Novel Approaches to Optimize and Mitigate the Impact of High Penetration Level of Electric Vehicles on the Distribution Network

by

Claude EL-BAYEH

MANUSCRIPT-BASED THESIS PRESENTED TO ÉCOLE DE TECHNOLOGIE SUPÉRIEURE IN PARTIAL FULFILLMENT FOR THE DEGREE OF DOCTOR OF PHILOSOPHY
Ph.D.

MONTREAL, JULY 8, 2019

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
UNIVERSITÉ DU QUÉBEC

BOARD OF EXAMINERS

THIS THESIS HAS BEEN EVALUATED

BY THE FOLLOWING BOARD OF EXAMINERS

M. Ambrish Chandra, Thesis Supervisor
Department of Electrical Engineering at École de Technologie Supérieure

M. Maarouf Saad, Thesis Co-supervisor
Department of Electrical Engineering at École de Technologie Supérieure

M. Tony Wong, President of the Board of Examiners
Department of Systems Engineering at École de Technologie Supérieure

M. Pierre Jean Lagacé, Member of the jury
Department of Electrical Engineering at École de Technologie Supérieure

M. Akshay Rathore, External independent examiner
Department of Electrical Engineering at Concordia University

M. Serge Lefebvre, External evaluator
Research Institute of Hydro-Quebec

THIS THESIS WAS PRESENTED AND DEFENDED

IN THE PRESENCE OF A BOARD OF EXAMINERS AND THE PUBLIC

JUNE 25, 2019

AT ÉCOLE DE TECHNOLOGIE SUPÉRIEURE

ACKNOWLEDGMENT

First of all, I would like to thank Hydro-Quebec's Research Institute (IREQ) and École de Technologie Supérieure for providing me with the financial resources needed to complete the project.

I would also like to thank my director Professor Ambrish Chandra and my co-director Professor Maarouf Saad at the École de Technologie Supérieure, Professor Imad Mougharbel and Doctor Dalal Asber for their help and moral support, their involvement, their wise advice and their leadership in the success of this project. I would like to thank Professor Tony Wong who accepted to be the president of the board of examiners. I would like to thank Professor Pierre Jean Lagacé for his kindness and for his acceptance to let me participate in his course "ENR840 Comportement des réseaux électriques". Professor Pierre Jean helped me to elaborate a good understanding of the power and distribution systems and was happy to answer all my questions.

I am deeply grateful to all members of the jury for agreeing to read the manuscript and to participate in the defense of this thesis.

Finally, I would like to thank my parents Ziad and Georgette for their confidence, their love, and their support during all these years of study and encouragement.

Without the support of all members of my family, I would never finish this thesis and I would never find the courage to overcome all these difficulties during this work.

Nouvelles approches pour optimiser et réduire l'impact des véhicules électriques avec une pénétration élevée sur le réseau de distribution

Claude EL-BAYEH

RÉSUMÉ

Ces dernières années, l'intégration des véhicules électriques (VEs) sur le réseau de distribution a fait l'objet de plusieurs études approfondies. L'une des principales préoccupations est que les VEs consomment beaucoup d'énergie pendant une courte période, lorsque la plupart d'entre eux sont connectés simultanément pour charger leurs batteries même s'ils ne sont pas utilisés (pendant la nuit ou pendant les heures de travail). Par conséquent, si les problèmes de la charge simultanée ne sont pas résolus, des charges de pointe indésirables peuvent apparaître sur le réseau de distribution. C'est la raison pour laquelle la recherche se concentre actuellement sur des algorithmes d'optimisation et de contrôle à exécuter à différents niveaux du réseau. Étant donné que le nombre de véhicules électriques augmente considérablement, la demande en énergie pendant des périodes spécifiques de la journée causerait de graves problèmes sur le réseau. En fait, une demande de pointe élevée peut réduire de manière exponentielle la durée de vie des transformateurs et endommager certains équipements du réseau. Les conséquences peuvent être une grave chute de tension et des coupures de courant dans certaines régions ou sur l'ensemble du réseau. Pour résoudre ce problème, de nombreuses études ont été menées dans le but de réduire l'impact de l'intégration des véhicules électriques sur le réseau. Leur principal objectif était de limiter la demande de pointe créée par les véhicules électriques afin de protéger le réseau de distribution de tout dommage. Pour ce faire, de nombreuses techniques et stratégies d'optimisation ont été utilisées. L'objectif principal de l'utilisation de ces techniques est de planifier la charge et la décharge des VEs pendant leur période de connexion, au cours de laquelle leur charge sera décalée vers des périodes où la demande sur le réseau est faible. À cette fin, les programmes de réponse à la demande (PRD) sont utilisés pour inciter les utilisateurs à consommer lorsque les prix sont bas et à réduire leurs consommations lorsque les prix de l'électricité sont élevés. Comme son nom l'indique, le PRD utilise des modèles d'offre et de demande pour établir le prix de l'électricité en fonction de la consommation électrique de l'utilisateur et de l'énergie disponible générée par le service public. Le prix de l'électricité peut varier dans le temps et, dans les périodes de consommation élevée, il sera élevé afin de permettre aux utilisateurs de transférer leur consommation à d'autres périodes où le prix de l'électricité est moins cher. Cette stratégie aidera le fournisseur d'électricité à mieux contrôler la demande des utilisateurs et à réduire la charge pendant certaines périodes de la journée.

Malgré les avantages d'utiliser le PRD pour contrôler la demande totale de charge sur le réseau de distribution, ce programme reste limité par sa réponse à long terme (tarification d'un jour à l'avance, paramètres de durée d'utilisation prédéfinis pendant une saison, etc.). Par conséquent, un PRD est utile lorsque le temps de réponse n'est pas un problème critique, c'est-à-dire lorsque les pertes doivent être réduites, les dépenses des clients doivent être

minimisées ou les avantages pour l'opérateur doivent être maximisés. Un PRD ne peut éliminer aucune variation soudaine de la charge susceptible de provoquer une panne d'électricité, des dommages aux composants ou même une réduction de leur durée de vie.

Les recherches ont en effet suggéré plusieurs méthodes pour trouver des solutions rapides afin d'éviter tout phénomène technique ou économique indésirable sur le réseau. La revue de la littérature montre que les études existantes offrent une solution partielle du problème. On constate que les résultats publiés montrent une amélioration des problèmes techniques, économiques ou d'implémentation, mais à notre connaissance, les approches existantes ne peuvent pas trouver une solution optimale globale considérant tous les aspects de la distribution électrique (tarification, maintenance, satisfaction des clients, pertes techniques, stabilité, disponibilité, etc.). L'approche suggérée a une vision plus large du problème, car (a) elle considère la pénétration des VEs à différents niveaux du réseau, (b) elle considère aussi si l'infrastructure du réseau est classique ou modernisée, (c) elle prend en compte la durée de vie des transformateurs de distribution, (d) elle minimise les pertes et introduit un algorithme collaboratif pour trouver la solution optimale. Des études comparatives montrent les avantages de l'approche suggérée par rapport aux approches existantes. Les principales conclusions de cette thèse peuvent être résumées comme suit (i) la charge totale demandée au transformateur respecte sa limite, ce qui augmentera sa durée de vie, (ii) le profil de tension respecte les limites du réseau et la capacité des transformateurs, (iii) les pertes d'énergie sur le réseau sont réduites, (iv) le coût d'amortissement du réseau est réduit, (v) les revenus du gestionnaire de réseau et de distribution d'électricité sont augmentés, (vi) et enfin les utilisateurs sont satisfaits, car les stratégies proposées les aident à réduire leurs coûts en électricité. Par conséquent, les utilisateurs et le fournisseur d'électricité sont satisfaits.

Mots-clés: programme de réponse à la demande (PRD), réseau de distribution, véhicules électriques, gestion de l'énergie, optimisation, réseau intelligent, transformateur de distribution.

Novel approaches to optimize and mitigate the impact of high penetration level of electric vehicles on the distribution network

Claude EL-BAYEH

ABSTRACT

In recent years, the integration of Electric Vehicles (EVs) into the distribution network is studied intensively. One of the major concerns is that EVs consume lots of energy during a short period when most of them are simultaneously connected to the grid (during the night or during working hours). Therefore, in case the consequence of simultaneous charging is not resolved, undesired peak loads may appear on the distribution network. This is the reason why research is actually focusing on optimization and control algorithms to be executed at different levels of the network. Since the number of EVs increases drastically, the power demand during specific periods of the day would cause severe issues on the network. As a matter of fact, high peak demand may exponentially reduce the lifetime of the transformers and may damage some elements on the network. Therefore, severe voltage drop and blackouts of some regions or on the complete network can be the consequences. To solve the problem, many studies were conducted to reduce the impact of integrating EVs on the network. Their main goal was to limit the peak demand created by the EVs in order to protect the distribution grid from any damages. To do so, many optimization techniques and control strategies were used to mitigate the impact of EVs on the network. The main goal of using optimization techniques is to schedule the charging and discharging of EVs during their connection period, in which their charging will be shifted to periods where the demand on the network is low. For this purpose, Demand Response Programs (DRP) are used to incite the end-users consuming during low electricity prices and reducing their consumptions during high prices. As its name indicates, the DRP uses the supply and demand models to price the electricity depending on the power consumption of the end-users and the available power generated by the power utility. The electricity price may vary in time, in which in periods when the consumption is high, the electricity price will be high in order to let the end-users shift their power consumption to other periods when the price and the consumption are low. This strategy will help the power utility to control the power demand of the end-users and reduce the burden in certain periods in a day.

Despite the advantages of using the DRP in controlling the total load demand on the distribution network, it is still limited by its long-time response (one day ahead pricing, hour-ahead pricing, etc.). Therefore, DRPs are useful when the speed of response to a certain unfavorable situation does not require an instant action or intervention, in other words, when losses are to be reduced, customer expenses are to be minimized, and operator benefits are to be maximized. DRPs can't eliminate any sudden variation of the load which may produce a blackout or damage some components or even reduce their lifetime.

Researchers have indeed suggested multiple methods for finding fast response solutions in order to prevent any technical or economic undesired phenomena occurring on the network.

Literature review shows that these existing studies offer a solution for a partial aspect of the problem. It is seen that published results show the improvement on either technical or economic or implementation issues, but to the best of our knowledge, existing approaches cannot find a global optimum, considering all the electrical distribution aspects (pricing, maintenance, customer satisfaction, technical losses, stability, availability, etc.). The suggested approach has a wider view of the problem since it considers EV penetration at different levels of the network, it considers if the network's infrastructure is conventional or modernized, it considers the lifetime of the distribution transformers, it minimizes losses and it introduces a collaborative algorithm for finding the global optimum solution. Comparative studies show the advantages of the suggested approach compared to the existing ones. Major findings in this thesis can be summarized as follows (i) the total load demand on the transformer respects its limit, which will increase its lifetime, (ii) the voltage profile respects the limits on the network and the transformers, (iii) the energy losses on the network are reduced, (iv) the depreciation cost of the network is reduced, (v) the revenue of the power utility and distribution system operator is increased, (vi) and finally the end-users are satisfied because the proposed strategies help them to reduce their electricity cost. Therefore, both end-users and power utility are satisfied.

Keywords: Demand Response Program (DRP), Distribution Network, Electric Vehicles, Energy Management, Optimization, Smart Grid, Distribution Transformer.

TABLES OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BSS	Battery Storage System at home
CS	Centralized Control Strategy
DN	Distribution Network
DRP	Demand Response Program
DS	Decentralized Control Strategy
DSO	Distribution System Operator
DT	Distribution Transformer
EPU	Electrical Power Utility, such as Hydro-Quebec
EPU/DSO/ER	Electrical Power Utility, Electricity Retailer, Distribution System Operator who can provide the electricity price to the end users and can control their load in case it is needed
EWH	Electric Water Heater
EV / PEV	Plug-in Electric Vehicle
HS	Hierarchical Control Strategy
HSC	Power Soft-Constraint at Home
LC	Local Controller
LOL	Loss Of Life of the Distribution Transformer
MAS	Multi-Agent Control Strategy
MILP	Mixed Integer Linear Programming
PT	Programmable Distribution Transformer
PL	Parking Lot
PV	Photovoltaic
RES	Renewable Energy Sources

RTP	Real Time Price of Electricity
SDS	Soft-Constrained Distributed Strategy
SHEMS	Smart Home Energy Management System
SN	Serial Number of the DT
SOC	State Of Charge of the Battery in pu
TOU	Time Of Use Electricity Price
WT	Wind Turbine

LIST OF SYMBOLS AND MEASUREMENT UNITS

α	Constant expressed in the transformer aging equations
β	Binary variable, which designs the activation or deactivation of the Transformer Critical Power Limit
$\Delta\theta_r^{HS}$	the rated hottest-spot temperature rise over ambient at 1.0 per unit load, $[^oC]$
$\Delta\theta_t^{TO}$	Top-oil rise over ambient temperature, $[^0C]$
$\Delta\theta_t^{G}$	Winding hottest-spot rise over top-oil temperature, $[^0C]$
$\Delta\theta_{TO,R}$	Top-oil rise over ambient temperature at rated load on the tap position to be studied
$\Delta\theta_{G,R}$	Winding hottest-spot temperature at rated load on the tap position to be studied
Δt	Interval step of time, $[h]$, (e.g., 0.5 hours)
η_e^{Ch}	Charging Efficiency of the EV “e”
$\eta_{j,t}^{P}$	Ratio between the Distribution Transformer critical power limit and the total consumed power of all homes
η_j^{E}	Ratio between the Distribution Transformer critical energy limit and the total consumed power of all homes
π_t^{buy}	Buying electricity price from the grid, [$/kWh]
π^E	Proposed energy-based incentive programs, [$/kWh]
π^P	Proposed power-based incentive programs, [$/kW]
π_t^{RTP}	Real-Time Electricity Price, $[\$/kWh]$
π_t^{sell}	Selling electricity price from home to the grid, [$/kWh]
θ_0	Freezing temperature of the water, (273 Kelvin)
θ_{avg}^{A}	Average temperature during a year in a certain region. 5^0C is a safety margin
θ_{ref}	Reference temperature of the DT winding, $[\,^0C]$

θ_t^A	Ambient temperature, $[{}^0C]$
θ_t^{HS}	Winding hottest-spot temperature of the distribution transformer, $[{}^0C]$
$\mu_{j,t}^P$	Ratio between the Distribution Transformer's critical power limit and the sum of the installed circuit breaker rate of all homes
ADC_T^{Tr}	Actual depreciation cost of the transformer, [$]
B_e^{Cap}	Battery Capacity of the EV "e", [kWh]
C_{Tr}	Cost of the Transformer, [$]
$\cos(\phi_e^{EV})$	Power Factor of the EV number "e", it is equal to unity
e	EV number in the set $e \in [0, E]$
E^{DT}	Distribution transformer's critical energy limit during a day, [kWh]
E_T^{Ex}	excess of energy above the Energy-based Infrastructure Limit (E_j^{IL}) and the Energy-based Soft Constraint's limit (E_j^C) at home "j"
E_i^{buy}	Buying energy from the grid at home "i" for a day
E_i^{sell}	Selling energy to the grid from home "i" for a day
E_j^C	Energy-based Soft Constraint's limit at home "j"
E_j^{IL}	Energy-based Infrastructure Limit
F_t^{AA}	Aging Acceleration Factor
F_{EQA}	Equivalent Aging Factor of the DT for a period T
$k_{j,t}^{CP}$	satisfaction index of the power limit at home provided by an agreement between the power utility and the householder
k_j^{CE}	satisfaction index of the energy limit at home provided by an agreement between the power utility and the householder
$k_{j,t}^{IP}$	satisfaction index of the infrastructure power limit at home provided by an agreement between the power utility and the householder
k_j^{IE}	satisfaction index of the infrastructure energy limit at home provided by an agreement between the power utility and the householder

L_N	Normal insulation life in a DT, $[h]$, (e.g., 180 000 hours)
$LOL_{\%}$	Loss of life of the transformer in percentage
LOL_T	Loss Of Life of the transformer for the period T, in this paper the period T is equal to one day
m	Empirically derived exponent used to calculate the variation of $\Delta\theta_t^G$ with changes in load
N	number of homes on the same Distribution Transformer
p	Empirically derived exponent used to calculate the variation of $\Delta\theta_t^{TO}$ with changes in load
P_t^{buy}	Buying power from the grid, [kW]
P_i^{CB}	Circuit breaker rate at home "i", [kW]
$P_{e,t}^{EV}$	Charging power of the EV number "e" at instant "t", [kW]
$P_{e,t}^{EV,Max}$	Maximum charging power limit of the EV number "e" at instant "t", [kW]
$P_{\forall t}^{Ex}$	excess of power above the Power-based Infrastructure Limit ($P_{j,t}^{IL}$) and the Power-based Soft Constraint's limit ($P_{j,t}^{IL}$) for any instant "t" during a day
P_t^{sell}	Selling power from home to the grid, [kW]
$P_{e,t}^{Status}$	Charging status of the EV number "e" at instant "t", [kW]
$P_{i,t}^{buy}$	Buying power from the grid at home "i" at instant "t", [kW]
$P_{i,t}^{sell}$	Selling power to the grid from home "i" at instant "t", [kW]
$P_{j,t}^{IL}$	Power-based Infrastructure Limit from home "j" at instant "t", [kW]
$P_{j,t}^{C}$	Power-based Soft Constraint limit at home "j" at instant "t", [kW]
P_t^{DT}	Distribution transformer's critical power limit, [kW]
R	Ratio of load loss at rated load to no-load loss
RT_{DT}	Remaining lifetime of the distribution transformer

RDC_T^{Tr}	Reference depreciation cost of the transformer during a period T, [$/T]
S_{NR}	Transformer nameplate rating, [kVA]
S_t^{Load}	Total Load demand on the Distribution Transformer, [kVA]
S_t^{TCL}	Distribution transformer's critical power limit, [kVA]
SOC_e^i	Initial State Of Charge of the EV number "e" when arriving to the Parking Lot
SOC_e^f	Desired Final State Of Charge of the EV number "e"
t	Time in the set $t \in [0, T]$
T	Period of study, (e.g., 24 hours)
t_e^A, t_e^D	Arrival and Departure time of the EV "e"
x_t^{buy}	binary decision variable for buying power, which guarantee that the home cannot buy and sell energy at the same time
x_t^{sell}	binary decision variable for selling power, which guarantees that the home cannot buy and sell energy at the same time

INTRODUCTION

In order to reduce the pollution and fight the climate change, many countries started to integrate Renewable Energy Sources (RES) and incite the drivers to buy Electric Vehicles (EVs) instead of conventional cars with internal combustion engines. Particularly, the government of Quebec set goals in the near future to become a more sustainable and greener province with less pollution. Some of the most significant goals were to see the number of EVs account for one-third (33.33%) of the total sold cars by 2030. It is predicted that the total number of vehicles in Quebec will be about 8 million vehicles in 2030 based on the data from reference (Gouvernement-du-Québec, 2018). Therefore, if EVs account for 33% of the total market as stated in (Gouvernement-du-Québec, 2018), there will be over 2.6 million EVs on the roads of Quebec in 2030.

Despite the many advantages of the EVs in reducing pollution and maintaining a more sustainable and greener environment, their integration on the distribution network (DN) will create challenges and may cause severe problems when their penetration level becomes significant without any policy for implementing coordinated charging and discharging. EVs have a double-edged sword, in which their integration can bring lots of benefit to the Electrical Power Utility (EPU) such as Hydro-Quebec. This can only happen if intelligent algorithms for energy management are launched, otherwise, they can cause severe damages to the whole network. Furthermore, Distribution System Operators (DSOs) may experience important economic losses, which could reach several hundred billions of dollars. Therefore, their integration should be taken too seriously and they urge quick solutions to integrate them in an efficient way and reduce their negative impact on the grid.

Many studies were done in this field in order to mitigate the impact of integrating EVs on the network. Each published research paper has its advantages and limitations. Some of them are realistic to be realized in the near future and others are not. All these studies require that the integration of EVs and RES should be done within the context of a smart grid. However, the actual situations in Quebec and many other states and regions are still using conventional power systems. Therefore, the upgrading from a conventional to a smart grid needs time and requires lots of investment, which is rarely affordable in the near future. Considering the case in Quebec where, as mentioned before, about 2.6 million EVs will be on the road in 10 years. Due to the pace toward a greener environment, Hydro-Quebec would experience lots of pressure to compete with other regions in the world. As a matter of fact, the shifting from a conventional to a smart grid is much slower than the increased demand on the EVs. Hence, Hydro-Quebec should find, in the near future, quick and cheap solutions to mitigate the impact of EVs, meanwhile, the distribution network will be progressively shifted from a conventional to a smarter one.

To solve the mentioned problem and to fill the gap in the literature, this thesis proposes novel and cost-effective solutions to be implemented in the near future. This thesis is a part of a research project for Hydro-Quebec, which focuses more on electrical distribution in residential regions where end-users are involved in the energy management process. In this work, new electrical energy optimization models based on communication strategies are proposed. These strategies improve the global performance on the distribution system and increase its reliability, stability, and efficiency. Moreover, they reduce the energy losses on the network, maintain the power and voltage within the recommended limits, and increases the revenue of Hydro-Quebec while satisfying the end-users. In conclusion, win-win strategies are proposed to satisfy both Electrical Power Utility and customers.

This chapter is organized as follows. In the first section, the motivation and problem statement of the research are presented. In the second section, general and specific objectives are discussed. Then it is followed by the methods and the contributions. Finally, the organization of the thesis is presented.

0.1. Motivation and Problem Statement

In Quebec, a conventional distribution network is still used to transport energy from the power utility to the consumers. The conventional distribution network is not ready to support a high penetration level of Distributed Generations, Renewable Energy Sources (RES), Energy Storage Systems (ESS) and EVs. Hydro-Quebec has introduced new technologies to its power and distribution systems in order to improve the control and the efficiency of the network. The major introduced technologies can be described as follows:

1- Smart Meters: A smart meter is an electronic device, which records the power and energy consumptions at the end-user levels (e.g., homes, residential and commercial buildings, parking lots, etc.). It transmits the data and communicates with the Distribution System Operator (DSO) or the electricity supplier for billing and monitoring purposes. The smart meter can have more options in which the DSO or the electricity retailer can use to control some critical and non-critical loads at home (such as electric water heater). However, this control policy is still in its premature stage in Quebec because of privacy issues.

2- Electricity rates: Hydro-Quebec uses different electricity rates for different end-users depending on their consumption profiles and customer types. For example, domestic rates, rates for small, medium, and large power demands, etc. For the studied case in this thesis which is mainly domestic users, different rates are also presented according to (Hydro-Quebec, 2018). Rates D, DP, DM and DT are mostly used. These different electricity rates allow the end-users to better control their power and energy consumptions and to reduce their electricity bill. These rates are not variable in time; therefore, they are not ideal for a smarter grid. To implement optimization techniques and improve the scheduling of the controllable loads, it is necessary to use variable time-based electricity price.

Despite the many advantages of deploying smart meters, actually, they do not serve the Electrical Power Utility (EPU) more than monitoring the power consumption at homes. They could be advantageous if they are used to control some elements, such as heating systems in order to reduce the peak demand. However, without applying an optimized and adequately scheduled consumption profile, the use of smart meters would be inefficient. A more advanced control system should be deployed in which the load can be optimized by the end-users or by the Electrical Power Utility/Electricity Retailer/Distribution System Operator (EPU/ER/DSO). In addition, the actual policy related to electricity tariff is efficient for a short term, however, it will cause problems on a long term period, when the penetration level of RES and EVs increases. Therefore, to avoid this problem, a new electricity tariff policy should be considered.

0.2. Objectives

0.2.1. General objectives

The main objective of this research is to propose new control strategies and electricity tariff systems, which may help Hydro-Quebec to progressively shift from a traditional to a smarter grid. Suggested solutions provide Hydro-Quebec with practical ideas for facing the coming penetration of consumers having the possibility to inject power to the grid (also known as prosumers) without changing its existing infrastructure. Moreover, they will protect the infrastructure components (such as transformers, cables, buses, circuit-breakers, etc.) from damaging and lifetime reduction. For this purpose, the research work presented in this thesis has considered the following issues:

a- Use the existing power and distribution infrastructure,

b- Shift from a conventional to a smarter grid with the minimum investment cost,

c- Maximize the penetration level of RES and EVs on the grid without affecting the stability of the system,

d- Minimize the electricity cost at the end-user levels,

e- Minimize the power and energy losses on the network and their related electricity cost,

f- Maximize the revenue of Hydro-Quebec even in the worst case scenarios,

g- Minimize the damages to the network caused by a high penetration level of EVs and RES.

0.2.2. Specific objectives and methodology

The specific objectives can be summarized as follows:

a- Propose a new transformer limit called "Critical Power Limit of the Transformer", in which it guarantees that the lifetime of the transformer is equal or higher than the defined one by the manufacturer if it is respected.

Methodology: To address this specific objective, it is important to find the relation between this critical limit and the characteristics of the transformer as follows:

1- Find a mathematical expression of the proposed critical power limit in terms of:
- The ambient temperature,
- The hottest spot temperature of the transformer,
- The internal characteristics of the transformer,
- The aging acceleration factor of the transformer,
- and the Loss of Life of the transformer.

2- Propose a novel algorithm that solves the problem of nonlinearity of the mathematical expression and calculates the power profile of this limit,

3- Compare this limit to the nameplate rating limit regarding their impact on:
- The electricity cost of an EV parking lot,
- the Loss of Life of the transformer,
- The remaining lifetime of the transformer,
- Best financial profit increase for the aggregator (e.g., parking lot owner),
- Actual depreciation cost.

b- Propose a Soft-Constrained Distribution Strategy at home level in order to mitigate the impact of high penetration level of EVs on the Distribution network.

Methodology: To address this specific objective, the following steps should be considered:

1- Study extensively different types of control strategies in the literature review,

2- Find the best control strategy used for homes,

3- Propose a novel Home Energy Management System Algorithm, which considers EV load at home,

4- Deduce a novel communication strategy between the system operator, the electricity retailer and the end-users at home level,

5- Suggest new electricity pricing mechanisms in order to improve the performance of the algorithm and to better incite the end-users and increase the benefit of the system operator,

6- Optimize and schedule the consumption in homes according to the previously suggested ideas. Optimal results are compared with those published in the literature considering the following context,

   - The objective function is the same, although some modifications are performed for implementation reason.
   - Existing constraints related to the elements at home that will be optimized
   - Apply additional constraints to improve the optimization performance
   - Include the critical power limit of the transformer in the constraint part
   - Consider the suggested soft-constraint limit at home, which is function of the transformer critical power limit and the circuit breaker rates (of all homes supplied by the same transformer)

7- Compare the impact between the suggested strategy and existing one on:

   - The power consumption at homes and on the transformer,
   - The electricity cost at homes,
   - The loss of life and the remaining lifetime of the transformer, and its depreciation cost,
   - The voltage deviation on the transformer and the network,
   - Energy loss on the network and its cost.

c- Propose a programmable distribution transformer and an adequate control strategy to improve the energy management and reduce the congestion on the transformer level.

Methodology: To address this specific objective, the following steps will be considered:

1- Study different control strategies on the network and home levels,

2- Investigate the implementation of appropriate demand response programs,

3- Suggest a suitable scheme for bidirectional information flow between the system operator and the transformer,

4- Suggest a suitable scheme for bidirectional information flow between the transformer and the end-users,

5- Propose an algorithm in which it can control and manage the load demand of all homes on the transformer,

6- Compare our proposed strategy to an existing one in the literature,

7- Compare both strategies regarding their impact on,
   - The electricity cost at homes,
   - Power demand at homes and on the transformer,
   - Voltage deviation on the transformer and the network,
   - Energy losses on the transformer, the lines, and the network, and their cost,
   - The loss of life and the remaining lifetime of the transformer,
   - The depreciation cost of the transformer,
   - The upgrading cost of the infrastructure if our strategy will be used,
   - The total revenue of Hydro-Quebec.

0.3. Original contributions

Guided by the specific objectives and the methodology presented in subsection 0.2, to the best of the author's knowledge, the following original contributions have been achieved during this thesis work.

a- A critical power limit describes exactly the power profile limit of the transformer is suggested. It takes into account many factors such as the ambient temperature, the internal characteristics and the nameplate rating of the transformer, and many others,

b- A novel algorithm that solves the problem of nonlinearity and calculates this limit, c- A novel scheme of bidirectional data flow between the system operator and the end-users is suggested. It improves energy management at the end-users' level and respects the limits of the distribution network,

d- A soft-constrained distribution strategy is suggested to be used at homes. It takes into account the "Critical Power Limit of the transformer" and many other parameters,

e- An optimization model is suggested to improve energy management at home and on the distribution network,

f- An electricity tariff scheme is suggested to be associated with the optimization model. It incites the customers to use the proposed strategy, reduce their electricity cost, and maximize the benefit of the system operator,

g- Propose a Programmable Distribution Transformer (PDT), in which it uses distributed control strategy in order to control the total load of the end-users. It ensures that a total load of all homes will respect the distribution network limits and maximize the satisfaction of the customers by reducing their electricity cost.

0.4. List of publications

The contributions listed in Section 0.3 were presented in three journal papers and four conferences. The complete list of publications during the Ph.D. are listed below.

0.4.1. Journal papers

Published:

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Asber, D., Lenoir, L., & Lefebvre, S. (1 November 2018). Novel Soft-Constrained Distributed Strategy to Meet High Penetration Trend of PEVs at Homes. *Energy and Buildings*. Volume 178, Pages 331-346.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Asber, D., & Lefebvre, S. (1 October 2018). Novel Approach for Optimizing the Transformer's Critical Power Limit. *IEEE Access*. Volume: 6, Pages 55870 – 55882.

Under review:

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Asber, D., & Lefebvre, S. (2019). A Novel Approach for Mitigating the Impact of Electric Vehicles High Penetration on the Smart Grid. *IET Smart Grid*. Under Review.

Alzaareer, K., Saad, M., El-Bayeh, C. Z., Asber, D., Lefebvre, S. (2019). A New Sensitivity Approach for Preventive Control Selection in Real-time Voltage Stability Assessment. *IET Generation, Transmission & Distribution.* Under Review.

0.4.2. Conference papers

Published:

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., & Asber, D. (1-2 November 2018). Impact of Considering Variable Battery Power Profile of Electric Vehicles on the Distribution Network. *International Conference on Renewable Energies for Developing Countries*. Beirut, Lebanon.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., & Asber, D. (1-2 November 2018). Novel Multilevel Soft Constraints at Homes For Improving the Integration of Plug-in Electric Vehicles. *International Conference on Renewable Energies for Developing Countries*. Beirut, Lebanon.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., Asber, D. & Lenoir, L. (13-15 July 2016). A detailed review on the parameters to be considered for an accurate estimation on the Plug-in Electric Vehicle's final State Of Charge. *International Conference on Renewable Energies for Developing Countries*. Zouk Mosbeh, Lebanon.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., Asber, D. & Lenoir, L. (17-21 July 2016). A novel approach for sizing electric vehicles Parking Lot located at any bus on a network. *IEEE Power and Energy Society General Meeting (PESGM)*. Boston, MA, USA.

0.4.3. Newsletters

Published:

El-Bayeh, C. Z., Alzaareer, K. (June 2019). Control of Smart Distribution Networks for Voltage Correction and Transmission Network Support. Smart Grid Power Quality. *IEEE Smart Grid Newsletter.*

El-Bayeh, C. Z., Alzaareer, K. (May 2019). Adoption of Renewable Energy to Provide Ancillary Services. Provision Ancillary Grid Services. *IEEE Smart Grid Newsletter.*

El-Bayeh, C. Z. (March 2019). EV Scheduling for Distribution Peak Load and Grid Congestion Management. *IEEE Smart Grid Newsletter.*

Accepted:

El-Bayeh, C. Z., Alzaareer, K. (August 2019). Energy Management in Smart Grid. *IEEE Smart Grid Newsletter.* Accepted to be published in August 2019.

0.5. Thesis outline

The thesis includes 5 chapters and it is organized as follows:

a- Chapter 1 shows a general literature review related to the integration of electric vehicles on the network. Basic notions on the EVs are presented showing why it is important to shift from a conventional car with an internal combustion engine to an electric one. Then, it shows ancillary services that can be provided by EVs. Afterward, different charging and control strategies are presented and compared. Subsequently, a literature review on demand response and energy management at homes are presented. Finally, a conclusion is written in which the limitations in the literature are highlighted, and the current situation in Quebec is discussed.

b- Chapter 2 presents the fundamental concept in which each flowing chapter is based on. The main goal of this chapter is to give a basic idea about the formulation of the concept and methods used in the following chapters (paper-based chapter). Some results are discussed in order to show the obtained improvement using our proposed strategies and methods.

c- Chapter 3 presents the first published journal paper in ***IEEE Access*** (Impact Factor 3.557, 2018). The main goal of this chapter is to propose a critical power limit of the transformer, which guarantees a lifetime equal to the predefined one by the manufacturer. For simulation purposes, an EV parking lot is chosen as a case study, in which two methods are applied. The first method uses the conventional nameplate rating of the transformer (e.g., 100kVA), while the second one uses our proposed “critical power limit”. The main goal is to optimize the charging of the EVs in a way to minimize the electricity cost in the parking lot. Results show that our proposed power limit has increased the lifetime of the transformer and minimized the electricity cost under different weather conditions and different penetration levels of EVs.

d- Chapter 4 represents the second published journal paper in ***Energy and Buildings-Elsevier*** (Impact Factor 4.457, 2018). The main goal of this chapter is to propose a communication strategy between the DSO and the end-users (e.g., homes) in order to improve energy management on the distribution network. To do so, a soft-constrained power limit is suggested to be used at homes in order to guarantee that the summation of the total load demand of all homes will not exceed the transformer's power limit. For simulation purposes, two methods were used. In the first one, we use an existing strategy in the literature. In the second one, we use our proposed strategy. Both strategies are compared and results show that our strategy minimizes the energy and economic losses on the network and homes, increases the lifetime of the transformer, and respects the limits on the distribution network.

e- Chapter 5 represents the third paper submitted to ***IET Smart Grid***. The main goal of this chapter is to propose a novel smart algorithm, in which it improves the communication and energy management between the system operator and the end-users. To do so, we propose a novel programmable transformer, in which it can be remotely programmed to perform certain tasks such as managing energy between end-users. Moreover, a special communication infrastructure should be dedicated to facilitating the integration of the programmable transformer. Results show that the proposed algorithm and the proposed programmable transformer have improved the total performance of the network in the presence of high penetration level (43% and 100%) of electric vehicles and renewable energy sources. In addition, the proposed method shows a good return on investment, which encourages the system operator to use it in which its revenue will increase drastically compared to existing methods in the literature.

f- Finally, a conclusion and some recommendations are presented at the end, in which we conclude the whole work and propose some ideas to be considered in future works.

CHAPTER 1

LITERATURE REVIEW

1.1 Introduction

In this chapter, a thorough review of the literature regarding the integration of Electric Vehicles (EVs) on the distribution network is presented. In this regard, this chapter starts with a brief summary to show the basic notions of EVs and their advantages over conventional cars. Afterward, different charging and control strategies are analyzed. Moreover, this chapter presents a literature review on demand response programs, and energy management systems at homes, in which they are used to mitigate the impact of integrating EVs on the network. Finally, the actual situation in Quebec concerning the integration of EVs is explained and analyzed.

1.2 Background and problem statement

Climate change and global warming are considered one of the major issues that the globe is facing today (Pachauri et al., 2014). The global surface temperature of the earth is increasing every year (IPCC, 2014). Currently, the temperature has increased more than 1.1ºC above the pre-industrial levels (1720-1800 A.D.), (Hawkins et al., 2017). To prevent the gradual increase of the earth's surface temperature, the Paris Agreement set a limit in order to keep the temperature below 2ºC above the pre-industrial levels (Hawkins et al., 2017). Higher temperature rise can yield disasters to the life on earth such as mass extinction of species, rise in the sea levels, expansion of deserts, extreme weather events, etc. (Zeng & Yoon, 2009), (Council, 2012). According to (IPCC, 2007), the Earth's average surface temperature is increasing by 0.13ºC every decade. It means that in about six decades (≈2070 A.D.) the temperature will reach the limit of 2ºC. In references (Field et al., 2014) and (Field, 2014) they predict that the limit will be reached by 2050 for a high emission scenario. In fact, the increase in the average temperature is exponential due to the high increase in the population and the consumption (Hawkins et al., 2017), (IPPC, 2007). Therefore, the limit will be reached much earlier than the predicted ones.

The main cause of increasing the temperature of the globe is the high emission of greenhouse gases such as CO_2 and methane (Stocker, 2014). Unfortunately, the transportation sector produces about 15% of the total CO_2 emission worldwide (Rodrigue, Comtois, & Slack, 2016). Therefore, to overcome this situation, many countries have started to shift from conventional Internal Combustion Engine (ICE) vehicles to Electric Vehicles (EVs) in order to reduce the emission of greenhouse gases (Bunsen et al., 2018). The future of EVs is prominent, in which their integration is increasing every year. According to (Bunsen et al., 2018), the sales of electric vehicles in 2017 has surpassed one million units worldwide with an increase of 54% compared to 2016. In Norway, EVs presented a market share of 39% of the newly sold vehicles in 2017. It is predicted that the total number of EVs will reach 565 million by 2030 (Bunsen et al., 2018). Moreover, gas-powered cars will be banned by 2025. In Germany, all new cars must be EVs by 2030 (University of Central (University-of-Central-Florida, 2015). Despite the many advantages of the EVs in reducing the pollution, they may have a negative impact on the Distribution Network (DN) (Rajakaruna, Shahnia, & Ghosh, 2016), (Williamson, 2013), (Lu & Hossain, 2015), (X. Yang et al., 2017). High penetration level may perturb the network, create severe voltage drops (Qian, Zhou, & Yuan, 2015), and reduce the lifespan of some elements (Claude Ziad El-Bayeh et al., 2018), (C. Z. El-Bayeh et al., 2018), which will cost billions of dollars (US-Department of Energy, 2018). Therefore, it is necessary to work on reducing the negative impact of EVs on the power systems.

Before studying the existing control strategies related to the process of charging/discharging EVs, some basic notions of EVs will be presented. This would help the reader to understand why it is important to optimize their charging process and what will happen if they are optimized. Afterward, the chapter presents a brief literature review on the demand response, and different energy management systems used at homes to coordinate the charging of EVs with other controlled elements.

1.3 Basic notions of Electric Vehicles

1.3.1 Why is the integration of EVs an interesting topic to study?

The future direction towards a smarter grid consists of introducing smart elements such as Distributed Generations, which can be controlled and can supply energy to the power grid. A sophisticated communication between the Distributed Generations and different parties (such as the Power and Distribution System Operators (DSO), Electricity Retailer (ER), and end-users) is required in order to improve the performance of the grid and reduce the risk of any possible perturbations. Some examples of Distributed Generations are, but not limited to, Photovoltaics (PVs), Wind Turbines (WT), Energy Storage Systems (ESSs), Electric Vehicles (EVs), and many others. The main role of the Distributed Generation is to provide as much as possible a continuous balance between generation and consumption (i.e. supply energy to the grid when it is needed, and consume/store energy when there is an excess of generation on the network). Despite the many advantages of ESSs such as batteries, space heating, Electric Water Heaters (EWH), etc., current studies are focusing on the integration of electric vehicles, because they may offer a positive contribution to the grid stability and provide ancillary services without any noticeable investment. In the following subsections, a brief introduction about EVs is presented, the advantages and barriers facing their intensive integration on the network are briefly discussed.

1.3.2 Different types of Electric Vehicles

An Electric Vehicle (EV) in this thesis refers to every vehicle that is fully or partially powered by electricity to supply its electric or traction motors, and its internal needs of electricity. The electricity can come from off-vehicle sources or self-contained with a battery, photovoltaic, or an electric generator that converts fuel to electricity. The EVs include, but not limited to, electric cars, electric aircraft, electric spacecraft, electric-bikes, electric trains, electric boats, etc. However, in this thesis, we are limiting the term to only the electric cars, which can be plugged in and charged from the grid. There are different types of EVs, some of them are stated as follows:

- Plug-in Full Battery Electric Vehicle (PEV), in which its total energy consumption comes from a battery, which is charged by connecting it to the power grid, without the need of any additional source of energy,
- Plug-in Hybrid Electric Vehicle (PHEV), in which it uses at least two sources of energy to supply its needs. The first one is a fuel-based Internal Combustion Engine, the second one is a battery, which can be charged by plugging it to the power grid or by converting the fuel energy to electricity,
- Plug-in Hybrid Range Extender Electric Vehicle (REEV), in which it is similar to the PHEV, in addition, it uses an additional engine to convert fuel energy to electricity for supplying the vehicle's needs,
- Hybrid Electric Vehicle (HEV) is similar to the PHEV, but its battery is only charged by converting fuel and breaking energy to electricity. The HEV cannot be plugged into the power grid.

1.3.3 Electric Vehicle vs. internal combustion engine car

Electric Vehicles are emerging technologies and newly deployed in the market. Despite their high price compared to an Internal Combustion Engine (ICE) car, in the long term, they can be more beneficial for the customers for many reasons which are stated in Table 1.1.

Table 1.1 Comparative Summary between the EV and an ICE car

Description	Electric Vehicle	ICE Car
Charging cost per 100km	2.1$ Per 100 km	10.65$ Per 100 km (for a conventional compact car) (Bruemmer, 2018)
Maintenance frequency	Few	Very frequent
Maintenance expenses	Low (fewer parts)	High
Green House Gases emission and Pollutant particles	No	Yes (CO2, CO, NOx, SOx, PM10, PM2.5, etc.
Noise pollution	No	Yes
Energy Conversion Efficiency	High (≈90%)	Low (≈30%)
Return on Investment period	Shorter (EVs are less expensive in the long term compared to ICE cars)	Longer
Range of Operating speed	Wide (no need for gears, to move through their full speed range)	Few
Regenerative breaking (generate energy from the break)	Yes	No
Provide full torque from stationary	Yes	No
Less pollutant source of energy	Yes (can be electrically charged from non-pollutant sources such as PV, WT, Hydroelectric power plants, nuclear plants, etc.)	No (they need fuel to function which is very pollutant source)
Government support	Yes, many governments (such as the Quebec government) provide subsidies and rebates to encourage people buying EVs instead of ICE cars, (2019)	No

It was expected that the market share of the EVs would increase rapidly. However, the increasing rate is slow (2.1% worldwide of the newly sold cars in 2018), since the major barriers come from the battery storage system and other factors as they will be presented as follows:

- EVs are more expensive than the ICE cars for the same categories and specs (despite it is much cheaper in the long term; customers always tend to see the proposed price without considering the long term benefits),

- EVs are difficult to be charged when the charging infrastructure is not well deployed in the region or the country,
- Batteries are costly, and their lifetime is short compared to the ICE car's engine. Therefore, they should be changed every 5 to 10 years (It depends on the quality of the battery and the frequency of usage),
- The battery's degradation depends on many factors; it is very high in hot and extreme cold weathers. However, in extremely cold regions (such as in Quebec in winter), the range anxiety is drastically increased (Range anxiety is the fear that a vehicle has insufficient range to reach its destination). EV may stop working after a few kilometers from the departure, even if it is fully charged,
- The Lithium-Ion battery can explode if it is overheated,
- The range anxiety is high compared to a normal ICE car,
- The driving range is lower than the same model of an ICE car. It is one of the major drawbacks of an EV,
- Energy density is low compared to an ICE car. In other words, to produce the same amount of energy, EVs should be much heavier than a similar ICE car. It is because the battery should be larger in order to generate the same amount of energy.

These barriers will be limited in the future, since the price of the battery is declining every year, and its performance and lifetime are increasing. Hence, the deployment of EVs is very promising and urges fast and efficient solutions in order to mitigate their impact on the distribution network.

1.3.4 Ancillary services provided using Electric Vehicles

Electric Vehicles can be considered as a good source to provide ancillary services to the distribution network. Ancillary services provided are well explored in the literature. In Figure 1.1, we classify them into different categories. The first category is the regulation of voltage and frequency, in which the EVs can be used to maintain the voltage and frequency on the network within the recommended limits. This can be done using the on-board (e.g., inside the EVs) and off-board converters (e.g., chargers in the parking lot) in which the variation of the phasing angle change the flow of the active and reactive power from the EV to the grid and vice versa. Therefore, it allows the correction of voltage and frequency. EVs can be used to compensate the active and reactive power depending on the needs of the distribution network. It means if there is a shortage of the active power on the network (in another meaning, the network needs additional energy to supply the users), EVs can react as spinning reserve and provide active power to balance the demand-supply ratio on the grid. Moreover, the advantage of EVs is that they can be charged at homes, in parking lots and charging stations, on the road, in industries, in residential and commercial buildings, in which they reduce the investment cost of the network regarding the installation of additional storage systems, bank capacitors, etc. They can improve the energy management in which they act instantly by shaving the peak load, reducing the congestion on the network. Hence, the grid stability and quality are improved.

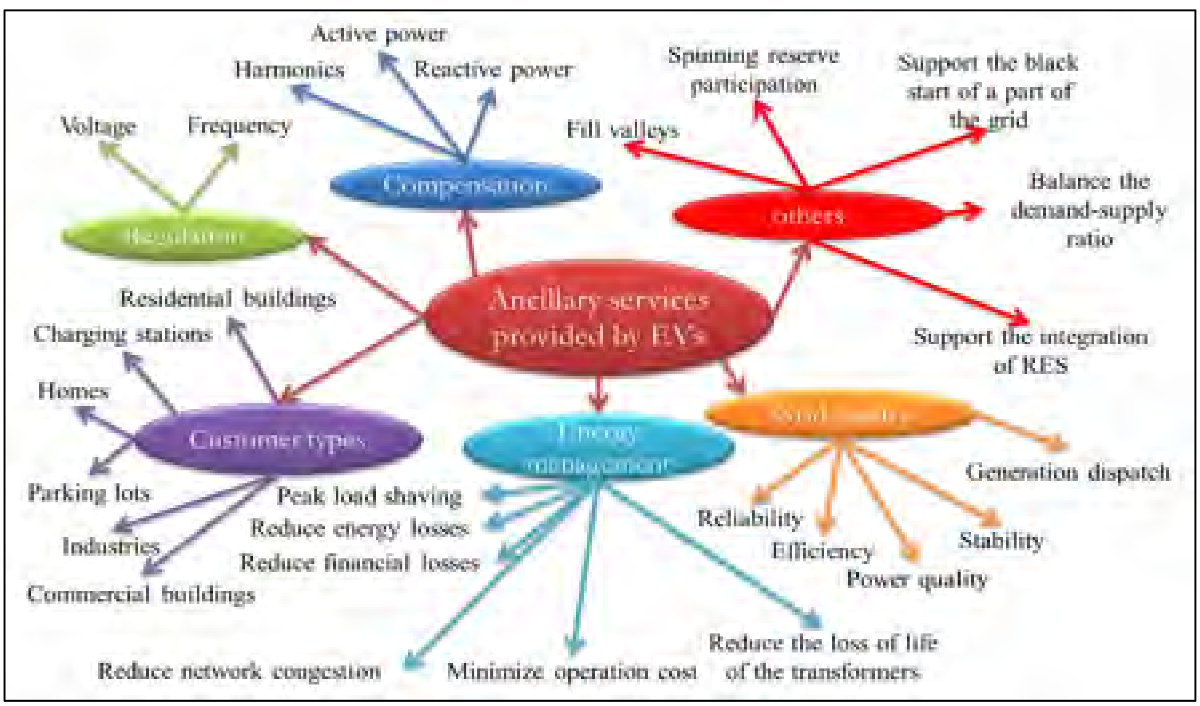


Figure 1.1 Illustration of the main ancillary services provided by a fleet of EVs

1.4 Charging strategies

In the previous subsection, ancillary services provided by EVs are presented and classified. However, the successful level of providing ancillary services depends on the charging strategies used to charge and control EVs efficiently. In this subsection, the four main charging strategies are presented and compared regarding their advantages and barriers from the viewpoint of the EV owner, aggregator, distribution system operator, and from an environmental perspective. The four main categories of charging strategies are as follows:

- **Uncoordinated Charging (UC)**: EV starts charging when it is plugged to the electrical outlet without any delay. It is the case of all existing EVs in the market. Moreover, the charging is neither controlled nor optimized. Hence, it may cause problems to the distribution network in case many EVs are simultaneously connected,
- **Uncoordinated Charging and Discharging (UCD)**: it is similar to the previous one; however, the discharging process is applied. EVs can supply energy to the grid or the aggregator. The discharging process is neither controlled nor optimized. Hence, it is not an ideal way to reduce the electricity cost by discharging the EV in an uncoordinated manner,
- **Coordinated Charging (CC)**: A smart algorithm is used to control and schedule the charging process of a single or a fleet of EVs. Even when EVs are plugged, they will not necessarily start charging immediately, they follow certain charging schedules. This strategy guarantees an optimal charging process in terms of the owner's satisfaction and distribution network stability. However, the cost of implementation is higher than the uncoordinated charging,
- **Coordinated Charging and Discharging (CCD)**: It is the best strategy among all those mentioned. It allows EVs to smartly charge and discharge using smart algorithms considering one or more objective functions, and many constraints. Sophisticated optimization techniques and models are used. These smart algorithms schedule the time of charging and discharging of EVs and other controllable loads, in a way that the electricity

cost is minimized respecting certain constraints and limits. This strategy will be discussed in the next subsection, in which sophisticated control strategies are used to optimize and schedule the electrical loads.

The mentioned charging strategies are compared from different perspectives as shown in Table 1.2. The interest of the EV owner is to minimize the charging electricity cost while maintaining the battery's lifetime. The aggregator (e.g., parking lot owner, charging station owner) is interested in maximizing his benefit, respecting the DSO's limits, and meeting the needs of the EV owners. The main goal of the DSO is to maintain the stability on the network, reduce the economic and energy losses, minimize the damages, and cut down the operation cost. Therefore, sophisticated optimization algorithms are required. It is also mandatory to consider the impact of the mentioned strategies on the environment because the main goal of introducing EVs and other RES is to reduce the pollution and the emission of GHGs.

The comparison between different control strategies is presented in the form of likert scale. Likert scale is used to simplify the comparison without presenting many details regarding the results. However, the information and results for each point can be found in the corresponding reference. In general, CCD is more advantageous compared to other strategies because it uses bidirectional power flow, which may support the grid when additional generation energy is needed. Moreover, because optimization techniques are used, the CCD has the ability to adapt the charging of EVs considering other factors on the network and their limits. While for the case of UCD, each end-user charge and discharge his EV independently without considering other factors on the network, which may cause problems.

Table 1.2 Advantages and barriers of different charging strategies

Likert scale: ★☆☆☆ Strongly disagree; ★★★★ Strongly agree **Description:**	**UC**	**UCD**	**CC**	**CCD**
Perspective: EV owner				
Minimize charging electricity cost (Ito et al., 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Impact on the battery • Fast degradation of the battery's lifetime (Ahn, Li, & Peng, 2011)	★☆☆☆	★★★★	★☆☆☆	★★★☆
• Increase cycling wear	★☆☆☆	★★★★	★☆☆☆	★★★☆
• Reduce the storage capacity due to the lifetime degradation (Dogger, Roossien, & Nieuwenhout, 2011)	★☆☆☆	★★★★	★☆☆☆	★★★☆
High cost of EV due to the complex topology of the converters (Yilmaz & Krein, 2013a)	★☆☆☆	★★★☆	★★☆☆	★★★★
The final SOC is equal to the desired one by the EV's owner (Clement-Nyns, Haesen, & Driesen, 2010),	★★★★	★★☆☆	★★★☆	★★☆☆
Perspective: Aggregator (Parking lot, householder, commercial & residential building, etc.)				
Minimize total demand electricity cost (Fotouhi Ghazvini et al. 2017)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Complex charging algorithm for EVs (Van-Linh et al. 2014)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Require complex control, communication, and data acquisition for EVs, aggregator, distribution network and other parties (G. Xu, May 2013),	★☆☆☆	★☆☆☆	★★★☆	★★★★
Maximize the financial benefit of the aggregator (Amjad, Ahmad, Rehmani, & Umer, 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Respect the limits imposed by the DSO (Uddin et al., 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Perspective: Distribution System Operator				
Network limits are respected (C. Z. El-Bayeh et al., 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Response time for ancillary services is shorter than other conventional power generators (Yao, Lim, & Tsai, 2017)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Reduce the LOL of the transformer due to high power demand (Claude Ziad El-Bayeh et al., 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Provide Ancillary services (Milanes-Montero, Martinez, E. Gonzalez, Romero-Cadaval, & Barrero-Gonzalez, 2016)	★☆☆☆	★☆☆☆	★★★☆	★★★★
• Frequency regulation (Falahi, Hung-Ming, Ehsani, Le, & Butler-Purry, 2013)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Improve grid stability (Singh, Kumar, & Kar, 2012),	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Voltage regulation (A. S. Masoum, Deilami, Abu-Siada, & Masoum, 2015)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Reduce Total Harmonic Distortion (M. A. S. Masoum, Deilami, & Islam, 2010)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Support the integration of RES (Al-Awami & Sortomme, 2012)	★☆☆☆	★☆☆☆	★★★☆	★★★★
• Spinning reserve participation (Khodayar, Lei, & Shahidehpour, 2012)	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• EVs are used as Virtual Energy Storage Plants (Peterson, Whitacre, & Apt, 2010)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Improve power quality (A. S. Masoum et al., 2015)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Improve grid efficiency and reliability (Srivastava, Annabathina, & Kamalasadan, 2010),	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Active and Reactive power flow regulation (A. S. Masoum et al., 2015), (Milanes-Montero et al., 2016),	★☆☆☆	★★☆☆	★★☆☆	★★★★

Table 1.2 Advantages and barriers of different charging strategies (Continued)

Likert scale: ★☆☆☆ Strongly disagree; ★★★★ Strongly agree **Description:**	**UC**	**UCD**	**CC**	**CCD**
• Improve generation dispatch (Yilmaz & Krein, 2013b)	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• Replace large-scale energy storage systems (Yilmaz & Krein, 2013b),	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• Black start of a part of the grid (Yifeng, Venkatesh, & Ling, 2012)	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• Peak shaving (Yilmaz & Krein, 2013a)	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• Shift the hourly generation portfolio (A. S. Masoum et al., 2015)	★☆☆☆	★☆☆☆	★☆☆☆	★★★★
• Balance the Load by valley filling and minimize load variance (Moghbel, Masoum, & Fereidoni, 2014)	★☆☆☆	★☆☆☆	★★★☆	★★★★
• Generate revenue from ancillary services (Khodayar et al., 2012)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Reduce network congestion and load factor (Moghbel et al., 2014),	★☆☆☆	★☆☆☆	★★☆☆	★★★★
Operation cost is reduced for				
• Power plants (Saber & Venayagamoorthy, 2010)	★☆☆☆	★☆☆☆	★★☆☆	★★★★
• Power grid (A. S. Masoum et al., 2015)	★☆☆☆	★★☆☆	★★★☆	★★★★
• Reduce dependency on small/micro expensive power units (Saber & Venayagamoorthy, 2010)	★☆☆☆	★★☆☆	★★★☆	★★★★
• Turn off some generators during on-peak time by providing energy to the grid using V2G (Khodayar et al., 2012),	★☆☆☆	★★☆☆	★★★☆	★★★★
• Avoid additional investment on the infrastructure	★☆☆☆	★★☆☆	★★★☆	★★☆☆
• Reduce the possibility of a blackout, which may be costly	★☆☆☆	★★☆☆	★★★☆	★★★★
• Reduce line losses and their cost (C. Z. El-Bayeh et al., 2018)	★☆☆☆	★★☆☆	★★★☆	★★★★
Power and Energy Losses are reduced (Claude Ziad El-Bayeh et al., 2018)	★☆☆☆	★★☆☆	★★★☆	★★★★
Upgrade the infrastructure to support the high penetration of EVs, which will have a high-cost impact (A. S. Masoum et al., 2015)	★☆☆☆	★★★☆	★★☆☆	★★★★
Respect the limits of the network (C. Z. El-Bayeh et al., 2018)	★☆☆☆	★☆☆☆	★★★☆	★★★★
Perspective: Environment				
Emission of GHG and pollution such as CO2, NOx, etc. are reduced for: • EV (Bunsen et al., 2018)	★★★★	★★★★	★★★★	★★★★
• Conventional Power plants due to the charging of EVs	★☆☆☆	★☆☆☆	★★☆☆	★★★☆
• During peak demand (Bruemmer, 2018)	★☆☆☆	★☆☆☆	★★☆☆	★★★★

From Table 1.2, it can be remarked that the “Coordinated Charging and Discharging Strategy” is the best one amongst all others. However, it requires complex algorithms and infrastructure to be implemented. This strategy is the main focus of this thesis. Therefore, it is necessary to explore how its implementation could be simplified in a cost-effective way and how the EVs and other controllable loads can be controlled and optimized. In the following subsections, a literature review is conducted concerning different control strategies and algorithms used to optimize and schedule the power flow of EVs and other controllable loads.

1.5 Literature review on different control strategies

To overcome the negative impact of integrating EVs on the distribution network, many control strategies were developed to optimize and schedule the power flow of EVs and other controllable loads. There are mainly four major control strategies, which are used for this purpose: (i) centralized, (ii) hierarchical, (iii) Multi-Agent, and (iv) decentralized, as shown in Figure 1.2. The goal of these strategies is to optimize the charging/discharging of a single or a fleet of EVs in the presence of controllable and non-controllable loads, in a way to minimize the total electricity cost. These four control strategies are presented as follows:

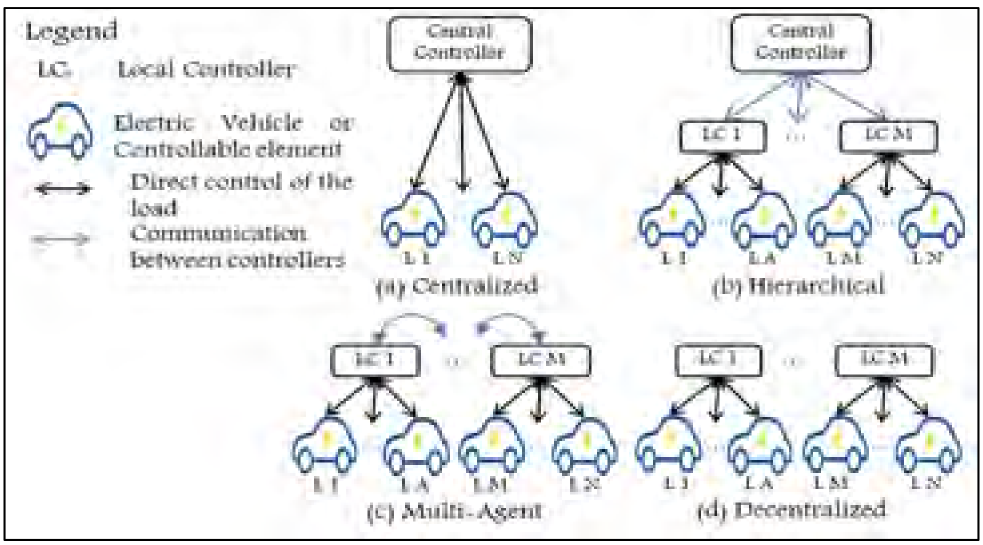


Figure 1.2 Different control strategies for the same number of loads
(a) Centralized, (b) Hierarchical, (c) Multi-agent, and (d) Decentralized

1.5.1 Centralized control strategy

In a centralized control strategy (CS), as shown in Figure 1.2.a, a central controller is responsible for managing and scheduling elements such as EVs and other controllable electrical loads (Morstyn, Hredzak, & Agelidis, 2016). For example, in an EV parking lot, the aggregator uses a single optimization algorithm (local controller) that is able to schedule and optimize the charging and discharging of its all EVs. The objective function could be minimizing the total electricity cost, or maximizing the revenue and the financial benefit of the aggregator. The optimization is based on respecting the constraints of the aggregator, the power network, and the end-users.

This strategy is mostly used in parking lots (Shao, Wang, Shahidehpour, Wang, & Wang, 2017), (Yao et al., 2017), (El-Bayeh et al., 2016b) and charging stations (Anand, de Salis, Yijie, Moyne, & Tilbury, 2015; Yong, Ramachandaramurthy, Tan, & Mithulananthan, 2015), (Wang, Xiao, & Wang, 2017) when a central controller is needed. It ensures that a globally optimal solution is obtained when controlling and scheduling elements such as EVs. Therefore, both aggregator and end-users are satisfied. The aggregator maximizes its revenue while satisfying the EV owners by charging their batteries to the desired State of Charge SOC levels, and reducing their charging cost. This strategy is not suitable when EVs are charged in separate units such as in homes, commercial and residential buildings, which are the studied case in this thesis. This is due to the privacy issues of the customers and due to the complexity of controlling separate units. Some customers do not allow the aggregator or the power utility to control their own load and do not want them to know what they are using as electrical appliances. Therefore, the EPU/DSO/ER should respect their will and privacy. Moreover, the centralized strategy becomes difficult when the number of customers increases. Consequently, the number of different constraints set by customers will be definitely increased. This would make the optimization problem more complicated and much time-consuming.

1.5.2 Hierarchical control strategy

In a hierarchical control strategy (HS), as shown in Figure 1.2.b, different control levels in form of a hierarchical tree are used to manage and schedule elements such as EVs and other controllable electrical loads (Morstyn et al., 2016). The central controller (first control level) is responsible for making decisions and organizing the coordination between secondary controllers to attain a global objective (Shao et al., 2017). In return, the secondary controllers receive the order from the central controller, and they act accordingly in commanding tertiary level controllers. The process repeats until the lowest level controller directly optimizes the electrical loads of the end-users. Each level returns feedback (the optimal solution) to its higher level controller (Z. Xu, Su, Hu, Song, & Zhang, 2016). The feedback serves the higher level controllers at correcting the scheduling process in order to attain a globally optimal solution.

Because the centralized strategy is difficult to be used on a larger scale network, the hierarchical one is considered instead. This strategy reduces the complexity of the system and the time response. However, it has limitations also, the global solution is not the optimal one, and this strategy is complicated and not very efficient compared to other strategies. Bidirectional communication is required which may cost lots of money for the power utility. Moreover, it has many problems regarding controlling and managing the power flow in the presence of energy storage systems (Morstyn et al., 2016). This strategy is less common to be used to control the loads at homes and residential buildings due to its complexity. Therefore, other control strategies such as multi-agent and decentralized are used, which provide better energy management at homes and residential buildings.

1.5.3 Distributed multi-agent control strategy

In a distributed multi-agent control strategy (MAS), as shown in Figure 1.2.c, each local controller optimizes the power demand of its load and exchange data with its neighbors in order to achieve cooperative objectives (Morstyn et al., 2016). This strategy improves the performance of the control compared to the decentralized strategy, and it has advantages in terms of flexibility, scalability, and robustness over the centralized one. Despite the many advantages of this strategy, complex communication infrastructure is needed between the local controllers, which may cost a fortune for the power utility. All the three mentioned strategies are less common to control loads at homes, while in this paper, our interest is to manage energy at home level while satisfying both the end-users and the system operator.

1.5.4 Decentralized control strategy

In a decentralized control strategy (DS), as shown in Figure 1.2.d, each local controller tries to manage its loads without communicating with any external agents or units (Morstyn et al., 2016), (Paterakis, Erdinç, Bakirtzis, & Catalão, 2015), (Steen, Tuan, & Carlson, 2016), (Xiaohua Wu, Hu, Teng, Qian, & Cheng, 2017). The local controller optimizes its controllable elements using an objective function (such as minimizing the electricity cost at home) and many constraints for each element. The optimization process guarantees that the optimal solution is obtained, which is much better than any other control strategy (such as the previously mentioned ones). The satisfaction factor of the householders by using this strategy is very high because of the significant reduction in their electricity costs. Despite the advantages of this strategy from the viewpoint of the end-users, it has many barriers and limitations on the network level. The system operator will not be satisfied for many reasons. The end-users (e.g., householders) do not take into account external factors and network constraints into their optimization model (Fotouhi Ghazvini et al., 2017), (Melhem, Grunder, Hammoudan, & Moubayed, 2017). Moreover, obtaining an optimal local solution for each householder does not necessarily contribute to a global one on the distribution network. Therefore, many end-users can have high power demands in the same period, which may create problems.

1.5.5 General conclusion regarding the control strategies

In Table 1.3, we present a comparison between the mentioned strategies regarding their advantages and limitations. It can be shown that the most satisfying strategy for the system operator is the worst one for the end-users and vice versa. All these limitations in these four mentioned strategies led us to think about another way of controlling load, in which both end-users and the system operators will be satisfied. On one side, end-users reduce their electricity cost while their constraints are met. On the other side, the system operator is satisfied because energy and economic losses on the network are reduced, revenue and profit are increased, with the minimum upgrading cost of the infrastructure. For this purpose, two novel strategies are proposed in Chapters 4 and 5 to fill the gap in the literature.

Table 1.3 Advantages and limitations of the controlled strategies

Description	CS	HS	MAS	DS
Minimize the electricity cost of all loads on the network from the viewpoint of the aggregator (G. Xu, May 2013), (Khodayar et al., 2012),	★★★★	★★★☆	★★☆☆	★☆☆☆
Minimize the electricity cost of particular end-users such as in homes, (Khodayar et al., 2012),	★☆☆☆	★★☆☆	★★★☆	★★★★
High satisfaction factor of the system operator (e.g., parking lot), (A. S. Masoum et al., 2015),	★★★★	★★★☆	★★☆☆	★☆☆☆
High satisfaction factor of the end-users (e.g., EV owner), (G. Xu, May 2013)	★☆☆☆	★★☆☆	★★★☆	★★★★
Power losses are minimized on the feeder or power network (Sortomme & El-Sharkawi, 2011), (Khodayar et al., 2012)	★★★★	★★★☆	★★☆☆	★☆☆☆
Maintain the feeder within its operating constraints (Sortomme & El-Sharkawi, 2011), (Khodayar et al., 2012), (A. S. Masoum et al., 2015)	★★★★	★★★☆	★★☆☆	★☆☆☆
The amount of data increases significantly when the number of connected load increases (Leemput et al., 2011)	★★★★	★★★☆	★★☆☆	★☆☆☆
Large and complex communication infrastructure is needed to handle the data (Leemput et al., 2011)	★★★★	★★★☆	★★☆☆	★☆☆☆
Flexible in direct controlling elements (Morstyn et al., 2016)	★☆☆☆	★★☆☆	★★★☆	★★★★
Scalable (it can be applied on large scale network) (Morstyn et al., 2016)	★☆☆☆	★★☆☆	★★★☆	★★★★
Robustness in the optimization and control (Morstyn et al., 2016)	★☆☆☆	★★☆☆	★★★☆	★★★★
Fast convergence to the optimal solution	★☆☆☆	★★☆☆	★★★☆	★★★★
Local optimal solution	★☆☆☆	★★☆☆	★★★☆	★★★★
Global optimal solution	★★★★	★★★☆	★★☆☆	★☆☆☆
Simplicity of the control	★☆☆☆	★★☆☆	★★★☆	★★★★
Best suited for a large number of controlled elements	★☆☆☆	★★☆☆	★★★☆	★★★★
Best suited for a small number of controlled elements	★★★★	★★★☆	★★☆☆	★☆☆☆

*Likert scale: ★☆☆☆ for strongly disagree, ★★★★ for strongly agree.

The success of the control strategies and optimization algorithms cannot be accomplished without introducing time-based electricity price and demand response programs. The main reason is that the optimization and the control work better in a variable electricity price environment. The algorithm always shifts the major energy consumption to periods when the price is low and reduces consumption when the price is high. The Distribution System

Operator (DSO) and the Electricity Retailer (ER) define the electricity price and demand response depending on their strategies and goals. For example, when they see that the most power demand occurs in the morning, they can increase the electricity price during this period, in order to let the customers shift their electrical loads to periods when the price and the consumption are low. In this way, the DSO/ER can control indirectly the total load on the network in a way to reduce the energy congestion. A brief literature review on the demand response is presented in the next subsection.

1.6 Literature review on demand response

Demand Response (DR) is the change in the electrical power demand of the customers on the power grid to better match their power consumption with the power supply from the Electric Power Utility (EPU). The EPU may send signals (e.g., time-varying electricity price) to the customers requesting them to change their power consumptions in order to shift their demand to off-peak time. In the case the customer responds to this request, his electricity cost will be reduced. If not, it could become higher, or some additional electricity tariffs can be applied. Figure 1.3 shows an example of a demand response when three different time-based electricity prices are applied. The first one uses Time-of-Use (ToU), in which the price is divided into three block levels, on-peak, mid-peak, and off-peak prices. The second shows are Real-Time Price (RTP), and the third shows block prices for energy consumption.

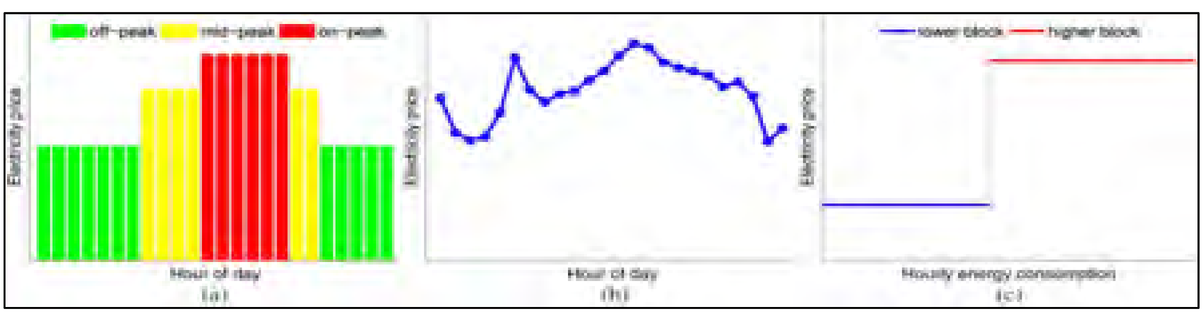


Figure 1.3 Example of Demand Response using time-based pricing tariffs. (a) Time-of-Use, (b) Real-time price, (c) Inclining-block rate Taken from (Deng, Yang, Chow, & Chen, 2015)

The development of smart meters enables two-way communications between the end-users and the power utility, by which demand response becomes an essential characteristic of a smart grid (Deng et al., 2015). Customers can benefit from the demand response to reschedule their energy demand in accordance with the incentive and electricity prices. In addition, DR is an effective way to reduce the congestion on the network and reduce operating expenses of expensive generators when the loads are rescheduled (Deng et al., 2015). Hence, the global performance, efficiency, and reliability of the power and distribution systems are improved. DR is mainly divided into two main branches as follows (Deng et al., 2015):

1.6.1 Incentive-based program

Under the incentive-based program, DSO/ER pays end-users for demand reduction in certain periods when there is a need to balance between the supply and the demand in order to maintain the stability and reduce the losses on the network. Some additional tariffs may be applied to the end-users who do not participate in the DR program. The main programs are listed as follows:

- **Direct load control:** The power utility has the authority to remotely control certain loads of the end-users such as air conditioner, water heater, space heating, etc., in order to reduce the peak demand in certain periods. End-users will benefit from this program by reducing their electricity bill. This program is mostly offered to residential and small commercial customers,
- **Interruptible/Curtailable load:** End-users will get benefits by reducing their electricity bills in case they participate in reducing their load demand in some periods when the grid reliability is jeopardized and risks losing its stability,
- **Demand bidding and buyback:** customers benefit from bidding price to save their electricity cost by participating in electricity curtailment. This program is mostly offered for large customers (1 MW and more),
- **Emergency demand reduction:** Sometimes, the peak demand can appear in a very short period, which may put the network in a danger and make the grid out of the

reserve. Therefore, the power utility needs an urgent reduction in the load demand in these short periods, in which the customers can get paid in case they participate in the load curtailment. Usually, large customers can provide auxiliary services to the power utility.

1.6.2 Price-based program

When we talk about the smart grid, we talk about smart pricing in which the electricity prices change in time according to the demand and supply. Flat electricity price is mostly used in conventional grids in most of the countries. However, a flat price (also called fixed or constant price) is not ideal for the smart grid because it doesn't encourage users to shift their loads to off-peak time nor reduce their consumption during the on-peak time. Therefore, the electricity price should vary in time and depend on the needs of the EPU/DSO/ER. It is supposed that the price-based program will encourage users to consume less when the price is high (high power demand), and consume more when the price is low (low power demand). This program implicitly induces end-users to dynamically control their load demand, without direct intervention from the EPU/DSO/ER in scheduling their loads. The most important price-based programs are presented as follows:

- **Time-of-Use (ToU) Pricing:** Usually ToU price is composed of several blocks of price during a day, as shown in Figure 1.3.a. The time period of a block is usually more than one hour. The block prices are chosen in a way to increase the electricity charge during the on-peak time, and reduce the charge during off-peak time. They may vary during days, months and seasons. This type of pricing is employed in Ontario, Canada,
- **Critical peak pricing (CPP):** It is similar to the ToU for normal days; however, in some periods in a year, when the grid reliability is jeopardized for certain reasons, the EPU/DSO/ER sets a predefined higher value during critical hours in order to reduce the risk on the network,

- **Real-time Pricing (RTP):** it is also called dynamic pricing, in which the electricity price is always variable in small interval steps (e.g., 15 minutes) during a day. The price is predefined hour-ahead or day-ahead. It provides more flexible pricing compared to other prices and regarded as one of the most efficient price-based programs. It is deployed in Illinois, USA (Deng et al., 2015),
- **Inclining block rate (IBR):** This tariff is based on energy consumption during an hour, or a day, or a month, in which it suggests two levels of prices. The first level is a basic level of tariff and the second one is when the consumption exceeds a threshold during specific periods as mentioned before. It is adapted in many countries such as in British Columbia, Canada.

1.6.3 Other demand response programs

In the above subsections, price-based and incentive-based programs are presented. However, there are many other programs offered in the literature and can be summarized as follows:

- **Energy-based program:** This tariff is independent of the price-based program. It penalizes or rewards the end-users depending on their energy consumptions. End-users are penalized if their energy consumptions exceed a predefined limit during a certain period (e.g., a day, a week, or a month), else, they are rewarded. This tariff is mostly used to incite the end-users to limit their energy consumption during a certain period, in which it may help the EPU/DSO to match the supply and demand of energy,
- **Power-based program:** This tariff is independent of the price-based program. Its main goal is to limit the power consumption during critical periods in which there is a possibility of energy congestion on the network. End-users who exceed a certain predefined value will pay additional fees. Some power utilities such as Hydro-Quebec is using this tariff for large institutions such as at Ecole de Technologie Superieure, Canada, in which a power consumption above a certain limit (e.g., 5MW) is charged by a high tariff.

Figure 1.4 shows a summary of the most used demand response programs as stated in the previous subsections.

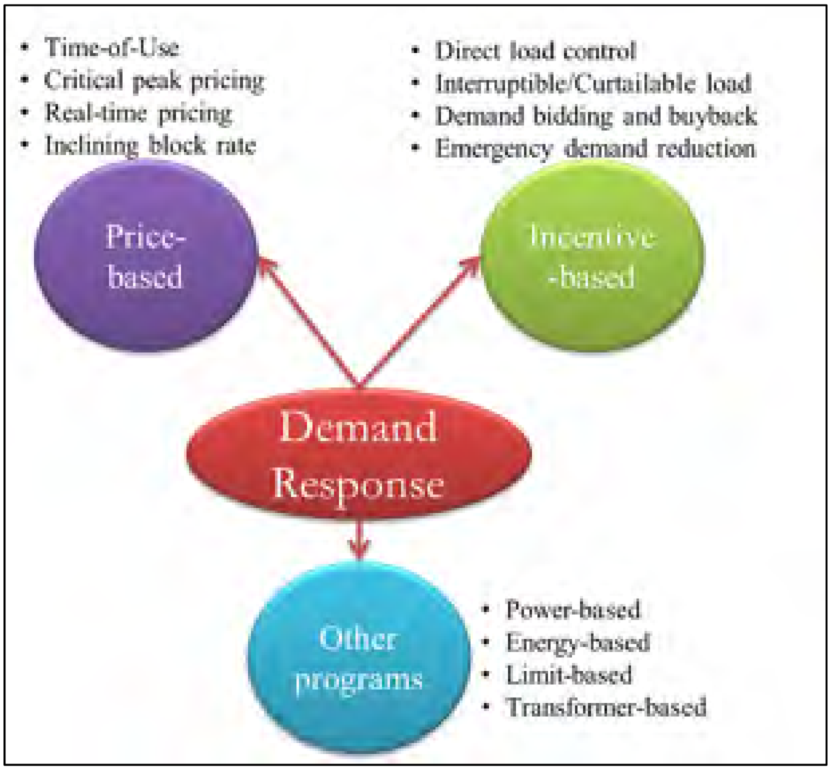


Figure 1.4 Illustration of different demand response programs

1.6.4 Limitation of the existing demand response programs

Despite the advantages of the proposed demand response programs, each one of them has some drawbacks and limitations. Demand response can help the end-users to reschedule their loads based on the electricity price provided by the EPU/DSO/ER. However, the high penetration level of EVs may cause severe problems on the network even if DR programs are deployed. Let us take an example of one of the best demand response program which is RTP. In this case, if RTP is used with a step interval of 15 minutes, and during low electricity price, most of the EVs will charge extensively in order to minimize their charging electricity cost. Therefore, high peak demand can be created in this period in which the EPU/DSO/ER has no authority to change the price, it has been already set. Therefore, DR is not enough to be deployed alone in the future smart grid. It is necessary to find new pricing mechanisms in order to limit the impact of high energy demanding elements such as EVs and BSS. In this thesis, we propose a decentralized demand response and incentive programs in which each end-user has his proper DR program. The decentralization of DR according to each end user's energy consumption needs will show great advantages to the EPU/DSO/ER, which will be discussed in the next chapters.

Moreover, DR programs cannot be considered successful programs without the help of the customers, in which they should use smart algorithms and energy management systems to reschedule and control their electrical loads. Hence, it is necessary to do a literature review on the energy management algorithms used to control the load demands at homes, which is the main goal of this thesis.

1.7 Literature review on energy management at homes

The main goal of a Smart Home Energy Management System (SHEMS), is to optimize and schedule the electrical load at home in response to the demand of the EPU/DSO/ER. The literature review on the energy management at homes is performed on three main related topics, (i) optimization algorithms, (ii) objective function, and (iii) constraints. These topics are extensively explored in order to improve the performance of the energy management at homes according to the offered DR program and electricity prices.

1.7.1 Optimization algorithms

To better manage the electric appliances at home in response to the needs of the EPU/DSO/ER, smart algorithms should be used in order to optimize energy consumption. For this purpose, many optimization algorithms were introduced and developed in the literature. Their main goal is to solve the optimization problem with the minimum required time while maintaining a good level of accuracy, and respecting the constraints. These most used algorithms in home energy management can be classified as presented in Table 1.4.

Table 1.4 Most common optimization algorithms

Algorithm	Reference
Mathematical programming	
• Convex programming	(Deng et al., 2015)
• Linear	(G. Xu, May 2013)
• Nonlinear	(Høyland & Wallace, 2001)
• Mixed-integer linear	(Fady Y. Melhem, April 28, 2017)
• Mixed-integer nonlinear	(Lunci, Jia, & Chi, 2014)
• Quadratic	(Ramachandran & Ramanathan, 2015)
• Mixed-integer quadratic	(Ramchurn, Vytelingum, Rogers, & Jennings, 2011)
• Stochastic	(Al-Awami & Sortomme, 2012)
• Dynamic	(Yunjian & Feng, 2012)
Meta-heuristic	
• Genetic Algorithm	(Jinghong, Xiaoyu, Kun, Chun, & Shouzhen, 2013)
• Particle Swarm Optimization	(JunHua, Fushuan, Zhao Yang, Yusheng, & Kit Po, 2012)
• Ant Colony Optimization	(Ciornei & Kyriakides, 2012)
• Biogeography-based optimization	(Simon, 2008)
• Differential evolution	(Storn & Price, 1997)
• Simulated annealing	(Aarts & Korst, 1989)
• Tabu search	(Pereira Junior, Cossi, Contreras, & Sanches Mantovani, 2014)
Artificial Intelligence	
• Artificial Neural Networks	(Ahmed, Mohamed, Shareef, Homod, & Ali, 14-16 Nov. 2016)

1.7.2 Objective function

The mostly used objective function at home is to minimize the electricity cost (Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017), (Xiaohua Wu et al., 2017), (Steen et al., 2016). It is also called “cost function”, in which the energy can be bought and sold from the network (Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017), (Xiaohua Wu et al., 2017), (Steen et al., 2016). Some papers consider unidirectional power flow in which the home only buys energy from the grid (Xiaohua Wu et al., 2017), (Steen et al., 2016), (X. Wu, Hu, Yin, & Moura, 2016), (Rassaei, Soh, & Chua, 2015). Other papers consider bidirectional power flow in which the home can buy and sell energy from/to the grid (Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017), (Paterakis et al., 2015). The consumed energy includes home appliances, EVs, and BSS. The sold energy comes from EVs, BSS, PV, and wind turbine.

1.7.3 Constraints and elements at home

The electrical elements at home can be divided into two main categories, controllable and non-controllable elements. Controllable elements are included in the optimization model, in which a smart controller has the authority to reschedule these elements and optimize their power and energy consumptions. While the non-controllable elements do not participate in the rescheduling process nor included in the optimization model. For example, a water heater can be considered as a controllable element at home "A" because it is included in the optimization model, while it is considered as a non-controllable element at home "B" because it is not included in the model.

In the literature, constraints in the optimization model are considered for different elements at home such as appliances, source of energy, energy storage, etc. To better choose how to optimize and include each element in the optimization model, we have classified them into five major types as presented below, and as depicted in Figure 1.5.

- **Fixed Power consumption (FP):** it means that the element always consumes a fixed power and it is not possible to change its value during its operation. For example, a TV consumes a fixed power (e.g., 0.5kW) and it is hard to change it. To control this element, we can just turn it on and off without changing its power demand value,
- **Variable Power consumption (VP):** On the contrary, a VP means that the power of the element could be changed or controlled in the optimization process. For example, we can control the power demand of a water heater and change its power consumption at each instant. E.g., instead of consuming 3kW at 07:00, it may consume 1kW based on the optimal results,

- **Shiftable Load (SL):** It means that the load can be shifted in time to other periods in which it doesn't affect the satisfaction of the user. For example, the householder needs to wash his clothes by the end of the day. Therefore, it doesn't matter if the washing machine functions in the morning, noon, or afternoon. The main goal is to get his clothes washed before the end of the day. Hence, the smart controller considers that the washing machine is a shiftable load and can be shifted to work in periods when the electricity price is low while it is performing the same job without affecting the satisfaction of the householder,
- **Non-shiftable Load (NL):** It means that the load cannot be shifted in time to another period due to some restrictions. For example, a fridge at home should always be turned on and cannot be turned off and shifted to another period. Another example, turning on a lamp cannot be shifted when someone enters a room in the evening, it should be always turned on,
- **Long-term Load (LL):** It means that the load is always consuming power and cannot be turned off in normal conditions such as a fridge.

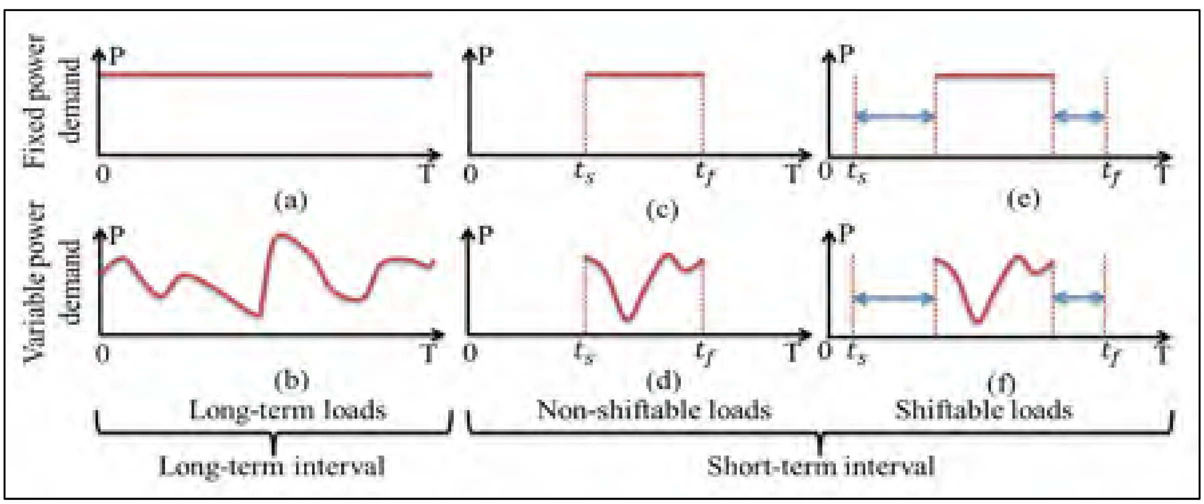


Figure 1.5 Illustration of power and time domains for different load categories

Table 1.5 shows some elements, which are considered in the optimization model in the literature. Each element has both power and time domains. A power domain can have the form of fixed or variable power consumption, while the time domain can have a form of shiftable, non-shiftable, or long-term loads.

Table 1.5 Constraints of electrical loads at home

Type of elements	**Home Elements**	**Reference**	**Power domain**		**Time domain**		
			FP	**VP**	**NL**	**SL**	**LL**
Power grid	Power balance	(Fotouhi Ghazvini et al., 2017)		✓			✓
	Main circuit breaker	(Fotouhi Ghazvini et al., 2017)	✓				✓
Storage system	EV	(Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017), (Xiaohua Wu et al., 2017), (Steen et al., 2016)		✓		✓	
	Home Battery	(Xiaohua Wu et al., 2017), (Paterakis et al., 2015)		✓			✓
RES	Photovoltaic	(Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017)		✓		✓	
	Wind turbine	(Melhem et al., 2017)		✓			✓
Appliances	Air conditioner	(Fady Y. Melhem, April 28, 2017)	✓			✓	
	clothes dryer	(Steen et al., 2016)	✓			✓	
	dishwasher	(Steen et al., 2016)	✓			✓	
	EWH	(Fotouhi Ghazvini et al., 2017), (Fady Y. Melhem, April 28, 2017)		✓		✓	
	hot water boiler	(Steen et al., 2016)		✓			✓
	HVAC	(J. H. Yoon, Baldick, & Novoselac, 2016)		✓		✓	
	Refrigerator	(Fady Y. Melhem, April 28, 2017)	✓			✓	
	Washing machine	(Steen et al., 2016)	✓			✓	

1.7.4 Limitations of the existing literature

Despite sophisticated algorithms are used to schedule the electrical loads at homes, and despite many elements are used to improve the performance and increase the reliability of the optimization, there is a gap in the literature. This gap can be summarized as the missing link between what is inside and outside the home. Sophisticated optimization of the load demand at home will not be enough to solve the high penetration level of RES and EVs. A local optimal solution at each home may not guarantee that the total load on the network will not exceed its limits. Therefore, this thesis tries to solve the problem in which the transformer's critical power limit should be introduced (as in Chapter 3), and considered in the optimization model and constraints, as it is presented in Chapters 4 and 5. In addition, because of the topology of the decentralized strategy, which exists in most of the research papers in the field, the optimization process will always have flaws even if more controllable elements are added and sophisticated algorithms are used. To address this issue, we propose new control strategies and topologies of the network in Chapters 4 and 5, in which the problem of a high penetration level of EVs and RES is solved. Moreover, we propose a decentralized demand response program in which each end-user is provided by a special DR according to his needs and his consumption's behavior.

1.8 Situation in Quebec

Quebec is one of the leading provinces and regions in the world, in which they are trying to encourage people to buy EVs and find solutions to their integration on the network. Some of the most encouraging news about the situation of EVs in Quebec are stated as follows:

- The government of Quebec issued policies that grant rebates on EV purchases ($8,000 for an all-electric car, $4,000 for an electric-gas hybrid), (Bruemmer, 2018),
- The province set an ambitious target of getting 100,000 EVs on its roads by 2020. However, only 24,000 of them are on its roads until now (≈2.2% of the overall automotive sales in the province), (Bruemmer, 2018),
- The government set a goal to see EVs account for one-third of all new vehicle sales by 2030, (Bruemmer, 2018),
- The electricity rates in Quebec is the cheapest in North America because it comes from hydro-electric power, (Bruemmer, 2018),
- The selling of EVs is increasing every year. In 2017, the purchases of EVs are increased by 44% compared to 2016, (Bruemmer, 2018),

- In Quebec, there are about 1,500 public charging stations, and 110 of them are fast charging stations, (Bruemmer, 2018),
- The dealers' policies encourage the clients to buy cheaper conventional cars because they can sell faster cars and in big quantities, which increase their income. Moreover, these cars require more maintenance, which guarantees more incomes to the dealers, (Bruemmer, 2018).

Despite the many efforts done by the government of Quebec to incite the citizens to buy EVs, the current situation is not favorable to support a high penetration level of EVs in the market. There are lots of impediments, which can delay their integration in large numbers. These impediments can be summarized as follows:

- The existing conventional power and distribution systems do not favor a high penetration level of emerging technologies in its current form (such as EVs and RES), unless it is upgraded and includes intelligent communication and advanced control systems,
- The electricity pricing mechanisms used in Quebec are mostly fixed and progressive prices, which are not ideal for a future smart grid. The electricity price should be time-varying and demand response program should be applied. Therefore, they require two-way communication and data processing between the EPU, the DSO, the ER, and the end-users,
- End-users do not control nor optimize the scheduling of their loads, which may cause severe problems to the network if EVs are penetrated in large numbers,
- The temperature in winter is not favorable for the EVs. The range anxiety of EVs will be increased drastically because of the temperature that can reach -40°C.

It is of great importance that Hydro-Quebec should be aware of increasing the number of EVs on its roads without taking into account the negative consequences of their integration. Hydro-Quebec should take a further step as soon as possible in order to reduce the risks as stated before. It is not a question of budget, because the financial and economic losses caused by the integration of EVs will be much higher than the investment that could be done to upgrade the existing grid to a smarter one.

1.9 Conclusion

The integration of EVs on the distribution network is a hot topic that has been studied intensively in the last decade. Many researchers were trying to find solutions to mitigate their impact on the distribution network. However, there are always limitations to each solution. In general, most of the papers concentrated on short-term solutions where the integration level of EVs is low in the near future. These solutions may not be applicable when the penetration level of EVs is very high. There is a missing link between the proposed solutions on the distribution network level and at the end-users' level, in which the communication between the DSO and the end-users is almost absent because of security and privacy issues. For example, if we take the case of a set of homes on the same distribution transformer, many papers proposed novel optimization models and algorithms to optimize and schedule the load demand at each home separately. Therefore, each home attains its optimal solution and minimizes its electricity cost. However, the case is different on the distribution transformer, in which an optimal solution in each home does not contribute to a globally one on the distribution transformer. On the contrary, it may create problems because most of EVs will charge when the electricity price is low. Therefore, peak demand could be formed during low electricity price on the transformer. Hence, an excess of power can be formed, which exceeds the power limit of the transformer and causes a severe voltage drop. Consequently, the problem gets worse instead of being mitigated with the existing methods in the literature.

Particularly, in Quebec, conventional power systems are still used. The integration of EVs should be accompanied by shifting from a conventional to a smart grid, which is impossible to be reached in the near future. The upgrading requires new power, communication and security infrastructures, which demands huge investment in several trillions of dollars. Therefore, it urges us to find immediate and cheap solutions.

For this purpose, this thesis aims to propose novel solutions for Hydro-Quebec, which are practical to be implemented and less expensive compared to the ones in the literature. Moreover, the proposed solutions in this thesis, are specially designed to mitigate the impact of very high penetration level of EVs on the distribution network, which can be applied for the short and long terms. They require fewer upgrades to the infrastructure, which may cost less than the high-tech smart grid.

CHAPTER 2

FUNDAMENTAL CONCEPTS

2.1 Introduction

In the first chapter, a literature review is presented to give the readership a background on the state of the art related to the main subject of this thesis. Nevertheless, it is necessary to present some details on the research context related to this work. As mentioned previously, the main goal of this thesis is to mitigate the impact of a high penetration level of Electric Vehicles (EVs) on the distribution network (DN). Therefore, it is essential to study their impact seen from the end-users and distribution system operator (DSO) perspectives. The reason for including different viewpoints is to satisfy both end-users and the DSO regarding economic and technical impacts. To do so different control strategies are suggested in order to increase the satisfaction factor of both parties. The following sections present the assumptions in which this thesis is based on.

2.2 Assumptions for the study

This section gives a general idea about assumptions, methods and control strategies used in Chapters 3, 4 and 5. Each subsection describes the concept of each chapter and compares two methods. The first method is based on existing work in the literature as a reference, and the second one is the proposed method or strategy in each chapter. Afterward, some important aspects to be considered in the comparison are defined as in Figure 2.1. Finally, some results are presented, in which both methods are compared. They show how much our proposed models have improved the performance of the system in some aspects. Figure 2.1 shows the most significant aspects considered in the thesis. They are divided into economic and technical aspects. In the part of the economic aspects, we compared our proposed method in each chapter with an existing one in the literature regarding their impact on minimizing the electricity cost at home and in parking lot (parking lot is just studied in chapter 3 only). Also, we have studied how these methods affect the transformer’s depreciation cost and the cost of the losses of energy on the network, transformer and lines. We have studied the upgrading cost of the infrastructure only in chapter 5, in which we need to upgrade the network in order to implement the programmable transformer.

Regarding the technical aspects, the comparison of our method with the existing one in the literature concerns their impact on the power demand at home and the transformer, the power and energy losses at home, lines, transformer and the network. The voltage drop on the transformer and the network is also considered, and finally, the simulation time is compared only in chapter 5.

It is important to note that all these studied aspects consider three different viewpoints: (i) the end-user, (ii) the aggregator (such as a parking lot), (iii) and the DSO.

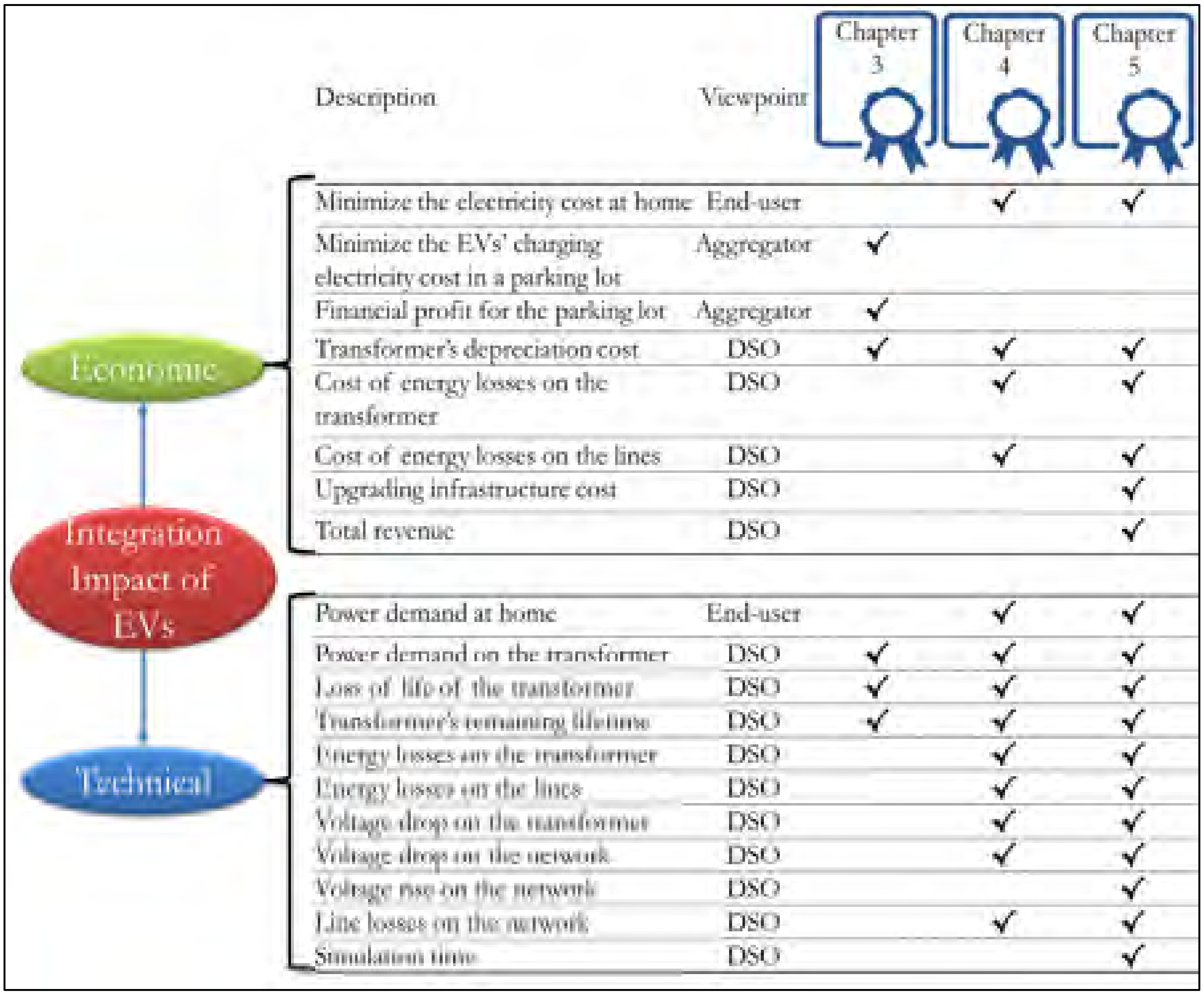


Figure 2.1 Main economic and technical aspects which are considered in the thesis

2.2.1 Assumptions for chapter 3

The main goal of chapter 3 is to show how it is important to consider the real power limit of the transformer instead of the nameplate rating in the optimization process. In fact, most of the pertinent studies consider the nameplate rating (e.g., 100kVA) as a limit in their optimization process as will be discussed in detail in the chapter. They were trying to minimize the electricity cost or maximize the benefit of the parking lot while respecting the nameplate rating. However, this limit does not reflect the real one, since the latter is highly affected by the ambient temperature and other factors which are not considered in calculating the nameplate rating. Moreover, to the best of our knowledge, economic and technical impacts of considering the nameplate rating or the real power limit are not studied in the literature. Hence, it is necessary to know which one is better to be considered and if the real power limit really affects the outcomes and the benefit of both the parking lot owner and the DSO.

In Chapter 3, we propose a new power limit of the transformer, which takes into account the fluctuation of the ambient temperature and other factors. This limit computation is called method 2, which represents the real power limit in which the transformer's loss of life is equal to unity. In another meaning, if the power consumption is equal to this limit, the transformer will not reduce its lifetime. If the consumption is higher, the lifetime of the transformer is reduced exponentially. If the consumption is lower than this limit, the lifetime of the transformer is extended. This is not the case of the nameplate rating (method 1), because it is not related to the transformer's lifetime and its loss of life.

Figure 2.2 shows a schematic diagram for an EV parking lot in which two methods are considered. Method 1 (red curve) considers the nameplate rating of the transformer (Zhang & Li, 2016), while method 2 (blue curve) considers our proposed "critical power limit" of the transformer. The main goal is to minimize the charging electricity cost of all EVs in the parking lot considering the same objective function and constraints as presented in Table 2.1. For a comparative purpose, all mathematical expressions are the same except the transformer limit.

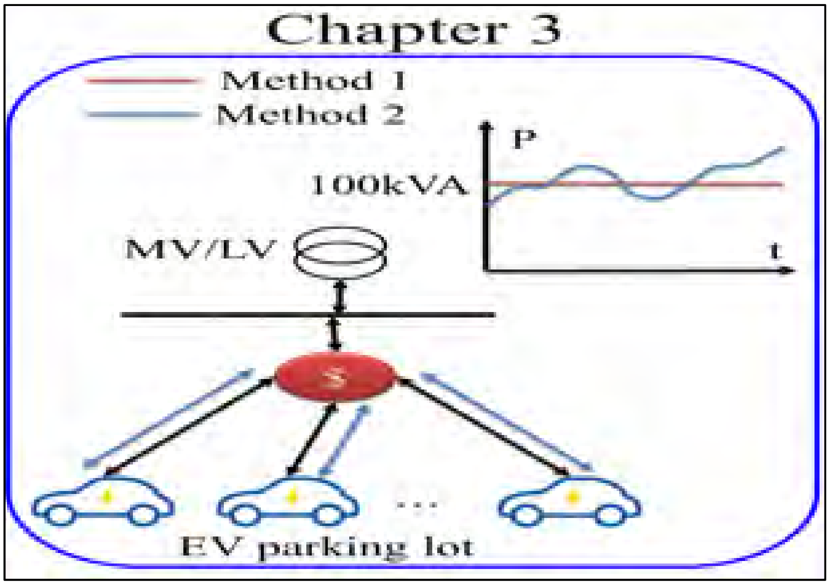


Figure 2.2 Illustration related to the context of chapter 3 showing a parking lot that considers both methods for defining the transformer power limit

Table 2.1 Optimization problem in Chapter 3 considering both methods

	Method 1 (M1)	Method 2 (M2)	Eq.
Objective function	Minimize the charging electricity cost of EVs	Same as M1	(3.16)
	Constraints		
Transformer	Nameplate rating (e.g., 100kVA)	Critical power limit (proposed in the chapter)	(3.17)
EVs (Nissan Leaf)	Maximum charging limit (6kW)	Same as M1	(3.18)
	Status of charging (On/Off)	Same as M1	(3.19) (3.20)
	Final State of Charge less than the unity (battery capacity 30kWh)	Same as M1	(3.21)
	Final State of Charge equal to the desired state of charge	Same as M1	(3.22)

Afterward, the important aspects and the main outcomes of the chapter are presented in Figure 2.1 and Figure 2.5. The proposed critical power limit of the transformer in Chapter 3 will be used in Chapters 4 and 5 instead of the nameplate rating limit.

2.2.2 Assumptions for chapter 4

The main goal of chapter 4 is to propose a soft-constrained distributed control strategy at homes in order to mitigate the impact of high penetration level of EVs on the distribution network. Figure 2.3 shows two methods in which different control strategies are considered. Method 1 uses a control strategy as shown in reference (Fotouhi Ghazvini et al., 2017), in which the main goal is to minimize the electricity cost at each home by implementing a Home Energy Management System (HEMS), and in presence of a demand response program. The optimized elements are 2 EVs, one rooftop PV, one BSS, and one EWH. Each home schedules its own elements without any communication with any external agents. However, method 1 did not consider the impact on the distribution transformer in the case when all EVs charge at the same time, which will affect negatively the lifetime of the transformer. It is remarked in Figure 2.3 that the total load on the transformer may exceed its limit in certain periods. To solve the problem, a novel soft-constrained distributed control strategy is proposed in method 2. It consists of limiting the power consumption at homes in a way that the total load demand on the transformer respects the critical power limit, which is calculated in Chapter 3. Method 2 requires communication between the DSO/ER and homes through a cloud-based platform, in which the power soft-constraint limit is calculated and sent to each home. The optimization process is similar to the first method, but the power soft-constraint is considered as a limit at homes.

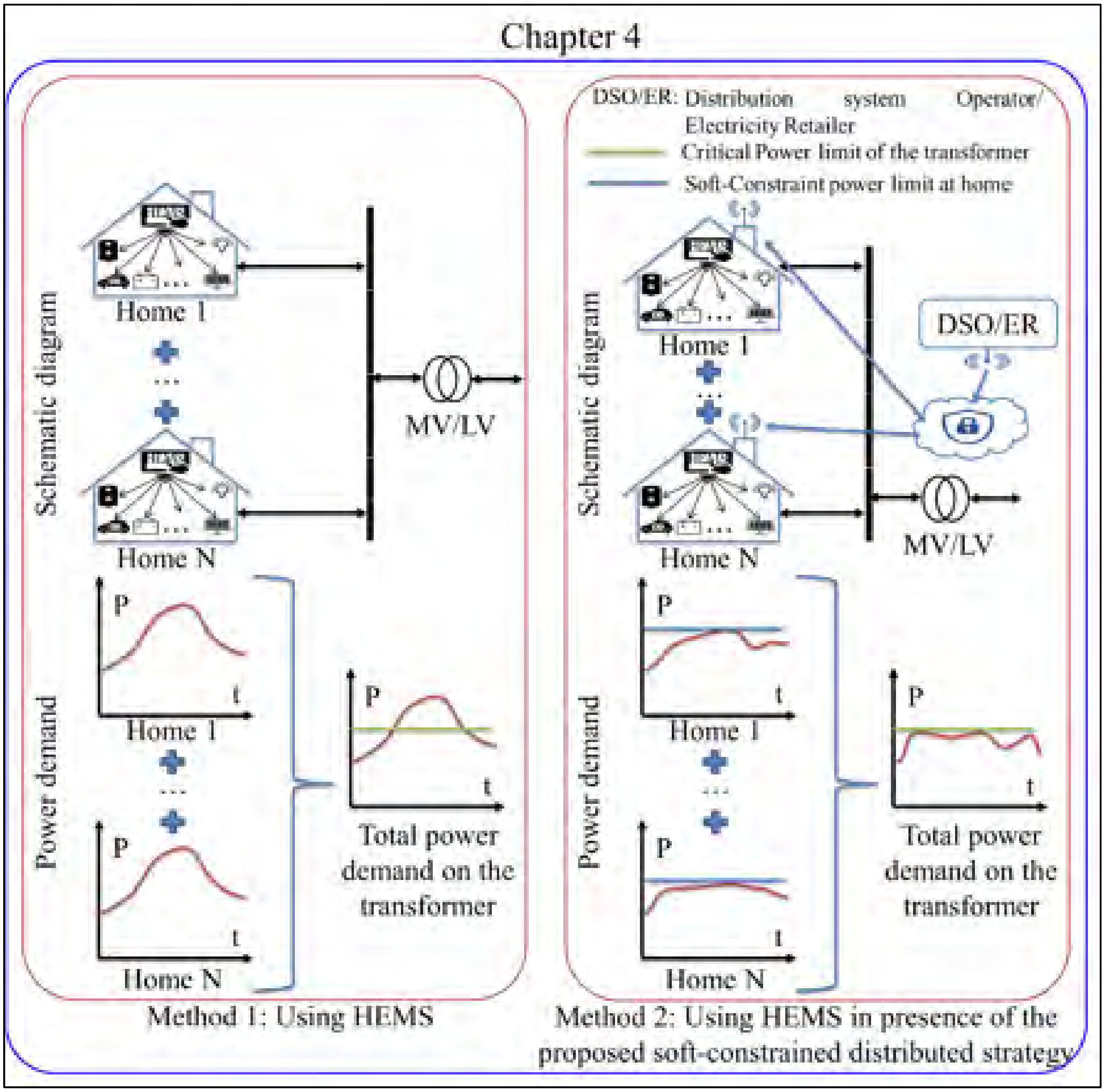


Figure 2.3 Illustration of the context in chapter 4 showing two control strategies

Table 2.2 shows the main objective function and constraints used in chapter 4 for both methods. It is clear that most of the constraints are the same. However, in our proposed strategy M2, slight changes are made in the objective function and four constraints are added in order to implement the proposed strategy at home level.

Table 2.2 Optimization problem in Chapter 4 considering both methods

	Method 1 (M1)	Method 2 (M2)	Eq.
Objective function	Minimize the electricity cost at home	Same as M1 (however, a new energy-based and power-based tariff is proposed in the objective function)	(4.5)
Constraints			
Home power balance	Buying power balance	Same as M1	(4.12)
	Selling power balance	Same as M1	(4.13)
	-	Limiting the power demand	(4.14)
	-	Limiting the energy demand	(4.15)
	-	Limiting the sold power to the grid	(4.16)
	-	Limiting the sold energy to the grid	(4.17)
EVs	Maximum charging limit	Same as M1	(4.18)
	Maximum discharging limit	Same as M1	(4.18)
	Status of charging (On/Off)	Same as M1	(4.18)
	Discharging to home and to the grid	Same as M1	(4.19)
	State of charge status	Same as M1	(4.20)
	State of Charge limits	Same as M1	(4.21)
	Final State of Charge equal to the desired state of charge	Same as M1	(4.22)
BSS	Maximum charging limit	Same as M1	(4.23)
	Maximum discharging limit	Same as M1	(4.23)
	Status of charging (On/Off)	Same as M1	(4.23)
	Discharging to home and to the grid	Same as M1	(4.24)
	State of charge status	Same as M1	(4.25)
	State of Charge limits	Same as M1	(4.26)
PV	Supplying home and the grid	Same as M1	(4.27)
EWH	Temperature at each instant	Same as M1	(4.28)
	Status of functioning status (On/Off)	Same as M1	(4.29)
	Temperature limits	Same as M1	(4.30)

Afterward, the important aspects and the main outcomes of the chapter are presented in Figure 2.6 for reference.

2.2.3 Assumptions for chapter 5

The main goal of this chapter is to fill the gap of Chapter 4 and increase the satisfaction factor of both end-users and the DSO. To do so, we have to propose a dynamic soft-constrained power limit at home levels, which is not the case of Chapter 4. In the previous chapter, the limit was fixed for all householders without taking into account their daily power and energy consumptions. Therefore, some householders may have average energy consumptions above the limit; hence they are obliged to pay more, which is not considered fair for them. At the same time, some householders may have average energy consumptions below the limit; hence they pay much less than it should be. To solve the problem, we have to propose a novel communication strategy between the DSO and the end-users, in which each transformer sets a power limit for each end-user that should be respected without controlling their loads and without a direct intervention from any external parties such as the DSO. Meanwhile, the transformers should be able to communicate with them, and between the low and high-level transformers as depicted in Figure 2.4. This complex communication requires smart programmable transformers, which are able to take their own decision in controlling their loads.

This chapter focuses more on the communication between the programmable transformer and the end-users such as householders. The main goal of the communication is to distribute the energy efficiently between the consumers, while the total load demand on the transformer respects its critical power limit (e.g., 100kVA). For example, suppose that we have 3 homes at the transformer. The transformer critical power limit is 10 kW. Therefore, the critical energy limit during a day is 240kWh/day (24 hours x 10kW). If we divide equally the energy limit between the three homes, each one is allowed to consume 80kWh/day (240/3=80). Let us suppose that the average energy consumption for home 1 is 40kWh/day, for home 2 is 90kWh/day, and for home 3 is about 100kWh/day. Therefore, homes 2 and 3 have energy consumptions above the limit. If the strategy in Chapter 4 is applied, homes 2 and 3 will always pay higher than they should be. Hence, in this chapter, the proposed strategy is dynamic and can share the available energy between end users and it happens as the following simple steps:

- We start by the home with the lowest energy consumption,
- Home 1 has an average of 40kWh/day,
- The remaining unused energy by home 1 is 80-40=40kWh/day,
- The remaining unused energy by home 1 will be transferred to home 2 and 3 equally,
- The energy limit of each of homes 2 and 3 becomes equal to 100kWh (80+40/2),
- Home 2 consumes 90kWh/day which is below the calculated energy limit (100kWh), therefore, there is not any additional tariff because the limit is already respected,
- The remaining unused energy by home 2 becomes equal to 100-90=10kWh,
- This remaining unused energy by home 2 will be transferred to home 3,
- Now, the energy limit at home 3 becomes equal to 110kWh (100+10 kWh) instead of 100kWh as was calculated before,
- The average energy consumption of home 3 is 100kWh which is below the calculated limit, hence, the householder will not pay any additional tariffs,
- Now the total energy consumption on the transformer for all homes is 40+90+100=230kWh/day, which is below its energy capacity of 240kWh,
- In this way, all householders and the DSO are satisfied in both economic and technical aspects.

For a comparative purpose, the proposed method in this chapter is compared to the reference (Fotouhi Ghazvini et al., 2017). The important aspects and the main outcomes are presented in Figure 2.7.

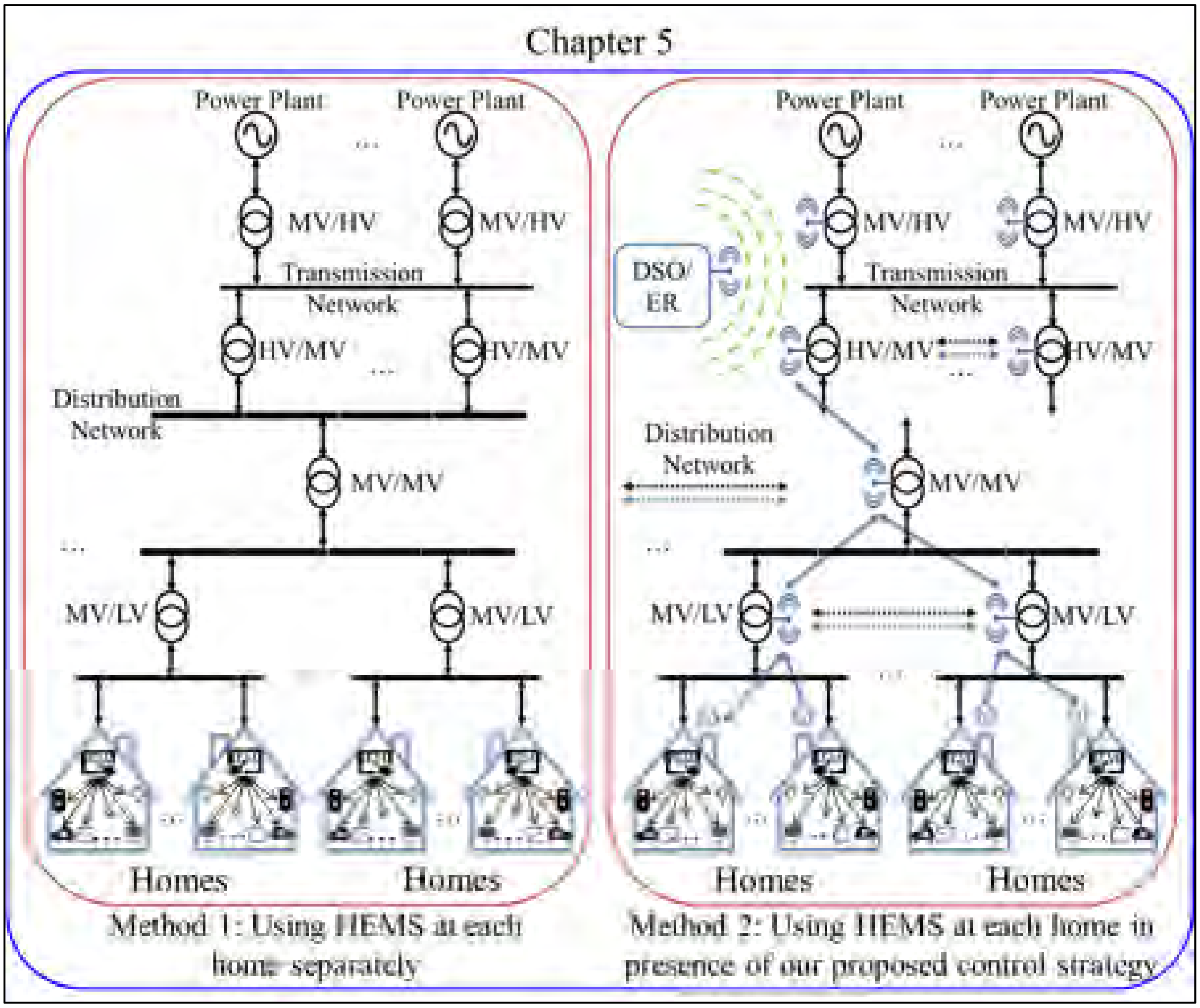


Figure 2.4 Illustration of the context of chapter 5 showing two control strategies

2.3 Most outcomes of the thesis

Chapter 3

This chapter studies the impact of integrating EVs in the parking lot considering four different penetration levels of EVs (40%, 60%, 80%, and 100%). The study concerns two days in 2016 which are the coldest and hottest days. Figure 2.5 presents the comparative results of both methods. It shows that our proposed method 2 has improved the integration of EVs regarding the technical and economic aspects. It can be concluded that respecting the transformer's critical power limit will reduce the transformer's depreciation cost, which is affected exponentially by the increase of the power demand. Moreover, the energy and economic losses follow quadratic functions; hence, a reduction in power consumption will reduce the losses on the transformer and the lines.

Outcomes of chapter 3

	Description	Viewpoint	Method 1	Method 2
Economic aspects	Minimize the electricity cost at home	End-user		
	Minimize the EVs' charging electricity cost in a parking lot	Aggregator	✓	Up to 4.4% better
	Increase the financial profit of the parking lot	Aggregator	✓	Up to 10% better
	Reduce the DT's depreciation cost	DSO	✓	Up to 10% better
	Reduce the losses cost on the DT	DSO	✓	Up to 62,9% better
	Reduce the losses cost on lines	DSO		
	Reduce the upgrading infrastructure cost	DSO		
	Increase the total revenue	DSO		
Technical aspects	Respect the power limit at home	End-user		
	Respect the DT's power limit	DSO	Exceeded	Slightly exceeded
	Reduce the DT's Loss of life	DSO	✓	Up to 62,9% better
	Increase the DT's remaining lifetime	DSO	✓	Up to 168% better
	Reduce losses on the DT	DSO		
	Reduce losses on the lines	DSO		
	Reduce line losses on the network	DSO		
	Reduce voltage drop on the DT	DSO		
	Reduce voltage drop on the network	DSO		
	Reduce voltage rise on the network	DSO		
	Reduce the simulation time	DSO		

Figure 2.5 Comparison between methods 1 and 2 in Chapter 3

Chapter 4

Figure 2.6 shows a comparison between the two methods. The first one is the same as in the reference (Fotouhi Ghazvini et al., 2017), in which the main goal is to minimize the electricity cost at home. While the second one is our proposed method in which a soft-constrained strategy is used. Method 2 shows better performance compared to method 1 from different viewpoints. It has reduced the electricity cost at home by 6% compared to M1. Economic and technical losses are reduced by 27% and 36% respectively. It can be concluded that respecting the soft-constraint power limit at home will increase the satisfaction factor of both end-users and the DSO. End-users reduce their electricity cost by respecting the soft-constraint limit, while the DSO reduces the economic and technical losses when the transformer critical power limits are respected.

Outcomes of chapter 4

	Description	Viewpoint	Method 1	Method 2
[illegible]	Minimize the electricity cost at home	End-user	✓	Up to 6% better
	Minimize the EVs' charging electricity cost in a parking lot	Aggregator	-	-
	Increase the financial profit of the parking lot	Aggregator	-	-
	Reduce the DT's depreciation cost	DSO	No	✓
	Reduce the losses cost on the DT	DSO	✓	Up to 27% better
	Reduce the losses cost on lines	DSO	✓	Up to 27% better
	Reduce the upgrading infrastructure cost	DSO	-	-
	Increase the total revenue	DSO	-	-
Technical aspects	Respect the power limit at home	End-user	No (exceeded by 200%)	✓
	Respect the DT's power limit	DSO	No (exceeded by 190%)	✓
	Reduce the DT's Loss of life	DSO	No	✓
	Increase the DT's remaining lifetime	DSO	No	✓
	Reduce losses on the DT	DSO	No	Up to 36% better
	Reduce losses on the lines	DSO	✓	Up to 36% better
	Reduce line losses on the network	DSO	No	✓
	Reduce voltage drop on the DT	DSO	No (exceeded by 7.2%)	Up to 7% better
	Reduce voltage drop on the network	DSO	No	✓
	Reduce voltage rise on the network	DSO	-	-
	Reduce the simulation time	DSO	-	-

Figure 2.6 Comparison between methods 1 and 2 in Chapter 4

Chapter 5

Figure 2.7 shows a comparison between the two methods. The first one is the same as in reference (Fotouhi Ghazvini et al., 2017), while the second one is our proposed method in Chapter 5. It can be shown that M2 gives better results regarding economic and technical impacts. However, M2 needs to upgrade the distribution network infrastructure. Despite the investment cost, results show that it is worthy in the long term to upgrade the infrastructure because the DSO will increase its revenue.

Outcomes of chapter 5

	Description	Viewpoint	Method 1	Method 2
Economic aspects	Minimize the electricity cost at home	End-user	✓	Reduced by 3%
	Minimize the EVs' charging electricity cost in a parking lot	Aggregator	-	-
	Increase the financial profit of the parking lot	Aggregator	-	-
	Reduce the DT's depreciation cost	DSO	No	Yes
	Reduce the losses cost on the DT	DSO	No	Reduced by 42%
	Reduce the losses cost on lines	DSO	No	Reduced by 42%
	Reduce the upgrading infrastructure cost	DSO	Yes	No (35% higher)
	Increase the total revenue	DSO	No	Yes
Technical aspects	Respect the power limit at home	End-user	No	Yes
	Respect the DT's power limit	DSO	Exceeded by 180%	Yes
	Reduce the DT's Loss of life	DSO	No	Yes
	Increase the DT's remaining lifetime	DSO	No	Yes
	Reduce losses on the DT	DSO	No	Reduced by 50%
	Reduce losses on the lines	DSO	No	Reduced by 50%
	Reduce line losses on the network	DSO	No	Reduced by 80%
	Reduce voltage drop on the DT	DSO	No	Yes
	Reduce voltage drop on the network	DSO	No	Yes
	Reduce voltage rise on the network	DSO	No	Yes
	Reduce the simulation time	DSO	No	Reduced by 36%

Figure 2.7 Comparison between methods 1 and 2 in Chapter 5

CHAPTER 3

NOVEL APPROACH FOR OPTIMIZING THE TRANSFORMER'S CRITICAL POWER LIMIT

Claude Ziad El-Bayeh[1], Imad Mougharbel[1], Dalal Asber[2], Maarouf Saad[1], Ambrish Chandra[1], Serge Lefebvre[2]

[1]Electrical Engineering Department, École de Technologie Supérieure,
1100 Rue Notre-Dame West, Montreal, Quebec, Canada H3C 1K3
[2] Hydro-Quebec's Research Institute, Varennes, Quebec, Canada J3X 1S1

Paper published in *IEEE Access*, October 2018

3.1 Abstract

The massive penetration of plug-in electric vehicles (EVs) may create challenges in the near future for the distribution network. Moreover, this may lead to an increase of the transformers' aging rate, and a reduction of the financial profits. In this paper, a novel approach is proposed, in which the operating margin of the transformer is optimized based on the transformer's internal characteristics, its loss of life, and the variation of the ambient temperature. This operational power limit should not be exceeded to guarantee that the loss of life of the transformer is equal to or less than the one provided by the manufacturer. For validation purposes, a comparative study between the conventional method and the suggested one is presented. This study is applied to a parking lot for charging EVs, which is supplied by a distribution transformer. In contrary to the conventional method, the one suggested in this study can guarantee a predefined transformer loss of life. Simulation results show that the proposed method increases the transformer lifetime, reduces the loss of life, and reduces its depreciation cost by 63% in certain conditions. Also, it increases the financial profit for the parking lot's owner up to 10% during cold weather.

Keywords: Electric Vehicles, Energy management, Load management, Parking Lot, Smart Grids, Transformers

3.2 Introduction

In distribution systems, dry-type and liquid filled distribution transformers (DT) are used to supply electricity to end-users (e.g., householders, commercial buildings, centers, Parking Lots, industries). Usually, DTs are rated from a few kVA to hundreds of kVA depending on the norm of each country (e.g., 10kVA-2.5MVA (2018)). Their cost could vary from thousands of dollars to several hundred thousands of dollars depending on their types, sizes, characteristics, quality and brand names (Siemens, 2007). For economic and technical reasons, the DT rating (S_{NR}) is always less than the sum of the total installed loads supplied by it (Volut & Schonek, 2016). Nowadays, existing standards such as IEC60050 and NFC14-100 related to the load utilization and diversity factors are no more suitable for increased penetration of new forms of elements (e.g., EVs, distributed storage), generations (e.g., wind, PV) and demand response programs (e.g., incentive, time-based, power-based, energy-based, etc.). Focusing on the new trend of EVs integration into the power grid, the dimensioning of the currently installed DTs does not take into account their presence as loads (IEC-60076). Shortly, their number will be increased, and a simultaneous charge of their large batteries will produce peak demand on the transformers. Therefore, a high penetration level of EVs is expected to reduce the transformers' lifetime, increase the power losses and create severe voltage drops.

To overcome this situation, many papers studied the impact of integrating EVs into the DTs and Distribution Network and proposed some solutions (Leou, Su, & Lu, 2014). They show how much different penetration level of EVs may affect the stability of the network regarding but not limited to the voltage drop (Leou et al., 2014), energy losses (Leou et al., 2014), (Sortomme, Hindi, MacPherson, & Venkata, 2011) power demand (Leou et al., 2014), frequency deviation (Ahn et al., 2011). Some papers studied the impact of penetrating EVs disregarding the S_{NR} limit (Ahn et al., 2011), while others considered it (El-Bayeh et al., 2016b). It is important to take into account the DT power limit to guarantee that its Loss of Life (LOL) is kept within an acceptable range (Aravinthan & Jewell, 2015). In reference (Aravinthan & Jewell, 2015), they calculated the number of EVs that should be connected while keeping the LOL within an acceptable range. For this purpose, a simplified mathematical model has been used, and many factors have been neglected. Reference (Qian et al., 2015) investigated the impact of penetrating EVs on the DT regarding peak demand and LOL. They showed that a percentage higher than 40% might increase the LOL of the DT even when smart charging algorithms are used. Many efforts were made to reduce the impact of penetrating EVs on the network such as introducing renewable energy sources (Weihao, Chi, Zhe, & Bak-Jensen, 2013), and limiting the power demand to the S_{NR} (El-Bayeh et al., 2016b), (Turker, Bacha, & Hably, 2014).

Peak load shaving is also used to reduce the high load demand of EVs on the network in specific periods (Uddin et al., 2018). Usually, PVs, wind turbines, bidirectional power flow EVs and batteries are used to support the grid by shifting or reducing the peak load and provide ancillary services such as voltage and frequency regulations (Neyestani, Damavandi, Shafie-khah, Bakirtzis, & Catalão, 2017). They should be accompanied by demand response programs to give better ancillary services (Fotouhi Ghazvini et al., 2017), (Kong & Karagiannidis, 2016). Despite the success of peak load shaving on the network level (Tan, Ramachandaramurthy, & Yong, 2016), it has some limitations even when sophisticated optimization algorithms and models are used to schedule the load demands (Melhem, Grunder, Hammoudan, & Moubayed, 2018). From the Distribution System Operator's (DSO) point of view, the operator's interest is in selling electricity to the end-users with minimal losses and damages to the distribution network and transformers. Transformers are sensitive and costly elements of the infrastructures. Any reduction in their lifetime implies significant financial losses, which may cost several million to billions of dollars (Georgilakis & Amoiralis, 2010). Therefore, the existing peak load shaving based on the DT nameplate rating limit is not an optimal solution for the DSO. The reason is that the DT nameplate rating does not reflect the real power limit of the transformer (Turker et al., 2014), (Xiaohua Wu et al., 2017). When peak load shaving is applied, the total load may respect the DT rating, but it may not guarantee a DT lifetime equal to the predefined one.

However, to the best of our knowledge, there is no publication on accurate relations between the DT power limit and the factors affecting it. These relations are necessary to guarantee a predefined DT lifetime. Also, in existing studies where S_{NR} is assumed constant (e.g., 100kVA), the fluctuations of the temperature and the load demand may increase the LOL of the DT and reduce its lifetime in certain periods. Moreover, it could reduce the profit of the end-users and retailers.

For this purpose, the following contributions are proposed:

- A new approach for finding an accurate power limit of the transformer is presented. The limit is called “DT Critical Power Limit” which depends on various factors such as the ambient temperature, a predefined LOL, and the internal characteristics of the DT,
- A parking lot on a DT is considered to investigate the impact of EVs on (i) the DT’s lifetime and depreciation cost, (ii) the cost of charging the EVs, and (iii) the revenue of the parking lot, all under fluctuating temperature, real-time pricing, and different EV's penetration level,
- The DT Critical Power Limit is added as a constraint to the optimization model. That limit restricts the power demand below the calculated one in order to maintain the LOL of the DT within the predefined value,
- Mathematical expressions related to the remaining lifetime of the transformer and its depreciation cost is proposed for evaluation purposes.

Our proposed model is compared to an existing one in the literature, both taking into account the same objective function and constraints except the ones related to the transformer power limit. Results show that the proposed approach guarantees a predefined LOL of the DT and improves the financial profit of the parking lot during specific periods.

The rest of the paper is organized as follows. In Section 3.3, the suggested power limit is developed. Results and discussions are shown in section 3.4. Finally, a conclusion is presented in Section 3.5.

3.3 Transformer critical power limit

According to the IEEE Std C57.91-2011, the life of the insulation is the overall life of an oil-immersed transformer. The dielectric insulating properties of the insulation can be weakened for temperatures above the limiting values. According to the IEEE Std C57.12.00-2000, power transformers are rated on a maximum ambient temperature of 40°C, and the average ambient temperature shall not exceed 30°C in a 24-hour period. This standard also states that the average temperature of the winding cannot exceed 65°C above ambient when operated at rated conditions. Maximum hottest-spot winding temperature cannot exceed 80°C above ambient temperature.

3.3.1 Limitations found in the literature

In the literature, the optimization model of the load demand assumes a S_{NR} as a constraint, which does not reflect the real power limit of the transformer (Turker et al., 2014). Therefore, in this section, we propose a novel limit called DT Critical Power Limit for both oil-immersed and dry-type transformers.

3.3.2 Oil immersed transformer critical power limit

We define DT critical power limit (S_t) as the accurate power limit of the transformer, which guarantees a predefined lifetime of the transformer. In most applications, it is recommended to set this predefined lifetime equal to the one provided by the manufacturer. A slight excess of the power demand over this limit may exponentially decrease the DT lifetime. In order to determine the S_t, it is necessary to perform the calculation respecting the following steps:

3.3.2.1 Hottest-spot temperature as a function of the aging acceleration factor

The hottest-spot temperature (θ_t^{HS}) indicates the hottest element in the transformer, in which a temperature above the reference temperature causes deterioration of the element and reduces the thermal lifetime of the transformer (Turker et al., 2014), (IEEE, 2012). It depends on many internal components of the DT such as, but not limited to, oil temperature, paper winding insulation, tap changer, tank, dielectric fluid, bushings, core, and windings. It also depends on the total load demand (S_t^{Load}), and the ambient temperature (θ_t^{A}). In this subsection, the winding hottest-spot temperature (θ_t^{HS}) of the DT is calculated as a function of the Aging Acceleration Factor (F_t^{AA}). θ_t^{HS} will be used in the next subsection in order to calculate S_t.

The Aging Acceleration Factor (F_t^{AA}) in Eq. (3.1) indicates how much the aging of the transformer is accelerated under certain loads and temperature beyond normal (Qian et al., 2015), (IEEE, 2012). $F_t^{AA} > 1$ if $\theta_t^{HS} > \theta_{ref}$, and $F_t^{AA} < 1$ if $\theta_t^{HS} < \theta_{ref}$. If $F_t^{AA} > 1$, it means that the aging of the DT is accelerated and its lifetime is reduced. If $F_t^{AA} < 1$, it means that the aging of the DT is decelerated and its lifetime is increased. For example, for a certain load demand and temperature, if $F_t^{AA} = 1.6$ (the DT aging is accelerated by $60\% = (1.6 - 1) \cdot 100\%$), it means that one hour of operation at the current load and temperature is equivalent to 1.6 hours of operation at the DT's reference temperature θ_{ref} and at rated load.

$$F_t^{AA} = e^{\left(\frac{\alpha}{\theta_{ref}+\theta_0} - \frac{\alpha}{\theta_t^{HS}+\theta_0}\right)} \tag{3.1}$$

To calculate the DT critical power limit, θ_t^{HS} is found as a function of F_t^{AA} as in Eq. (3.2).

$$\theta_t^{HS} = \frac{\alpha\left(\theta_{ref} + \theta_0\right)}{\alpha - \left(\theta_{ref} + \theta_0\right) \cdot \ln(F_t^{AA})} - \theta_0 \tag{3.2}$$

3.3.2.2 DT critical power limit as a function of the ambient temperature and the aging acceleration factor

In this subsection, we are interested in calculating S_t as a function of θ_t^A and F_t^{AA}. Equations (3.3), (3.4), and (3.5) are given as in (Turker et al., 2014), (IEEE, 2012). In these references, they calculated F_t^{AA} based on the known variables S_t^{Load} and θ_t^{HS}. While in our paper, we are interested to calculate S_t based on the given variables, which are F_t^{AA} and θ_t^A. To do so, Eq. (3.4), and (3.5) are substituted in Eq. (3.3), and S_t^{Load} is assumed to be S_t. A reverse calculation is done to find S_t as in Eq. (3.6). We are interested in finding the value of S_t based on the internal characteristics of the transformer, F_t^{AA} and θ_t^A. Eq. (3.6) is nonlinear; some advanced tools could be used to solve it. In this paper, we used the Newton-Raphson method to find S_t. Figure 3.1 shows a schematic flowchart that represents the steps to be considered while calculating S_t and considering it in the optimization process of the end-users' load. The first step consists of sending the necessary data to the end-user such as the aging acceleration factor, the ambient temperature and the DT internal characteristics. In the second step, the end-user calculates the DT critical power limit based on the received data using a solver such as Newton-Raphson. In the third step, the optimal consumption profile is generated according to predefined objective function and constraints including the constraint related to the already found DT critical power limit.

$$\theta_t^{HS} = \theta_t^A + \Delta\theta_t^{TO} + \Delta\theta_t^G \tag{3.3}$$

$$\Delta\theta_t^{TO} = \Delta\theta_{TO,R}\left(\frac{\left(\frac{S_t^{Load}}{S_{NR}}\right)^2 R + 1}{R+1}\right)^p \tag{3.4}$$

$$\Delta\theta_t^G = \Delta\theta_{G,R}\left(\frac{S_t^{Load}}{S_{NR}}\right)^{2m} \tag{3.5}$$

$$(S_t^2 R + S_C^2)^p + \frac{\Delta\theta_{G,R}}{\Delta\theta_{TO,R}}\frac{(R+1)^p}{S_{NR}^{2(m-p)}}S_t^{2m} - \frac{\theta_t^{HS} - \theta_t^A}{\Delta\theta_{TO,R}}\frac{(R+1)^p}{S_{NR}^{-2p}} = 0 \tag{3.6}$$

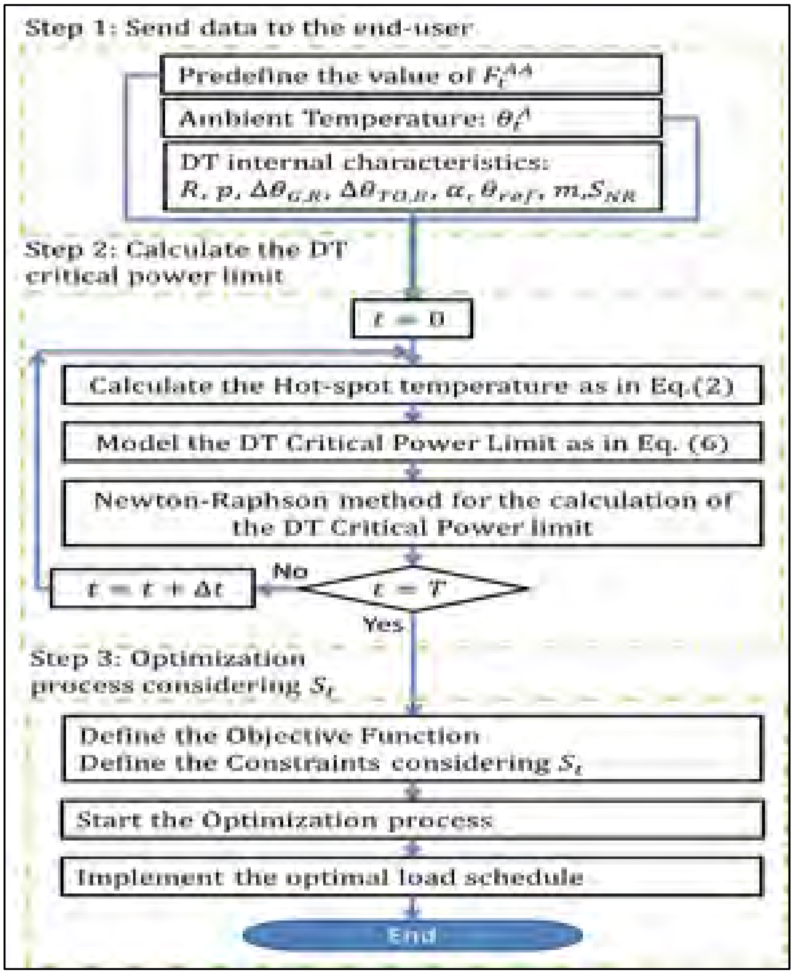


Figure 3.1 Proposed Algorithm for calculating the DT critical power limit and using it in the optimization

3.3.3 Dry-type transformer critical power limit

In the previous subsection, the Oil-immersed transformer is studied, and the transformer critical power limit is calculated. In this subsection, the same concept is applied hereafter on the dry-type transformer. There are many different types of dry-type transformers. However, because the method of calculation is very similar, we chose the self-cooled dry-type transformer according to the IEEE Std C57.96-2013 section 5.1. To determine the critical power limit of the dry-type transformer (S_t), it is necessary to perform the calculation following bethe low approach.

The hottest-spot temperature (θ_t^{HS}) indicates the hottest element in the dry-type transformer, in which a temperature above the reference temperature causes deterioration of the element and reduces the life expectancy of the transformer. It is expressed as in Eq. (3.7) for a continuous loading for each interval Δt according to the IEEE Std C57.96-2013 section 5.1. Where, θ_t^A is the ambient temperature. $\Delta\theta_t^{HS}$ is the hottest-spot temperature rise over ambient as in Eq. (3.8), in $[^oC]$. $\Delta\theta_r^{HS}$ is the rated hottest-spot temperature rise over ambient at 1.0 per unit load, in $[^oC]$. m is an empirical constant (0.8 is suggested unless another value can be justified by test data). S_{NR} is the transformer's nameplate rating. S_t^{Load} is the load at instant "t" on the transformer.

$$\theta_t^{HS} = \theta_t^A + \Delta\theta_t^{HS} \tag{3.7}$$

$$\Delta\theta_t^{HS} = \Delta\theta_r^{HS} \cdot \left(\frac{S_t^{Load}}{S_{NR}}\right)^{2m} \tag{3.8}$$

In this subsection, the winding hottest-spot temperature (θ_t^{HS}) of the DT is calculated as a function of the Aging Acceleration Factor (F_t^{AA}). Dry-type and oil-immersed transformers have the same mathematical expression for the Aging Acceleration Factor (F_t^{AA}) as in Eq. (3.1). Therefore, the same procedure can be used to calculate θ_t^{HS} as a function of F_t^{AA} as in Eq. (3.2). To calculate the proposed DT critical power limit (S_t) as a function of θ_t^A and F_t^{AA} for the dry-type case, Eq. (3.2) and (3.8) are substituted into Eq. (3.7) and S_t^{Load} is assumed to be S_t as in Eq. (3.9).

$$\overbrace{\frac{\alpha\left(\theta_{ref} + \theta_0\right)}{\alpha - \left(\theta_{ref} + \theta_0\right) \cdot \ln(F_t^{AA})} - \theta_0}^{\theta_t^{HS}} = \theta_t^A + \overbrace{\Delta\theta_r^{HS} \cdot \left(\frac{S_t}{S_{NR}}\right)^{2m}}^{\Delta\theta_t^{HS}} \tag{3.9}$$

From Eq. (3.9), we can deduce S_t as a function of other parameters and variables as shown in Eq. (3.10).

$$\overbrace{\frac{\alpha\left(\theta_{ref}+\theta_0\right)}{\alpha-\left(\theta_{ref}+\theta_0\right)\cdot\ln(F_t^{AA})}-\theta_0}^{\theta_t^{HS}}=\theta_t^A+\overbrace{\Delta\theta_r^{HS}\cdot\left(\frac{S_t}{S_{NR}}\right)^{2m}}^{\Delta\theta_t^{HS}} \tag{3.10}$$

Figure 3.1 shows a schematic flowchart that represents the steps to be considered while calculating S_t for the oil-immersed transformer. However, the same flowchart can be applied to the dry-type transformer with some modifications. In Step 1, the DT internal characteristics of the oil-immersed transformer are replaced by the internal characteristics of the dry-type one ($\Delta\theta_r^{HS}$, α, θ_{ref}, m, S_{NR}). In Step 2, Eq. (3.10) is used to calculate the DT critical power limit instead of using Newton-Raphson method and Eq. (3.2) and (3.6). Step 3 is the same.

3.3.4 Variation of the critical power limit as a function of the ambient temperature and the aging acceleration factor

This subsection shows the difference between the nameplate rating of the transformer (S_{NR}) and our proposed DT critical power limit (S_t). The nameplate rating is always considered constant by the manufacturer as shown in Figure 3.2 and Figure 3.3 (black curve), e.g., 100kVA. It does not take into account the influence of the ambient temperature on the transformer's power limit. While, our proposed DT critical power limit takes into account the influence of the ambient temperature. Therefore, a more accurate power limit is obtained according to the ambient temperature as in Figure 3.2 (red, green and blue curves). The red curve represents the limit in a hot day where the temperature varies between 26^{o}C and 41^{o}C. The blue curve represents the limit in a freezing day where the temperature varies between -15^{o}C and -9^{o}C. Finally, the green curve represents the limit in a cool day, where the temperature varies between 5^{o}C and 10^{o}C. It is shown that the variation of the ambient temperature affect the DT critical power limit a lot. Therefore, considering a variable power limit may affect the total load consumption on the transformer. Moreover, a power consumption greater than the proposed limit will reduce the lifetime of the transformer exponentially, while a lower power consumption will increase it.

In Figure 3.2, the curves of S_t (red, green and blue) represent the maximum power demand limit not to be exceeded in order to keep the LOL equal to unity, which corresponds to a lifetime set by the manufacturer. It is also seen that between hours 10 and 22, the DT critical power limit during a hot day (red curve) is lower than the S_{NR} (black curve). If the load demand exceeds the red curve without exceeding the black one, the LOL becomes higher than "1", and the lifetime of the transformer is reduced. Therefore, even if the load demand respects the S_{NR}, the LOL is not guaranteed to be equal or lower than one. While, if the load demand respects the red curve, the LOL is guaranteed to be equal or less than 1. Also, by looking at the same figure to the case of a cold day (blue and green curves), if the load demand is kept below the S_{NR} limit, the end-users will lose benefits from raising their loads during the periods where the electricity price is low. Therefore, even if the load demand has exceeded the S_{NR} during cold days, the LOL is always kept below or equal to 1, and the DT lifetime is not affected.

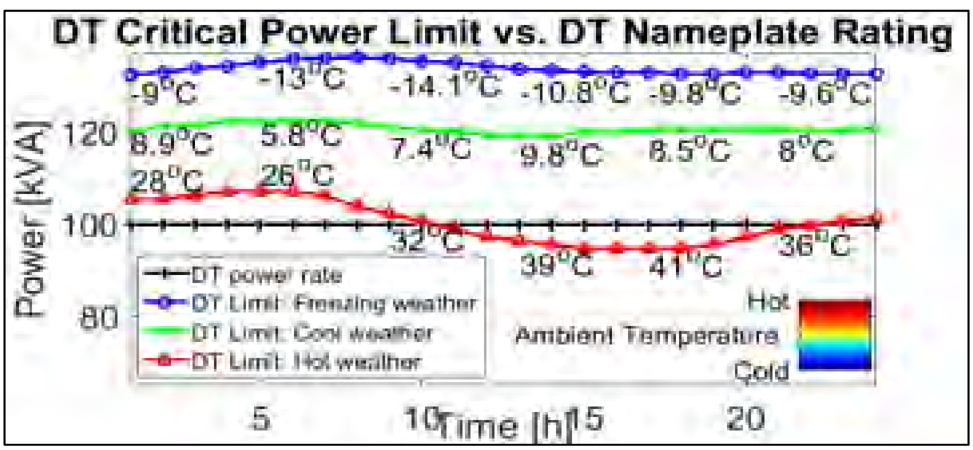


Figure 3.2 Influence of θ_t^A on the DT Critical Power Limit for a $F_t^{AA} = 1$

After showing the influence of the ambient temperature on the transformer's power limit, in Figure 3.3 we will focus on the influence of varying the Aging Acceleration Factor (F_t^{AA}) on the DT critical power limit. The study is applicable for both, the oil-immersed and dry-type transformers. It is important to note that the lifetime of the transformer is equal to the provided one by the manufacturer for an $F_t^{AA} = 1$, e.g., 20 years. However, for a certain reason, by increasing the F_t^{AA} to a higher value, the DT's lifetime is reduced. For example, if

$F_t^{AA} = 2$, it means that the lifetime of the transformer will be reduced twice faster, and it becomes equal to 10 years. If we reduce the value of F_t^{AA} to 0.5, it means that the lifetime of the transformer is increased twice and it becomes 40 years instead of 20. The variation of the Aging Acceleration Factor depends on the strategy of the DSO. For example, the DSO may accept a $F_t^{AA} = 1.2$ in a day where the consumption is high and may reduce F_t^{AA} to 0.8 in another day where the power consumption is low. The main goal of varying F_t^{AA} from one day to another is to maintain the transformer's lifetime to the one predefined by the manufacturer.

In Figure 3.3, S_t is represented in the orange curve for $F_t^{AA} = 1$. If we consider $F_t^{AA} > 1$, S_t becomes higher (e.g., blue and magenta curves), and it allows the end-users to consume more power in certain periods when there is a need. F_t^{AA} is determined by the DSO, it can be changed anytime in order to limit or increase the power demand on a transformer during a specific period. It helps the DSO to control the lifetime of the transformer. The variation of F_t^{AA} could be used as a power-based demand response program in which the DSO could incite or penalize the users if their power demands exceeded S_t for predefined values of F_t^{AA}.

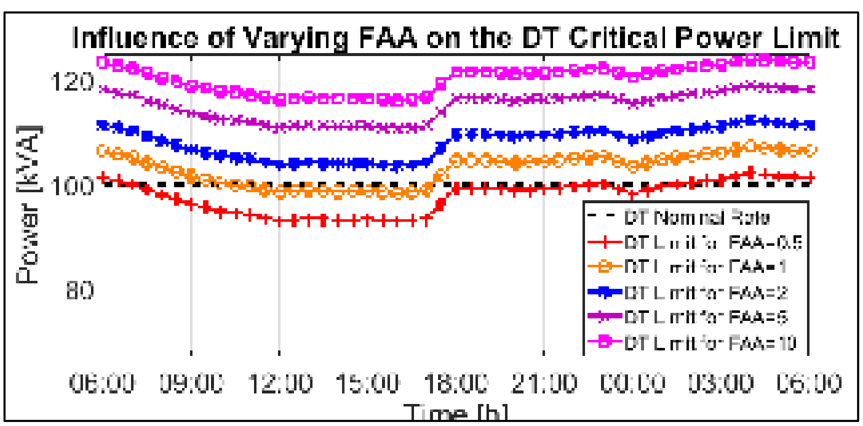


Figure 3.3 Influence of varying F_t^{AA} on the S_t

3.3.5 Evaluation parameters of the model

To evaluate the impact of the load demand on the DT using both limits S_t and S_{NR}, it is necessary to define some terms, which will be used in this chapter. These terms are applicable for both, oil-immersed and dry type transformers.

3.3.5.1 Equivalent aging factor

The Equivalent Aging Factor (F_{EQA}) of the transformer is defined in Eq. (3.11) according to (Qian et al., 2015), (IEEE, 2012). It is the sum of the total Aging Acceleration Factor during a period T (e.g., 24 hours). It is used to calculate the Loss of Life of the DT.

$$F_{EQA} = \frac{1}{T}\int_{0}^{T} F_t^{AA} dt = \frac{1}{T}\sum_{n=1}^{T/\Delta t} F_{t+(n-1)\Delta t}^{AA} \Delta t \tag{3.11}$$

3.3.5.2 Loss of life of the transformer

The Percent Loss Of Life of the DT ($LOL_{\%}$) is defined in Eq. (3.12) according to (Qian et al., 2015), (IEEE, 2012).

$$LOL_{\%} = \frac{F_{EQA} T}{L_N} \cdot 100\% \tag{3.12}$$

In this chapter, we are interested in calculating the Loss Of Life per day ($T = 24\ hours$). Therefore, in Eq. (3.13), we define it as the lost life of the transformer`s lifetime when a certain load is applied during one day of operation. E.g. $LOL_T = 3\ days$ means that one day of operation at a particular load demand and ambient temperature reduces 3 days of the transformer's lifetime. The normalized value is $LOL_T = 1$ under standard conditions when the hottest spot temperature is equal to the reference temperature, and the power demand is equal to S_{NR}.

$$LOL_T = \frac{LOL_{\%}}{100} \cdot \frac{L_N}{T} \tag{3.13}$$

3.3.5.3 Remaining lifetime of the transformer

We define the DT Remaining lifetime in Eq. (3.14) as the lasting period of the transformer if it is used at the same load profile every day. e.g. $RT_{DT} = 4000\ days$ means that the transformer lasts for 4000 days if it is used at the same load profile every day.

$$RT_{DT} = \frac{L_N}{LOL_T} \tag{3.14}$$

3.3.5.4 Actual depreciation cost

We define the reference depreciation cost (RDC_T^{Tr}) of the transformer as its total cost divided by its lifetime under standard conditions for a period T (second right term of the Eq. (3.15)). The standard conditions consider a rated load, and a standard ambient temperature.

In fact, the power demand profile is variable, and it can be higher or lower than the transformer's rating. Also, the ambient temperature is variable. Therefore, RDC_T^{Tr} does not reflect the fluctuation of the power demand and the ambient temperature, and it is just considered as a reference value for a comparative purpose. Hence, we define the actual depreciation cost (ADC_T^{Tr}) of the transformer in Eq. (3.15) as its loss of life during a period T multiplied by its reference deprecation cost. Also, it takes into account the fluctuation of the ambient temperature and the power demand on the depreciation cost of the transformer.

$$ADC_T^{Tr} = LOL_T \overbrace{\left(\frac{T \cdot C_{Tr}}{L_N}\right)}^{RDC_T^{Tr}} \tag{3.15}$$

3.4 Results and discussions

3.4.1 Assumptions for the study

To validate our model, we took a parking lot for charging EVs as an example. This study can be applied to any other type of loads such as residential, commercial, or industrial loads. The parking lot is more suitable for our study because we can control the charging of all its EVs. The following data are considered:

- The simulation results are in conformity with the IEEE standards such as Std C57.91-2011 and Std C57.12.00-2010. Table 3.1 shows values corresponding to our study.

Table 3.1 Chosen Parameters for this Study

$\alpha = 15000$	$T = 24\ hours$	$C_{Tr} = 10{,}000\$$
$L_N = 180{,}000 hours$	$m = 0.8$	$p = 0.8$
$S_{NR} = 100kVA$,1-φ, 60Hz, ONAN type	$R = 8$	$\theta_0 = 273$
$\theta_{ref} = 100^0C$ *	$\Delta\theta_{TO,R} = 55^0$C	$\Delta\theta_{G,R} = 20.3^0C$
$\Delta t = 0.5\ hours$	$\eta_e^{Ch} = 0.96$	$F_t^{AA} = 1$

*According to (IEEE, 2012), $\theta_{ref} = \Delta\theta_{TO,R} + \Delta\theta_{G,R} + \theta_{avg}^A + 5$. Where, θ_{avg}^A is the average temperature during a year in a certain region. 5^0C is a safety margin.

- The maximum energy that the parking lot can deliver per day is 2400kWh,
- The day is divided into two periods: from 06:30 to 18:00 and from 18:00 to 06:30. During the first period, the parking lot receives mainly cars owned by employees. During the second period, it receives cars owned by residents. Knowing that employees need to charge their cars during the day, and the residents during the night,
- Two days a year are studied, which are the coldest and the hottest days in 2016 in Montreal (TimeAndDate, 2018). The reason for choosing these two days is to compare the impact of charging EVs on the profit of the parking lot owner and the Loss Of Life of the DT for the two extreme temperature profiles,
- We consider $F_t^{AA} = 1$ as a reference for the DT critical power limit. In another term, the LOL per day is equal to 1. Therefore, the Remaining lifetime of the transformer is the same as the one provided by the manufacturer,

- Real-Time Electricity Price (π_t^{RTP}) is considered as in Figure 3.4 just as an example (Fotouhi Ghazvini et al., 2017), but any variable pricing mechanism could be considered. For a comparative purpose, the electricity price profile is assumed the same for all days in the year 2016.

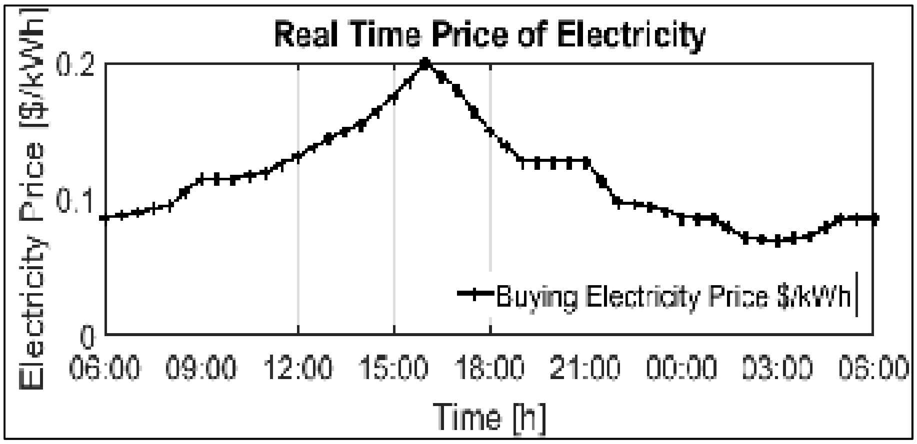


Figure 3.4 Real-Time Electricity Price Taken from (Fotouhi Ghazvini et al., 2017)

3.4.2 Optimization model for Electric Vehicle's parking lot

To validate our model, we compare our approach to an existing one in reference (Zhang & Li, 2016). The main goal of this paper is to minimize the electricity cost of charging EVs in a parking lot and validate our approach. Therefore, both methods should have the same objective function and the same constraints for a comparative purpose. Hence, we propose the same objective function for both methods as in Eq. (3.16). The constraints are the same as shown in Table 3.2 except for our novel DT critical power limit, which is used in Eq. (3.17.b). The existing approach is named Method 1 (M1), and our new approach is named Method 2 (M2). The optimized and controlled elements are only EVs. Both methods use the same objective function as in Eq. (3.16), and the same constraints as in Eq. (3.17) to (4.22). However, the difference is that M1 uses the DT rating (e.g. $S_{NR} = 100kVA$) as in Eq. (3.17.a) (A. S. Masoum et al., 2015) (Zhang & Li, 2016). While in M2, we use our proposed DT critical power limit as in Eq. (3.17.b).

Table 3.2 represents clearly the used equations for each method. The same optimization algorithm is used for both methods, which is Mixed Integer Nonlinear Programming in MATLAB. We note that in Eq. (3.17.b), β is a binary variable, which designs the activation or deactivation of the DT Critical Power Limit. If $\beta = 1$, Eq. (3.17.b) becomes equal to S_t, else if $\beta = 0$, it becomes equal to S_{NR}, which is similar to Eq. (3.17.a). In this way, the DSO has more flexibility to activate or deactivate the DT critical power limit according to its needs, benefits and conditions.

$$Electricity\ Cost = \min \sum_{t \in T} \left(\pi_t^{RTP} \left(\sum_{e \in E} P_{e,t}^{EV} \right) \Delta t \right) \tag{3.16}$$

In the constraints part, we consider the worst case, in which the EVs can only charge without discharging. The aggregated charging power of all EVs in the parking lot at instant "t" should be less than the transformer power limit as in Equation (3.17). The transformer's power limit is added as a soft constraint in Equation (3.17) in order to protect the transformer from overloading. However, it can be exceeded in case the needed energy to charge the EVs in the parking lot is higher than the energy that can be provided by the transformer's power limit. In this case, the load demand can exceed the DT's power limit in order to better serve the end-users.

$$\sum_{e \in E} \frac{P_{e,t}^{EV}}{\cos(\phi_e^{EV})} \leq \begin{cases} S_{NR} & (a) \\ S_t \beta + S_{NR}(1 - \beta) & (b) \end{cases} \quad \forall t \in T \tag{3.17}$$

According to (Zhang & Li, 2016), the charging power of each EV should have a maximum limit ($P_{e,t}^{EV,Max}$) as in Eq. (3.18).

$$0 \leq P_{e,t}^{EV} \leq P_{e,t}^{EV,Max} \quad \forall t \in T \tag{3.18}$$

Similar to (Zhang & Li, 2016), the charging power of each EV is equal to zero if it is outside its arrival and departure time, else it should be equal to $P_{e,t}^{EV}$ as in Eq. (3.19) and (3.20).

$$0 \leq P_{e,t}^{EV} \leq P_{e,t}^{Status} \quad \forall t \in T \tag{3.19}$$

$$P_{e,t}^{Status} = \begin{cases} 0 \; if \; t \notin [t_e^A, t_e^D] \\ 1 \; if \; t \in [t_e^A, t_e^D] \end{cases} \forall t \in T, \forall e \in E \tag{3.20}$$

The total charged energy of the EV "e" during T should be below or equal to its maximum battery capacity as in Eq. (3.21), and it should be equal to the desired final energy as in Eq. (3.22), (El-Bayeh et al., 2016a).

$$\sum_{t \in T} P_{e,t}^{EV} \leq \frac{B_e^{Cap}\left(1 - SOC_e^i\right)}{\Delta t \cdot \eta_e^{Ch}} \quad \forall e \in E \tag{3.21}$$

$$\sum_{t \in T} P_{e,t}^{EV} = \frac{B_e^{Cap}\left(SOC_e^f - SOC_e^i\right)}{\Delta t \cdot \eta_e^{Ch}} \quad \forall e \in E \tag{3.22}$$

Table 3.2 Comparative table of the used equations for each method

Type of Equation	**Method 1**	**Method 2**	**Reference**
Objective Function	Eq. (3.16)	Eq. (3.16)	In this chapter
Constraints	Eq. (3.17.a)	-	(Zhang & Li, 2016)
	-	Eq. (3.17.b)	In this chapter
	Eq. (3.18)	Eq. (3.18)	(Zhang & Li, 2016)
	Eq. (3.19)	Eq. (3.19)	(Zhang & Li, 2016)
	Eq. (3.20)	Eq. (3.20)	(Zhang & Li, 2016)
	Eq. (3.21)	Eq. (3.21)	(Zhang & Li, 2016)
	Eq. (3.22)	Eq. (3.22)	(Zhang & Li, 2016)

In this paper, and for simulation purposes, the data of the EVs are chosen as presented in Table 3.3.

Table 3.3 EVs Data and Characteristics for this study

Characteristics	Description
Charging Level	AC Level 2, 19.2kW, according to SAE J1772
EV brand	Nissan Leaf. For simplicity reasons, Nissan Leaf is chosen, because it is the most sold EV worldwide according to (NissanNews, 2017). However, multiple kinds of EVs could be considered in the optimization
Battery capacity B_e^{Cap}	30kWh
Maximum charging limit $P_{e,t}^{EV,Max}$	6 kW
Maximum Number of EVs in the Parking Lot	100 EVs in the parking for a day.
Initial SOC ($\boldsymbol{SOC_e^i}$)	20%, we chose all EVs having the same initial SOC for simplicity reasons. However, it could be random or normally distributed.
Final SOC ($\boldsymbol{SOC_e^f}$)	100%, all EVs should be fully charged before departure times.
$\boldsymbol{cos(\phi_e^{EV})}$	100%. Existing chargers/inverters techniques can easily provide a unity power factor.

3.4.3 Impact on the power demand in the parking lot

The primary goal of this subsection is to study the impact of both methods on the behavior of the total power consumption in the Parking Lot. Figure 3.5 to Figure 3.8 show the results for both methods for different hosting capacity (from 100% to 40%) in the coldest day in 2016. From Figure 3.5, the charging of EVs using M1 (red curve) is limited by the DT rating (100kVA or 1pu dashed black curve). EVs start to charge during low electricity price (refer to Figure 3.4 for the price) until the total load reaches the S_{NR} limit. If the EVs need more energy to attain their desired final State of Charge, they will also charge during high electricity price. While for M2 (blue curve), because the weather is cold, the DT critical power limit (dashed magenta curve) is higher than the S_{NR} (dashed black curve). In this case, the Parking Lot has more available energy to charge the EVs. Therefore, most of the EVs will benefit from charging during low electricity price until they are charged to their desired SOC level. By doing this, the PL is minimizing its electricity cost and gaining a higher income. Also, the unused energy, which is presented between 15:00 and 21:00 in Figure 3.5 could be used to charge additional EVs and increase the income of the PL (the area between the magenta curve and the blue curve). In Figure 3.6, the hosted capacity of the parking lot is 80%, the EVs have more flexibility to charge during low electricity price (from 06:00 till 15:00 and from 21:00 till 06:30). For M1, most of the EVs are charged during these intervals, while few of them are charged during high electricity price (between 18:30 and 21:00). The same for M2, but this time, because the power limit is higher than the DT rating, most of EVs charge during low electricity price and very few of them charge during high electricity price compared to M1. Therefore, the total electricity cost of the parking lot is lower compared to M1. When the hosted capacity of the parking lot becomes lower (60% and 40% as in Figure 3.7 and Figure 3.8), the EVs have more flexibility to charge during low electricity price (for electricity price, refer to Figure 3.4). Therefore, most of the EVs will charge between 06:00 and 12:00, and between 00:00 and 06:00 the next morning. This will increase the financial profit and satisfaction of the PL when all EVs are charging during low electricity price.

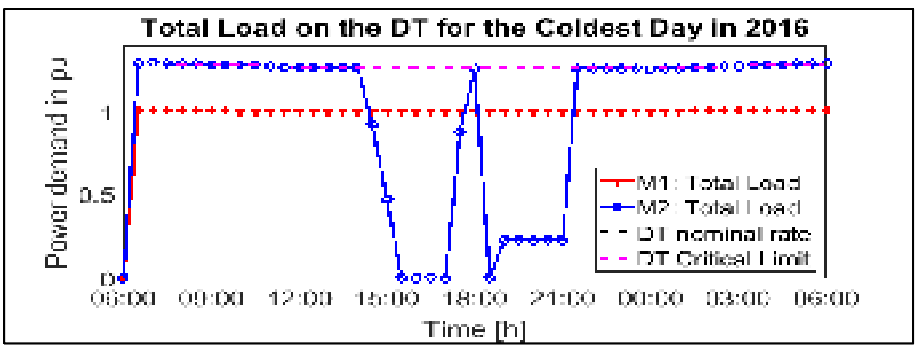


Figure 3.5 DT’s power demand with 100% of the used capacity of the PL

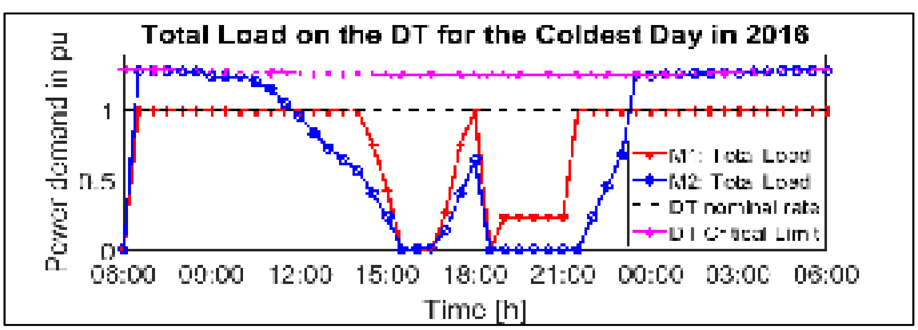


Figure 3.6 DT’s power demand with 80% of the used capacity of the PL

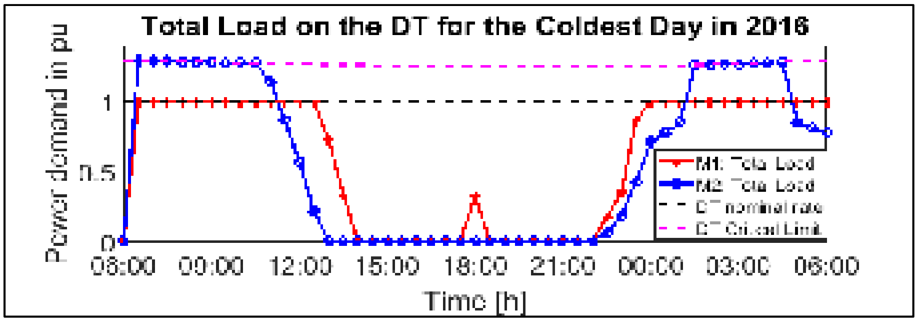


Figure 3.7 DT’s power demand with 60% of the used capacity of the PL

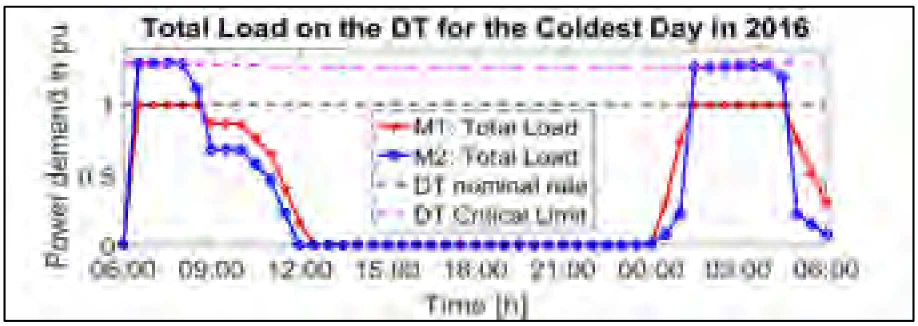


Figure 3.8 DT’s power demand with 40% of the used capacity of the PL

Figure 3.9 to Figure 3.12 show the results for both methods for the hottest day in 2016. The used capacity is 100% to 40% of the PL’s maximum energy capacity. Due to the hot weather, it is shown that the DT critical power limit (dashed magenta curve) is lower than the S_{NR} (dashed black curve). The red curves of M1 in Figure 3.9 to Figure 3.12 are similar to the ones in Figure 3.5 to Figure 3.8 when the weather was cold due to the DT rating constraint in Eq. (3.17.a), which is considered the same in the optimization model for the coldest and hottest weather. Therefore, there is no change in the power consumption if we consider the same electricity price. The case is different for M2 (blue curve) because the DT power limit is affected by the ambient temperature. In Figure 3.9 because the DT critical power limit is lower than its rating, the charging of EVs will find some difficulties to respect the limit for the case of 100% of the used capacity of the Parking Lot. When the power demand is higher than the DT critical limit, the LOL of the transformer is exponentially affected and reduced according to how much power is consumed above the limit. Therefore, both M1 and M2 have exceeded the limit, and both of them are reducing the lifetime of the transformer. Figure 3.10 and Figure 3.11 show that for a hosting capacity lower than 100%, M2 shows better results by respecting S_t. However, the charging electricity cost is higher. While for M1, the power demand respects S_{NR}, but exceeds S_t in some periods, which will increase the LOL of the DT and reduce its lifetime but the charging electricity cost is lower than M2.

In conclusion, when the temperature is high, the DT critical power limit is lower than its rating. M1 shows better results regarding the EVs charging electricity cost, while M2 shows better results regarding the DT lifetime. In the case of a lower hosting capacity as in Figure 3.12, both methods have approximately the same impact on the transformer because the total load demand is very low. Even if there is an excess of power in certain periods (from 06:00 till 09:00), the difference between M1 and M2 does not have a significant impact on the DT lifetime, and the total charging electricity cost of EVs.

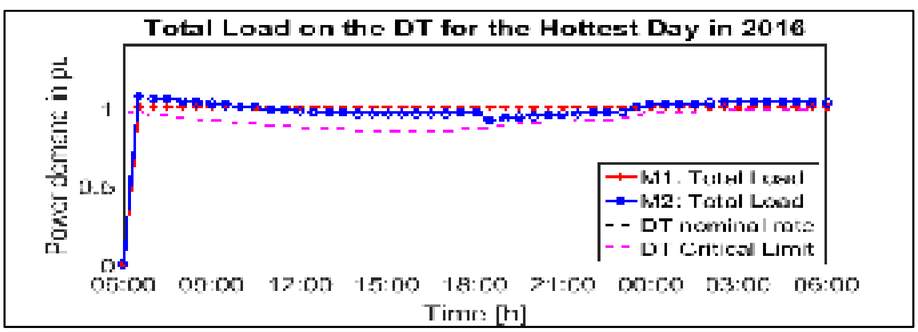


Figure 3.9 DT’s Power demand with 100% of the used capacity of the PL

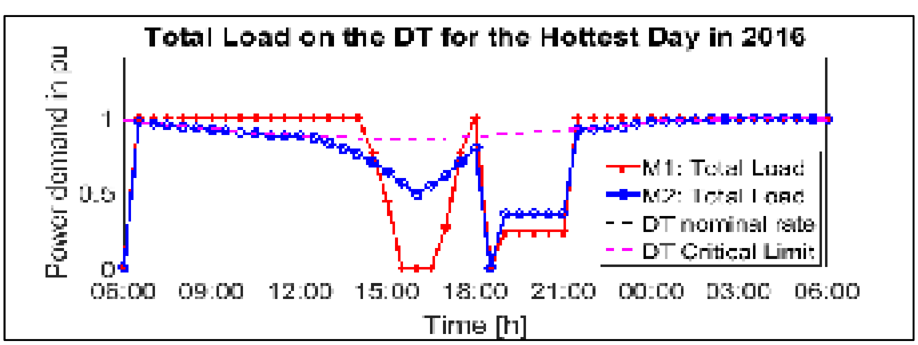


Figure 3.10 DT’s Power demand with 80% of the used capacity of the PL

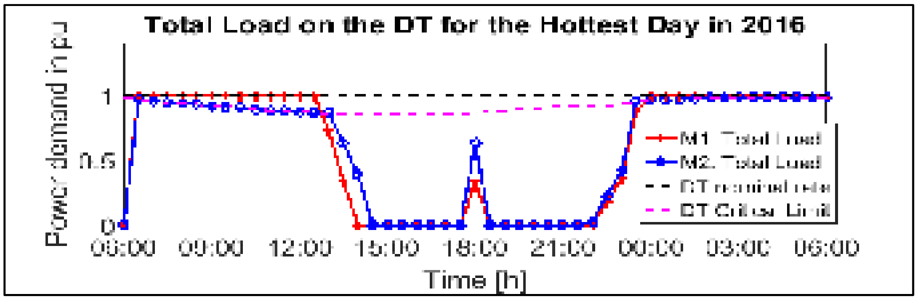


Figure 3.11 DT’s Power demand with 60% of the used capacity of the PL

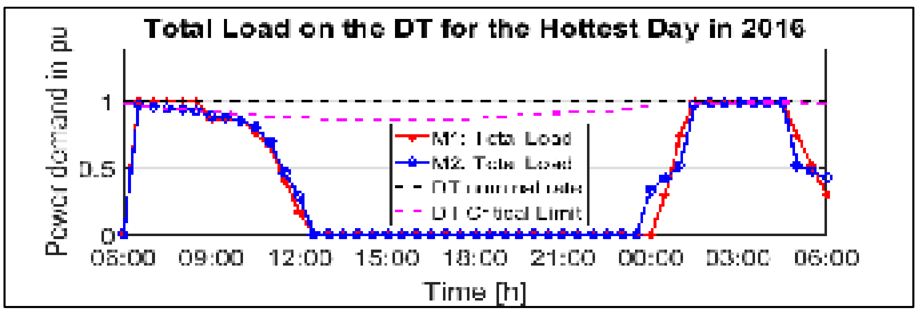


Figure 3.12 DT’s Power demand with 40% of the used capacity of the PL

3.4.4 Economic impact on the parking lot’s electricity cost

The primary goal of this subsection is to study the impact of both methods on the economy of the parking lot during a year. The objective function considers only the charging electricity cost of all EVs in the parking lot, which is the interest of this paper. Other costs will not be considered such as battery degradation and cycling cost. The electricity tariff is presented in Figure 3.4. Figure 3.13 to Figure 3.16 show the electricity cost of both methods for the first day of each month during a complete year. In Figure 3.13, M2 (blue curve) is always better during cold days (From October “10” until May “5”) and in hot weather (from June “6” until September “9”), the results are almost the same. Our method shows better performance regarding minimizing the electricity cost of charging EVs in the parking lot for a year. In Figure 3.14, results are obtained for a hosting capacity of 80%. They are comparable with Figure 3.13, but some exceptions appear when the temperature is very high (August “8”). In this case, M1 shows slightly better results compared to M2. From Figure 3.15 and Figure

3.16, when the hosted capacity of EVs in the PL becomes lower, the difference in the financial profit becomes lower as well (refer to Figure 3.17). In general, our method shows better results over a year.

Figure 3.17 shows the best financial profit increment of the parking lot's aggregator using M2 during a year for different hosting capacities. The best profit is for a hosting capacity of 100% and during cold weather because the DT power limit is higher during a colder period. Therefore, it allows the parking lot to increase the charging rate of its EVs during low electricity price without decreasing the lifetime of the transformer below its predefined one.

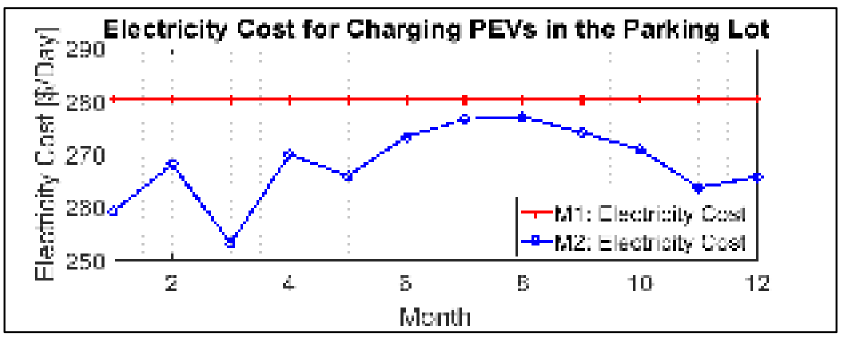


Figure 3.13 Monthly Electricity Cost for both methods with a hosting capacity of 100%

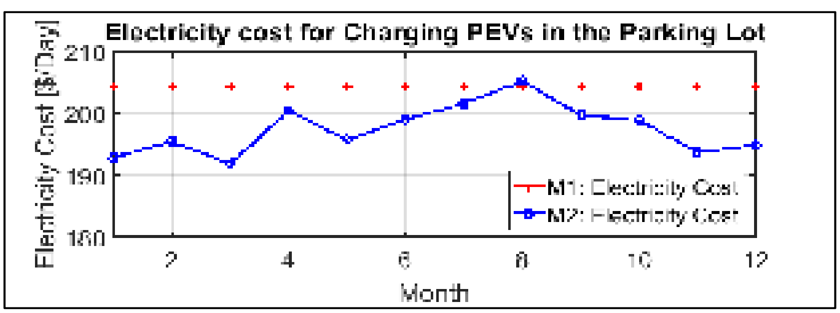


Figure 3.14 Monthly Electricity Cost for both methods with a hosting capacity of 80%

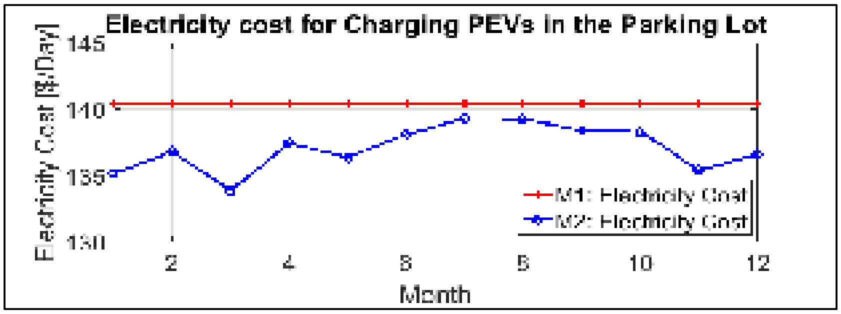


Figure 3.15 Monthly Electricity Cost for both methods with a hosting capacity of 60%

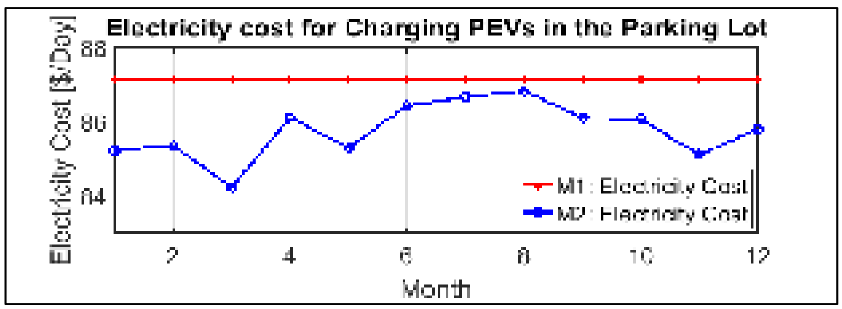


Figure 3.16 Monthly Electricity Cost for both methods with a hosting capacity of 40%

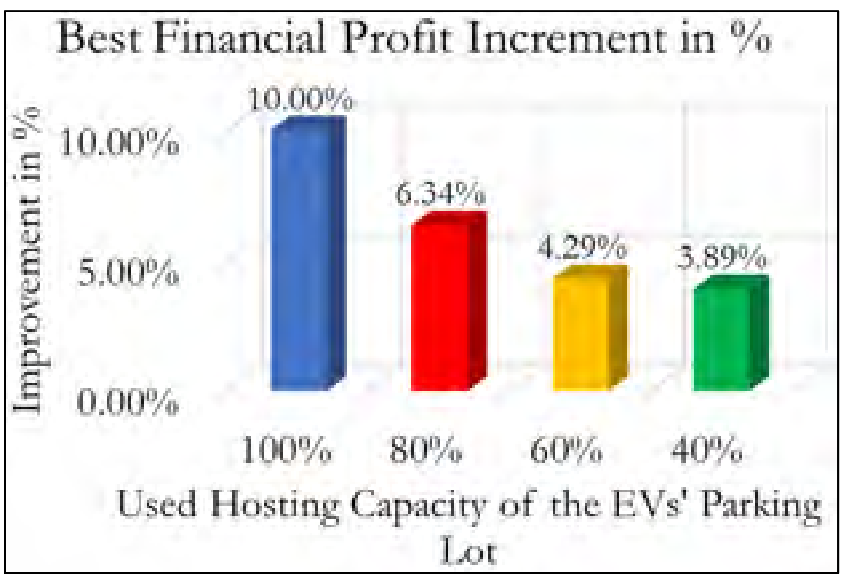


Figure 3.17 Best financial profit increment for the parking lot owner for March 01, 2016 for different hosting capacities

3.4.5 Loss of life and remaining time of the transformer

This subsection intends to study the impact of both methods on the Loss of Life and the Remaining lifetime of the transformer. Figure 3.18 and Figure 3.19 show the results for the hottest day in 2016 for different hosted capacity in the parking lot. In Figure 3.18, M2 is always better whatever the hosted capacity in the parking lot is. For 100% and 40% of the hosted capacity, results are close. For 80% and 60%, our method reduces the LOL up to 63%, compared to M1. Therefore, M2 increases the lifetime of the transformer and minimizes the possibility of replacing it in the short term.

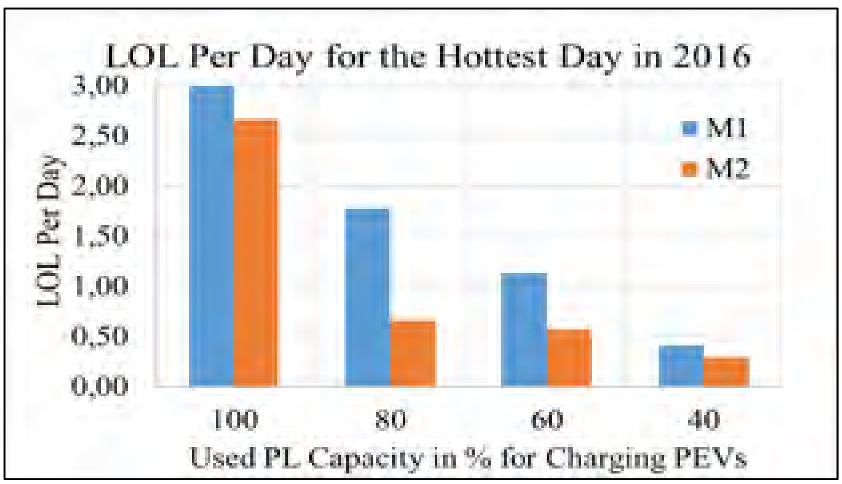


Figure 3.18 Impact of both methods on the DT's LOL for the hottest day

In Figure 3.19, from 80% to 40% of the hosted capacity, M2 increases the Remaining lifetime of the DT. While for 100%, our method shows a slightly better improvement regarding the DT remaining lifetime. The DT remaining lifetime is 20 years (180,000 hours) as given by the manufacturer. If the hosted capacity is 100%, the DT remaining lifetime is reduced to 7 years (first column). The DT remaining lifetime becomes higher when the load demand is lower since the stress on the transformer is reduced.

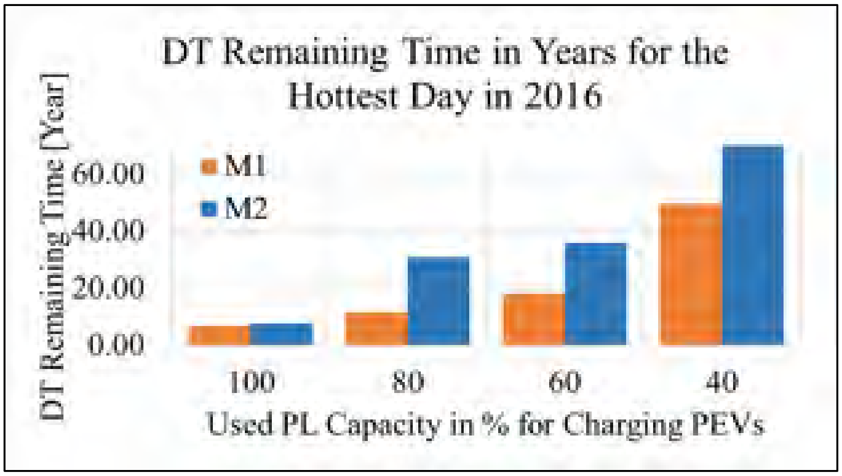


Figure 3.19 Impact of both methods on the DT remaining lifetime for the hottest day

3.4.6 Actual depreciation cost of the transformer

The reference depreciation cost of the transformer is $RDC_T^{Tr} = 1{,}33\$/day$. It is based on the values mentioned in the section 3.4.1. It means that the transformer is losing from its value every day 1,33$ in the normal case. For the hottest day in 2016, the Actual Depreciation Costs of the transformer for each hosting capacity are presented in Figure 3.20. It is seen that M2 shows better results in which the depreciation cost of the transformer is reduced. For 80% and 60% of the hosting capacity in the Parking Lot, M2 reduced the depreciation cost up to 63%, while for 100% and 40%, it shows a slightly better reduction. In another meaning, M2 is more beneficial for the DSO, because it reduces the depreciation cost of the infrastructure and increases its lifetime compared to M1.

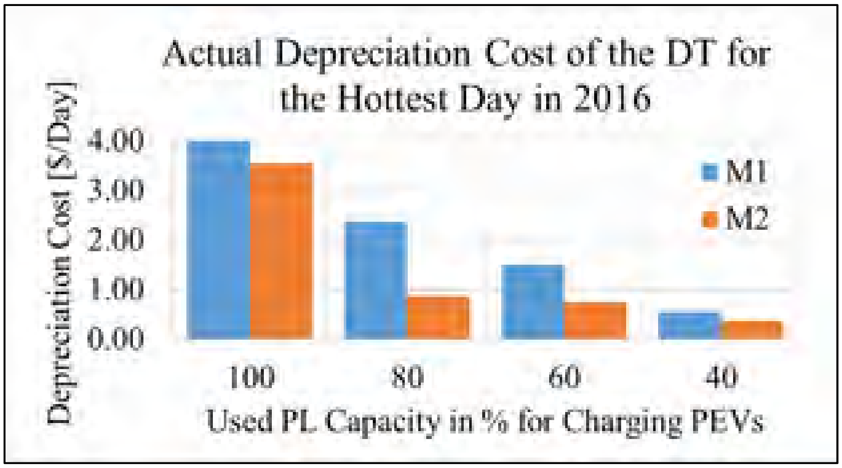


Figure 3.20 Impact of both methods on the depreciation cost of the DT for the hottest day

Table 3.4 shows a summary of the comparative study. M1 is better in some aspects and M2 is better in other aspects (for $\beta = 1$). For instance, M1 shows better results in terms of reducing the electricity cost of charging EVs for very high temperature, but in return, it reduces the DT's lifetime. Also, M1 is better for reducing the LOL of the DT when the ambient temperature is very low. In general, M2 shows better results in other cases. To improve the performance of M2 in all cases, β is introduced as a binary variable in which it can be activated or deactivated depending on the need of the DSO and the parking lot. Table 3.5 shows our recommendation regarding the activation or deactivation of β in certain conditions. When the conditions are favorable for M2 over M1, we activate β ($\beta = 1$). When they are favorable for M1 over M2, we deactivate β ($\beta = 0$).

Table 3.4 Summary Table

Description	θ_t^A	**M1**	**M2 ($\boldsymbol{\beta = 1}$)**
Minimize electricity cost	θ↗	Slightly better than M2 for extremely high temperature	Slightly better than M1
	θ↘	Yes	Better than M1
Respect the DT Critical Power Limit	θ↗	No	Better than M1
	θ↘	Yes	Yes
Sufficient energy to charge additional EVs	θ↗	No	No
	θ↘	No	Yes
Loss Of Life reduction	θ↗	No	Better than M1
	θ↘	Better than M2	Yes
Increase the Remaining lifetime of the DT	θ↗	No	Better than M1
	θ↘	Better than M2	Yes
Reduce the depreciation cost of the DT	θ↗	No	Better than M1
	θ↘	Better than M2	Yes

* θ↗ High Ambient Temperature. θ↘ Low Ambient Temperature. The bold red text represents the advantage of each comparison.

Table 3.5 Recommendation for Activation or Deactivation of β

Description	θ_t^A	$\boldsymbol{\beta}$	**Recommendation**	**Results**
Minimize electricity cost	θ↗	1 0	Activated for high temperature Deactivated for extremely high temperature	Same as M2 Same as M1
	θ↘	1	Activated	Same as M2
Respect the DT Critical Power Limit	θ↗	1	Activated	Same as M2
	θ↘	1	Activated	Same as M2
Sufficient energy to charge additional EVs	θ↗	1	Activated	Same as M2
	θ↘	1	Activated	Same as M2
Loss Of Life reduction	θ↗	1	Activated	Same as M2
	θ↘	0	Deactivated	Same as M1
Increase the Remaining Time of the DT	θ↗	1	Activated	Same as M2
	θ↘	0	Deactivated	Same as M1
Reduce the depreciation cost of the DT	θ↗	1	Activated	Same as M2
	θ↘	0	Deactivated	Same as M1

3.5 Conclusion and future work

This paper presents a new transformer power limit (for both, oil-immersed and dry-type transformers), which guarantees a transformer lifetime equal to the predefined one. It takes into account various factors such as the fluctuation of the ambient temperature, the internal transformer characteristics, and its predefined aging acceleration factor. Its significant advantages are noticed in a context where the load demand, the ambient temperature, and the electricity price produce high variations during a day. For validation purpose, a case study is considered, in which an oil-immersed transformer supplies a parking lot for EVs. The primary objective is to minimize the charging electricity cost of the EVs. A comparison with the conventional method based on the transformer rating is conducted using the same objective function. Results show that the suggested method has significantly reduced the charging electricity cost of the parking lot. Moreover, an improvement of about 60% on the loss of life and depreciation cost of the transformer has been noticed in some favorable situations. It is also noticed that for unfavorable situations, this approach can guarantee a given loss of life since the conventional one cannot do it. The limitations of this study are: (i) the transformer needs additional sensors to measure the ambient temperature, which may increase the cost of fabrication. (ii) It needs bidirectional data communication between the DSO, the transformer, and the end-users, which will increase the complexity of the system and its cost. (iii) Specific hardware and software should be installed in the transformer in order to calculate the DT's critical power limit and send the data to the end-users and the DSO. In general, a more complex system provides better results. However, its cost could be higher. Fortunately, this technology will be available soon in the presence of smart transformers and digital transformers. Further investigation will consider a network with multiple distribution transformers. A multi-objective function could also be considered, in which it aims at minimizing the electricity cost and the transformers LOL.

CHAPTER 4

NOVEL SOFT-CONSTRAINED DISTRIBUTED STRATEGY TO MEET HIGH PENETRATION TREND OF EVS AT HOMES

Claude Ziad El-Bayeh[1], Imad Mougharbel[1], Maarouf Saad[1], Ambrish Chandra[1], Dalal Asber[2], Laurent Lenoir[2], Serge Lefebvre[2]

[1]Electrical Engineering Department, École de Technologie Supérieure,
1100 Rue Notre-Dame West, Montreal, Quebec, Canada H3C 1K3
[2] Hydro-Quebec's Research Institute, Varennes, Quebec, Canada J3X 1S1

Paper published in *Energy and Buildings*, November 2018

4.1 Abstract

This chapter shows that the demand response program is not sufficient to solve the problem of high penetration level of Plug-in Electric Vehicles (EVs), even when energy management systems are used in homes. In the presence of Time-varying electricity price, EVs tend to charge during low price periods. The problem starts when the number of EVs exceeds a certain threshold. A total load of all homes on a transformer may exceed its capacity and create high peak-demand during low-electricity price. To overcome this situation, we propose a novel Soft-Constrained Distributed Strategy. The novelty consists of defining a new distributed information exchange between Power Utility and end-users, new constraints are developed at home level taking into account the transformer and Distribution Network's technical limits, and a new optimization model is proposed to implement the strategy. A case study is conducted using data provided by Hydro-Quebec. Simulations and comparative results show the validity of our approach. The proposed strategy reduces the peak-demand, energy loss, depreciation cost, transformer's loss of life, and voltage deviations. Lastly, our study shows that it is not necessary for the power utility (e.g. Hydro-Quebec) to upgrade all distribution transformers on the network and the infrastructure during the increasing penetration of EVs.

Keywords: Distributed control strategy; Demand response program, Distribution Network; Electric Vehicle; Energy management.

4.2 Introduction

In recent years, the integration of EVs into the distribution network has been studied intensively (Lu & Hossain, 2015; Rajakaruna et al., 2016; Williamson, 2013; X. Yang et al., 2017). According to (University-of-Central-Florida, 2015), the total sold EVs worldwide in 2015 is 565,668. In China, the sales were trebled compared to 2014, and the overall world growth of selling EVs is 79% in 2015 compared to the previous year. China set a goal to reach 5 million EVs by 2020, the same for India in which the target is 6 million EVs by 2020. The good news about the future of EVs is announced by Norway and Germany in which the first one banned the gas-powered cars by 2025 and the second one announced that all new cars must be electric vehicles by 2030. The penetration level of EVs is increasing every year (University-of-Central-Florida, 2015), (IEA, 2016). Studies have demonstrated that a high penetration level could create problems on the Distribution Transformer (DT) and the network such as overload, overheat, voltage deviations (Qian et al., 2015), and blackouts which may cost billions of dollars (US-Department-of-Energy, 2018). Therefore, different charging control strategies were suggested to schedule the charging of EVs.

4.2.1 Control strategies

In the literature, there are four main control strategies for the load management: (i) Centralized (Yao et al., 2017), (El-Bayeh et al., 2016b), (B. Yang et al., 2016), (ii) Hierarchical (Shao et al., 2017), (Anand, Salis, Cheng, Moyne, & Tilbury, 2015), (iii) multi-agent (Morstyn et al., 2016), and (iv) Decentralized (Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017). Under the centralized strategy (CS), a central controller makes decisions and controls the power flow of all its optimized loads (Figure 4.1 a). It is mostly used in Parking Lots, (Yao et al., 2017), (El-Bayeh et al., 2016b), (Shao et al., 2017) and Charging Stations (Anand, de Salis, et al., 2015; Yong et al., 2015), (Wang et al., 2017) when a small number of EVs is presented. If the number of loads and constraints increases (Shao et al., 2017), (Wang et al., 2017), this strategy becomes slower and impractical to be used. Also, it introduces security and privacy concerns to the end-users (Morstyn et al., 2016). An alternative strategy is used on a larger scale, which is the Hierarchical Strategy (HS) (Morstyn et al., 2016), (Shao et al., 2017). It is composed of different levels of control; each local controller controls its loads and sends the optimal solution to the controller of a higher level (Figure 4.1 b) (Z. Xu et al., 2016). Black arrows represent direct control, while blue arrows represent the communication between controllers and indirect control. L: Load, LC: Local Controller. If the higher level is the central controller, therefore, it gathers and analyzes the data of all local controllers. Based on that, it orders them to modify their optimal target to obtain an acceptable global solution. The problem with this strategy is that it is complicated and not very efficient compared to other strategies. Bidirectional communication is required which may cost lots of money for the power utility. Moreover, it has many problems regarding controlling and managing the power flow in the presence of energy storage systems (Morstyn et al., 2016). Another strategy was proposed which is Multi-Agent Strategy (MAS) (Morstyn et al., 2016). In this strategy, each local controller optimizes its loads and exchange data with its neighbors to achieve cooperative objectives (Figure 4.1 c) (Morstyn et al., 2016). The problem with this strategy is that communication infrastructure is needed between the local controllers that may cost a fortune to the power utility. All the three mentioned strategies are less common to control loads at homes, while in this paper, our interest is to optimize home appliances. For this purpose, only decentralized strategy (DS) can be used (Steen et al., 2016), (Xiaohua Wu et al., 2017). In DS (Figure 4.1 d), each local controller tries to manage its internal loads without communicating to external agents or units (Morstyn et al., 2016), (Steen et al., 2016), (Xiaohua Wu et al., 2017), (Paterakis et al., 2015). The problem with this strategy is that householders do not take into account external factors and constraints on the network into their optimization (Fotouhi Ghazvini et al., 2017), (Melhem et al., 2017). Obtaining an optimal local solution for each householder does not necessarily contribute to an optimal global solution for the distribution transformer (DT) and the network. Therefore, many end-users can have high peak demands in the same period causing problems on the DT and the network. Demand response programs (DRP) were introduced to solve the problem (S. G. Yoon, Choi, Park, & Bahk, 2016). Householders can use smart algorithms to optimize their electrical loads in a way to minimize their electricity cost, (Muratori & Rizzoni, 2016).

DRP can be price-based and incentive-based (Fotouhi Ghazvini et al., 2017). One or both of them could be used depending on the strategy of the utility or the aggregators (Xiaohua Wu, Hu, Moura, Yin, & Pickert, 2016). The main goal of the DRP is to provide a time-varying electricity price and incentive prices, to shift the power consumption of some loads to an off-peak time when the consumption is lower (Ito et al., 2017). Usually, Time Of Use (TOU), Real Time Price (RTP), and Dynamic Price are mostly used (X. Wu et al., 2016), (S. G. Yoon et al., 2016). DRP has limitations; papers (Ahn et al., 2011) and (Paterakis et al., 2015) show that DRP works appropriately until the number of EVs exceeds a particular limit. Because of the DRP, the EV charging time in all homes will be shifted to off-peak time, which may produce an undesired peak on the DT. The question is, shall the power utility provide different time-varying electricity prices for all end-users, for each group of end-users, or for individual end-users to solve the problem?

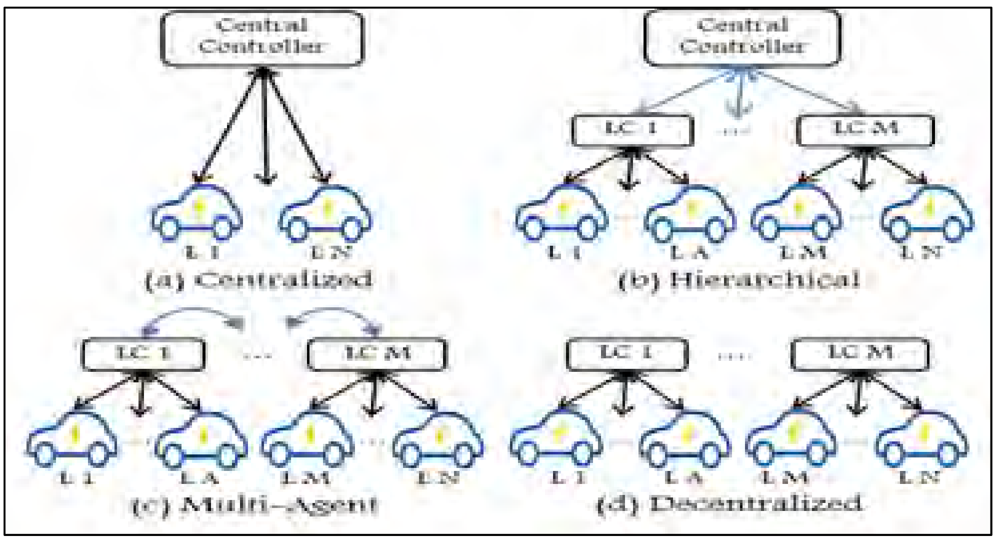


Figure 4.1 Control strategies for the same number of loads: (a) Centralized, (b) Decentralized, (c) Hierarchical, and (d) Multi-agent

4.2.2 Home energy management system: related works

To apply the Decentralized Strategy, an energy management system is needed at the home level. The home energy management is a hot topic of research in which many studies were done to improve the management of energy at homes using smart algorithms. For example, paper (Xiaohua Wu et al., 2017) used convex programming to minimize the electricity cost at home. It is relatively faster than other methods and more efficient. The cost of the battery and the charger are considered in the objective function, and the optimized elements are EV, Photovoltaic (PV) and Battery Storage System (BSS). However, the objective function in (Xiaohua Wu et al., 2017) is missing parameters related to DRP such as energy-based, price-based and incentive-based programs. Moreover, it did not consider the supplied energy to the grid. Therefore, it may not be implemented on a larger scale where many homes are connected to the same DT. In (Melhem et al., 2017), the objective function includes the generation and maintenance cost of the PV and Wind Turbine (WT) and the maintenance cost of the EV and BSS. Although WT is added and the Taguchi method is used for optimization, the results are not satisfying on a larger scale as the previous one. To solve the problem, paper (Fady Y. Melhem, April 28, 2017) added more elements to the optimization and the problem was formulated as a Mixed Integer Linear Programming (MILP). The weakness of (Melhem et al., 2017) and (Fady Y. Melhem, April 28, 2017) is that they only used price-based DRP. Therefore, it is neither efficient nor a motive way for users to reduce consumption during critical periods. To overcome this situation, paper (Fotouhi Ghazvini et al., 2017) introduced both incentive-based and price-based demand response program to its formulation. The results were satisfying, but the problem still exists during some periods when a total load of all homes may exceed the DT capacity. To deal with this issue, paper (Steen et al., 2016) developed new energy-based and power-based tariffs. The goal was to limit the total energy consumption during a day and limit power consumption during specific periods. Although many elements are controlled, this strategy does not guarantee that the total load on the transformer will not exceed the DT capacity. To limit the power consumption during specific periods at homes, paper (Paterakis et al., 2015) proposed using both price-based and power-limiting-based DRP strategies. Optimization is modeled as MILP in the presence of many controlled elements. The proposed model responds to contingencies and controls the market price. However, it does not consider transformer constraints and limits in the modeling that may create peak loads without the knowledge of the users and the retailers. Further to this related work analysis, in Table 4.1, we summarize all their used price-based DRPs and the controlled elements considered in their optimization models. It is important to note that all these references and many others did not consider the DT constraints in their optimization model.

Table 4.1 Controlled Elements and Pricing Mechanisms at Home

		Constraints														
References	Price-Based DR	Air conditioner	BSS	Circuit breaker	Clothes dryer	Dishwasher	EWH	Hot water boiler	HVAC	EV	Power balance	PV	Refrigerator	Wind Turbine	Washing machine	Others
(Fotouhi Ghazvini et al., 2017)	RTP & TOU		✓	✓			✓			✓	✓	✓				
(Melhem et al., 2017)	RTP		✓							✓	✓	✓		✓		
(Steen et al., 2016)	RTP, DBT, EBT, MBT[1]				✓	✓		✓		✓						✓
(Xiaohua Wu et al., 2017)	RTP		✓							✓	✓	✓				
(Paterakis et al., 2015)	RTP	✓	✓			✓	✓			✓	✓	✓			✓	✓
(Fady Y. Melhem, April 28, 2017)	RTP	✓	✓				✓			✓	✓	✓	✓	✓		
(J. H. Yoon et al., 2016)	RTP								✓							
(S. G. Yoon et al., 2016)	RTP									✓						

[1] DBT, EBT, and MBT: Energy-based, Daily-based, and Monthly-based Network Tariff respectively. EWH: Electric Water Heater.

4.2.3 Contributions

These papers and many other studies in the literature have provided useful contributions to the management of energy at homes. However, they failed to control the total energy on DT and DN because of the decentralized strategy concept. To tackle this issue, we propose a novel Soft-Constrained Distributed Strategy (SDS). It can solve the problem of high penetration level of EVs at homes without shifting to other complicated strategies such as HS and MAS. Also, it helps to improve the stability of the network; maintain the power consumption and the voltage on the transformers within the required limits; reduce the energy loss and loss of life of the transformer. SDS takes into account the transformer's technical constraints, which will be considered in the optimization algorithm of each home. In this way, a total load of all homes on the same transformer will not exceed its power capacity. Moreover, our paper shows that minimizing the electricity cost at homes may not be the best solution for the power utility. Using our study, the power utility (e.g., Hydro-

Quebec) could face the high penetration rate of EVs without doing considerable upgrades in its power and telecommunication infrastructures.

4.2.4 Paper organization

In Section 4.3, Soft-Constrained Distributed Strategy is proposed and developed. Assumptions are presented in section 4.4. Results and discussions are shown in Section 4.5. Finally, a conclusion summarizing the study is presented in section 4.6. The annexed Appendices presented at the end that shows the considered data for our study.

4.3 Soft-constrained distributed strategy

Soft-Constrained Distributed Strategy (SDS) is a novel strategy proposed in this paper. It is similar to the well-known Decentralized Strategy, in which each Local Controller (LC) controls its loads without communicating with any other LC or any external agent. The difference is that SDS introduces soft-constraints on the LC level that takes into account many external factors on the network. Therefore, it limits their power consumption in a way to respect the network technical limits and minimize their electricity cost. The proposed strategy consists of the following steps:

1. Firstly, we propose some constraints of the DT to be considered at the home level in 4.3.1.
2. In subsection 4.3.2, we suggest an optimization model at home that takes into account these constraints.
3. Finally, in subsection 0, the SDS operational steps are presented.

In this chapter, we define:

Soft Constraint: It is a constraint at home level, which takes into account the DT and Distribution Network (DN) limits. If it is exceeded, there is no direct impact on the technical limits at home. However, there is a risk that a total load of all homes may exceed the DT power limit. Thus, the loss of life of the DT may increase.

Base Load: It represents the consumption of home equipment, which is not affected by the optimization algorithm. For example, TV, fridge, microwave, dishwasher, and other loads which are not scheduled and controlled by the optimization algorithm, are considered as base loads, since BSS, PV, EWH, and 2 EVs consumption is affected by the optimization algorithm.

4.3.1 The proposed constraints to be considered

In this Subsection, we define new constraints at home level. They are introduced to distribute the energy management at each home keeping into account a global objective on the Distribution Network (DN) level. Both householders and the Distribution Network are satisfied by respecting their economic and technical limits. Power constraints reflect the DT and infrastructure technical limit. It is considered in the minimization of the DT Loss Of Life. Energy constraints reflect the consumption limit during a period (e.g., a day). It is considered in the minimization of the consumed energy cost knowing that additional cost will be applied in case this limit is exceeded.

4.3.1.1 Power-based and energy-based soft constraint

The Power-based Soft Constraint ($P^{C}_{j,t}$) at home "j" is defined as the maximum power consumption limit at instant "t", which a home can consume, without affecting the technical and economic limits on the DN (Eq. (4.1)). If a power consumption is greater than $P^{C}_{j,t}$, there is a risk that the DT and DN limits could be violated. The first term in Eq. (4.1) represents the ratio ($\eta^{P}_{j,t}$) between the DT critical power limit (P^{DT}_{t}) and the total consumed power of all homes ($\sum_{i=1}^{N}\left(P^{buy}_{i,t} - P^{sell}_{i,t}\right)$). If the ratio is greater than "1", home "j" can increase its power consumption by a percentage $\left(\eta^{P}_{j,t} - 1\right) \cdot 100\%$. For example, if the ratio $\eta^{P}_{j,t} = 1.4$, it means that home "j" can increase its power consumption by 40%. If $\eta^{P}_{j,t} = 0.8$, the home should reduce its power consumption by 20%. $\left(P^{buy}_{i,t} - P^{sell}_{i,t}\right)$ is the difference between the bought and sold power from the grid at home "i". N is the number of homes on the same DT.

$k_{j,t}^{CP}$ is the satisfaction index provided by an agreement between the power utility and the householder (If the householder needs a higher index, he may pay additional fees). In this paper, the satisfaction index is considered equal to one. Eq. (4.1) is valid for any home "*j*" on the same transformer.

Remark: We define P_t^{DT} as the critical power limit of the transformer in which the normalized Loss Of Life is equal to the unity (LOL=1). A LOL equal to the unity guaranties that the transformer will live as its expected lifespan provided by the manufacturer. A power consumption greater than P_t^{DT} will increase the LOL greater than 1. Thus, it reduces the life span of the transformer. The calculation of P_t^{DT} is out the scope of this paper.

$$P_{j,t}^{C} = \overbrace{\left(\frac{P_t^{DT}}{\sum_{i=1}^{N}\left(P_{i,t}^{buy} - P_{i,t}^{sell}\right)}\right)}^{\eta_{j,t}^{P}}\left(P_{j,t}^{buy} - P_{j,t}^{sell}\right) \cdot k_{j,t}^{CP} \tag{4.1}$$

Energy-based Soft Constraint in Eq. (4.2) represents the same concept as Eq. (4.1), but it is for energy instead of power. The main goal of introducing it is to limit energy consumption at home during a period of T (e.g., 24 hours). All energies in Eq. (4.2) are expressed as the sum of the corresponding powers in Eq. (4.1) during a period T. k_j^{CE} is the satisfaction index provided by an agreement between the power utility and the householder (If the householder needs a higher index, he may pay additional fees). In this paper, the satisfaction index is considered equal to one.

$$E_{j}^{C} = \overbrace{\left(\frac{E^{DT}}{\sum_{i=1}^{N}\left(E_{i}^{buy} - E_{i}^{sell}\right)}\right)}^{\eta_{j}^{E}}\left(E_{j}^{buy} - E_{j}^{sell}\right) \cdot k_{j}^{CE} \tag{4.2}$$

Eq. (4.1) and (4.2) require a real-time and bidirectional data flow between the local controllers of the end-users and the communication network. For implementation purposes, and since this paper is targeting a distributed infrastructure with minimum communication needs, these expressions are increased to their maximum limits as presented in Equations

(4.3) and (4.4) in the next subsection. The next subsection shows that these maximum limits are based on the static data of the infrastructure preventing any additional communication needs between homes, the distribution systems, and the communication network. Power utility may use Eq. (4.1) and (4.2) in case it will install a sophisticated communication infrastructure, while it can use Eq. (4.3) and (4.4) in case the communication infrastructure is far from being implemented shortly.

4.3.1.2 Power-based and energy-based infrastructure limits

Power-based ($P_{j,t}^{IL}$) and Energy-based (E_j^{IL}) Infrastructure Limits represent the technical maximum limit imposed by the DN infrastructure (*Eq.* (4.3) and (4.4)). They are particular cases of Eq. (4.1) and (4.2), in which the power utility may use to reduce the installation cost of the communication infrastructure. $\mu_{j,t}^{P}$ is the ratio between the DT power limit (P_t^{DT}) and the sum of the installed circuit breaker rate of all homes ($\sum_{i=1}^{N} P_i^{CB}$). μ_j^{E} is the ratio between the DT energy limit and the sum of maximum energy that could be consumed at homes ($\sum_{i=1}^{N} E_i^{CB}$). These limits guarantee that the total load at homes will respect the network hard constraints whatever the consumption at home is. $k_{j,t}^{IP}$ and k_j^{IE} are the satisfaction indices provided by an agreement between the power utility and the householder (If the householder needs a higher index, he may pay additional fees). In this paper, the satisfaction indices are considered equal to one.

$$P_{j,t}^{IL} = \overbrace{\left(\frac{P_t^{DT}}{\sum_{i=1}^{N} P_i^{CB}}\right)}^{\mu_{j,t}^{P}} P_j^{CB} \cdot k_{j,t}^{IP} \tag{4.3}$$

$$E_j^{IL} = \overbrace{\left(\frac{E_T^{DT}}{\sum_{i=1}^{N} E_i^{CB}}\right)}^{\mu_j^{E}} E_j^{CB} \cdot k_j^{IE} \tag{4.4}$$

4.3.2 Optimization model (objective function and constraints)

To show the importance of the proposed strategy and its constraints, an optimization model inspired by reference (Fotouhi Ghazvini et al., 2017) is developed. We improved this model to meet the requirements for both householders and the distribution network operator. Therefore, new constraints and variables are proposed.

The objective function is to minimize the electricity cost at home "j" as described in Eq. (4.5). For writing simplicity, the index "j" is removed from the variables in all expressions starting from (4.5), since all of them concern home "j." In (4.5), π_t^{buy} and π_t^{sell} are the buying and selling electricity price from/to the grid [$/kWh]. P_t^{buy} and P_t^{sell} are the buying and selling powers at home from/to the grid. x_t^{buy} and x_t^{sell} are binary decision variables, which guarantee that the home cannot buy and sell energy at the same time as in Eq. (4.6). Only the excess of energy can be sold to the grid when the supplied power is higher than the consumed one at home. Δt is the time slot. E_T^{Ex} and $P_{\forall t}^{Ex}$ are the excess of energy and power above the proposed limits respectively as presented in Equations (4.7), (4.8) and (4.9). π^E and π^P are our proposed energy-based and power-based incentive programs in [$/kWh] and [$/kW] respectively. The incentive programs could penalize or incite the end-user according to his energy and power consumptions. Equations (4.10) and (4.11) represent the used incentives in this paper, in which the user pays $+\pi_c^E$ or $+\pi_c^P$ if he consumes higher than the limits, whatever is the rate of the consumption. In addition, he gets financial benefits and reduces his electricity cost by $-\pi_c^E$ or $-\pi_c^P$ if he consumes less than the proposed limits. In this paper, we are not trying to penalize the user for exceeding the limits, but we will encourage him to use our proposed strategy and benefit from reducing his electricity cost (Table 4.2). Therefore, only the negative terms are used in Equations (4.10) and (4.11).

$$C = min \sum_{t \in T} \left(\pi_t^{buy} P_t^{buy} x_t^{buy} - \pi_t^{sell} P_t^{sell} x_t^{sell} \right) \Delta t + E_T^{Ex} \pi^E + P_{\forall t}^{Ex} \pi^P \tag{4.5}$$

$$x_t^{buy} + x_t^{sell} \leq 1 \tag{4.6}$$

The excess of energy (E_T^{Ex}) and power ($P_{\forall t}^{Ex}$) are presented in Equations (4.7), (4.8) and (4.9) respectively. α is a binary variable, in which it is equal to one when the proposed strategy is implemented with the Energy-based and Power-based Soft Constraint. It is equal to zero if the strategy is implemented with the Energy-based and Power-based Infrastructure limit.

$$E_T^{Ex} = \sum_{t \in T} \left(P_t^{buy} - P_t^{sell} \right) - \overbrace{\left(\alpha E_T^C + (1 - \alpha) \cdot E_T^{IL} \right)}^{E_T^{Limit}} \tag{4.7}$$

$$P_t^{Ex} = \left(P_t^{buy} - P_t^{sell} \right) - \overbrace{\left(\alpha P_t^C + (1 - \alpha) \cdot P_t^{IL} \right)}^{P_t^{Limit}} \tag{4.8}$$

$$P_{\forall t}^{Ex} = \max_{t \in T} [P_t^{Ex}] \tag{4.9}$$

$$\pi^E = \begin{cases} \pm \dfrac{\pi_c^E}{E_T^{Ex}} & if \pm E_T^{Ex} > 0 \\ 0 & if \pm E_T^{Ex} \leq 0 \end{cases} \tag{4.10}$$

$$\pi^P = \begin{cases} \pm \dfrac{\pi_c^P}{P_{\forall t}^{Ex}} & if \ \pm P_{\forall t}^{Ex} > 0 \\ 0 & if \ \pm P_{\forall t}^{Ex} \leq 0 \end{cases} \tag{4.11}$$

For comparative purposes, in this paper, the elements to be controlled are similar to those mentioned in reference (Fotouhi Ghazvini et al., 2017): 2 EVs, a PV, a BSS, and an EWH. According to our proposed strategy and DT limits, the new constraints for the optimization model become as follows:

4.3.2.1 Home power balance

As in (Fotouhi Ghazvini et al., 2017), Eq. (4.12) and (4.13) guarantee that the consumed and supplied powers at home from/to the grid are balanced. Where the buying power an instant "t" is composed of: the Base Load (P_t^{BL}), EWH (P_t^{EWH}), the charging of EVs ($P_t^{V,Ch}$), and the charging of the BSS ($P_t^{B,Ch}$). The internal power production consists of the discharging of EV (P_t^{V2H}) and BSS (P_t^{B2H}) to the home, and the supply of the PV to the home (P_t^{PV2H}). The selling power to the grid consists of discharging the EV (P_t^{V2G}) and the BSS (P_t^{B2G}) to the grid, and supplying the grid by the PV (P_t^{PV2G}). N_V and N_B are the number of EVs and BSS at home.

$$P_t^{buy} = P_t^{BL} + P_t^{EWH} + \sum_{V=1}^{N_V}\left(P_t^{V,Ch} - P_t^{V2H}\right) + \sum_{B=1}^{N_B}\left(P_t^{B,Ch} - P_t^{B2H}\right) - P_t^{PV2H} \tag{4.12}$$

$$P_t^{sell} = \sum_{V=1}^{N_V} P_t^{V2G} + \sum_{B=1}^{N_B} P_t^{B2G} + P_t^{PV2G} \tag{4.13}$$

4.3.2.2 Power and energy constraints

We added Eq. (4.14) to (4.17) to the constraints expressed in (Fotouhi Ghazvini et al., 2017). They ensure that the bought and sold power/energy is within the respected limits. Where in Eq. (4.14) and (4.15), P_t^{DR} is the power limit based on the DRP provided by the electricity retailer. P^{CB} is the circuit breaker rate at home. P_t^{Limit} and E_T^{Limit} are the proposed Power-based and Energy-based constraints in Eq. (4.1) to (4.4). P_t^{PU} and E_T^{PU} are the power and energy limits defined by the Power Utility for protection purpose of the grid in urgent cases. $P_t^{DT,V}$ is the power limit in which the voltage drop of the total load respects the minimum voltage limit on the DT.

$$P_t^{buy} - P_t^{sell} \le min\begin{Bmatrix} P_t^{DR}; P^{CB};\ P_t^{Limit} \\ P_t^{PU}; P_t^{DT,V} \end{Bmatrix} \tag{4.14}$$

$$\sum_{t\in T}\left(P_t^{buy} - P_t^{sell}\right)\Delta t \le min\left\{E_T^{Limit}; E_T^{PU}\right\} \tag{4.15}$$

The Power Utility could limit the sold power and energy to avoid excess in a power supply to the grid as in Eq. (4.16) and (4.17).

$$0 \le P_t^{sell} \le P_t^{sell,Max} \tag{4.16}$$

$$0 \le \sum_{t\in T} P_t^{sell}\Delta t \le E_T^{sell,Max} \tag{4.17}$$

4.3.2.3 EV constraints

EV constraints in Eq. (4.18) to (4.22) are similar to those in (Fotouhi Ghazvini et al., 2017). Eq. (4.18) represents the charging and discharging limits of the EV. Where $P_{Max,t}^{V,Ch}$ and $P_{Max,t}^{V,Dch}$ are the maximum allowed charging and discharging power at "*t*". $x_t^{V,Ch}$ and $x_t^{V,Dch}$ are the binary decision variables. One of them could be equal to "1" and the other "0".

$$\begin{gathered} 0 \leq P_t^{V,Ch} \leq P_{Max,t}^{V,Ch} \cdot x_t^{V,Ch} \\ 0 \leq P_t^{V,Dch} \leq P_{Max,t}^{V,Dch} \cdot x_t^{V,Dch} \\ x_t^{V,Ch} + x_t^{V,Dch} \leq 1 \end{gathered} \tag{4.18}$$

In Eq. (4.19), EV can supply energy to the home (P_t^{V2H}) or to the grid (P_t^{V2G}). $\eta^{V,Dch}$ is the discharging efficiency.

$$P_t^{V,Dch} \cdot \eta^{V,Dch} = P_t^{V2G} + P_t^{V2H} \tag{4.19}$$

Eq. (4.20) represents the SOC of the EV's battery at each time slot. It depends on the SOC of the previous time slot ($SOC_{t-\tau}^V$) and the difference between the charging ($P_t^{V,Ch}$) and discharging ($P_t^{V,Dch}$) power at instant "*t*". $\eta^{V,Ch}$ is the charging efficiency. The SOC should be between a minimum (SOC_{min}^V) and maximum (SOC_{max}^V) limits as in Eq. (4.21). The final SOC (SOC_{tf}^V) should be equal to the desired one (SOC_d^V) as in Eq. (4.22).

$$SOC_t^V = SOC_{t-\tau}^V + \frac{\left(\eta^{V,Ch} \cdot P_t^{V,Ch} - P_t^{V,Dch}\right)\Delta t}{B_{cap}^V} \tag{4.20}$$

$$SOC_{min}^V \leq SOC_t^V \leq SOC_{max}^V \tag{4.21}$$

$$SOC_{tf}^V = SOC_d^V \tag{4.22}$$

4.3.2.4 BSS constraints

BSS constraints in Eq. (4.23) to (4.26) are similar to those in (Fotouhi Ghazvini et al., 2017). Eq. (4.23) represents the charging and discharging limits of the BSS. Where $P_{Max}^{B,Ch}$ and

$P_{Max}^{B,Dch}$ are the maximum charging and discharging allowed power. $x_t^{B,Ch}$ and $x_t^{B,Dch}$ are the binary decision variables.

$$\begin{gathered} 0 \leq P_t^{B,Ch} \leq P_{Max}^{B,Ch} \cdot x_t^{B,Ch} \\ 0 \leq P_t^{B,Dch} \leq P_{Max}^{B,Dch} \cdot x_t^{B,Dch} \\ x_t^{B,Ch} + x_t^{B,Dch} \leq 1 \end{gathered} \tag{4.23}$$

In Eq. (4.24), BSS can supply energy to the home (P_t^{B2H}) or to the grid (P_t^{B2G}). $\eta^{B,Dch}$ is the discharging efficiency.

$$P_t^{B,Dch} \cdot \eta^{B,Dch} = P_t^{B2G} + P_t^{B2H} \tag{4.24}$$

The SOC of the BSS's battery at each time slot is expressed in Eq. (4.25). It depends on the SOC of the previous time slot ($SOC_{t-\tau}^B$) and the difference between the charging ($P_t^{B,Ch}$) and discharging ($P_t^{B,Dch}$) power at instant "*t*". $\eta^{B,Ch}$ is the charging efficiency. The SOC should be between a minimum (SOC_{min}^B) and maximum (SOC_{max}^B) limits as in Eq. (4.26).

$$SOC_t^B = SOC_{t-\tau}^B + \frac{\left(\eta^{B,Ch} \cdot P_t^{B,Ch} - P_t^{B,Dch}\right)\Delta t}{B_{cap}^B} \tag{4.25}$$

$$SOC_{min}^B \leq SOC_t^B \leq SOC_{max}^B \tag{4.26}$$

4.3.2.5 PV constraints

We also added the constraint expressed in Eq. (4.27) to guarantee that the produced power by PV is equal to the supplied ones to the home and the grid.

$$P_t^{PV} = P_t^{PV2H} + P_t^{PV2G} \tag{4.27}$$

4.3.2.6 EWH constraints

EWH constraints in Eq. (4.28) to (4.30) are similar to those in (Fotouhi Ghazvini et al., 2017). The temperature of the water (θ_t^{EWH}) at instant "t" is expressed in Eq. (4.28). Where,

θ_t^a is the ambient temperature. R and C are the thermal resistance and capacitance of the water. P_t^{EWH} is the power consumption. M is the capacity of the water tank. m_t is the hourly hot water usage. $\theta_{t-\tau}^{EWH}$ is the temperature of the previous time slot.

$$\theta_t^{EWH} = \theta_t^a + R \cdot P_t^{EWH} - \frac{M - m_t}{M}(\theta_t^a - \theta_{t-\Delta t}^{EWH})e^{-\frac{\Delta t}{RC}} \tag{4.28}$$

The EWH can be only turned on or off. Therefore, Eq. (4.29) considers the binary status of the EWH. Where P^{EWH} is the power consumption of the EWH, x_t^{EWH} is the binary decision variable that turns the EWH on “1” or off “0”.

$$P_t^{EWH} = P^{EWH} \cdot x_t^{EWH} \tag{4.29}$$

The water temperature of the EWH should be within a minimum ($\theta_{t,min}^{EWH}$) and a maximum ($\theta_{t,max}^{EWH}$) limit as in Eq. (4.30).

$$\theta_{t,min}^{EWH} \leq \theta_t^{EWH} \leq \theta_{t,max}^{EWH} \tag{4.30}$$

4.3.3 Soft-constrained distributed strategy

SDS is composed of three steps as in Figure 4.2. In the first step, the power utility sends data to a specific program on the internet such as DTs data, Distribution Network data, and DRP parameters. A unique serial number (SN) identifies each DT. The SN contains all necessary information about the DT, its location, number of connected loads (homes), and its internal characteristics including but not limited to its power rate, number of phases, frequency, and type of used fluid. The Distribution Network data includes but not limited to the voltage limits of each DT, cable sizes and lengths between the DT and the householders. The DRP could be price-based, incentive-based, power-based, energy-based, or any other type or a combination of different types. The used tariff could be RTP, TOU, Dynamic price or any other pricing mechanism defined by the power utility. Also, the weather forecasted data is sent to the internet cloud including but not limited to the ambient temperature of each region, the wind speed, and the solar irradiance.

The second step consists of collecting the data through a single website on the internet. Online software assembles the pertinent data and under a specific serial number for each DT on the network. The data concerning the DT and Distribution Network infrastructure are received once. The weather data and DRP are updated every day or every hour according to the strategy of the Power Utility. Then, each LC has access to its pertinent data through the internet.

In the third step, a Local Controller (LC) in each home receives the appropriate data. It calculates the DT critical power limit (P_t^{DT}) based on the provided data by the website. Then, it calculates the constraints defined in subsection 4.3.1. Based on the obtained constraints, the LC executes the appropriate optimization algorithm (Subsection 4.3.2) and schedules the power consumption of the controlled elements. For comparative purpose, the used optimization algorithm in this study is Mixed Integer Linear Programming (MILP) similar to (Fotouhi Ghazvini et al., 2017).

Because the data is transferred and collected through the internet via VPN, the website should be programmed to be protected from any hacking or cyber-attack. Therefore, it should use a continuously audited web server protected by reliable security software. The same for end-user components connected to the internet, protection should be provided using firewalls and antiviruses. The security issue is of importance during the implementation, which should be done according to security standards such as IEEE 1888.3-2013, IEEE 1686-2013, IEEE P1711, IEEE P2030.102.1, IEEE Std P2030.5-2013, RFC 8152, COSE (Concise Binary Object Representation-Object Signing and Encryption), and OSCoAP (Object Security for-Constrained Application Protocol). The proposed strategy does not require any infrastructure for communication other than the internet.

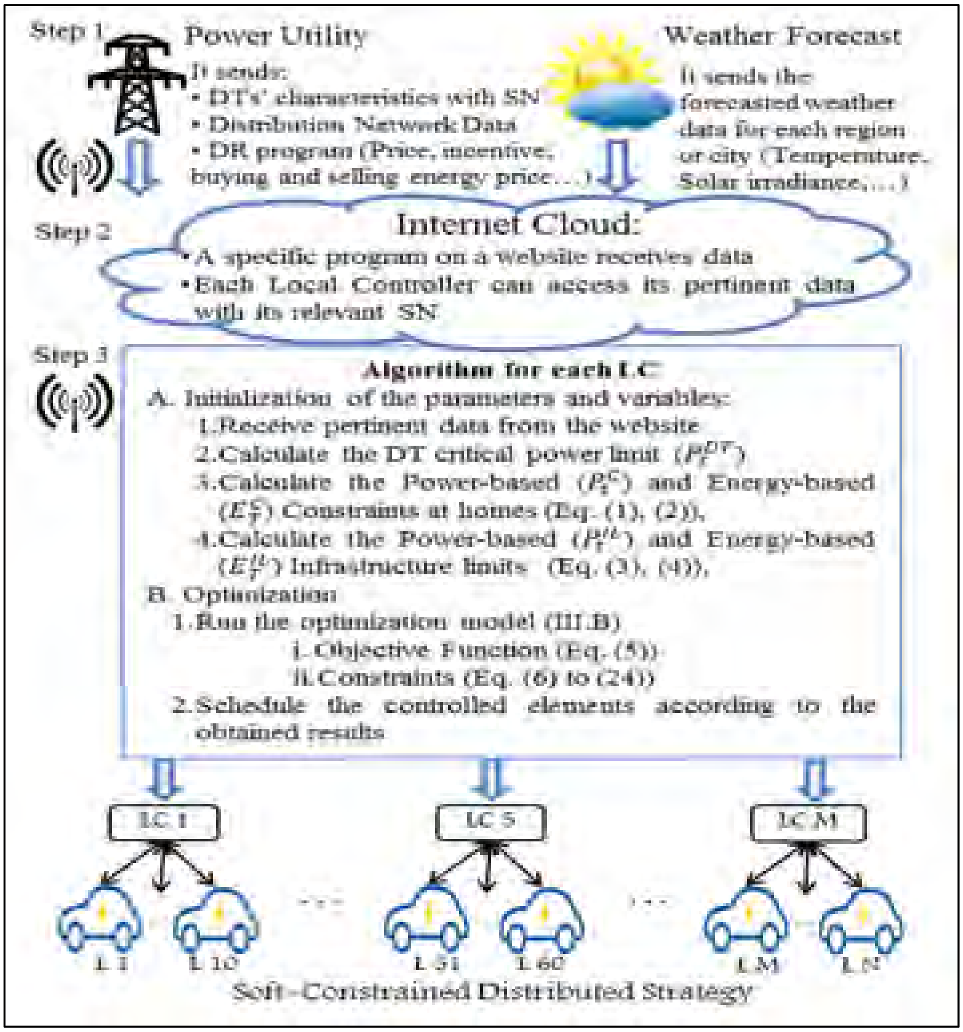


Figure 4.2 Structure of our proposed Soft-Constrained Distributed Strategy

4.4 Assumptions for the study

To validate the proposed strategy in this paper, we took a case study, in which a typical distribution transformer supplies ten homes in Montreal Canada, which is a typical distribution case in Quebec. The reason for this choice is to apply our strategy on a real system, which already exists in Quebec. However, this study can be applied to different capacities of distribution transformers with a different number of homes and loads. It will be seen that the increase of loads on the system will give the suggested strategy more advantages compared to others like the presented one in (Fotouhi Ghazvini et al., 2017).

Obviously, the more the total load on the transformer is smaller to its rating, the less the suggested method is advantageous. For simulation purposes, Hydro-Quebec Utility provided some data of a distribution transformer and the supplied homes as follows.

- DT data: 80kVA, 11kV/120V, 1-φ, 60Hz, (Table 4.7),
- Baseload power profiles at homes are provided in Figure 4.15,
- Water consumption profile at homes are provided in Figure 4.16,
- Solar irradiance and the production of the energy at home from PVs are presented in Figure 4.17 and Figure 4.18,
- For comparative purposes, Real-Time Price is considered as in Figure 4.19 similar to reference (Fotouhi Ghazvini et al., 2017),
- Data of the controlled elements (Figure 4.3): PV, EWH, BSS, and 2 EVs are presented in Table 4.5,
- To motivate the householders consuming less than E_T^{Limit} and P_t^{Limit}, we propose an incentive program as in Table 4.2. The user's benefit is 2.7$/day if he respects the limits. If not he will not pay any additional fees. These values are just estimation in order to motivate the consumers for signing a contract based on the suggested method. A detailed study for determining the optimal values could be done in future works.

Table 4.2 Our Proposed Pricing Mechanisms for Homes

Exceeded Value in %	$\boldsymbol{\pi^P}$ **(Tariff in \$/day)**	$\boldsymbol{\pi^E}$ **(Tariff in \$/day)**
≤0%	-2.7	-2.7
>0%	0	0

- In this paper, because the strategy is distributed, and because we are trying to improve the profile of the total load on the transformer without installing any infrastructure for communication between homes,
- In this paper, we consider that all EVs connected to the grid have a unity power factor (advanced converters technologies and structures are used in EVs, they respect the total harmonic distortion in conformity with the Standard EN 50160, and IEEE Std 519-2014). For lower power factors, the comparative study between the suggested strategy

and the others will remain valid since harmonics and reactive power would affect in the same way all the strategies.

To validate our strategy, the suggested approach is compared to the one presented in reference (Fotouhi Ghazvini et al., 2017). The same controlled elements (BSS, EWH, PV, and 2 EVs) and RTP (Figure 4.19) are considered. The strategy in (Fotouhi Ghazvini et al., 2017) is called Method 1 (M1), and our strategy is called Method 2 (M2). The same optimization technique (MINLP) is used for both methods to obtain good comparative results. Simulations are conducted in MATLAB R2016b and OpenDSS. For the implementation of our strategy on a larger network, IEEE 123 node test feeder is chosen. In the following section, we compared both strategies at homes and distribution transformer levels.

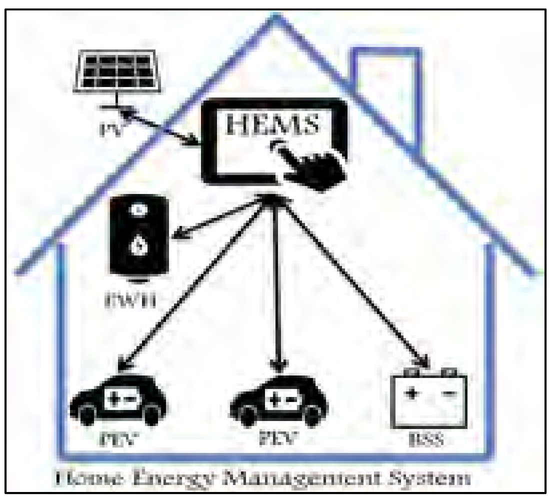


Figure 4.3 Controlled elements at homes

4.5 Results and discussions

4.5.1 Impact on the power consumption at homes

The main goal of this subsection is to see the impact of both methods on the behaviors of the total power consumption at home. Figure 4.4 and Figure 4.5 show two typical cases at homes. Figure 4.4 represents the case of homes (1, 2, 3, 4, 7, and 8) where our strategy respects the soft constraints at homes. Figure 4.5 represents the case of homes (5, 6, 9, and 10) where our strategy has slightly exceeded the soft constraints limit at homes. For all homes, M1 has exceeded the homes' soft constraints and created high peak demands. Figure 4.4 shows the profiles of the total load for both methods at home 4. The red curve represents the base load at home that cannot be controlled. For M1, the controlled elements tend to charge when the electricity price is low (between 21:00 and 09:00 of Figure 4.19). At 03:00, the power consumption is doubled compared to the soft constraint (P_t^C). In M2, the total load respects the soft constraint (P_t^C) without reducing the energy consumption of the controlled elements. EVs charge when the electricity price is low until the total load becomes equal to the soft constraint, if the charged energy is not enough, they charge during other periods when the electricity price is slightly higher (e.g., from 18:00 to 21:00 and from 09:00 to 12:00).

In Figure 4.5, home 10 is studied. M1 exceeds the soft constraint for a more extended period (21:00 to 09:00) when the electricity price is low. It is due to the high power consumption of the base load (red curve), and due to the high battery capacity of the EVs (Table 4.5). M2 shows better scheduling of the controlled elements. To charge the EVs to the desired SOC level, the soft constraint is slightly exceeded during some periods.

In this subsection, results show that by using M1, the total load demand at homes has exceeded the soft constraint at least by 200%. M2 shows that only two homes out of 10 have surpassed their soft constraint with a small value (150% in the worst case during short periods). It is due to the high base load consumption and the high needed energy to charge the battery of the EVs.

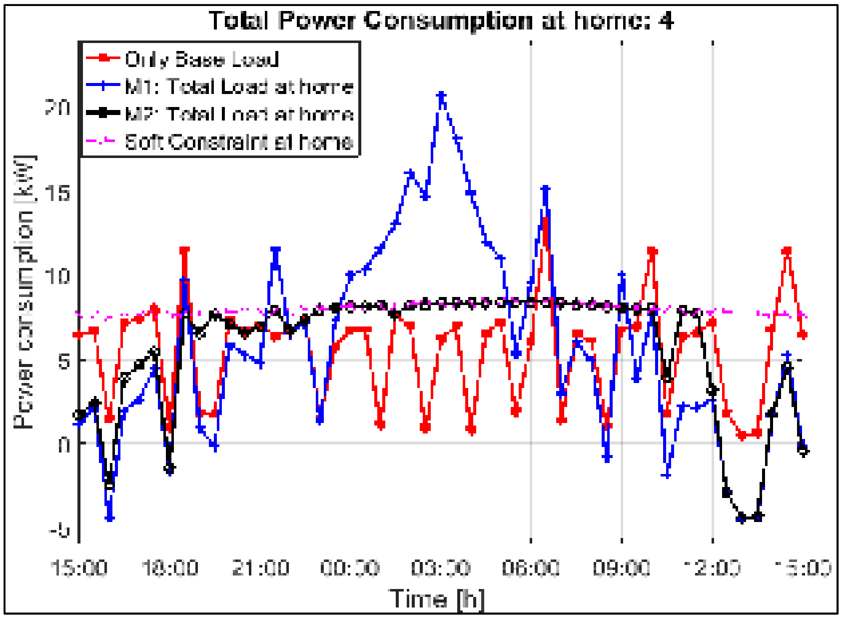


Figure 4.4 Total power consumption at home 4

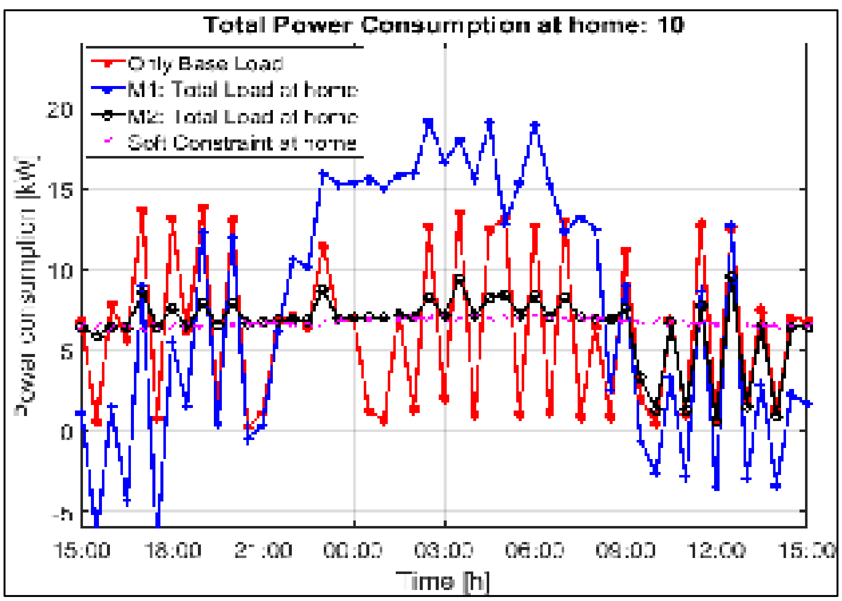


Figure 4.5 Total power consumption at home 10

4.5.2 Economic impact on the electricity price at homes

In this subsection, the economic impact of both methods on the electricity cost at homes is studied. Figure 4.6 represents the difference in electricity cost for both methods without using the proposed incentive programs (π^P and π^E). M2 shows a better reduction in electricity cost for 3 homes (1, 2 and 7), while M1 is better for others. It can be seen that the difference in the cost is not very high, the worst case is for home 5 where the difference in percentage is 13.89% for M1. The average of the difference cost is about 6.03% for M1. The reason for this difference is that the controlled elements in M1 tend to consume power when the buying electricity price is low and supply the grid when the selling electricity price is high without taking into account the DN Constraints. While for M2, the electricity cost is higher. The controlled elements may consume power when the electricity price is slightly higher in order to respect the DN constraints. By applying and considering our proposed incentive program in Table 4.2, both householders and Power Utility are satisfied. The householder benefits by respecting the DN constraints, and the Power Utility reduces the depreciation cost of its infrastructure. In Figure 4.6, the orange blocks represent the M2 results after introducing our incentive program. It can be seen that not all homes using M1, got benefit from the program. Because they exceeded the limits. While for M2, only four homes (5, 6, 9 and10) did not benefit because of their excess power consumption.

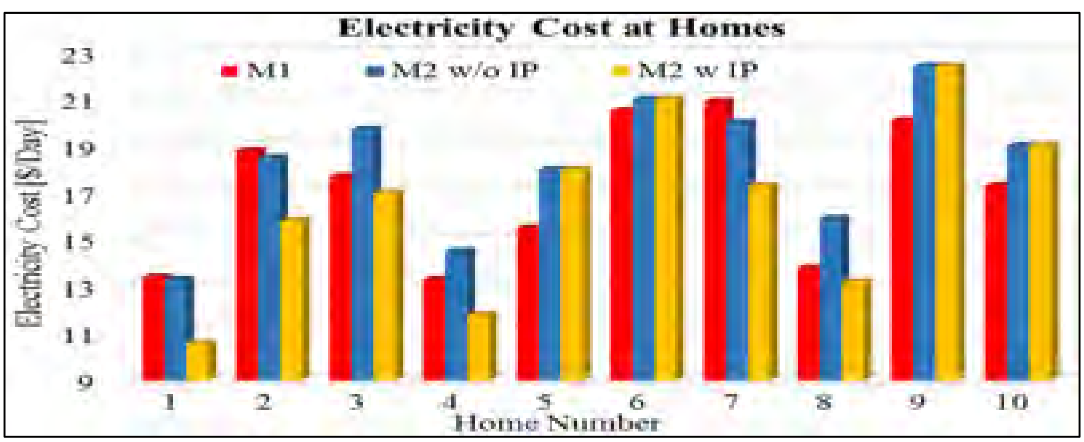


Figure 4.6 Electricity Cost at Homes in $/Day With/Without Incentive Programs. “w/o IP”: Without our proposed Incentive Program. “w IP”: with our proposed incentive Program

4.5.3 Technical impact on the distribution transformer

After studying the technical and economic impact of both methods at home levels. It is essential to study their impact on the DT and the DN level. In this paper, a typical DT supplies 10 homes with a capacity of 80kVA. The total load demands of all homes for the base load, M1 and M2 are presented in Figure 4.7. For simplicity reasons, it is assumed that the controlled elements at each home are: 2 EVs, BSS, PV, and EWH. In total, there are 20 EVs on the same DT, which is considered a very high penetration level. In M1, EVs tend to charge when the electricity price is low (between 21:00 and 09:00 of Figure 4.19) without considering the limits of the DT. Therefore, they create a very high peak demand on the DT (>190% of its limit), which reduces its lifetime drastically and create high voltage drop (Figure 4.8). M2 shows better performance on the DT level in which the power limit is almost respected. There are some few periods when the limit is slightly exceeded (i.e., 5.5% in the worst case at 03:30 a.m.).

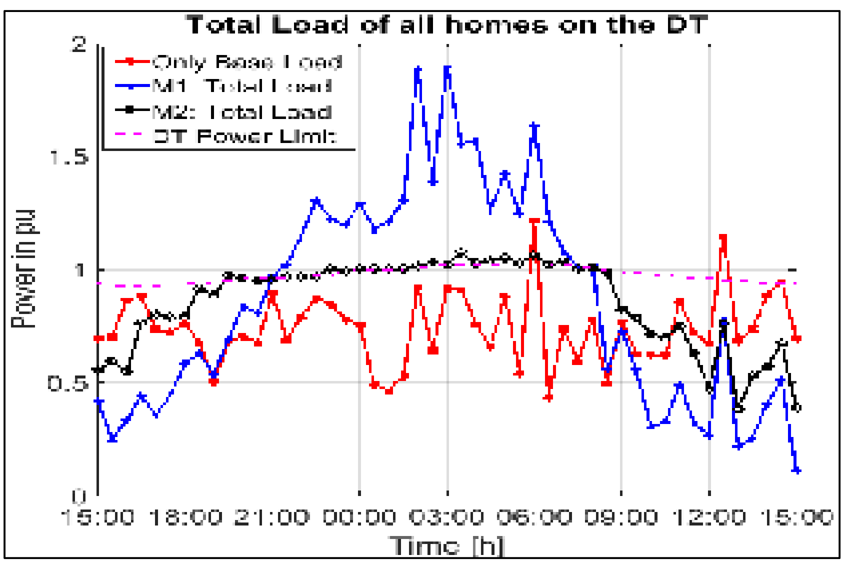


Figure 4.7 Total power consumption on the Distribution Transformer

In the case of M1, the voltage drop exceeded the recommended limit during low electricity price (between 22:30 and 6:30). It may cause severe problems on the DN and at homes. The voltage drop may damage some equipment at homes. Therefore, the Power Utility may pay for repairing the end-users' equipment, which is costly.

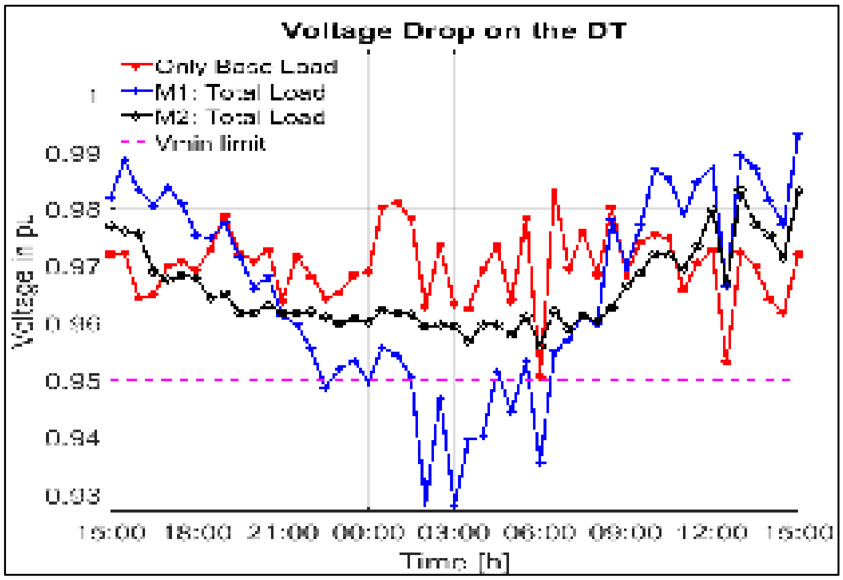


Figure 4.8 Voltage deviation on the Distribution Transformer

4.5.4 Economic impact on the distribution transformer

To study the impact on the DT, it is necessary to define some terms. We define the Loss of life during a day (LOL_{Day}) as the lost life of the transformer's lifetime when a certain load is applied during one day of operation, (Eq. (4.31) is expressed in a number of days). i.e. $LOL_{Day} = 2\ days$ means that one day of operation at a certain load is equivalent to 2 days of operations at the transformer full power capacity. Where $LOL_{\%}$ is the loss of life of the transformer in percentage (Qian et al., 2015), (Turker et al., 2014), (2012). L_N is the lifetime of the transformer in hours provided by the manufacturer (e.g., 180000 hours for this study ≈ 20.55 years) (2012). The details of calculating the Loss Of Life in percent ($LOL_{\%}$) is presented in Appendix I.

$$LOL_{Day} = \frac{LOL_{\%}}{100} \cdot \frac{L_N}{24} \tag{4.31}$$

We define DT Remaining Lifetime (Eq. (4.32)) as the lasting period of the transformer if it is used at the same load demand every day. e.g. $Rl_{DT} = 5000\ days$ means that the transformer lasts for 5000 days if it is used at the same load demand every day.

$$Rl_{DT} = \frac{L_N}{LOL_{Day}} \tag{4.32}$$

Table 4.3 shows the Loss of Life and the remaining lifetime of the DT caused by a total load of all homes. The first column represents the values of the base load without introducing the controlled elements. The second column represents the results for the M1 in which the LOL is very high, and the transformer will not last more than two days. It means that the transformer should be changed every two days, or the DSO should install a bigger one with at least two times the initial capacity. Changing the transformer every two days or installing a bigger one will cost thousands of dollars for just a small one. Our method shows better performance on the DT level. The loss of life and the DT remaining lifetime are close to the base load as if the EVs do not exist at homes. M2 shows its advantage over M1 even in the presence of a very high penetration level of EVs.

Despite that, M1 reduces the electricity cost at homes better than M2 (if our incentive programs are not applied); the impact on the transformer is higher and costly. Using M2, the DT is expected to last for 15 years, while for M1, it lasts less than two days (Table 4.3). M2 reduces the energy losses by 35.9% (Figure 4.9), and their electricity cost by 27.9% (Figure 4.10). Therefore, Power Utility reduces the cost of energy losses and save money. (For more details about how to calculate the energy losses, kindly refer to Appendices I.8 and I.9).

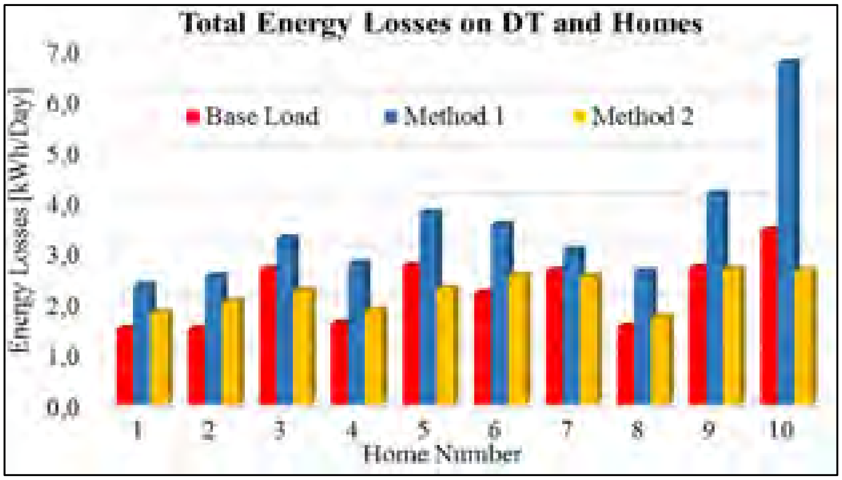


Figure 4.9 Total Energy Losses on DT and Homes [kWh/Day]

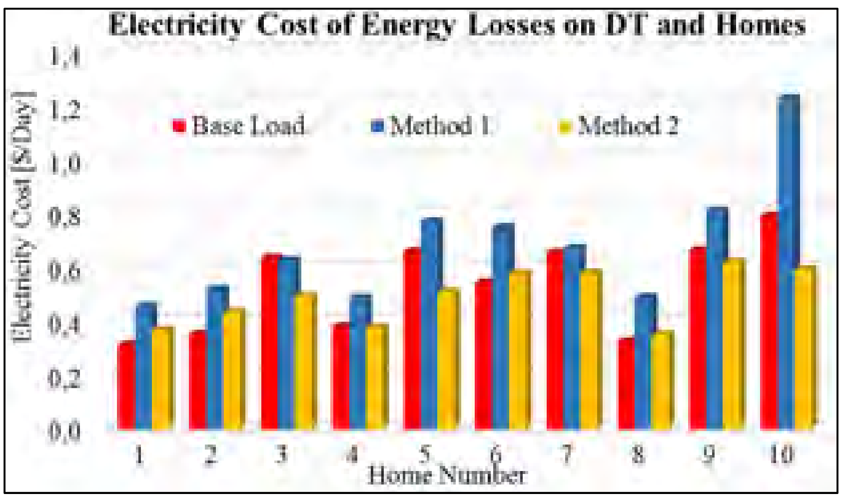


Figure 4.10 Electricity Cost of Energy Losses on DT and Homes [$/kWh/Day]

Table 4.3 Loss of Life and Remaining Lifetime of the Transformer

	Base Load	**Method 1**	**Method 2**
LOL per Day	1.21 days	4884.78 days 13,38 years	1.37 days
DT Remaining Lifetime	6190.3 days 16.96 years	1.5 days 0.0042 years	5473.8 days 15 years
Depreciation in $/Day	0,17	3907,03	0,29

*The depreciation cost means how much the Power Utility is losing from the cost of their transformers during a day. (Cost of the considered DT is 6000$).

4.5.5 Technical impact on the network

To validate the proposed model on a larger scale, IEEE 123-Node Test Feeder is chosen as an example. Many homes are distributed on the network with and without the controlled elements (in this paper the controlled elements are PV, EWH, BSS, and 2 EVs) as in Figure 4.11. The black nodes in Figure 4.11 represent the nodes where loads are connected (85 nodes). The loads are homes in our case, and they are divided into two categories. The first category (Only black nodes without red circles) is for homes with only baseload profiles without the mentioned controlled elements. While the second category (black nodes with red circles) is for homes that include the controlled elements. To be reasonable in the simulation, only 43% (37 nodes out of 85) of the connected homes are considered with the controlled elements. Therefore, we can consider that the total penetration level of EVs is about 43% of the network.

In this subsection, the two methods M1 and M2 are implemented at homes with the controlled elements. While other homes with only the base loads (black nodes without red circles), they are considered without a smart energy management system. Therefore, they are not capable of controlling and scheduling their appliances and loads. The homes have different demand profiles during a day. However, for simplicity reasons, we considered that they have the same profile in per unit but with different power consumption values. This consideration will not affect too much the result. The impact on the network of both methods is studied. Figure 4.12.a and 4.12.b show the voltage drop on all buses of the IEEE 123 Node Test Feeder at 03:00 a.m. when the electricity price is low (refer to Figure 4.19 for the electricity price profile). Each color represents a different phase (black color represents the phase a, the red color is for the phase b, the blue color is for phase c). By comparing both figures, it can be seen that M1 has a higher impact on the network, in which the voltage drop is higher than M2 on all buses. Notably, bus 66 indicates the higher voltage drop on the network. The main reason for this high voltage drop is that all EVs at homes on the network tend to charge during low electricity price. However, by using our method M2, the voltage drop is reduced because the total load consumptions at homes are limited below our proposed power-based soft constraints.

In the far future when all cars become EVs, their penetration level will become 100%. Therefore, it is essential to see what will happen on the network if all homes have EVs. Figure 4.13.a and 4.13.b show the voltage drop on all buses of the network. It can be seen that when M1 is used, the voltage drop becomes lower than the recommended limit (0.95pu) in some buses, which may create some problems on the network and create some perturbations. This can cause blackouts of some transformers on the network because of the voltage drop, and the network may lose its stability. While for the case of M2, even with a penetration level of 100% of EVs, the network maintains its stability within the recommended limits (1.05 and 0.95 pu). Therefore, our method M2 shows better performance on the network and maintains its stability even when the penetration level of EVs is 100%. Figure 4.14 shows the total losses on the network for 43% and 100% of the penetration level of the controlled elements. M1 shows an increase in the losses for both penetration percentages. While M2 shows a reduction of 209.5% and 313.6% compared to M1 for 43% and 100% penetration levels of controlled elements respectively.

In conclusion, it can be seen clearly that all EVs on the network tend to charge during low electricity price, which will create a heavy burden on the network and increase the voltage drop and the power losses. M2 shows less impact on the network since the power consumption at a particular instant is limited. Therefore, it is logic to see that the voltage drop and the power losses are reduced. A small penetration level of EVs on the network will not show a big difference between both methods. However, a very high penetration will create severe problems if M1 is used instead of M2. Moreover, the cost of the losses and damages caused by M1 could be very high, which will oblige the power utility (Hydro-Quebec in our case) to shift to another efficient strategy on a larger scale. Therefore, M2 could be the solution in this case.

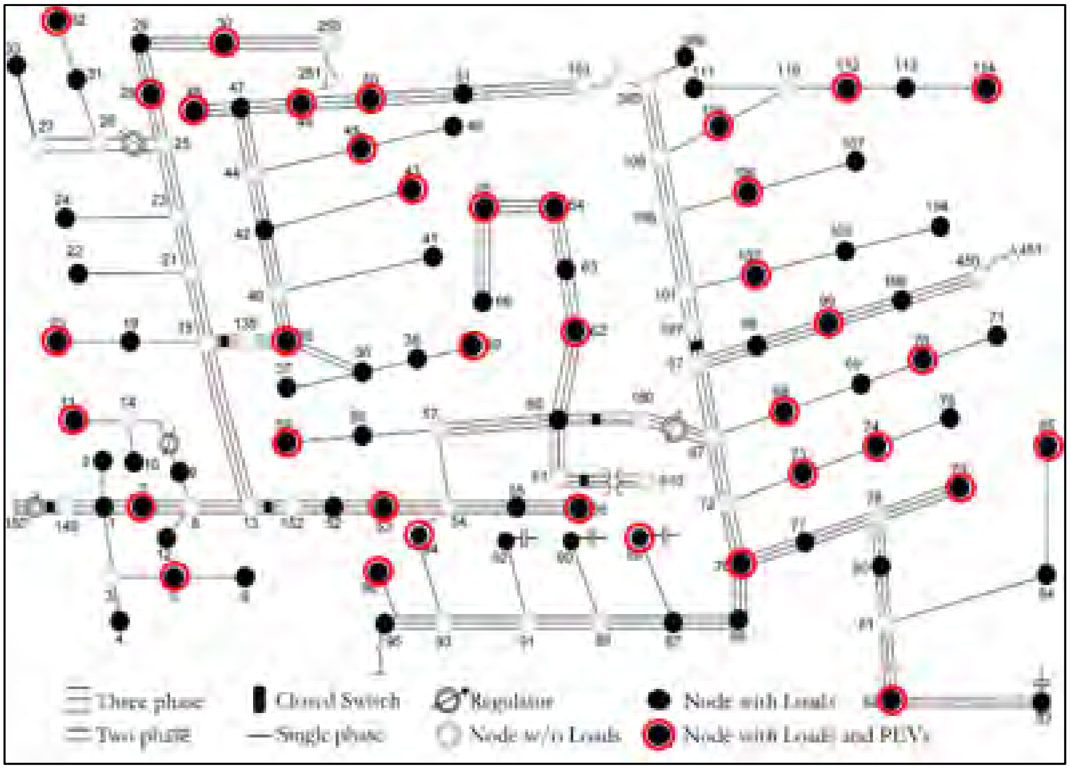
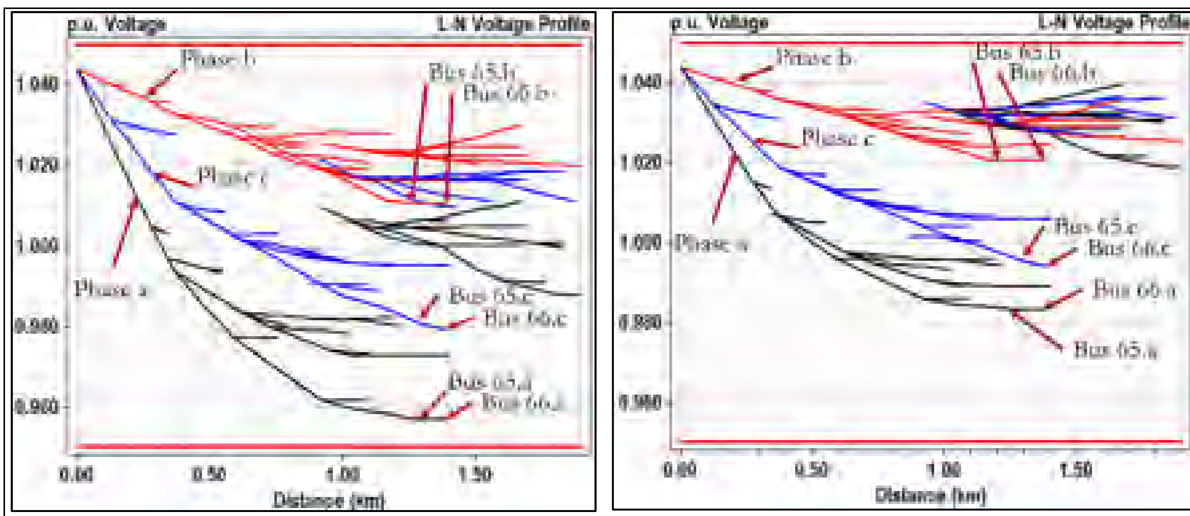


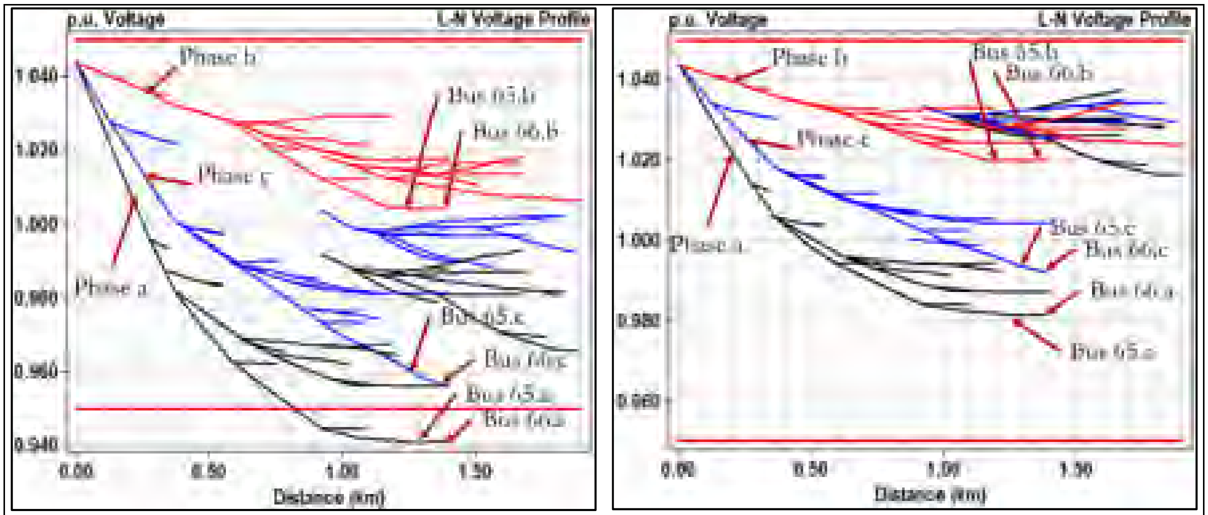
Figure 4.11 Schematic Diagram of IEEE 123 Nodes Test Feeder



(a) Voltage profiles on all buses of the network using M1

(b) Voltage profiles on all buses of the network using M2

Figure 4.12 Voltage Drop on all buses for both methods M1 and M2



(a) Voltage profiles on all buses of the network using M1

(b) Voltage profiles on all buses of the network using M2

Figure 4.13 Voltage Drop on all buses for both methods M1 and M2

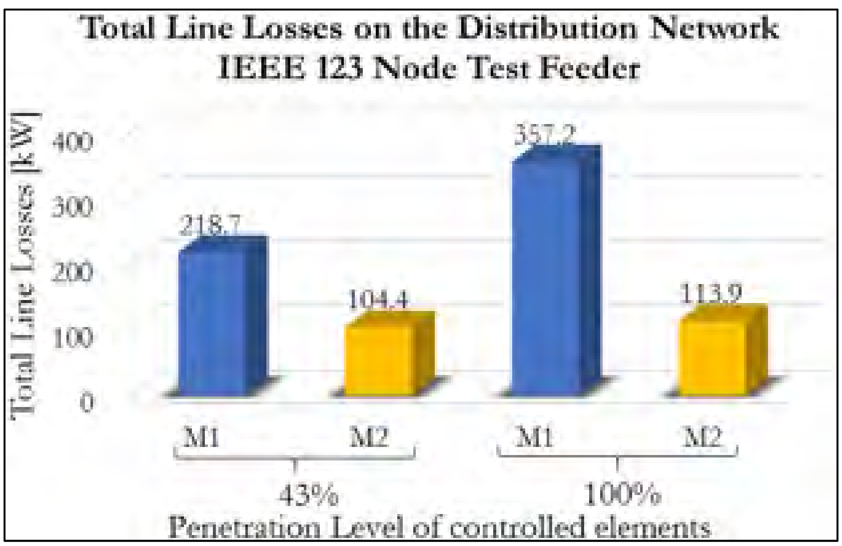


Figure 4.14 Total line losses on the Distribution Network for 43% and 100% of the penetration level of the controlled elements

Finally, Table 4.4 represents a comparative summary of both methods. It shows that M2 is better than M1 in some aspects. The red color represents the advantage of each method.

Table 4.4 Summary Table

Level	Description	M1	M2
Home	Minimize electricity cost at home	**Very good**	Good (≈6% higher)
	Consider the constraints of the DT and Distribution Network	No	**Yes**
Distribution Transformer	Advantages in implementing the method when the power demand on the transformer is higher than its rating	No	**Yes**
	Advantages in implementing the method when the power demand on the transformer is lower than its rating	Maybe	Maybe
	DT Critical limit is exceeded	Highly exceeded	**Slightly exceeded**
	Loss of life of the DT	High, lasts for a few days	**Low, lasts for years**
	Peak Demand on DT	Very high	**Low (≈46% Lower)**
	Optimal solution on DT level	No	**Yes**
	Voltage drop on the DT	High (7.2%)	**Low (4.3%)**
	Power and energy losses	High	**Low (≈36% lower)**
	Electricity cost of energy loss	Very High	**Low (≈28% lower)**
	Depreciation cost of DTs	Very high	**Low (≈99.993% lower)**
Distribution Network	Voltage Drop on the DN	High	**Low (≈4% lower in some cases)**
	Line Losses on the DN	High	**Low (313.6% lower for 100% Penetration Level of EVs)**
	Complex approach	**Medium**	Very High

4.6 Conclusion and future work

This paper shows three original contributions to the literature: (i) a Soft-Constrained Strategy is proposed to be used at homes for energy management purpose. (ii) new soft constraints are proposed at the home level, which takes into account the DT and DN constraints and limits. (iii) A new optimization model is developed to adapt the constraints of the proposed strategy. Also, it shows that the most used Decentralized Strategy and the Demand Response programs are not sufficient to solve the high penetration level of EVs even when energy management systems are used at homes. The traditional Decentralized Strategy may not cause problems to the DTs and DN in case a few numbers of EVs are connected to the grid. The problem appears when the penetration level of EVs is very high as seen in this paper. Because the EVs tend to charge during low electricity price and off-peak times, the total load demand may exceed the infrastructure capacity of the DN and DT causing severe problems. The issue of high penetration level of EVs is solved in our proposed strategy. A comparative study is done between our proposed Soft-Constrained Distributed Strategy and the traditional Decentralized Strategy. Results show that our strategy respects the DT and DN constraints and limits. It reduces the peak demand by 46%, the energy loss by 36%, the depreciation cost of DTs by 99.993%, and the electricity cost of energy loss by 28%. The disadvantage of our study is that it is more complicated than the traditional Decentralized Strategy. Moreover, the optimal electricity price is higher by 6% compared to the traditional strategy. To compensate for this weakness, we added a new incentive program. The power utility encourages the householders to apply our strategy by rewarding them if they respect the proposed limits. This paper concentrated on the impact of penetrating a high number of EVs on the same DT and IEEE 123 Nodes Test Feeder. However, it could be applied to any networks where the number of connected EVs is increasing gradually. This paper shows that power utility (e.g., Hydro-Quebec) could support a high penetration level of EVs without the necessity to upgrade all distribution transformers and the infrastructure of the network.

4.7 Data section

4.7.1 Baseload data

The baseload data of the home consumptions is presented in Figure 4.15. The data is provided by Hydro-Quebec for the date (April 17, 2016). The base load data may vary from day to day and from season to another. However, this will not affect too much the result of the proposed strategy and the comparison. In winter, the consumption is higher due to the frequent utilization of the heating systems, the base load increases; therefore, the total power demand on the transformer also increases and may create some peaks, which can exceed the transformer rating in some periods. In summer, the consumption is lower, and the excess power on the transformer is lower. However, the base load may not affect too much the simulation results, because the real problem appears in the penetration of EVs, which can consume very high energy during short periods.

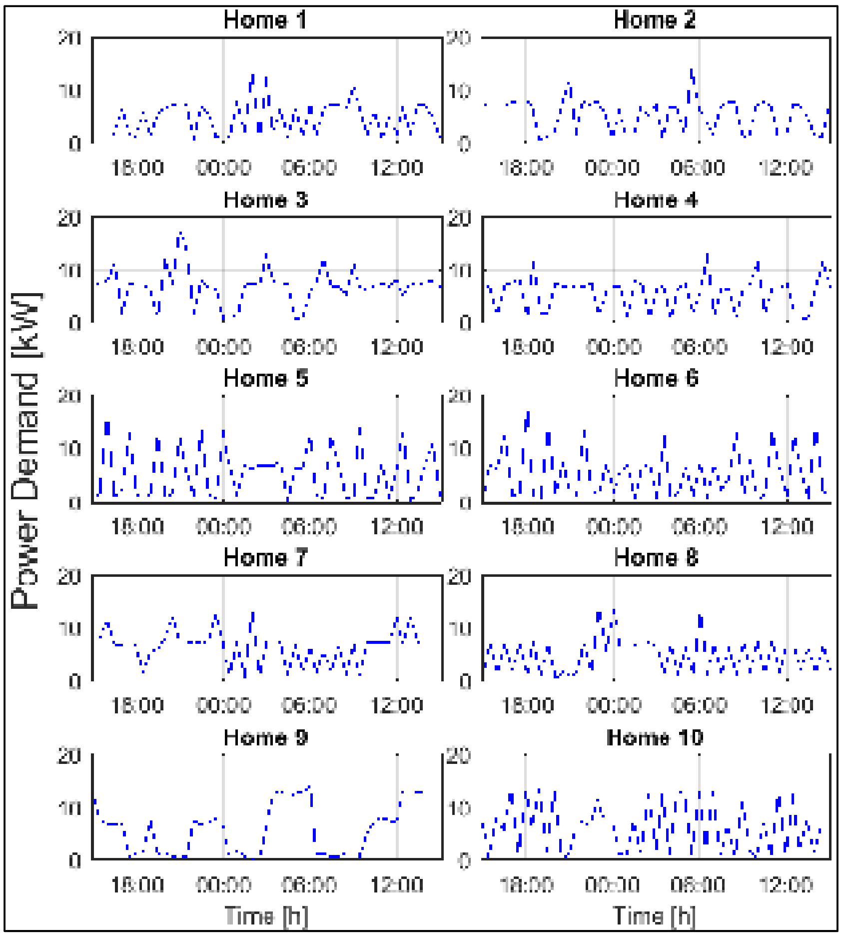


Figure 4.15 Baseload at homes before introducing the controlled elements (April 17, 2016)

4.7.2 Average water consumption data

The data for the average water consumption for the ten homes are presented in Figure 4.16. Because it is almost difficult to obtain real data, especially when it is confidential, we propose Eq. (4.33), in which we can generate estimated profiles for 10 homes based on the provided data by Hydro-Quebec, and by other references (CAA-Quebec, 2018). Where, $m_{t,h}$ is the estimated water consumption at home "h" at instant "t". $m_{t,h}^{Max}$ is the peak consumption. $m_{t,h}^{Min}$ is the lowest consumption. t_h^{Max} is the time of the peak period of consumption during the day at home "h". $\chi_{t,h}$ is a binary value representing the turning on or off of the water consumption at instant "t" and home "h". In this paper, it is generated using a distributed random function as in Eq. (4.34). A probability density function could also be used to generate profiles. $randi(\,)$ is a uniformly distributed pseudorandom integers, in which it generates random variables between r_{min} and r_{max} in a matrix $T \times H$ (MathWorks, 2018). $round(\,)$ is a function that round up a number to the nearest decimal or integer (e.g. round(0.6)=1, round(0.4)=0).

$$m_{t,h} = \chi_{t,h} \cdot \left[\left(\frac{m_{t,h}^{Max} - m_{t,h}^{Min}}{2} \right) \cos\left(\frac{2\pi}{T} (t - t_h^{Max}) \right) + \left(\frac{m_{t,h}^{Max} + m_{t,h}^{Min}}{2} \right) \right] \quad (4.33)$$

$$\chi_{t,h} = round(randi([r_{min}, r_{max}], T, H)) \quad (4.34)$$

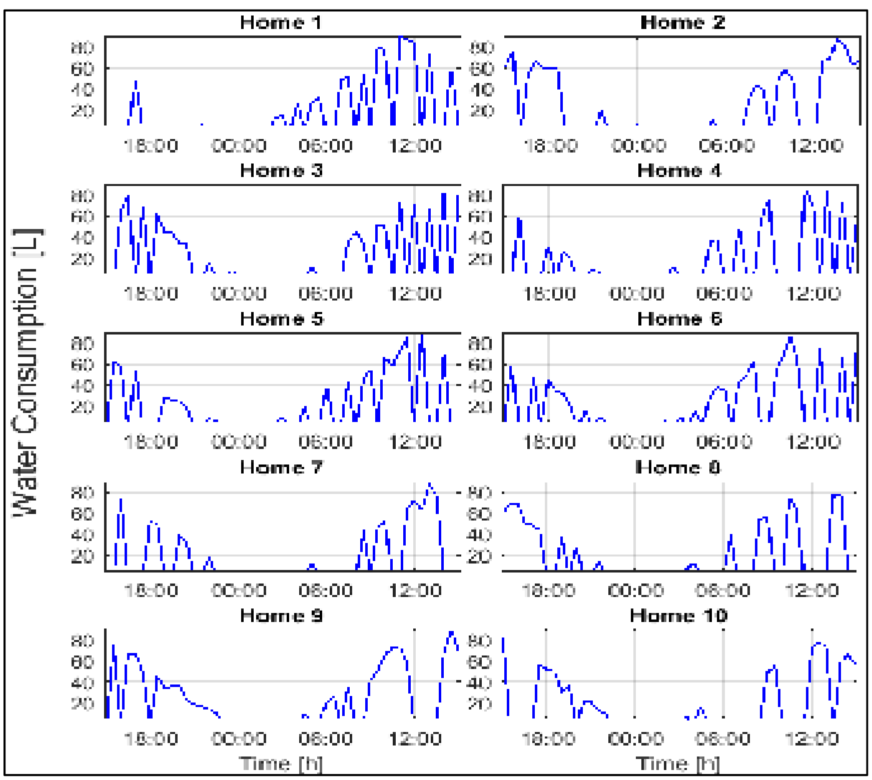


Figure 4.16 Water consumption at homes in Liter (Estimated data based on water consumption at homes in Quebec, Canada)

4.7.3 Solar irradiance and power generated by PVs at home

Figure 4.17 shows the solar irradiance in Montreal on April 17, 2016 (Stats, 2018). The corresponding power generated for each home is presented in Figure 4.18. The generation depends on the PV size and efficiency as presented in Table 4.5.

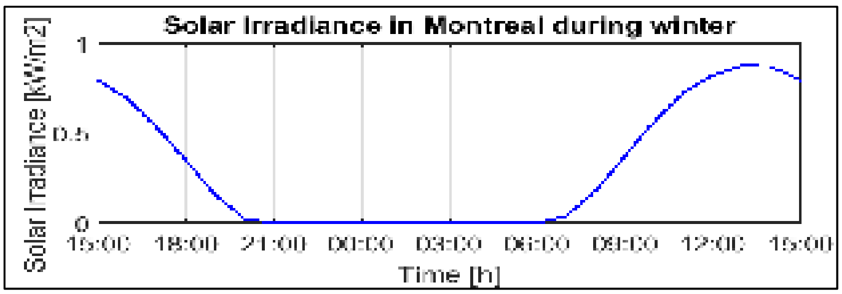


Figure 4.17 Solar irradiance in Montreal on April 17, 2016 taken from (Stats, 2018)

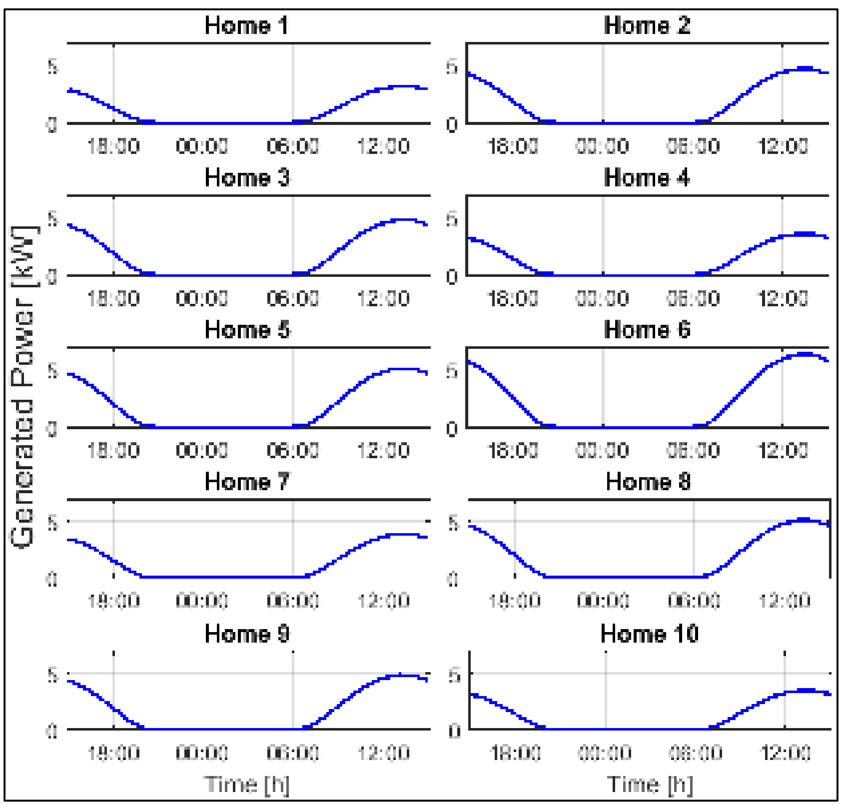


Figure 4.18 PV generated power at homes based on the data of the solar irradiance on April 17, 2016

4.7.4 Electricity price

For comparative purposes, the used electricity price in this paper is the Real-Time Price (RTP) similar to (Fotouhi Ghazvini et al., 2017). The buying electricity price is RTP while the selling electricity price is constant as in Figure 4.19.

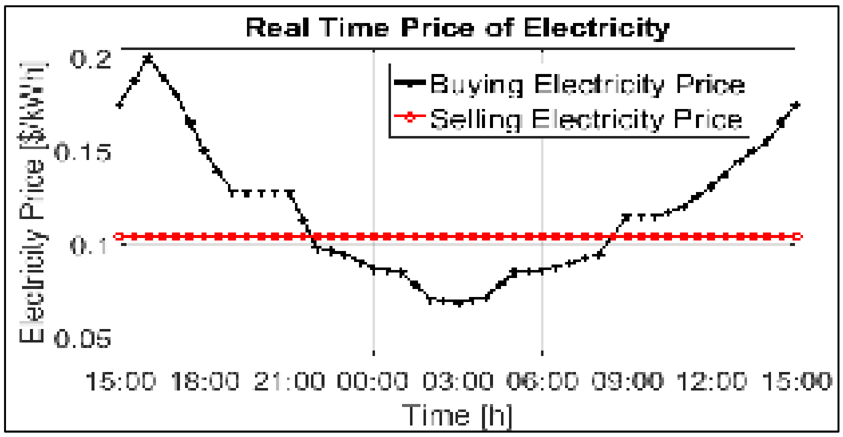


Figure 4.19 Buying and selling Electricity Price using RTP
Taken from (Fotouhi Ghazvini et al., 2017)

4.7.5 Data of the controlled elements

The data of the controlled elements at homes are presented in Table 4.5. Each home can control and optimize two EVs, one Battery Storage System (BSS), an Electric Water Heater (EWH) and a PV. The EV types are presented in Table 4.6.

Table 4.5 Data of Controlled Elements at Homes

	Home	H 1	H 2	H 3	H 4	H 5	H 6	H 7	H 8	H 9	H 10
	P^{CB} [kW]	24	24	24	24	24	24	24	24	24	24
EV 1	B_{cap}^{V} [kWh]	34	78	60	33	50	70	36	80	40	100
	$P_{Max}^{V,Ch}$ [kW]	3,9	5,8	3,6	4	3,3	5,1	5,5	5	4,5	5,3
	$P_{Max}^{V,Dch}$ [kW]	3,9	4,1	3,9	5,3	1,9	4,2	2	1,5	3,7	3
	$\eta^{V,Ch}$	0,9	0,92	0,94	0,89	0,92	0,89	0,95	0,94	0,88	0,92
	$\eta^{V,Dch}$	0,91	0,91	0,95	0,88	0,88	0,86	0,96	0,92	0,9	0,92
	t_A [h]	18,5	19,5	18,5	21	18,5	22	17	16	15	15
	t_D [h]	33,5	30	32,5	32	34	33	31	33,5	34	32,5
	SOC_i^V	0,75	0,68	0,74	0,74	0,69	0,6	0,66	0,68	0,65	0,64
	SOC_{tf}^V	0,99	0,94	0,99	0,94	0,98	0,94	0,98	0,98	0,94	0,92
EV 2	B_{cap}^{V} [kWh]	60	24	30	30	78	60	34	60	30	24
	$P_{Max}^{V,Ch}$ [kW]	6,1	5	6,4	5,5	5,1	6	6,2	6,6	3	6,2
	$P_{Max}^{V,Dch}$ [kW]	3,8	5,5	3,4	3,2	4,6	2	3,2	5,1	3,6	4,8
	$\eta^{V,Ch}$	0,93	0,92	0,87	0,92	0,86	0,92	0,92	0,93	0,95	0,96
	$\eta^{V,Dch}$	0,94	0,91	0,96	0,91	0,85	0,86	0,95	0,9	0,95	0,87
	t_A [h]	18	19	15	19,5	17	15,5	19	16,5	15,5	16,5
	t_D [h]	31	32	34	34	31	31,5	32,5	33	33	32
	SOC_i^V	0,75	0,61	0,78	0,79	0,8	0,78	0,76	0,7	0,63	0,68
	SOC_{tf}^V	0,91	0,9	1	0,93	0,93	0,93	0,95	0,97	0,9	0,99
BSS	B_{cap}^{B} [kWh]	39	48	32	56	47	38	40	76	64	53
	$P_{Max}^{B,Ch}$ [kW]	6,3	3,3	5,7	5,7	5	3,6	5,2	4,1	3,4	3,7
	$P_{Max}^{B,Dch}$ [kW]	6,2	2,3	3,1	2,2	4	2	6,2	2,9	2,4	3,4
	$\eta^{B,Ch}$	0,9	0,86	0,96	0,88	0,88	0,85	0,88	0,85	0,91	0,94
	$\eta^{B,Dch}$	0,92	0,86	0,85	0,94	0,95	0,91	0,86	0,94	0,89	0,88
	SOC_{min}^B	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2
	SOC_i^B	0,85	0,78	0,7	0,53	0,89	0,67	0,81	0,87	0,55	0,56
EWH	P^{EWH} [kW]	5,2	3,7	5,2	6	5,6	3,2	4,1	4,1	5,1	4,8
	M [L]	437	310	262	226	432	261	316	366	268	393
	R (°C/kW)	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52
	C (kWh/°C)	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4
PV	A^{PV} [m2]	49	52	24	52	42	23	30	39	54	54
	η^{PV}	0,1	0,15	0,15	0,12	0,14	0,1	0,12	0,15	0,14	0,15

Table 4.6 Suggested Electric Vehicles to be Used in Homes

Home	EV1	EV2
1	Ford Focus Electric	Chevrolet Bolt
2	BYD e6	Fiat 500e
3	Chevrolet Bolt	Nissan Leaf
4	BMW i3	Nissan Leaf
5	Tesla Model 3	BYD e6
6	Tesla Model 3	Chevrolet Bolt
7	Volkswagen e-Golf	Ford Focus Electric
8	Tesla Model S	Chevrolet Bolt
9	Nissan Leaf II	Nissan Leaf
10	Tesla Model S	Fiat 500e

4.7.6 Transformer data

To validate the proposed model, Table 4.7 presents the values of the transformer's parameters, which are considered.

Table 4.7 Chosen Transformer's Parameters for this Study

$F_t^{AA} = 1$	$T = 24\ hours$	$C_{Tr} = 6{,}000\$$
$L_N = 180{,}000 hours$	$m = 0.8$	$p = 0.8$
DT data: $80kVA$, 11kV/120V, 1-φ, 60Hz	$R = 8$	$\Delta t = 0.5\ hours$
$\theta_{ref} = 100^0 C$	$\Delta\theta_{TO,R} = 55^0$C	$\Delta\theta_{G,R} = 20.3^0 C$

4.7.7 Simulation results at homes

Detailed simulation results for the home 4 and 10 using both methods M1 and M2.

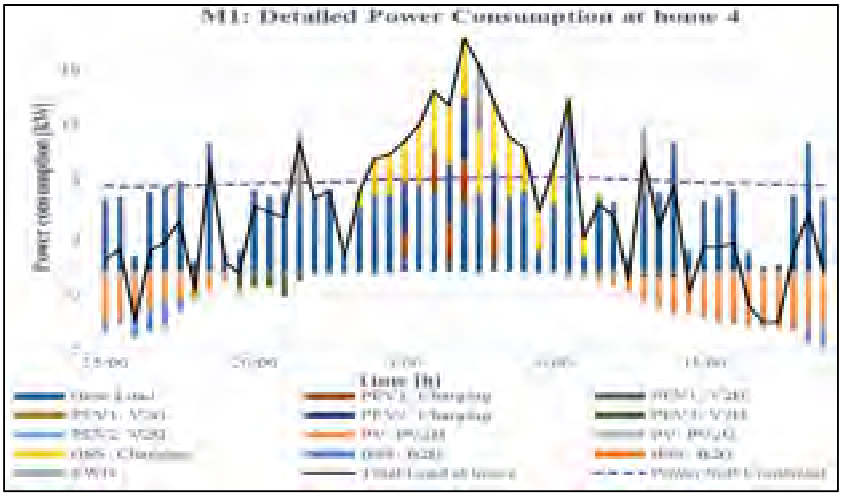


Figure 4.20 Detailed power consumption of the controlled elements using M1 at home 4

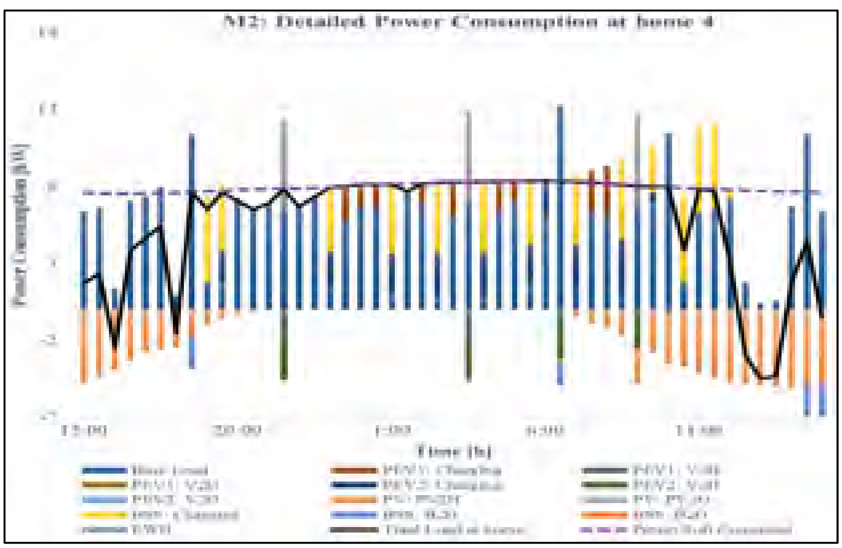


Figure 4.21 Detailed power consumption of the controlled elements using M2 at home 4

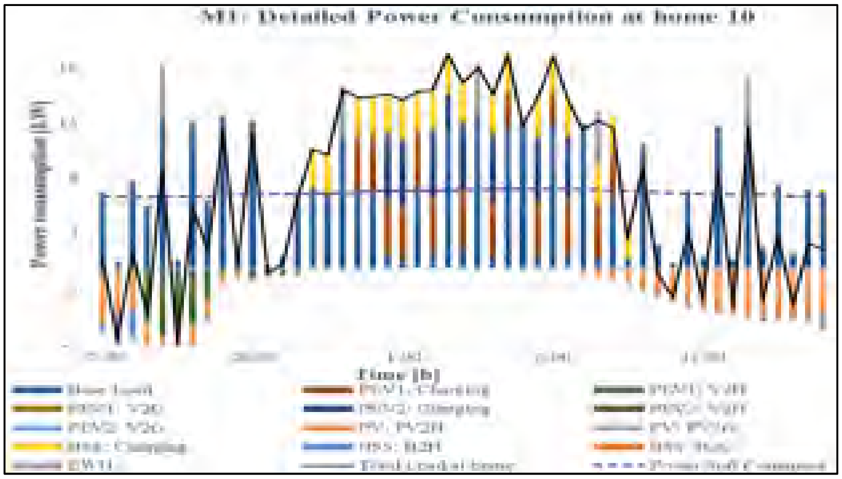


Figure 4.22 Detailed power consumption of the controlled elements using M1 at home 10

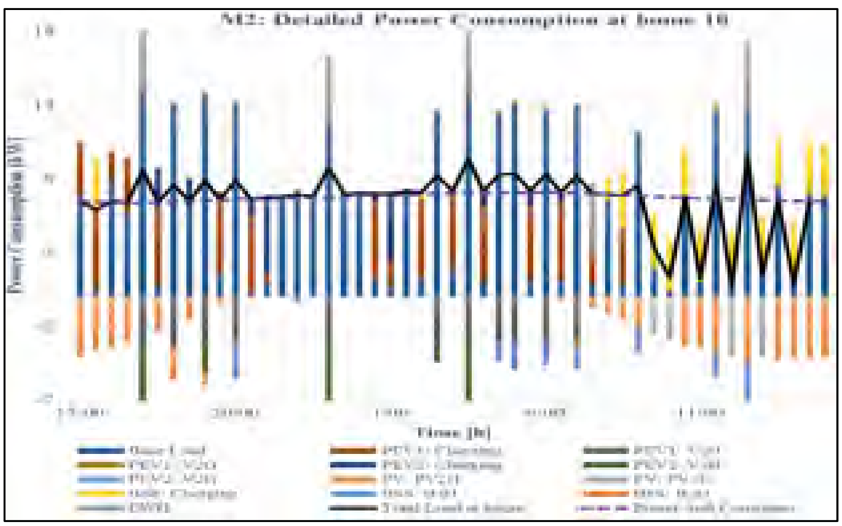


Figure 4.23 Detailed power consumption of the controlled elements using M2 at home 10

CHAPTER 5

A NOVEL APPROACH FOR MITIGATING THE IMPACT OF ELECTRIC VEHICLES HIGH PENETRATION ON THE SMART GRID

Claude Ziad El-Bayeh[1], Imad Mougharbel[1], Dalal Asber[2], Maarouf Saad[1], Ambrish Chandra[1], Serge Lefebvre[2]

[1]Electrical Engineering Department, École de Technologie Supérieure,
1100 Rue Notre-Dame West, Montreal, Quebec, Canada H3C 1K3
[2] Hydro-Quebec's Research Institute, Varennes, Quebec, Canada J3X 1S1

Paper submitted to *IET Smart Grid*, March 2019

5.1 Abstract

Intensive research is conducted to mitigate the impact of high penetration level of Electric Vehicles (EVs) on the Distribution Network (DN). The problem may still exist even when electricity is distributed through smart grid supported by demand response and incentive programs. The major reason is due to the limitation caused by the conventional transformers having no ability to manage the energy consumption of the end-users. To overcome this situation, we propose an energy-management algorithm on the transformer level, which requires a bidirectional power and data flows between end-users, the Distribution System Operator (DSO) and transformers. The realization of the algorithm requires: (i) a novel Programmable Transformer (PT), which can perform certain tasks such as controlling and optimizing the total load demand of the end-users. (ii) a new framework of the DN, which requires a special communication infrastructure to support the integration of PTs. The Energy-management algorithm optimizes the PT's operation and manages the distribution of energy between the end-users. Results show that the proposed strategy has improved the performance and the voltage stability on the network. It has minimized the energy and financial losses, increased the lifetime of the transformers, and maintained the voltage within the recommended limits.

Keywords: Demand Response; Electric Vehicle; Energy management; Distribution Transformer; Smart Grid.

5.2 Introduction

5.2.1 Motivation and background

Climate change and global warming are considered one of the major issues that the globe is facing today (Hawkins et al., 2017). The global surface temperature of the earth is increasing every year and it may reach the 2°C limit in a few decades (Field, 2014). The emission of greenhouse gases (e.g., CO_2 and methane) is the main cause of increasing the globe's temperature (Stocker, 2014), in which 15% of the total CO_2 emission worldwide comes from the transportation sector (Rodrigue et al., 2016). To overcome this situation, many countries started to shift from conventional Internal Combustion Engine vehicles to Electric Vehicles (EVs) to reduce the greenhouse gases' emissions (Bunsen et al., 2018). The future of EVs is prominent, in which their integration is increasing every year exponentially. According to (Bunsen et al., 2018), the sales of EVs in 2017 have surpassed one million units worldwide with an increase of 54% compared to 2016. In Norway, the number of new sold EVs is 39% in 2017. It is predicted that the total number of EVs will reach 565 million by 2030 (Bunsen et al., 2018). Good news is announced by Norway, which has banned the gas-powered cars by 2025, and Germany in which all new cars must be EVs by 2030 (University-of-Central-Florida, 2015). Despite the many advantages of EVs in reducing pollution, they may have negative impacts on the Distribution Network (DN) (Rajakaruna et al., 2016), (X. Yang et al., 2017). A high penetration level may perturb the network, create severe voltage drops (Qian et al., 2015), and reduce the lifespan of some elements on the network (Claude Ziad El-Bayeh et al., 2018), (C. Z. El-Bayeh et al., 2018), which will cost billions of dollars (US-Department-of-Energy, 2018). Therefore, it is necessary to mitigate the integration of EVs in order to reduce their impact on the network.

5.2.2 Literature review

5.2.2.1 Control strategies

To overcome the negative impact of integrating EVs on the DN, many control strategies were proposed to optimize the scheduling of the loads: (i) Centralized (Yao et al., 2017), (El-Bayeh et al., 2016b), (B. Yang et al., 2016), (Anand, Salis, et al., 2015), (Wang et al., 2017), (Shao et al., 2017) (ii) Hierarchical (Shao et al., 2017), (Anand, Salis, et al., 2015), (Z. Xu et al., 2016), (Morstyn et al., 2016) (iii) Multi-Agent (Morstyn et al., 2016), and (iv) Decentralized (Morstyn et al., 2016), (Fotouhi Ghazvini et al., 2017), (Steen et al., 2016), (Xiaohua Wu et al., 2017), (Paterakis et al., 2015). According to (Claude Ziad El-Bayeh et al., 2018), the decentralized control strategy is mostly used to control the loads at home due to privacy and security issues (Steen et al., 2016), (Xiaohua Wu et al., 2017). Each home has its own local controller (LC), which controls and optimizes the scheduling of its internal elements without communicating with any external agents (Morstyn et al., 2016), (Steen et al., 2016), (Xiaohua Wu et al., 2017), (Paterakis et al., 2015). An optimal solution at each home does not necessarily contribute to a globally optimal solution on the DT and the network. Many end-users may consume high power demand during low electricity prices; therefore, the total power demand may exceed the Distribution Transformer's (DT) limit in certain periods and create problems on the network.

5.2.2.2 Demand response program

To reduce the impact on the DT and DN, Demand Response Programs (DRPs) were introduced (S. G. Yoon et al., 2016), (Xiaohua Wu et al., 2016), (Ito et al., 2017). DRPs can have many forms such as, but not limited to (i) price-based (Paterakis et al., 2015), (Steen et al., 2016), (Melhem et al., 2018) (ii) incentive-based (Claude Ziad El-Bayeh et al., 2018), (Fotouhi Ghazvini et al., 2017) (iii) power-based (Fotouhi Ghazvini et al., 2017), (Steen et al., 2016), and (iv) energy-based (Fotouhi Ghazvini et al., 2017), (Steen et al., 2016). The main goal of introducing DRPs is to limit the power and energy consumption in certain periods when there are lots of electricity burdens (Erdinc, Paterakis, Mendes, Bakirtzis, & Catalão, 2015), (Ito et al., 2018). Authors in (Paterakis et al., 2015), (Ahn et al., 2011) show that DRP has limitations. Paper (Claude Ziad El-Bayeh et al., 2018) shows that the impact of the EVs' integration using DRP may affect negatively the network when their number exceeds a certain limit. Most EVs charge when the electricity price is low and when the incentive program is high. Therefore, DRP may not guarantee a good functioning of the system on the DN.

5.2.2.3 Related works on the home energy management systems

To apply the decentralized strategy and the DRP at home, an energy management system is used, in which a smart algorithm performs certain tasks such as optimize the scheduling of the electrical loads in order to minimize the electricity cost. In the paper (Xiaohua Wu et al., 2017), a convex programming optimization technique is used to minimize the home electricity cost. The method is faster and more efficient than other methods. The optimized elements are EV, PV, and BSS. The battery and the charger's costs are considered in the objective function. However, the objective function does not include incentive programs and cannot supply energy to the grid. Therefore, it is not ideal to be implemented on a larger scale. In (Melhem et al., 2017), the objective function considers the generation and maintenance cost of some elements such as wind turbine, PV, EV, and BSS. Although good results are obtained by adding Renewable Energy Source (RES) and using Taguchi algorithm, this approach is no more valid at the network's level when it is applied to multiple homes supplied by the same DT. The reason is that most of the energy in homes is consumed during low electricity prices (in case of Real-Time Price (RTP) and Time-of-Use). Therefore, peak demands can be formed on the DT and DN. Paper (Melhem et al., 2018) minimized the electricity cost at home using only price-based DRP. However, the price-based DRP is not sufficient to motivate the end-users to reduce their consumption during critical periods. To deal with this issue, paper (Fotouhi Ghazvini et al., 2017) considered price-based and incentive-based DRPs. The results were better than the previous ones, however, peak demand may still be created in some periods and the DT's limit can be easily exceeded if many homes are using the same DRPs on the same DT. To overcome this situation, in reference (Steen et al., 2016), new power-based and energy-based tariffs were developed. These two DRPs are important in limiting the power and energy consumption during specific periods. Although many optimized elements are considered in the optimization model, the method will not guarantee that the total load on the DT will not exceed its capacity. In the paper (Paterakis et al., 2015), price-based and power-limiting-based DRPs are considered. The model controls the market price and responds to the contingencies. However, DT's constraints are not considered in the model, which may not help in respecting the DT's limits. In (Claude Ziad El-Bayeh et al., 2018), a decentralized strategy was proposed to limit the power consumption on the DT's level. It shows a good performance on the DN level. However, some end-users are not satisfied because the strategy limits their energy and power consumption which will increase their electricity bill if they exceed these limits.

5.2.2.4 Transformer

It is clear that many efforts were made to improve the integration of RES and EVs on the network. However, there are always limitations for each study. The actual problem arises from the existing infrastructure of the power grid, which is considered passive. Therefore, it does not help the integration of new emerging technologies. For example, the DTs are considered as passive elements, because they only transmit energy from the network to the end-users or change the voltage rate. Therefore, it is difficult to improve the integration of RES and EVs without taking the next step toward a smart grid. To solve the problem, many leading companies such as ABB (ABB, 2017), and Siemens (Siemens, 2018a) have introduced the new technology of transformers called Digital Transformer. It is equipped with sensors, in which it measures, stores, analyzes and generates real-time digital data of the transformer's operation (Siemens, 2018b). The most important measured data are but not limited to the oil level, top-oil temperature, winding current and voltage, GPS location, local weather information such as ambient temperature and humidity. It calculates many important parameters such as but not limited to the lifetime of the DT and total harmonic distortion. End-users and the operators can access the real-time data of the DT, which will allow better energy management and increase the efficiency of the power and distribution systems (Siemens, 2018a). The Digital Transformer securely transmits the required data to a cloud-based storage and visualization platform, in which the operators can access the data and get a comprehensive overview of their assets (Siemens, 2018a). A further step into the smart grid is the introduction of the Solid-State Transformer (SST) (Helali, Bouallegue, & Khedher, 2016). In contrary to the conventional transformer which is mainly composed of coils that increase or decrease the primary voltage at the output, an SST is mainly composed of semiconductors and power electronics, which converts from AC to DC and then from DC to AC using different topologies. Its main function is to regulate the voltage, improve the management of the distribution system, ease the integration of RES and storage elements, provide better bidirectional power flow, reduce harmonics and power losses, and protect the load from power fluctuations. However, the operation of digital and solid-state transformers needs to be controlled and supervised through an efficient algorithm. Hence, this paper proposes a novel energy-management algorithm to mitigate the integration of highly fluctuating loads and sources such as EVs and RESs.

5.2.3 Contribution

To overcome the limits of the current topology of the power grid in presence of EVs and RESs on the DN, we propose a novel energy-management algorithm, which is implemented on a “Programmable Distribution Transformer” (PT). Its main goal is to manage the energy demand of all end-users and respect the network’s limits and constraints. The main contribution is achieved according to the following steps:

- Present the topology of a novel PT,
- Suggest the necessary infrastructure to facilitate the integration of the PT,
- Elaborate a smart energy-management algorithm for the PT. Its main goal is to improve the energy management on the transformer and the network,
- Define the algorithm parameters which could be remotely set by the DSO according to their objective to be reached,

- To implement the proposed strategy at the end-users' level, some modifications of their optimization model are required.

Our strategy is compared to another existing one in the literature (using a conventional DT). The impacts of both methods at home, on the DT and DN levels, are studied.

5.2.4 Paper organization

The rest of the paper is organized as follows. In Section 5.3, the concept of the PT and the proposed infrastructure are presented. Some assumptions and results are discussed in Section 5.4. Finally, a conclusion summarizing the study is presented in section 5.5.

5.3 A novel programmable distribution transformer

5.3.1 Why is it important to propose a PT?

In the presence of new emerging technologies such as distributed generations, RESs, EVs, Energy Storage Systems (ESS), etc., the power demand becomes highly stochastic. The end-users can consume and supply energy to the DN without even the request from the DSO and the Electricity Retailer (ER). Therefore, it becomes challenging to control the total load on the network and for each end-user. Centralized control strategies may work for certain types of end-users such as in EV parking lots, while they are not suitable for other customers such as residential buildings and homes. Decentralized control strategies are more often used to control the loads for the latter ones. However, there are many limitations and barriers in their implementations. Therefore, it is necessary to create a new strategy, which guarantees the independence of the end-users and protect their privacy, while respecting the transformer and the DN limits and requirements.

To fill the gap in the literature, a PT and its new energy-management distribution strategy are proposed. The PT is used as energy, data, and control hubs, in which it has the ability to exchange information with the customers' in order to reach an optimal solution based on economic and technical considerations. It is significant to implement this concept instead of the conventional control strategies such as centralized (DSO level), and decentralized (end-users level) for many reasons as follows:

- The Energy-management algorithm can be remotely set and programmed by the DSO through the internet to perform certain tasks,
- The Algorithm on the PT works autonomously, it calculates the power profile limit for each end-user and smartly distributes the energy between them,
- It protects the privacy of the end-users and does not intervene through direct control of their own loads. However, it suggests them to respect the calculated power profile limit while they are optimizing their loads,
- It has bidirectional communication with the DSO, the end-users and other neighbor PTs to increase the performance of the system. (It can be considered as a combination of Centralized, Hierarchal, Decentralized, and Multi-Agent Communication Strategies),
- The concept of the PT can be extended to a substation,
- This concept is applied to a radial connected distribution network in the presented chapter. However, it can be considered for any network configurations,
- Fewer damages to the network compared to the centralized strategy in case of failure happen in the software or/and in the hardware levels,
- It improves the global performance on the network including, but not limited to, reducing the energy and financial losses on the network; reducing the loss of life and the depreciation cost of the transformer; increasing the load factor; maintaining the voltage profile within the required limits, and increasing the revenue of the DSO.

To implement the PT on the network, specific infrastructure and algorithms should be considered. There are mainly four different algorithm levels (Figure 5.1).

a- Algorithm for the DSO that controls all the PTs on the network (Figure 5.1.a),

b- Algorithm for a PT that controls lower level PTs (Figure 5.1.b), (e.g., an MV/MV transformer controls MV/LV Transformers, which are supplied by it), c- Algorithm for the PT that calculates the soft-constrained power limit that should not be exceeded for all end-users (Figure 5.1.c), (e.g., homes, residential buildings, etc.),

d- Algorithm for each home that optimizes the power consumption of its internal controllable loads (Figure 5.1.d).

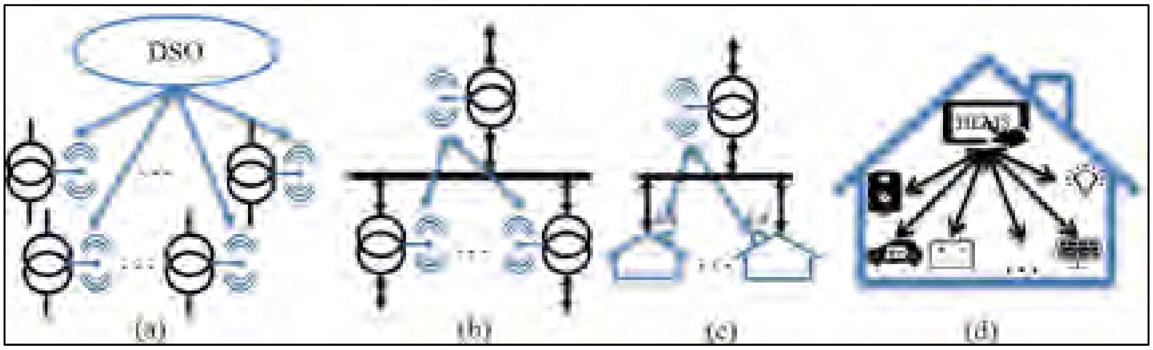


Figure 5.1 Four different algorithm levels are used to implement the PT concept

However, this paper focuses only on the algorithm presented in point (c). Other algorithms will be the subject of future works. The following subsections present the proposed infrastructure scheme and the algorithms used to control the system.

5.3.2 Topology of the programmable distribution transformer

The topology of the PT is shown in Figure 5.2. It is composed of four major elements as follows:

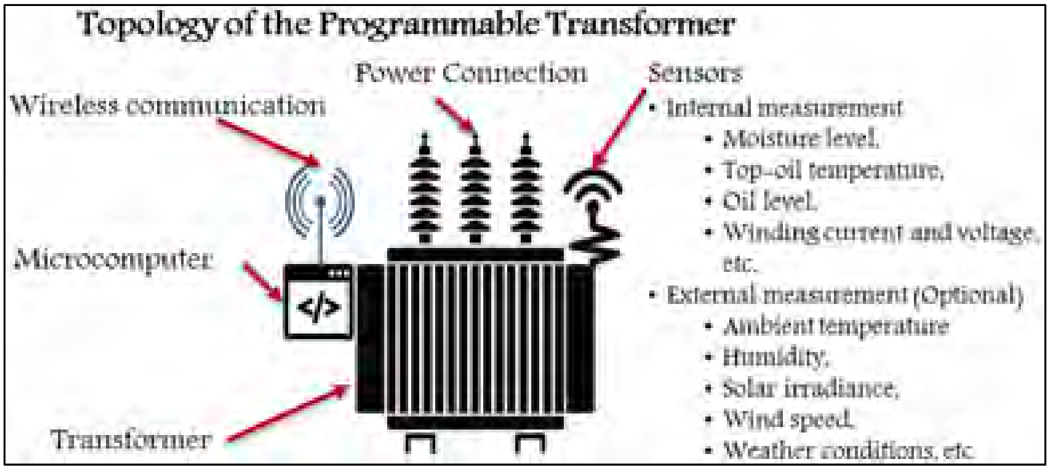


Figure 5.2 Schematic topology of the proposed PT

Transformer:

It can be a conventional, a digital, or a solid-state transformer. However, to be considered as a PT, the three remaining elements are mandatory to be included.

Sensors:

Sensors are embedded in the PT. Their main task is to measure and collect real-time data from inside and outside the PT. There are two types of sensors. The first one measures local weather data, and the second one measures the transformer's internal data (Figure 5.3).

Microcomputer:

It has many functions including:

- Store and analyze the measured data from the sensors and the built-in data,
- Calculate:
  - The lifetime and the loss of life of the transformer,
  - The total harmonic distortion,
  - The optimization process of the load demand,
  - The critical power limit of the transformer,

- The energy and power consumptions of the end-users,
- The profile of the power demand limit at homes, in which the total summation is less or equal to the transformer power limit,
- The available energy and power on the PT.

* Set the power demand profile of the end-users according to the program set by the DSO,
* Suggest and calculate the active and reactive power flow that should be injected/consumed by the load.

Wireless communication:

Bidirectional wireless communication is required between the PT, DSO, end-users, Electricity Retailer (ER), and other PTs in order to maximize the benefit of using the network infrastructure. The communication is done through a highly secured cloud-based visualization platform on the internet (using the most recent technology and algorithms, such as Ethernet with the state-of-the-art cybersecurity). It lets the end-users, the DSO/ER access the real-time data for better energy management. In contrary to the conventional transformer, the PT needs lots of information and data to perform the required tasks as in Figure 5.3.

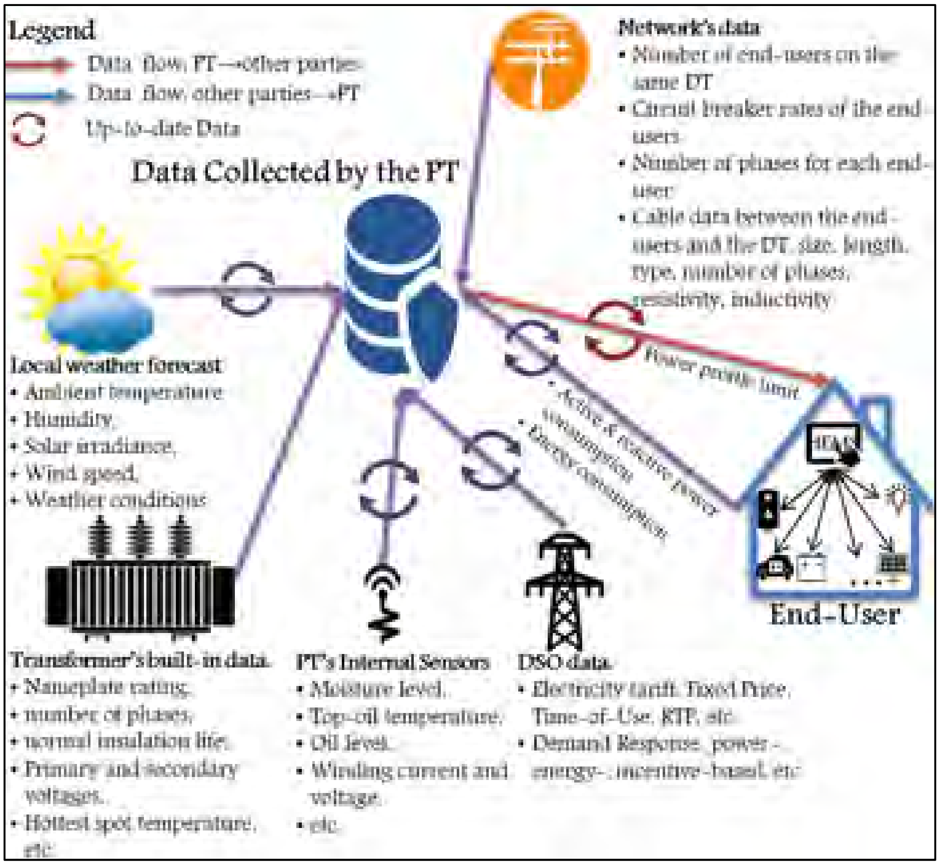


Figure 5.3 Needed data by the PT

5.3.3 Proposed distribution network infrastructure framework

To implement the PT on the network, it is mandatory to upgrade the infrastructure of the conventional DN as presented in Figure 5.4. The upgrading requires the replacement of the conventional transformers by programmable ones and the integration of an internet cloud-based platform (Figure 5.5). This platform provides bidirectional communications between the DSO, the PTs, and the end-users, which is the cheapest way of communication because the internet exists already and the communication between the DSO, the end-users and the internet exists also. End-users are equipped with smart energy-management algorithms that communicate with PTs (through the internet) to optimize their power demand profile and electricity cost. PT also takes care of its own loads according to a customized program set by the DSO. The task may change based on the need of the DSO. Figure 5.4 shows the proposed infrastructure's configuration, in which the PTs are implemented. In the first level of communication (CL1), the end-users (e.g., homes) communicate with their related PT in order to optimize and control their total power demand profiles. In this level, the PT guarantees that the total load of all end-users (supplied by the same PT) will not exceed its limits. In the second communication level (CL2), a single MV/MV-PT supplies many MV/LV-PTs. The upper and lower level PTs communicate to ensure that the total power demand on the upper-level PT will always respect its power limit. The same concept is applied for any communication levels. The main goal of this structure is to ensure that the total load demand on any PT will not exceed its power limit. This paper focuses on the implementation of PT at the end-users level of the distribution network. Therefore, only the algorithm related to this peripheral PT is presented. The control between different PTs of different levels will be presented in future works. Figure 5.5 and Figure 5.6 show detailed schematic diagrams of integrating the PT at the end-users' level into the DN with a sequence of operations of the proposed algorithm. The DSO sends/receives pertinent data to/from the PT through a cloud-based platform (blue arrow). It can also set and adjust the parameters of the PT's energy management algorithm to perform certain tasks through the platform. The power flow is bidirectional considering a smart grid in which the end-users can consume or supply power to the grid. The PT can receive and transmit data from/to the end-users (red and green arrows). In this way, the electrical distribution via the PTs can improve the reliability, stability, efficiency and the performance of the power system compared to the conventional DN.

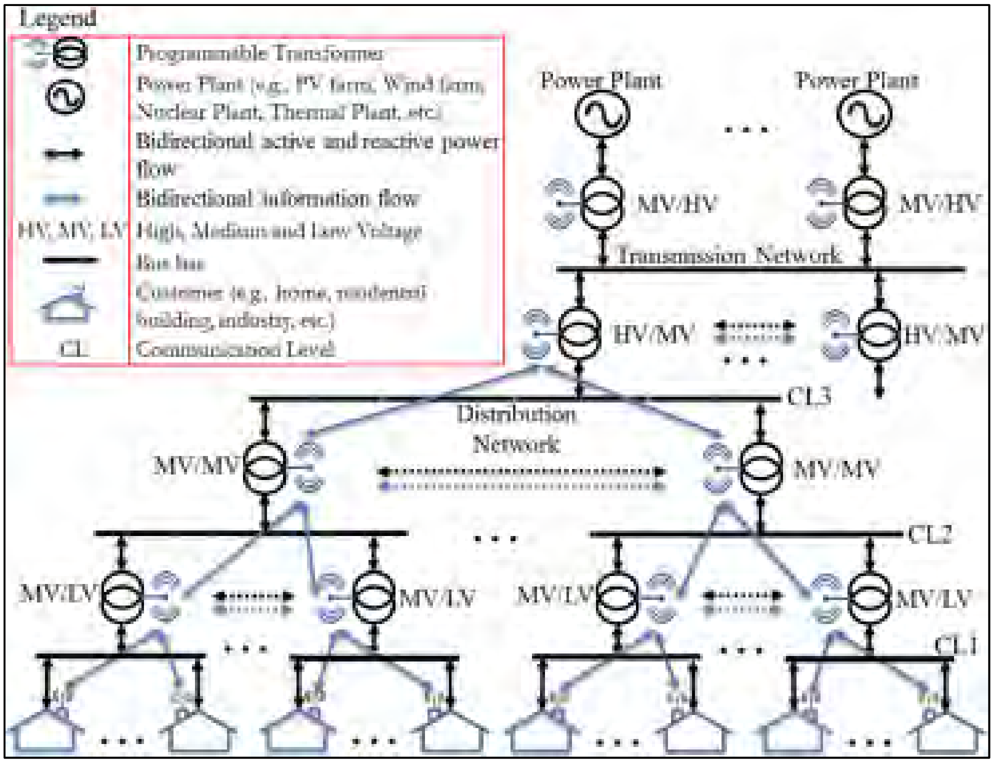


Figure 5.4 Example of the proposed distribution network infrastructure

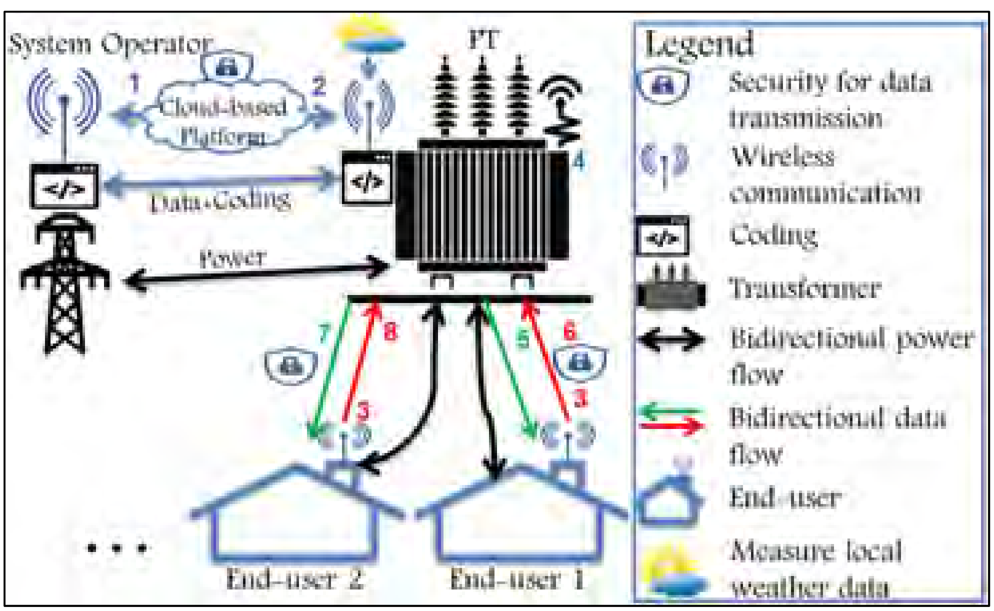


Figure 5.5 Connectivity of the Programmable Transformer on the network

5.3.4 Proposed algorithm for optimal distribution of energy via the PT

In this subsection, a novel energy-management algorithm is proposed in Figure 5.6, in which it calculates the power demand limit at homes and manages the total load on the PT. Its main goal is to optimize the total power demand on the DT level in a way to respect its constraints and respect the end-user's requirements and satisfaction. This is due to a collaborative exchange of information used for setting for each home the appropriate consumption limit. This limit is defined as the Power Soft-Constraint Limit at home (HSC). HSC should not be exceeded by the load demand for each home to guarantee that the total load demand of all homes will not exceed the DT power limit. It takes into account the DT nameplate rating, the number of end-users on the same DT, and the circuit breaker capacity of the end-users. Therefore, it guarantees a lifetime of the DT equal to the predefined one. To explain in more details how the algorithm works, a sequence of operations is listed below.

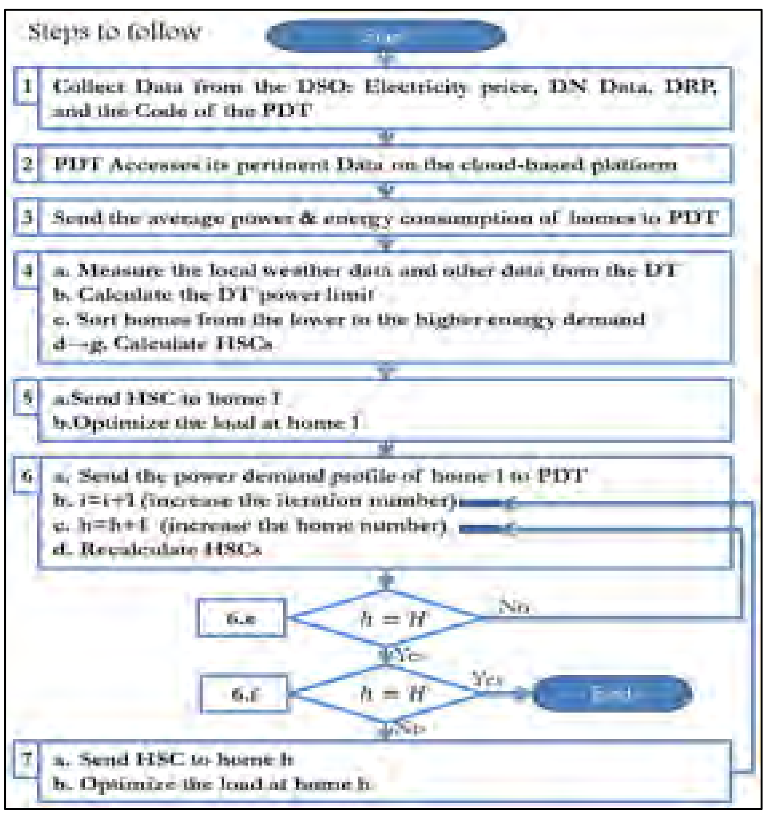


Figure 5.6 Simplified Flowchart of the proposed algorithm in steps

Algorithm 5.1 Sequence of operation of the algorithm

The sequence of operation: (Refer Figure 5.5 and Figure 5.6 for each step)

1.The DSO/ER send appropriate data to a cloud-based platform. The data is securely transmitted and stored on the platform using the most recent cybersecurity programs. The transmitted data are:

- End-users' data
  - Number of end-users on the same DT
  - Circuit breaker rates of the end-users
  - Number of phases for each end-user
- Cable data between the end-users and the DT:
  - size, length, type, number of phases, resistivity, inductivity
- Electricity price: Fixed Price, Time-of-Use, Real-Time Price, etc.
- Demand Response Program: power-, energy-, incentive-based, etc.

2.Each PT on the network accesses its pertinent data on the cloud-based platform using a unique serial number and identification code.

3.a- The Local Controller (LC) at home registers the active and apparent power, and the energy consumption for D days (e.g., 365 days)

b- It calculates the home's average power consumption in "t" as in Eq. (5.1). Actually, both active and apparent power should be calculated and registered because they will be used in the optimization model. Where, $S_{h,t,d}^{Load}$ and $P_{h,t,d}^{Load}$ are the apparent and active power of the home "h" at instant "t" and day "d". The average power consumption of the end-users will help to determine the Home Soft-Constraint Limit (HSC), which should not be exceeded. It will be calculated in Eq. (5.5) and (5.11).

$$S_{h,t}^{Load,avg} = \frac{\sum_{d=1}^{D} S_{h,t,d}^{Load}}{D} \ ; \ P_{h,t}^{Load,avg} = \frac{\sum_{d=1}^{D} P_{h,t,d}^{Load}}{D} \quad (5.1$$

c- Eq. (5.2) calculates the average energy consumption during a day.

$$E_{h}^{Load,avg} = \sum_{t\in T} P_{h,t}^{Load,avg} \cdot \Delta t \quad (5.2)$$

d- LC sends the data to the PT via secured wireless communication.

4.a- The PT measures the local weather data and other data including:

- Local weather data:
  - Ambient temperature, humidity, solar irradiance, wind speed, weather conditions, and alert
- Internal DT data:
  - Moisture level, top-oil temperature, oil level, winding current and voltage
- DT characteristics:
  - Nameplate rating (e.g., 100kVA), number of phases, normal insulation life (e.g. 180,000 hours), GPS location

b- Start analyzing the collected data and calculates the critical power limit of the transformer (S_t^{TCL}) (refer to (C. Z. El-Bayeh et al., 2018) for detailed calculation).

c- Use a sorting algorithm to sort the end-users from the lowest to the highest average energy consumption during a day. Associate values from h=1 to h=H to the sorted homes from the lowest to the highest energy consumption.

d- Calculate the aggregated circuit breaker capacities of all homes as in Eq. (5.3). Where S_h^{CB} is the circuit breaker rate at home "h".

$$S_{Total}^{CB} = \sum_{h=1}^{H} S_h^{CB} \quad (5.3)$$

e- Eq. (5.4) calculates the soft-constraint at home's level in per unit (α_t). α_t has the same value for all homes on the same DT because it is in per unit. ε_t is a margin in per unit set by the DSO that can be changed anytime to limit the DT's power demand below ($\varepsilon_t S_t^{TCL}$) during certain periods of time. DSO can use it to control the lifetime of the DT and its power demand. For example, if $S_t^{TCL} = 100kVA$ and $\varepsilon_t = 0.96$, therefore, the total load of all homes should not exceed 96kVA. If the DSO accepts in a certain period that the power demand on the DT exceed 10% ($\varepsilon_t = 1.1$), therefore, the total load should be lower than $110kVA$. To calculate the soft constraint for each home in terms of power, Eq. (5.5) is used. In this way, each home has its corresponding soft constraint, which can be different from other homes depending on their circuit breaker rates. This soft constraint should be respected at all homes in order to guarantee that the total load on the DT respects its critical power limit. However, if the home's power demand exceeds $S_{h,t}^{HSC}$, it will not cause any direct problems to the home, but an excess of power demand can appear on the DT level. E_h^{HSC} is the energy soft-constraint limit at home in Eq. (5.6).

$$\alpha_t = \frac{\varepsilon_t S_t^{TCL}}{S_{Total}^{CB}} \tag{5.4}$$

$$S_{h,t}^{HSC} = \alpha_t \cdot S_h^{CB} \tag{5.5}$$

$$E_h^{HSC} = \sum_{t \in T} P_{h,t}^{HSC} \tag{5.6}$$

f- The energy consumption of the householders may vary significantly from one to another. Therefore, they may need a higher or lower soft constraint limit ($S_{h,t}^{HSC}$) to meet their demand needs during a day. For this reason, it is appropriate to adjust the value of the power soft-constraints in homes by iterating and optimizing them, taking into account the average energy demand of each home. To do so, $S_{h,t}^{HSC}$ is replaced by $S_{h,t}^{HSC(i)}$ as in Eq. (5.8), where i is the iteration number. Starting from ($i = 1$), $S_{h,t}^{HSC(i)}$ is iterated for all homes for any "t". In addition, Eq. (5.9) is used which represents the ratio of the power soft constraint at home and the DT's critical power limit. $\beta_{h,t}^{(i)}$ is used later to determine $S_{h,t}^{HSC(i)}$ for homes $h = 2 \rightarrow H$. However, it is not used for the first home. $c_{h=1}$ is a correction factor for the prediction of the total energy at home 1. It is used to increase or decrease the power limit according to the actual energy consumption at home. $\gamma_{h,t}$ is a factor that adjusts the HSC at home 1 in a way such that $E_h^{Load,avg} \lesssim E_h^{HSC}$.

$$S_{h=1,t}^{HSC(i=1)} = \alpha_t \cdot S_{h=1}^{CB} \frac{E_{h=1}^{Load,avg}}{\sum_{t \in T} P_{h=1,t}^{HSC}} c_{h=1} \; for \begin{cases} h \in [1, H] \\ t \in [1, T] \end{cases} \tag{5.7}$$

$$S_{h,t}^{HSC(i)} = \alpha_t \cdot S_h^{CB} \; for \begin{cases} h \in [1, H] \\ t \in [1, T] \end{cases} \tag{5.8}$$

$$\beta_{h,t}^{(i)} = \frac{S_{h,t}^{HSC(i)}}{\varepsilon_t S_t^{TCL}} \gamma_{h,t} \; for \begin{cases} h \in [1, H] \\ t \in [1, T] \end{cases} \tag{5.9}$$

g- After calculating the first iteration of $S_{h,t}^{HSC(i)}$ and $\beta_{h,t}^{(i)}$ for all homes, these are sent to the first home "h=1" in order to be used as a constraint in the optimization. $S_{h,t}^{HSC(i)}$ for all homes should be always respected to guarantee a lifetime of the DT equal to the predefined one.

5.a- Then, $S_{h,t}^{HSC(i)}$ and $\beta_{h,t}^{(i)}$ are sent to the LC of the first home "h=1".

b- After receiving them, the LC at home "h=1" starts optimizing and scheduling the controlled elements according to an optimization model with specific objective function and constraints, which are already programmed inside the software of the LC.

6.a- When the optimization is done, the LC sends the calculated power demand at home ($P_{h,t}^{Load}$ and $S_{h,t}^{Load}$) to the PT.

b- PT receives the data and increases i by 1 ($i = i + 1$), e.g., $i = 2$, it means a second iteration of the power soft-constraints of all homes

c- PT increases h by 1 ($h = h + 1$), e.g., $h = 2$, it means that the calculation of the power soft constraint starts from the second to the last home $h = H$

d- PT recalculates $S_{h,t}^{HSC(i)}$ and $\beta_{h,t}^{(i)}$ as in Eq. (5.10) and (5.11). For this time, their values are for homes with $h > 1$.

$$\beta_{h,t}^{(i)} = \beta_{h,t}^{(i-1)} / \sum_{h=i}^{H} \beta_{h,t}^{(i-1)} \tag{5.10}$$

$$S_{h,t}^{HSC(i)} = \beta_{h,t}^{(i)}\left(S_{i-1,t}^{HSC(i-1)} - S_{i-1,t}^{Load}\right) + S_{h,t}^{HSC(i-1)} \tag{5.11}$$

e- h is compared to H in order to verify if the power soft-constraint is changed for all homes starting from home $h = h + 1$ (e.g., $h = 2$), to $h = H$. If not, return to step 6.d. If yes, set $h = i$ (e.g., $h = 2$).

f- A second comparison between h and H shows that if $h = H$, it means that the calculation of the soft constraint is finished for all homes, and the optimization processes have been accomplished in homes. If not, the data of the $S_{h,t}^{HSC(i)}$ and $\beta_{h,t}^{(i)}$ are sent to home $h = i$ (e.g., h=2) through step 7, 9, 11, etc.

7.a- The data of the $S_{h,t}^{HSC(i)}$ and $\beta_{h,t}^{(i)}$ are sent to home $h = i$ (e.g., h=2)

b- After receiving them, the LC at home "h" starts optimizing and scheduling the controlled elements similar to step 5.b.

- The loop is repeated until the second comparison in step 6.f gives a result h=H. Therefore, the algorithm ends the simulation for that day.
- The final value of $S_{h,t}^{HSC}$ and E_{h}^{HSC} will be used as a soft-constraint in homes

5.3.5 Implementation of the proposed strategy at home using a home energy management system

This section shows how a Home Energy Management System (HEMS) should be adapted with the suggested energy-management algorithm. Two methods will be compared which have the same optimization model as inspired by reference (Fotouhi Ghazvini et al., 2017). Method 1 (M1) has exactly the same mathematical expressions as in (Fotouhi Ghazvini et al., 2017). While in our proposed Method 2 (M2), we use the same optimization model as in M1, with the same optimized elements (PV, EWH, BSS and 2 EVs); however, some modifications are made in order to implement the proposed algorithm and to meet the requirements of the DSO and the end-users. To reduce the redundancy of the mathematical expressions and the optimization model, only the necessary adaptations are listed below.

- The objective function is the same, however, the energy and power limits are replaced by the calculated Energy Soft-Constraint Limit (E_{h}^{HSC}) and the power soft-constraint limit at home ($P_{h,t}^{HSC}$),
- An incentive program is proposed to incite the end-users using M2 and respect the limits ($P_{h,t}^{HSC}$) and (E_{h}^{HSC}). The end-user gains 2.9$/day and 2$/day, if they respect the power and energy limits, respectively (they represent about 19% and 13.15% of the average electricity bill (15.2$/day)). However, the incentive program will not penalize them in case these limits are exceeded. The proposed incentive program is applied for both methods M1 and M2 for comparative purposes.

Remark: the proposed incentive program is made within the context of the electricity market mentioned in (Fotouhi Ghazvini et al., 2017). It can be changed depending on the strategy of the DSO/ER. However, the proposed incentive program guarantees a good satisfaction factor of both end-users and the DSO/ER. End-users will reduce their electricity cost if they respect the DT limits, and the DSO/ER will reduce their financial losses and protect the network from overheating and lifetime reduction.

5.4 Results and discussions

To validate the suggested approach and show its advantages over other existing approaches, a case study is chosen in Quebec, Canada, in which a typical DT (e.g., 75kVA, 1-φ) supplies ten homes (circuit breaker 200A, 1-φ for each home). The power utility in Quebec provides the data of the power demand. Water consumption is estimated in this paper based on data provided by Hydro-Quebec and (CAA-Quebec, 2018) (refer to Section 4.6.3). For comparative purposes, the Real-Time Electricity Price is similar to (Fotouhi Ghazvini et al., 2017) which is considered as in Figure 5.7. For the implementation the strategy presented in this paper on a larger network, IEEE 123-Node Test Feeder is chosen and solved in OpenDSS. The impact of both methods at homes, on the DT and the DN, is studied. The simulation is conducted in MATLAB R2016b using Mixed-Integer Nonlinear Programming (MINLP) and the used solver is fmincon and the algorithm is SQP. The sampling time is 30 minutes (Δt), the period of the analysis is 24 hours.

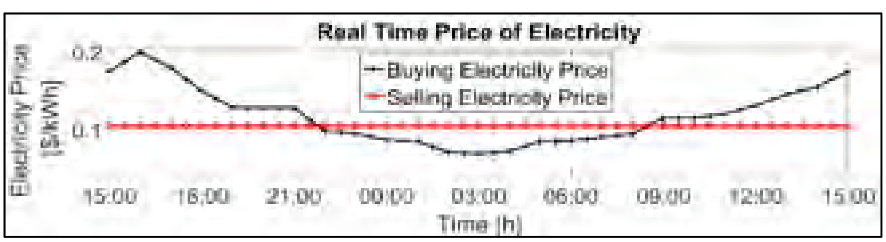


Figure 5.7 Buying and selling Electricity Price using RTP Taken
from (Fotouhi Ghazvini et al., 2017)

5.4.1 Impact at home's level

This subsection aims at studying the impact of both methods on the total power demand and the electricity cost at homes. Figure 5.8 represents the case of home 4 (similar to homes 1, 2, 3, 4, 5, 7, 8, and 9 among the ten homes supplied by the DT) when the power demand using M2 respects the power soft-constraint limit at home (HSC in magenta curve), while for homes 6 and 10 in Figure 5.9, the power demands using M2 have slightly exceeded the HSC (maximum of 40% at 04:30). On the contrary, the power demands at all homes using M1 have highly exceeded the HSC up to 2.5 times the limit because most of the EVs are charging during the same period when the electricity price is low (e.g., at 05:00 in Figure 5.8). In Figure 5.8, the red curve presents the power profile of the baseload (home load excluding the optimized elements such as PV, BSS, EVs, and EWH), which is not considered in the optimization process in this paper and reference (Fotouhi Ghazvini et al., 2017). In the case of M1 (blue curve), the power demand at home highly exceeds the HSC during low electricity prices periods (between 21:00 and 09:00 of Figure 5.7). In contrast, in periods when the electricity price is high (between 15:00-21:00 and 09:00-15:00 of Figure 5.7), the power demand appears negative because the BSS and PV supply energy to the grid to minimize the electricity cost. While for M2 (black curve), the power demand respects the HSC, in which the EVs charge when the electricity price is low without exceeding the HSC. Sometimes, the energy needed to charge the EVs to the desired SOC level is high, hence, they cannot be fully charged during low electricity price, especially when our proposed power soft-constraint is applied. Therefore, they might continue charging during other periods when the electricity price is higher. Consequently, the total electricity cost at homes will be higher for M2 compared to M1. However, because our proposed incentive program is implemented, M2 becomes cost-effective and it shows slightly better results than M1 (average improvement of ≈2.96%) in Figure 5.10. The chosen incentive program is optimized in a way that the total electricity cost of all householders is somehow lower than the one for M1; meanwhile, the DSO will not reduce too much its margin of profit. End-users get a reduction of 2.9$/day and 2$/day in case the power and energy limits are respected. Figure 5.10 shows better results for M2 in which six homes (1, 2, 3, 4, 5 and 9) have respected both power and energy limits and have reduced their electricity cost even lower than M1. While for homes (6, 7, 8, and 10) only the power limit is exceeded; therefore, the reduction in the electricity cost was not enough to become lower than M1. Despite the close values of the electricity cost obtained using both methods, the next subsections show how much the technical issues are improved using M2.

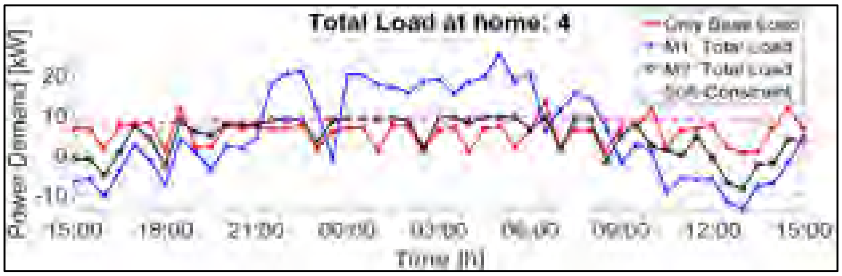


Figure 5.8 Power demand profiles for the baseload, M1, and M2 at home 4

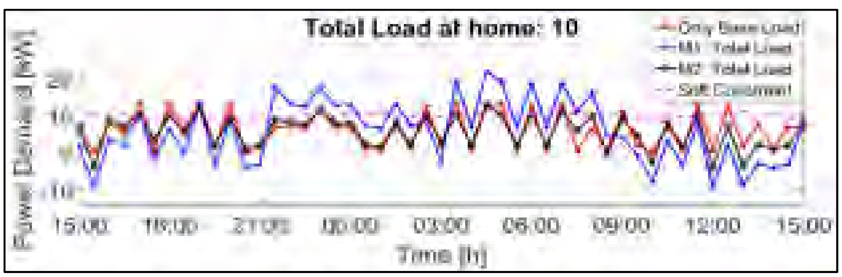


Figure 5.9 Power demand profiles for the baseload, M1, and M2 at home 10

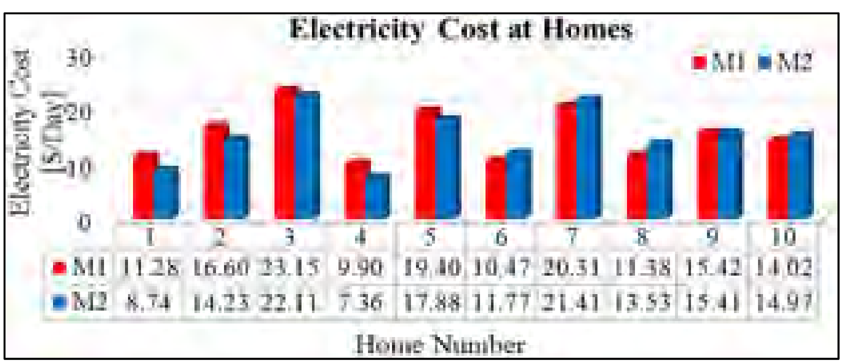


Figure 5.10 Electricity Cost in Homes in $/Day

5.4.2 Impact on the distribution transformer

The main goal of this subsection is to study the technical and economic impact of both methods on the DT level. Figure 5.11 and Figure 5.12 present the total power and voltage profiles on the DT for the baseload (red curve), M1 (blue curve) and M2 (black curve). In total, it is assumed that 20 EVs are connected to the DT (2 in each home); therefore, the penetration level is considered high. It is clear that the power demand using M1 would highly exceed the DT power limit, but protective devices will be activated preventing this destructive operation at the expense of power outages and cascading failure that could be expanded to a larger area of the network. Therefore, the high excess of power demand in Figure 5.11 and the severe voltage drop in Figure 5.12 are just to give an idea about the ineffectiveness of M1 compared to M2 (between 21:30 and 08:00, a peak of 180% occurs at 06:00). M1 has succeeded in minimizing the electricity cost in homes, but it creates severe problems on the DT and the DN. Therefore, not only technical problems can occur, but also economic, security and environmental problems. Concerning method M2, it is clear from Figure 5.11 and Figure 5.12 that the algorithm has assured operation of the transformer on its rating limits in order to maximize its usability without any risk of activating protective devices. M2 has reduced the peak demand by 57.37% and the voltage drop by 6.43% (at 06:00).

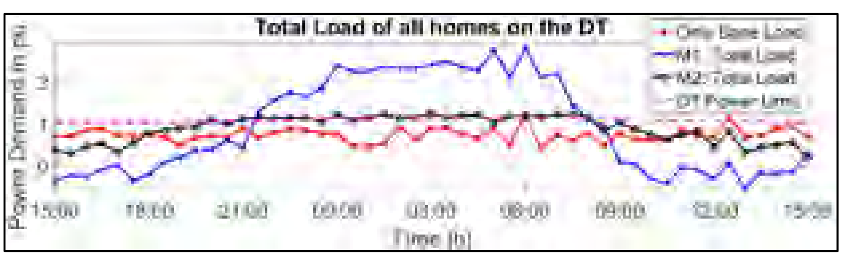


Figure 5.11 Total power consumption on the Distribution Transformer

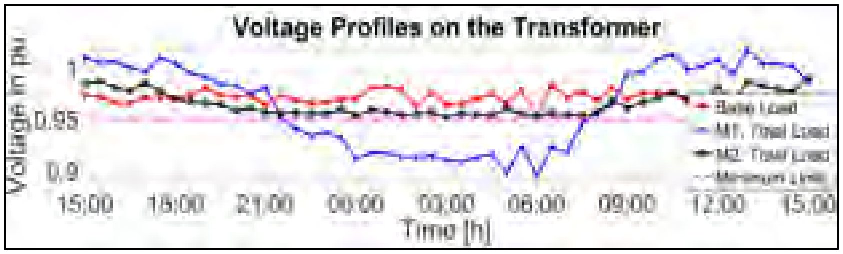


Figure 5.12 Voltage deviation on the Distribution Transformer

Figure 5.13 and Figure 5.14 show the energy losses and their cost on the DT and the lines between the DT and the homes caused by each householder. It is clear that when M1 is used (blue columns) its energy loss is much higher than M2, because M1 creates some peak demand in certain periods and because the losses squarely increase with the power demand. M2 has reduced about 50% the average loss on the DT and in homes, and it has reduced 42.3% the cost of these losses compared to M1.

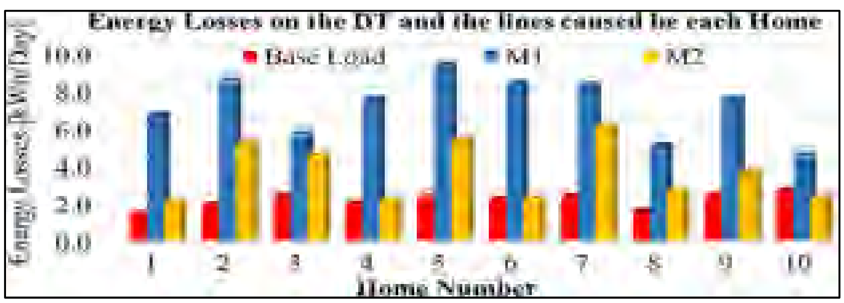


Figure 5.13 Energy losses on the DT and the lines between the DT and the homes caused by each householder

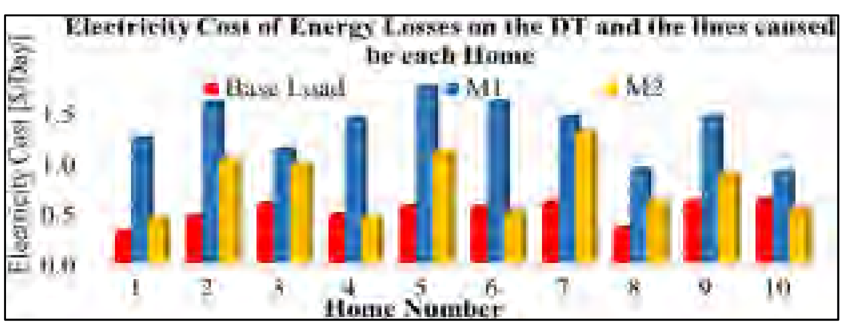


Figure 5.14 Electricity Cost of the Energy losses on the DT and the lines between the DT and the homes caused by each householder

Table 5.1 presents the results of the DT's Loss of Life (LOL) per day, its remaining lifetime and its depreciation cost. A LOL per day equal to 1.81 (for M2) means that one day of operation at the actual power demand on the DT is equal to 1.81 days of operation at the DT's full power capacity. M1 has exponentially increased the LOL of the DT, which reduces its lifetime to one day. In other words, the DT has lost its whole life in one day of operation at the load demand using M1. This is due to the high penetration level of EVs and the BSS, which are trying to consume much energy during low electricity price and sell energy when the price is higher. However, as discussed in subsection 5.4.2, the protective devices will prevent this severe LOL of the DT, but the protective devices (e.g., fuses, thermal relays) will be activated and may be damaged because of the severe excess of power demand. Hence, the blackout of the DT can occur leaving householders without electricity for a certain period. While for M2, the lifetime of the DT is reduced from 20.55 years to 11.35 years and its LOL per day is reduced to 1.81 days. It can be concluded that M2 is more beneficial for the DSO because it reduces the damages on the network even if the income from the electricity bills paid by the end-users are reduced using M2wIP compared to M1 (Figure 5.10). Certainly, some protection systems such as fuses and thermal relays will protect the DT from the high excess of power demand. However, this study illustrates what can happen if both methods are used. M2 guarantees a good functioning of the system without the necessity to activate the protection systems. On the other hand, because M1 exceeds almost 2.5 times the DT's power limit, the protection systems are activated, therefore, they trip the power supply to the end-users leaving them without electricity. Hence, the DSO will send technicians to repair the damaged protection elements such as fuses, which will cost lots of money.

Table 5.1 Loss Of Life, Remaining Lifetime And Depreciation Cost of The DT

Description	M1	M2
LOL per day	20.55 years	1.81 days
DT Remaining Lifetime	1 day	11.35 years
Depreciation Cost of the DT	6000 $/day*	1.45 $/day

*Remark: Since some protection devices such as fuses are installed to protect the transformer, this value will not be reached. However, the lifetime of the transformer is exponentially reduced and there is a risk that these devices will trip or be damaged leaving the end-users without electricity.

5.4.3 Technical impact on the network

For validation purposes on a larger scale, both methods are applied on IEEE 123-Node Test Feeder (Figure 5.15). The main goal of this subsection is to compare the impact of both methods on the voltage profile, power losses and the cost of the energy losses on the distribution network for a penetration level of 43% of smart homes with EVs. The simulation is performed on OpenDSS and MATLAB. Figures 5.16 and 5.17 show a comparison between both methods regarding the voltage deviation on the IEEE 123 Node Test Feeder. The comparison is done at time 06:00 and 13:00 respectively and for a penetration level of 43% of EVs on the DN. In Figure 5.16 at time 06:00 when M1 has the highest power demand, it shows that phase A (black curves) of a large part of the network has a voltage drop below the recommended limit (0.95pu). M2 shows better performance in which the minimum voltage limit is respected. Even for a penetration level of 100% of EVs, M2 always respects the limits, while M1 shows that a severe voltage drop on phases A and C (blue curves) for a large part of the network (the voltage drop reaches 0.8pu). Therefore, it can be concluded that M2 has improved the voltage stability on the network better than M1, even with a very high penetration of EVs. On the other hand, in Figure 5.17 at time 13:00 when M1 has the lowest negative value, it shows a rise in the voltage above the limit (1.05pu) for a large part of the network. A negative value indicates a reverse power flow from homes to the grid. It is because most of the homes are supplying the grid at the same time in order to minimize their electricity cost. It happens when there is an abundance of solar energy, and when the electricity price is high. Voltage rises can cause problems on the network in which they can damage some equipment at homes or even can create blackouts in some regions on the network. For the case of M2, it shows a more stable power demand during a day, and few nodes have exceeded the voltage limit.

Figure 5.18 shows a comparison between M1 and M2 regarding the line losses on the distribution network. In Figure 5.18.a, it is clear that M2 is better than M1, in which it reduces the line losses by at least 72% (for EVs' penetration level of 43%) and by a maximum of 80.6% (for a penetration level of 100%). The case is different at time 13:00

(Figure 5.18.b), M1 shows better results in which all homes supply energy to the grid. Therefore, less power demand may result in lower line losses. However, for a penetration level of 100% using M1 (Figure 5.18.b), the line losses are higher compared to M2 due to the fact that a reverse power flow has increased squarely the losses on the lines, and the network is perturbed and may lose its voltage stability.

In conclusion, M2 shows better performance on the network level regarding voltage stability and line losses. M1 may perturb the stability of the network and create severe problems, in which the damages may be costly for the power utility. Therefore, it is necessary to use PTs, in which the control of the distribution system becomes more efficient.

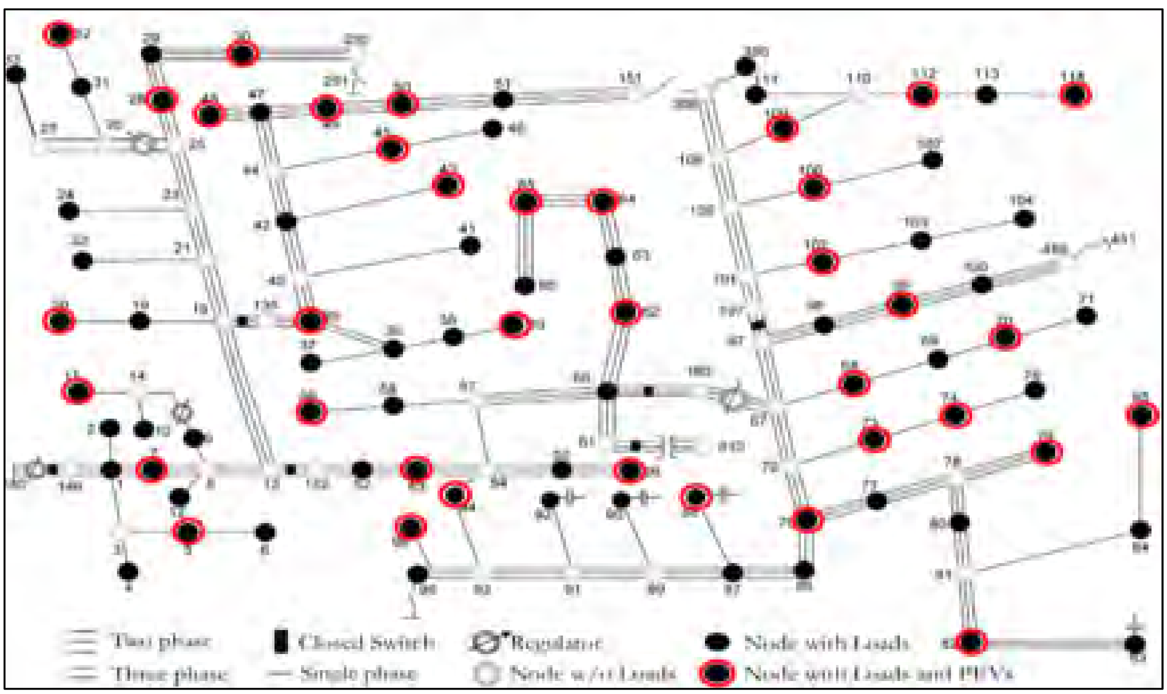
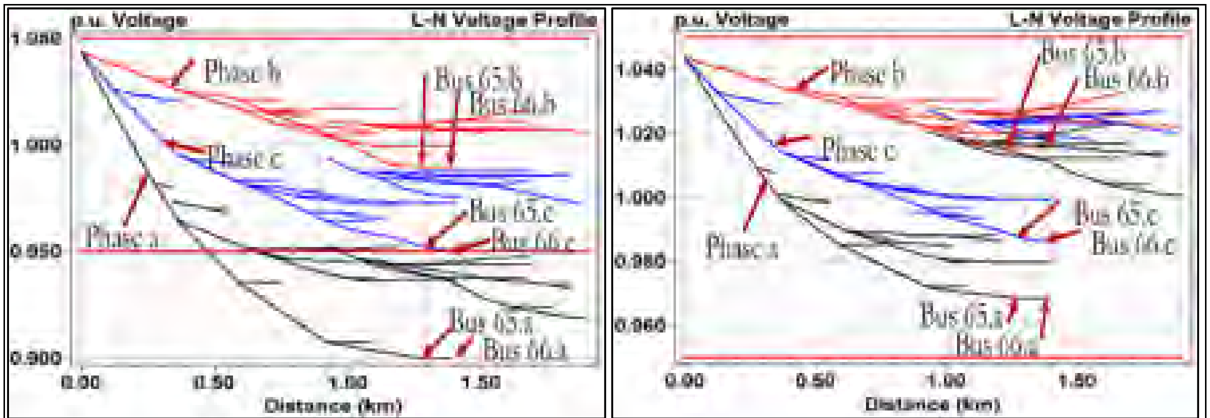
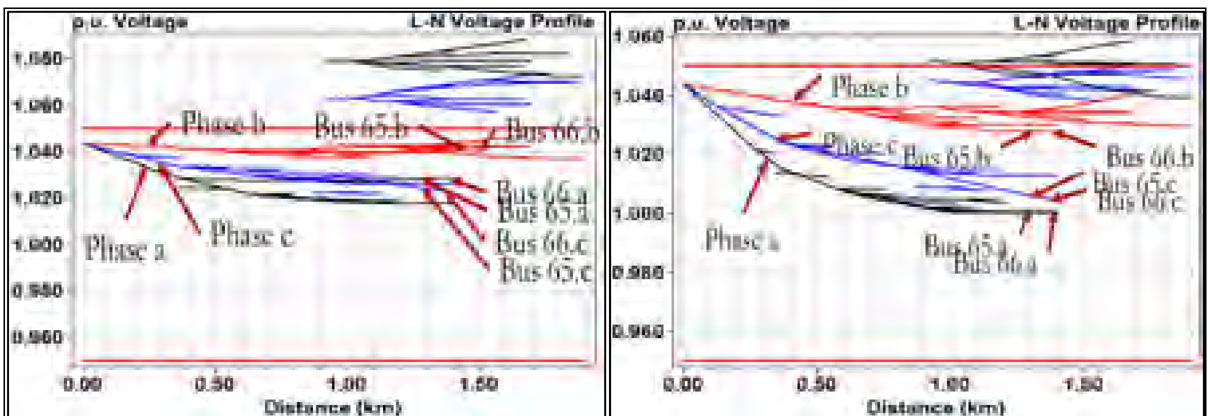


Figure 5.15 Schematic Diagram of IEEE 123 Nodes Test Feeder



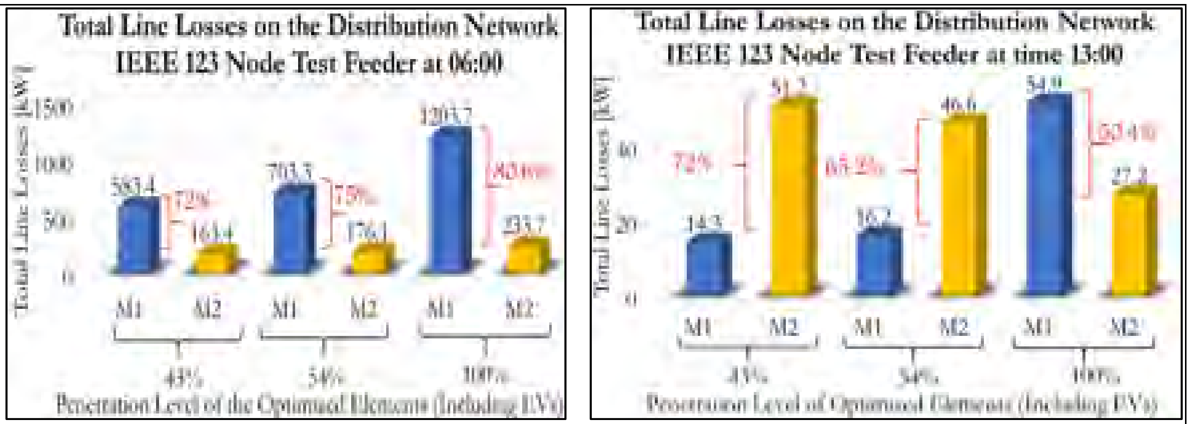
(a) Voltage drops on all buses using M1 | (b) Voltage drops on all buses using M2

Figure 5.16 Voltage drop on all buses of the IEEE 123 Node Test Feeders for a penetration level of 43% at 06:00



(a) Voltage drops on all buses using M1 | (b) Voltage drops on all buses using M2

Figure 5.17 Voltage rise on all buses of the IEEE 123 Node Test Feeders for a penetration level of 43% at 13:00



(a) Total line losses for different penetration levels at time 06:00

(b) Total line losses for different penetration levels at time 13:00

Figure 5.18 Comparison between M1 and M2 of the total line losses on the IEEE 123 Node Test Feeders for different penetration levels*

*Remark: The total line losses for the case of M1 are based on the assumption that the protection devices on the transformer are not activated. However, it gives an idea of how losses would be for a high penetration level of EVs.

To conclude the study, Table 5.2 presents the income and the cost from the viewpoint of the DSO for a penetration level of 43% of the EVs. For M1, the DSO is collecting 5134.9$/day from the householders, however, there are high losses on the DTs (-449.5$/day), lines (-807.1$/day), and the depreciation cost of the DTs (-294 000$/day), which is considered the main problem of M1. In total, the DSO is losing (-290 121.7$/day) if M1 is used. The case is different for M2, in which the DSO has always a positive revenue (4335.2$/day). For the case of M2, the end-users are satisfied because they pay lower tariff compared to M1. M2 satisfies both end-users and the DSO. On the one hand, it reduces the technical and financial losses of the network and increases its lifetime and voltage stability even for 100% penetration level of EVs. On the other hand, it reduces the electricity cost of the end-users. Table 5.3 shows a comparative summary between M1 and M2. The comparison is performed from the viewpoint of the householders, the DT, and the DSO.

Table 5.2 Total Revenue Of the DSO For a Penetration Level of 43%

Description	Unit	M1	M2
Electricity tariff paid by end-users to the DSO	$/Day	5 134.9	4 982.8
Cost of Total Losses on the DTs	$/Day	-449.5	-260.3
Cost of Total Losses on the lines	$/Day	-807.1	-316.4
Depreciation cost of the DTs (Average cost of the transformer is 6000$)	$/Day	-294 000	-71.0
Upgrading cost of the infrastructure (≈30% of the actual infrastructure)	$/Day	0	-13.7
Total revenue of the DSO	**$/Day**	**-290 121.7**	**4 326.08**

*According to (Rhodes, 2017), (Paraskova, 2017) the upgrading cost of the distribution network infrastructure is about 35% of the existing network's cost. In this table, only 43% of the network (IEEE 123 node test feeder) is upgraded based on the penetration level of the controlled elements.

Table 5.3 Summary Table

Level	Description	M1	M2
Home	Minimize the electricity cost in homes	🗐🗐🗐🖺	🗐🗐🗐🗐 (≈2.96% lower)
	Respect the home soft-constraint limit	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the voltage drop at home	🗐🗐🖺🖺	🗐🗐🗐🗐
	DT and DN constraints are considered at home level	🗐🖺🖺🖺	🗐🗐🗐🗐
	Low risk of damaging some equipment in homes	🗐🗐🖺🖺	🗐🗐🗐🗐
	Householders are satisfied	🗐🗐🗐🖺	🗐🗐🗐🗐
Distribution Transformer	Respect the DT's critical power limit	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the transformer's Loss of Life	🗐🖺🖺🖺	🗐🗐🗐🗐
	Increase the DT's Remaining lifetime	🗐🖺🖺🖺	🗐🗐🗐🗐
	Depreciation Cost of the DT is reduced	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the energy losses on the DT & lines	🗐🖺🖺🖺	🗐🗐🗐🗐
	Cost of the energy losses is reduced	🗐🖺🖺🖺	🗐🗐🗐🗐
	Voltage drop on the DT is reduced	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the risk of the DT's explosion and the risk of environmental problems	🗐🖺🖺🖺	🗐🗐🗐🗐
	Low Installation cost	🗐🗐🗐🗐	🗐🖺🖺🖺
	Less simulation time*	🗐🗐🗐🖺	🗐🗐🗐🗐 (36.4% lower)
Distribution System	Voltage drop respects the DN's limits	🗐🗐🖺🖺	🗐🗐🗐🗐
	Reduce the total losses on the DTs	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the Line Losses on the DN for a Grid to Homes power flow	🗐🖺🖺🖺	🗐🗐🗐🗐
	Reduce the energy and line losses cost	🗐🖺🖺🖺	🗐🗐🗐🗐
	Increase the total revenue of the DSO	🗐🖺🖺🖺	🗐🗐🗐🗐
	The approach is simple to be implemented in homes and the DN and less costly	🗐🗐🗐🗐	🗐🗐🖺🖺

Likert scale: 🗐🖺🖺🖺 Strongly disagree, 🗐🗐🗐🗐 Strongly agree

*The simulation was performed using MATLAB and OpenDSS. Because the problem is formulated as Mixed Integer Nonlinear Programming, the simulation time is higher than other software such as Python or C++.

5.5 Conclusion

This chapter shows three original contributions to the literature: (i) a novel energy-management algorithm designed for the Programmable Transformer (PT) is proposed, (ii) a new programmable transformer, in which it can control the power and data flow between end-users; (iii) a new framework and infrastructure that support the integration of PTs in suggested. This paper demonstrates that the conventional distribution network is not ideal for a high penetration level of EVs and other fluctuating loads and sources even when DRPs and smart algorithms are applied at home levels. Two methods are compared, the first one (M1) uses an existing strategy to control and optimize the load demand at homes in the presence of the conventional DN, while for the second one (M2), a PT with its acquisition and communication infrastructure is used. Results show that M2 has reduced the peak demand on the DT by 57.37%, the voltage drop by 6.43%, the Loss of Life and the depreciation cost of the DT by 99.976%, and the line losses by at least 72% compared to M1. The revenue of the DSO for M1 is negative (-290 121.7$/day), while for M2, it is positive (+4 335.2$/day). It is because most of the financial losses of the DSO come from the depreciation cost of the DTs. Therefore, in order to shift from the existing power network to a smarter grid, it is necessary that all elements on the network should be smart. Hence, the PT will be the next step towards a smarter grid.

5.6 Data section

This Section shows some data used for simulation purposes in this chapter. Section 5.6.1 presents the data for the controlled elements considered, such as PV, two EVs, BSS, and EWH. Section 5.6.2 is dedicated to the baseload power profiles at homes provided by Hydro-Quebec. Finally, in section 5.6.3, the water consumptions at homes are estimated based on some data collected from Hydro-Quebec and other references.

5.6.1 Controlled elements

Table 5.4 shows the data used for the controlled elements in ten homes. In each home two EVs, one PV, one Electric Water Heater (EWH), and one Battery Storage System (BSS) are considered in the simulation. The EV types are presented in Table 5.5.

Table 5.4 Data of controlled elements at homes

	Home	H 1	H 2	H 3	H 4	H 5	H 6	H 7	H 8	H 9	H 10
	Circuit breaker [kW]	24	24	24	24	24	24	24	24	24	24
EV 1	Battery capacity [kWh]	34	78	60	33	50	70	36	80	40	100
	Max charging power [kW]	3,9	5,8	3,6	4	3,3	5,1	5,5	5	4,5	5,3
	Max discharging power [kW]	3,9	4,1	3,9	5,3	1,9	4,2	2	1,5	3,7	3
	Charging efficiency	0,9	0,92	0,94	0,89	0,92	0,89	0,95	0,94	0,88	0,92
	Discharging efficiency	0,91	0,91	0,95	0,88	0,88	0,86	0,96	0,92	0,9	0,92
	Arrival time [h]	18,5	19,5	18,5	21	18,5	22	17	16	15	15
	Departure time [h]	33,5	30	32,5	32	34	33	31	33,5	34	32,5
	Initial SOC	0,75	0,68	0,74	0,74	0,69	0,6	0,66	0,68	0,65	0,64
	Final SOC	0,99	0,94	0,99	0,94	0,98	0,94	0,98	0,98	0,94	0,92
EV 2	Battery capacity [kWh]	60	24	30	30	78	60	34	60	30	24
	Max charging power [kW]	6,1	5	6,4	5,5	5,1	6	6,2	6,6	3	6,2
	Max discharging power [kW]	3,8	5,5	3,4	3,2	4,6	2	3,2	5,1	3,6	4,8
	Charging efficiency	0,93	0,92	0,87	0,92	0,86	0,92	0,92	0,93	0,95	0,96
	Discharging efficiency	0,94	0,91	0,96	0,91	0,85	0,86	0,95	0,9	0,95	0,87
	Arrival time [h]	18	19	15	19,5	17	15,5	19	16,5	15,5	16,5
	Departure time [h]	31	32	34	34	31	31,5	32,5	33	33	32
	Initial SOC	0,75	0,61	0,78	0,79	0,8	0,78	0,76	0,7	0,63	0,68
	Final SOC	0,91	0,9	1	0,93	0,93	0,93	0,95	0,97	0,9	0,99
BSS	Battery capacity [kWh]	39	48	32	56	47	38	40	76	64	53
	Max charging power [kW]	6,3	3,3	5,7	5,7	5	3,6	5,2	4,1	3,4	3,7
	Max discharging power [kW]	6,2	2,3	3,1	2,2	4	2	6,2	2,9	2,4	3,4
	Charging efficiency	0,9	0,86	0,96	0,88	0,88	0,85	0,88	0,85	0,91	0,94
	Discharging efficiency	0,92	0,86	0,85	0,94	0,95	0,91	0,86	0,94	0,89	0,88
	Minimum SOC	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2
	Initial SOC	0,85	0,78	0,7	0,53	0,89	0,67	0,81	0,87	0,55	0,56
EWH	Power consumption [kW]	5,2	3,7	5,2	6	5,6	3,2	4,1	4,1	5,1	4,8
	Water capacity [L]	437	310	262	226	432	261	316	366	268	393
	R (°C/kW)	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52	1,52
	C (kWh/°C)	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4	863,4
PV	Surface of the PV panels [m2]	49	52	24	52	42	23	30	39	54	54
	Efficiency of the PV	0,1	0,15	0,15	0,12	0,14	0,1	0,12	0,15	0,14	0,15

Table 5.5 Suggested electric vehicles to be used in homes

Home	EV1	EV2
1	Ford Focus Electric	Chevrolet Bolt
2	BYD e6	Fiat 500e
3	Chevrolet Bolt	Nissan Leaf
4	BMW i3	Nissan Leaf
5	Tesla Model 3	BYD e6
6	Tesla Model 3	Chevrolet Bolt
7	Volkswagen e-Golf	Ford Focus Electric
8	Tesla Model S	Chevrolet Bolt
9	Nissan Leaf II	Nissan Leaf
10	Tesla Model S	Fiat 500e

5.6.2 Baseload data

Figure 5.19 shows the baseload power profiles at homes on April 17, 2016. The data is provided by Hydro-Quebec. The data includes space heating.

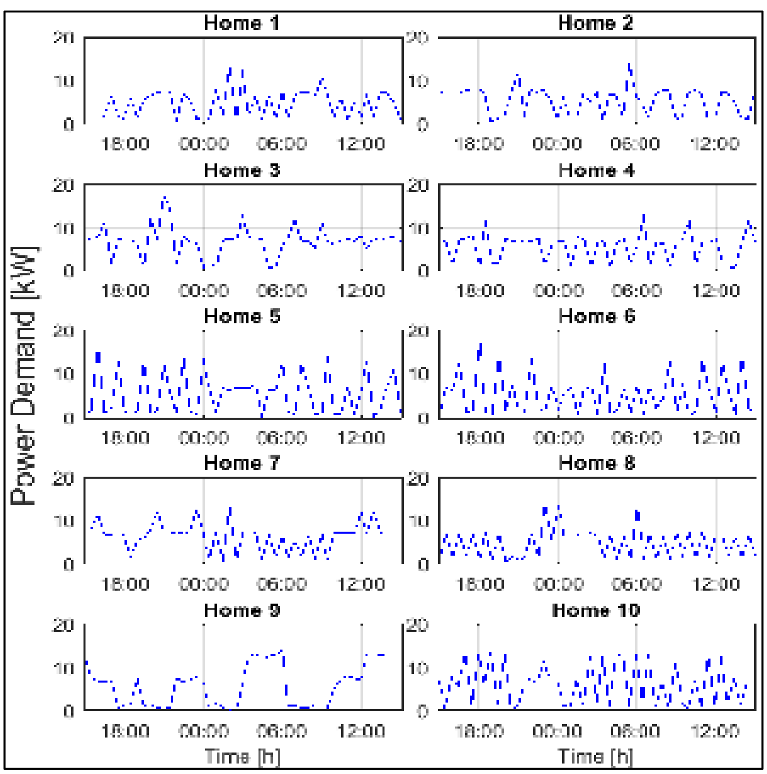


Figure 5.19 Baseload power profiles at homes on April 17, 2016

5.6.3 Average water consumption data

Figure 5.20 presents the data for the average water consumption in each home used by the EWH on April 17, 2016. Because it is almost difficult to obtain real data especially when it is confidential, we propose Equations 5.12 and 5.13 in order to generate the water consumption profile based on basics data provided by Hydro-Quebec, and by (CAA-Quebec, 2018).

$$m_{t,h} = \chi_{t,h} \cdot \left[\left(\frac{m_{t,h}^{Max} - m_{t,h}^{Min}}{2} \right) \cos\left(\frac{2\pi}{T} (t - t_h^{Max}) \right) + \left(\frac{m_{t,h}^{Max} + m_{t,h}^{Min}}{2} \right) \right] \tag{5.12}$$

$$\chi_{t,h} = round(randi([r_{min}, r_{max}], T, H)) \tag{5.13}$$

Where, $m_{t,h}$ represents the estimated water consumption for home "h" in "t". $m_{t,h}^{Max}$ and $m_{t,h}^{Min}$ present the peak and the minimum water consumption in "t". t_h^{Max} is the peak period time of the water consumption at home "h" during a day. $\chi_{t,h}$ is a binary decision variable, which represents the status of the EWH (on/off) in "t" and at home "h". A distributed random function is used to generate the value of $\chi_{t,h}$ as in Equation 4.13. $randi(\,)$ is a uniformly distributed pseudorandom integers, in which it generates random variables between r_{min} and r_{max} in a matrix $T \times H$ (MathWorks, 2018). $round(\,)$ is a function that round up a number to the nearest decimal or integer (e.g. round(0.7)=1, round(0.3)=0).

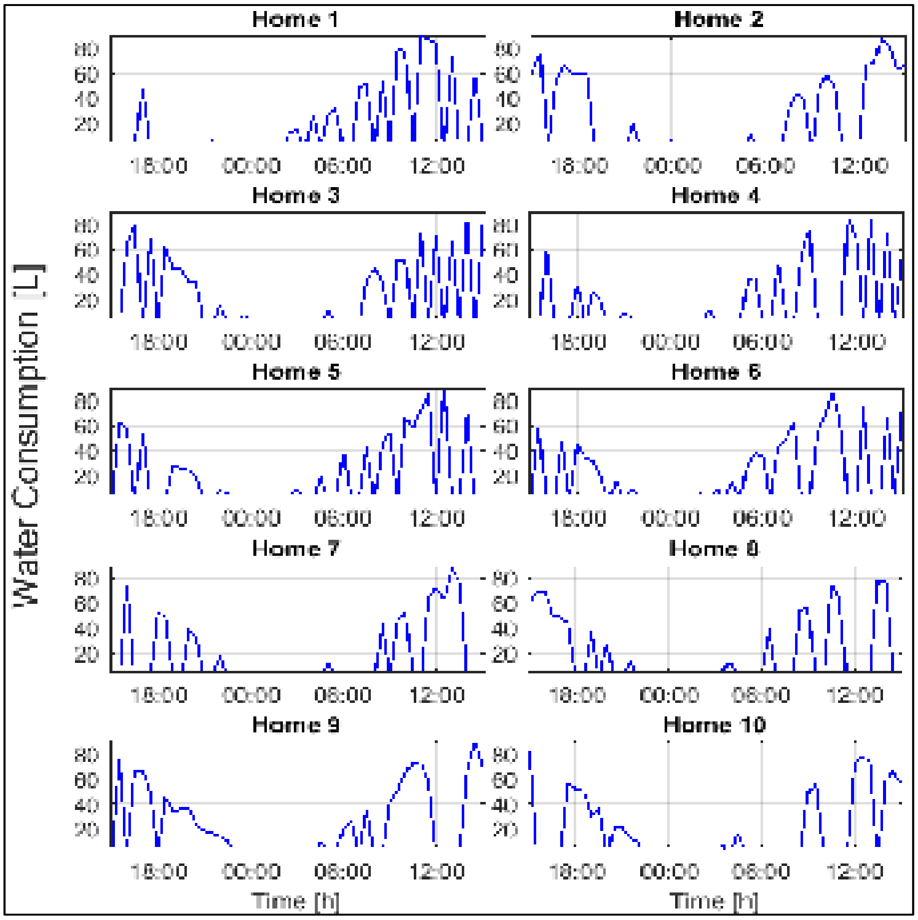


Figure 5.20 Water consumption at homes in Liters (Estimated data based on water consumption at homes in Quebec, Canada)

CONCLUSION AND RECOMMENDATIONS

Conclusion

This thesis proposes novel approaches to mitigate the impact of Electric Vehicles (EVs) on the Distribution Network (DN). It intends to find solutions in order to help Hydro-Quebec to face the high penetration level of EVs, without the necessity of a high investment or remarkable upgrading of the network's infrastructure.

In the first chapter, a literature review concerning the integration of EVs on the network is presented. It shows and compares different charging and control strategies used to integrate efficiently EVs on the grid. Afterward, a brief literature review on the demand response program is presented and their limitations are discussed. Then, this chapter shows a literature review regarding energy management at homes and their limitations. Finally, the actual situation in Quebec concerning the integration of EVs is discussed. The first chapter allowed us to present the next chapters in which we propose efficient and low-cost solutions to mitigate the impact of introducing a high number of EVs on the grid.

The second chapter presents some fundamental concepts of the proposed strategy in each chapter. It compares two methods. In the first one, we use an existing strategy in the literature, while in the second one, we use our proposed one. Some results are presented, in which our proposed strategies show the significant improvement in terms of the technical and economic impact on the network, on the transformer, and at the end-users' level.

Chapter 3 proposes a new transformer power limit (for both, oil-immersed and dry-types), which guarantees a transformer lifetime equal to the predefined one. It predicts exactly how much the power limit changes according to internal and external factors, in contrast to the nameplate rating, which is considered constant by the manufacturer (e.g., 100kVA). The most important factors that affect the variability of the power limit are the fluctuation of the ambient temperature, the internal characteristics of the transformer, and its predefined aging acceleration factor. The proposed power limit shows significant advantages over the conventional nameplate rating in many aspects. For validation purpose, a case study is conducted in an EV parking lot, in which an oil-immersed transformer is considered. The primary objective is to minimize the charging electricity cost of EVs. A comparison with the conventional method based on the transformer rating is examined and analyzed using the same objective function and constraints. The only difference is that in the traditional method, the nameplate rating is considered as a power limit for the transformer, while in our proposed method, the critical power limit of the transformer is considered. Results show that the suggested method has significantly reduced the charging electricity cost of the parking lot. Moreover, an improvement of about 60% on the loss of life and depreciation cost of the transformer has been noticed in some favorable situations. It is also noticed that for unfavorable situations, this approach can guarantee a given loss of life since the conventional one cannot. In case the suggested solution will be implemented on a conventional infrastructure, the following requirements should be considered, (i) the transformer needs additional sensors to measure the ambient temperature. (ii) It needs bidirectional data communication between the DSO, the transformer, and the end-users. (iii) Specific hardware and software should be installed in the transformer in order to calculate the DT's critical power limit and send the data to the end-users and the DSO. These requirements would definitely increase the cost of a more complex implementation, but thanks to the technology, which will be available very soon using smart and digital transformers. The transformer critical power limit will be used in the next two chapters.

Chapter 4 considers the case of the integration of EVs on the network, in which a transformer supplies ten homes. Two EVs, one PV, one Electric Water Heater (EWH), and one Battery Storage System (BSS) are considered as the controlled elements at each home. In this chapter, we propose three main contributions to the literature: (i) a soft-constrained strategy, which is used at homes to better manage the energy. (ii) new soft constraints are proposed that take into account the transformer and the network constraints and limits. (iii) a new optimization model is developed to adapt the constraints of the proposed strategy. This chapter shows that the most used decentralized strategy and demand response are not sufficient to solve the high penetration level of EVs even when energy management systems are used at homes. The traditional decentralized strategy may not cause problems to the transformers and DN in case a few numbers of EVs are connected to the grid. However, the problem appears when the penetration level of EVs becomes very high. This is due to the tendency of EVs to charge during low electricity price and off-peak times, the total load demand may exceed the infrastructure capacity of the DN and transformer causing severe problems. The issue of high penetration level of EVs is solved in our proposed strategy. A comparative study is done between our proposed Soft-Constrained Distributed Strategy and the traditional decentralized strategy. Results show that our strategy respects the transformer and the network limits. It reduces the peak demand by 46%, the energy loss by 36%, the depreciation cost of transformers by 99.993%, and the electricity cost of energy loss by 28%. As mentioned previously, the implementation complexity of our suggested solution will be overpassed when in the near future the smart infrastructure will be deployed. Moreover, the optimal electricity price is higher by 6% compared to the traditional strategy. To solve this issue, we added a new incentive program. The power utility encourages the householders to use the proposed strategy by rewarding them if they respect the limits. This chapter shows that the power utility (e.g., Hydro-Quebec) could support a high penetration level of EVs without the necessity to upgrade all the distribution transformers and the network's infrastructure. In this chapter, the same soft-constraint power profile for all householders is considered, which may not satisfy them. This issue is solved in the next chapter.

In Chapter 5, we propose an approach to solve the limitation in Chapter 4. Thus, it is necessary to introduce a new strategy to control the load at the end-users level in an efficient way, while satisfying both end-users and the Distribution System Operator (DSO). This chapter presents three original contributions: (i) a novel energy-management algorithm is proposed to be implemented on the transformer level, (ii) a new Programmable Transformer (PT) that controls the power and data flow between end-users; (iii) a new framework and infrastructure that support the integration of PTs in suggested. This chapter shows that the conventional distribution network is not ideal for a high penetration level of EVs and other fluctuating loads and sources even when DRPs and smart algorithms are applied at home levels. Two methods are compared, the first one (M1) uses an existing strategy to control and optimize the load demand at homes in the presence of the conventional network, while the second one (M2), a PT with its acquisition and communication infrastructure is used. Results show that our proposed method has reduced the peak demand on the transformer by 57.37%, the voltage drop by 6.43%, the Loss of Life and the depreciation cost of the transformer by 99.976%, and the line losses by at least 72% compared to M1. The revenue of the DSO for M1 is negative (-290 121.7$/day), while for M2 it is +4 335.2$/day. It is because most of the financial losses of the DSO come from the depreciation cost of the DTs. Therefore, in order to shift from the existing power network to a smarter grid, it is necessary that all elements on the network should be smart. Hence, the PT will be the next step towards a smarter grid.

In the end, Appendix I presents some basic concepts of calculating the transformer's critical power limit, its loss of life, its economic losses and depreciation cost, the power losses on the lines and the transformer, and the voltage drop on the cables and the transformer. Moreover, it shows how the optimization model is formulated, and what the most used objective functions and the constraints in this thesis are.

Recommendations

In this section, some recommendations are presented for future works. In Chapter 3 "Novel Approach for optimizing the transformer's critical power limit", the studied case is a typical oil-immersed transformer. However, the emerging technology of smart transformers opens a new gate of revolutionary transformers which are worthy to investigate. The smart transformer is based on power electronics circuits and converters, in which the power utility can regulate the active and reactive power flow by controlling the phase angles of the converters. This technology will improve the stability on the network and increase its efficiency, therefore, it is suggested to be the case study of future works.

In Chapter 4 "Novel Soft-Constrained Distribution Strategy to Meet High Penetration Trend of EVs at Homes", the study is based on a futuristic network in which the power utility, the electricity retailer, the distribution system operator and the end-users are able to communicate and share information on a web-based platform. However, further investigation is necessary to show how such communication can be implemented and secured. It is also important to consider a futuristic smart home in which most of its elements can be controlled and scheduled. In addition, a deterministic power consumption profile is considered using a day-ahead prediction. However, in reality, the real power curve can be different. Therefore, it is important to optimize in real time which may give better and more accurate results.

Chapter 5 is quite similar to Chapter 4. However, a more dynamic soft-constraint power profile is considered at home, which may improve the global satisfaction factor of the end-users and the system operator. Despite the results are satisfactory, some suggestions can be helpful to improve the work in the future as follows:

- The studied network is IEEE 123-Node Test Feeder, it is suggested to study a larger network such as IEEE 8500-Node Test Feeder which could be more realistic,
- A deterministic power profile is considered in the study, however, it is suggested to consider a real-time power profile which can lead to more accurate results,
- Smart algorithm is considered on the transformer level, in which it manages and supervises the power and energy flow of the end-users. Nevertheless, the introduction of Artificial Intelligence and Machine Learning in the control system can improve drastically the performance of the network,
- This chapter does not answer the question, “What happens if the total energy demand exceeds the transformer and network capacity?” Therefore, further investigation should consider this case and try to find solutions for the worst case scenario,
- For large scale real system, it is preferable to use advanced optimization software such as AMPL, LINGO, etc., rather than MATLAB.

APPENDIX I

DETAILS ON THE ECONOMIC AND TECHNICAL CALCULATIONS

In this Appendix, some detailed calculations are presented in order to help the readership to understand how the calculations are done in the chapters.

A.1. Transformer's power limit

A.1.2. Transformer's critical power limit vs. nameplate rating

The first aspect in which the DSO is interested in is to increase the lifetime of the distribution transformer (reduce its loss of life) for many reasons. The distribution transformer (DT) is expensive equipment and may cost from several thousands of dollars to several hundred thousands of dollars depending on their size, characteristics and brand names. Therefore, if the DSO needs to reduce its financial losses on the network due to peak demand, it should either increase the DTs size or limit the power consumption within a certain limit. The first case costs the DSO lots of money because a distribution network may contain several hundred thousands of distribution transformers. Therefore, upgrading the infrastructure is not the ideal way to mitigate the high penetration level of EVs and other loads. The second case is much cheaper; the DSO limits the power demand, in which the total load will respect the transformer's nameplate rating. Despite this method is more reasonable than the first one, it has many limitations. In fact, the transformer's nameplate rating (e.g., 100kVA) does not reflect its real power limit, because the limit depends on many factors such as the ambient temperature as presented in Figure-A I-1. For example, in summer and in hot weather, even if the power consumption is lower than the nameplate rating, the transformer's lifetime is reduced because the power demand may exceed the real power limit (Figure-A I-1, red curve between 10:00 and 21:00). Therefore, it is necessary to define this critical power limit in which the normalized loss of life is set to the unity in order to guarantee that the transformer will not loose from its life whatever the external conditions are.

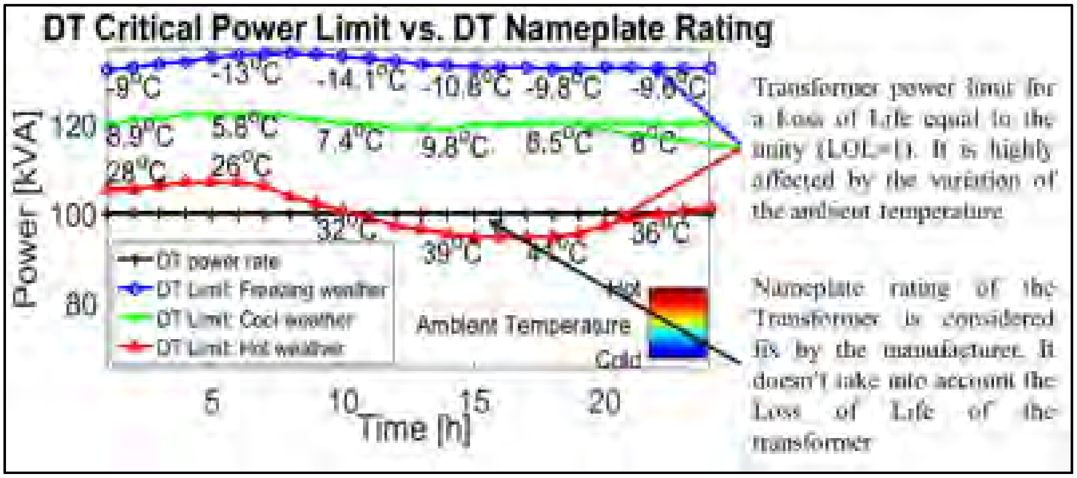


Figure-A I-1 Impact of the ambient temperature's variation on the transformer's power limits

To do so it is necessary to determine the critical power limit of the transformer in which the load should not exceed in order to ensure a LOL equal to the predefined one (set by the manufacturer). In Chapter 3 entitled "Novel Approach for optimizing the transformer's critical power limit", this limit is calculated; however, in this section, a more detailed calculation is provided.

A.1.3. Hot-spot temperature as a function of the aging acceleration factor

A typical transformer uses liquid oil to cool down and dissipate the heat produced by the energy losses in the wiring and the core of the transformer. The oil should not exceed a certain temperature (e.g., 110ºC) in order to avoid its fast degradation and to reduce the lifetime of its insulation materials. The transformer's lifetime is the same as the lifetime of its weakest element. Hence, to calculate the transformer's lifetime and loss of life, it is necessary to determine the hottest-spot temperature (θ_t^{HS}) in the transformer, which is the temperature of the winding. The transformer's per unit life depends on the θ_t^{HS} and it is defined as in Eq. (A I-1), according to IEEE Standard C57.91-2011, (Qian et al., 2015), (IEEE, 2012). Where $\alpha = 15000$, $\beta = 9.8 \cdot 10^{-18}$, $\theta_0 = 273$. A high increase in the θ_t^{HS} reduces exponentially the lifetime of the transformer. Hence, it is necessary to determine the aging acceleration factor (F_t^{AA}) as in Eq. (A I-2) by which the transformer's lifetime is affected taking into account θ_t^{HS}, and the reference temperature θ_{ref} by which the hottest-spot temperature should not exceed ($\theta_t^{HS} \leq \theta_{ref}$) to guarantee a lifetime equal to the predefined one by the manufacturer (e.g., a lifetime of the transformer is 20 years if θ_{ref} is always respecting during the whole operation process).

$$Per\ Unit\ Life = \beta \cdot \exp\left(\frac{\alpha}{\theta_t^{HS} + \theta_0}\right) \tag{A I-1}$$

The transformer's per unit insulation life as expressed in Eq. (A I-1) is used to calculate the aging Acceleration Factor (F_t^{AA}) in Eq. (A I-2). F_t^{AA} indicates how much the transformer's aging is accelerated under certain loads and temperature (Qian et al., 2015). F_t^{AA} is directly proportional to $exp\left(\theta_t^{HS} - \theta_{ref}\right)$ as described in Eq. (A I-3), which can exponentially increase and decrease according to the value of θ_t^{HS}. For $\theta_t^{HS} > \theta_{ref}$, $F_t^{AA} > 1$, and for $\theta_t^{HS} < \theta_{ref}$, $F_t^{AA} < 1$.

In IEEE Standard C57.91-2011, $\theta_{ref} = 110^0C$, however, it may vary depending on many factors such as the average ambient temperature during a year (IEEE, 2012). Therefore, we can express it as in Eq. (A I-4). Where, θ_{avg}^A is the average temperature during a year in a certain region. 5^0C is a safety margin.

$$F_t^{AA} = exp\left(\frac{\alpha}{\theta_{ref} + \theta_0} - \frac{\alpha}{\theta_t^{HS} + \theta_0}\right) \tag{A I-2}$$

$$F_t^{AA} \propto exp\left(\theta_t^{HS} - \theta_{ref}\right) \tag{A I-3}$$

$$\theta_{ref} = \Delta\theta_{TO,R} + \Delta\theta_{G,R} + \theta_{avg}^A + 5 \tag{A I-4}$$

Example:

For a certain load demand and a certain ambient temperature, if $\theta_t^{HS} = \theta_{ref}$, Eq. (A I-2) becomes:

$$F_t^{AA} = exp\left(\frac{\alpha}{\theta_{ref} + \theta_0} - \frac{\alpha}{\theta_{ref} + \theta_0}\right) = exp(0) = 1$$

It means that the combination of the ambient temperature's variation and the load demand does not exceed the reference temperature limit. Therefore, the aging acceleration is normal, and the transformer will last as predicted by its manufacturer's data (e.g., 20 years).

On the contrary, if the load demand and/or the ambient temperature increase in a way that θ_t^{HS} becomes 10% higher than θ_{ref} ($\theta_t^{HS} = 1.1\,\theta_{ref}$), the aging of the transformer is accelerated 3 times as will be demonstrated as follows:

$$\Rightarrow F_t^{AA} = exp\left(\frac{\alpha}{\theta_{ref} + \theta_0} - \frac{\alpha}{1.1\theta_{ref} + \theta_0}\right)$$

$$\Rightarrow F_t^{AA} = exp\left(\frac{\alpha(0.1\theta_{ref})}{(\theta_{ref} + \theta_0)(1.1\theta_{ref} + \theta_0)}\right)$$

$$\Rightarrow F_t^{AA} = exp\left(\frac{15000(0.1 \cdot 110)}{(110 + 273)(1.1 \cdot 110 + 273)}\right)$$

$$\Rightarrow F_t^{AA} = exp\left(\frac{165000}{383 \cdot 394}\right) = exp(1.0934) \approx 2.98$$

It means that one day of operation is equivalent to three days of operation at standard temperature (25°C) and load demand (power consumption equal to the nameplate rating of the transformer, e.g., 100kVA).

However, in this thesis, we are interested to set the aging acceleration factor to a certain value (e.g., $F_t^{AA} = 1$) and calculate the corresponding hottest-spot temperature as a function of it ($\theta_t^{HS} = f(F_t^{AA})$) as will be described in Eq. (A I-5).

$$\ln(F_t^{AA}) = \ln\left(exp\left(\frac{\alpha}{\theta_{ref} + \theta_0} - \frac{\alpha}{\theta_t^{HS} + \theta_0}\right)\right)$$
$$\Rightarrow \ln(F_t^{AA}) = \frac{\alpha}{\theta_{ref} + \theta_0} - \frac{\alpha}{\theta_t^{HS} + \theta_0} \quad \text{(A I-5)}$$

$$\Rightarrow \frac{\alpha}{\theta_t^{HS} + \theta_0} = \frac{\alpha}{\theta_{ref} + \theta_0} - \ln(F_t^{AA})$$

$$\Rightarrow \theta_t^{HS} + \theta_0 = \frac{\alpha(\theta_{ref} + \theta_0)}{\alpha - (\theta_{ref} + \theta_0) \cdot \ln(F_t^{AA})}$$

Finally, we get

$$\theta_t^{HS} = \frac{\alpha\left(\theta_{ref} + \theta_0\right)}{\alpha - \left(\theta_{ref} + \theta_0\right) \cdot \ln(F_t^{AA})} - \theta_0$$

A.1.4. Calculate the DT critical power limit as a function of the ambient temperature and the aging acceleration factor

After defining the equation $\theta_t^{HS} = f(F_t^{AA})$, it is necessary to define the elements of the hottest-spot temperature as shown in Eq. (A I-6), (A I-7) and (A I-8), (Turker et al., 2014), (Qian et al., 2015), (IEEE, 2012). Where, θ_t^{A} is the ambient temperature at instant “t”. $\Delta\theta_t^{TO}$ is the Top-oil rise over ambient temperature $[^0C]$. $\Delta\theta_{TO,R}$ designs the Top-oil rise over ambient temperature at rated load on the tap position to be studied. $\Delta\theta_t^{G}$ represents the Winding hottest-spot rise over top-oil temperature $[^0C]$. $\Delta\theta_{G,R}$ is the winding hottest-spot temperature at rated load on the tap position to be studied. R is the Ratio of load loss at rated load to no-load loss. p is the empirically derived exponent used to calculate the variation of $\Delta\theta_t^{TO}$ with changes in load. m is the empirically derived exponent used to calculate the variation of $\Delta\theta_t^{G}$ with changes in load. S_t^{Load} is the total load on the transformer. S_{NR} is the transformer nameplate rating.

$$\theta_t^{HS} = \theta_t^{A} + \Delta\theta_t^{TO} + \Delta\theta_t^{G} \tag{A I-6}$$

$$\Delta\theta_t^{TO} = \Delta\theta_{TO,R}\left(\frac{\left(\frac{S_t^{Load}}{S_{NR}}\right)^2 R + 1}{R + 1}\right)^p \tag{A I-7}$$

$$\Delta\theta_t^G = \Delta\theta_{G,R}\left(\frac{S_t^{Load}}{S_{NR}}\right)^{2m} \tag{A I-8}$$

In the above-mentioned equations and references, S_t^{Load} is considered as a known variable, in which it is used to calculate the aging acceleration factor (F_t^{AA}). However, in our case, we considered that F_t^{AA} is already defined and set by the DSO, (e.g., $F_t^{AA} = 1.05$). Hence, we have to calculate the transformer's critical power limit (S_t^{TCL}) as a function of F_t^{AA}. To do so, Equations (A I-7) and (A I-8) are substituted in Eq. (A I-6), then Eq. (A I-9) is formed. Afterward, S_t^{Load} is replaced by S_t^{TCL} as presented in Eq. (A I-10).

$$\begin{aligned}
&\Rightarrow \Delta\theta_t^{TO} + \Delta\theta_t^G = \theta_t^{HS} - \theta_t^A \\
&\Rightarrow \Delta\theta_{TO,R}\left(\frac{\left(\frac{S_t^{Load}}{S_{NR}}\right)^2 R+1}{R+1}\right)^p + \Delta\theta_{G,R}\left(\frac{S_t^{Load}}{S_{NR}}\right)^{2m} = \theta_t^{HS} - \theta_t^A \\
&\Rightarrow \left(\frac{\left(\frac{S_t^{Load}}{S_{NR}}\right)^2 R+1}{R+1}\right)^p + \frac{\Delta\theta_{G,R}}{\Delta\theta_{TO,R}}\left(\frac{S_t^{Load}}{S_{NR}}\right)^{2m} = \frac{\theta_t^{HS} - \theta_t^A}{\Delta\theta_{TO,R}}
\end{aligned} \tag{A I-9}$$

$$\left(\frac{\left(\frac{S_t^{TCL}}{S_{NR}}\right)^2 R+1}{R+1}\right)^p + \frac{\Delta\theta_{G,R}}{\Delta\theta_{TO,R}}\left(\frac{S_t^{TCL}}{S_{NR}}\right)^{2m} - \frac{\theta_t^{HS} - \theta_t^A}{\Delta\theta_{TO,R}} = 0 \tag{A I-10}$$

$$\left(\frac{\left(\frac{S_t^{TCL}}{S_{NR}}\right)^2 R+1}{R+1}\right)^p + \frac{\Delta\theta_{G,R}}{\Delta\theta_{TO,R}}\left(\frac{S_t^{TCL}}{S_{NR}}\right)^{2m} - \frac{\left(\frac{\alpha\left(\theta_{ref}+\theta_0\right)}{\alpha-\left(\theta_{ref}+\theta_0\right)\cdot\ln\left(F_t^{AA}\right)}-\theta_0\right)-\theta_t^A}{\Delta\theta_{TO,R}} = 0 \tag{A I-11}$$

Eq. (A I-11) is nonlinear and it is almost difficult to find S_t^{TCL} as a function of θ_t^{HS}, θ_t^{A} and other internal parameters. Therefore, it is necessary to use an algorithm such as Newton-Raphson in order to determine its value as depicted in Figure-A I-2.

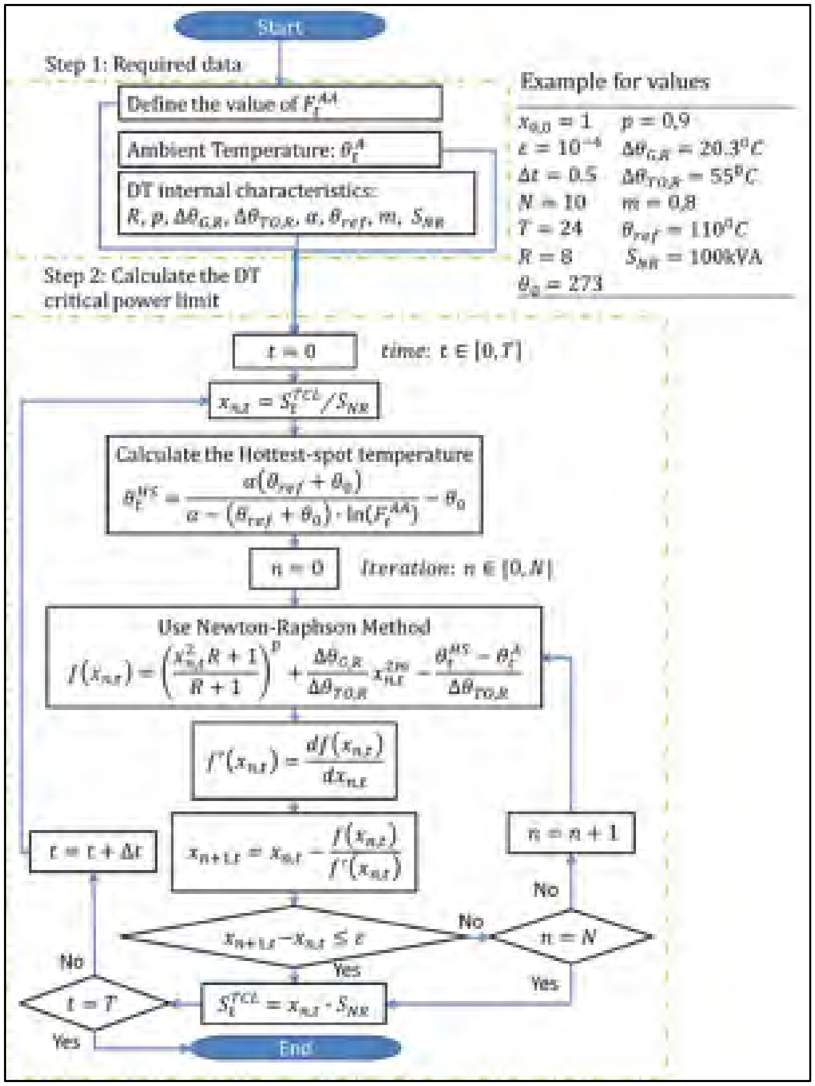


Figure-A I-2 Suggested algorithm that calculates the transformer's critical power limit

A.1.5. Loss of life of the transformer

The interest of the DSO is to reduce the losses of physical and intangible assets and increase its revenue. Transformers are one of the most expensive parts of the distribution network.

Therefore, a reduction in the transformers lifetime increases their depreciation cost. Hence, DSO is obliged to replace them with new ones before the expected end of life. For example, suppose a transformer costs about $20,000 and it has a lifespan of 20 years, a high peak demand during a certain period may reduce its lifetime to 15 years. Consequently, the depreciation cost is equal to $5,000 ((20years-15years) x ($20,000/20years)). To calculate the loss of life of the transformer, it is necessary to define some terms.

A.1.6. Equivalent aging factor

In Eq. (A I-12), the Equivalent Aging Factor (F_{EQA}) is defined as the total sum of the aging acceleration factor (F_t^{AA}) during a period T (e.g., 24 hours), (Qian et al., 2015), (IEEE, 2012).

$$F_{EQA} = \frac{1}{T}\sum_{n=1}^{T/\Delta t} F_{t+(n-1)\Delta t}^{AA}\Delta t \tag{A I-12}$$

A.1.7. Loss of life

The Equivalent Aging Factor is used to calculate the loss of life of the transformer. Eq. (A I-13) represents the percent loss of life ($LOL_{\%}$), while Eq. (A I-14) represents the loss of life during a period T (e.g., $T = 24\ hours$), which is equivalent to the F_{EQA}.

$$\begin{gathered} LOL_{\%} = \frac{F_{EQA}T}{L_N}\cdot 100\% \\ \Rightarrow LOL_{\%} = \frac{1}{T}\sum_{n=1}^{T/\Delta t} F_{t+(n-1)\Delta t}^{AA}\Delta t\frac{T}{L_N}\cdot 100\% \\ \Rightarrow LOL_{\%} = \frac{100\%}{L_N}\sum_{n=1}^{T/\Delta t} F_{t+(n-1)\Delta t}^{AA}\Delta t \end{gathered} \tag{A I-13}$$

$$LOL_T = \frac{LOL_{\%}}{100} \cdot \frac{L_N}{T}$$
$$\Rightarrow LOL_T = \frac{\frac{F_{EQA}T}{L_N} \cdot 100\%}{100} \cdot \frac{L_N}{T} \qquad \text{(A I-14)}$$
$$\Rightarrow LOL_T = F_{EQA}$$

For example, suppose that $F_{EQA} = 4$ during a day (24 hours), it means that one day of operation for a particular load profile and temperature during a day reduces four days of the transformer lifetime. However, in standard conditions (hottest spot temperature is equal to the reference temperature, in another meaning, power demand=nameplate rating and ambient temperature=reference ambient temperature), $F_{EQA} = 1$. It means that the combination of the load profile and the ambient temperature has affected the functioning of the transformer and reduced its lifetime by 3 additional days (4 days – 1 day).

A.1.8. Remaining lifetime of the transformer

In this thesis, the remaining lifetime of the transformer (RT_{DT}) is defined as its lasting period if the load profile and ambient temperature are considered the same every day, as in Eq. (A I-15). The index is important to determine how long the transformer will last if the power consumption continues to be the same every day. For example, suppose that the loss of life per day is equal to 5 days under certain conditions. It means that one day of operation reduces 5 days from the transformer's lifetime. In this case, $RT_{DT} = \frac{20years}{5} = 4\ years$. In another meaning, if the load consumption continues as it is in that day, the transformer will last just for 4 years instead of 20 years. Hence, this factor is important to show how the transformer will last under certain load demands.

$$RT_{DT} = \frac{L_N}{LOL_T}$$
$$\Rightarrow RT_{DT} = \frac{L_N}{F_{EQA}} \qquad \text{(A I-15)}$$

A.2. Economic losses of the transformer

A.2.1. Reference depreciation cost of the transformer

In Eq. (A I-16) the reference depreciation cost (RDC_T^{Tr}) of the transformer is defined as how much the transformer is losing from its cost for a period T (e.g., one day) under standard conditions (hottest-spot temperature = reference temperature). It is equal to the transformer's cost C_{Tr} (e.g., \$6000) multiplied by the period of study T (e.g., 24 hours), and divided by the lifetime of the transformer in hours L_N (e.g., 180,000 hours).

$$RDC_T^{Tr} = \frac{T \cdot C_{Tr}}{L_N} \tag{A I-16}$$

For example, suppose $T = 24\ hours$, $C_{Tr} = \$6000$, $L_N = 180{,}000\ hours$. RDC_T^{Tr} becomes equal to 0.8\$/day. It means that the transformer is losing 0.8\$ per one day of operation at standard conditions.

A.2.2. Actual depreciation cost of the transformer

The reference depreciation cost (RDC_T^{Tr}) does not reflect how much the transformer is losing from its value due to the variation of the load demand and the ambient temperature. In order to calculate the actual depreciation cost of the transformer (ADC_T^{Tr}) for a period T, RDC_T^{Tr} should be multiplied by the loss of life for the same period (LOL_T) as in Eq. (A I-17). ADC_T^{Tr} takes into account the impact of the fluctuation of the ambient temperature and the power demand on the economic losses.

$$ADC_T^{Tr} = LOL_T \cdot RDC_T^{Tr} \tag{A I-17}$$

For example, suppose that $RDC_T^{Tr} = 0.8\$/day$ as presented in the previous example, and the loss of life per day is $LOL_T = 2$. It means that the actual depreciation cost is equal to $1.6\$/day$.

A.2.3. Benchmark depreciation cost of the transformer

In Eq. (A I-17), the actual depreciation cost was defined. However, sometimes we need to know exactly how much a certain load has impacted the life of the transformer and its depreciation cost. Therefore, it is necessary to set a reference limit in which value equal to zero means that the depreciation cost is normal under standard conditions. A positive value means that the transformer is losing from its lifetime and depreciation cost, and a negative value means that losses are less than the normal one under standard conditions. To do so, Eq. (A I-18) is introduced in which it represents the benchmark depreciation cost of the transformer (BDC_T^{DT}) for a period T.

$$BDC_T^{DT} = RDC_T^{Tr} \cdot (LOL_T - 1) \tag{A I-18}$$

If $BDC_T^{DT} = 0$, it means that the transformer is working under standard conditions without any additional losses. If $BDC_T^{DT} = 2 \geq 0$, it means that the transformer is losing additional 2\$/day from its value due to the excess load in period T. If $BDC_T^{DT} = -1 \leq 0$, it means that the transformer is gaining 1\$/day from its value because the load demand is lower than the critical power limit or because the hottest-spot temperature is lower than the reference temperature.

A.3. Power losses calculation

A.3.1. Power loss on the transformer

The power loss on the transformer at instant "t" is expressed in Eq. (A I-19). Where, Z_{pu} is the internal impedance of the transformer in per unit, it is given by the manufacturer (e.g., 0.0562). V_t is the voltage on the secondary of the transformer [V]. S_{NR} is the transformer nameplate rating [kVA]. I_t^{Tr} is the total load current on the transformer [A]. The energy losses are the sum of the total power losses during a day.

$$S_{j,t}^{Loss} = Z_{pu} \overbrace{\overbrace{\left(\frac{V_t^2}{S_{NR} \cdot 1000}\right)}^{Z_{base}} \cdot \frac{(I_t^{Tr})^2}{1000}}^{Z_{actual}} \tag{A I-19}$$

A.3.2. Power losses on the cables and lines

The line loss for home "j" at instant "t" is expressed in Eq. (A I-20). Energy loss is the sum of the total power losses during a day. $I_{j,t}$ is the current consumption at home "j" and at instant "t". $R_{c,j}$ is the resistance of cable "c" $[\Omega/km]$. $l_{c,j}$ is the length of the cable "c" between the secondary of the transformer and the distribution panel board at home "j".

$$P_{j,t}^{Loss} = I_{j,t}^2 \left(\sum_{c=1}^{C} R_{c,j} l_{c,j} \right) \tag{A I-20}$$

A.4. Voltage drop calculation

In this thesis, OpenDSS 811.10 Software is used to calculate the losses on the network (EPRI, 2016). However, hereafter, we present a simplified model that could be used to calculate the voltage drop on the transformer and lines.

A.4.1. Voltage drop on cables

The voltage drop calculation could be found in some standards and references such as (Chou et al., 2017), (Liban-Cables, 2003), (IEEE-Standard, 1991). Moreover, some sophisticated software such as OpenDSS provides the voltage drop calculation on the distribution network level. In this thesis, OpenDSS is used to generate results. However, we can use Eq. (A I-21) to calculate the voltage drop on cables between homes and the transformer. Where, $V_{j,t}^{Drop}$ is the voltage drop at home "j" and at instant "t" on the secondary distribution board [V]. $I_{j,t}$ is the actual current consumption at home [A]. $\cos(\varphi_{j,t})$ is the power factor at home, $\varphi_{j,t}$

power factor angle. $c \in [1, C]$ is the number of cables between the secondary of the transformer and the secondary distribution board at home "j". $R_{c,j}$ is the resistance of cable "c" $[\Omega/km]$. $l_{c,j}$ is the length of cable "c" $[km]$. $w = 2\pi f$ is the angular frequency $[rad/s]$. L_c is the inductance $[H/km]$.

$$V_{j,t}^{Drop} = 2I_{j,t} \cdot \left(\cos(\varphi_{j,t}) \cdot \left(\sum_{c=1}^{C} R_{c,j} l_{c,j} \right) + \sin(\varphi_{j,t}) \cdot w \cdot \left(\sum_{c=1}^{C} l_{c,j} L_{c,j} \right) \right) \quad \text{(A I-21)}$$

A.4.2. Voltage drop in the transformer

The transformer voltage drop is expressed in Eq. (A I-22) for single phase, and in Eq. (A I-23) for three phases. I_t^{Tr} is the total current on the transformer at instant "t" [A]. R_{act} is the actual resistance of the transformer [Ω]. X_{act} is the actual reactance of the transformer [Ω]. φ_t is the power factor angle. $R_{\%}$ and $X_{\%}$ are the resistance and reactance of the transformer given by the manufacturer in %. V_{Sec} is the voltage rating of the secondary of the transformer [kV]. S_{Cap}^{Tr} is the transformer rating [kVA].

$$V_{t,1\varphi}^{Tr,Drop} = I_t^{Tr} \cdot (R_{act} \cos(\varphi_t) + X_{act} \sin(\varphi_t)) \quad \text{(A I-22)}$$

$$V_{t,3\varphi}^{Tr,Drop} = \sqrt{3} \cdot I_t^{Tr} \cdot (R_{act} \cos(\varphi_t) + X_{act} \sin(\varphi_t)) \quad \text{(A I-23)}$$

$$R_{act} = \frac{10 \cdot R_{\%} \cdot V_{Sec}^2}{S_{Cap}^{Tr}} \quad \text{(A I-24)}$$

$$X_{act} = \frac{10 \cdot X_{\%} \cdot V_{Sec}^2}{S_{Cap}^{Tr}} \quad \text{(A I-25)}$$

A.5. Optimization problem

An optimization problem is used in this thesis to schedule and control the load demand at the end-users' level. Hence, it is necessary to show some basics of the optimization model, which are used in this thesis. Mathematical optimization is defined as the selection of the best solutions according to some criteria in a set of elements. Mathematical optimization is widely used because of its simplicity and accuracy in solving complicated problems and finding the best solutions. Generally, the optimization problem consists of a single or multi-objective function as in Eq. (A I-26), and some constraints as in Eq. (A I-27), in which the solution should obey the defined domain.

$$\min_{X} f(X) \tag{A I-26}$$

Subject to:

$$\begin{cases} A \cdot X \leq B \\ A_{eq} \cdot X = B_{eq} \\ C(X) \leq 0 \\ C_{eq}(X) = 0 \\ LU \leq X \leq UB \end{cases} \tag{A I-27}$$

Where $f(X)$ is the objective function that should be minimized. X is a vector or matrix of variables, in which we are looking for their best values to get the optimal solution. A_{eq} and A are the equality and inequality matrices. B_{eq} and B are the equality and inequality vectors. $C_{eq}(X)$ and $C(X)$ are the equality and inequality nonlinear functions. LU and UB refer to the lower and upper bound vectors or matrices, in which the solution should be limited. The used optimization problem in this thesis consists of minimizing the electricity cost at home taking into account some constraints. Therefore, it is necessary to show the algorithm, the objective functions and the constraints used in this thesis.

A.5.1. Optimization algorithm

For the sake of solving optimization problems, many algorithms can be used. However, in this thesis, the problem is formulated as mixed-integer nonlinear programming. MATLAB 2016b and 2018a are used to solve the optimization problem considering a nonlinear programming solver "fmincon" (Find the minimum of constrained nonlinear multivariable function). The used algorithms are "sqp" and "interior-point" (MATLAB, 2019). Some simulations were done using a genetic algorithm in MATLAB. In order to verify the accuracy of the results, we compared the simulation of the same model using genetic algorithm, fmincon with sqp as solver, and fmincon with interior-point as solver. Other optimization algorithms are used for verification purposes, and we find that fmincon with sqp algorithm gives accurate results with the less simulation time and iterations. Therefore, it is considered the best method in the case of this thesis.

A.5.2. Objective function

The main objective function in this thesis is to minimize the electricity cost at home. Eq. (A I-28) presents a general case in which the first part represents the cost function of the buying and selling energy, while the second part represents the tariffs regarding the excess of energy and power above certain limits. The presented tariffs show different types of demand response and incentive programs.

$$\min\left[\left(\sum_{t\in T}\left(\pi_t^{buy}P_t^{buy}-\pi_t^{Sell}P_t^{Sell}\right)\Delta t\right)+\left(\begin{array}{c}+E_T^{L}\pi_E^{L}+P_t^{L}\pi_P^{L}\\+E_T^{An}\pi_E^{An}+P_t^{An}\pi_P^{An}\\+E_T^{IP}\pi_E^{IP}+P_t^{IP}\pi_P^{IP}\\\cdots\end{array}\right)\right] \qquad \text{(A I-28)}$$

π_t^{buy} and π_t^{Sell} represent the time-based electricity tariff (e.g., ToU, RTP), [$/kWh]

P_t^{buy} and P_t^{Sell} denote the bought and sold power from/to the grid, [kW]

π_E^{L} and π_P^{L} are the limit-based electricity tariff of the energy [$/kWh] and power [$/kW] respectively

E_T^{L} and P_t^{L} are the energy and power limit that should be respected in order to avoid the additional tariff

π_E^{An} and π_P^{An} stand for the ancillary service-based electricity price for the energy [$/kWh] and power [$/kW] respectively

E_T^{An} and P_t^{An} are the energy and power needed to provide ancillary services

π_E^{IP} and π_P^{IP} show the incentive-based electricity tariff for the energy [$/kWh] and power [$/kW] respectively

E_T^{IP} and $P_{\forall t}^{IP}$ are the incentive-based energy and power limits

A.5.3. Constraints

After defining the objective function, it is necessary to define the most used constraints in this thesis. Table-A I-1 shows the most used optimized elements in this thesis and their constraints. Where, P_t^{buy} and P_t^{sell} represent the buying and selling power at instant "t". P_t^{Min} and P_t^{Max} represent the minimum and maximum power limits of the buying and selling power at instant "t". E^{Min} and E^{Max} stand for the minimum and maximum buying and selling energy during a period T. $P_t^{Sell,Min}$ and $P_t^{Sell,Max}$ are the minimum and maximum selling power at instant "t". $E^{Sell,Min}$ and $E^{Sell,Max}$ represent the minimum and maximum selling energy during a period T. $P_t^{V,Ch}$ and $P_t^{V,Dch}$ represent the charging and discharging power of the EV at instant "t". $P_{Max,t}^{V,Ch}$ and $P_{Max,t}^{V,Dch}$ are the maximum charging and discharging power at instant "t". SOC_{min}^{V} and SOC_{max}^{V} stand for the minimum and maximum State of Charge of the EV. $\eta^{V,Ch}$ and $\eta^{V,Dch}$ are the charging and discharging efficiency of the EV. B_{cap}^{V} is the battery capacity of the EV. SOC^{Min}, SOC^{Max} and SOC_i are the minimum, maximum and initial state of charge of the EV's battery. SOC_{tf}^{V} and SOC_d^{V} are the final and desired final state of charge of the EV's battery. P_t^{V2G} and P_t^{V2H} are the discharging power from the EV to the grid and to home respectively. The same constraints used for the EV are also used for the BSS. P_t^{PV2H} and P_t^{PV2G} represent the supplied power from the PV to home and to the grid respectively.

Table-A I-1 Most used optimized elements and their equations

Optimized element	Constraints	Equation
Total load at home	Power limits	$P_t^{Min} \leq P_t^{buy} - P_t^{sell} \leq P_t^{Max}$
	Energy limits	$E^{Min} \leq \sum_{t \in T} (P_t^{buy} - P_t^{sell}) \Delta t \leq E^{Max}$
	Selling power limit	$P_t^{Sell,Min} \leq P_t^{sell} \leq P_t^{Sell,Max}$
	Selling energy limit	$E^{Sell,Min} \leq \sum_{t \in T} (P_t^{sell}) \Delta t \leq E^{Sell,Max}$
EV	Charging power limit	$0 \leq P_t^{V,Ch} \leq P_{Max,t}^{V,Ch}$
	Discharging power limit	$0 \leq P_t^{V,Dch} \leq P_{Max,t}^{V,Dch}$
	State of Charge limit	$SOC_{min}^V \leq SOC_t^V \leq SOC_{max}^V$ $\Leftrightarrow$ $\sum_{t \in T} \left(\eta^{V,Ch} P_t^{V,Ch} - \frac{P_t^{V,Dch}}{\eta^{V,Dch}} \right) \begin{cases} \leq \frac{B_{cap}^V (SOC^{Max} - SOC_i)}{\Delta t} \\ \geq \frac{B_{cap}^V (SOC^{Min} - SOC_i)}{\Delta t} \end{cases}$
	Final State of Charge	$SOC_{tf}^V = SOC_d^V$ $\Leftrightarrow$ $\sum_{t \in T} \left(\eta^{V,Ch} P_t^{V,Ch} - \frac{P_t^{V,Dch}}{\eta^{V,Dch}} \right) = \frac{B_{cap}^V (SOC_d^V - SOC_i)}{\Delta t}$
	Discharging to home and grid	$P_t^{V,Dch} \cdot \eta^{V,Dch} = P_t^{V2G} + P_t^{V2H}$
BSS	Charging power limit	$0 \leq P_t^{B,Ch} \leq P_{Max,t}^{B,Ch}$
	Discharging power limit	$0 \leq P_t^{B,Dch} \leq P_{Max,t}^{B,Dch}$
	State of Charge limit	$SOC_{min}^B \leq SOC_t^B \leq SOC_{max}^B$ $\Leftrightarrow$ $\sum_{t \in T} \left(\eta^{B,Ch} P_t^{B,Ch} - \frac{P_t^{B,Dch}}{\eta^{B,Dch}} \right) \begin{cases} \leq \frac{B_{cap}^B (SOC^{Max} - SOC_i)}{\Delta t} \\ \geq \frac{B_{cap}^B (SOC^{Min} - SOC_i)}{\Delta t} \end{cases}$
	Final State of Charge	$SOC_{tf}^B = SOC_d^B$ $\Leftrightarrow$ $\sum_{t \in T} \left(\eta^{B,Ch} P_t^{B,Ch} - \frac{P_t^{B,Dch}}{\eta^{B,Dch}} \right) = \frac{B_{cap}^B (SOC_d^B - SOC_i)}{\Delta t}$
	Discharging to home and grid	$P_t^{B,Dch} \cdot \eta^{B,Dch} = P_t^{B2G} + P_t^{B2H}$
PV	Discharging to home and grid	$P_t^{PV} = P_t^{PV2H} + P_t^{PV2G}$

In Table-A I-2, we present the general mathematical expressions used for each type of load. Where, P_t is the power consumption at time "t". P_{Elem} denotes the nominal power consumption of the element, which is constant. Δt represents the time slot (e.g., 0.5 hours). E_{Elem} shows the total energy consumption of the element during the period T (e.g., one day). P_t^{min} and P_t^{max} are the minimum and maximum power consumption limits of the element at instant "t", respectively. E_{Elem}^{Min} and E_{Elem}^{Max} stand for the minimum and maximum energy consumption limits for the element during the period T, respectively. t_s and t_f are the starting and finishing time of the optimization process for the element, in which $0 \leq t_s \leq t_f \leq T$. χ_t is a binary decision variable in which it has two values, "0" for an OFF status and "1" is for an ON status of the element, in which it can be only turned on or off without the capability of changing its power consumption value.

Table-A I-2 Type of loads and their power and energy constraints

Power and energy constraints	Time constraints	Power		Time			Example
		FP	VP	SL	NL	LL	
$P_t = P_{Elem}$ $\sum P_t \cdot \Delta t = E_{Elem}$	$t \in [0 \rightarrow T]$	✓				✓	Fridge
$P_t^{min} \leq P_t \leq P_t^{max}$ $E_{Elem}^{Min} \leq \sum P_t \cdot \Delta t \leq E_{Elem}^{Max}$	$t \in [0 \rightarrow T]$		✓			✓	BSS
$P_t = \chi_t P_{Elem}\ ;\ \chi_t = \begin{cases} 1\ if t \in [t_s, t_f] \\ 0\ else \end{cases}$ $\sum P_t \cdot \Delta t = E_{Elem}$	$t \in [t_s \rightarrow t_f]$	✓			✓		Light in a room
$\chi_t P_t^{min} \leq P_t \leq \chi_t P_t^{max}\ ;\ \chi_t = \begin{cases} 1\ if t \in [t_s, t_f] \\ 0\ else \end{cases}$ $E_{Elem}^{Min} \leq \sum P_t \cdot \Delta t \leq E_{Elem}^{Max}$	$t \in [t_s \rightarrow t_f]$		✓		✓		Electric Water heater
$P_t = \chi_t P_{Elem}\ ;\ \chi_t = \begin{cases} 1\ if t \in [t_s, t_f] \\ 0\ else \end{cases}$ $\sum P_t \cdot \Delta t = E_{Elem}$	$t \in [t_s \rightarrow t_f]$	✓		✓			Washing machine
$P_t^{min} \leq P_t \leq P_t^{max}$ $E_{Elem}^{Min} \leq \sum P_t \cdot \Delta t \leq E_{Elem}^{Max}$	$t \in [t_s \rightarrow t_f]$		✓	✓			EV

* FP: Fixed power consumption; VP: Variable Power consumption: SL: Shiftable load; NL: Non-shiftable load; LL: Long-term load.

Remark:

In the thesis, we presented the binary decision variables as $x_t^a + x_t^b \leq 1$, which turn the optimization problem into mixed-integer programming. However, this complicates the programming using MATLAB for the presented optimization models in this thesis. To reduce the complexity, we turned the problem from a mixed-integer to a nonlinear programming in which the binary decision variables ($x_t^a + x_t^b \leq 1$) becomes as $x_t^a \cdot x_t^b = 0$. In this way, one of the variables should be equal to 1 value and the other should be equal to zero.

BIBLIOGRAPHY

Aarts, E., & Korst, J. (1989). *Simulated annealing and Boltzmann machines: a stochastic approach to combinatorial optimization and neural computing*. New York, NY, USA: John Wiley & Sons, Inc.

ABB. (2017). TXpert The world's first digital distribution transformer (Ed. 1). 901 Main Campus Drive Raleigh, NC 27606, USA: ABB Inc.

Ahmed, M. S., Mohamed, A., Shareef, H., Homod, R. Z., & Ali, J. A. (14-16 Nov. 2016). *Artificial neural network based controller for home energy management considering demand response events.* In 2016 International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES), (pp. 506-509). Putrajaya, Malaysia. IEEE.

Ahn, C., Li, C.-T., & Peng, H. (2011). Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid. *Journal of Power Sources, 196*(23), 10369-10379.

Al-Awami, A. T., & Sortomme, E. (2012). Coordinating Vehicle-to-Grid Services With Energy Trading. *IEEE Transactions on Smart Grid, 3*(1), 453-462.

Amjad, M., Ahmad, A., Rehmani, M. H., & Umer, T. (2018). A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques. *Transportation Research Part D: Transport and Environment, 62*, 386-417.

Anand, D. M., de Salis, R. T., Yijie, C., Moyne, J., & Tilbury, D. M. (2015). A Hierarchical Incentive Arbitration Scheme for Coordinated PEV Charging Stations. *IEEE Transactions on Smart Grid, 6*(4), 1775-1784.

Anand, D. M., Salis, R. T. d., Cheng, Y., Moyne, J., & Tilbury, D. M. (2015). A Hierarchical Incentive Arbitration Scheme for Coordinated PEV Charging Stations. *IEEE Transactions on Smart Grid, 6*(4), 1775-1784.

Aravinthan, V., & Jewell, W. (2015). Controlled Electric Vehicle Charging for Mitigating Impacts on Distribution Assets. *IEEE Transactions on Smart Grid, 6*(2), 999-1009.

Bruemmer, R. (July 14, 2018). The shift to electric cars: Are we there yet? *Montreal Gazette*. Retrieved on December 03, 2018 from https://montrealgazette.com/news/local-news/the-shift-to-electric-cars-are-we-there-yet

Bunsen, T., Cazzola, P., Gorner, M., Paoli, L., Scheffer, S., Schuitmaker, R., Teter, J. (2018). *Global EV Outlook 2018: Towards cross-modal electrification*. Paris, France. Organisation for Economic Co-operation and Development.

CAA-Quebec. (2018). Household water consumption - Maison École'Eau. Retrieved on December 03, 2018 from https://www.caaquebec.com/en/at-home/advice/tips-and-tricks/tip-and-trick/ show/su-jet/household-water-consumption-maison-ecoleau/

Chou, M. H., Su, C. L., Lee, Y. C., Chin, H. M., Parise, G., & P. (2017). Voltage-Drop Calculations and Power Cable Designs for Harbor Electrical Distribution Systems With High Voltage Shore Connection. *IEEE Transactions on Industry Applications, 53*(3), 1807-1814.

Ciornei, I., & Kyriakides, E. (2012). A GA-API Solution for the Economic Dispatch of Generation in Power System Operation. *IEEE Transactions on Power Systems, 27*(1), 233-242.

Clement-Nyns, K., Haesen, E., & Driesen, J. (2010). The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid. *IEEE Transactions on Power Systems, 25*(1), 371-380.

Council, N. R. (2012). *Climate Change: Evidence, Impacts, and Choices: Set of 2 Booklets, with DVD*. Washington, DC: National Academies Press.

Deng, R., Yang, Z., Chow, M., & Chen, J. (2015). A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches. *IEEE Transactions on Industrial Informatics, 11*(3), 570-582.

Dogger, J. D., Roossien, B., & Nieuwenhout, F. D. J. (2011). Characterization of Li-Ion Batteries for Intelligent Management of Distributed Grid-Connected Storage. *IEEE Transactions on Energy Conversion, 26*(1), 256-263.

El-Bayeh, C. Z., Mougharbel, I., Asber, D., Saad, M., Chandra, A., & Lefebvre, S. (2018). Novel Approach for Optimizing the Transformer's Critical Power Limit. *IEEE Access, 6*, 55870-55882.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Asber, D., Lenoir, L., & Lefebvre, S. (2018). Novel Soft-Constrained Distributed Strategy To Meet High Penetration Trend of PEVs at Homes. *Energy and Buildings*, 178(1), 331-346.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., Asber, D., & Lenoir, L. (2016a). A detailed review on the parameters to be considered for an accurate estimation on the Plug-in Electric Vehicle's final State of Charge. In *2016 3rd International Conference on Renewable Energies for Developing Countries (REDEC), Beirut, Lebanon,* July 13-15, 2016, (pp. 1-6). IEEE.

El-Bayeh, C. Z., Mougharbel, I., Saad, M., Chandra, A., Lefebvre, S., Asber, D., & Lenoir, L. (2016b). A novel approach for sizing electric vehicles Parking Lot located at any bus on a network. In *2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA,* July 17-21, 2016, (pp. 1-5). IEEE.

EPRI. (2016). OpenDSS EPRI Distribution System Simulator. Retreived on December 04, 2018 from https://sourceforge.net/projects/electricdss/

Erdinc, O., Paterakis, N. G., Mendes, T. D. P., Bakirtzis, A. G., & Catalão, J. P. S. (2015). Smart Household Operation Considering Bi-Directional EV and ESS Utilization by Real-Time Pricing-Based DR. *IEEE Transactions on Smart Grid, 6*(3), 1281-1291.

Melhem, F. Y., Zakaria Hammoudan, O. G., Moubayed, N. (2017). Thermal and Electrical Load Management in Smart Home Based on Demand Response and Renewable Energy Resources. In *The Third International Conference on Electrical and Electronic Engineering, Telecommunication Engineering and Mechatronics, Faculty of Engineering, Lebanese University, Campus of Hadath, April 28, 2017,* (pp.1-6). IEEE.

Falahi, M., Hung-Ming, C., Ehsani, M., Le, X., & Butler-Purry, K. L. (2013). Potential Power Quality Benefits of Electric Vehicles. *IEEE Transactions on Sustainable Energy, 4*(4), 1016-1023.

Field, C. B. (2014). *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. New York, NY 10013-2473, USA: Cambridge University Press.

Field, C. B., Barros, V. R., Dokken, D., Mach, K., Mastrandrea, M., Bilir, T., Genova, R. (2014). *IPCC, 2014: Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press,.

University of Central Florida, (2015). Project 5: Prediction of Electric Vehicle Penetration. Retrieved on January 13, 2016 from http://evtc.fsec.ucf.edu/research/project5.html.

Fotouhi Ghazvini, M. A., Soares, J., Abrishambaf, O., Castro, R., & Vale, Z. (2017). Demand response implementation in smart households. *Energy and Buildings, 143*, 129-148.

Georgilakis, P. S., & Amoiralis, E. I. (2010). Distribution transformer cost evaluation methodology incorporating environmental cost. *IET Generation, Transmission & Distribution, 4*(7), 861-872.

Quebec Government. (2019). Discover Electric Vehicles. Retreived on May 12, 2019 from http://vehiculeselectriques.gouv.qc.ca/english/.

Hawkins, E., Ortega, P., Suckling, E., Schurer, A., Hegerl, G., Jones, P., Oldenborgh, G. J. v. (2017). Estimating Changes in Global Temperature since the Preindustrial Period. *Bulletin of the American Meteorological Society, 98*(9), 1841-1856.

Helali, H., Bouallegue, A., & Khedher, A. (2016). A review of smart transformer architectures and topologies. In *2016 17th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA),* Sousse, Tunisia, December 19-21, 2016, (pp. 449-454). IEEE.

Høyland, K., & Wallace, S. W. (2001). Generating scenario trees for multistage decision problems. *Management Science, 47*(2), 295-307.

Hydro-Quebec. (2018). *2018 Electricity Rate, Effective April 1, 2018* (Report). Quebec, Canada: Hydro-Quebec.

IEA. (2016). *Global EV Outlook 2016* (Report). Paris, France: International Energy Agency.

IEEE. (2012). IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators. *IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995)*, 1-123.

IPCC. (2007). *Climate change 2007: The physical science basis* (Report nº 07). Geneva, Switzerland: The Intergovernmental Panel on Climate Change (IPCC).

IPCC. (2014). *Part, B: Climate Change 2014 Impacts, Adaptation, and Vulnerability*. Geneva, Switzerland: The Intergovernmental Panel on Climate Change.

IPPC, (2007). A report of Working Group I of the Intergovernmental Panel on Climate Change, Summary for Policymakers. Geneva, Switzerland: The Intergovernmental Panel on Climate Change.

Ito, A., Kawashima, A., Suzuki, T., Inagaki, S., Yamaguchi, T., & Zhou, Z. (2017). Model Predictive Charging Control of In-Vehicle Batteries for Home Energy Management Based on Vehicle State Prediction. *IEEE Transactions on Control Systems Technology, PP*(99), 1-14.

Ito, A., Kawashima, A., Suzuki, T., Inagaki, S., Yamaguchi, T., & Zhou, Z. (2018). Model Predictive Charging Control of In-Vehicle Batteries for Home Energy Management Based on Vehicle State Prediction. *IEEE Transactions on Control Systems Technology, 26*(1), 51-64.

Jinghong, Z., Xiaoyu, W., Kun, M., Chun, Z., & Shouzhen, Z. (2013). Aggregation Model-Based Optimization for Electric Vehicle Charging Strategy. *Smart Grid, IEEE Transactions on, 4*(2), 1058-1066.

JunHua, Z., Fushuan, W., Zhao Yang, D., Yusheng, X., & Kit Po, W. (2012). Optimal Dispatch of Electric Vehicles and Wind Power Using Enhanced Particle Swarm Optimization. *IEEE Transactions on Industrial Informatics, 8*(4), 889-899.

Khodayar, M. E., Lei, W., & Shahidehpour, M. (2012). Hourly Coordination of Electric Vehicle Operation and Volatile Wind Power Generation in SCUC. *IEEE Transactions on Smart Grid, 3*(3), 1271-1279.

Kong, P. Y., & Karagiannidis, G. K. (2016). Charging Schemes for Plug-In Hybrid Electric Vehicles in Smart Grid: A Survey. *IEEE Access, 4*, 6846-6875.

Leemput, N., Van Roy, J., Geth, F., Tant, P., Claessens, B., & Driesen, J. (2011). Comparative analysis of coordination strategies for electric vehicles. In *Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on, Manchester, UK, Dec. 5-7, 2011* (pp. 1-8). IEEE.

Leou, R. C., Su, C. L., & Lu, C. N. (2014). Stochastic Analyses of Electric Vehicle Charging Impacts on Distribution Network. *IEEE Transactions on Power Systems, 29*(3), 1055-1063.

Liban Cables. (2003). *Industrial and Distribution Low Tension Cables* (Catalog). Beirut: Liban Cables.

Lu, J., & Hossain, J. (2015). *Vehicle-to-grid: Linking Electric Vehicles to the Smart Grid*. London, United Kingdom: The Institution of Engineering and Technology IET.

Lunci, H., Jia, W., & Chi, Z. (2014). Adaptive Electric Vehicle Charging Coordination on Distribution Network. *IEEE Transactions on Smart Grid, 5*(6), 2666-2675.

Masoum, A. S., Deilami, S., Abu-Siada, A., & Masoum, M. A. S. (2015). Fuzzy Approach for Online Coordination of Plug-In Electric Vehicle Charging in Smart Grid. *IEEE Transactions on Sustainable Energy, 6*(3), 1112-1121.

Masoum, M. A. S., Deilami, S., & Islam, S. (2010). Mitigation of harmonics in smart grids with high penetration of plug-in electric vehicles. In *Power and Energy Society General Meeting, July 25-29, 2010, Providence, RI, USA,* (pp. 1-6). IEEE.

MathWorks. (2018). randi, Uniformly distributed pseudorandom integers. Retreived on December 03, 2018 from https://www.mathworks.com/help/matlab/ref/randi.html

MATLAB. (2019). fmincon, Find minimum of constrained nonlinear multivariable function. Retreived on May 15, 2019 from https://www.mathworks.com/ help/optim/ug/fmincon.html

Melhem, F. Y., Grunder, O., Hammoudan, Z., & Moubayed, N. (2017). Optimization and Energy Management in Smart Home Considering Photovoltaic, Wind, and Battery Storage System With Integration of Electric Vehicles. *Canadian Journal of Electrical and Computer Engineering, 40*(2), 128-138.

Melhem, F. Y., Grunder, O., Hammoudan, Z., & Moubayed, N. (2018). Energy Management in Electrical Smart Grid Environment Using Robust Optimization Algorithm. *IEEE Transactions on Industry Applications, 54*(3), 2714-2726.

Milanes-Montero, M. I., Martinez, M. A. G., E. Gonzalez, R., Romero-Cadaval, E., & Barrero-Gonzalez, F. (2016). Active and reactive power control strategies for electric vehicles in smart grids. In *2016 10th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG),* Bydgoszcz, Poland, August 18, 2016, (pp. 114-119). IEEE.

Moghbel, M., Masoum, M. A. S., & Fereidoni, A. (2014). Coordinated charging of plug-in electric vehicles in unbalanced three-phase residential networks with smart three-phase charger. In *2014 Australasian Universities Power Engineering Conference, AUPEC 2014 – Proceedings, Perth, WA, Australia, September 28-October 1, 2014*. IEEE.

Morstyn, T., Hredzak, B., & Agelidis, V. G. (2018). Control Strategies for Microgrids with Distributed Energy Storage Systems: An Overview. *IEEE Transactions on Smart Grid,* 9(4), pp. 3652-3666.

Muratori, M., & Rizzoni, G. (2016). Residential Demand Response: Dynamic Energy Management and Time-Varying Electricity Pricing. *IEEE Transactions on Power Systems, 31*(2), 1108-1117.

Neyestani, N., Damavandi, M. Y., Shafie-khah, M., Bakirtzis, A. G., & Catalão, J. P. S. (2017). Plug-In Electric Vehicles Parking Lot Equilibria With Energy and Reserve Markets. *IEEE Transactions on Power Systems, 32*(3), 2001-2016.

NissanNews. (2017). PRESS KIT: Nissan Intelligent Mobility at CES. Retreived on December 12, 2018 from http://nissannews.com/en-US/nissan/usa/channels/us-nissan-2017-ces/releases/press-kit-nissan-intelligent-mobility-at-ces?la=1

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., Dasgupta, P. (2014). *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland, IPCC.

Paraskova, T. (2017). U.S. Electric Grid Could Cost $5 Trillion To Replace. *Oil Price*. Mar 23, 2017. Retreived on December 12, 2018 from https://oilprice.com/Energy/Energy-General/US-Electric-Grid-Could-Cost-5-Trillion-To-Replace.html

Paterakis, N. G., Erdinç, O., Bakirtzis, A. G., & Catalão, J. P. S. (2015). Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies. *IEEE Transactions on Industrial Informatics, 11*(6), 1509-1519.

Pereira Junior, B. R., Cossi, A. M., Contreras, J., & Sanches Mantovani, J. R. (2014). Multiobjective multistage distribution system planning using tabu search. *Generation, Transmission & Distribution, IET, 8*(1), 35-45.

Peterson, S. B., Whitacre, J. F., & Apt, J. (2010). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Journal of Power Sources, 195*(8), 2377-2384.

Qian, K., Zhou, C., & Yuan, Y. (2015). Impacts of high penetration level of fully electric vehicles charging loads on the thermal ageing of power transformers. *International Journal of Electrical Power & Energy Systems, 65*, 102-112.

Gouvernement du Québec. (2018). Nombre de véhicules en circulation selon le type d'utilisation, le type de véhicule et l'âge du véhicule, Québec et régions administratives. Access date September 25, 2018.

Rajakaruna, S., Shahnia, F., & Ghosh, A. (2016). *Plug in electric vehicles in smart grids*. Van Godewijckstraat 30, 3311 GX Dordrecht, Netherlands: Springer.

Ramachandran, B., & Ramanathan, A. (2015). Decentralized demand side management and control of PEVs connected to a smart grid. In *Power Systems Conference (PSC), 2015 Clemson Univ*ersity, Clemson, SC, USA, March 10-13, 2015, (pp. 1-7). IEEE.

Ramchurn, S. D., Vytelingum, P., Rogers, A., & Jennings, N. (2011). Agent-based control for decentralised demand side management in the smart grid. In *The 10th International Conference on Autonomous Agents and Multiagent Systems, Volume 1, Taipei, Taiwan, May 02 - 06, 2011*, (pp. 5-12).

Rassaei, F., Soh, W. S., & Chua, K. C. (2015). Demand Response for Residential Electric Vehicles With Random Usage Patterns in Smart Grids. *IEEE Transactions on Sustainable Energy, 6*(4), 1367-1376.

Rating, E. (2018). Distribution Transfromers. Retreived on February 26, 2019 from http://www.energyrating.gov.au/products/distribution-transformers

Rhodes, J. D. (March 16, 2017). The old, dirty, creaky US electric grid would cost $5 trillion to replace. Where should infrastructure spending go? *The Conversation, Academic rigour, journalistic flair*. Retreived on December 03, 2018 from https://theconversation.com/the-old-dirty-creaky-us-electric-grid-would-cost-5-trillion-to-replace-where-should-infrastructure-spending-go-68290

Rodrigue, J.-P., Comtois, C., & Slack, B. (2016). *The geography of transport systems*. New York: Routledge.

Saber, A. Y., & Venayagamoorthy, G. K. (2010). Intelligent unit commitment with vehicle-to-grid-A cost-emission optimization. *Journal of Power Sources, 195*(3), 898-911.

Shao, C., Wang, X., Shahidehpour, M., Wang, X., & Wang, B. (2017). Partial Decomposition for Distributed Electric Vehicle Charging Control Considering Electric Power Grid Congestion. *IEEE Transactions on Smart Grid, 8*(1), 75-83.

Siemens. (2007). *SPEEDFAX 2007–2008 Product Catalog, power distribution & control*. Munich, Germany: Siemens.

Siemens. (2018a). *SensformerTM: Born connected, Introducing the digital transformers family*. 97058 Erlangen, Germany: Seimens.

Siemens. (2018b). T*ransformers meet connectivity: Siemens introduces Sensformer at Hannover Messe*. Werner-von-Siemens-Straße 1, 80333 Munich, Germany: Siemens.

Simon, D. (2008). Biogeography-Based Optimization. *IEEE Transactions on Evolutionary Computation, 12*(6), 702-713.

Singh, M., Kumar, P., & Kar, I. (2012). Implementation of Vehicle to Grid Infrastructure Using Fuzzy Logic Controller. *IEEE Transactions on Smart Grid, 3*(1), 565-577.

Sortomme, E., & El-Sharkawi, M. A. (2011). Optimal Charging Strategies for Unidirectional Vehicle-to-Grid. *IEEE Transactions on Smart Grid, 2*(1), 131-138.

Sortomme, E., Hindi, M. M., MacPherson, S. D. J., & Venkata, S. S. (2011). Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses. *IEEE Transactions on Smart Grid, 2*(1), 198-205.

Srivastava, A. K., Annabathina, B., & Kamalasadan, S. (2010). The Challenges and Policy Options for Integrating Plug-in Hybrid Electric Vehicle into the Electric Grid. *The Electricity Journal, 23*(3), 83-91.

IEEE Standard, (1991). IEEE Recommended Practice for Electric Power Systems in Commercial Buildings. *IEEE Std 241-1990*, 1-768.

Stats, W. (2018). Weather Stats: Data Download for Montreal (Database of the weather in Montreal). Retreived on December 03, 2018 from https://montreal.weatherstats.ca /download.html

Steen, D., Tuan, L. A., & Carlson, O. (2016). Effects of Network Tariffs on Residential Distribution Systems and Price-Responsive Customers Under Hourly Electricity Pricing. *IEEE Transactions on Smart Grid, 7*(2), 617-626.

Stocker, T. (2014). *Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change*. New York, NY 10013-2473, USA: Cambridge University Press.

Storn, R., & Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization, 11*(4), 341-359.

Tan, K. M., Ramachandaramurthy, V. K., & Yong, J. Y. (2016). Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renewable and Sustainable Energy Reviews, 53*, 720-732.

TimeAndDate. (2018). Past Weather in Montréal, Quebec, Canada. Access date April 19. Retreived on April 19, 2018 from https://www.timeanddate.com/weather /canada/montreal/historic.

Turker, H., Bacha, S., & Hably, A. (2014). Rule-Based Charging of Plug-in Electric Vehicles (PEVs): Impacts on the Aging Rate of Low-Voltage Transformers. *IEEE Transactions on Power Delivery, 29*(3), 1012-1019.

Uddin, M., Romlie, M. F., Abdullah, M. F., Abd Halim, S., Abu Bakar, A. H., & Chia Kwang, T. (2018). A review on peak load shaving strategies. *Renewable and Sustainable Energy Reviews, 82*, 3323-3332.

US Department of Energy. (2018). *The Smart Grid: An Introduction* (Report). United States Of America: U.S. Department of Energy.

Van-Linh, N., Tuan, T.-Q., Bacha, S., & Be, N. (2014). Charging strategies to minimize the peak load for an electric vehicle fleet. In *Industrial Electronics Society, IECON 2014 - 40th Annual Conference of the IEEE, Dallas, TX, USA, October 29 - November 01 2014,* (pp. 3522-3528).

Volut, S., & Schonek, J. (2016). *Electrical installation guide according to IEC International Standards*. Valence, France: Schneider Electric.

Wang, R., Xiao, G., & Wang, P. (2017). Hybrid Centralized-Decentralized (HCD) Charging Control of Electric Vehicles. *IEEE Transactions on Vehicular Technology, 66*(8), 6728-6741.

Weihao, H., Chi, S., Zhe, C., & Bak-Jensen, B. (2013). Optimal Operation of Plug-In Electric Vehicles in Power Systems With High Wind Power Penetrations. *Sustainable Energy, IEEE Transactions on, 4*(3), 577-585.

Williamson, S. S. (2013). *Energy management strategies for electric and plug-in hybrid electric vehicles*. New York: Springer.

Wu, X., Hu, X., Moura, S., Yin, X., & Pickert, V. (2016). Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array. *Journal of Power Sources, 333*, 203-212.

Wu, X., Hu, X., Teng, Y., Qian, S., & Cheng, R. (2017). Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle. *Journal of Power Sources, 363*, 277-283.

Wu, X., Hu, X., Yin, X., & Moura, S. (2018). Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage. *IEEE Transactions on Smart Grid, 9*(3), 2065 - 2075.

Xu, G. (May 2013). *Optimal scheduling for charging electric vehicles with fixed setup costs* Louisville, Kentucky, USA: University of Louisville.

Xu, Z., Su, W., Hu, Z., Song, Y., & Zhang, H. (2016). A Hierarchical Framework for Coordinated Charging of Plug-In Electric Vehicles in China. *IEEE Transactions on Smart Grid, 7*(1), 428-438.

Yang, B., Li, J., Han, Q., He, T., Chen, C., & Guan, X. (2016). Distributed Control for Charging Multiple Electric Vehicles with Overload Limitation. *IEEE Transactions on Parallel and Distributed Systems, 27*(12), 3441-3454.

Yang, X., Zhang, Y., Zhao, B., Huang, F., Chen, Y., & Ren, S. (2017). Optimal energy flow control strategy for a residential energy local network combined with demand-side management and real-time pricing. *Energy and Buildings, 150*, 177-188.

Yao, L., Lim, W. H., & Tsai, T. S. (2017). A Real-Time Charging Scheme for Demand Response in Electric Vehicle Parking Station. *IEEE Transactions on Smart Grid, 8*(1), 52-62.

Yifeng, H., Venkatesh, B., & Ling, G. (2012). Optimal Scheduling for Charging and Discharging of Electric Vehicles. *Smart Grid, IEEE Transactions on, 3*(3), 1095-1105.

Yilmaz, M., & Krein, P. T. (2013a). Review of Battery Charger Topologies, Charging Power Levels, and Infrastructure for Plug-In Electric and Hybrid Vehicles. *Power Electronics, IEEE Transactions on, 28*(5), 2151-2169.

Yilmaz, M., & Krein, P. T. (2013b). Review of the Impact of Vehicle-to-Grid Technologies on Distribution Systems and Utility Interfaces. *Power Electronics, IEEE Transactions on, 28*(12), 5673-5689.

Yong, J. Y., Ramachandaramurthy, V. K., Tan, K. M., & Mithulananthan, N. (2015). Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation. *International Journal of Electrical Power and Energy Systems, 64*, 300-310.

Yoon, J. H., Baldick, R., & Novoselac, A. (2016). Demand response control of residential HVAC loads based on dynamic electricity prices and economic analysis. *Science and Technology for the Built Environment, 22*(6), 705-719.

Yoon, S. G., Choi, Y. J., Park, J. K., & Bahk, S. (2016). Stackelberg-Game-Based Demand Response for At-Home Electric Vehicle Charging. *IEEE Transactions on Vehicular Technology, 65*(6), 4172-4184.

Yunjian, X., & Feng, P. (2012). Scheduling for charging plug-in hybrid electric vehicles. In *2012 IEEE 51st Annual Conference on Decision and Control (CDC). Maui, Hawaii, USA December 10-13, 2012,* (pp. 2495-2501). IEEE.

Zeng, N., & Yoon, J. (2009). Expansion of the world's deserts due to vegetation-albedo feedback under global warming. *Geophysical Research Letters, 36*(17), 1-5.

Zhang, L., & Li, Y. (2016). A Game-Theoretic Approach to Optimal Scheduling of Parking-Lot Electric Vehicle Charging. *IEEE Transactions on Vehicular Technology, 65*(6), 4068-4078.