	19	44	35	14	24
EV_{12}	40	39	18	10	45
# EVs	≤ 3	≤ 2	≤ 5	≤ 1	≤ 2

Table 3. Values of assignment coefficients for time $t = t_0$.

The following table (Table 4) summarizes the obtained results.

Charging station	S_1	S_2	S_3	S_4	S_5
# of authorized EVs	3	2	5	1	2
# of assigned EVs	3	2	4	1	2
Assigned EVs & Optimal value of $c(i,j,t_0)$	EV_3 11 EV_{10} 36 EV_{11} 19	EV_1 10 EV_8 10	EV_4 19 EV_6 13 EV_7 10 EV_{12} 18	EV_5 12	EV_2 25 EV_9 26

Table 4. Optimal assignment of EVs to charging stations.

Based on these results, we remark that all problem constraints are satisfied:

- All EVs are assigned and each one is assigned to exactly one charging station.
- The number of authorized EVs at each charging station is not exceeded.

- Each assignment is carried out with the minimum value of $c(i, j, t)$. The minimum value cannot be chosen when a constraint may not be met. In this case another value of $c(i, j, t)$ close to the minimum value will be considered.
- The global assignment score of all EVs is optimized.

V. Conclusion

This chapter proposes an integrated platform for increasing the synergy between electric vehicles and charging stations. The interaction and communication between the EVs and the platform is ensured by the use of strengths of information and communication technologies, Web services and geo-positioning techniques. Based on information provided by the platform mainly, the status of charging stations and the status of the EVs as well as their locations and the remaining power in their batteries, we study the scheduling and assignment of EVs to charging stations as an optimization problem. We first formulate the problem by a linear program, in which the assignment of all EVs should verify certain constraints such as the status of charging stations and the characteristics of EVs with additional information regarding drivers such as making some shopping or go to restaurant while charging their EVs. The obtained results showed that the proposed assignment algorithm provides the optimal solution.

After proving the feasibility of the assignment problem under certain functioning constraints and in order to study the behavior of the considered charging system, we propose in the following chapter a modelling approach based on two formalisms of dynamic discrete event systems (DDES). The objective is to study the analytical and graphical behavior of the charging system in DDES point of view.

CHAPTER 3

MODELLING APPROACH USING (MAX, +) ALGEBRA

This chapter is composed of two main sections: graphical modelling and the mathematical modelling. In the graphical modelling section, the studied system is represented by Petri nets models in order to study its behavior and then verify and validate some of its qualitative properties. Thereafter, the system behavior will be represented by linear equation in (max, +) algebra. The objective of this analytical study is to analyze and evaluate some quantitative properties of the system using (max, +) assets. These two formalisms will be used to predict the behavior of the system.

I.	INTRODUCTION	50
II.	GRAPHICAL MODELLING	51
	<i>II.1. Introduction to TEG</i>	<i>51</i>
	<i>II.2. TEG models</i>	<i>52</i>
	<i>II.3. Global TEG model.....</i>	<i>56</i>
III.	MATHEMATICAL MODELLING	58
	<i>III.1. Basics of (max, +) algebra</i>	<i>58</i>
	<i>III.2. (Max, +) linear model</i>	<i>61</i>
	<i>III.3. Evaluation and analysis</i>	<i>62</i>
IV.	CONCLUSION	64

I. Introduction

In the literature, many research efforts have been made to further develop and promote electric vehicles. However, little attention has been paid so far to the fact that charging process for electric vehicles is completely different from refueling process of vehicles that are powered by conventional power. Indeed, for charging management of EVs many parameters should be taken into account in order to adequately satisfy users and optimize the quality of provided services. To do so, novel predictive methods are required, since the task is to suggest the adequate charging station rather than just the nearest one.

In Chapter 2 subject to the management of electric vehicles charging [36], we have addressed one of the major issues related to the wish of drivers to get suitable and vacant places at charging stations. In this chapter, we continue these efforts and try to propose a formal approach aiming to anticipate, plan and propose adequate charging solutions for EVs. These solutions should take into account several parameters such as the location of the EV, the remaining energy in the battery, traffic condition, the length of queuing in each charging station, etc.

In this chapter, the system is considered as a dynamic discrete event system in which each event evolves in a discrete space. Indeed, the charging management of EVs within a charging station with performance metrics such as arriving of vehicles to a charging point, number of vehicles to serve, required charging time, etc. can be seen as discrete events. In this point of view, many appropriate tools have been developed in the literature to model and analyze such systems using dynamic discrete event systems theory. In this chapter, we are interested in the use of Timed Event Graphs which is a subclass of Petri nets, combined with $(\max, +)$ algebra for charging management of EVs. These tools have been proposed in the literature as powerful tools for modelling and performance analysis

issues ([9], [10], [11] and [61]). More precisely, the goal of the proposed models in this contribution is to act appropriately on the service time of each involved service in the process in order to serve a maximum of charging demands while satisfying all EV constraints. The proposed models allow defining a predictive functioning of the charging process by providing useful information and suggesting adequate charging station for each EV when it is necessary.

II. Graphical modelling

We introduce timed event graphs (TEG) as a high-level subclass of Petri Nets already used efficiently for modelling, evaluation and analysis of discrete event systems such as transportation, manufacturing and telecommunication systems [11], [37], [61]. Afterward, TEG models describing the graphical behavior of the system components are detailed.

II.1. Introduction to TEG

A Petri net is a graph with two kinds of nodes: places and transitions. Oriented arcs connect some places to some transitions, or conversely. To each arc, we associate a weight (nonnegative integer). The dynamic of the graph is governed by a set of tokens that participate to the firing of transitions and change the system states. In a formal way, a PN is a 5 tuple $PN = (P, T, A, W, M_0)$ where:

$P = \{p_1, \dots, p_n\}$ is a finite set of places (represented by circles);

$T = \{T_1, \dots, T_n\}$ is a finite set of transitions (line segments);

$A \subseteq (P \times T) \cup (T \times P)$ is a finite set of oriented arcs;

$W = A \rightarrow \{1, 2, \dots\}$ is the weight function associated with arcs;

$M_0 = P \rightarrow \{0, 1, 2, \dots\}$ is the initial marking of the graph.

A Timed Event Graph is a subclass of Petri Nets for which each place has exactly one upstream transition and one downstream transition. TEG is well known to be rather adapted to problems with synchronization and parallelism phenomena, and then which suppose the absence of conflicts and resources sharing. More details about this formalism and its properties can be found in [37] and [38].

We denote the place P_{ij} , representing a system state or a task to accomplish, the output (resp. input) place of the transition x_i to x_j . These transitions represent respectively the beginning and the ending of an event (e.g. arrival of an EV to a charging station and departure from the charging station). The required time to accomplish the task that related to the state P_{ij} is denoted τ_{ij} and associated with the place P_{ij} . The temporization τ_{ij} corresponds to the minimal sojourn time of tokens in the place P_{ij} . In the context of charging process of EVs, these temporizations correspond to the required times to accomplish assigned tasks to each involved service in charging process. It is worth noting that the main objective of these temporizations is to act appropriately on the service time (temporizations of the TEG model) of each involved service in the process in order to serve a great number of requests in the case of several instant demands.

II.2. TEG models

In order to represent and visualize graphically the concrete working of the charging process, the three components of the process are modelled separately. The obtained models will be then grouped into only one TEG model describing the whole process as well as different interactions between its components.

The Figure 4 represents the TEG model of the EV component. As illustrated in this figure part (a), this component can be seen as a loop. When the battery level reaches a fixed threshold (an energy level from which the driver is alerted), a warning message "Charging Alarm" appears on the scoreboard for the driver. Thereafter, a "Request" is sent to the collaborative Platform (CPL) using General Packet Radio Service (GPRS) communication (as illustrated in the Figure 4 (a)). After getting a "Response" from the platform, the "Charging" operation can be start after reaching the notified station. At the end of charging operation, driver can continue its travel while releasing the occupied charging point. When the battery level decreases and reach the fixed threshold, the process will start again in the same way. The proposed TEG of this part is illustrated by Figure 4(b) where the significance of transitions and places of the model are given in the Table 5.

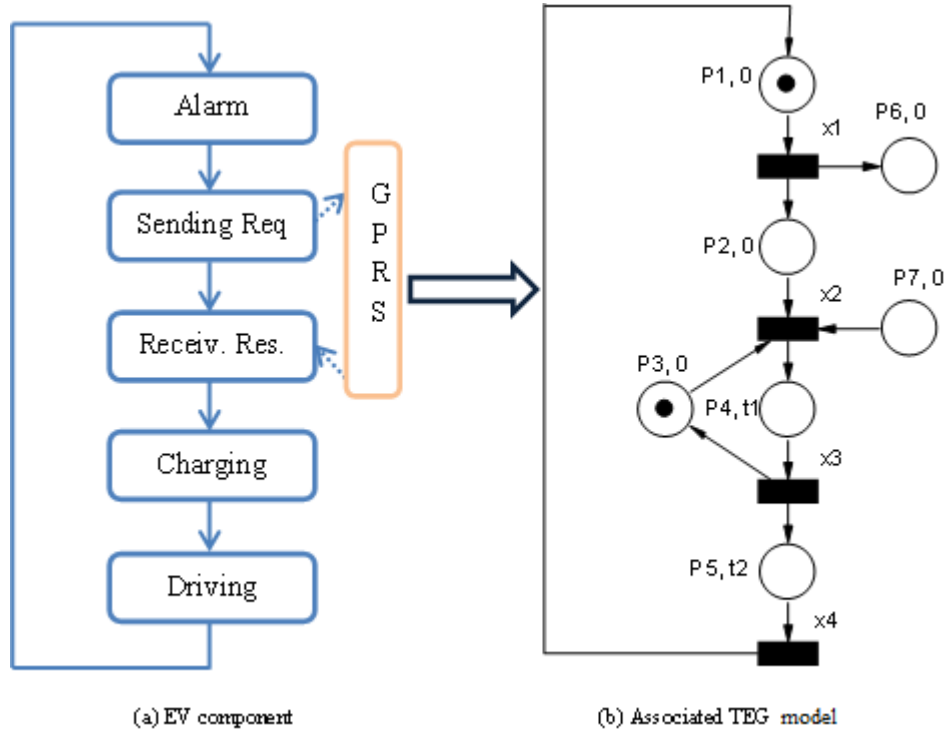


Figure 4. TEG model of EV component

Places	Transitions/Temporizations
P1: Warning for charging	x1: Sending a request to the CPL
P2: Waiting for a response from CPL	x2: Receiving a response from CPL
P3: Number of EV to support a the same time	x3: End of charging
P4: Charging operation	x4: Sending warning to driver
P5: Driving after charging operation	t1: Required time for EV charging
P6: Sending request from EV to CPL	t2: Driving time after charging (or battery autonomy)
P7: Sending response from CPL to EV	

Table 5. Significance of TEG elements of the EV component

The second component of the process is the collaborative Platform. As depicted in Figure 5(a), after getting a charging request from an EV, the main task of the CPL component is "*Finding FrCS*" which allows finding an adequate charging station (CS) while satisfying all driver points of interest (PoI). This hard task, surrounded on the figure by dotted lines, may take a variable time depending on the status of stations and availability of all involved Web services. When a free CS is found, a reservation request is sent to the concerned CS via the Web is illustrated in the Figure 5(a). After updating the CPL database, a response is sent to the EV while suggesting the name and location of adequate CS. The TEG representing the CPL component is given in Figure 5(b). All elements of this model are explained in Table 6.

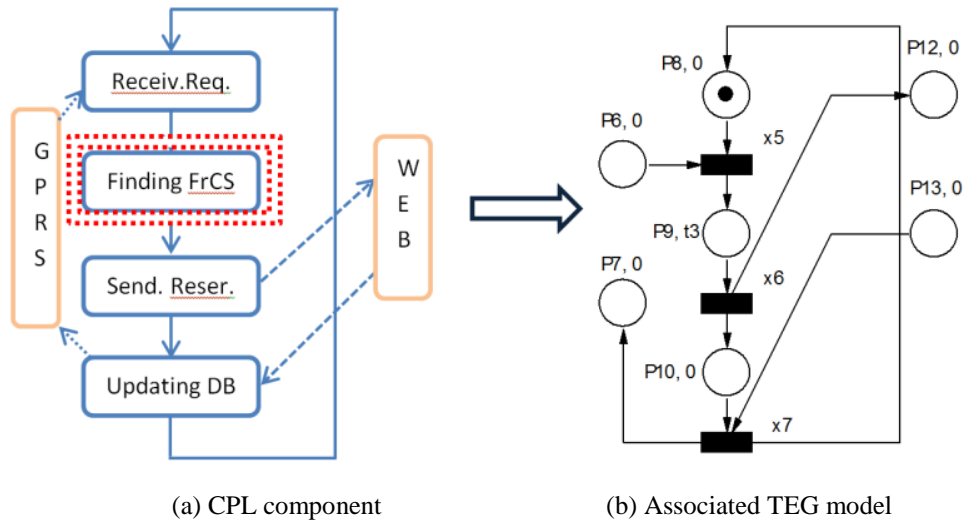


Figure 5. Collaborative Platform TEG model

Places	Transitions/temporizations
P8: CPL availability to handle a request	x5: Receiving request from an EV
P9: Searching free/adequate CS	x6: Asking for booking a charging point
P10: Updating CPL data base (DB)	x7: Sending response to EV
P12: Sending request from CPL to CS for reserving a free charging point	t3: Spent time for searching free/adequate CS
P13: Confirmation from CS.	

Table 6. Significance of TEG elements of the CPL

The third component of the process is charging station, which is represented by the TEG model of Figure 6 (a). After searching and finding free and adequate CS, the CPL sends a booking request to the CS for a given time. When getting this request from the CPL, the CS responds by a confirmation and then the charging operation can be start when the EV arrives at the CS. At the end of this task, the charging point will be available and can be used once again for another charging task. The associated TEG is illustrated in Figure 6(b) and the legend is given in Table 7.

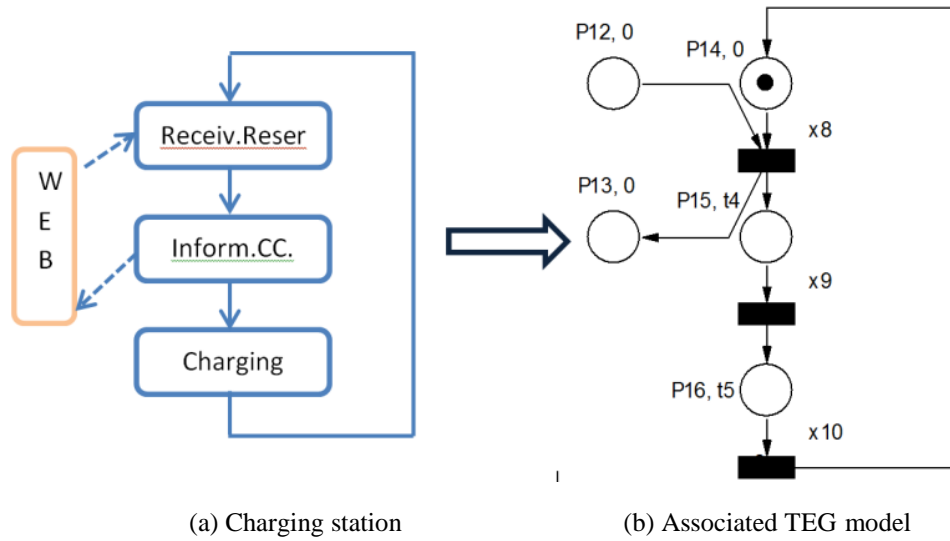


Figure 6. TEG of CS component

Places	Transitions/temporizations
P14: Availability of a free CS	x8: Confirmation of booking
P11: Waiting for an EV	x9: Start of charging operation
P15: Waiting for charging operation	t4: Time from sending response till starting charging operation
P16: Charging operation	x10: End of charging and releasing of charging point for next use
	t5 (t1): Charging time

Table 7. Significance of TEG elements of the CS

II.3. Global TEG model

For creating the global TEG model describing the system behavior, we merge the TEG models describing the three components of the system. The whole process and resultant TEG model are given in Figure 7. The place P11 linking the two components EV and CS represents a sent signal from EV to CS for starting the charging operation. Based on this TEG model, certain properties of the studied system are verified and validated. By observing the evolution of the model and the firing of its transitions we remark a perfect synchronization between all system components. Also, the proposed model is deadlock-

free. In addition the proposed model will serve as a support to translate the system behavior into (Max, +) linear equations. To do so, we associate to each transition a variable that will be used later as a key element for determining the date of each firing of the transition.

In the next section, we expose some needed basic elements of (max, +) algebra. Then we give the (max, +) linear model describing the charging process. This last will be than analyzed, evaluated using the (max, +) equations.

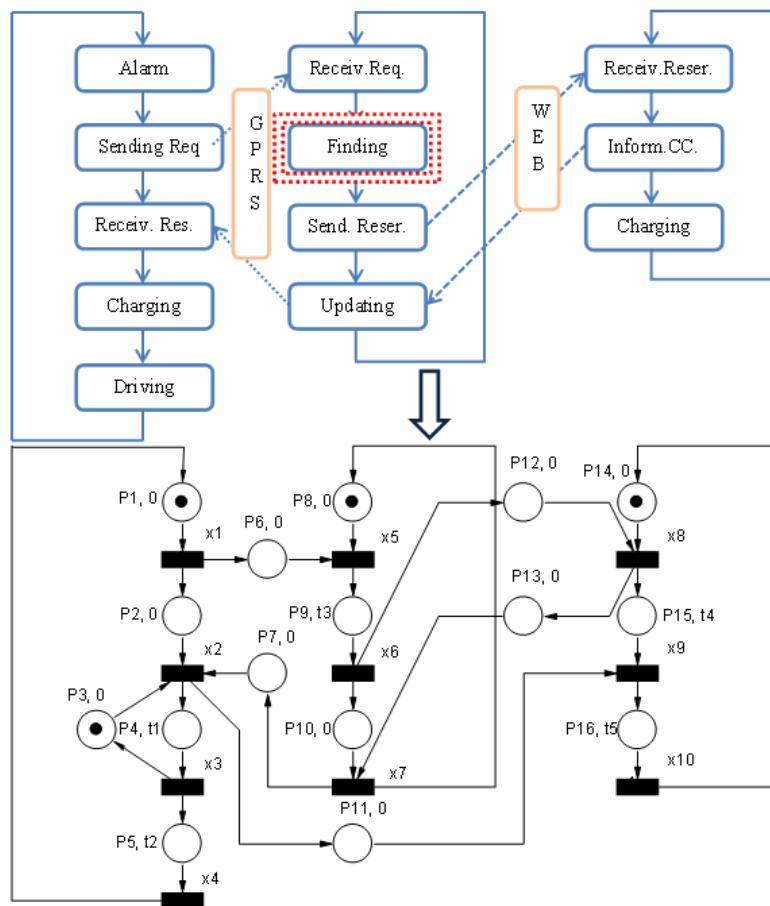


Figure 7. Charging process TEG model

III. Mathematical modelling

III.1. Basics of (max, +) algebra

To complete the modelling approach proposed in this chapter we combine TEG modelling with (max, +) algebra modelling. Indeed, as said previously, TEG modelling enables to model and visualize the evolution of the process, it allows also to study and evaluate some qualitative properties of the process. Nevertheless, it is limited for studying the quantitative aspect of the process. For example, it should be completed with a complimentary formal tool in order to ensure a complete and efficiency study of the system. (Max, +) algebra will be then used to describe the analytical behavior of the process by translating the TEG model into linear equations. These lasts will be used to evaluate the process by determining the required time to accomplish each task of the process. In addition, it is possible to propose a predictive charging for EVs under critical cases such as when the CPL receives many charging requests with only one available CS. The main objective is to control the charging operation while satisfying a maximum number of requests.

Firstly, let us introduce some basic elements of (max, +) algebra we will use in this study. The (max, +) algebra is defined with two main operators. Maximization and addition, which are denoted respectively by \oplus and \otimes . The set $\mathbb{R}_\varepsilon \stackrel{\text{def}}{=} \mathbb{R} \cup \{-\infty\}$ endowed these two operators is called a dioid (i.e. $(\mathbb{R}_\varepsilon, \oplus, \otimes)$), \mathbb{R} is the set of real numbers [9]. These operators are defined as follows. For all $x, y \in \mathbb{R}_\varepsilon$.

$$x \oplus y = \max(x, y)$$

$$x \otimes y = x + y$$

Usually we call \oplus the (max, +) addition, and \otimes the (max, +) multiplication. We specify the following elements in (max, +) algebra:

- The zero element for \oplus is $\varepsilon \stackrel{\text{def}}{=} -\infty$. We have $\forall a \in \mathbb{R}_\varepsilon, a \oplus \varepsilon = a = \varepsilon \oplus a$.
- The neutral element of \otimes is $e \stackrel{\text{def}}{=} 0$. We have $\forall a \in \mathbb{R}_\varepsilon, a \otimes e = a = e \otimes a$.
- The element ε is called absorbing element for $\otimes, \forall a \in \mathbb{R}_\varepsilon, a \otimes \varepsilon = \varepsilon = \varepsilon \otimes a$.
- Let $r \in \mathbb{R}$ the r^{th} (max, +) algebraic power of $x \in \mathbb{R}_\varepsilon$ is denoted by $x^{\otimes r}$ and corresponds to $r \cdot x$ (with “ \cdot ” is the multiplication in conventional algebra). For $x \in \mathbb{R}_\varepsilon$ then $x^{\otimes 0} = e$ and the opposite element of x for \otimes is $x^{\otimes -1} = -x$. There is no inverse element for ε since ε is absorbing for \otimes . If $r > 0$ then $\varepsilon^{\otimes r} = \varepsilon$. If $r < 0$ then $\varepsilon^{\otimes r}$ is not defined.

Like for the conventional algebra, matrix calculation in the (max, +) algebra is also possible and enables to solve infinity of problems. The basic (max, +) algebraic operations are extended to matrices as follows:

- $\forall A, B \in \mathbb{R}_\varepsilon^{m \times n}$ and $C \in \mathbb{R}_\varepsilon^{n \times p}$ (where $\mathbb{R}_\varepsilon^{m \times n}$ is the dioid of matrices with m lines and n columns. The elements of these matrices are scalars in \mathbb{R}_ε , then for all i, j :

$$(A \oplus B)_{ij} = a_{ij} \oplus b_{ij} = \max(a_{ij}, b_{ij})$$

$$(A \otimes C)_{ij} = \bigoplus_{k=1}^n a_{ik} \otimes c_{kj} = \max_k(a_{ik} + c_{kj})$$

- The matrix $\varepsilon_{m \times n}$ is the $m \times n$ (max, +) algebraic zero matrix: $(\varepsilon_{m \times n})_{ij} = \varepsilon$ for all i, j .
- The matrix E_n is the $n \times n$ (max, +) algebraic identity matrix: $(E_n)_{ii} = e$ for all i and $(E_n)_{i,j} = \varepsilon$ for all i, j with $i \neq j$.

- The (max, +) algebraic matrix power of $A \in \mathbb{R}_\varepsilon^{n \times n}$ is defined as follows: $A^{\otimes 0} = E_n$ and $A^{\otimes k} = A \otimes A^{\otimes k-1}$ for $k = 1, 2, \dots$
- The Kleene star of a matrix A is given by $A^* = E_n \oplus A \oplus A^{\otimes 2} \oplus \dots$. We show later, how this matrix will be used to evaluate different states of the process whose behavior is expressed with a (max, +) implicit equation (3.4).

According to these (max, +) elements, we show hereafter how to translate an algebraic system of equations from conventional algebra into (max, +) linear equations.

$\forall k > 1,$

$$\begin{cases} x_1(k) = \max[t_2 + x_2(k-1), u_1(k)] \\ x_2(k) = t_1 + x_1(k) \\ x_3(k) = \max[t_4 + x_4(k-1), u_2(k)] \\ x_4(k) = \max[t_3 + x_3(k), u_2(k)] \end{cases} \quad (3.1)$$

Using the two operators of (max, +) algebra, addition and multiplication or also \oplus and

\otimes the system (3.1) can be written as follows:

$\forall k > 1,$

$$\begin{cases} x_1(k) = t_2 \otimes x_2(k-1) \oplus u_1(k) \\ x_2(k) = t_1 \otimes x_1(k) \\ x_3(k) = t_4 \otimes x_4(k-1) \oplus u_2(k) \\ x_4(k) = t_3 \otimes x_3(k) \oplus u_2(k) \end{cases} \quad (3.2)$$

It is well known that the dynamical behavior of a TEG can be expressed by a system of linear inequalities in the (max, +) algebra as detailed in [10]. To do so, we associate to each transition x_i of the TEG a *dater* $x_i(k)$, which corresponds to the date of the k^{th} firing of the transition x_i . This parameter will play a major role in the evaluation of the

accomplishment time of each task of the charging process. A complete definition and all properties of these operators are detailed in [9], [10].

III.2. (Max, +) linear model

The behavior of the TEG model of Figure 7 is translated into the (max, +) linear equation as follows. For all $k > 1$,

$$\begin{cases} x_1(k) = x_4(k-1) \\ x_2(k) = x_1(k) \oplus x_3(k-1) \oplus x_7(k) \\ x_3(k) = t_1 \otimes x_2(k) \\ x_4(k) = t_2 \otimes x_3(k) \\ x_5(k) = x_1(k) \oplus x_7(k-1) \\ x_6(k) = t_3 \otimes x_5(k) \\ x_7(k) = x_6(k) \oplus x_8(k) \\ x_8(k) = x_6(k) \oplus x_{10}(k-1) \\ x_9(k) = x_2(k) \oplus t_4 \otimes x_8(k) \\ x_{10}(k) = t_5 \otimes x_9(k) \end{cases} \quad (3.3)$$

This system can be written in a matrix form as follows: for all $k > 1$,

$$X(k) = A_0 X(k) \oplus A_1 X(k-1) \quad (3.4)$$

Where:

- $X(k) = [x_1(k), x_2(k), \dots, x_{10}(k)]^t$ - regroups all daters of the model. It called also the state vector.
- A_0 and A_1 are the characteristic matrices of the system whose components represent needed times to accomplish various tasks of the process.

$$A_0 = \begin{bmatrix} \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ e & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & e & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & t_1 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & t_2 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ e & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_3 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & e & \varepsilon & e & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & e & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & e & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_4 & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_5 & \varepsilon \end{bmatrix}; A_1 = \begin{bmatrix} \varepsilon & \varepsilon & \varepsilon & e & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & e & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & e & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & e \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \end{bmatrix}.$$

When we consider the system input, a third member may be added to the equation (3.8) expressing the impact of this input on the system evolution. As we will see in the next chapter, the new expression of the equation (3.8) with the system input becomes:

For all $k > 1$,

$$X(k) = A_0X(k) \oplus A_1X(k - 1) \oplus BU(k) \tag{3.5}$$

Where:

- $U(k) = [u_1(k), u_2(k), \dots]^t$ regroups all inputs of the system. These inputs are known, a priori, for each $k \geq 1$.
- B is the characteristic matrix of the system representing the impact of the input system on its evolution.

III.3. Evaluation and analysis

In order to calculate the starting and ending times of each process task for each k^{th} charging request, we determine the values of the state vector $X(k)$, for $k = 1, 2, \dots$ by solving the equation (3.4). The solution of (3.4) is given by replacing $X(k)$, iteratively, by its expression as follows. As we will show, this calculus uses the Kleene star A_0^* .

$\forall k > 1$,

$$\begin{aligned}
 X(k) &= A_0 X(k) \oplus A_1 X(k-1) \\
 &= A_0 [A_0 X(k) \oplus A_1 X(k-1)] \oplus A_1 X(k-1) \\
 &= A_0^2 X(k) \oplus A_0 A_1 X(k-1) \oplus A_1 X(k-1) \\
 &= A_0^2 X(k) \oplus [A_0 \oplus E_{10}] A_1 X(k-1) \\
 &= A_0^3 X(k) \oplus [A_0^2 \oplus A_0 \oplus E_{10}] A_1 X(k-1) \\
 &= \dots \\
 &= \underbrace{A_0^{10} X(k)}_{=\varepsilon} \oplus \left[\bigoplus_{i=0}^{i=9} A_0^i \right] A_1 X(k-1) \\
 &= A_0^* A_1 X(k-1)
 \end{aligned} \tag{3.6}$$

Where $\forall k > 1$, $A_0^{10} X(k) = \varepsilon$, since $A_0^{\otimes k} = \varepsilon$ for $\forall k \geq 10$,

$$A_0^* = E_{10} \oplus A_0 \oplus A_0^{\otimes 2} \dots \oplus A_0^{\otimes 9} \text{ and } E_{10} \in \mathbb{R}_{\varepsilon}^{10 \times 10}. \text{ With } E_{10} = \begin{bmatrix} e & \dots & \varepsilon \\ \vdots & \ddots & \vdots \\ \varepsilon & \dots & e \end{bmatrix}$$

The state vector $X(k)$ will be then calculated as follows: $\forall k > 1$,

$$\begin{aligned}
 X(2) &= A_0^* A_1 X(1); \\
 X(3) &= A_0^* A_1 X(2) = (A_0^* A_1)^{\otimes 2} X(1); \\
 &\dots \\
 X(k) &= (A_0^* A_1)^{\otimes k-1} X(1)
 \end{aligned} \tag{3.7}$$

Where $X(1)$ represents the initial condition of the system corresponding to the first firing of the model transitions. In other words, the components of this initial vector correspond to the starting and ending times of each process task for the first charging request, which are always known. Formally, and while considering the immediate response of each system component and the behavior of the associated TEG, the initial vector is given by

$$X(1) = [0, 0, t_1, t_1 + t_2, 0, t_3, t_3, t_3, t_3 + t_4, t_3 + t_4 + t_5]^t \tag{3.8}$$

Considering this vector, and the characteristic matrices of the model, response times of all received charging requests can be calculated iteratively as given by (3.7).

IV. Conclusion

In this chapter, we propose a based modelling approach for charging system. The process is studied in the point of view of discrete event systems using $(\max, +)$ algebra combined with timed event graphs. First, the system behavior is represented by a TEG model and some of its qualitative properties are verified and validated. Thereafter, the analytical behavior of the charging system is presented by $(\max, +)$ linear equations. The obtained $(\max, +)$ model allows to evaluate the starting time and ending time of each charging operation based on the exchanged information between all system components. In the next chapter we will extended the studied system by considering charging stations with more than one charging points. We show the impact of this system evolution on the associated graphical and analytical models.

CHAPTER 4

ADAPTIVE BASED APPROACH

The studied system in chapter 3 will be extended in the current chapter by proposing an adaptive based approach for EVs charging. Based on a Petri net model and associated (max, +) equations, an algorithm is proposed to predict charging times and charging rates for the EV demands.

I.	INTRODUCTION	66
II.	MODELLING WITH TEG	66
III.	(MAX, +) STATE REPRESENTATION	71
IV.	RESOLUTION OF (MAX, +) STATE MODEL	75
V.	PREDICTIVE CHARGING APPROACH	76
	<i>V.1. Numerical and evaluation study</i>	76
	<i>V.2. Improvements: sizing results</i>	82
VI.	CONCLUSION	83

I. Introduction

Nowadays, one of the most major challenges of EVs is their charging with a minimum amount of time while conserving maximum performances they provide. Among these performances: have a good autonomy (travel a long distance), use of the on board services (air conditioning, radio, lighting, etc.). In order to conserve these performances we propose in this chapter adaptive based approach to predict and anticipate the charging of EVs. In fact, we further develop the proposed modelling approach in the previous chapter by showing through a case study that allying timed event graphs with $(\max,+)$ -algebra is not only a powerful methodology for specification and modelling, but also an adequate tool for behavior prediction and decision-making. In order to improve the provided charging service to each EV in terms of charging rate a dimensioning study is proposed with the aim to find a minimum charging stations (or charging points) to use for satisfy à maximum charging demands. This case may be met when the platform must treat a great number of charging demands and a great number of charging stations are occupied or out of order.

II. Modelling with TEG

In this section we consider a new configuration of the charging system. Indeed, to make a connection with the platform, each EV should subscribe to access to all provided services such as searching a charging point, reserving a charging point, asking for additional PoI while charging the EV, etc. The access control to provided services for EVs by the charging system will be represented as a synchronization phenomenon. Furthermore, in this new configuration we will take into account the fact that the service time for certain tasks are unknown a priori such as searching an adequate charging station, or waiting a notification. In order to satisfy all received charging demands and accomplish

the charging process successfully subject to these new constraints, we represent the behavior of the new system by a graphic-based model using another subclass of Petri nets. We will use P-Timed Event Graph (PTEG) [38], for which time intervals are associated with certain places. The sojourn time of a token in such places varies between the lower bound and upper bound of the interval. It is worth noting that in this work, we do not consider timed transitions, which are associated with firing delays. All transitions are immediate transitions, which fire in zero time. The Petri net model describing the new configuration of the charging system is represented in the Figure 8. For further visibility and understanding of the model, we assign a significant name with each model component (places and transitions).

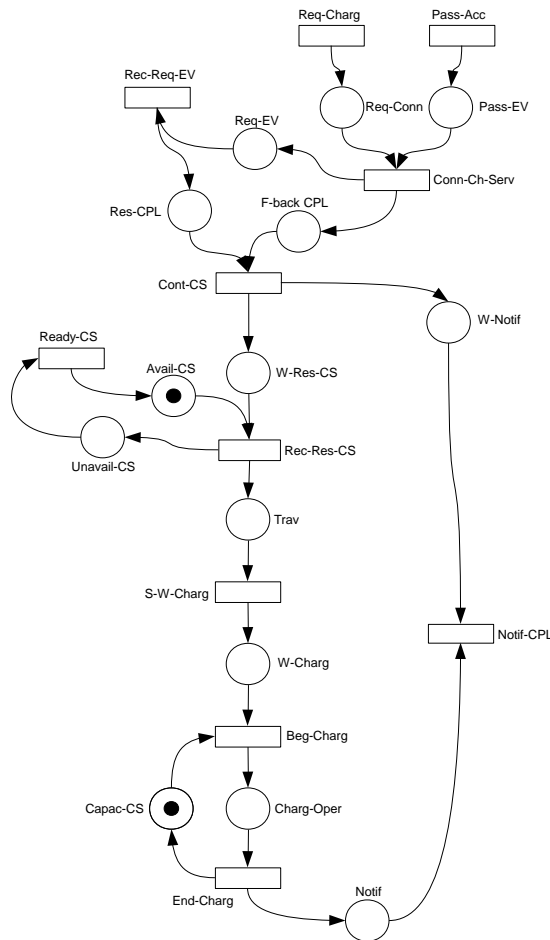


Figure 8. Event Graph model of the charging process

The complete names of these elements are given in Table 8. The Petri net of the Figure 8 consists of three major parts:

- EV part with its access rights.
- Platform side or CPL.
- Charging station with available points.

System component	TEG node	Designation	Significance
EV	Places	- Req-Conn - Pass-EV - Req-EV - F-back CPL - W-Notif - Trav - W-Charg	- Charging request and connection to the CPL - Driver password - EV request sent to the CPL - Waiting the CPL feedback - Waiting for notification to update the CPL DB - Traveling to the charging station - Waiting for charging
	Transitions	- Req-Charg - Pass-Acc - Conn-Ch-Serv - Cont-CS - S-W-Charg	- Request for charging - Password to access to the CPL - Connecting and sending a request to the CPL - Sending EV request to a charging station - Beginning of the wait for the availability of a charging point
CPL	Places	- Res-CPL - W-Res-CS	- Response from the CPL - Waiting response from CS
	Transitions	- Rec-Req-EV - Rec-Res-CS	- Receiving request from EV - Receiving response from a charging station
CS	Places	- Unavail-CS - Avail-CS - Capac-CS - Charg-Oper - Notif	- Unavailability of charging station - Availability of a CS - Capacity of the CS - Charging operation - Notification of the charging operation end
	Transitions	- Ready-CS - Beg-Charg - End-Charg - Notif-CPL	- A charging station is ready to charge an EV - Beginning of charging operation - Ending of charging operation - Notifying CPL (update the CPL DB)

Table 8. Legend of Figure 8

In Table 8 indicated these system components, the associated nodes (places and transitions) and their significances. Each place or transition has own short name (designation) and its meaning (significance).

The Petri net model of charging process works systematically. Just before sending a charging request which represented by the firing of the transition *Req-Charg* and adding of a token in the place *Rep-Conn*, the EV driver connects to the CPL with his own login and password in order to access to all offered charging services. This is represented by the firing of the transition *Pass-Acc* and adding of a token in the place *Pass-EV*. The firing of the transition *Conn-Ch-Serv* means that the EV is authorized to access to the CPL services, and then the charging request is sent (presence of a token in the place *Req-EV* that participates to the firing of *Rec-Rep-EV*). The CPL receives the request and connects to the database of charging stations (presence of a token in *Res-CPL* and firing of *Cont-CS*). In the same time a token is waiting in the place F-back CPL meaning the waiting of the CPL feedback (suggestion of a charging station). After the firing of *Cont-CS*, a token is added to the place *W-Res-CS* representing the waiting for a feedback from the database (or form a charging station). When a charging point is available (firing of *Ready-CS* and presence of a token in *Avail-CS*), the transition *Rec-Res-CS* is fired. This means that a positive response is received from a charging station and a charging point is reserved for the current charging demand. A token is put in the place *Trav* meaning that the EV is travelling to the suggested charging station and then the transition *S-W-Charg* can be fired when the EV reach the charging station (the end of the sojourn time associated to the place *Trav* or also travelling time form EV location to the charging station location). The added token into the place *W-Charg* represents the waiting (if there is any till the availability of the token presented in the place *Capac-CS*) of EV within the charging

station and the firing of *Beg-Charg* represents the beginning of charging operation which takes the charging time associated to the place *Char-Oper*. In this study, we consider that charging time and then charging rate each EV is defined according to the arrival date of next EV for charging. This point will be further developed and discussed hereafter in to regulate the charging rate according to the number of charging demands to treat. Furthermore, the number of tokens presented in the place *Capac-CS* represents the number of charging points. In this model, the only token means that we consider only one charging point.

At the end of charging operation, the transition *End-Charg* is fired and one token is put in the place *Notif*. This token and the one already presented in the place *W-Notif* participate to the firing of the transition *Noti-CPL* and that represents a notification sent to the CPL about the release of a charging point. This will be used to update the CPL database. This charging process will be repeated for each incoming charging demand.

The standard qualitative analysis of the proposed charging process is done: in particular, all considered properties are analysed and verified on the Petri net model (Figure 8) using the Visual Object Net++ software [39]. The designed model is used for verifying the process working and obtained results such as sojourn times of tokens in each place, transition firings, reachable states, etc., show that the considered properties are verified.

After the validation of these properties and in order to evaluate and analyze other process performances such as evaluation of time occurrence of each event (e.g. waiting, charging, notifying), process improvement, etc., the process behavior is described, by translating the Petri net model, using a state representation in the $(\max, +)$ algebra.

III. (Max, +) State representation

In this section, we translate the Petri net model into (max, +) linear equations. To do so, we define the variables of the system by associating with each model transition a state variable (or input and output variables for respectively input and output transition). Thereby, we associate input variables (denoted by u_1 and u_2) with input transitions and state variables (x_1, x_2, \dots, x_8) with internal transitions, and finally we associate output variables (denoted by y) with the output transition. In addition, we assign time intervals to certain places. A time interval associated with a given place means that the sojourn time of a token in this place varies between a lower and an upper bound. All places with time intervals represent the process components, e.g. CPL, for which the responses are not often immediate and require a time for answering a query. Time intervals can also be assigned to places wherein the tokens wait for responses, e.g. an EV waiting to be charged. These time intervals will be the key elements in the performances improvement of the process. Fixed times, which represent the necessary time to accomplish a task of the process is assigned with other places of the model.

While taking into account these elements and introducing these new variables, the fixed times and the time intervals, we obtain the TEG model of Figure 9.

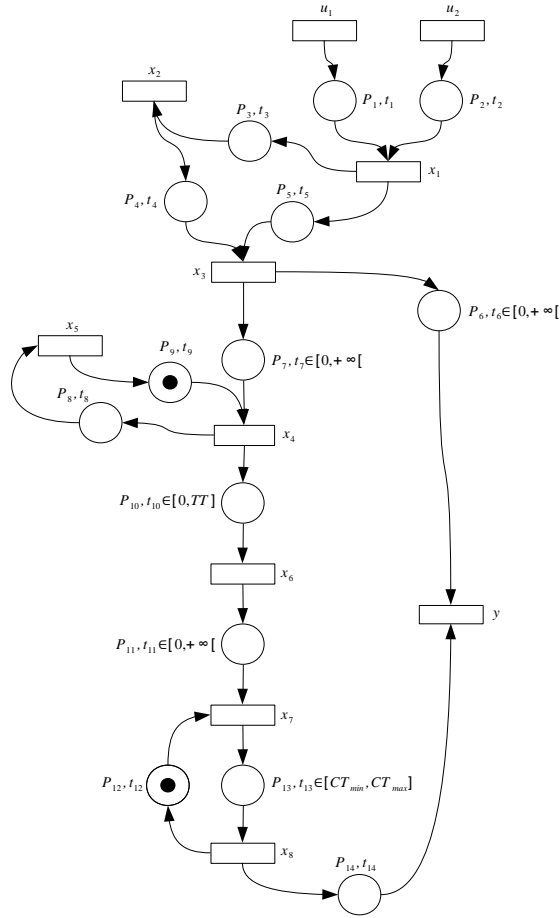


Figure 9. PTEG model of the charging process labelled with variables and times

In this new Petri net model (Called in the rest of this chapter P-Timed Event Graph model since certain places are endowed with time intervals), we define the following parameters

- CT_{max} : Required time for a full charging (100%) of the battery;
- CT_{min} : Required time for minimum acceptable charging rate (this parameter depends on the used battery technology);
- TT_i : Trip Time from the i^{th} EV location to the charging station.

By following the same demarche as that proposed in the chapter 2, the behavior of the system can be described by the following (max, +) – state model: $\forall k \geq 2$

$$\begin{cases} X(k) = A_0 \otimes X(k) \oplus A_1 \otimes X(k - 1) \oplus B \otimes U(k) \\ Y(k) = C \otimes X(k) \end{cases} \quad (4.1)$$

The first equation of the system (4.1) computes the system state, and the second one computes the system output. The three terms on the right of the first equation of (4.1) are given such that the two first terms $(A_0 \otimes X(k))$ and $(A_1 \otimes X(k - 1))$ represent the impact of the internal state of the process on its evolution, and the second one $(B \otimes U(k))$ models the influence of the process input on its evolution (the successive arrivals of charging requests). In the (max, +) system (4.1) we define the following elements:

- k is the k^{th} charging request corresponding to the k^{th} EV;
- $U(k)$ is the arrival time of the k^{th} request;
- $X(k)$ contains state variables of the system corresponding to the execution times of all process tasks (connection, waiting, charging, notifying, updating, etc.) for the k^{th} charging request;
- A_0, A_1, B and C are the characteristic matrices of the process. These matrices contain the required times to perform all tasks from connection until receiving notification and ending charging process;
- $Y(k)$ is the notification of ending charging process time of the k^{th} .

After defining all system key elements and variables, we label each model variable $x_i (1 \leq i \leq 8)$, by the dater $x_i(k)$, and $u_i (1 \leq i \leq 2)$ $u_i(k)$ and the output variable y by the dater $y(k)$. Using all daters and times (time intervals and fixed times), we obtain various equations that model the process behavior. For doing so, we distinguish two cases according to delays associated with the places. We recall the rules to translate a graphical

model with time intervals, into the mathematical equations. Then we express the whole (max, +)-linear system.

The all (max, +) equations representing the system behavior are given by the model (4.2).

$$\left\{ \begin{array}{l} \forall k \geq 2, \\ x_1(k) = t_1 \otimes u_1(k) \oplus t_2 \otimes u_2(k) \\ x_2(k) = t_3 \otimes x_1(k) \\ x_3(k) = t_4 \otimes x_1(k) \oplus t_5 \otimes x_2(k) \\ x_4(k) = t_7 \otimes x_3(k) \oplus t_9 \otimes x_5(k-1) \\ x_5(k) = t_8 \otimes x_4(k) \\ x_6(k) = t_{10} \otimes x_4(k) \\ x_7(k) = t_{11} \otimes x_6(k) \oplus t_{12} \otimes x_8(k-1) \\ x_8(k) = t_{13} \otimes x_7(k) \\ y(k) = t_6 \otimes x_3(k) \oplus t_{14} \otimes x_8(k) \end{array} \right. \quad (4.2)$$

Taking into account the fact that time intervals are associated with certain places of the PTEG model, the parameters $t_6, t_7, t_{10}, t_{11}, t_{12}$ are defined as follows: $t_6 \in [0, \infty[$, $t_7 \in [0, \infty[$, $t_{10} \in [0, TT]$, $t_{11} \in [0, \infty[$, $t_{12} \in [CT_{min}, CT_{max}]$.

The equations of the system (4.2) will be written as a first order recurrent matrix equation in order to facilitate its resolution. In doing so, we redefine the following vectors:

- Input vector $U = [u_1, u_2]^t$;
- State vector $X = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8]^t$;
- Output vector $Y = y$.

By using these vectors, the equations of the system (4.2) can be written as (4.1), where $A_0 \in \mathbb{R}_{max}^{8 \times 8}$, $A_1 \in \mathbb{R}_{max}^{8 \times 8}$, $B \in \mathbb{R}_{max}^{8 \times 2}$, $C \in \mathbb{R}_{max}^8$ are the characteristic matrices of the model.

Explicitly, these matrices are given by:

$$A_0 = \begin{pmatrix} \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ t_3 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ t_4 & t_5 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & t_7 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & t_8 & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & t_{10} & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_{11} & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_{13} & \varepsilon \end{pmatrix} \quad A_1 = \begin{pmatrix} \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_9 & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & t_{12} \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \end{pmatrix}$$

$$B^t = \begin{pmatrix} t_1 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \\ t_2 & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon & \varepsilon \end{pmatrix}, \quad C = (\varepsilon \quad \varepsilon \quad t_6 \quad \varepsilon \quad \varepsilon \quad \varepsilon \quad t_{14}).$$

IV. Resolution of (max, +) state model

In order to solve the implicit equation given by the system (4.1), we proceed by the following way: we replace in the first equation of (4.1), successively, $X(k)$ with its expression to obtain the smallest solution of the first equation of (4.1):

$$\left\{ \begin{aligned} X(k) &= A_0 X(k) \oplus A_1 X(k-1) \oplus BU(k) \\ &= A_0 [A_0 X(k) \oplus A_1 X(k-1) \oplus BU(k)] \oplus A_1 X(k-1) \oplus BU(k) \\ &= A_0^2 X(k) \oplus A_0 A_1 X(k-1) \oplus A_0 BU(k) \oplus A_1 X(k-1) \oplus BU(k) \\ &= A_0^2 X(k) \oplus [A_0 \oplus Id] A_1 X(k-1) \oplus [A_0 \oplus Id] BU(k) \\ &= \dots \\ &= A_0^n X(k) \oplus \bigoplus_{i=0}^{n-1} A_0^i [A_1 X(k-1) \oplus BU(k)] \\ &= \bigoplus_{i=0}^{n-1} A_0^i A_1 X(k-1) \oplus \bigoplus_{i=0}^{n-1} A_0^i BU(k) \\ &= (\bigoplus_{i=0}^{n-1} A_0^i) A_1 X(k-1) \oplus (\bigoplus_{i=0}^{n-1} A_0^i) BU(k) \\ &= A_0^* A_1 X(k-1) \oplus A_0^* BU(k) \end{aligned} \right. \quad (4.3)$$

Where A_0^* is defined by: $A_0^* = \bigoplus_{i=0}^{+\infty} A_0^i$. As mentioned above about the calculation of the Kleene star A_0^* , A_0^n for $n \geq 8$ (A_0 is an (8x8) matrix), does not contribute to the sum of A_0^* . In other words, $\forall n \geq 8, A_0^n = \varepsilon$. So, $A_0^* X(k) = \varepsilon, \forall n \geq 8$ and $\forall k \geq 1$. Let us recall that the matrix Id introduced in the system (4.1) is the identity matrix E_n in (max, +) algebra.

The evaluation of the system will be done knowing that the numerical values of the system input $U(k)$, for all k , and the system initial state $X(1)$ are given. The solution of (4.1) is given by: $\forall k \geq 2$

$$\begin{cases} X(k) = A_0^* A_1 X(k-1) \oplus A_0^* B U(k) \\ = (A_0^* A_1)^{k-1} X(1) \oplus \bigoplus_{i=0}^{k-2} (A_0^* A_1)^i (A_0^* B) U(k-i) \\ Y(k) = C X(k) \\ = C((A_0^* A_1)^{k-1} X(1) \oplus \bigoplus_{i=0}^{k-2} (A_0^* A_1)^i (A_0^* B) U(k-i)) \end{cases} \quad (4.4)$$

V. Predictive charging approach

V.1. Numerical and evaluation study

For the evaluation study, we will assign numerical values to various parameters (see Table 9). These various numerical values are defined as follows: each system operation can be done within a given time interval $[a, b]$, where the lower bound “ a ” is the required minimum time to perform the operation and the upper bound “ b ” is the maximum time to execute the task. The values of t_{10} and t_{12} are fixed within the time intervals (as given in Table 9) according to some criteria, such as the charging operation, availability of a CS to perform a task. Other parameters t_6, t_7 and t_{11} represent the waiting for receiving response and then to perform next task. These waiting times vary from “0”, which means that the waiting time for receiving response is null, to $+\infty$ which means that the response

will never be received. In most cases, the waiting time is defined and bounded. In addition, we propose a feasibility study and performances improvement of the process. For a concrete application, these timing parameters may be changed slightly but the principle remains the same.

Times	t ₁	t ₂	t ₃	t ₄	t ₅	t ₆	t ₇	t ₈
Numerical values	0	0	0	0	0	€[0, +∞[€[0, +∞[0
	t ₉	t ₁₀	t ₁₁	t ₁₂		t ₁₃	t ₁₄	
	0	€[0, TT]	€[0, +∞[€[CT _{min} , CT _{max}]		0	0	

Table 9. Numerical values of system parameters

The obtained results in this section are based on random numerical values of arrival dates of charging demands. In our case, we consider for example that the maximal and minimal charging times are given by $CT_{max} = 40$ and $CT_{min} = 20$.

As said previously, we predict the charging time, as well as charging rate, of each EV asking to be charged according to the frequency of arrival dates of all EV demands and the trip time $TT(k)$ of each EV. These arrival dates, $u_1(k)$, for all $k \geq 2$, are known a priori and registered within the database of the CPL. Charging times $t_1(k)$ and associated charging rates are defined according to the flowchart of the Figure 10. As depicted in this figure, time for full charging and minimum charging (we consider in this case that the acceptable minimum charging rate is 50%) are given with arrival dates of charging requests. The parameter $\Delta(k)$, for each k^{th} charging demand, is calculated according to the arrival dates of $k-1^{st}$ and k^{th} charging requests. Afterwards, $\Delta(k)$ is checked with 3 conditions and that allows predicting the charging time of the $k-1^{st}$ charging request. The three tests to do for $\Delta(k)$ are :

- 1) $\Delta(k) \geq CT_{\max}$: meaning that the inter-arrival between the $k-1^{\text{st}}$ and k^{th} charging requests is large enough, so the $k-1^{\text{st}}$ has enough time to be fully charged,
- 2) $\Delta(k) \geq CT_{\min}$: meaning that the inter-arrival between the $k-1^{\text{st}}$ and k^{th} charging requests is average (neither too big nor too small). In this case, the $k-1^{\text{st}}$ EV continues its charging operation till the arrival of the k^{th} EV. The charging time will be then arranged between CT_{\min} and CT_{\max} .
- 3) $\Delta(k) < CT_{\min}$: meaning that the inter-arrival between the $k-1^{\text{st}}$ and k^{th} charging requests is very small. So, in order to avoid a great waiting of the k^{th} EV within the charging station, the $k-1^{\text{st}}$ EV will be charged only with the minimum acceptable charging rate corresponding to the charging time CT_{\min} . When the minimum charging rate is reached, the charging operation for $k-1^{\text{st}}$ will be stopped and then the k^{th} EV can start its charging.

Based on these conditions, charging times $t_1(k)$ and charging rates are calculated respectively. This process continues until $k = N$ (number of considered charging requests). This charging time is calculated with the following flowchart.

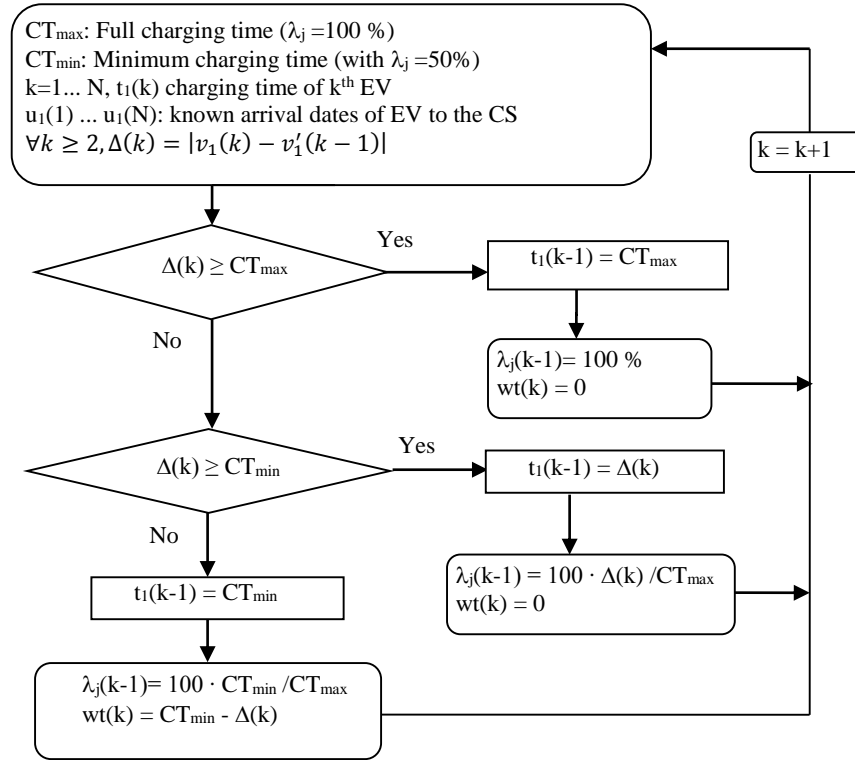


Figure 10. Flowchart of calculation charging time and rate

For all $k \geq 2$, we define $\Delta(k)$ representing the time slot between two consecutive arrivals of charging demands k and $(k - 1)$ including the theoretical waiting time of the k^{th} demand before freeing the charging point by the $(k - 1)^{th}$ EV. The parameter $\Delta(k)$ includes also travelling time from the EV location to the charging station. Let us denote $wt(k)$ this waiting time. The parameter $\Delta(k)$ is defined by:

$$\forall k \geq 2, \Delta(k) = |v_1(k) - v'_1(k - 1)| \quad (4.5)$$

With: $v_1(k) = u_1(k) + TT(k)$,

$$\begin{aligned} v'_1(k - 1) &= v_1(k - 1) + wt(k - 1) \\ &= u_1(k - 1) + TT(k - 1) + wt(k - 1), \end{aligned}$$

Based on the flowchart of the Figure 10, we predict the charging time and the end of each charging request. Hereafter are given some obtained simulation results regarding

charging times for each received request. We represent also the evolution of the inter-arrival of successive charging demands.

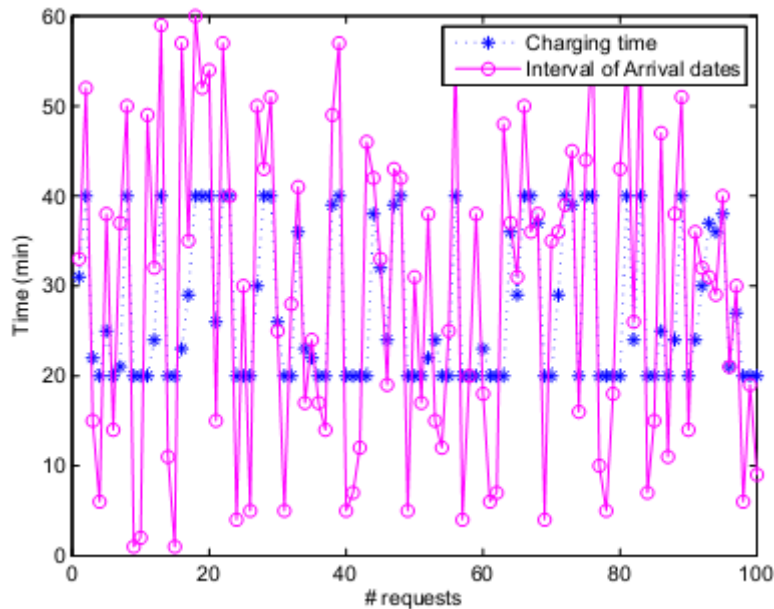


Figure 11. Comparison of the evolution of charging time with arrival dates of charging requests.

In this Figure 11 is depicted charging time (blue) for each demand and ending time of charging process (red) accordingly this charging time. As presented in this figure, charging time varies between $CT_{\min} = 20$ and $CT_{\max} = 40$ minutes. From these results we remark that the $(k - 1)^{\text{th}}$ EV can be charged fully when the inter-arrival dates of $(k-1)^{\text{th}}$ and $(k)^{\text{th}}$ requests is superior to $\Delta(k)$. This means that the $(k-1)^{\text{th}}$ EV has enough time to be charged fully without any constraint for leaving the charging point. When the inter-arrival of two consecutive requests is too short the charging time decreases to reach $CT_{\min} = 20$ some times. In this case the first EV ($(k-1)^{\text{th}}$ EV) has to stop its charging and leave the charging point when the acceptable charging minimum rate is reached. Sometimes, the next EV ($(k)^{\text{th}}$ EV) has to wait till the previous one reach the acceptable charging minimum rate.

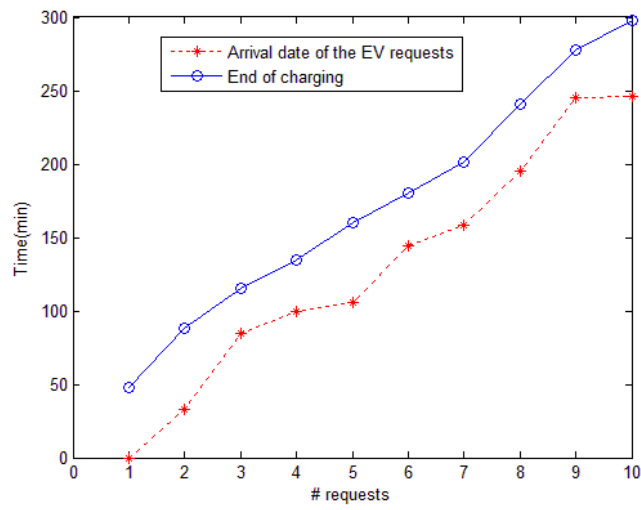


Figure 12. Difference between arrival dates of the requests and the end of charging

The Figure 12 shows the difference between the arrival date of each charging request and the end of charging of the same request. In this figure, we limit the x-axis to only to 10 requests in order to show clearly the difference between the two curves (arrivals of charging requests end of charging processes). We observe for example the requests number 3 and number 5. The charging times of these tow EVs are note the same. Indeed, the charging rate of EV number 5 is great than the one of EV number 3. This is due to the numerical values of $\Delta(3)$ and $\Delta(4)$ for the third EV, and of $\Delta(5)$ and $\Delta(6)$ for the 5th EV.

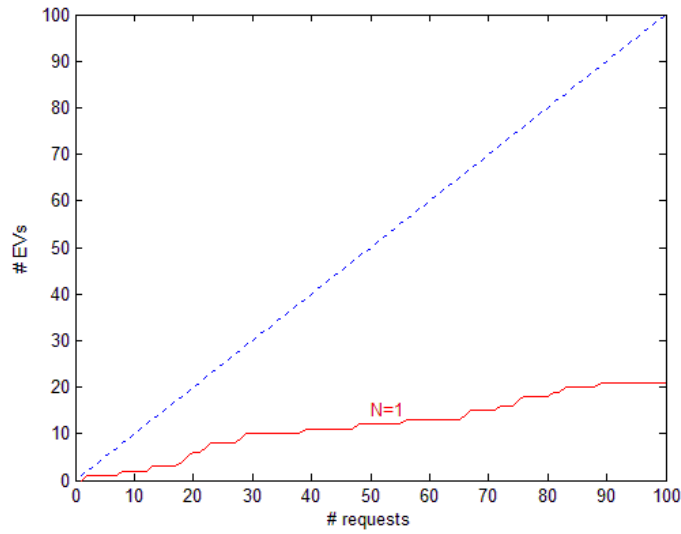


Figure 13. Number of fully charged EVs

The main goal in this study is to charge EVs fully as more as possible. By using only one charging point and according to the arrival dates and travel times of the EVs, we can define exact number of fully charged EVs (see Figure 13). In this case, the charging rate is very low regarding the number of used charging points. Next step is to find a compromise between the number of used charging point and the number of charging requests to handle allowing to improve the charging rates of EVs.

V.2. Improvements: sizing results

The objective of this improvement study is to increase charging rate of each EV (ideally reaching a SoC of 100 %). For doing so, we show how the increasing of the number of charging points (the minimum possible) participate to reach this goal. The Figure 14 shows the rate of fully charged EVs according to the number of used charging points. Let note that for all obtained results in this case, we consider the same numerical values given in Table 9 and the same arrival dates of all charging requests.

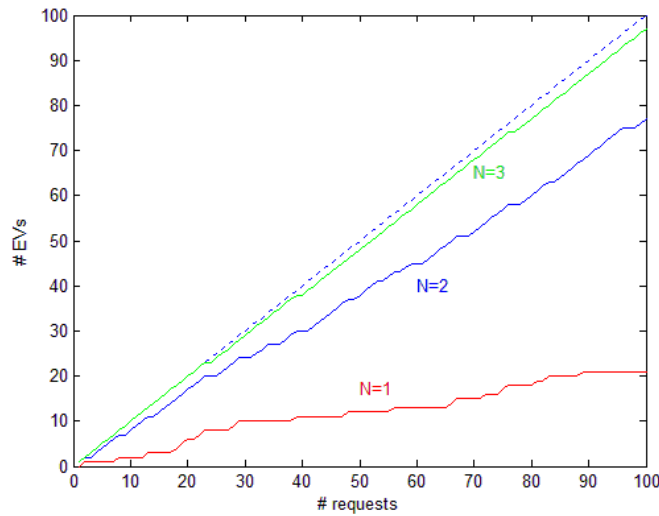


Figure 14. Evaluation result considering Table 9 and using several points

The simulation results show that, when only one charging point is used, 21% EVs will be charged fully, with two charging points 77% and 97% EVs will be charged fully when used three charging points (see Figure 14). As a conclusion, with only three charging points within a charging station, the full charging of almost all EVs is ensured. Using four charging points, the obtained results, show that all EVs can be fully charged and the four CPs are not fully exploited.

VI. Conclusion

In this chapter, a charging process was modelled, evaluated and improved using $(\max, +)$ algebra. The process was first modelled using a P-timed event graph, and some appropriate properties of this process were evaluated through this graphical model. $(\max, +)$ equations describing the analytic behavior of the process are then derived from the PTEG model. The required performance metrics are evaluated using these linear equations. A performance-tuning algorithm was proposed on to improve the quality of service offered to EVs increasing the charging rate. This tuning method allows studying

the tradeoff between the number of charging requests and the number of charging points required to satisfy them, e.g., charge a maximum of EVs by using a minimum number of charging points. Furthermore, this study can be seen as a predictive charging policy to anticipate the assignment and the guidance of EV to charging stations. A numerical example was worked out and simulation results are reported and show the added value of the proposed predictive charging approach. Throughout this study, we demonstrated how the proposed methodology can be used for validation of qualitative properties as well as issues of performance analysis, evaluation, and improvement.

CHAPTER 5

PREDICTIVE AND SCALABLE APPROACH

In this chapter we focus on a predictive based approach for charging process. The outcome is a trade-off between a large number of charging demands and an average charging rate acceptable for all EVs to support large-scale systems. Predictive charging approach is proposed to anticipate and improve the provided services to drivers and to suggest an adequate charging station. Average charging rates and charging times are calculated according to the predictive and scalable approach based, first on a predictive function, and then on an extended case of the (max, +) equations.

I.	INTRODUCTION	86
II.	A TRADE-OFF BASED APPROACH FOR PREDICTIVE CHARGING	86
	<i>II.1. Used predictive function: Parameters identification.....</i>	<i>86</i>
	<i>II.2. Prediction of charging rate and charging time.....</i>	<i>89</i>
III.	PREDICTION USING (MAX, +) ALGEBRA: EXTENDED CASE STUDY	95
	<i>III.1. Use of one charging point</i>	<i>95</i>
	<i>III.2. Case of multiple charging points.....</i>	<i>101</i>
	<i>III.3. Analysis and discussions</i>	<i>103</i>
IV.	CONCLUSION	107

I. Introduction

In the chapter 4, an assignment approach for charging EVs is proposed using an optimization algorithm. Each charging request is treated individually and the charging rate is evaluated according to the inter-arrival of charging demands. In the current chapter, we complete this study by introducing a predictive function-based model for handling multiple charging demands and predicting their average charging rates and charging times. The main objective is to minimize simultaneously the waiting time of each received request and the occupation time of charging stations. All parameters of the used predictive function are identified according to the charging system data and the inter-arrivals of charging requests. In order to serve a maximum charging EVs while minimizing their waiting within charging station an optimization algorithm is proposed. To find a compromise between these two objectives, a charging policy is adopted in this study. The charging rate of each EV is defined according to its needs in terms of energy corresponding to the needs of driver in terms of the distance to travel. In fact without considering a required energy of an EV, it occupies the charging point till a full charged. In this case the accumulation of waiting times within the charging station becomes more and more raised with the arrival of other charging requests. Nevertheless, when each EV is charged just with required energy the accumulated waiting of EVs can be considerably reduced. We show how this charging policy impacts the charging operations and improve the offered service to EV drivers.

II. A trade-off based approach for predictive charging

II.1. Used predictive function: parameters identification

We consider that each charging station is composed of several charging points. We recall that all information regarding charging stations (including their status, provided

charging power, location, etc.) are collected and stored into the platform database as explained in previously [32].

The first proposed approach in this chapter is based on an integrated predictive function illustrated in the Figure 15 and presented by the equation (5.1). The differential properties of this predictive function are described in [40].

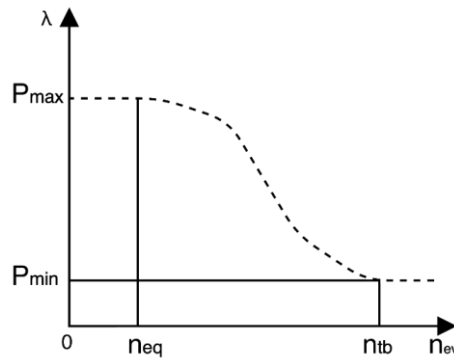


Figure 15. Predictive function and its parameters

$$\lambda = \frac{P_a}{1 + P_b \cdot e^{P_c \cdot x}} + P_{min} \quad (5.1)$$

According to the studied charging system, the basic parameters of this predictive function are given as follows:

- P_{max} : is the maximum value of charging rate. In the most cases, this value is fixed at 100 %. This parameter will be used for the evaluation of the parameter λ ;
- P_{min} : represents a minimum threshold which corresponds to the accepted minimum value of charging rate;
- λ : represents the average charging rate (expressed in %) and varies between P_{min} and P_{max} ,

- P_a : is the difference between P_{max} and P_{min} ,
- P_b and P_c are constants, which are calculated according to the number of charging points, charging requests and arrival dates of charging requests,
- The parameter x can be expressed as follows:

$$x = \frac{n_{ev}}{n_{cp}} \cdot \Delta k \quad (5.2)$$

Where:

- n_{ev} : is the number of EVs which are under charging at the same time ($n_{ev} \geq 1$),
- n_{cp} : is the number of available charging points ($n_{cp} \geq 1$),
- Δk : is the inter-arrival between the k^{th} and $(k - 1)^{th}$ charging requests expressed as follows: $\Delta k = U_1(k) - U_1(k - 1)$.

The two parameters identified in the Figure 15, n_{eq} and n_{tb} are defined as follows:

- n_{eq} : this value corresponds to the case where available charging point number and the number of requests are equal each other's,
- n_{tb} : this value corresponds to the case where the number of charging requests is two times bigger than the number of available charging point.

Evaluating an average charging time of each EVs' set could be made using by the followed equations according to the number of EVs compared with the number of charging points within a charging station. We consider two cases

1) $n_{ev} \leq n_{cp}$:

The number of charging points is bigger than the number of presented EVs within the charging station. In this case, the average charging time is given by the equation (5.3).

$$t_e = \frac{\lambda \cdot CT_{max}}{100} \quad (5.3)$$

If we decide to charge the EVs fully ($\lambda = \text{SoC} = 100\%$), this charging time equals to CT_{max} .

2) $n_{ev} > n_{cp}$:

In this case, the number of EVs within the charging station is bigger than the number of charging points. We distinguish the two following sub cases:

a) $n_{ev} < 2 \cdot n_{cp}$,

$$t_e = \frac{\left\{ \frac{n_{ev}}{n_{cp}} \right\} \cdot CT_{max} + \left(n_{ev} - \left\{ \frac{n_{ev}}{n_{cp}} \right\} \right) \cdot t_\lambda}{n_{cp}} \quad (5.4)$$

b) Otherwise

$$t_e = \frac{CT_{max} \cdot \left(2 \cdot \left\{ \frac{n_{ev}}{n_{cp}} \right\} + n_{cp} \cdot \left(\left\{ \frac{n_{ev}}{n_{cp}} \right\} - 1 \right) - \left\{ \frac{n_{ev}}{n_{cp}} \right\}^2 \right)}{n_{ev}} \quad (5.5)$$

These three cases are identified to determine the average charging times according the number of EVs demands and the numbers of available charging points.

II.2. Prediction of charging rate and charging time

This section shows the application of the predictive function of the function (5.1) for predicting the charging rates of a set of EVs. In order to determine the parameters of the predictive function, first we consider an arrival frequency of recharge requests. According to inter-arrivals of charging requests, it is possible to determine the maximum quantity of the energy to serve for each EV. By applying this charging policy, the queue of EVs within charging stations can be controlled and the long waiting of EV can be avoided. By fixing a given charging time for each EV and knowing the number of charging points, the

function (5.1) expressing the variation of the average charging rate leads to the results depicted in Figure 16. The three curves of this figure correspond to different numbers of charging points. In this case, we consider a charging station with 5 (blue line in the figure), 6 (brown line), and 7 (grey line) charging points to evaluate the evolution of the predictive function. The number of EV requests varies for 1 until 15 requests. Also, as shown in this Figure 16, the accepted charging minimum rate is fixed to $P_{min} = 50 \%$. In addition, we limit the charging rate to $P_{max} = 80\%$ corresponding to the fast charging (20 min to 30 min). It is worth noting that certain batteries, such as Li-Ion technologies (see Table 1), can be charged until 80% in less than 30 min, and the last 20% (from 80% to 100%) are charged very slowly according to the battery characteristics (usually about 5 hours are required for reaching the full charging (100%) [41].

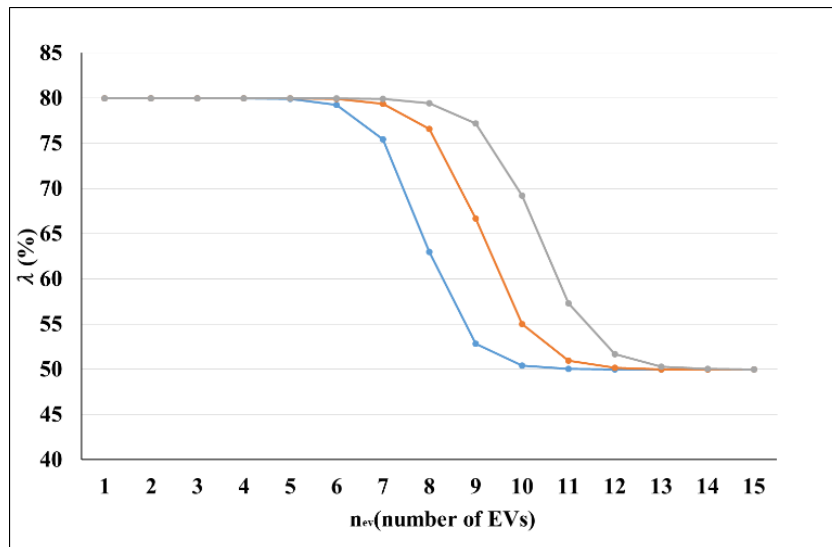


Figure 16. Charging rate vs. the number of EVs

The predictive approach using the equation (5.6) allows informing the EV drivers about the needed quantity of energy and required charging time according to the characteristics and needs of driving.

The Figure 17 shows the average charging time for the two cases: the fully charging for each EV, and while considering only the needed energy for the EV according to the driver needs and inter-arrival of charging requests. From these results, we remark that using only required energy for EVs, the charging stations are less occupied and the EVs waiting are less important.

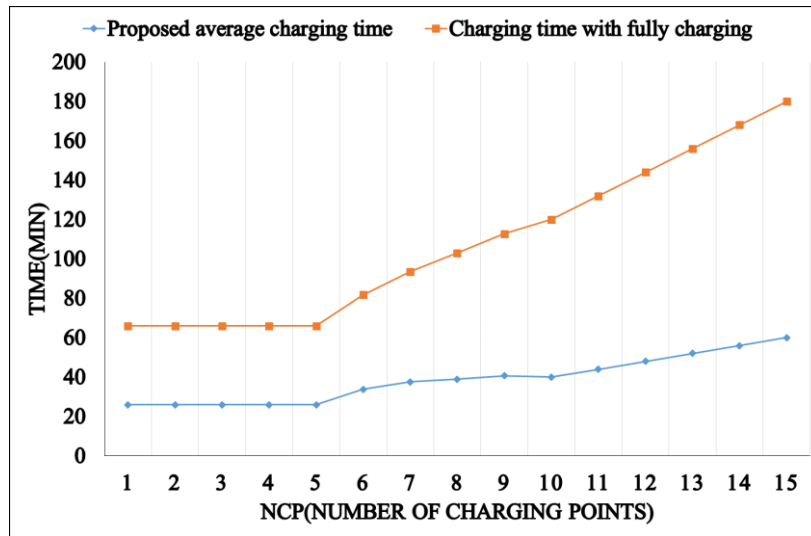


Figure 17. Comparison of the average charging times for two cases

To obtain these results, a charging algorithm based on the predictive function is proposed for predicting charging rates and times. By applying this algorithm, the required amount of energy for EVs according to the SoC of the battery could be predicted. More precisely, the SoC of the battery is one of the most major parameters in the charging process. The proposed algorithm is mainly based on this parameter in order to avoid the long waiting and spend more time in the charging process. This algorithm is depicted by the flowchart of Figure 18, where CT_{max} is the corresponding charging time to the parameter P_{max} , and the charging time CT_{min} corresponds to P_{min} . The algorithm allows determining the average charging rates and average charging times for multiple charging demands. In fact, the average charging rate (λ) varies between P_{max} (when $n_{ev} = n_{eq}$)

and P_{min} (for $n_{ev} = n_{tb}$). Thus, the algorithm checks the number of received charging requests n_{ev} , the arrival dates of these requests, and then calculates average charging rates and average charging times for a long time. With the proposed charging times and charging rates, the accumulation of waiting times becomes more and more raised with the arrival of other charging requests.

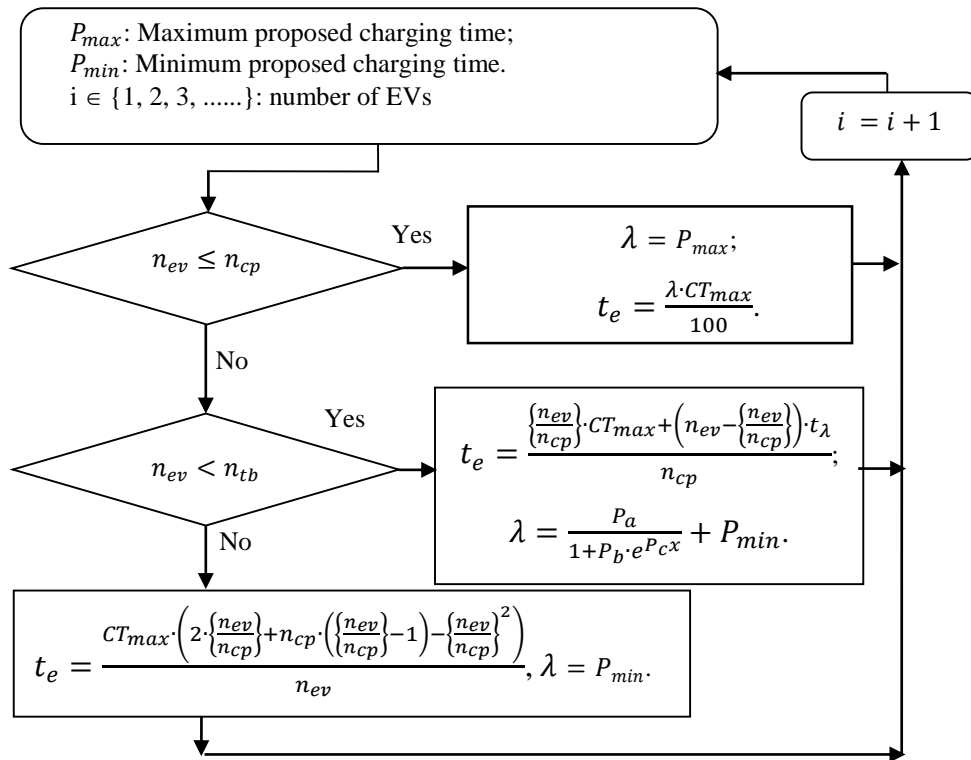


Figure 18. Predicting the average charging times and rates for a set of EVs

In what follows we present the results of two scenarios: charging process with and without considering required energy for EVs. These results show the differences between the two charging policies. The Gantt chart of the Figure 19 shows the charging time and waiting time for each EV without considering the needed energy for charging requests. Without considering this energy each EV is planned to be fully charged, consequently certain EVs have to wait for long times. Thus, the accumulation of waiting times becomes more and more raised with the arrival of other charging requests.

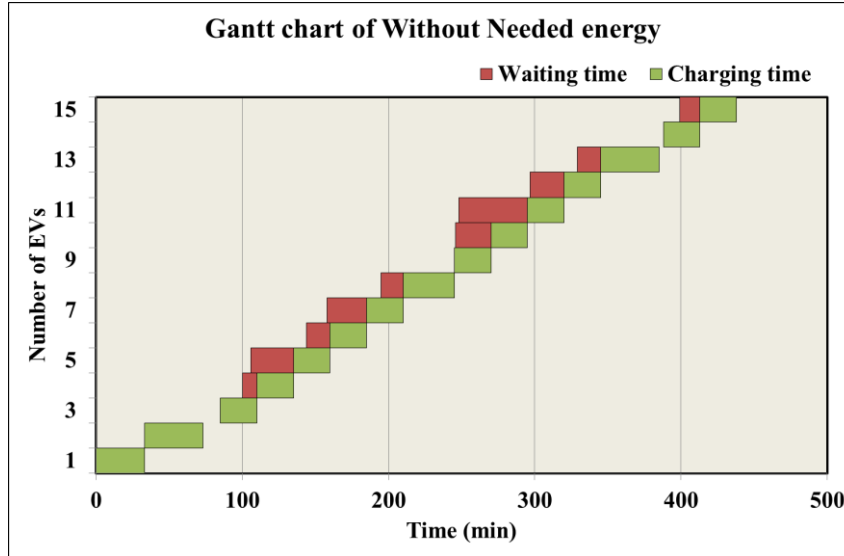


Figure 19. Waiting time and charging time without considering needed energy.

By considering the required energy of each demand and the inter-arrival of all charging requests, the predictive charging time varies from minimum charging time CT_{min} , corresponding in our case to the minimum accepted charging rate P_{min} , to the arrival time of the next accepted charging request which is limited by CT_{max} . If the next charging demand arrives after CT_{max} , the charging point is free and can be used at any time. In this case, the EVs will be charged with at least an accepted amount of energy and the accumulated waiting of EVs can be considerably reduced. The Gantt chart depicted in Figure 20 illustrates the results of this second case. Here, we consider that the needed battery energy varies between 20 and 80 %. We keep our first charging condition, which charges each battery at least 50%, when the next EV charging demand arrives before the desired time and the battery can be charged for more than 50%.

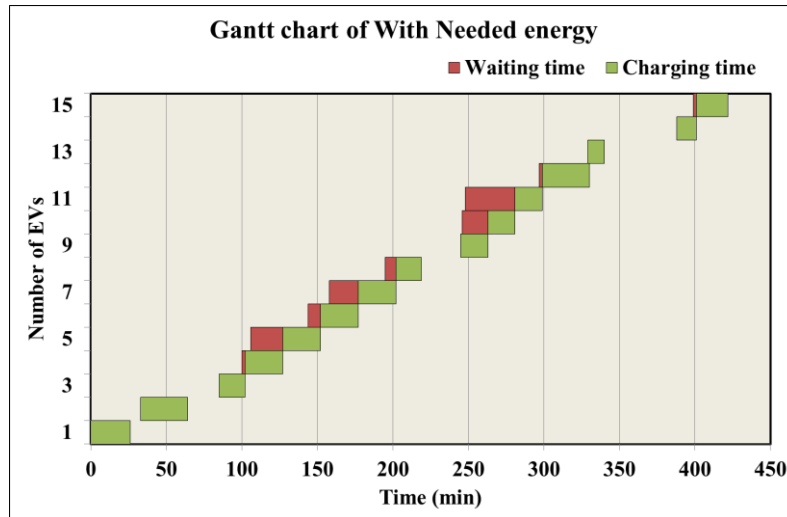


Figure 20. Waiting time and charging time with considering needed energy.

Furthermore, Figure 21 presents the difference between charging rates for the two studied cases (with and without considering needed energy of each EV). In fact, when we consider the needed energy, an amount of energy is proposed to charge the EV (so called proposed charging rate).

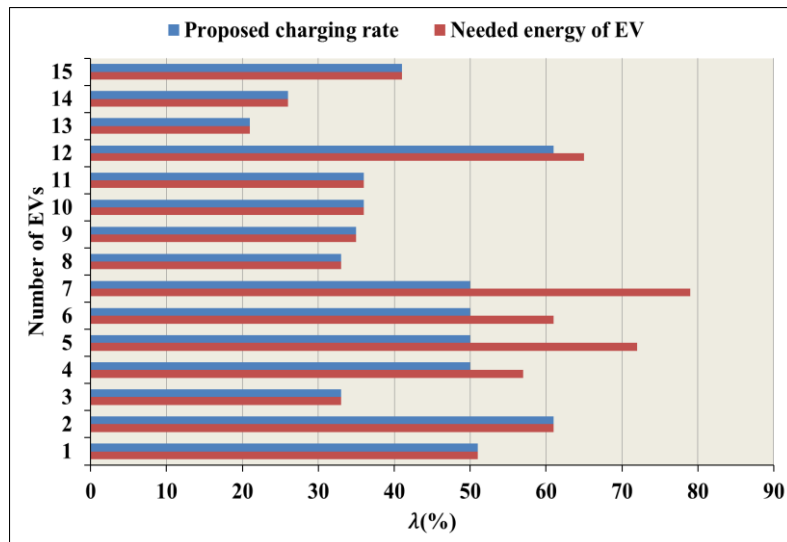


Figure 21. Difference of the desired charging rate and proposed charging rate

The Figure 22 presents the differences of the waiting times for the two studied cases. The large scale reducing of the waiting times is compared to the battery SoC and charging without this information. Battery energy information such as the SoC and related charging technology (lent or fast charging) can be helpful for the companies of energy distribution and smart grids in order to schedule daily loading costs. When the decision of charging EVs with 100% of energy is not kept, the accumulation of EVs waiting times can be reduced until 49.8%.

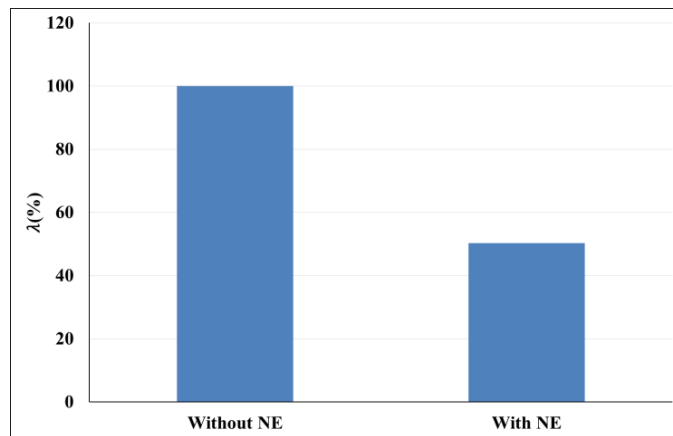


Figure 22. Waiting time evolution

III. Prediction using (max, +) algebra: extended case study

III.1. Use of one charging point

In this section we extend the study proposed in the chapter 4 for predicting the charging behavior using (max, +) equations. In fact, in order to predict the behavior of the system with the aim to satisfy maximum charging requests, we propose a predictive approach based the extension of the developed (max, +) in chapter 4 as well as a charging management algorithm. In the section, we present the adopted approach as well as the models that represent the system behavior in an extended case study. The proposed

algorithm will be detailed and obtained results through an illustrative example will be analyzed and reported.

Based on the (max, +) model describing the analytical behavior of the process, we show how to act on the charging time, or also charging rate, for each charging demand in order to serve a maximum request of EVs while avoiding a long waiting of vehicles. To prove the feasibility of the proposed approach, we will consider in this study only one charging station equipped with a unique charging point. In this case, many EV requests are addressed to the unique charging station successively with random time slots. Second, we will extend the study by considering a more general system with many charging points. The objective is to manage in an optimal way the charging process and reduce as much as possible the queuing of EVs within the charging station.

In this study, we show how to regulate the charging process according to the number of charging requests while ensuring a minimum power of each EV. Through the proposed predictive charging approach, we try to find a compromise between the number of charging requests and allocated time to the charging point for each charging operation. More precisely, with the aim to maintain the waiting times of each EV less than an acceptable threshold, we reduce the charging rate of certain EV in order to satisfy a maximum number of charging demands.

The new PTEG representing the charging process while considering the number of charging requests as system input is given by following graph. For this step of modelling and simulation, we assume what follows:

- H1: spent time for searching free/adequate charging station by the CPL is supposed to be fixed; the temporization " t_3 " in the PTEG model equals to a constant.

- H2: the charging station should ensure at least 50% of charging rate for each request
($50\% \leq \text{SoC} \leq 100\%$).

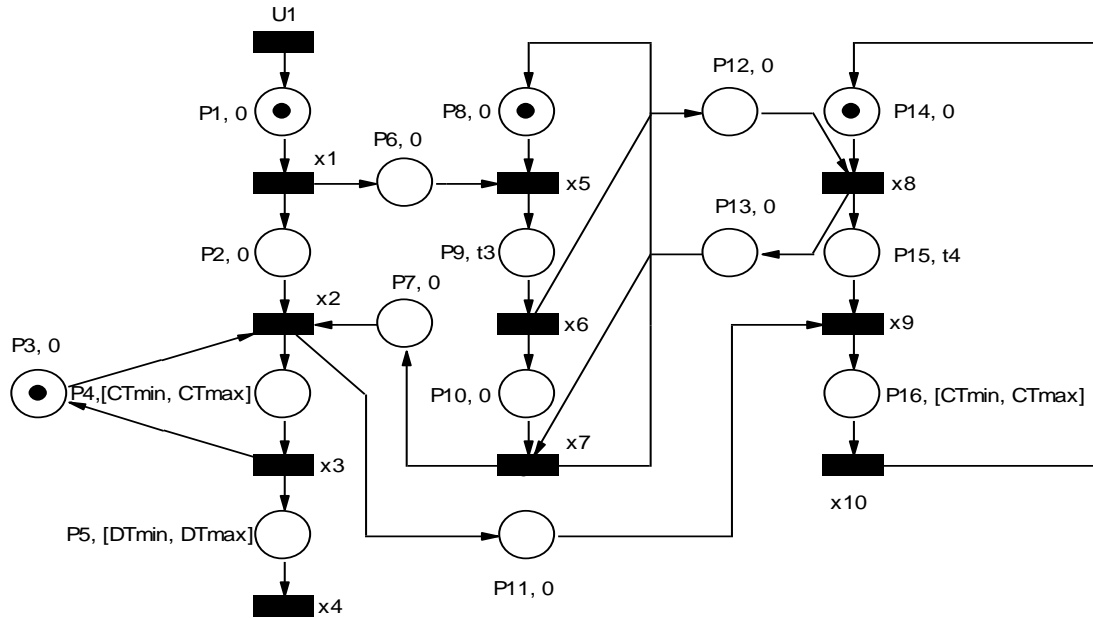


Figure 23. Charging process PTEG model with an open loop control

The analytical behavior, using $(\max, +)$ equations and using the system parameters, of the new PTEG is represented by for all $k > 1$,

$$\left\{ \begin{array}{l}
 x_1(k) = u_1(k) \\
 x_2(k) = x_1(k) \oplus x_3(k-1) \oplus x_7(k) \\
 x_3(k) \geq CT_{\min} \otimes x_2(k) \\
 x_3(k) \leq CT_{\max} \otimes x_2(k) \\
 x_4(k) \geq DT_{\min} \otimes x_3(k) \\
 x_4(k) \leq DT_{\max} \otimes x_3(k) \\
 x_5(k) = x_1(k) \oplus x_7(k-1) \\
 x_6(k) = t_3 \otimes x_5(k) \\
 x_7(k) = x_6(k) \oplus x_8(k) \\
 x_8(k) = x_6(k) \oplus x_{10}(k-1) \\
 x_9(k) = x_2(k) \oplus t_4 \otimes x_8(k) \\
 x_{10}(k) \geq CT_{\min} \otimes x_9(k) \\
 x_{10}(k) \leq CT_{\max} \otimes x_9(k)
 \end{array} \right. \quad (5.7)$$

Where DT_i is the Driving Time (under normal conditions) using the remaining battery power of the i^{th} EV. The associated temporizations with the places P4, P5 and P16 will be determined according to the system input. These temporizations correspond respectively to charging time (for t_1 associated with P4 and P16) and driving time after charging (for t_2 associated with P5). It depends on the arrival times of charging requests. The (max, +) state equations (5.7) are qualified then to be non-stationary because of the variable character of these temporizations. The equations (5.7) can be written with the non-stationary character for the certain temporizations as follows. For all $k > 1$,

$$\left\{ \begin{array}{l} x_1(k) = u_1(k) \\ x_2(k) = x_1(k) \oplus x_3(k-1) \oplus x_7(k) \\ x_3(k) = t_1(k) \otimes x_2(k), \text{ with } t_1(k) \in [CT_{\min}, CT_{\max}] \\ x_4(k) = t_2(k) \otimes x_3(k), \text{ with } t_2(k) \in [DT_{\min}, DT_{\max}] \\ x_5(k) = x_1(k) \oplus x_7(k-1) \\ x_6(k) = t_3 \otimes x_5(k) \\ x_7(k) = x_6(k) \oplus x_8(k) \\ x_8(k) = x_6(k) \oplus x_{10}(k-1) \\ x_9(k) = x_2(k) \oplus t_4 \otimes x_8(k) \\ x_{10}(k) = t_5(k) \otimes x_9(k), \text{ with } t_5(k) \in [CT_{\min}, CT_{\max}] \end{array} \right. \quad (5.8)$$

The matrix form of this system (5.8) can be expressed with a light modification of characteristic matrices which become matrices with variable coefficients (depend on the parameter k). In a general way, the (max, +) state equation obtained from system (5.8) can be expressed as given in the equation (5.9).

$$X(k) = A_0(k)X(k) \oplus A_1(k)X(k-1) \oplus B(k)U(k) \quad (5.9)$$

In our case, only the matrix A_0 depends on the parameter k. Other characteristic matrices are expressed with constant components. For all k, $A_1(k) = A_1$ and $B(k) = B$.

Solving the equation (5.9) leads to the solution (5.10).

$$\begin{aligned} X(k) &= A_0^*(k)A_1X(k-1) \oplus A_0^*(k)BU(k) \\ &= \Psi(k)^{\otimes(k-1)}X(1) \oplus \bigoplus_{i=2}^{i=k} \Psi(k)^{\otimes(k-1)}\Phi(k)U(i) \end{aligned} \quad (5.10)$$

With $\Psi(k) = A_0^*(k)A_1$ and $\Phi(k) = A_0^*(k)B$.

As said previously, we predict the charging time, as well as charging rate, of each EV asking to be charged according to the frequency of arrival dates of all EV demands. These arrival dates, $u_1(k)$ for all $k \geq 1$, are known a priori and registered within the database of the CPL.

For all $k > 1$, we define $\Delta(k)$ that represents the time slot between two consecutive arrivals of charging k^{th} and $(k - 1)^{\text{th}}$ demands including the waiting time of the k^{th} demand before freeing the charging point by the $(k - 1)^{\text{th}}$ EV. Let us denote $wt(k)$ this waiting time. The parameter $\Delta(k)$ is defined by: $\forall k > 1$,

$$\Delta(k) = |u_1(k) - u'_1(k - 1)| \quad (5.11)$$

With

$$u'_1(k - 1) = u_1(k - 1) + wt(k - 1)$$

$$\text{and } wt(1) = 0$$

Predictive charging time for each demand can be expressed as given in the equation (5.12). This result corresponds to the use of only one charging point. We note that the charging time t_1 is represented by the temporization associated with the place P4

For all $k > 1$,

$$t_1(k - 1) = \begin{cases} CT_{max}, & \text{if } \Delta(k) \geq CT_{max} \\ \Delta(k), & \text{if } CT_{min} \leq \Delta(k) \leq CT_{max} \\ CT_{min}, & \text{if } \Delta(k) \leq CT_{min} \end{cases} \quad (5.12)$$

The charging rate is expressed by the following equation:

$$\lambda(k - 1) = \begin{cases} 100\%, & \text{if } \Delta(k) \geq CT_{max} \\ \frac{100 \cdot \Delta(k)}{CT_{max}}, & \text{if } CT_{min} \leq \Delta(k) \leq CT_{max} \\ \frac{100 \cdot CT_{min}}{CT_{max}}, & \text{if } \Delta(k) \leq CT_{min} \end{cases} \quad (5.13)$$

$$wt(k) = \begin{cases} 0, & \text{if } \Delta(k) \geq CT_{min} \\ CT_{min} - \Delta k, & \text{otherwise} \end{cases} \quad (5.14)$$

In Figure 24, the charging times and rates are depicted according to arrival time – interval (Δk) of each EVs as a Gantt chart to present the evolution of charging times and rates when the number of charging point equals to one ($M=1$). In this case, the simulation study is carried out for 15 charging requests.

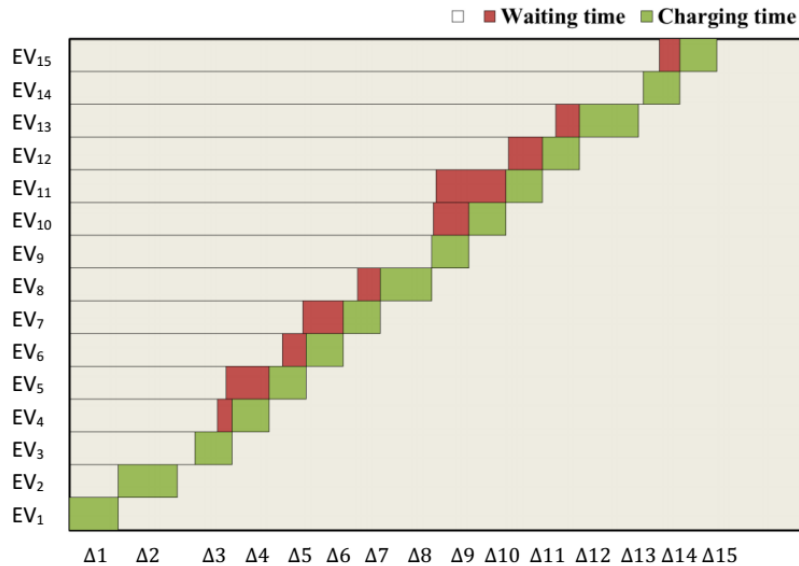


Figure 24. Waiting time and charging time with $M=1$

In this Figure 24, the evolution of the charging time and waiting time for each EV is expressed according to the inter-arrival dates of successive charging demands Δk (x-axis). These results are too similar to those obtained in Figure 19.

III.2. Case of multiple charging points

Let us consider M (with $M > 1$) charging points within a charging station for satisfying all charging demands. For this configuration, two cases are possible. The first

case concerns the use of all charging points at the same time. For the second case, we check among already used charging points if there is one free point. If there is any, this point will be used once again instead of a new point. This last case enables to minimize the usage of charging points. In our study, we consider the first case where all charging points are exposed to be used. The idea here is to maximize the use of existing resources.

In this case, charging time (t_1 associated with P4 and P16), charging rate and waiting time for each EV are given by:

For $1 \leq k \leq M$,

$$\begin{cases} t_1(k) = CT_{max} \\ \lambda(k) = 100 \% \\ wt(k) = 0 \end{cases} \quad (5.15)$$

For all $k > M$,

$$t_1(k - M) = \begin{cases} CT_{max}, & \text{if } \Delta(k) \geq CT_{max} \\ \Delta(k), & \text{if } CT_{min} \leq \Delta(k) \leq CT_{max} \\ CT_{min}, & \text{if } \Delta(k) \leq CT_{min} \end{cases} \quad (5.16)$$

$$\lambda(k - M) = \begin{cases} 100 & \text{if } \Delta(k) \geq CT_{max} \\ \frac{100 \cdot \Delta(k)}{CT_{max}}, & \text{if } CT_{min} \leq \Delta(k) \leq CT_{max} \\ 50 & \text{if } \Delta(k) \leq CT_{min} \end{cases} \quad (5.17)$$

$$wt(k) = \begin{cases} 0, & \text{if } \Delta(k) \geq CT_{min} \\ CT_{min} - \Delta k, & \text{otherwise} \end{cases} \quad (5.18)$$

With:

$$\Delta(k) = |u_1(k) - u'_1(k - M)|;$$

$$u'_1(k - M) = u_1(k - M) + wt(k - M);$$

$$wt(1) = wt(2) = \dots = wt(M) = 0.$$

The values of obtained charging times $t_1(k)$, for all k , will be injected in the (max, +) equations representing the charging process and then all states of the system are evaluated.

The obtained results by increasing the number of charging points are depicted in Figure 25. In this case, reducing the waiting times of EVs are presented clearly according to the arrival time – interval of the demands. These results are based on the same numerical values that are used for other obtained results previously.

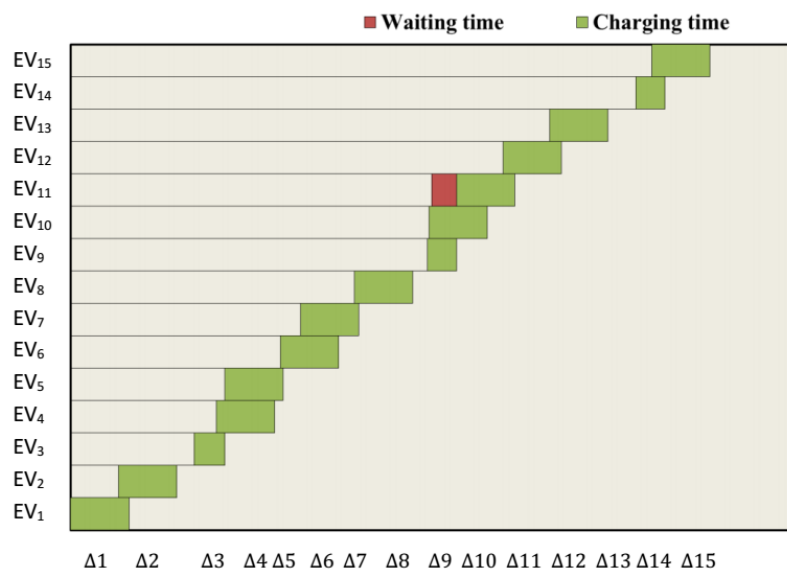


Figure 25. Waiting time and charging time of EV with M=2

In the Figure 25, we can observe a non-null waiting time for the EV₁₁. In fact, according to the used arrival dates of charging requests and charging operations of EVs, the EV₁₁ should wait until the freeing of a charging point by stopping an EV for which the charging rate reached 50%.

III.3. Analysis and discussions

With the aim to illustrate the proposed approach with more charging demands, we consider a hundred EVs asking to be charged ($k = 1 \dots 100$). Charging rates, charging

times and waiting times for each EV is defined according to the given arrival dates. We recall that the obtained results in this section are based on random numerical values of arrival dates of charging demands. The maximal and minimal charging times are given by $CT_{max} = 40$ min, $CT_{min} = 20$ min. By Using the (max, +) equation developed previously and the developed predictive algorithm, we report hereafter the obtained results.

As given in Figure 26, we can see the evolution of the charging time and waiting time versus the arrival dates of charging demands. If the waiting time of the k^{th} EV is high, then the $(k - 1)^{th}$ EV cannot be charged fully. In this case, the charging time decreases toward CT_{min} . Otherwise, if there is no waiting of the k^{th} EV (the inter-arrival between k^{th} and $(k - 1)^{th}$ EV is large enough), the $(k - 1)^{th}$ EV can be fully charged and the charging time reaches the maximum value.

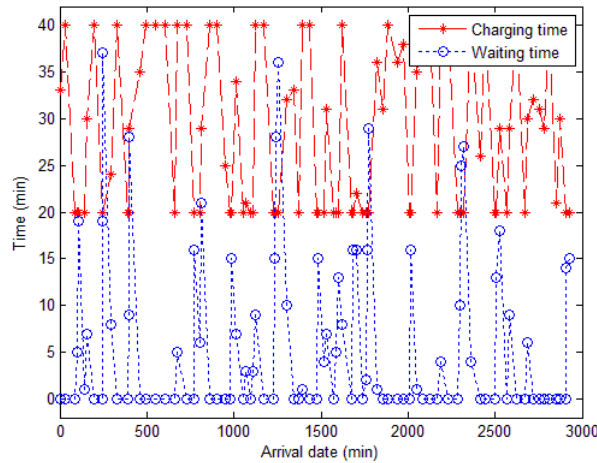


Figure 26. Charging times and waiting times versus arrivals of requests

The Figure 27 shows the evolution of the charging time and inter-arrival (or time slot) of charging demands versus the number of demands k . We remark that when the inter-arrival of two consecutive charging demands is widely large, the charging time reach the

maximum value CT_{max} . When the time slot is small, the charging time decreases toward CT_{min} . For example, for the $k = 20^{th}$ charging request, the time slot reaches its maximum value, so the charging time reserved for this request reaches $CT_{max} = 40$ min. Whereas for the $k = 70^{th}$ charging request, the time slot is at its minimum value, then the charging time for this request is only $CT_{min} = 20$ min.

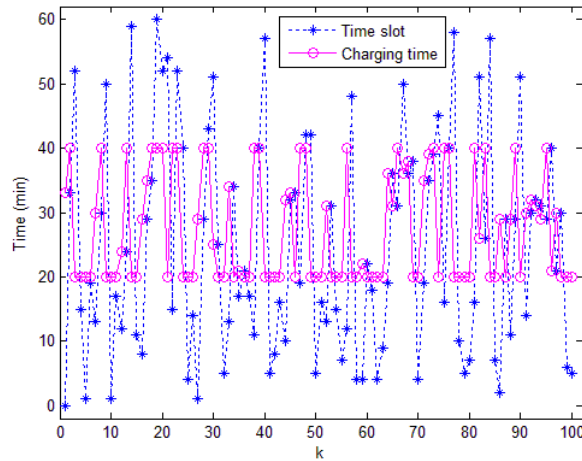


Figure 27. Comparison of the evolution of charging time and time slot

For the second study case where we consider two charging points. Below we give some obtained figures with the same arrival dates as in the previous case.

$$k = 1 \dots 100, wt(1) = 0, \dots, wt(100) = 0, CT_{max} = 40 \text{ min}, CT_{min} = 20 \text{ min}.$$

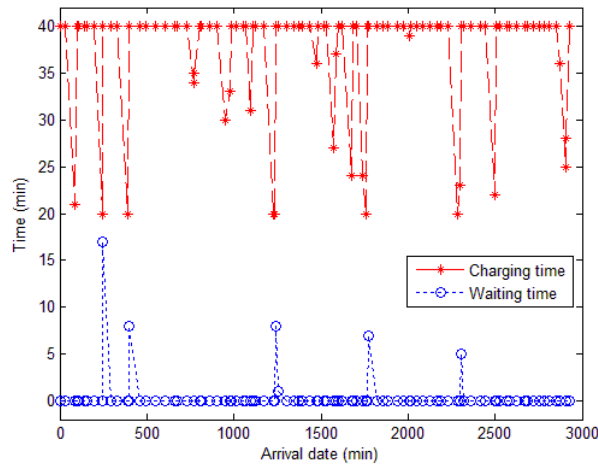


Figure 28. Charging times and waiting times vs. Arrival time (M=2)

By analyzing the Figure 28, we remark that using two charging points, the whole of charging requests are handled with a maximum charging time except some of them for which the waiting times are not null. When the waiting time of a given EV is different from zero this means that one of the two EVs already under charging cannot be fully charged and it has to leave the charging point before reaching maximum charging rate (just when reaching the minimum charging rate 50%). This assertion is confirmed by the results of the Figure 29 in which the charging time is around CT_{max} for the majority of charging EVs.

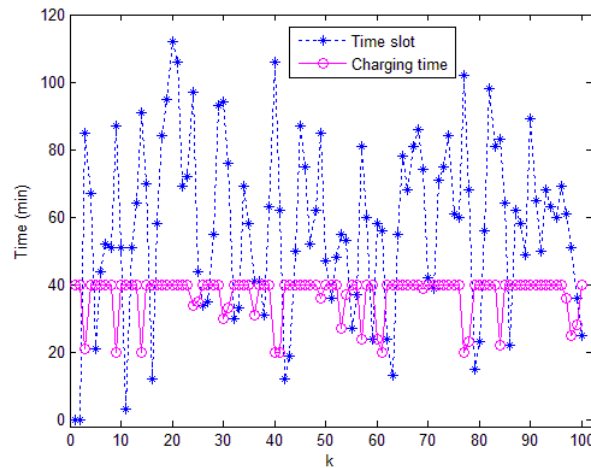


Figure 29. Time slot and charging time

As illustrated in Figure 28 and Figure 29 we remark that charging with two points participate considerably to reduce the waiting time for each EV and increase its charging rate.

IV. Conclusion

In this chapter, we have proposed a charging policy for multiple EVs charging demands using charging stations with several charging points. The objective is to remedy the long waiting problem of EVs within charging stations. We have introduced a predictive algorithm based on predictive function fundamentals. Basics and parameters of this function in the context of charging process are identified and explained. According to these parameters, the prediction of the average charging time and charging rate using this trade-off approach is explained. The obtained results are compared using two cases: full charging of EV batteries, and using uniquely required energy according to the arrival of charging requests and the expressed needs of drivers.

Furthermore, we extended the $(\max, +)$ approach presented in the chapter 4. Through this study, we find a compromise between the number of charging requests and allocated

time to the charging point for each charging operation. This compromise is fined for the two cases: using one and two charging points within a same charging station. For each case, a numerical example is worked out and the obtained results are reported and compared. These results show that a maximum number of charging demands are satisfied. Also, the waiting times and charging times can be regulated according to the inter-arrival of charging requests and the concrete needs in terms of energy.

CONCLUSIONS AND PERSPECTIVES

I.	SUMMARY	110
II.	FUTURE WORKS	113

I. Summary

The work presented in this thesis deals with information regarding to the charging processes for electric vehicles. According to the parameters and energy needs of EVs, which are transmitted to a collaborative platform, adequate charging stations are suggested the EVs drivers. To do so, optimization based approaches for optimal scheduling and assignment of EVs to the suitable charging stations are proposed. The overall aims are satisfying each EV with a maximum charging rate and a minimum waiting for charging.

In the chapter 2, we proposed an integrated platform for increasing the synergy between the EVs and charging stations. The interaction and communication are described using information and communication technologies strengths, Web services and ge-positioning techniques. The scheduling and the assignment of EVs to CSs have tackled as an optimization problem. First of all, the problem is formulated by a linear program, in which the assignment of all EVs should verify certain constraints such as the status of CSs and the characteristics of EVs. The objective of assigning EVs to CSs is reached and all considered EVs are guided to the suitable CSs while satisfying all problem constraints.

A (max, +) based approach is proposed in chapter 3 to represent and evaluate the occurrence dates of a sequence of charging events and states of the charging process. Three main components of the system are represented: EVs and charging stations as discrete entities, and an integrated platform that ensures the synergy between the two mentioned entities. The charging process, and especially the behavior of the three system components, are studied in the Discrete Events System point of view using (max, +) algebra combined with Petri nets (especially Timed Event Graph). These tools are chosen because of their efficient use in the literature for the modelling and evaluation of other

types of Discrete Event Systems (DES). Based on these tools, the developed graphical and analytical models are used to evaluate and analyze the system behavior and verify and validate certain of its qualitative and quantitative properties.

In the chapter 4, an adaptive charging policy is proposed to anticipate the assignment and the guidance of EV to CSs. This approach is based on a tuning method allowing to study a trade off between the number of charging requests and the number of charging points required to satisfy them. The objective is charging a maximum of EVs by using a minimum number of charging points (or charging stations). We also managed the increasing the charging rates and reducing waiting times as well as avoiding the accumulation of EVs within the suggested charging stations. In other word, the tuning based approach is proposed in order to improve the quality of service offered to EVs by adjusting the charging rates and the charging times at a given time interval.

In that chapter 5 we considered multiple EVs charging demands and using CSs with several charging points at a given time (i.e., periodically). The objective is to avoid appearance a long queue of EVs within charging stations. For doing so, prediction models have introduced to anticipate the average charging rates and the charging times for a set of EVs. In one hand, the predictive function is used to determine the average charging rates and times. In the other hand, the (max, +) model is extended to represent a more concrete configuration of the charging system while considering more than one charging point. The obtained results show the benefit of the use of the two scalable in terms of charging of maximum EVs with a minimum waiting times (or without waiting sometimes).

Contributions	Advantages(✓) and disadvantages(✗)
Optimal assignment and scheduling approaches	<ul style="list-style-type: none"> ✓ Linear programming for assignment of EVs to charging stations; ✗ EV Charging rates determination; ✗ EV Charging times determination;
Modelling approaches using (max, +) algebra	<ul style="list-style-type: none"> ✓ Global TEG model; ✓ (Max, +) linear model;
Adaptive based approaches	<ul style="list-style-type: none"> ✓ (Max, +) algebra; ✓ Charging the maximum number of EVs with the minimum CPs number; ✓ Adjustment charging rates and charging times; ✓ Charging battery at least 50% in order to reduce waiting times; ✗ Scalability: using multiple EV demands; ✗ Anticipation: considered only one EV for the time interval
Predictive and scalable approaches	<ul style="list-style-type: none"> ✓ Predictive algorithm based on average charging rates and charging times; ✓ A global anticipation of demands; ✓ Average charging rates and charging times for a set of EVs; ✓ Charging rates and charging times for each EVs individually.

Table 10. Contributions

II. Future works

In our future work, we will extend these proposed approaches in this study by developing further formal models. In other words, we will extend this methodology to model and evaluate the performance of a complex and large distributed charging system. More precisely, the behavior of the proposed charging process will be modelled as a probabilistic/stochastic process. The proposed models will be extended while combining $(\max, +)$ algebra with queuing theory to predict the charging process for EVs taking into account the random evolution of the system. Also, we will further develop the predictive function while studying more concrete situations of the system. Furthermore, real time issue will be taken into account and integrated into the developed models for real time management of EVs charging.

List of personal publications

International journals

- [1] A. Ruzmetov, A. Nait-Sidi-Moh, M. Bakhouya and J. Gaber “A Model-based approach for predicting the charging of electric vehicles” Minor revision: *Journal of Universal Computer Science (JUICS)*, 2015.
- [2] A. Ruzmetov, A. Nait-Sidi-Moh, M. Bakhouya, J. Gaber and M.-A. Manier “A discrete event-driven model for electric vehicles predictive charging”, Accepted in *International Journal of Adaptive, Resilient and Autonomic Systems (IJARAS)*, 2015.

International conferences

- [3] A. Ruzmetov, A. Nait-Sidi-Moh, M. Bakhouya and J. Gaber, “A (max - plus)-based approach for charging management of electric vehicles,” in *The 2nd World Conference on Complex Systems (WCCS14)*, Agadir, Morocco, 2014.
- [4] A. Ruzmetov, A. Nait-Sidi-Moh, M. Bakhouya and J. Gaber, “Towards an optimal assignment and scheduling for charging electric vehicles,” in *International Renewable and Sustainable Energy Conference (IRSEC)-2013*, Ouarzazate, Morocco, 2013.

List of Tables

Table 1. Comparative study for battery technologies and performances	25
Table 2. Assignment coefficients of EVs to Charging Station	42
Table 3. Values of assignment coefficients for time $t = t_0$	47
Table 4. Optimal assignment of EVs to charging stations.....	47
Table 5. Significance of TEG elements of the EV component.....	54
Table 6. Significance of TEG elements of the CPL	55
Table 7. Significance of TEG elements of the CS	56
Table 8. Legend of Figure 8.....	68
Table 9. Numerical values of system parameters	77
Table 10. Contributions	112

List of Figures

Figure 1. Charging process architecture	36
Figure 2. Communications V2G and G2V	38
Figure 3. The block diagram of general algorithm of charging process.....	40
Figure 4. TEG model of EV component.....	53
Figure 5. Collaborative Platform TEG model	55
Figure 6. TEG of CS component	56
Figure 7. Charging process TEG model	57
Figure 8. Event Graph model of the charging process	67
Figure 9. PTEG model of the charging process labelled with variables and times ...	72
Figure 10. Flowchart of calculation charging time and rate	79
Figure 11. Comparison of the evolution of charging time with arrival dates of charging requests.	80
Figure 12. Difference between arrival dates of the requests and the end of charging	81
Figure 13. Number of fully charged EVs	82
Figure 14. Evaluation result considering Table 9 and using several points	83
Figure 15. Predictive function and its parameters	87
Figure 16. Charging rate vs. the number of EVs	90
Figure 17. Comparison of the average charging times for two cases	91
Figure 18. Predicting the average charging times and rates for a set of EVs	92
Figure 19. Waiting time and charging time without considering needed energy.	93
Figure 20. Waiting time and charging time with considering needed energy.	94
Figure 21. Difference of the desired charging rate and proposed charging rate.....	94

Figure 22. Waiting time evolution	95
Figure 23. Charging process PTEG model with an open loop control	97
Figure 24. Waiting time and charging time with $M=1$	101
Figure 25. Waiting time and charging time of EV with $M=2$	103
Figure 26. Charging times and waiting times versus arrivals of requests	104
Figure 27. Comparison of the evolution of charging time and time slot	105
Figure 28. Charging times and waiting times vs. Arrival time ($M=2$)	106
Figure 29. Time slot and charging time	107

Literatures

- [1] W. Ait-Cheik-Bihi, M. Bakhouya, J. Gaber, R. Outbib, E. Coatanéa, X. Z. Gao and K. Zenger, "Towards an Integrated Service-oriented Energy Management Platform for Plug-in Hybrid Electric Vehicles," in *2nd IFAC Workshop on Multivehicle Systems*, Espoo, Finland, 2012.
- [2] "Electrifying the Automobile–Variations, Strategy for the Electro-era," *Magazine ADAC*, p. 19, April 2011.
- [3] A. Ruzmetov, A. Nait-Sidi-Moh and J. Gaber, "A (max - plus)-based approach for charging management of electric vehicles," in *The 2nd World Conference on Complex Systems(WCCSI4)*, Agadir, Morocco, 2014.
- [4] B. Saeid, J. M. Scott, C. F. Joel and K. F. Hosam, "Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity," *Journal of Power Sources*, pp. vol. 196, no. 1, pp.541-549, 2011.
- [5] H. Wiegman, *A review of battery charging algorithms and methods*, University of Wisconsin – Madison, Nov 28, 1999.
- [6] A. E.-S. A. Nafeh, "An effective and safe charging algorithm for lead-acid batteries in PV systems," *International Journal of Energy Research*, vol. 35, no. 8, pp. 733-740, 2011.
- [7] S. Bessler and J. Grønbaek, "Routing EV users towards an optimal charging plan," *International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*, vol. 56, 2012.
- [8] S. Gokay, C. Terwelp, C. Samsel, K.-H. Krempels, S. Rabenhorst and B. Greber, "Parking Lot Management for Charging Stations," in *SMARTGREENS 2014-3rd International Conference on Smart Grids and Green IT Systems*, Barcelona, Spain, 2014.
- [9] B. De Schutter and T. van den Boom, "Max – plus algebra and max – plus linear discrete event systems: An introduction," in *Proceedings of the 9th International Workshop on Discrete Event Systems (WODES'08)*, Göteborg, 2008.
- [10] F. Baccelli, G. Cohen, G. J. Olsder and J.-P. Quadrat, *Synchronization and linearity: an algebra for discrete Event Systems*, John Wiley & Sons, 1992.
- [11] A. Nait-Sidi-Moh, M.-A. Manier and A. El Moudni, "Spectral analysis for performance evaluation in a bus network," *European journal of operational research*, pp. 289-302, 2009.

- [12] "BCAA," [Online]. Available: <http://www.bcaa.com/campaigns/electric-vehicles/types-of-vehicles/battery-electric>. [Accessed June 2015].
- [13] "Hybrid Electric and Battery Electric Vehicles," *AEA Energy and Environment*, 2007.
- [14] "U.S. department of Energy," [Online]. Available: <https://www.fueleconomy.gov/feg/phevtech.shtml>. [Accessed June 2015].
- [15] K. Young, C. Wang, L. Y. Wang and K. Strunz, "Electric vehicle battery technologies," in *Electric Vehicle Integration into Modern Power Networks*, Springer, 2013, pp. 15-56.
- [16] "Bestgopower," Bestgo Power Co., Ltd. , [Online]. Available: <http://www.bestgopower.com/faq/30-what-is-depth-of-discharge-dod.html>. [Accessed 06 2015].
- [17] M. Coleman, W. G. Hurley and C. K. Lee, "An improved battery characterization method using a two-pulse load test," *IEEE Transactions on Energy Conversion*, vol. 23, pp. 708-713, 2008.
- [18] "energy4me," [Online]. Available: <http://energy4me.org/all-about-energy/what-is-energy/>. [Accessed June 2015].
- [19] M. Yilmaz and P. T.Krein, "Review of charging power levels and infrastructure for plug-in electric and hybrid vehicles," Greenville, SC, 2012.
- [20] "CLP online," [Online]. Available: https://www.clponline.com.hk/ev/Pages/ChargingSystem_ChargingMethods.aspx. [Accessed June 2015].
- [21] F. Pan, R. Bent and A. Berscheid, "Online dynamic scheduling for charging PHEVs in V2G," Los Alamos National Laboratory (LANL), 2011.
- [22] F. Pan, R. Bent, A. Berscheid and D. Izraelevitz, "Locating phev exchange stations in v2g. Smart Grid Communications (SmartGridComm)," in *2010 First IEEE International Conference on, Gaithersberg, MD*, IEEE, 2010.
- [23] O.Sundström and C.Binding, "Planning electric-drive vehicle charging under constrained grid conditions," in *International Conference on Power System Technology*, 2010.
- [24] Y. He, B. Venkatesh and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," vol. 3, no. IEEE transactions on smart grid, 2012.

- [25] J. Kang, S. J. Duncan and D. N. Mavris, "Real-time scheduling techniques for electric vehicle charging in support of frequency regulation," *Procedia Computer Science*, no. Elsevier, pp. 767-775, 2013.
- [26] H. Qin and W. Zhang, "Charging scheduling with minimal waiting in a network of electric vehicles and charging stations," in *Proceedings of the Eighth ACM international workshop on Vehicular inter-networking*, ACM, 2011, pp. 51-60.
- [27] S. Vandael, K. D. Craemer, N. Boucké, T. Holvoet and G. Deconinck, "Decentralized coordination of plug-in hybrid vehicles for imbalance reduction in a Smart Grid," in *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems – Innovative Applications Track (AAMAS 2011)*, Taipei, Taiwan, 2011.
- [28] B. Lunz, H. Walz and D. U. Sauer, "Optimizing vehicle-to-grid charging strategies using genetic algorithms under the consideration of battery aging," in *Vehicle Power and Propulsion Conference (VPPC)*, Chicago, IL, 2011.
- [29] Y. He, B. Venkatesh and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Transactions on Smart Grid*, pp. 1095-1105, 2012.
- [30] O. Sundstrom and C. Binding, "Planning electric-drive vehicle charging under constrained grid conditions," in *Power System Technology (POWERCON), 2010 International Conference on*, Hangzhou, 2010.
- [31] H.-J. Kim, J. Lee, G.-L. Park, M.-J. Kang and M. Kang, "An efficient scheduling scheme on charging stations for smart transportation," in *Security-Enriched Urban Computing and Smart Grid*, Springer, 2010, pp. 274-278.
- [32] E. W. Dijkstra, "A note on two problems in connection with graphs," *Numerische mathematik*, vol. 1, no. Springer, pp. 269-271, 1959.
- [33] R. Bellman, "On a routing problem," DTIC Document, 1959.
- [34] S. E. Dreyfus, "An appraisal of some shortest path algorithms," *Operations research*, vol. 17, no. INFORMS, pp. 395-412, 1969.
- [35] automobiles.honda.com. [Online]. Available: <http://automobiles.honda.com/information/frequently-asked-questions.aspx?Question=1>. [Accessed september 2015].
- [36] A. Ruzmetov, A. Nait-Sidi-Moh, M. Bakhouya and J. Gaber, "Towards an optimal assignment and scheduling for charging electric vehicles," IEEE, Morocco, 2013.

- [37] T. Murata, "Petri nets: properties, analysis and applications," in *In Proce. of IEEE 77 (4)*, 1989.
- [38] S. Collart-Dutilleul, «Les réseaux de Petri P-temporels: Modelisation et validation d'exigences temporelles,» chez *HDR(Habilitation à diriger des recherches)*, 2008.
- [39] VisualObjectNet, "http://www.r-drath.de/Home/Visual_Object_Net++.html," June 2014. [Online].
- [40] D.A.Alekseev, "Investigation of parameters of a logistic function and their economic interpretation," *Cybernetics and Systems Analysis*, vol. 36, no. 2, pp. 248-250, 2000-03-01.
- [41] R. Mkahl, A. Nait-Sidi-Moh and M. Wack, "Modeling and Simulation of Standalone Photovoltaic Charging Stations for Electric Vehicles," *In proc. of ICCCISE*, vol. 9, no. 1, pp. 72-80, 2015.
- [42] A. Boucherit. Conception d'un convertisseur de puissance pour les véhicules électriques multi-sources. Thèse de doctorat, Université de Technologie de Belfort–Montbéliard, 2011.
- [43] D. Diop. Contribution à la gestion de l'énergie d'un véhicule hybride série. Thèse de doctorat, Franche Comté, 2004.
- [44] J. C. Parejo, 24 Octobre 2008.
<http://www.petervaldivia.com/technology/energy/solar-power.php>.
- [45] D. Lu. Conception et contrôle d'un générateur PV actif à stockage intégré Application à l'agrégation de producteurs-consommateurs dans le cadre d'un micro réseau intelligent urbain. Thèse de doctorat, école centrale de Lille, 2010.
- [46] A. Nouh. Contribution au développement d'un simulateur pour les véhicules électriques routiers. Thèse de doctorat, Franche Comté, 2008.
- [47] R. Mosdale. Transport électrique routier batteries pour véhicules électriques. Techniques de l'ingénieur, (D5565), 2003.
- [48] B. Multon, O. Gergaud, G. Robin, and H. Ben Ahmed. Consommation d'énergie et ressources énergétiques. Techniques de l'ingénieur, (D3900), 2003.
- [49] J. Gallardo-Lozano, I. Milanés-Montero, M. A. Guerrero-Martínez, and E. Romero-Cadaval. Electric vehicle battery charger for smart grids. *Electric Power Systems Research*, 90 :18–29, Sep 2012.

- [50] G . Haines, A. McGordon, and P. Jennings. The simulation of vehicle-to-home systems – using electric vehicle battery storage to smooth domestic electricity demand. 2009.
- [51] J. Soares, T. Sousa, H. Morais, Z. Vale, and P. Faria. An optimal scheduling problem in distribution networks considering v2g. In IEEE, 2011.
- [52] R. Mkahl, A. Nait-Sidi-Moh, M. Wack. A Linear Optimization Approach for Electric Vehicles Charging. Accepted for publication in the Proc. of the 3rd International Renewable and Sustainable Energy Conference (IRSEC'15). Marrakech, Dec, 2015.
- [53] R. Mkahl, A. Nait-Sidi-Moh, M. Wack. Towards an Optimal Planning Approach for Electric Vehicle Mobility. Accepted for publication in the Proc. of the European Battery, Hybrid and Fuel Cell Electric Vehicle Congress (EEVC'15). Brussels, Dec 2015.
- [54] Thomas Erl. SOA Principles of Service Design. Prentice Hall PTR, Upper Saddle River, NJ, USA, 2007.7.
- [55] W. Ait-Cheik-Bihi. Approche orientée modèles pour la vérification et l'évaluation des performances de l'interopérabilité et l'interaction des services. Thèse de doctorat de l'Université de Technologie de Belfort Montbéliard.
- [56] Jean-Marie Chauvet. Service Web avec SOAP, WSDL,UDDI, ebXML... Eyrolles edition, mars 2002. 8.
- [57] A. Nait-Sidi-Moh, M. Bakhouya, J. Gaber, M. Wack. Geopositioning and Mobility. Wiley-ISTE, Networks and Telecommunications series; 272 pages. ISBN: 978-1-84821-567-2, May 2013
- [58] A Nait-Sidi-Moh, W Ait-Cheik-Bihi, M Bakhouya, J Gaber, M Wack. On the Use of Location-Based Services and Geofencing Concepts for Safety and Road Transport Efficiency. In: MobiWIS 2013 Workshops, CCIS 183 Edited by: M. Matera and G. Rossi. pp. 135–144, Springer International Publishing Switzerland, August 2013.
- [59] K Dar, M Bakhouya, J Gaber, M Wack, P Lorenz. Wireless Communication Technologies for ITS Applications IEEE Communications Magazine 48: 5. 156-162.
- [60] W Ait-Cheik-Bihi, A Nait-Sidi-Moh, M Bakhouya, J Gaber, M Wack. TransportML platform for collaborative Location-based services Service Oriented Computing and Applications 6: 4. 363-378.

- [61] A. Nait-Sidi-Moh. Contribution à la Modélisation, à l'Analyse et à la Commande des Systèmes de Transport Public par les Réseaux de Petri et l'Algèbre (Max, Plus). Thèse de doctorat de l'université de Technologie de Belfort Montbéliard. 2003.

Abstract:

In the last decades, very great research and development efforts have been made to develop and promote electric vehicles (EVs). Most efforts have been made to further develop the power engine of these vehicles and batteries technologies. However, one of the major obstacles to the large deployment of EVs is the uncertainty of drivers to get a suitable and vacant place at a charging station (CS). In this manuscript, we focus on the charging process modelling using formal approaches based on discrete event system tools namely (max,+) algebra and Petri nets. In addition, an optimization approach based on linear programming is proposed to optimally assign and reroute EVs to the suitable CSs and schedule their charging operations. In order to predict, manage and handle charging needs of EVs, a dedicated model based on a predictive function is introduced. The aim is to predict the average charging rate and time while considering the inter-arrival of charging requests and the state of charging of EVs. Using this approach, charging operations could be planned while minimizing waiting times of EVs and avoiding queuing situations within CSs. Simulation results showed that the proposed approaches allow assigning adequately and optimally EVs to CSs while satisfying all process constraints.

Keywords:

Electric vehicles; Optimal scheduling and assignment; Modelling and evaluation; (Max, +) algebra; Petri nets; Predictive function.

Résumé :

Au cours des dernières décennies, de grands efforts en recherche et développement ont été faits pour développer et promouvoir les véhicules électriques (VEs). La plupart de ces recherches portent essentiellement sur le développement des moteurs électriques de ces véhicules et des technologies de batteries de recharge. Cependant, un des obstacles majeurs pour le déploiement des VEs à grande échelle réside dans l'incertitude d'assister et de guider les conducteurs de ce type de véhicule d'une façon appropriée pour atteindre les stations de recharge tout en satisfaisant leurs souhaits (points de recharge disponibles, moins d'attente possible, proposition d'autres points d'intérêts : restaurant, shopping, etc.). Afin de remédier à ce manque, nous proposons dans ce travail de thèse une approche distribuée et adaptative orientée modèles pour la gestion de l'énergie pour la recharge des VEs. Pour ce faire, nous nous sommes focalisés sur la modélisation des processus de recharge en utilisant une approche formelle basée sur des outils de systèmes à événements discrets, à savoir l'algèbre (max, +) et les réseaux de Petri. Les modèles développés ont permis d'étudier, d'analyser et d'évaluer le comportement du système de recharge. De plus, une approche d'optimisation basée sur la programmation linéaire est proposée afin d'affecter et d'orienter d'une façon optimale les VEs vers les stations de recharge appropriées et ordonnancer leurs opérations de recharge. Afin de prédire le taux et la durée de recharge moyens des VEs compte tenu des dates d'arrivée des demandes de recharge et l'état de recharge de chaque véhicule, une approche dédiée basée sur une fonction prédictive est proposée. En utilisant cette approche, les opérations de recharge pourraient être planifiées en minimisant les temps d'attente des VEs au sein des stations de recharge et en assurant un taux de recharge acceptable pour chaque demande. Les résultats d'analyse et de simulations obtenus ont montré que les approches de modélisation, d'optimisation et de prédiction proposées permettent d'affecter de façon adéquate et optimale les VEs aux stations de recharge tout en satisfaisant toutes les contraintes du processus de recharge.

Mots clés :

Véhicules électriques ; Ordonnancement et affectation optimales ; Modélisation et évaluation ; Algèbre (Max, +) ; Réseaux de Petri; Fonction prédictive.



SPIM

Thèse de Doctorat



école doctorale sciences pour l'ingénieur et microtechniques
UNIVERSITÉ DE TECHNOLOGIE BELFORT-MONTBÉLIARD

**DISTRIBUTED AND ADAPTIVE APPROACHES FOR ENERGY
MANAGEMENT**

 **Azizbek RUZMETOV**