Energy Management Strategies Based on Dynamic Programming for Applications with Energy Storage Capacity

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PAR

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He aprendido que el mundo quiere vivir en la cima de la montaña,
sin saber que la verdadera felicidad está en la forma de subir la escarpada.
— Gabriel García Márquez

Aita ta Amari…

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Eskerrik asko danori,
Muchas gracias a todos,
Many thanks to all,
Mille mercis à tous.
Endika

Summary

Nowadays, the energy storage systems are being incorporated in many applications. For example, they are enabling a better integration of renewables. Apart from the stationary applications, these devices are also presented in mobility applications. The electric vehicle is a good example of this kind of applications. Energy storage systems have some limitations, such as safety and lifetime, which are being addressed during the last years. Nevertheless, these are not the only challenges that need to be faced, as their optimal rating and exploitation are also critical.

In fact, when an energy storage system is introduced in any application, two main issues must be solved. On the one hand, the energy storage system must be rated in order to satisfy the application requirements, mainly the power and energy requirements. On the other hand, it must be optimally managed in order to make the most of the installed capacity. Moreover, these two aspects are strongly coupled. In this thesis, it is proposed to address this problem, opening this coupling and solving the management problem first (assuming a given energy rating).

Between the different possible energy management strategies, this work is focused on a rule based control strategy which is optimized by implementing a Dynamic Programming based optimization technique. For that purpose, an implementation methodology is proposed for a systematic development and implementation of these optimized control strategies, valid for deterministic and stochastic applications. The cost function proposed for the optimization technique is based on the stock management theory. In addition, a new representation of stochastic applications is also proposed, which relates the energy requirements of an application with their probabilities of occurrence.

The proposed methodology has been applied to a vertical transport application with energy storing capacity. The proposed control strategy has been tested first in simulation and then experimentally validated in a full-scale elevator with a supercapacitors based energy storage tank. In addition, a non-optimized rule based control strategy has also been analyzed, developed, implemented and compared to the optimized control strategy. These results have validated the proposed methodology and demonstrated that the optimization techniques based on Dynamic Programming are well-suited for energy management applications, and they achieve an optimal behavior of the system.

Key Words: Dynamic Programming, elevators, energy management, energy storage, modeling, optimization, stochastic systems, supercapacitors.

Résumé

De nos jours, les systèmes de stockage d'énergie sont introduits dans nombre d'applications. Par exemple, ces systèmes permettent une meilleure intégration des 'energies renouvelables. Au delà d'applications stationnaires, ces systèmes sont aussi présents dans les applications embarquées. Le véhicule électrique est un bon exemple de ce type d'applications. Les systèmes de stockage ont des limites, telles que la sécurité et la durée de vie, qui ont été prises en compte au cours des dernières années. Néanmoins, ce ne sont pas les seuls défis qui doivent être relevés. En effet, leur dimensionnement ainsi que leur exploitation optimale sont également des éléments essentiels.

De fait, lorsqu'un système de stockage d'énergie est introduit dans n'importe quelle application, deux problèmes principaux doivent être résolus. D'un côté, le système de stockage d'énergie doit être évalué pour satisfaire correctement les conditions d'application, spécialement la puissance et l'énergie. D'un autre côté, il doit être géré de façon optimale, afin d'exploiter au mieux la capacité installée. Ces deux aspects sont de plus fortement liés, puisqu'un nouveau degré de liberté est ajouté au système. Dans cette thèse, il est proposé de résoudre cette problématique, en associant le dimensionnement d'un accumulateur aux considérations liées à la gestion de l'énergie stockée (en supposant un taux d'énergie donnée).

Parmi les différentes stratégies possibles de gestion de l'énergie, ce travail est basé sur une stratégie de contrôle établie sur des règles, et mise en œuvre par une technique de Programmation Dynamique optimale. Dans ce but, une méthodologie d'implémentation est proposée pour un développement systématique de ces stratégies de contrôle, tant pour des systèmes déterministes que stochastiques. La fonction de coût proposée par la technique d'optimisation repose sur la théorie de gestion du stock. Par ailleurs, une nouvelle représentation des applications stochastiques est présentée, qui met en évidence les besoins énergétiques de l'application et leurs probabilités d'événement.

La méthodologie proposée a été mise en œuvre sur une application de transport verticale avec une capacité de stockage d'énergie. Cette stratégie de contrôle a été premièrement vérifiée en simulation, puis validée expérimentalement dans un ascenseur à échelle réelle. Ce dernier comprend un accumulateur de type supercondensateurs. Par ailleurs, un contrôle basé sur une stratégie non-optimisé a aussi été analysé, développé, exécuté et comparé par rapport à la stratégie de contrôle optimisée. Ces résultats ont validé la méthodologie proposée et ont confirmé que les techniques d'optimisation basées sur la Programmation Dynamique conviennent pour les applications de gestion de l'énergie, permettant un comportement optimal du système.

Mots Clés: Programmation Dynamique, élévateurs, gestion de l'énergie, stockage d'énergie, modélisation, optimisation, systèmes stochastiques, supercondensateurs.

Contents

Notations

Abbreviations

AC	Alternating Current
ANN	Artificial Neural Network
CAES	Compressed Air Energy Storage
COF	CuttOff Frequencies
DC	Direct Current
DDP	Deterministic Dynamic Programming
DOD	Depth Of Discharge
DP	Dynamic Programming
EDLC	Electric Double-Layer Capacitor
EMR	Energetic Macroscopic Representation
EMS	Energy Management Strategy
ESS	Energy Storage System
EV	Electric Vehicle
FL	Fuzzy Logic
GA	Genetic Algorithm
GESD	Generalized Energetic and Statistical Description
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
LP	Linear Programming

MCS	Maximum Control Structure
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
MPEMS	Modular Power and Energy Management Structure
NLP	NonLinear Programming
PE	Power Electronics
PHEV	Plug-in Hybrid Electric Vehicle
PI	Proportional Integral
PMSM	Permanent Magnet Synchronous Machine
PV	Photo Voltaic
QP	Quadratic Programming
RBS	Rule Based Strategy
RES	Renewable Energy System
Scaps	Supercapacitors
SDP	Stochastic Dynamic Programming
SMES	Superconducting Magnetic Energy Storage
SOC	State Of Charge

Symbols

τ	Traction torque	$[Nm]$
a	Acceleration	$[m/s^2]$
c	Weighting factor of the variable cost term	
C_s^r	(r-s) combinations	
C_{bus}	Dc-link capacitance	$[F]$
C_{sc}	Supercapacitors tank capacitance	$[F]$
DOD_{scaps}	Supercapacitors depth of discharge	$[J]$
E	Energy	$[J]$

$E_{crowbar}$	Braking resistor energy	$[J]$
$E_{elevator}$	Elevator mission energy	$[J]$
E_{grid}	Grid energy	$[J]$
E_{max}	Maximum energy	$[J]$
E_{scaps}	Supercapacitors energy	$[J]$
ECS	Parameters of an elevator mission	
F_i	Power enumeration	$[N]$
f_k	State variable function	
F_t	Traction force	$[N]$
g	Gravitational acceleration	$[m/s^2]$
g_k	Cost function	
h	Weighting factor of the storage cost term	
h_f	Height between floors	$[m]$
I	Current	$[A]$
i_{br_ref}	Braking resistor converter current reference	$[A]$
i_{br}	Braking resistor converter current	$[A]$
$i_{couple\_simp\_ref}$	Simple coupling current reference	$[A]$
i_{couple_simp}	Simple coupling current	$[A]$
$i_{couple\_total\_ref}$	Total coupling current reference	$[A]$
i_{couple_total}	Total coupling current	$[A]$
i_{dcdc_ref}	Dc-dc converter current reference	$[A]$
i_{dcdc}	Dc-dc converter current	$[A]$
$i_{elevator}$	Electromechanical conversion system current	$[A]$
i_{rect}	Rectifier current	$[A]$
I_{scaps_max}	Supercapacitors maximum current	$[A]$
i_{sc}	Supercapacitors current	$[A]$
i_{sr}	Braking resistor current	$[A]$

J_k	Dynamic Programming algorithm equation	
k	Dynamic Programming event	
k_d	Distribution factor	
k_{grid}	Proportional gain of dc-link controller	
L_{dcdc}	Dc-dc converter inductance	$[H]$
m	Length of the perturbation variable	
m_{c1}	Cable left side mass	$[kg]$
m_{c2}	Cable right side mass	$[kg]$
m_c	Counterweight mass	$[kg]$
m_e	Cabin mass	$[kg]$
M_f	Cable complete mass	$[kg/m]$
m_i	Mass enumeration	$[kg]$
m_{pass}	Passenger mass	$[kg]$
m_p	Total of passengers mass	$[kg]$
N	Dynamic Programming problem dimension	
N_p	Number of passengers	
N_{scaps}	Supercapacitors life cycles	
n_{uk}	Decision variable dimension	
P	Power	$[W]$
p	Weighting factor of the shortage cost term	
$P_{crowbar}$	Braking resistor power	$[W]$
P_e	Motor drive electric power	$[W]$
P_{grid_dp}	Grid power limit for the DP strategy	$[W]$
P_{grid_rbs}	Grid power limit for the RBS strategy	$[W]$
P_{grid}	Grid power	$[W]$
P_{max}	Maximum power	$[W]$
P_{min}	Minimum power	$[W]$

P_{scaps}	Supercapacitors power	$[W]$
P_{wk}	Statistical data of the perturbation variable	
r	Set of optimization objectives	
$R_{crowbar}$	Braking resistor resistance	$[\Omega]$
s	Subset of optimization objectives	
S_{br}	Braking resistor converter modulation factor	
S_{dcdc}	Dc-dc converter modulation factor	
t	Time	$[s]$
t_{dp}	DP strategy period of time	$[s]$
U_k	Decision variable domain	
u_k	Decision variable	
V	Voltage	$[V]$
v	Velocity	$[m/s]$
v_{bus_ref}	Dc-link voltage reference	$[V]$
v_{bus}	Dc-link voltage	$[V]$
V_{rbs_0}	RBS zero energy voltage threshold	$[V]$
V_{rbs_max}	RBS maximum energy voltage threshold	$[V]$
V_{rbs_min}	RBS minimum energy voltage threshold	$[V]$
V_{rbs_nom}	RBS nominal energy voltage threshold	$[V]$
v_{sc_max}	Supercapacitors maximum voltage	$[V]$
v_{sc}	Supercapacitors voltage	$[V]$
v_{sl_ref}	Dc-dc converter inductance voltage reference	$[V]$
v_{sl}	Dc-dc converter inductance voltage	$[V]$
v_{sr}	Braking resistor voltage	$[V]$
W	Potential energy	$[J]$
w_k	Perturbation variable	
x	Position	$[m]$

x_k	State variable	
X_{max_travel}	Cabin maximum travel length	$[m]$
X_{max}	The maximum capacity of an energy storage system	$[J]$
cpm	cycles-per-mission ratio	

1

Introduction

Summary

Nowadays, energy storage systems are used in many applications such as the integration of renewable energy systems and mobility. However, there are many challenges associated to their use that must be solved yet. Two of these aspects are on the one hand their optimal rating and on the other hand their optimal management. Indeed both aspects are strongly coupled. This chapter introduces the main energy storage technologies, the dilemma between rating and management and some management strategies.

1.1 Energy Storage Systems

In this section the benefits of storing energy are firstly stated. After that, the main energy storage technologies are presented and compared. Then, several applications that include energy storage systems are analyzed. And finally, the rating principle of an energy storage system is described.

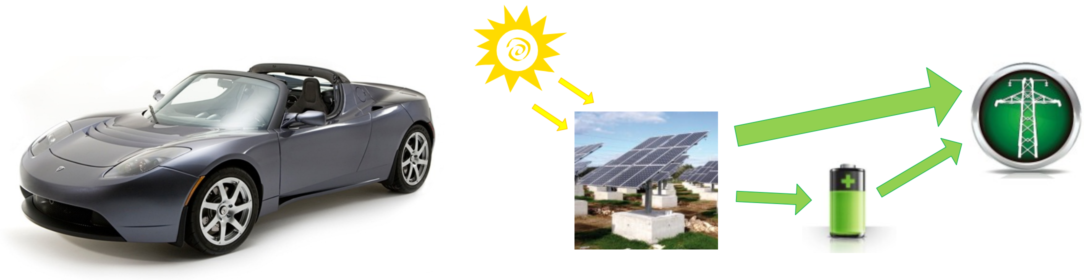
1.1.1 The Benefits of Energy Storing

The introduction of an Energy Storage System (ESS) into an electric application transforms the concept of the application itself. There are two main reasons for introducing an ESS in an application. On the one hand, allowing the operation in isolated, using the ESS as the primary power supply and suppressing the dependence on other energy supplies. On the other hand, it can provide new functionalities and operation modes to the application and even an efficiency improvement. Figure 1.1 presents two examples of applications that incorporate ESS.

The first group is formed by applications where the ESS are used as the primary power supply such as consumer electronic devices [1], Electric Vehicles (EV) [2] and some special tramways [3]. In this type of application the main objective is to replace the main power supply (grid, internal combustion engines or Renewable Energy System).

The applications of the second group combine ESS with other power generation units in order to increase the functionalities of the conformed combination. The benefits obtained depend on the application (RES integration, domestic and transport applications, etc). For example, the grid integration of renewable power plants (like wind and solar farms) can considerably be improved thanks to ESS [5–7]. An appropriately controlled ESS could filter the power variations due to weather fluctuations (wind, solar radiation, temperature) of renewable power plants and hence allow a more constant power production [8, 9].

Concerning home applications, the ESS in combination with Renewable Energy Systems can reinforce a self consumption pattern and even a zero-energy building behavior [10]. Other additional functionalities that could be achieved are the peak-shaving [11]



(a) (b)

Figure 1.1: Examples of applications with energy storage systems: (a) electric vehicle (Tesla Roadster [4]) and (b) renewables application with energy storing capacity.

and the load leveling by means of power smoothing to reduce the power level contracted from the utility [12].

In transport applications, ESS have given way to the Hybrid Electric Vehicle (HEV) and to the Plug-in Hybrid Electric Vehicle (PHEV). In both cases the ESS allow to minimize and even completely remove fuel consumption and hence maximize the efficiency [13]. In vertical transport applications, with the introduction of ESS the power smoothing can be achieved and an automatic rescue mode can be implemented for outage cases [14].

As it has been stated in this section, the application areas and benefits of introducing energy storage systems are divers, interesting and plausible. For that reason, in the following section a state of the art and comparison of the most representative and widely established energy storage technologies is presented.

1.1.2 Energy Storing Technologies

Once the interest of storing energy has been pointed out, in the following the main energy storage technologies are presented. Basically, these systems can be classified into three main categories: mechanical, electrical and electrochemical systems.

Concerning the first ones, the mechanical systems, the principle consists in storing energy as a potential or a kinetic energy, as shown in figure 1.2. The potential energy can be stored in two different ways. Pumped hydro systems are composed by two water reservoirs located at different vertical levels which are connected by a duct, and where, a turbine or group of turbines is installed inside it. The upper reservoir works as the energy store as the amount of stored energy is directly related to the mass of water at the top and height between the two reservoirs. The system is discharged when the water flows from the upper reservoir to the lower reservoir, generating power in the turbines.

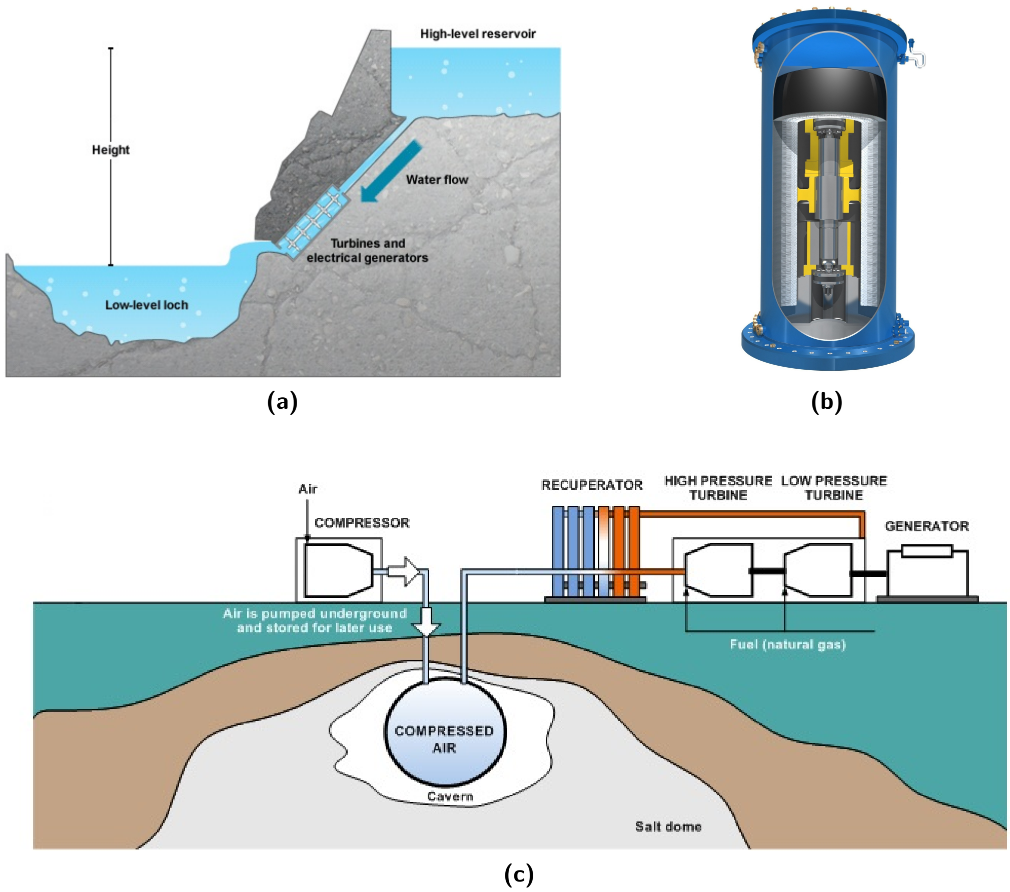
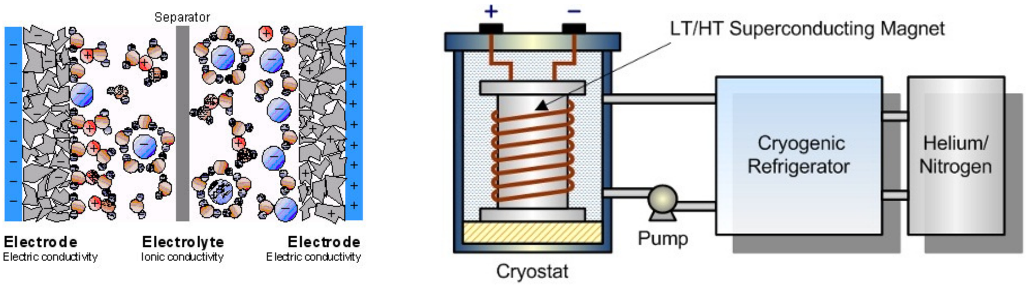


Figure 1.2: Mechanical energy storage systems: (a) pumped hydro, illustration extracted from [15], (b) flywheel (Beacon Power [16]) and (c) compressed air energy storage, illustration extracted from [17].

In contrast, the system is charged when the turbines pump water from the lower level to the upper level, consuming power in the turbines.

The Compressed Air Energy Storage (CAES) technology also stores energy as potential energy. In this case, the energy is stored as a pressure difference. The principle consists in compressing air in a tank using a pneumatic motor and hence consuming power. After that, the air inside the tank is released through the pneumatic motor and power is generated. This is a pure CAES application, but these systems are usually combined with a gas turbine which uses this compressed air in combination with the gas as fuel to burn it in the turbine and generate power. That means that the pneumatic motor is only used to compress the air.

Flywheels store energy as kinetic energy. The principle consists in rotating a disk making it possible to store the energy while the disk is rotating. The amount of stored energy is directly related to the moment of inertia of the disk (mass and disk morphology)



(a) (b)

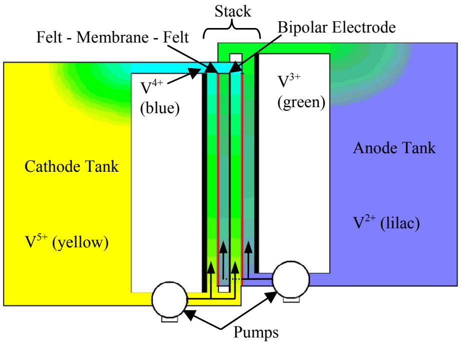
Figure 1.3: Electrical energy storage systems: (a) supercapacitor, illustration extracted from [18] and (b) superconducting magnetic energy storage, illustration extracted from [19].

and proportionally related to the square of the rotational velocity. The motor connected to the disk consumes electric power to increase the speed. In the discharging process, the speed is decreased as the motor is generating power.

Electrical energy storage systems are capable of storing the energy as a potential field or as a magnetic field, see figure 1.3. The Supercapacitors (Scaps), also called Electric Double-Layer Capacitors (EDLC) or Ultracapacitors, store the electrostatic charge as a potential field. They are composed of two electrodes into an electrolyte with a separator between them. Although an electrolyte is required, Scaps are not electrochemical devices due to absence of electrochemical reactions. The amount of stored energy is directly related to the electrodes surface and inversely related to the distance between electrodes, similar to capacitors.

The Superconducting Magnetic Energy Storage (SMES) systems store energy as a magnetic field. They are composed of a coil which is cooled to low temperatures (cryogenic levels) in order to become a superconducting material. The resistance is almost zero, and by injecting direct current through the coil, a magnetic field is created and energy is stored. The amount of stored energy is directly related to the coil inductance and is proportional to the square of the direct current. The key point of this ESS is the operating temperature.

Concerning electrochemical energy storage systems, batteries are the most representative devices, as it can be seen in figure 1.4. Their operation principle consists in storing energy in a chemical mode. They are composed of two electrodes (cathode and anode) immersed in an electrolyte where the chemical reactions create a potential voltage between electrodes, necessary to make it possible the circulation of electric current. When each electrode is immersed in different electrolytes, these electrolytes are separated by a membrane. When the current flows from the anode to the cathode, the battery is being charged. The battery is being discharged when the current sense is changed, flowing



(a)

(b)

Figure 1.4: Electrochemical energy storage systems: (a) vanadium redox battery, illustration extracted from [20] and (b) lithium-ion battery (Saft Batteries [21]).

from the cathode to the anode. It must be noted that there are many different technologies of batteries: lead-acid, nickel-metal hybrid, lithium-ion, vanadium redox flow, etc.

1.1.3 Technology Comparison

Once the main energy storage technologies have been presented, a comparative analysis between them is carried out. In this analysis, the first step consists in well defining the parameters in which the comparison will be based on. An energy storage system is mainly defined by two parameters in order to answer two main questions: “How Much” and “How”. There are obviously more characteristics to compare the different technologies (lifecycles or lifetime, capital cost, volume, weight, temperature, safety, efficiency, etc.), but in the scope of this PhD the comparison will be focused on these two parameters in order to get a global overview of the differences between technologies.

The first question, “How Much”, is referred to the amount of energy that can be stored. It represents the capacity of the energy storage system which is commonly measured in Watt-hours, or in Joules. The second question, “How”, is referred to the charged/discharged ratio of the ESS. In other words it represents the maximum power level of the ESS. It is measured in Watts $[W]$ and it can be positive or negative. The sign criterion is commonly adopted to represent the charging process of the ESS by positive values, and the discharging process of the ESS by negative values.

As it can be observed, these two parameters are linked by the time factor. The power is instantaneous while the energy is the evolution of this power. Figure 1.5 shows the relationship between the power and the discharge time at rated power of different energy storage technologies.

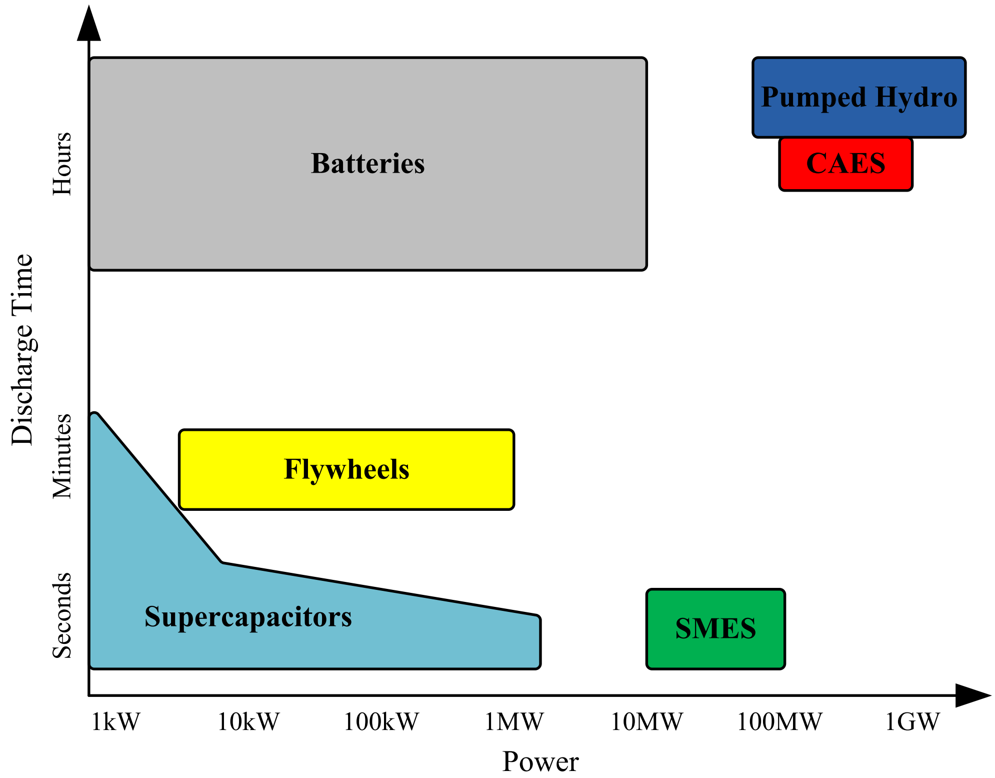
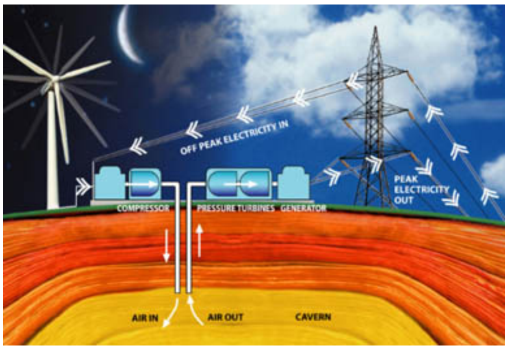


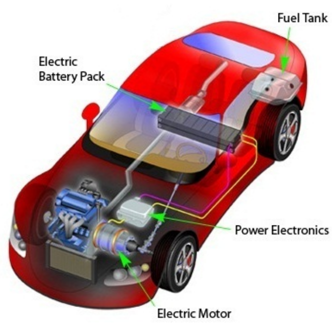
Figure 1.5: Energy storage systems power rating vs. discharge time at rated power, illustration extracted from [22].

Pumped hydro and CAES are technologies are able to store very large amounts of energy. Their rated power is also high because their installations are composed of turbines and gas turbines. In consequence, these technologies are well adapted for applications characterized by a long discharge time and high power. The batteries are able to store large amounts of energy, specially the flow batteries and vanadium redox flow batteries, but their rated power is lower than the one of pumped hydro and CAES technologies. Other technologies of batteries like lithium, have a larger capacity than flow batteries but with a lower rated power. To sum up, it can be concluded that these three technologies (pumped hydro, CAES and batteries) are well-suited for long-term energy applications.

The other three technologies (supercapacitors, flywheels and SMES) are capable of storing less energy. From the point of view of the rated power, Scaps have a wide range of operation from low power applications to medium power applications. Flywheels can store more energy but their power operation range is smaller. Therefore they are adapted for medium power applications. Finally, SMES are able to inject or absorb high power, but as it is shown in the figure, their energy capacity is limited. In brief, it can be concluded that these technologies are designed for short-term energy applications.



(a)



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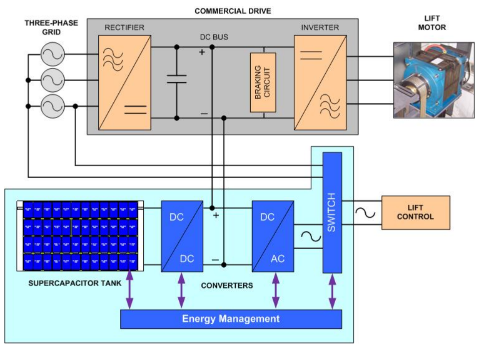

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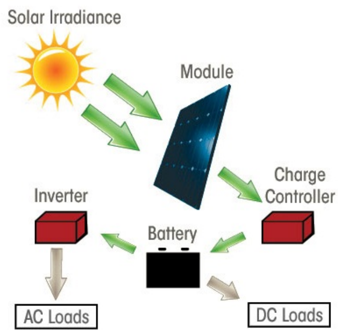


(d)

Figure 1.6: Applications with energy storing capacity: (a) wind power and ESS based on CAES, illustration extracted from [23], (b) HEV and battery based ESS, illustration extracted from [24], (c) elevator and Supercapacitors based ESS, illustration extracted from [25] and (d) solar PV and battery based ESS, illustration extracted from [26].

1.1.4 Representation of Energy Storing Capacity Applications

Once the benefits of storing energy stated and the main technologies of ESS presented, in this section four common applications (depicted in figure 1.6) are analyzed. The objective is to show that all the applications can be represented by the same general block diagram.

In the first application a wind farm is combined with a CAES based ESS. The wind turbines generate power that can be injected to the grid, or stored in the CAES in order to use this energy in the on-peak hours. The CAES can also be charged through the grid, during the off-peak hours.

The second application is a hybrid electric vehicle with a battery system. The electric motor of the vehicle is powered by an Internal Combustion Engine (ICE) and an energy storage system based on batteries. The batteries are charged by the ICE, as well as by the electric motor during the braking process, improving the efficiency of the whole system.

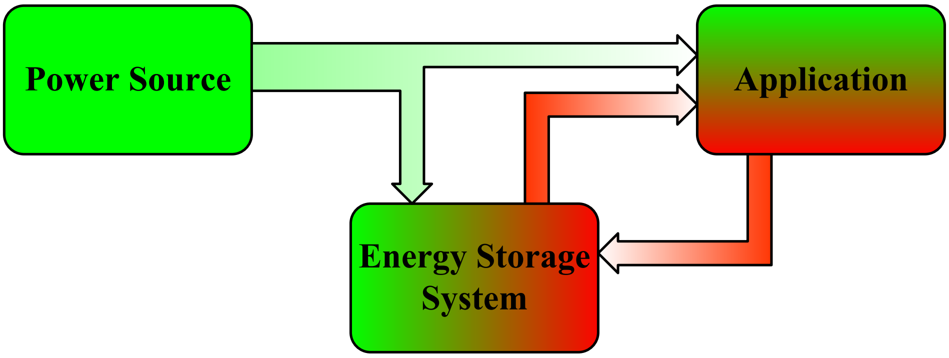


Figure 1.7: General block diagram representation of applications with energy storing capacity.

The third application is a vertical transport application, composed of an elevator and a supercapacitor based ESS. The elevator is powered during the traction process by the grid and the energy storage system. On the contrary, in the braking process, the regenerative power is stored in the Scaps that can be also charged from the grid in order to add new functionalities to the system (i.e. automatic rescue mode).

The last example is another RES system composed of a solar Photo Voltaic (PV) plant accompanied by an ESS based on batteries. The batteries are charged by the PV panels and they are discharged through the loads (considering a stand-alone application).

These four different examples or systems can be represented by the same generic scheme: a power supply accompanied by an ESS and the application. It should be pointed out in this PhD the application is referred to a part of the whole system, encompassing the part of the system that must be powered or whose power must be absorbed, such as, for example active or passive loads. Indeed, the system consists of a primary power supply responsible for satisfying the power and energy requirements of the application in combination with an energy storage system. This ESS can be charged through the primary power supply, or by the application (in cases where the application is capable of generating power). For this reason, a general block diagram, shown in figure 1.7, is proposed in order to represent all these systems with energy storage capacity. The three blocks represent the main elements of the system: Power Source, Energy Storage System and the Application.

In order to clarify and validate the proposed representation, the main elements of the four examples have been identified and shown in Table 1.1. It can be concluded that the proposed general block diagram is valid to represent all these energy systems independently of the application and ESS technology.

System	Power Source	Energy Storage System	Application
Wind power	Aerogenerator	CAES	Grid
HEV	ICE	Battery	Motor
Vertical transport	Grid	Supercapacitors	Elevator
Solar PV power	PV panel	Battery	AC & DC Loads

Table 1.1: System elements identification in the general block diagram.

1.1.5 Rating of Energy Storage Systems

In previous sections the interest of storing energy has been stated, the main technologies of ESS have been presented and the applications where ESSs are introduced have been analyzed. Finally, in this section, and based on the general block diagram shown in figure 1.7, the basic steps of energy storage systems rating are presented.

The rating process of an ESS considered in the scope of this PhD is based on a methodology applied to supercapacitors [27] which can be extended also for other technologies. The methodology consists of three steps, as it can be seen in figure 1.8. In the following, these steps will be presented.

System Requirements Definition

In this step the requirements and constraints of the system are defined. The requirements are referred to the application power and energy needs. The power requirements are defined by the maximum power level injected by the power source and by the maximum power level injected or absorbed by the application. In consequence, the energy requirements are related to the evolution of these two power profiles over time. Once these values are defined, and according to the figure 1.5 and as a first approximation, the adequate energy storage systems technologies can be identified.

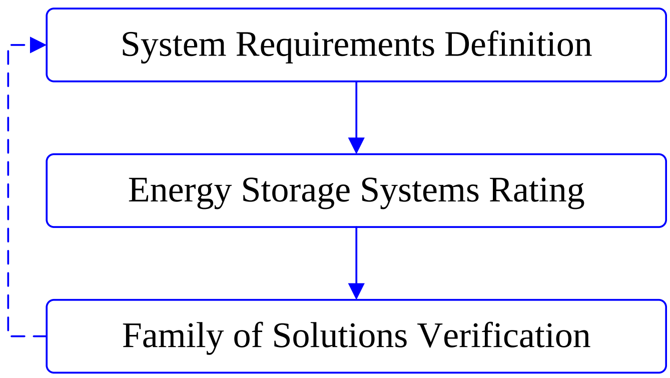


Figure 1.8: Methodology for an energy storage system rating.

Type	Parameter
Requirement	Power and energy.
Constraint	Voltage, volume, mass, capital costs, lifecycles, operating temperature, efficiency...

Table 1.2: Summary of requirements and constraints of an energy storage system rating.

After that, the constraints are analyzed and applied to limit the variables of the rating process. These constraints are related to the characteristics of the application, such as electrical parameters (voltage), mechanical parameters (volume and mass), capital costs, etc. Table 1.2 summarizes the objective of this step.

Energy Storage Systems Rating

According to the defined requirements and constraints, the second step consists in the rating process in order to obtain a solution or a family of potential solutions. It is divided into two parts: characterization and rating. The characterization of ESS devices consists in obtaining the main parameters of commercial energy storage devices. The subsequent rating process consists in defining a commercial device or a combination of devices, connected in different configurations (in series/parallel), which accomplishes previously defined requirements and constraints [28]. The resultant equivalent energy storage systems are the potential solutions of the rating problem. Table 1.3 summarizes the objective of this step.

Family of Solutions Verification

In the third and last step of this methodology, the solution or family of solutions are verified (see figure 1.9). The objective is to define the ESS that will be installed in the application. For that, a comparison of all the equivalent energy storage systems that fulfill the requirements and constraints is carried out. At this point, two ways, the last step or the dashed arrow to the first step, are identified as it has been presented in figure 1.8. On the one hand, the definitive energy storage system can be obtained. In that case, the rating process is finished in the last step. On the other hand, new constraints can be redefined in order to reevaluate the rating process and get a new family of solutions that improve the results of the previous ones, going back to the first step and becoming an iterative rating process.

Task	Description
Characterization	To extract the main parameters of commercial ESS devices.
Rating	To obtain a family of equivalent energy storage systems.

Table 1.3: Summary of tasks required in order to carry out the rating process.

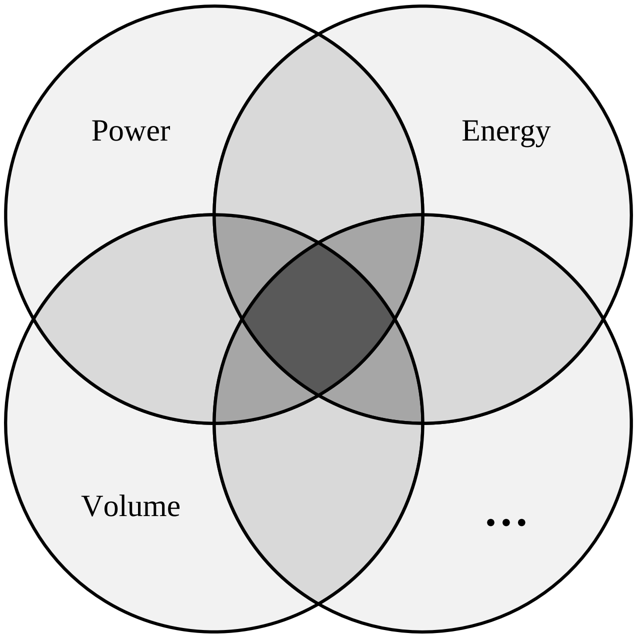


Figure 1.9: Family of potential solutions for an energy storage system rating.

1.2 The Dilemma of an Energy Storage System: Rating vs. Management

In this section the dilemma of energy storage systems is presented and analyzed. When an ESS is introduced into an application, two important questions arise. One it is related to the rating of the storage system which has been addressed in the previous section. And the other one it is related to the management of the storage system since a new degree of freedom is introduced in the control of the system in order to satisfy the application requirements. As it will be proved both aspects (rating and management) are strongly coupled, and how, these aspects cannot be simultaneously addressed. In this section this coupling is analyzed and a solution is proposed to address it.

1.2.1 The Representation of the Problem

In the rating process of an ESS, the system requirements and constraints are firstly defined. Regarding to the requirements, they are composed of power and energy values. As it has been explained in the previous section, power requirements are defined by the maximum power level injected by the power source and by the maximum power level injected or absorbed by the application. The energy requirements are obtained from the power evolution over time.

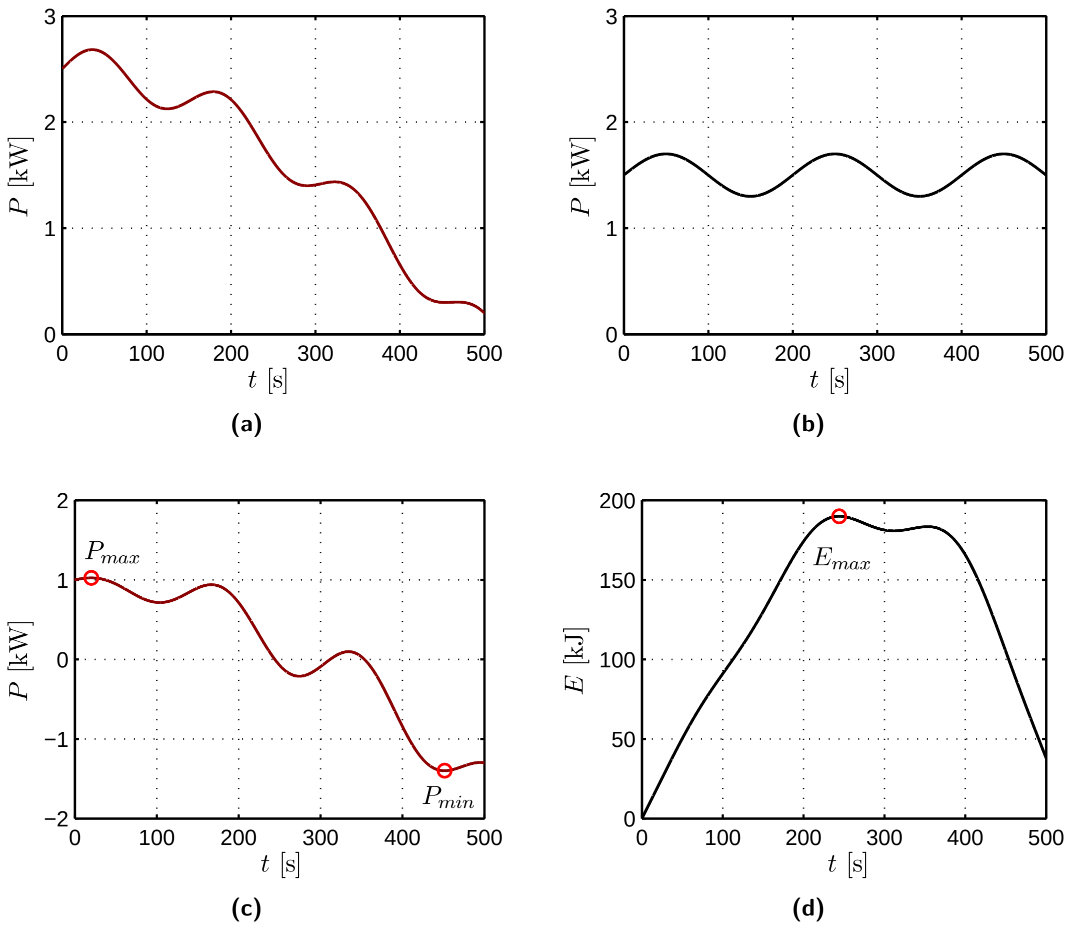


Figure 1.10: Analysis for an ESS rating where the power source and application power profiles are well-known: (a) power source power profile, (b) application power profile, (c) ESS power profile and (d) ESS energy profile.

Figure 1.10 shows an example of the power and energy requirements of a system where the power source and application power profiles are well-known and the power source cannot be controlled. In this case the ESS operates as a buffer, storing energy when the power generation is higher than the consumption (positive values) and injecting power when the generation is lower than the consumption (negative values). From the ESS power profile, the maximum and minimum power values are obtained (P_{max}, P_{min}) and from the ESS energy profile (the integral of power over time), the maximum energy capacity is identified (E_{max}).

Once an ESS is rated and included in a system, it must always be managed as the amount of energy to be charged/discharged, or alternatively the state of charge of the system must be defined. In this example the ESS is managed in order to achieve the load balancing by means of compensating the difference between the generation and

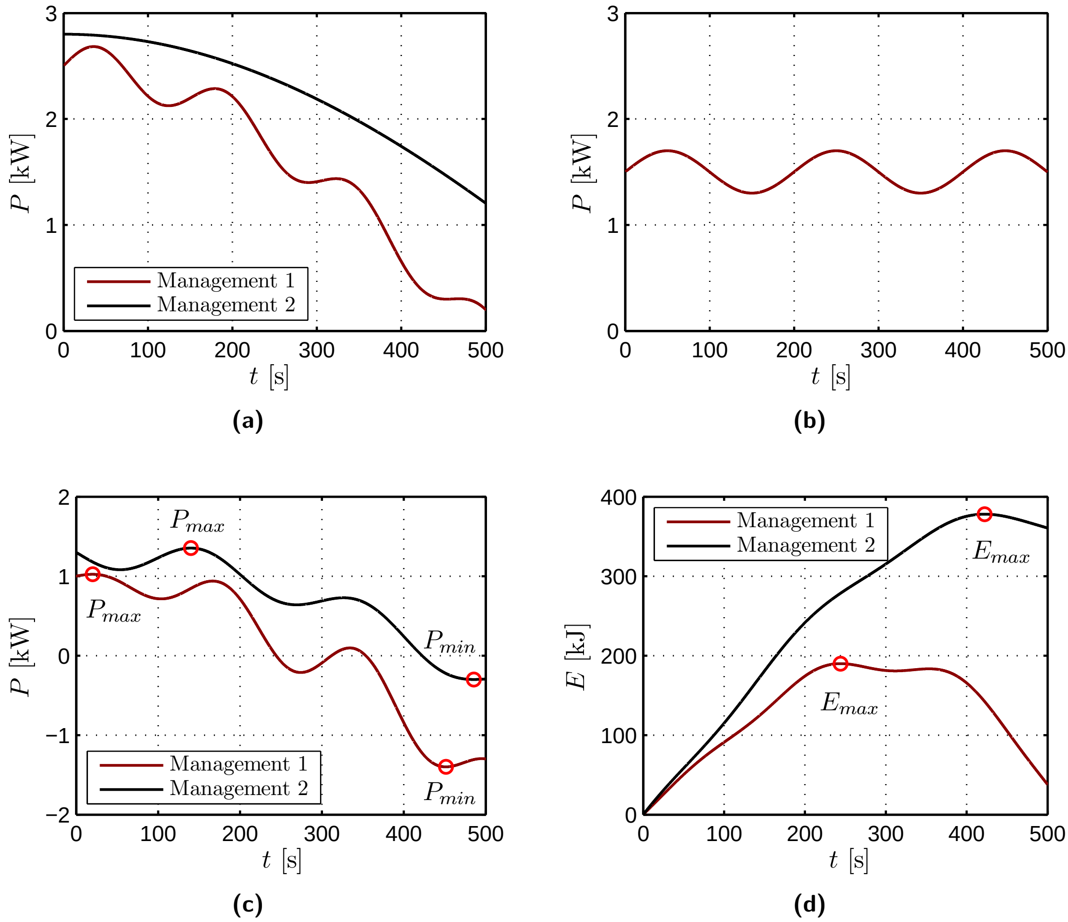


Figure 1.11: Analysis for an ESS rating where the application power profile is well-known and the power source and ESS are controlled: (a) power source power profiles, (b) application power profile, (c) ESS power profiles and (d) ESS energy profiles.

consumption. The problem of rating arises when the power source is also manageable. In this case, the rating of the ESS is more complex since the application requirements must be satisfied by the combination of the power source and the energy storage system. In fact, ESS requirements (power and energy) are influenced by the management strategy of the power source and on ESS adopted.

Figure 1.11 shows two energy storage system requirements for two different management strategies of the power source and ESS, while the application power profile is maintained. The capacity requirement (E_{max}) is lower for the management strategy 1 than for the management strategy 2. On the contrary, the power requirements (P_{max}, P_{min}) are more restrictive in the case of management strategy 1.

From these results it can be concluded that the rating of an energy storage system

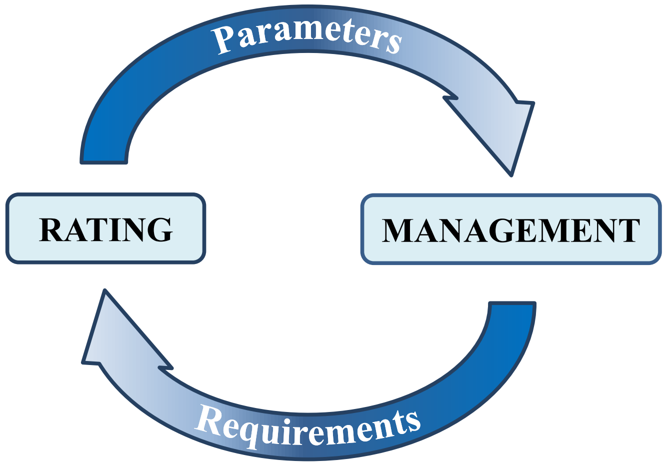


Figure 1.12: The representation of the energy storage system dilemma: rating vs. management.

for a specific application with particular power and energy requirements is dependent on the power source and ESS management strategy adopted.

At the same time, the management strategy is dependent on some of the parameters of the ESS, such as its State Of Charge (SOC), or simply, the capacity of the ESS (1.1).

$$\text{Power Source} = f(SOC, Capacity, Voltage, Lifecycles \cdots) \tag{1.1}$$

It is therefore shown that both aspects, rating and management, are coupled. The close loop created between both aspects and that represents the dilemma of an energy storage system is depicted in figure 1.12. Once the management strategy is defined, the requirements for the ESS rating can be determined. At the same time, the management strategy is based on ESS rating parameters.

It must be pointed out that this conclusion is valid both for applications where the application requirements are known in advance as well as for applications where these requirements are unknown (i.e. hybrid electric vehicle).

1.2.2 The Approach to Solve the Problem

In this section a solution to the coupling problem between the rating and the management of an ESS is proposed. It must be remarked that both aspects cannot be addressed simultaneously. Consequently, the closed loop shown in figure 1.12 should be opened.

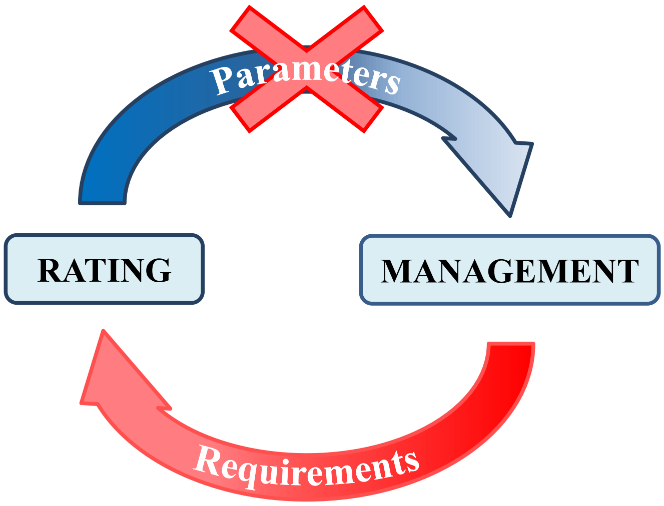


Figure 1.13: The approach to solve the dilemma of energy storage systems.

In this context, there are two possibilities to proceed. The approach adopted in the scope of this PhD consists in tackling the management aspect before the rating. The proposal is depicted in figure 1.13. According to that, first of all the management is developed regardless to the accurate values of the ESS and then the rating requirements are specified. It must be pointed out that the definition of some basic ESS parameters is necessary to begin with the management strategy development.

The main reason for adopting this approach is that the rating methodology is already developed and it is well-known, as it has been presented in the previous section. Thereby, if the system requirements are correctly defined, the rating can be successfully developed. In contrast, the management strategies are usually customized for each energy application. In the literature, there exist several management strategies oriented to applications including energy storage, but there are no formalized methodologies for their development and implementation. In addition, the lack of consideration of the management strategy in the rating process could lead to an oversized ESS.

Therefore, this PhD is focused on the analysis and the proposal of optimized energy management strategies for applications with energy storing capacity.

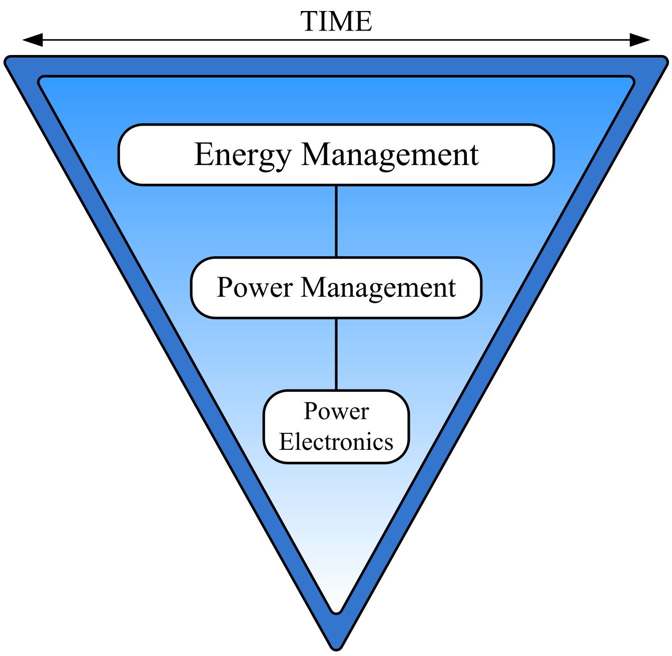


Figure 1.14: Representation of the hierarchical control and management of a power electronic system, illustration extracted from [32].

1.3 Energy Management Strategies

In this section, a review of different Energy Management Strategies (EMS) is presented. The review is complemented with an analysis of the optimization methods and techniques that can be implemented in order to get an optimal behavior of EMS [29,30]. But first of all, the framework and the objectives of an EMS are stated.

In [31] Rosario et al propose the hierarchical structure depicted in figure 1.14 to represent the control and management structure of any manageable power device. This structure is known as Modular Power and Energy Management Structure (MPEMS).

The energy management level is located at the top of this hierarchy and its objective is to define the long-term evolution of the system, i.e., to define the strategy. This is the reason of its lowest dynamics (in the order of few seconds). This control level defines the control parameters such as the operation modes, as well as the limits and constraints for the Power Management level.

The main objective of the Power Management level is to define the medium-term evolution of the system, i.e., to define the policy. It defines the power references for the next control level in order to carry out the strategy set in the upper level. The time response of this control level is faster than the one of the Energy Management level (in the order of few milliseconds).

Level	Objective	Output	Timing
Energy management	Strategy	Control parameters	Long-term $[s]$
Power management	Policy	Power references	Medium-term $[ms]$
Power electronics	Process	Modulation	Short-term $[\mu s]$

Table 1.4: Main characteristics of the MPEMS hierarchy.

Finally, the objective of the power electronics level, which is at the bottom of this hierarchy, is to physically manipulate the interface, i.e. to execute the process. This control level includes all the control loops from the power references to the modulation of the converter and it acts is in the order of microseconds.

This hierarchy can also be analytically represented in order to identify the different links between control levels. The link between the power management level and the energy management level is represented in equation (1.2). The energy is the evolution of the power over time. For this reason, the energy management level should be slower than the power management level.

$$E = \int P \, dt \tag{1.2}$$

The link between the power management level and the power electronics level is given by equation (1.3). Indeed, the power is the product of the voltage and the current that flows through a power converter. These variables are controlled by inner control loops implemented in the power electronics level.

$$P = V \cdot I \tag{1.3}$$

The main characteristics of the hierarchical structure of the control and management of power electronics applications (MPEMS) are summarized in table 1.4.

1.3.1 Review of Energy Management Strategies

The main energy management strategies are presented and analyzed in this section. In particular four different control strategies are considered: rule based strategy, cuttoff frequencies, Fuzzy Logic and Artificial Neural Network.

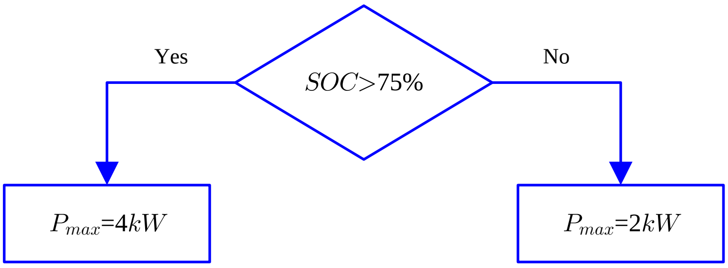


Figure 1.15: Rule based strategy to control the state of charge of an energy storage system.

The strategies based on rules are algorithms where decisions are taken on the basis of the current state of the system. The **Rule Based Strategy (RBS)** states a set of conditions, commonly implemented like IF-CONDITION-THEN sentences, in order to set the control parameters. These strategies are characterized by a combinational behavior, in other words, the decisions are adopted regarding to the current information of the application, neglecting the past information or future estimations related to the evolution of the system. A typical structure of these kinds of strategies is shown in figure 1.15.

This kind of energy management strategies is widely implemented. In some Photo Voltaic applications for instance the energy management is based on relatively simple strategies. The EMS checks the difference between the power generation of the PV and the load power in order to set the control parameters for the energy storage system [33,34]. These strategies are more complex in the case of elevator or traction applications with Supercapacitors based ESS. In those applications the EMS considers the State Of Charge of the ESS and the operation mode of the elevator (traction or regenerative) to set the control parameters [25, 35]. Finally in Electric Vehicle, Hybrid Electric Vehicle and Plug-in Hybrid Electric Vehicle applications the control strategy is even more complex. The EMS sets the control parameters taking into account several conditions such as the SOC of the ESS, the power requirements of the vehicle, the vehicle speed and the operation mode (accelerating or braking), etc [36, 37].

These energy management strategies require a low computational cost, and in consequence, they are suitable for an online implementation. They can also be developed and implemented relatively fast. In contrast, they require a wide knowledge of the application to set the conditions in an adequate manner. Besides, they are hardly appropriate for a large number of control parameters since the set of conditions can increase hugely if all possible combinations must be considered. Concerning their robustness, these strategies are subject to the model of the application. In consequence, if the system is modified, the energy management strategy could not work correctly. Moreover the self learning ability is totally dismissed.

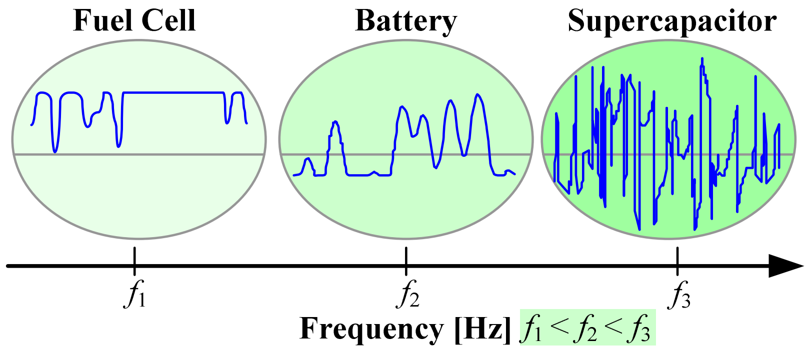


Figure 1.16: Energy management strategy based on the cuttoff frequencies for a hybrid energy storage systems composed of fuel cell, battery and supercapacitor, illustration extracted from [40].

In energy management strategies based on **cutoff frequencies (COF)** the control parameters are set according to the dynamics of the power consumed by the application (loads) and the capability of response of the different power sources (power supplies and energy storage systems). The idea is to divide the power requirements of the application in the frequency domain, implementing low-pass filters in order to filter the instantaneous system power consumption. Then, the control parameters are set according these requirements and taking into account the dynamics of power sources. The objective is to avoid any damage in the power sources. Figure 1.16 illustrates this EMS.

COF strategies are usually implemented in applications composed of hybrid energy storage systems. A possible application can be a hybrid vehicle where the electric motor is supplied by a combination of a fuel-cell, a battery and supercapacitors [38–40]. In that case, the slowest dynamics is assigned to the fuel-cell, the middle-term dynamics to the battery and the fastest dynamics to supercapacitors. COF can also be implemented in wind power applications with energy storage systems composed of batteries and supercapacitors, assigning low dynamics to the batteries and high dynamics to the supercapacitors [41].

These energy management strategies must be executed online since they are composed of filters. They require a relative low computational cost because digital filters can be implemented in a control unit based on a digital signal processor. The key point and difficulty of these control strategies is how to define the bandwidth of each filter. For that, the model of each power source must be known in order to be able to define its dynamics. In this case the number of control parameters is equal to the number of filters or, the number of power sources. The robustness is tightly tied to the behavior of power sources. If they are time invariant, which is unlikely to happen, the EMS will be robust. The self learning ability is dismissed because once the filters are developed and implemented, they cannot be modified.

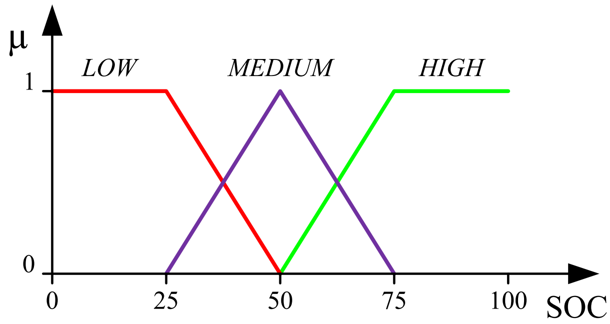


Figure 1.17: Fuzzyfication process of the state of charge of an energy storage system in a fuzzy logic based EMS.

The energy management strategies based on **Fuzzy Logic (FL)** are capable of setting configuration parameters for situations where the information has a high uncertainty degree. The information cannot be absolutely quantified and it is relatively quantified between two values (known as heuristics rules), becoming a subjective information. This control strategy is divided in three steps. First, the subjective information is extracted in the fuzzification process from measurable variables, as shown in figure 1.17. Then, this subjective information is compared to heuristic rules. Finally, the defuzzification process is carried out, setting the control parameters from the obtained result in heuristic rules.

These control strategies are used in applications with complex models or which are difficult to model. They are extensively used in HEV vehicles or buses where the energy storage system is composed of different technologies (fuel-cell, batteries and supercapacitors) and the application requirements, from an electrical point of view, are difficult to define. In these cases the objective of the EMS is to define the control parameters according to the operation modes, SOC of the ESS and trying to achieve the maximum efficiency of the whole system [42–44]. They can also be used in RES applications (wind and photovoltaic) [45, 46] as well as in load regulation applications [47].

These energy management strategies are generally executed online. They require a low computational cost to carry out the three steps of the algorithm. The fuzzification and defuzzification process are composed of arithmetic operations and the heuristic rules are implemented with IF-CONDITION-THEN sentences. Nevertheless, it is required a wide knowledge of the application to set the heuristic rules since the decisions are adopted taking into account subjective information. These strategies are able to manage several control parameters but the heuristic rules increase exponentially. The main advantage of these algorithms is their robustness, because they use low precise and subjective information. In addition to that these algorithms have optionally the self learning ability.

The energy management strategies based on **Artificial Neural Network (ANN)** are based on a computing methodology inspired on biological models. These control strategies are composed of a high number of simple elements, known as nodes, that are

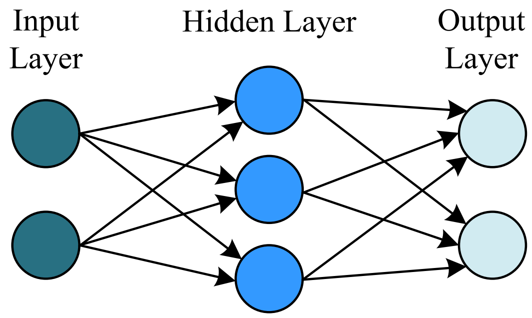


Figure 1.18: Representation of the layers of an Artificial Neural Network based energy management strategy.

interconnected. These nodes process the information in terms of their dynamic state as an answer to the external inputs. These nodes are grouped in different layers, and in each layer, the nodes are not interconnected. An ANN consists of three layers (input, hidden and output), as it can be seen in figure 1.18.

The characteristics of artificial neural networks make it possible their use in several applications. Typically, neural networks have been implemented in fields such as pattern recognition [48], prediction problems [49], or robotics [50]. In energy management applications, they have been implemented in applications composed of hybrid energy storage systems [51, 52] and for load profile prediction purposes [53]. It is also possible to complement them with FL strategies, using the FL to solve the energy management problem and the ANN to solve the prediction problem [54].

These energy management strategies are executed online with a fast time response. However, the computational cost is increased if the number of layers and their nodes is high, since they are composed of arithmetic operations. The key point of these control strategies is that they must be trained before their implementation. To do so, all possible situations where the EMS can be found should be considered. They are appropriate for applications with complex models or systems that are difficult to model. In contrast, the casuistry of these systems must be known in advance in order to train the ANN and this training process can be long. The main advantage of these control strategies is their robustness and the fact that, they can incorporate the self learning ability.

1.3.2 Optimization Techniques for Energy Management Strategies

In the previous section, some examples of energy management strategies used in applications including ESS have been presented and analyzed. These management strategies are capable of controlling the applications, but they do not guarantee an optimal behavior of the system. The optimal behavior of the application could be achieved by applying optimization methods to the management strategies. In this section the main optimization methods applied to energy management strategies are described.

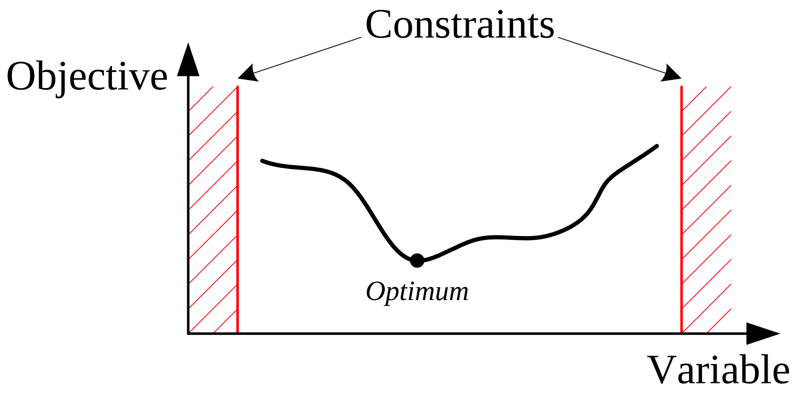


Figure 1.19: Representation of an optimization process composed by the main three elements.

All the optimization techniques are composed of three elements:

- Objective or cost function: It is a measure element that is used to quantify the quality of the results or solutions. All the calculated solutions are compared in order to minimize or maximize this cost function and define the best solution for the optimization problem.
- Variables: They are the elements of the system that can be modified by the optimization process in order to get a family of potential solutions of the optimization problem.
- Constraints: They represent the restrictions or bounds of the system variables and are represented as inequations or equations.

The optimization process is applied as follows. The optimization method modifies the variables of a system that are subjected to constraints, and as a result it gets a family of possible solutions. These solutions are later quantified by means of evaluating the defined cost function, as it is shown in figure 1.19.

Depending on the implemented energy management strategy, the objective of the optimization process could be different. In the case of rule based control strategies, these optimization methods are usually implemented in order to define thresholds of conditional sentences. For cutoff frequencies, they are implemented to define the bandwidths of low-pass filters for each energy storage system. In the case of fuzzy logic based strategies, they are used to optimize the fuzzification process. And finally in ANN based control strategies, they are usually used to try to build the best architecture of layers and nodes.

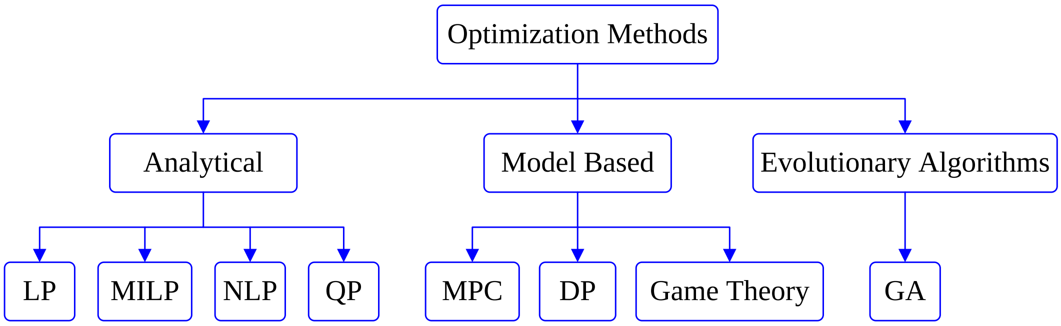


Figure 1.20: Classification of optimization methods for energy management applications.

In order to complete the analysis of optimization methods, in the following, the main optimization methods applied in energy storage applications are described. Optimization methods can be classified according to various criteria, as it can be seen in figure 1.20. From an analytical approach, the optimization can be carried out using Linear Programming (LP) for applications where the optimization problem is formulated as a linear function (cost function and system model), variables are real and positive, and constraints are also linear [55]. The major problem is that the system model must be linear or it must be linearized, decreasing the accuracy of the optimization problem. In applications with energy storing capacity it is more suitable to use the Mixed Integer Linear Programming (MILP) [56, 57] when the problem can be formulated linearly. It is a variation of the LP method. The difference is that variables are real, positive, and some of them are necessarily integer. In case the application model can be obtained but it is strongly nonlinear and neither can be linearized, or simply, the objective function or constraints are nonlinear and variables are real and positive, the Nonlinear Programming (NLP) could be the solution [58, 59]. There is particular case of the Nonlinear Programming where the cost function form is already defined (Lagrange multiplier). In that case, the Quadratic Programming (QP) is able solve the problem faster than NLP [60, 61].

These last optimization methods are related to the analytical formulation of the problem and they are capable to get an optimal solution or a sequence of independent optimal solutions. However, there are optimization problems which require a solution formed by a sequence of dependent decisions, getting an optimal behavior of the sequential problem. These applications are classified in function of the knowledge of the system evolution, i.e., according to the system model. If the system evolution cannot be known in advance, being totally unknown or only it can be described from a statistical point of view, it is known as a stochastic system. In contrast, if the system evolves over time in a totally known manner, i.e. its statistical value is always equal to one, it is a deterministic system.

For deterministic systems, the Model Predictive Control (MPC) is well suited, using a dynamic model of the application and evaluating a finite horizon of decisions [62, 63]. The Dynamic Programming (DP) or Deterministic Dynamic Programming (DDP) is also implemented for these kinds of optimization problems [64, 65]. The principle is to break the sequential problem into subproblems, and then, each subproblem is solved individually. The main advantage is that the computational cost is decreased because each subproblem is solved once, and the global solution, is the sum of subproblem solutions. In contrast, memory requirements are increased. In the case of stochastic systems, the Dynamic Programming can also be implemented, known as Stochastic Dynamic Programming (SDP). It is solved similarly to Deterministic Dynamic Programming, incorporating the statistical description of the system or introducing a Markov decision process of the application [66, 67]. The Game Theory can be implemented, identifying the application and energy storage systems as players and trying to find the best strategy in order to define the best interaction between players for solving the problem [68, 69].

When the optimization problem is strongly complex and nonlinear, the best option is to use a Genetic Algorithm (GA) [70–72]. They belong to the evolutionary algorithms (stochastic methods of optimization), solving the problem inspired by natural evolution. Genetic Algorithms are capable to find the optimal solution, or at least a very good approximation for different problems. However, these techniques require a high computational cost.

1.4 Motivation of the Present Work

The main challenges associated to the installation of energy storage systems in different applications are their rating and their management, and both aspects are strongly coupled. In the scope of this PhD, the approach proposed to open this coupling consists in first of all addressing the management aspect and then carrying out the rating by applying an already known procedure and previously presented. The main reason for adopting this approach is that there is a lack of systematic formalized methodologies for the development and implementation of energy management strategies oriented to applications including energy storage.

In this context, the objective of this PhD is to propose a methodology to adapt and implement a particular energy management strategy for applications with energy storing capacity. The proposal includes an optimization procedure of the management strategy, aimed at reaching the optimal behavior of the application. The selected energy management strategy is based on rules and is optimized by a Dynamic Programming based optimization technique. The proposed methodology has been applied to a vertical transport application including energy storage and experimentally validated in a full-scale elevator.

1.5 Structure of this Document

Regarding to the structure of this document, apart from this introductory chapter where the problem of applications with energy storing capability is explained and the motivation of the work is presented, the document is composed by another four chapters.

In the second chapter an implementation methodology for energy management strategy based on Dynamic Programming is proposed. Firstly this optimization technique is introduced. After that, its application in systems with energy storing capacity is presented, and besides, the implementation methodology is also proposed. Additionally, the cost function evaluated by the optimization technique is presented and a new modeling for stochastic applications is proposed, relating the energy requirements of the application with its statistical description.

In the third chapter the case study selected for this PhD is presented. It is an elevation system with energy storing capacity based on Supercapacitors. First the introduction to the elevation application is carried out. After that, the system modeling is developed, applying the energetic macroscopic representation, analyzing the electromechanical conversion system and carrying out the proposed representation for stochastic applications. Finally, the implementation methodology is applied to the elevator and simulation tests are carried out. Additionally, a simple rule based strategy is also implemented in order to compare with the optimized control strategy.

In the fourth chapter the experimental validation on a full-scale elevator is presented. Firstly the test bench is presented. Then, the results of three experimental tests are presented in order to validate the optimized energy management strategy. The methodology and the energy management based on Dynamic Programming is experimentally validated, demonstrating a superior behavior compared to a non-optimized but conventional rule based control strategy.

In the fifth and last chapter of this document the conclusions and contributions extracted and drawn from this thesis are presented and some possible future works are presented as well.

2

Dynamic Programming Based Energy Management Strategy

Summary

In this chapter a new methodology to develop and to implement Dynamic Programming (DP) control strategies is proposed. The methodology consists of five steps, in which the cost function is based on the stock management theory. In addition, a new representation for stochastic applications, relating the energy requirements of an application and the probabilities of occurrence, is also proposed in this chapter.

2.1 Introduction to the Dynamic Programming

The Dynamic Programming optimization method was originally introduced by R. Bellman in 1952 [73]. One year later, this technique was firstly introduced for solving problems known as "bottleneck" problems [74], where the goal was to define an optimal decisions policy. The first book regarding to the Dynamic Programming was published by R. Bellman in 1957 [75], in which "the principle of optimality" was presented and the "Dynamic Programming Algorithm" was formulated. Some years later, the IEEE association recognized this field as a system analysis and engineering topic. Since then, this optimization method has been widely used in computer science [76, 77], economics [78, 79] and engineering [80, 81].

The objective of the Dynamic Programming is to solve a decision problem in an optimal way, achieving an optimal decision policy. This optimization method can be applied to deterministic or stochastic systems, to discrete or continuous time systems and to finite or infinite horizon problems.

The Dynamic Programming optimization method splits a large decision problem into smaller subproblems. The principle of optimality states that any optimal policy has the property that, whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision [75]. Taking into account this principle, any large decision problem can be solved step by step evaluating all subproblems, and finally, obtaining the optimal decision policy.

The solution is achieved implementing the Dynamic Programming algorithm, which is a recursive manner to solve the problem. The main advantage of this method is that the computational cost is relatively low because the intermediary operation results are stored in a table, and later, they are used for the following decisions (due to the coupling between all the decisions of the sequence).

When a decision problem is solved by the Dynamic Programming optimization method, four fundamental objects must be identified and defined, as it is outlined in table 2.1. These four objects define how long the problem is (the dimension), in which state the system is (the state variables), which the optimal system evolution should

Object	Description
Dimension	It is the size of the decision problem.
State variable(s)	It defines the current situation of the system.
Decision variable(s)	It defines the desirable evolution of the system.
Objective function	It quantifies the cost of the possible decisions.

Table 2.1: Main objects of a system controlled by a DP based strategy.

be (the decision variable) and how each potential decision is quantified (the objective function). It can be noted, that depending on the application, additional objects can be identified and defined such as perturbation variables.

Figure 2.1 shows a well-known example, the shortest path problem, which is optimally solved implementing the Dynamic Programming technique. The objective is to start from state 1 and to finish in state 9, going through intermediate states and achieving the lowest possible cost. The main objects are presented in table 2.2.

In this study, this optimization method will be used for applications with energy storing capacity in order to manage optimally the system during a period of time. For this purpose in the next section, the development and implementation of this advanced technique is presented.

2.2 DP Applied to Energy Management Applications

A new methodology for a systematic implementation of an optimized DP control strategy is proposed. The methodology consists of five steps.

Figure 2.2 shows an application with energy storing capacity. It is composed of three elements: the power source, the application and the energy storage system. The power source supplies the energy to the application and to the energy storage system. The application consumes or provides energy, depending on the nature of the system. Finally, the ESS is capable to decouple the power source from the application.

Object	Identification
Dimension	4 (from 1 to 9)
State variable	Circles (1 .. 9)
Decision variable	Arrows
Objective function	Arrow's value

Table 2.2: Shortest path problem objects.

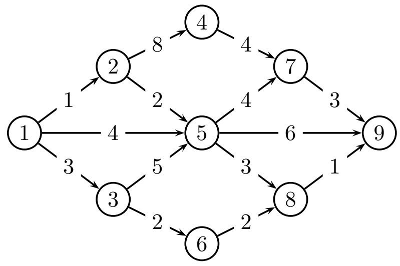


Figure 2.1: Shortest path problem.

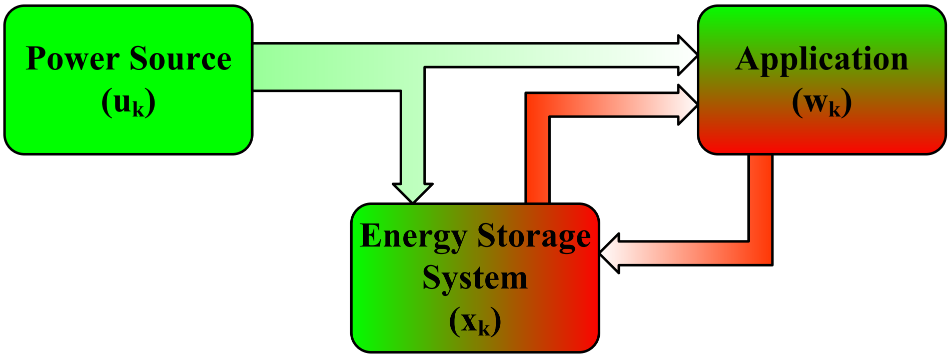


Figure 2.2: Elemental energy management problem representation for applications with energy storing capacity.

As it has been shown in the previous chapter, an energy management strategy is required in order to define the necessary power flow to satisfy the application requirements. Besides, if this power flow should be defined during a time period, this problem becomes a sequential decision problem, where the Dynamic Programming optimization method is especially well-suited.

As it has been explained in the previous section, the main objects of the system must be identified in order to achieve an optimized control strategy based on DP. Table 2.3 summarizes these objects. The problem dimension (N) has been associated to the number of times in which energy is absorbed from the power source in a period of time. The state variable (x_k) is related to the state of charge of the energy storage system. The decision variable (u_k) is related to the energy absorbed from the power source. The objective function (g_k) is based on the stock management theory, which is able to quantify the decisions (it will be described in the following section). Finally, as it can be seen on the table, an optional object has been introduced, a perturbation variable (w_k) which is related to the application energy requirements.

Once identified the main objects of the considered system, the objective of the DP based EMS for this kind of application can be stated as:

> *"The objective of the optimized energy management strategy based on Dynamic Programming for applications with energy storage capacity is to define a sequential energy consumption strategy from the power source in order to satisfy the energy requirements of the application and using the ESS as a decoupling system. Moreover, this decision strategy is aimed at achieving the optimal value of the cost function based on the stock management theory."*

In this work, a new methodology is proposed for the development and implementation of this kind of control strategies in the next section.

Notation	Object	Identification
N	Dimension	Times of energy consumption from the power source.
x_k	State variable	State of charge of the energy storage system.
u_k	Decision variable	Energy absorbed from the power source.
g_k	Objective function	Cost function based on the stock management theory.
w_k	Perturbation variable	Energy consumed or provided by the application.

Table 2.3: Main objects of application with energy storing capacity controlled by a Dynamic Programming based strategy.

2.2.1 Implementation Methodology For DP Techniques

The implementation of these optimization techniques in energy management applications can be unintuitive. For this reason, a new implementation methodology is proposed in order to explain in detail the required steps for developing this kind of optimized control strategies.

Figure 2.3 shows the proposed methodology, which consists of five steps. The first three steps prepare the sequential decision problem to reach the optimal solution. The last two steps carry out the analytical resolution of the problem, defining an optimal decisions policy. In the following sections, each step of the proposed methodology will be analyzed.

1 - Decisions and Costs Map Creation

In this first step two features of the application are considered. On the one hand, the possible values that the decision variable can have are analyzed. In addition, the influence of this variable and the perturbation variable on the possible values of the state variable is also analyzed. The objective of this step is to represent the different states in which the system is, as well as the values that must be assigned to the decision variable in order to move from one state to the next one.

In equation (2.1) the state variable of the system in the next instant (x_{k+1}) is presented, where (x_k) is the state variable of the system in the instant (k), (u_k) is the variable of the adopted decision in the instant (k), (w_k) is the perturbation variable of the energy requirements of the applications and (f_k) is the function that describes the evolution of the system from instant (k) to instant ($k+1$), according to the current state

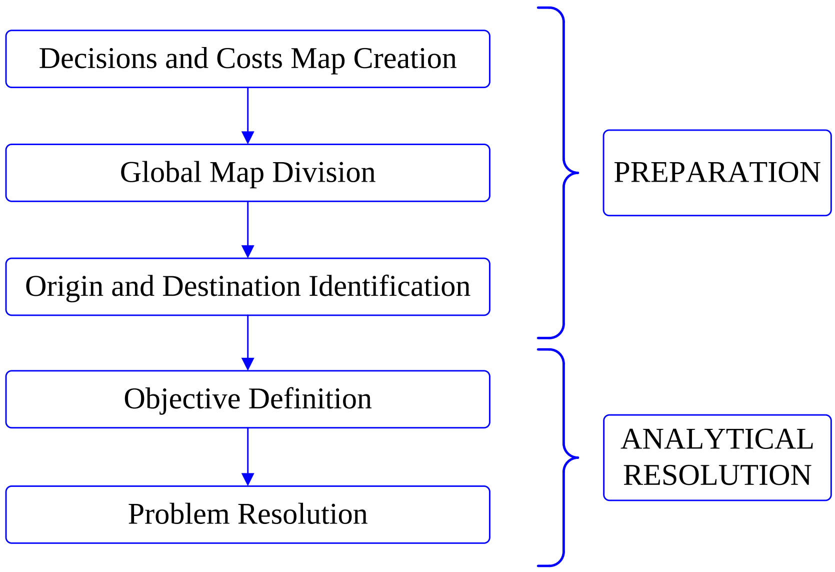


Figure 2.3: Proposed Dynamic Programming based control strategy implementation methodology flowchart.

and the adopted decision.

$$x_{k+1} = f_k(x_k, u_k, w_k) \tag{2.1}$$

On the other hand, the costs related to the system evolution are also defined. The objective is to represent the associated cost (it does not have to be dimensional), of modifying the state of the system from instant (k) to instant $(k+1)$, by setting a value to the decision variable while it is being disturbed by the perturbation variable. The mathematical expression that defines this cost is represented by the function (g_k) (2.2).

$$g_k(x_k, u_k, w_k) \qquad \rightarrow \qquad \text{Stock Management Theory Cost Function} \tag{2.2}$$

Finally, by evaluating all the possible states, the adopted decisions and the associated cost, it is possible to create an optimal decision map. It has to be underlined that these maps can be one-dimensional or multi-dimensional, depending on the nature of the application (w_k).

In the case of deterministic applications where the behavior of the application is completely defined, the representation is one-dimensional, as it can be seen in figure 2.4 (the circles represent the values of the state variable and the arrows represent transitions

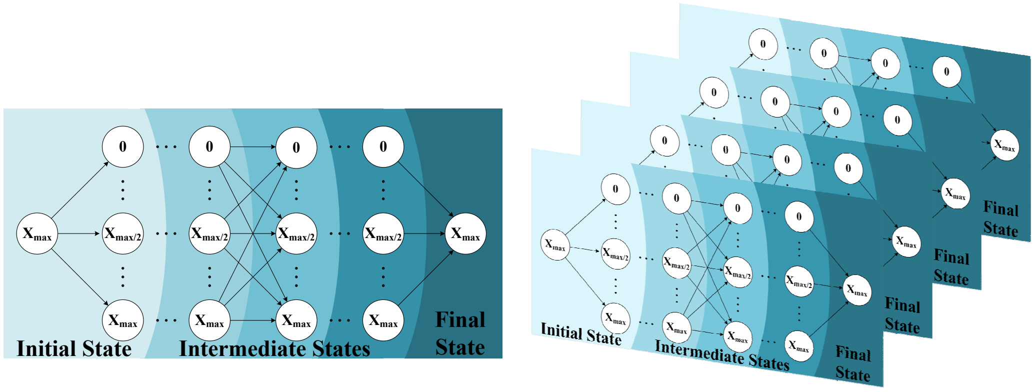


Figure 2.4: Decisions and costs maps representation: (a) deterministic application and (b) stochastic application.

between two consecutive states, defined by the decision and perturbation variable). However, for stochastic applications where the behavior of the application is unpredictable, the representation is multi-dimensional, as it is shown in figure 2.4. Each map represents one of possible evolution of the decision variable (the circles represent the state variable, the arrows represent transitions between two consecutive states, which are defined by the perturbation variable).

2 - Global Map Division

Once the maps have been defined, the next step consists of dividing the map in different zones, according to the instants where the decisions will be taken (2.3). The objective of this step is double. On the one hand, the first objective is to divide the global problem into different subproblems with a sequential behavior, in order to apply the Bellman's principle of optimality.

$$k = 1, 2, 3, \ldots, N + 1 \tag{2.3}$$

On the other hand, the second objective is to define when the algorithm must take the decisions. Furthermore the problem dimension is defined, i.e., the number of decisions that must be determined by the optimized energy management strategy (N). The result of this division is presented in figure 2.5. Note that all maps are divided identically, either for deterministic or stochastic applications.

3 - Origin and Destination Identification

Once the map is divided into different subsections, the origin and destination of the

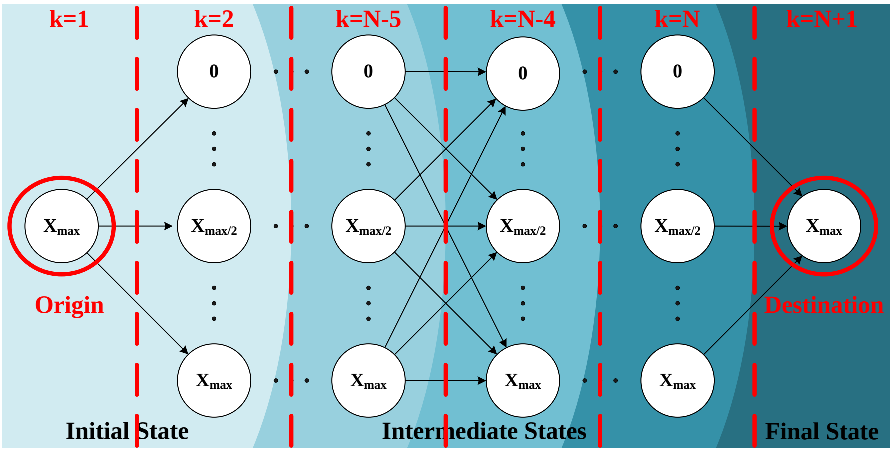


Figure 2.5: Decisions and costs map division and origin/destination identification.

problem must be defined. Then, it is possible to set the values of (k) to every subproblem, as it can be seen in figure 2.5. In the previous step, the dimension of the problem has been established, and in this step, the direction of the system evolution is established. The objective is to define how the problem will be solved during the resolution phase.

4 - Objective Definition

In this step, the objective is to define the behavior of the system. Thus, the equation to evaluate the costs is formulated in order to quantify the system behavior in a sequence of decisions. Objective functions are usually equations in which the costs are maximized or minimized.

As it can be seen in the example (2.4), the objective is to minimize the costs over (N) decisions. It can be underlined that one more term has been introduced, for instant $(N+1)$, in order to take into account a possible final cost of the system due to the adopted decision at instant (N).

$$\min_{u_k \in U_k} E[g_{N+1}(x_{N+1}) + \sum_{k=1}^{N} g_k(x_k, u_k, w_k)] \tag{2.4}$$

5 - Problem Resolution

The fifth and last step of the proposed methodology is the problem resolution. The resolution is carried out systematically using a technique called "backward induction" [82]. The objective of this step is to obtain a decision policy, from the origin to the destination, fulfilling the defined objective in an optimum way.

The algorithm can be executed online or offline. In the case of deterministic systems the algorithm is usually executed offline due to the fact that the evolution is well known. Therefore, it is possible to evaluate the algorithm before taking the final decisions. For stochastic systems, the algorithm can be executed online or offline but, as the behavior of the system is unpredictable, it is advisable to evaluate the system online in order to obtain an optimal decisions policy using the most recent information (statistical information) extracted from the application. In this case, the algorithm includes the self learning capability, providing a wide range of adaptation to different situations.

The problem is solved from the destination to the origin of the decisions and costs map, evaluating at each step back the costs associated to all possible decisions. Once the costs have been evaluated in each step, it is unnecessary to evaluate them again. Thus, this principle decreases significantly the total computational cost.

The analytical expression (recursive formula) which achieves the optimal decisions policy is presented in equation (2.5), being a modified expression of the objective function (2.4) which incorporates the backward induction principle.

$$\begin{aligned} &J_{N+1}(x_{N+1}) = g_{N+1}(x_{N+1}) \\ &J_k(x_k) = \min_{u_k \in U} E[g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k))] \qquad k = N, \ldots, 2, 1 \end{aligned} \tag{2.5}$$

The implementation of this recursive formula is less intuitive. Thus, a flowchart with three nested loops is proposed in figure 2.6. The flowchart is composed of three nested loops. The main loop (events) goes from the last event to the first one, carrying out the backward induction. Inside this loop, the state variable loop (values x_k) can be found, which analyzes all possible values of this variable (taking into account all possibilities of the state variable in each event). Finally and inside this second loop, the decision variable loop (values u_k) is in charge of evaluating the cost function. Thus, it quantifies each decision for each state variable in each event. After that, the best decision is defined (Cost Function Optimization) and the result is stored for the next computations.

Once these five steps have been carried out, an optimal decision policy has been achieved. In the case of deterministic applications, the decision variable is defined depending on the current instant of the system (k) (shown in figure 2.7). However, for stochastic applications, the decision variable is defined depending not only on the current instant of the system, but also on the current value of the state variable (k, x_k), as it can be seen in figure 2.7.

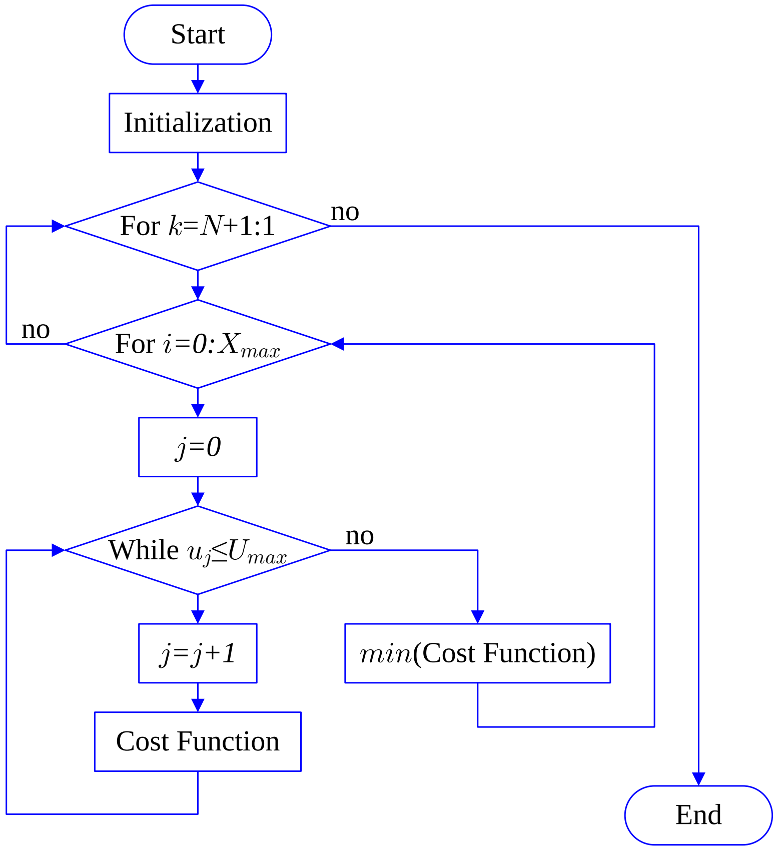


Figure 2.6: "Backward induction" based flowchart proposed for the problem resolution.

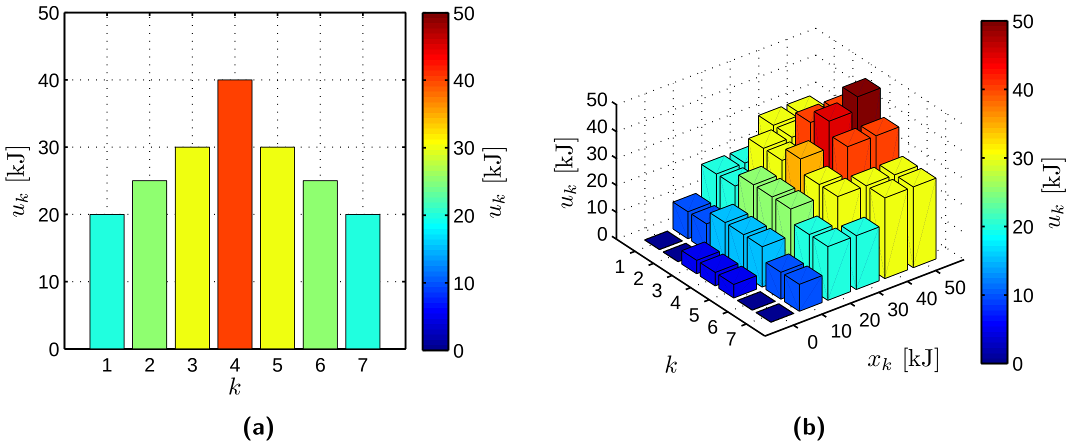


Figure 2.7: Control Strategy based on Dynamic Programming: (a) deterministic application and (b) stochastic application.

2.2.2 Stock Management Theory Based Cost Function

The cost function used in these kinds of applications is based on the stock management theory. It is widely used in economics [83], where it is used to define the best provisioning policy in order to satisfy client requirements and to obtain the maximum profit or the minimum cost. This cost function has been modified and adapted for engineering applications [84], and particularly, when an optimal decision policy is required (in deterministic or stochastic applications).

In our case and taking as reference figure 2.2, the client is associated to the application while the best provisioning policy must be defined by the optimized control strategy based on Dynamic Programming. The warehouse in this case is associated to the energy storage system. Finally, the profits are the objectives of the energy management strategy.

The stock management theory defines a general expression composed by four elements in order to evaluate the costs (2.6). Depending on the application, the expression may have fewer terms, because some costs could not exist or cannot be quantified.

$$\begin{pmatrix} Total \\ Cost \end{pmatrix} = \begin{pmatrix} Fixed \\ Cost \end{pmatrix} + \begin{pmatrix} Variable \\ Cost \end{pmatrix} + \begin{pmatrix} Storage \\ Cost \end{pmatrix} + \begin{pmatrix} Shortage \\ Cost \end{pmatrix} \tag{2.6}$$

In this study, the elements of the cost function have been associated to the energy flow of the system (power source, energy storage system and application), stated in the first step of the methodology and expressed as (g_k) by linking expressions (2.2) and (2.6). The description and association of each term of the expression is:

- Total Cost: It is the overall cost corresponding to the addition of all individual costs.
- Fixed Cost: It is a cost that is independent from the number of goods that are introduced into the system. This cost term has been removed, because the power source does not generate costs apart from the variable costs.
- Variable Cost: It is a cost that depends on the number of goods that are introduced into the system. This cost has been associated to the amount of energy absorbed from the power source. It represents the cost of introducing energy from the power source into the system.
- Storage Cost: It is the cost corresponding to the fact of storing goods in the warehouse, proportional to the quantity. This cost has been associated to the amount of energy wasted in the application. It represents the situations of energy recovering from the application to the energy storage system. Once is fully charged, it will not be able to absorb more energy.

- Shortage Cost: It is the cost corresponding to the goods not provided to the client, proportional to the quantity. This cost has been associated to the non-provided energy to the application. It represents the situations where the energy absorbed from the power source and the energy stored in the ESS are not enough to satisfy the energy requirements of the application.

Finally, the general expression of the cost function based on the stock management theory for implementing a DP based EMS in applications with energy storing capacity is obtained (2.7). As it can be seen, three terms of the expression are weighted (c, h, p), because not all terms have the same relevance depending on the the application. Another term for limiting the capacity (X_{max}) of the energy storage system is added. Besides, the perturbation variable has also been introduced (w_k).

$$\underbrace{g_k(x_k, u_k, w_k)}_{Total\ Cost} = \underbrace{c \cdot u_k}_{Variable\ Cost} + \underbrace{h \cdot [x_k + u_k - X_{max} - w_k]^+}_{Storage\ Cost} + \underbrace{p \cdot [w_k - x_k - u_k]^+}_{Shortage\ Cost} \tag{2.7}$$

As the application requirements are stochastic, the previous expression must be modified in order to introduce a statistical description of the application. This means that it is necessary to introduce the probability of occurrence of them (P_{wk}) for evaluating the cost function (2.8).

$$\begin{aligned} g_k(x_k, u_k, w_k) = & c \cdot u_k + \\ & h \cdot \sum_{1}^{m} \left(P_{wk} \cdot [x_k + u_k - X_{max} - w_k]^+ \right) + \\ & p \cdot \sum_{1}^{m} \left(P_{wk} \cdot [w_k - x_k - u_k]^+ \right) \end{aligned} \tag{2.8}$$

2.2.3 Stochastic Systems Approach: Generalized Energy and Statistical Description

In this section, a new representation for stochastic applications called GESD (Generalized Energy and Statistical Description) is proposed. In this representation, the energy requirements are related to the probability of occurrence. The objective is to be able to describe the application from a statistical point of view for upcoming energy requirements. Besides, this information is requested by the cost function evaluated in the DP based control strategy in equation (2.8).

Two parameters are taken into account for the representation (2.9). First, all possible energy requirements values of the application (w_k) are considered (in this case, the perturbation variable). And then, the probabilities of occurrence for each energy requirement (P_{wk}) are defined. Figure 2.8 shows the graphical representation of the proposed model.

$$w_k \quad vs. \quad P_{wk} \tag{2.9}$$

In the vertical axis the normalized probability of occurrence (P_{wk}) is defined while in the horizontal axis the energy requirements of the application are defined in (w_k in kJ). As it can be seen, there are positive and negative values for the energy requirements. Keeping in mind figure 2.2, negative values represent the energy provided from the application to the energy storage system (the power source is not capable to absorb power). Positive values represent the energy absorbed by the application from the power source, from the energy storage system or from a combination of both.

These two figures describe the same application with different resolutions of the perturbation variable (w_k). It means that different energy requirements can be grouped when the differences between them are less than the considered resolution. And in consequence, the probability is increased. As it can be seen in figure 2.8, there are more bars on the top figure due to the fact that the resolution is three times higher than on the bottom figure. Thus, the probabilities are smaller on the first case.

Furthermore, in the proposed representation the repetition of energy requirements is also considered, i.e., if these energy values are required several times in a period of time, its probability increases. Moreover, some GESD representations can be developed according to different periods of time (hours, days, months, season...), or depending on the desired accuracy. In addition, if the behavior of the system is modified, the representation can be updated online (monitoring the energy consumption of the application). In consequence, the optimized control strategy can be reevaluated online, improving the energy manager and incorporating the self learning ability.

It can be concluded that the representation is able to group similar requirements, and to define more accurately upcoming energy requirements. Besides, the time factor (taking into account the repetitions and periods of time) and the capability to provide the self learning ability to the optimized control strategy (monitoring online the application energy requirements) are introduced.

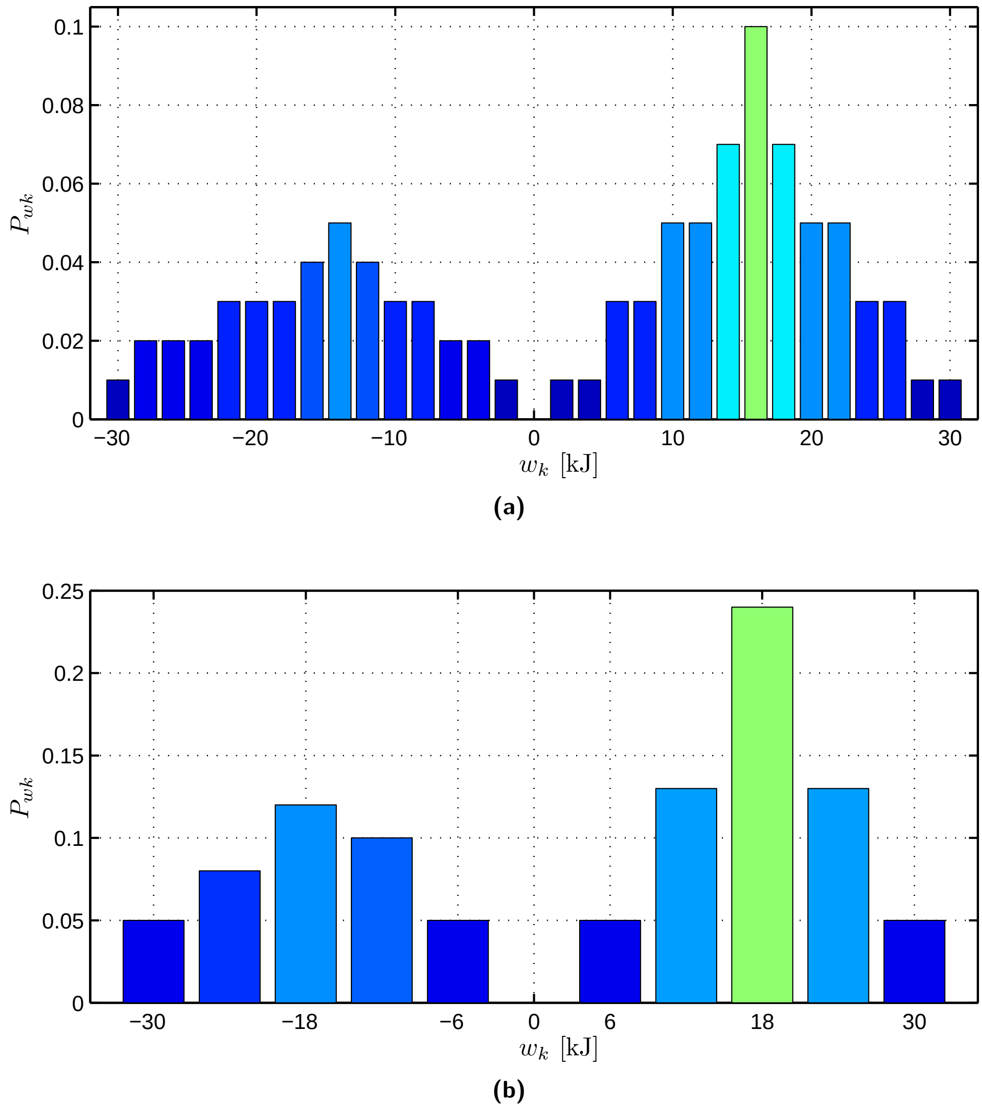


Figure 2.8: Generalized Energy and Statistical Description (GESD) of an stochastic energy application: (a) incremental of $2kJ$ and (b) incremental of $6kJ$.

2.3 Conclusions

In this chapter the Dynamic Programming optimization method has been presented. The objective of this advanced algorithm is to solve a sequential decision problem in an optimal way, achieving an optimal decision policy.

Furthermore, a new methodology has been proposed to develop and to implement these optimized control strategies. It consists of five steps, where the first three steps prepare the problem (defining the decisions and cost maps, dividing these maps and identifying the origin and destination of these maps). And, in the last two steps, the analytical resolution is carried out (defining the objective and solving the problem in a recursive way, backward induction).

In addition, a cost function based on the stock management theory has been proposed due to the similarity between a warehouse and an energy storage system (where this theory is able to quantify its use). Finally, a new representation for stochastic energy applications has been proposed (GESD), relating the energy requirements and their probabilities of occurrence.

3

Improved Elevation System with Energy Storing Capacity

Summary

This chapter presents an introduction to an improved elevation system with energy storing capacity, as well as, to its modeling. Then, the objectives of the energy management strategy are defined and analyzed. After that, an optimized control strategy based on Dynamic Programming is developed, by applying the proposed implementation methodology within this thesis. In addition, a non-optimized but conventional rule based strategy is also developed in order to make a comparison. Finally, the control strategies are tested in simulation.

3.1 Introduction to the Elevation Systems

The objective of transport applications is to displace passengers and loads between two different places or levels. The displacements can be carried out horizontally (places), or vertically (levels). Vertical transport applications, known as elevators, mainly comprised of escalators and elevators. This thesis is focused on elevation systems.

In the field of elevators, the displacement of passengers and loads between two levels or floors is known as a mission or single mission. Similarly, the evolution of these missions over time, or simply, a sequence of missions, is known as the elevator traffic profile. The traffic term can also be referred to a single elevator or a group of elevators of a building. Regarding elevation system technologies, elevators can be classified in three groups: pneumatic vacuum elevators, electromechanical elevators and hydraulic elevators, as it can be seen in figure 3.1.

Pneumatic vacuum elevators are based on the operation principle of pressure difference between the top and the bottom of the cabin. When the cabin is going up, the pressure at the cabin top is lower than the pressure at the bottom (atmospheric pressure). A turbine is responsible for suctioning this air. When the cabin is going down, the pressure at the top is regulated by a valve, releasing air and increasing the pressure in a controlled manner. It should be pointed out that the cabin top must be sealed in order to assure the turbine suctioning. The pressure beneath the cabin must be atmospheric in order to assure passenger transportation.

Hydraulic elevators are based on the principle operation of the cabin displacement through a fluid-driven piston inside a cylinder and directly connected to the cabin. When the cabin is going up, the fluid is driven (usually oil) from the reservoir to the cylinder through a rotary pump, increasing the pressure, expanding the piston and pushing up the cabin. When the cabin is going down the process is similar to the pneumatic vacuum, a valve between the cylinder and reservoir is opened, releasing the pressure in a controlled manner in order to return the fluid, collapsing the piston and lowering the cabin.

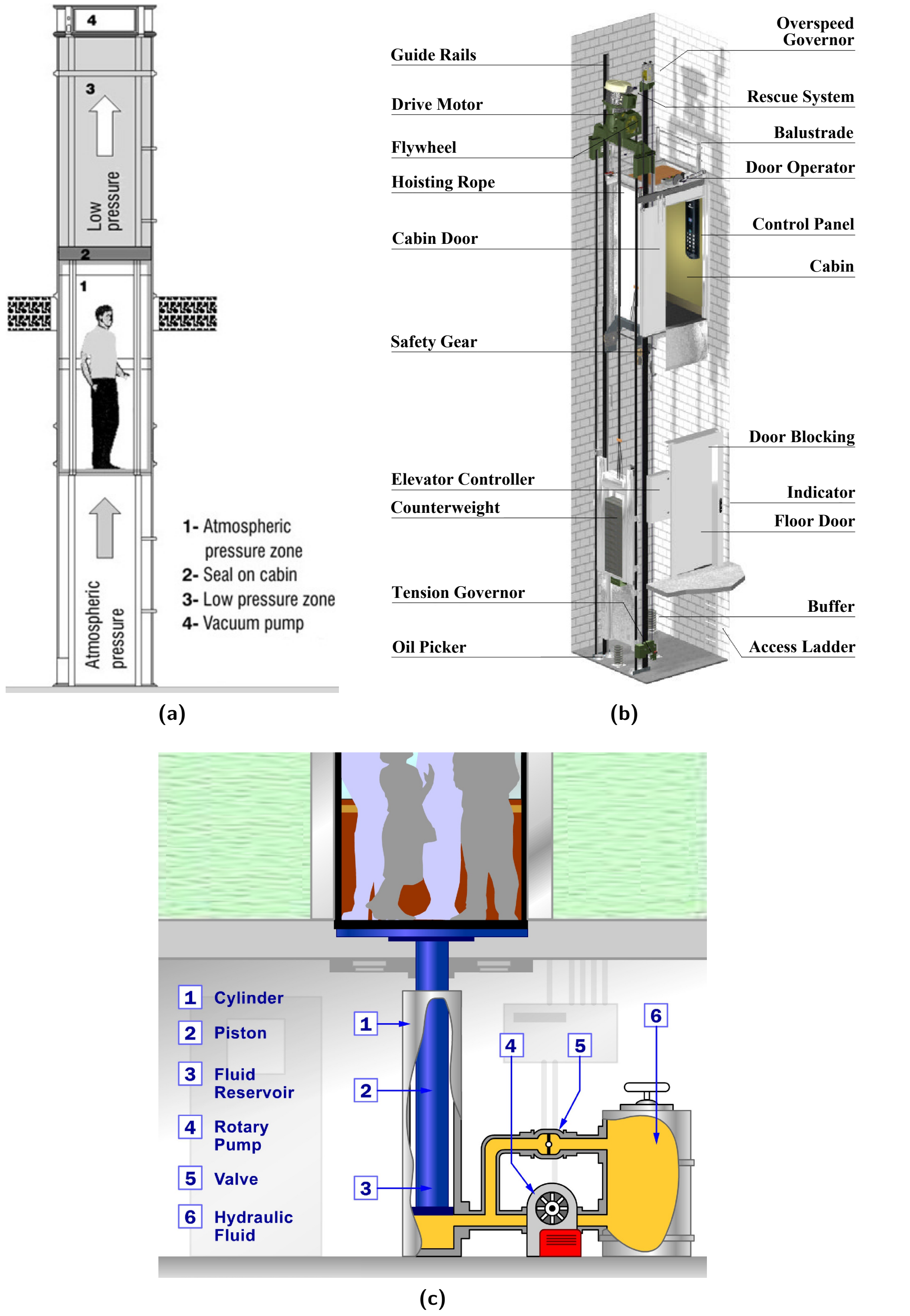


Figure 3.1: Elevation system technologies: (a) pneumatic vacuum elevator, illustration extracted from [85], (b) electromechanical elevator, illustration extracted from [86] and (c) hydraulic elevator, illustration extracted from [87].

Electromechanical elevators convert electric power into mechanical power in order to get the cabin displacement through an electric motor (electromechanical conversion system). The motor has a pulley installed in the motor shaft where the cables of the elevator are supported. The cabin is attached at one end of the cables while the counterweight is attached to the other end. Depending on the rotation direction, the cabin can be displaced upward or downward. Obviously, the counterweight is moved in the opposite direction. The counterweight is mainly used by two reasons; to balance the mass displacement, in order to reduce the power consumption, and to limit the maximum torque of the electromechanical conversion system.

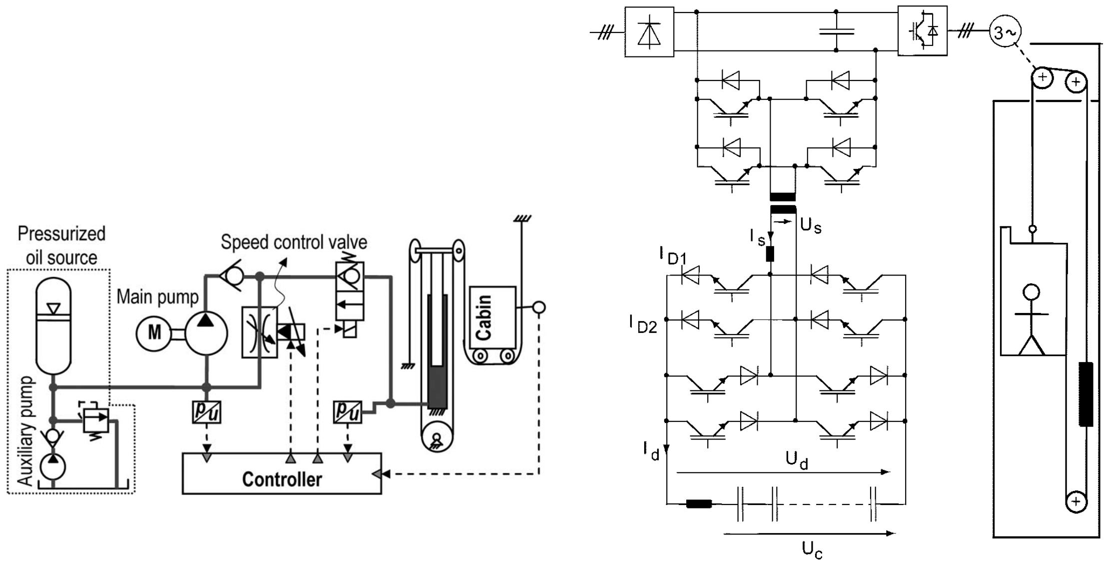
In any case, from an energy point of view, when a mission is completed, it means that the potential energy of passengers and loads has been increased or decreased, due to the height difference between two floors (3.1). Therefore, elevation systems independently of their technology must be capable of providing and absorbing this amount of energy in each mission.

$$\Delta W = m_e \cdot g \cdot \Delta h_f \tag{3.1}$$

In the case of pneumatic vacuum and hydraulic elevators, it can be deduced that the system must be powered for upward missions in order to increase the potential energy, with the turbine and rotary pump, respectively. While the cabin is going down the elevator must be able to absorb that power, releasing the air and fluid pressures through their respective valves.

In contrast, in electromechanical elevators, due to the counterweight mass balancing effect, the upward motion of the cabin does not necessarily mean that the system must be powered. In these systems, there are two masses on the move, cabin and counterweight. Therefore, while the cabin acquires potential energy, the counterweight yields potential energy. In consequence, the electromechanical conversion unit must be capable of providing and absorbing the difference between these two potential energies. As an example, if the counterweight is heavier than the cabin, i.e. if the latter one is empty and it is moving downward, the system will consume power in order to complete the mission. In this kind of systems, the electromechanical conversion unit is reversible. On the one hand, when the motor is consuming, i.e. when power is injected from the grid, the elevator is in traction mode. On the other hand, if the motor is generating power, i.e. generating electric power (generally dissipated in a braking resistor), the elevator is in regenerative mode.

Therefore, it can be concluded that an elevator, regardless of the technology, must be able to provide and to absorb power in order to complete the mission. Whenever the elevator is transferring energy to the passengers and loads, this energy is consumed from



(a) (b)

Figure 3.2: Elevation systems with energy storing capacity: (a) hydraulic elevator, illustration extracted from [88] and (b) electromechanical elevator, illustration extracted from [14].

a power source. On the contrary, when this energy must be absorbed, the power source, is not always reversible and the recovered power is wasted. In the case of pneumatic vacuum and hydraulic systems, the pressure of fluid is released or the fluid temperature is increased. Electromechanical elevators waste this power through a braking resistor, or also known as crowbar resistor.

Due to this fact, an energy storage system could be an efficient solution to avoid wasting energy. In the case of pneumatic vacuum elevators, the recovered power is always wasted. In theory, it could be stored, but in practice, it is never stored. On the contrary, in the other two technologies, the energy can be stored, as it can be seen in figure 3.2.

Regarding hydraulic elevators, during an upward mission the fluid is driven from the reservoir to the cylinder, consuming pump power and increasing the pressure. In a downward mission, that same fluid is returned to the reservoir. Therefore, in hydraulic elevation systems the energy can be stored as the potential energy of the fluid, similar to the case of a compressed air energy storage system (CAES), although this pressurized fluid is used for a different purpose. In these type of elevators, the objective is to store that pressurized fluid in a pressurized reservoir in order to use it later, avoiding the need of pressurizing it again, and in consequence, reducing the power consumption in the pump [88].

Characteristic	Pneum. Vacuum	Hydraulic	Electromechanical
Power consuming	Upward	Upward	Traction mode
Power generating	Downward	Downward	Regenerative mode
Storing capacity	No	Yes	Yes
ESS technology	–	Mechanical (Compressed fluid)	Electrical (Supercapacitors)
Objective of ESS	–	Efficiency	Efficiency and New functionalities

Table 3.1: Summary and comparison of vertical transport elevation systems.

As it has been mentioned previously, an electromechanical elevator consumes power from the grid when it is operating in traction mode, not necessarily on upward missions because of the counterweight. Meanwhile, when the elevator operates in regenerative mode, the motor is working as a generator and the power is transferred from the mechanical system to the electrical one. In that point, between the power source and the electromechanical conversion unit, it is possible to install an energy storage system [14, 89]. The supercapacitors are the most extended and applied technology for this kind of applications. They are well-suited due to the low energy and high power requirements of the application as well as the required large number of lifecycles. The main objective of the ESS is to improve the efficiency, reducing the power consumption from the grid. Additionally, more functionalities can be added like storing regenerative energy, or even charging capabilities from the grid, such as grid power smoothing due to cabin accelerations [90, 91] and automatic rescue in case of a blackout [25].

Table 3.1 presents a summary of the main characteristics of vertical transport elevation systems. In this thesis, an electromechanical elevator with energy storing capacity based on Scaps will be studied.

3.2 Modeling of an Improved Elevator with Energy Storing Capacity

Figure 3.3 shows the general block diagram of an electromechanical elevator with energy storing capacity with the following main elements:

- Power Source: The primary power source is the grid which is connected through a three-phase non-controllable rectifier (unidirectional).
- Energy Storage System: The ESS consists of a supercapacitors tank and a six channels interleaved reversible boost converter [25].
- Application: The application is composed of an electromechanical conversion sys-

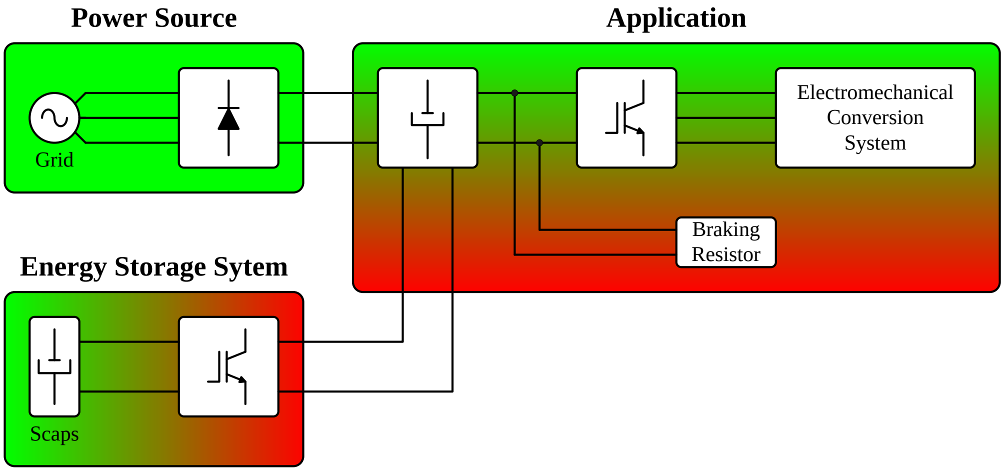


Figure 3.3: General block diagram representation of an electromechanical elevator with energy storing capacity.

tem (converter + motor) connected to a common dc-link where the power source and the energy storage system are also connected. Note that a braking resistor is connected to the common dc-link for safety reasons.

Once the general system diagram has been introduced, the system modeling will be presented. First of all, the Energetic Macroscopic Representation (EMR) and the Maximal Control Scheme (MCS) representation are used in order to define all power flows and control loops of the system regardless of the elevator mission. After that, the electromechanical conversion unit will be modeled in order to define the elevator energy requirements. Finally, the Generalized Energy and Statistical Description (GESD) is used out in order to represent the behavior of an stochastic elevator in a one day traffic profile.

3.2.1 Energetic Macroscopic Representation and Maximal Control Scheme

In order to clarify and represent all the energy interactions between the different subsystems of the elevator an Energetic Macroscopic Representation (EMR) has been applied. It is a graphical tool for modeling and controlling mono-physical and multi-physical systems. This method is based on the action-reaction principle according to the physical integral causality [35, 92].

Basically, it consists of: energy sources (green blocks), accumulation elements related to state variables such as inductances and capacitors (orange blocks with an oblique bar), conversion elements such as power electronic converters (orange blocks), and coupling elements (orange overlapped blocks).

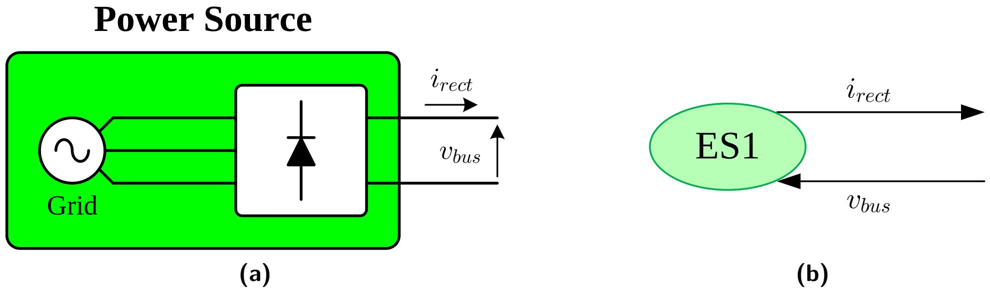


Figure 3.4: Power source modeling: (a) general block diagram representation and (b) EMR representation.

In our case, this method is applied to the three elements of the general block diagram (power source, ESS and application), and finally, all elements are gathered, achieving the whole system representation. After that, the model is inverted in order to obtain the Maximum Control Structure (MCS) and to define all the necessary control loops.

Power Source

The power source in this case is a three-phase non-controllable rectifier connected to the grid, as it can be seen in figure 3.4.

The EMR representation of the power source is an energy source circle (ES1) related to the rectified three-phase current (i_{rect}) and connected to the common dc-link of the application (v_{bus}). In this representation the action is the rectifier grid current (i_{rect}) and the reaction is the dc-link capacitor voltage (v_{bus}). As it can be seen, there is no conversion block. This is, because the rectifier is uncontrollable and the grid connection can be represented as a current source.

Energy Storage System

The energy storage system is composed of a supercapacitor tank and a six channels interleaved reversible boost converter presented in [25] and specifically designed for elevation systems (see figure 3.5).

The EMR representation consists of a source (ES3) related to the supercapacitors tank (v_{sc}, i_{sc}) and connected to the common dc-link (v_{bus}) through the dc-dc converter. The converter includes an inductance (L_{dcdc}) in order to be able to control the dc-dc current (i_{dcdc}), by imposing the inductance voltage (v_{sl}).

The analytical expressions of the supercapacitors tank are defined in equations (3.2)

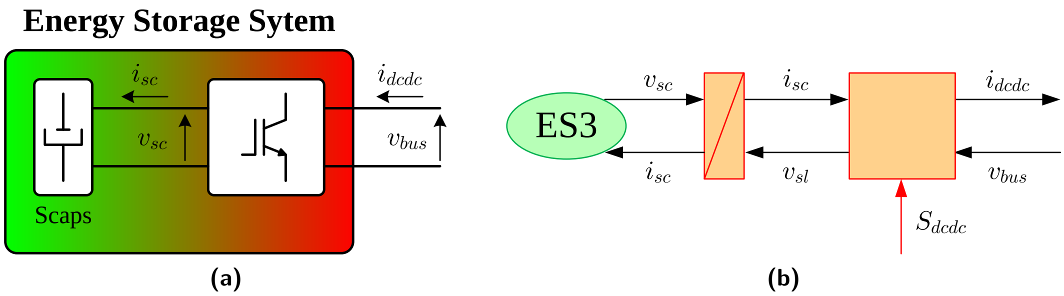


Figure 3.5: Energy storage system modeling: (a) general block diagram representation and (b) EMR representation.

and (3.3).

$$v_{sc} = \frac{1}{C_{sc}} \cdot \int i_{sc}\, dt \tag{3.2}$$

and

$$i_{sc} = \frac{1}{L_{dcdc}} \cdot \int (v_{sl} - v_{sc})\, dt \tag{3.3}$$

Regarding the dc-dc converter, voltage and current relations (3.4) are defined by the modulation factor (S_{dcdc}). It should be pointed out that the converter has been modeled as an average model, i.e. neglecting semiconductor switchings and focusing only on the system level power exchange.

$$i_{dcdc} = i_{sc} \cdot S_{dcdc} \qquad \text{and} \qquad v_{sl} = v_{bus} \cdot S_{dcdc} \tag{3.4}$$

Application

The application is composed of an electromechanical conversion system connected to a common dc-link where the power source and the energy storage system are also connected. In addition, a braking resistor is also connected in order to protect the system from overvoltages. The application is shown in figure 3.6.

The EMR representation consists of a dc-link capacitor (C_{bus}, v_{bus}) where all the sources and the dissipator are connected. This is the reason why two coupling blocks have been introduced (i_{couple_total}, i_{couple_simp}). The electromechanical conversion sys-

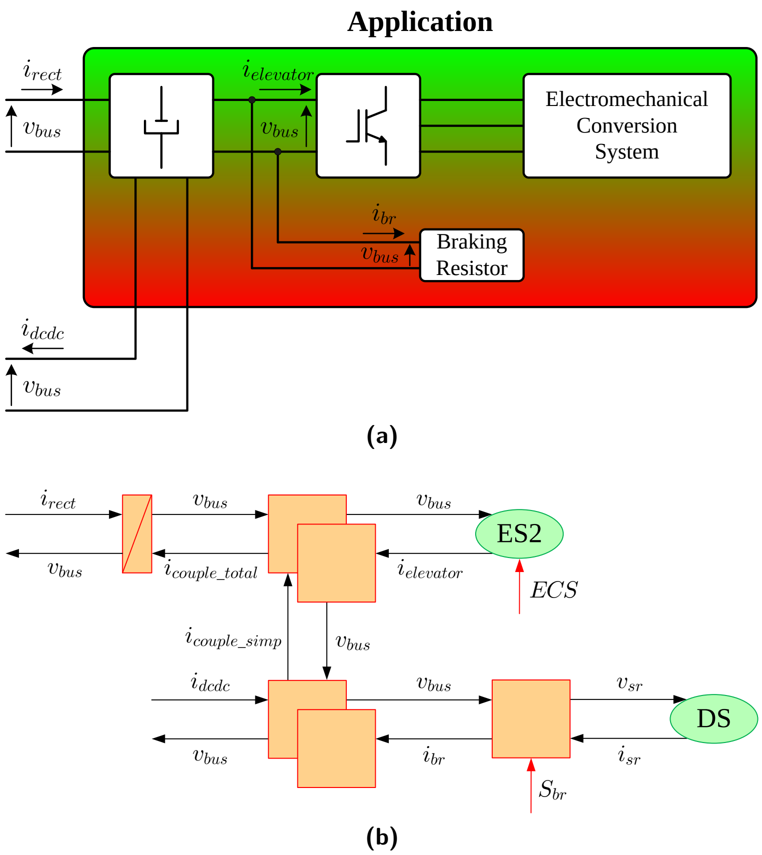


Figure 3.6: Application modeling: (a) general block diagram representation and (b) EMR representation.

tem, responsible for carrying out the elevator mission, is represented as a source (ES2), defining the mechanical power requirements from the electrical point of view ($i_{elevator}$) (equation (3.5)). Note that this source is defined by the mission's parameters (ECS) that will be analyzed in a following section. Finally, the braking resistor ($R_{crowbar}$) is represented as a dissipator (DS) connected to the common dc-link through a chopper (i_{br}), by imposing the braking resistor voltage (v_{sr}).

$$i_{elevator} = f(v_{bus},\ ECS) \tag{3.5}$$

The analytical expression of the dc-link is expressed in (3.6) while the coupling blocks connected to the dc-link are defined in equation (3.7).

$$v_{bus} = \frac{1}{C_{bus}} \cdot \int (i_{rect} - i_{couple\_total})\, dt \tag{3.6}$$

where

$$i_{couple\_total} = i_{elevator} + i_{couple\_simp} \qquad \text{and} \qquad i_{couple\_simp} = i_{dcdc} + i_{br} \tag{3.7}$$

The general expression of the currents is defined in equation (3.8).

$$i_{rect} = i_{dcdc} + i_{br} + i_{elevator} \tag{3.8}$$

Concerning the braking resistor, the current is defined in equation (3.9) and its associated chopper is controlled through the modulation factor (S_{br}) as shown in equation (3.10).

$$i_{sr} = \frac{v_{sr}}{R_{crowbar}} \tag{3.9}$$

and

$$i_{br} = i_{sr} \cdot S_{br} \qquad \text{and} \qquad v_{sr} = v_{bus} \cdot S_{br} \tag{3.10}$$

Elevation System Representation

The main advantage of this representation is that all the variables of the control system are clearly identified and graphically represented. The conversion blocks and their effect in the accumulation elements represent the state variables responsible for transferring the power between sources.

In our case and as it can be seen in figure 3.7, the Energetic Macroscopic Representation of the system is composed of three sources (grid, supercapacitors and electromechanical conversion system) and a dissipator (braking resistor), where all of them are connected in a common dc-link through two coupling blocks. There are two control variables related, on the one hand, to the energy storage system (S_{dcdc}) and, on the other hand, to the braking resistor (S_{br}) of the dc-dc converter. These variables control the state variables of the system, i.e. an inductor (L_{dcdc}) and a capacitor (C_{bus}). The requirements of the electromechanical conversion system ($i_{elevator}$) must be satisfied by means of these control variables in order to carry out the elevator missions.

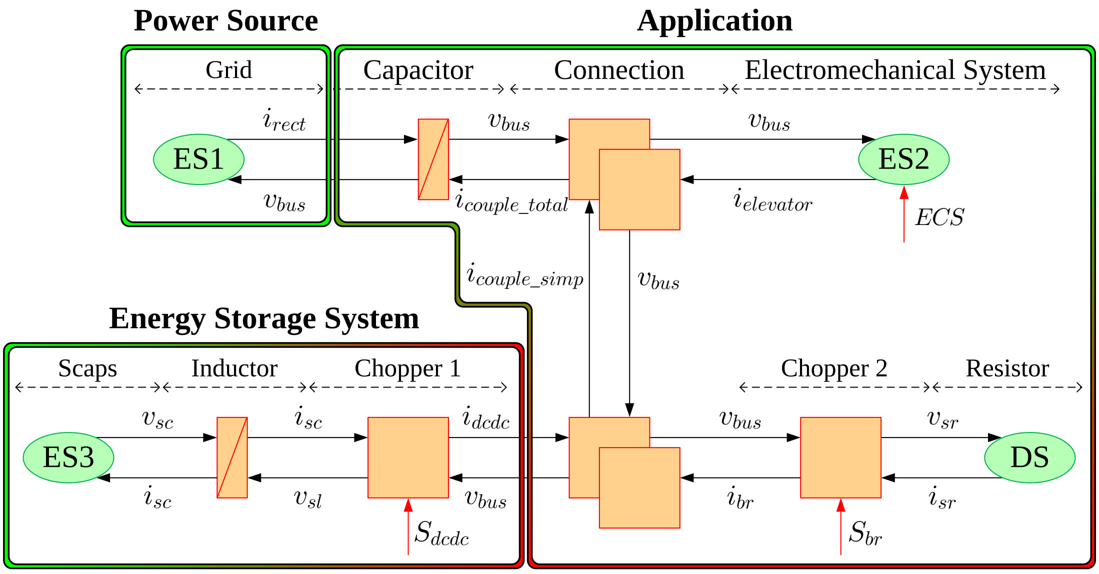


Figure 3.7: EMR representation of an improved elevation system with energy storing capacity.

Table 3.2 summarizes all these elements, in which the EMR elements are related to the system terms and the state variables.

Once the system modeling has been developed with the Energetic Macroscopic Representation, the question that must be answered is how the state variables should be controlled in order to be able to transfer the desired energy between all the sources. For that purpose, the Maximal Control Scheme is developed and presented as follows.

EMR Element	Term	Description
Source ES1	i_{rect}	Rectified grid current.
Source ES2	$i_{elevator}$	Electromechanical system current.
Source ES3	v_{sc}	Supercapacitors voltage.
Source DS	i_{sr}	Braking resistor current.
Accumulation capacitor	v_{bus}	Dc-link capacitor voltage.
Accumulation inductor	i_{sc}	Supercapacitors current.
Conversion	S_{dcdc}	ESS dc-dc converter.
	S_{br}	Braking resistor dc-dc converter.
Coupling	$i_{coupling\_simp}$	Connection to the common dc-link.
	$i_{coupling\_total}$	Connection to the common dc-link.

Table 3.2: EMR representation summary of an improved elevation system with energy storing capacity.

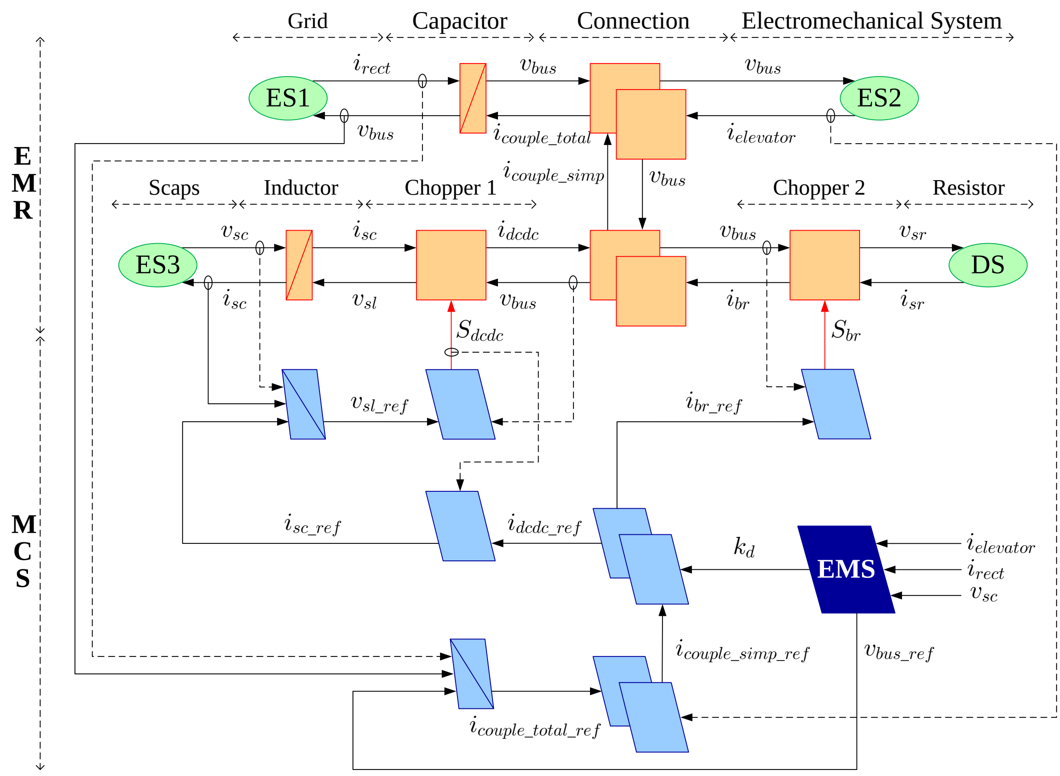


Figure 3.8: Energetic Macroscopic Representation and Maximal Control Scheme representations of an improved elevation system with energy storing capacity.

Elevation System Control

The control scheme of the system can be deduced from a step-by-step model inversion, obtaining what is known as the Maximal Control Scheme (MCS) and defining the inner and outer control loops. Each block of the EMR has its equivalent block in the control scheme. Figure 3.8 shows the MCS representation of the elevator system as well as the EMR representation. As it can be seen, each orange block (EMR) has its equivalent blue block (MCS). Note that the energy sources have no equivalent block in the control scheme.

The control of accumulation elements is implemented with basic controllers such as feedforward Proportional Integral (PI) controllers. The objective is to control the state variables of the system, the inductor current and the capacitor voltage (i_{sc}, v_{bus}), to their references (i_{sc_ref}) and (v_{bus_ref}). The output of the current controller is the voltage that must be imposed to the inductor to obtain the desired current (v_{sl_ref}), while the output of the voltage controller is the current reference to the capacitor ($i_{couple\_toral\_ref}$).

This system consists of two conversion systems, the braking resistor and the ESS. The braking resistor is modulated with the chopper modulation factor (S_{br}) determined from the resistor current reference (i_{br_ref}). The ESS dc-dc converter is modulated with the dc-dc modulation factor (S_{dcdc}) determined from the voltage reference of the inductor controller (v_{sl_ref}). Note that the modulation factor can also be used for estimating variables (i_{dcdc_ref}, i_{sc_ref}).

The coupling blocks are represented by the relation between the terms they link. The objective is to define the value of each reference term according to the kind of coupling. The lower coupling is defined by expression (3.11), with two well-known terms (inputs), and a third one (output), which is the consequence of the two first terms.

$$i_{couple\_simp\_ref} = i_{elevator} - i_{couple\_toral\_ref} \tag{3.11}$$

In contrast, the upper coupling is more difficult to define. The block consists of two outputs (i_{dcdc_ref}, i_{br_ref}) and a single input ($i_{couple\_simp\_ref}$). Therefore, an additional input is required in order to be able to define the outputs. The solution is to introduce a distribution factor (k_d) between 0 and 1, responsible for sharing the input current reference into two output current references.

The analytical expressions are (3.12) and (3.13).

$$i_{dcdc\_ref} = i_{couple\_simp\_ref} \cdot k_d \tag{3.12}$$

and

$$i_{br\_ref} = i_{couple\_simp\_ref} \cdot (1 - k_d) \tag{3.13}$$

However, the difficulty lies in the definition of the distribution factor. For that purpose, an additional block must be introduced, which represents the energy management strategy, shown as the EMS block. Light blue blocks can be grouped and referred as the Power Management Strategy (PMS) level, responsible for controlling the system instantaneously. On the contrary, the dark blue block can be referred as the EMS level, responsible for driving the system in a desired manner over time. This is the hierarchical structure introduced by Rosario [31] and identified in the EMR and MCS representations.

Therefore, the EMS block is responsible for defining the distribution factor. Moreover, the dc-link voltage reference (v_{bus_ref}) must also be defined by the same block because there is no other outer control loop to define it. In order to be able to make the correct decisions, the EMS block inputs must provide the necessary information for the system. In this case, three terms are required; First, the electromechanical conversion system current which is necessary in order to know the power and energy requirements and the operation mode (traction or regenerative). Second, the grid current (i_{rect}) in order to control the grid energy consumption. And finally, the supercapacitors voltage (v_{sc}) in order to estimate the state of charge of the ESS. The analytical expression of the EMS block is defined in equation (3.14).

$$[k_d,\, v_{bus\_ref}] = f(i_{elevator},\, i_{rect},\, v_{sc}) \tag{3.14}$$

The EMR and the MCS have allowed the modeling of an improved elevation system with energy storing capacity in order to determinate the framework of the DP based energy management strategy. Furthermore, the input and output terms of the optimized control strategy have also been identified and defined.

3.2.2 Electromechanical Conversion System Analysis

In the previous section the elevation system has been modeled from an energy and control point of view. The framework of the optimized control strategy has also been defined. The control strategy needs information from both the energy storage system and the electromechanical conversion system. The ESS has already been analyzed in a previous section but the electromechanical conversion unit has not yet been analyzed and modeled. For that reason, the electromechanical system is physically analyzed in this section in order to be able to formulate the analytical expressions for defining the electrical power and energy requirements of the source (ES2) and its variable ($i_{elevator}$) in the EMR representation.

The electromechanical elevator is composed of several elements, as shown in figure 3.9:

- Cabin: The element where the passengers are mounted. It is composed of the cabin mass (m_e) and the passengers mass (m_p).
- Cable: The connecting element between the cabin and the counterweight. The cable mass is divided in two parts, the cabin side mass (m_{c1}) and the counterweight side mass (m_{c2}).
- Counterweight: The balancing element which reduces the maximum torque of the motor. This mass is defined by (m_c).

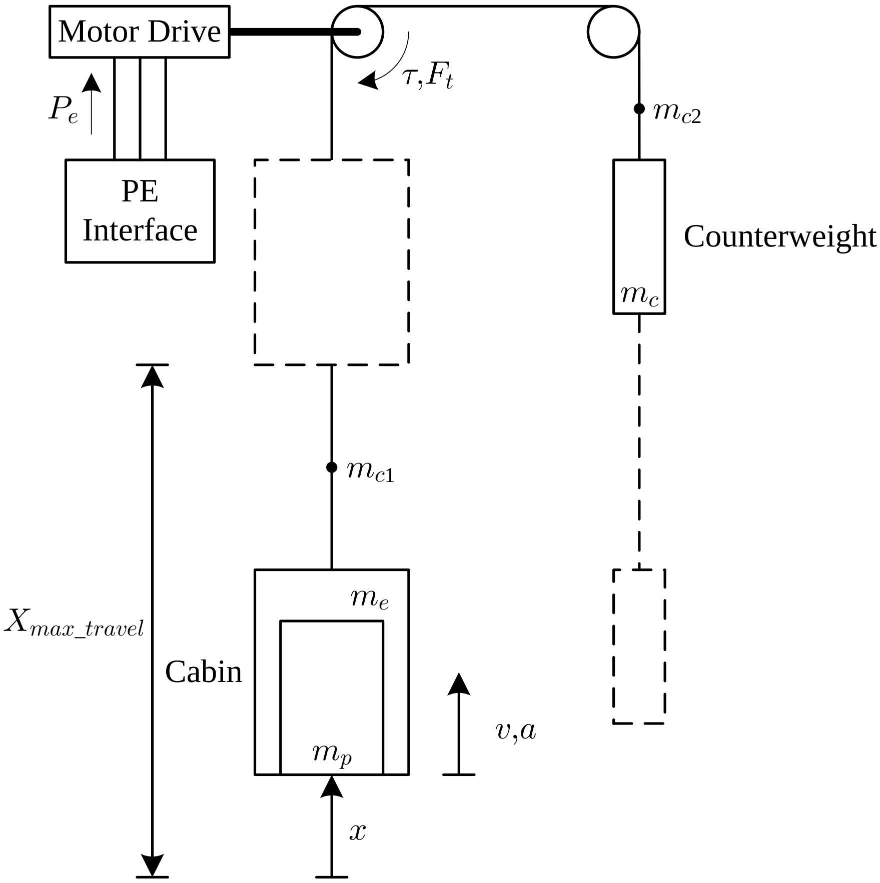


Figure 3.9: Electromechanical representation of an elevator.

- Motor drive: The eletromechanical conversion system. It is able to transform electrical power in mechanical power (τ, F_t) and vice versa.
- Power Electronics (PE) interface: It is responsible for providing or absorbing power from the motor drive, according to the operation mode. It provides or absorbs the elevator electric power (P_e).

The constraints and sign criteria must be defined before analysing the system. The maximum travel length is expressed as the (X_{max_travel}) parameter and the positive direction of position, velocity and acceleration is for upward missions. The second law of Newton is formulated in equation (3.15).

$$\sum F_i = \sum m_i \cdot a \tag{3.15}$$

Taking into account all these considerations, the general expression is formulated in equation (3.16).

$$F_t - m_p \cdot g - m_e \cdot g - m_{c1} \cdot g + m_{c2} \cdot g + m_c \cdot g = (m_p + m_e + m_{c1} + m_{c2} + m_c) \cdot a \quad (3.16)$$

When the elevator is moving with a constant velocity (v), the mechanical power is equal to the electrical power divided by the cabin velocity (3.17), neglecting the efficiency terms.

$$F_t = \frac{P_e}{v} \quad (3.17)$$

The total cable mass is constant (M_f), but depending on the cabin position (x), the mass in each side (cabin and counterweight) is different, according to equation (3.18).

$$m_{c1} = M_f \cdot (X_{max\_travel} - x) \qquad \text{and} \qquad m_{c2} = M_f \cdot x \quad (3.18)$$

The passengers mass is directly related to the number of passengers (N_p) multiplied by the average weight of a person (m_{pass}) (3.19).

$$m_p = N_p \cdot m_{pass} \quad (3.19)$$

By introducing these considerations and by sorting out equation (3.16), the general expression of an electromechanical elevator is obtained (3.20). The electric power is composed by three terms. The first term is due to the cabin acceleration. The second term is due to the cabin velocity. And finally, the third term is due to the cable displacement.

$$\begin{aligned} P_e = {} & a \cdot v \cdot (N_p \cdot m_{pass} + m_e + M_f \cdot X_{max\_travel} + m_c) + \\ & v \cdot g \cdot (N_p \cdot m_{pass} + m_e + M_f \cdot X_{max\_travel} - m_c) - \\ & 2 \cdot v \cdot x \cdot g \cdot M_f \end{aligned} \quad (3.20)$$

In the previous section, it was introduced a vector regarding to the mission's parameters (ECS) in order to evaluate the power requirements of the electromechanical conversion system (P_e). And now, the terms of this vector have been identified in (3.21).

$$ECS = [a \quad v \quad x \quad g \quad M_f \quad m_c \quad m_e \quad m_{pass} \quad N_p \quad X_{max\_travel}] \tag{3.21}$$

Once the general expression is stated, the two operation modes of the elevator must be identified. For that purpose, from these three terms of the equation only the second one is considered, the one referred to the cabin velocity. The term related to the cabin acceleration is neglected due to the short time lapse during the starting and ending mission phases. The term related to the cable can also be neglected due to its low mass compared to the cabin and passengers mass.

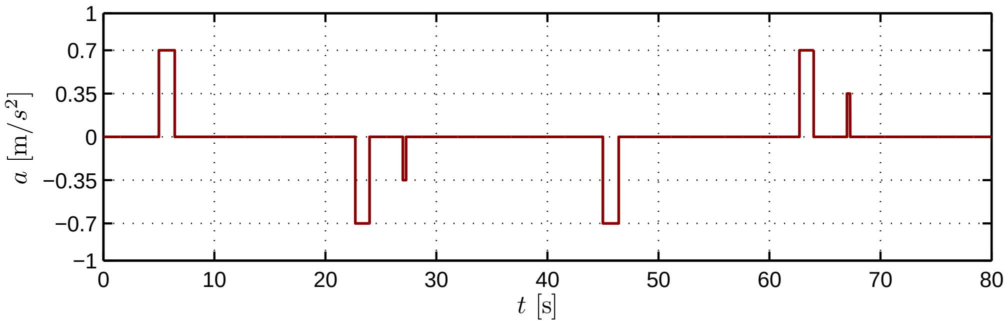
Therefore, only taking into account the velocity term, the operation mode is directly related to the cabin moving direction and the number of passengers. The elevator is in traction mode when the elevator is moving upwards and the combination of the cabin and passengers mass is heavier than the counterweight. Or on the contrary, when it is moving downwards and the combination of the cabin and passengers mass is lighter than the counterweight (3.22). It should be pointed out that for positive values of (P_e) the system is in traction mode, while for negative values it is in regenerative mode.

$$\begin{array}{c}\text{Traction}\\ \text{mode}\end{array} = \begin{cases} v > 0 & \rightarrow \quad N_p \cdot m_{pass} + m_e > m_c + M_f \cdot (2 \cdot x - X_{max}) \\ v < 0 & \rightarrow \quad N_p \cdot m_{pass} + m_e < m_c + M_f \cdot (2 \cdot x - X_{max}) \end{cases} \tag{3.22}$$

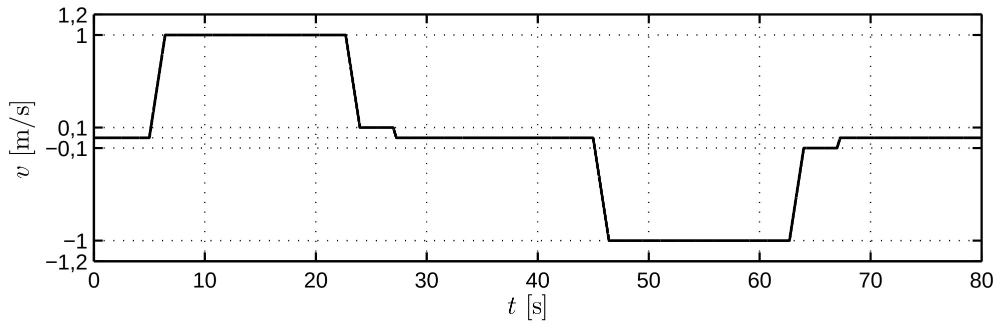
$$\begin{array}{c}\text{Regenerative}\\ \text{mode}\end{array} = \begin{cases} v > 0 & \rightarrow \quad N_p \cdot m_{pass} + m_e < m_c + M_f \cdot (2 \cdot x - X_{max}) \\ v < 0 & \rightarrow \quad N_p \cdot m_{pass} + m_e > m_c + M_f \cdot (2 \cdot x - X_{max}) \end{cases} \tag{3.23}$$

In order to verify the stated expression, some acceleration, velocity and position profiles have been defined, as shown in figure 3.10. These profiles are generated by the elevator controller and they are extracted from a double speed elevator. The cabin is accelerated until reaching the rated velocity. When the elevator is arriving to the floor, it is decelerated to the approximation velocity. And finally, the cabin is stopped in order to complete the mission. Note that the first half of the profile, from ($t = 0s$) to ($t = 40s$), presents an upward mission and the second half, from ($t = 40s$) to ($t = 80s$), presents a downward mission. Both of them show a mission of 18 meters long.

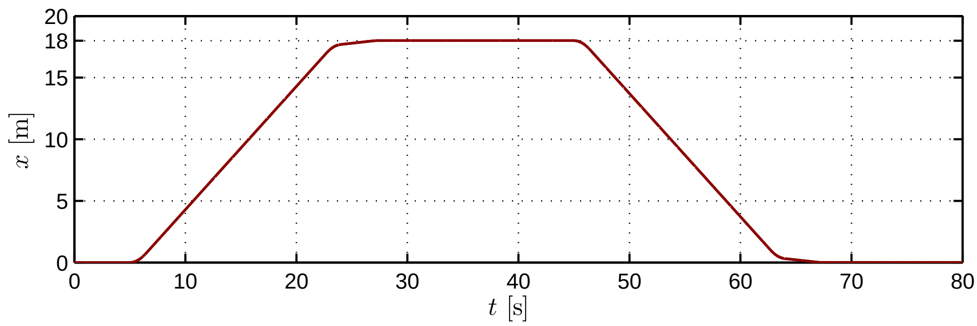
Figure 3.11 shows the electric power profiles (P_e) of an elevator with the parameters summarized in table 3.3. As it can be seen, for the same two missions, and only modifying the number of passengers, the elevator works in different operation modes. In the first



(a)



(b)

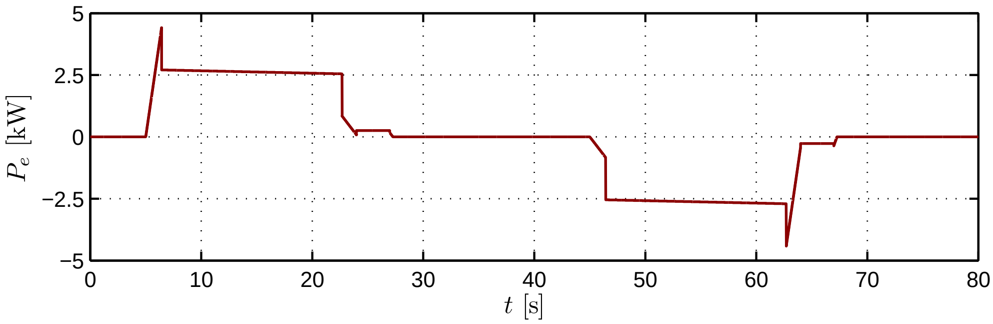


(c)

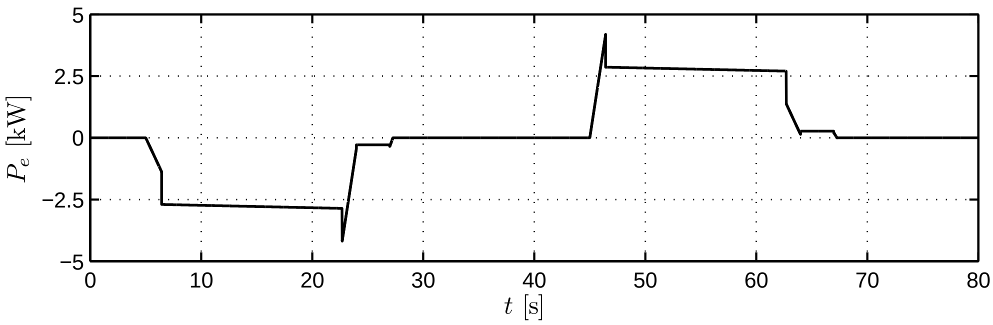
Figure 3.10: Elevator controller upward and downward displacement profiles for a 18 meters mission: (a) acceleration, (b) velocity and (c) position.

mission, from $(t = 0s)$ to $(t = 40s)$, the top figure shows that the elevator is in traction mode because the cabin and passengers are heavier than the counterweight. In contrast, the bottom figure shows the elevator in regenerative mode because the cabin is empty. The second mission, from $(t = 40s)$ to $(t = 80s)$, presents the opposite case. The fully charged cabin is in regenerative mode and the fully discharged cabin is in traction mode.

Finally, as the EMR representation needs these power profiles, the mechanical system model must be reflected in the $(i_{elevator})$ term. The relation between these power profiles



(a)



(b)

Figure 3.11: Electromechanical conversion system upward and downward power profiles for a 18 meters mission: (a) 7 passengers ($N_p = 7$) and (b) 0 passengers ($N_p = 0$).

and the elevator current is presented in equation (3.24).

$$i_{elevator} = \frac{P_e}{v_{bus}} \tag{3.24}$$

It can be concluded that the general expression (3.20) is valid and that the operation mode of an electromechanical elevator is related to the cabin charge and the moving direction. Consequently, these power profiles have been introduced in the EMR

Term	Value	Term	Value
M_f	$0.5kg/m$	N_p	0 or 8
m_c	$1083.5kg$	X_{max_travel}	$18m$
m_e	800	g	$9.81m/s^2$
m_{pass}	$78.75kg$		

Table 3.3: Summary of simulation parameters for the electromechanical conversion system power profiles.

representation of the system in order to define the application requirements.

3.2.3 Generalized Energy and Statistical Description of an Improved Elevator

As it has been shown, the power and energy requirements of an electromechanical elevator can easily be obtained in a mission. The problem arises when a sequence of missions must be defined. The behavior of an elevator is apparently stochastic and there is no analytical expression to model it. The missions sequence of an elevator is directly related to the passengers needs and the place where it is installed. These requirements can be different, depending on the number of passengers and the kind of building (residential, public, hospital...).

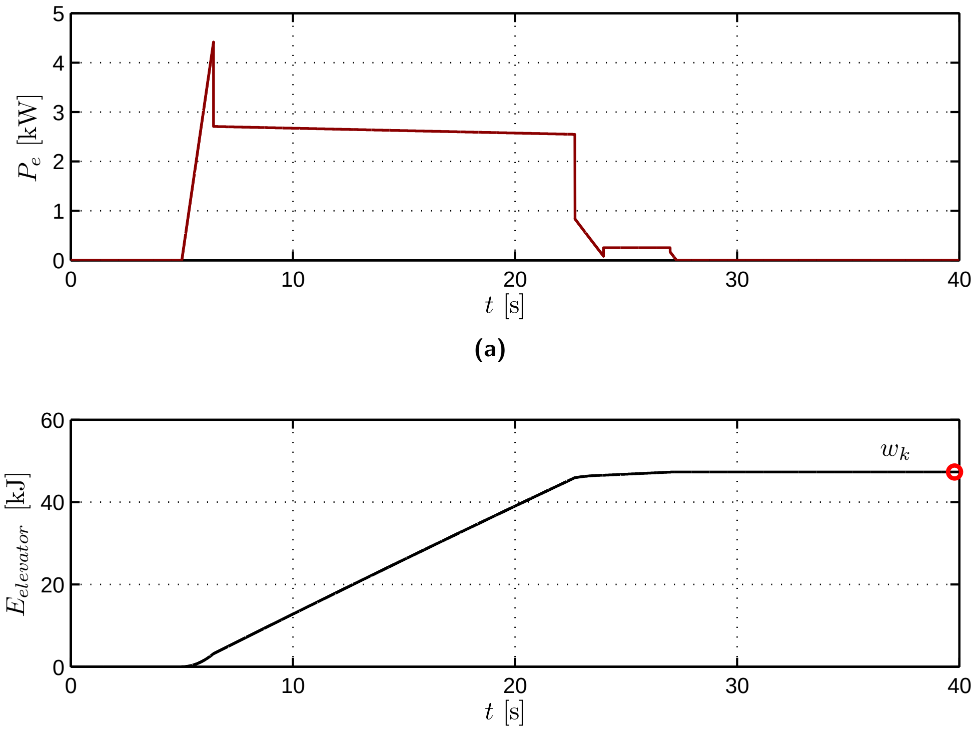
In these systems, the Generalized Energy and Statistical Description (GESD) could be a plausible solution. The objective of this modeling is to represent the energy requirements of an stochastic application (w_k) and to relate them with their probability of occurrence (P_{wk}). Therefore, the energy requirements and their probabilities of occurrence must be identified and defined in order to carry out the statistical representation of an elevator. Concerning the energy requirements (w_k), they can be evaluated by integrating the general expression of the electric power of the electromechanical conversion system in a single mission (P_e), obtaining the energy value ($E_{elevator}$) expressed as (3.25).

$$E_{elevator} = \int P_e \, dt \tag{3.25}$$

Figure 3.12 shows the power and energy profiles of a mission corresponding to a 18 meters upward displacement with seven passengers inside the cabin. The energy requirement (w_k) is defined by the end value of the energy profile ($E_{elevator}$).

The probability of occurrence (P_{wk}) was provided by the elevation systems company Orona based on empirical data obtained from a residential system composed of a five floors elevator shaft and a maximum of eight passengers capability (Orona M34 - $1m/s$, 5 floors, 8 passengers) in a one day traffic profile.

The elevation system considered in this thesis is represented by the GESD shown in figure 3.13. In this system, there are as many different energy requirements as combinations of passengers as well as starting and ending floors. There are 90 possible combinations (5 floors upward and downward, from 0 to 8 passengers). However, with an incremental value of $2kJ$ the number of combinations is significantly reduced as shown in this figure.



(b)

Figure 3.12: Electromechanical conversion system upward mission profiles of 18 meters and 7 passengers: (a) power profile and (b) energy profile.

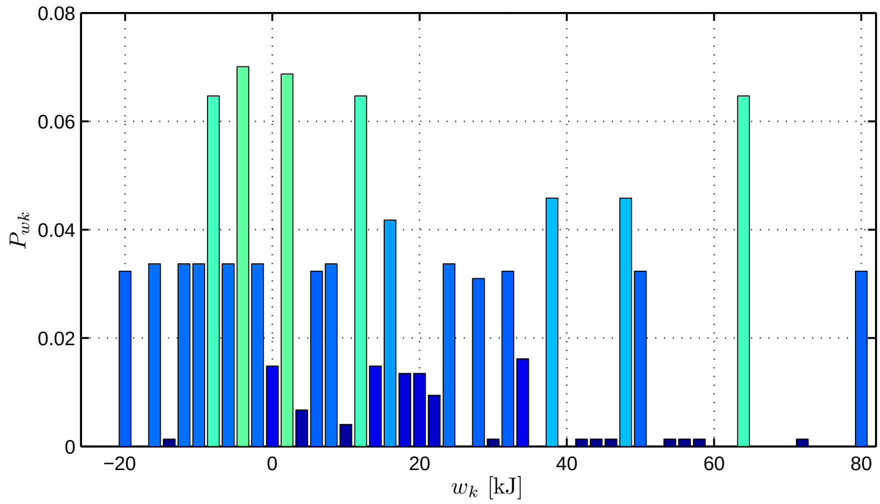


Figure 3.13: The Generalized Energy and Statistical Description (GESD) of an elevation system in a one day traffic profile and $2kJ$ incremental grouping.

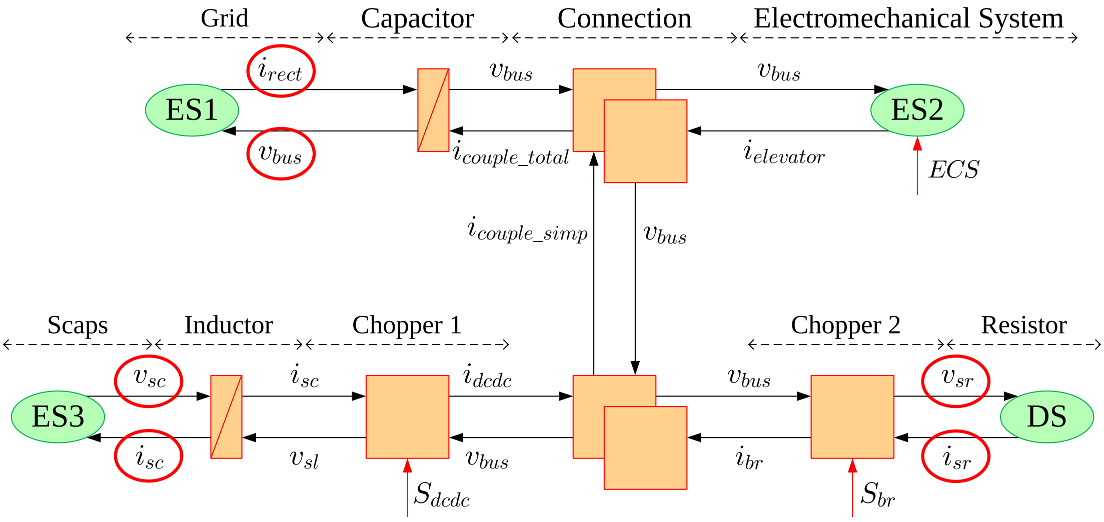


Figure 3.14: Parameters identification on the EMR representation of the considered elevation system.

3.3 Energy Management Strategy Implementation

In the present chapter an energy management strategy for the considered case study is going to be developed and tested in simulation. For that purpose, firstly an analysis of potential objectives for the EMS are presented. Taking the EMR representation as a reference, the objectives are identified and the interest of optimizing them are presented. Finally, the objectives for the optimization are selected and justified.

Then, two particular energy management strategies are developed. On the one hand, the proposed methodology for Dynamic Programming based control strategy is applied and an optimized energy management strategy is obtained. After that, a non-optimized rule based strategy is also developed in order to make a comparison between both solutions. These two energy management strategies are tested in simulation. The objective is to be able to quantify the superior behavior of the DP based control strategy compared to the non-optimized one.

3.3.1 Energy Management Objectives Analysis

The objective of an EMS in these systems is to satisfy the application requirements, and at the same time, to optimize the behavior of the system, for example improving the efficiency or reducing the energy consumption from an energy source. For that purpose, in this section the potential objectives that could be optimized by the EMS are going to be identified and defined.

The EMR representation of the elevation system shown in figure 3.14 allows the identification of some key parameters of the system (rounded in red). These parameters are directly related to the two energy sources, the grid and the energy storage system, as well as with the dissipative source, the braking resistor. These parameters are responsible for satisfying the electromechanical conversion system requirements ($i_{elevator}$) which is non-controllable. In our system, these terms are related to electric magnitudes. Therefore, they correspond to voltage and current parameters, and they define instantaneously the power and therefore also the energy. In addition, in the case of the ESS based on Scaps, these terms also provide information about the state of the supercapacitors tank.

In the next lines, the potential optimization objectives are presented and described. It should be noted that when a potential objective is identified, the optimization aims to reach its maximum or minimum value. In our case, all of them must be minimized.

Grid (ES1)

In the case of the grid, the degrees of freedom are the rectified current (i_{rect}) and the dc-link voltage (v_{bus}). When the current is controlled, the power consumption from the grid is also controlled (P_{grid}), equation (3.26) and consequently the energy consumption too (E_{grid}), equation (3.27).

$$P_{grid} = i_{rect} \cdot v_{bus} \tag{3.26}$$

and

$$E_{grid} = \int P_{grid}\, dt = \int i_{rect} \cdot v_{bus}\, dt \tag{3.27}$$

Therefore, the optimization objectives of the EMS are related to the power and energy consumption from the grid, equations (3.28) and (3.29), respectively. In the case of the grid power, the objective is to reduce short-term power peaks due to cabin accelerations. And in the case of the grid energy, the energy consumption must be reduced in order to improve efficiency.

$$\min(P_{grid}) = \min_{i_{rect} \in [0,\infty)} (i_{rect} \cdot v_{bus}) \tag{3.28}$$

and

$$\min(E_{grid}) = \min\left(\int P_{grid}\, dt\right) = \min_{i_{rect}\in[0,\infty)}\left(\int i_{rect} \cdot v_{bus}\, dt\right) \tag{3.29}$$

Energy Storage System (ES3)

Regarding to the supercapacitors, the degrees of freedom are their current (i_{sc}) and voltage (v_{sc}). As in the case of the grid, the Scaps power (P_{scaps}) and the exchanged energy between Scaps and the application (E_{scaps}) are expressed in equations (3.30) and (3.31), respectively. Furthermore, the depth of discharge (DOD) of the Scaps can also be controlled, equation (3.32). Additionally, the maximum current through the supercapacitors (I_{scaps_max}) and the number of life cycles (N_{scaps}) can also be optimized.

$$P_{scaps} = i_{sc} \cdot v_{sc} \tag{3.30}$$

and

$$E_{scaps} = \int |P_{scaps}|\ dt = \int |i_{sc}| \cdot v_{sc}\, dt \tag{3.31}$$

and

$$DOD_{scaps} = \left(1 - \left(\frac{v_{sc}}{v_{sc\_max}}\right)^2\right) \cdot 100 \tag{3.32}$$

The optimization objectives for the energy storage system are expressed in equations (3.33), (3.34), (3.35) and (3.36). The Scaps power can be limited in order to reduce losses or to limit the maximum power of the ESS. The Scaps energy amount exchanged between the ESS and the application can be limited due to the Scaps capacity limitation or due to the energy losses during the charging-discharging processes. The ESS depth of discharge can also be limited in order to prevent the premature degradation of supercapacitors. The maximum current through supercapacitors can be reduced due to the ESS current limitations. Finally, the number of life cycles can be controlled in order to prevent the

Scaps degradation, and in consequence, the loss of energy storage capacity.

$$\min(P_{scaps}) = \min_{i_{sc}\in\mathbb{R}}(i_{sc} \cdot v_{sc}) \tag{3.33}$$

and

$$\min(E_{scaps}) = \min\left(\int |P_{scaps}|\ dt\right) = \min_{i_{sc}\in\mathbb{R}}\left(\int |i_{sc}| \cdot v_{sc}\ dt\right) \tag{3.34}$$

and

$$\min(DOD_{scaps}) = \min_{v_{sc}\in[0,v_{sc\_max}]}\left(\left(1-\left(\frac{v_{sc}}{v_{sc\_max}}\right)^2\right)\cdot 100\right) \tag{3.35}$$

and

$$\min(I_{scaps\_max}) \qquad and \qquad \min(N_{scaps}) \tag{3.36}$$

Braking Resistor (DS)

For the braking resistor, the degrees of freedom are the current (i_{sr}) and the voltage (v_{sr}). When the voltage is imposed, the power dissipated in the braking resistor is controlled ($P_{crowbar}$), equation (3.37), and consequently the energy losses too ($E_{crowbar}$), equation (3.38).

$$P_{crowbar} = i_{sr} \cdot v_{sr} \tag{3.37}$$

and

$$E_{crowbar} = \int P_{crowbar}\, dt = \int i_{sr} \cdot v_{sr}\, dt \tag{3.38}$$

Source	Objective	Description
Grid (ES1)	$\min(P_{grid})$	Short-term power peak reduction.
	$\min(E_{grid})$	System consumption reduction.
ESS (ES3)	$\min(P_{scaps})$	ESS efficiency improvement.
	$\min(E_{scaps})$	ESS efficiency improvement.
	$\min(DOD_{scaps})$	ESS technology limitation.
	$\min(I_{scaps\_max})$	ESS system limitation.
	$\min(N_{scaps})$	ESS system limitation.
B. Resistor (DS)	$\min(E_{crowbar})$	System efficiency improvement.

Table 3.4: Summary of potential optimization objectives for the improved elevation system.

The optimization objective for the braking resistor is expressed in equation (3.39). In this case, there is only one objective because the power, as well as the energy dissipated in the braking resistor, are only related to the system efficiency. Therefore, the system efficiency can only be increased minimizing the energy losses.

$$\min(E_{crowbar}) = \min\left(\int P_{crowbar}\, dt\right) = \min_{v_{sr}\in[0,\infty)}\left(\int i_{sr}\cdot v_{sr}\, dt\right) \tag{3.39}$$

Optimization Objectives Selection

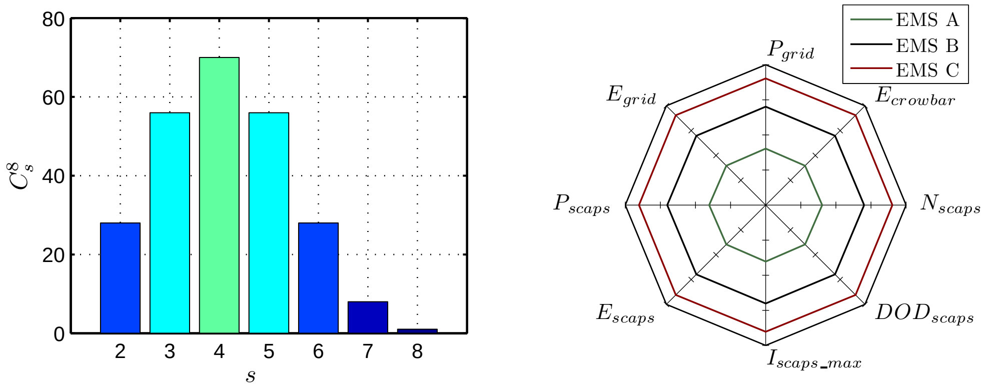
Table 3.4 summarizes all the potential optimization objectives. As it can be seen, there are eight potential optimization objectives for the EMS.

These objectives can be achieved individually (mono-objective) or they can also be grouped for a multi-objective EMS. The problem of the latter ones is the number of possible combinations, as shown in equation (3.40).

$$C_s^r = \frac{r!}{(r-s)!\cdot s!} \tag{3.40}$$

Figure 3.15 shows the number of possible subsets in function of the multi-objective order (s) by using the eight basic mono-objectives. It can be appreciated how the number of combinations grows up, until reaching 70 different combinations for a fourth order multi-objective control strategy. Then, the combinations go down until a single EMS of 8th order.

Figure 3.15 shows a comparison chart (spider chart) between control strategies where



(a) **(b)**

Figure 3.15: Optimization objectives grouping: (a) number of possible combinations and (b) EMS comparison chart.

the axis are the potential optimization objectives, presented in table 3.4.

Between all the possible objectives, the energy management strategy will be developed for a multi-objective optimization based on two objectives.

The grid is mainly affected by two aspects in elevation systems: on the one hand, the energy consumption (E_{grid}), and on the other hand, the power peaks due to cabin accelerations (P_{grid}). Both of them can be reduced when an ESS is introduced and correctly managed. The grid power smoothing or short-term power peaks reduction presents more advantages than the energy consumption reduction. First, the electric installation or switchgear can be smaller if the maximum power peak is reduced. Furthermore, if this power peak is significantly reduced, the elevator could even be connected to a single-phase grid instead of using present three-phase connections. Moreover, from the economic point of view, it is also more interesting to reduce the maximum power peak instead of reducing the energy consumption. Therefore, the maximum power peak from the grid must be minimized:

- **EMS Objective 1**: Grid power smoothing ($\min(P_{grid})$).

Nevertheless this is not the only aspect to be taken into account. The considered elevation system incorporates a dissipative source, the braking resistor. If this term is not taken into account by the control strategy, much energy could be wasted in regenerative mode as the ESS would always be completely charged in order to provide energy for maximum grid power smoothing in traction mode. Therefore, it is necessary to minimize braking resistor losses too:

- **EMS Objective 2**: Braking resistor energy losses minimizing ($\min(E_{crowbar})$).

Notation	Object	Case Study Identification
x_k	State variable	State of charge of supercapacitors tank.
u_k	Decision variable	Energy absorbed from the grid.
w_k	Perturbation variable	Energy consumed or provided by the electromechanical conversion system.
g_k	Objective function	Stock management theory cost function.
P_{wk}	Occurrence of w_k	Statistical information extracted from the GESD.
m	Length of P_{wk}	Statistical information array length extracted from the GESD.
X_{max}	ESS capacity	Supercapacitors tank maximum capacity.

Table 3.5: Main objects of a Dynamic Programming based strategy for an improve elevation system with energy storing capacity.

Note that no objectives referred to the energy storage system have been considered. The reason is that the system has been designed and developed as efficient as possible (P_{scaps}, E_{scaps}), and furthermore, it does not any significant present operational limitations for this application (DOD_{scaps}, I_{scaps_max}, N_{scaps}).

3.3.2 Dynamic Programming Based Energy Management Strategy

Following, the proposed implementation methodology for energy management strategies based on Dynamic Programming is going to be applied in order to develop and to obtain an optimal control strategy for an elevation system with energy storing capacity based on supercapacitors.

1 - Decisions and Costs Map Creation

In this step, the possible values of the decision variable (u_k) are analyzed, and also, how this variable and the perturbation variable (w_k) influence the possible values of the state variable (x_k). The objective is to represent the different states where the system is, and the values that have to be assigned to the decision variable in order to evolve from one state to the next one. It should be pointed out that due to the stochastic behavior of the considered elevator, the result will be a multi-dimensional representation of decisions and costs maps.

But first, the variables for the DP based EMS must be identified. For that purpose, table 3.5 summarizes all the variables identified in the considered system.

The evolution of the considered system (f_k), from the instant (k) to ($k+1$), is defined by equation (3.41). The SOC of Scaps (x_k) is increased of decreased in function of the amount of energy exchanged with the grid (u_k) and the amount of energy that has been

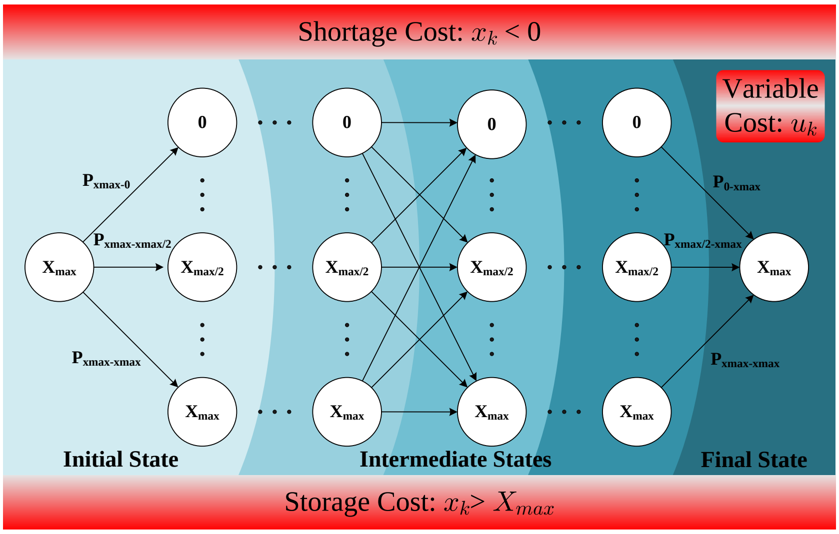


Figure 3.16: Graphical representation of the cost function in the decisions and cost maps.

consumed or provided by the electromechanical conversion unit (w_k).

$$x_{k+1} = f_k(x_k, u_k, w_k) = x_k + u_k - w_k \tag{3.41}$$

Once the evolution expression is stated, the associated costs for each decision must be defined using a proper cost function (g_k). In this case, as mentioned before, the function is based on the stock management theory (equation (3.42)).

$$\begin{aligned} g_k(x_k, u_k, w_k) =& c \cdot u_k + \\ & h \cdot \sum_{1}^{m} \left(P_{wk} \cdot [x_k + u_k - X_{max} - w_k]^+ \right) + \\ & p \cdot \sum_{1}^{m} \left(P_{wk} \cdot [w_k - x_k - u_k]^+ \right) \end{aligned} \tag{3.42}$$

In order to present graphically the penalties introduced by the cost function, a single decisions and costs map extracted from the multi-dimensional representation is shown in figure 3.16. The three terms of equation (3.42) are represented as red blocks. The first term, referred to the variable cost and the optimization objective of power smoothing, is associated to each map of the multi-dimensional representation. The second term, referred to the storage cost and the optimization objective of energy losses reduction, represents the situation where the Scaps are fully charged and some power is absorbed from the grid or regenerated by the electromechanical conversion system. Therefore, this power must be dissipated in the braking resistor. The last term, referred to the shortage cost, represents situations in which the power absorbed from the grid and the energy stored in the Scaps is not enough to satisfy the electromechanical conversion system needs.

Finally, by evaluating all the possible states, the adopted decisions and the associated cost, it is possible to create a multi-dimensional map where the decisions are taken in an optimum way by the DP strategy. Note that the representation is the same as the one presented in figure 2.4 for the stochastic application and the number of maps ($n_{uk} + 1$) is equal to the possible discrete values of the decision variable (u_k), expressed in (3.43).

$$u_k = [0, 1, 2, \ldots, n_{uk}] \cdot \Delta u_k \tag{3.43}$$

2 - Global Map Division

In this step, the maps are going to be divided in zones, defining the instants where the decisions must be taken, and also, the number of decisions that must be taken by the optimized control strategy (N), (3.44).

$$k = 1, 2, 3, \ldots, N + 1 \tag{3.44}$$

Figure 3.17 presents the global maps division. As it can be seen, all maps are identically divided. It should be pointed out that the global map division breaks the sequential decision problem into smaller subproblems, making it possible to apply the Bellman's principle of optimality in order to reach an optimal solution.

3 - Origin and Destination Identification

When the map is divided into different zones, the origin and destination of the problem must be identified. After that, the values of (k) related to every subproblem are set, as it can be seen in figure 3.17. The objective is to define the way of solving the problem in the last step of the proposed methodology.

4 - Objective Definition

In this step, the objective is defined, namely, it is decided if the cost function must be

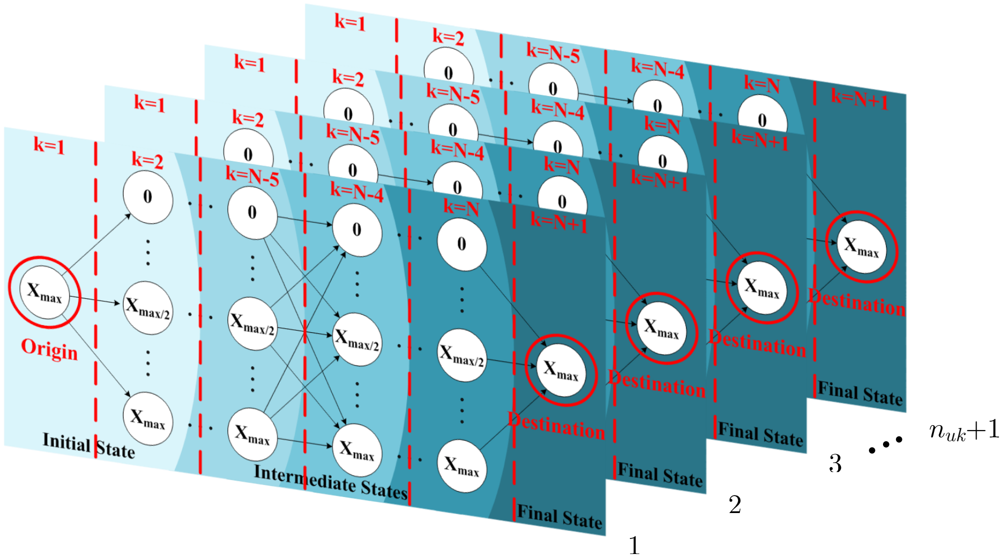


Figure 3.17: Improved elevation system decisions and costs maps division and origin/destination identification.

maximized o minimized. In our case, the objective is clear because the multi-objective control strategy is aimed at reducing the maximum short-term power peak from the grid (EMS objective 1), and also, at reducing the energy losses in the braking resistor (EMS objective 2). Therefore, the cost function must be minimized.

The objective is defined in equation (3.45) for a sequence of (N) decisions. The cost function (g_k) was previously defined in equation (3.42). Note that one more term is introduced, for the instant ($N+1$), in order to take into account a possible final cost of the system due to the adopted decision at instant (N).

$$\min_{u_k \in [0, n_{uk} \cdot \Delta u_k]} E[g_{N+1}(x_{N+1}) + \sum_{k=1}^{N} g_k(x_k, u_k, w_k)] \tag{3.45}$$

5 - Problem Resolution

In this last step, the problem is solved and the optimized DP control strategy is obtained. For that purpose, the resolution is carried out through the backward induction technique, where subproblems are solved from the last instant ($k = N + 1$) to the first one ($k = 1$), and finally, getting an optimal decision policy for the sequence of decisions.

In order to carry out the resolution, the recursive expression of the DP algorithm must be reformulated, taking as reference the general expression (2.5) and introducing the considered cost function for the elevation system (3.46).

Term	Value	Term	Value
w_k	GESD (figure 3.13)	c	1
P_{wk}	GESD (figure 3.13)	h	55
X_{max}	$60kJ$	p	5
Δu_k	$0.3kJ$	N	7
n_{uk}	150	m	53

Table 3.6: Summary of parameters for the resolution of the control strategy.

$$
\begin{aligned}
&J_{N+1}(x_{N+1}) = 0 \\
&J_k(x_k) = \min_{u_k \in U_k, w_k} E[c \cdot u_k + \\
&\qquad h \cdot \sum_{1}^{m} P_{wk} \cdot [x_k + u_k - X_{max} - w_k]^+ + \\
&\qquad p \cdot \sum_{1}^{m} P_{wk} \cdot [w_k - x_k - u_k]^+ + \\
&\qquad \sum_{1}^{m} P_{wk} \cdot J_{k+1}\left([x_k + u_k - w_k]^+\right)] \qquad k = N, \ldots, 2, 1
\end{aligned} \tag{3.46}
$$

Once all steps are completed, the analytical resolution can be carried out, evaluating the DP algorithm in each subproblem of the global map and applying the backward induction technique for minimizing the cost function. The algorithm is going to be executed offline, and then, it will be tested in simulation. For that purpose, table 3.6 summarizes the parameters for the analytical resolution. Note that several values, such as the ESS capacity and the GESD representation, are referred to a full-scale elevator, where finally, this energy management strategy will be experimentally validated.

Figure 3.18 presents the obtained DP based EMS for an stochastic application. In each mission of the sequence (k) and according to the energy stored in the supercapacitors just before starting the mission (x_k), the control strategy defines the energy that must be absorbed from the grid during this mission (u_k), (3.47). Note that the EMS has been presented in a two-dimensional figure instead of a three-dimensional figure. The reason is that the figure contains too many bars for a three-dimensional representation.

$$
u_k = f(k,\ x_k) \tag{3.47}
$$

This control strategy is able to manage an elevator in seven different missions, as it

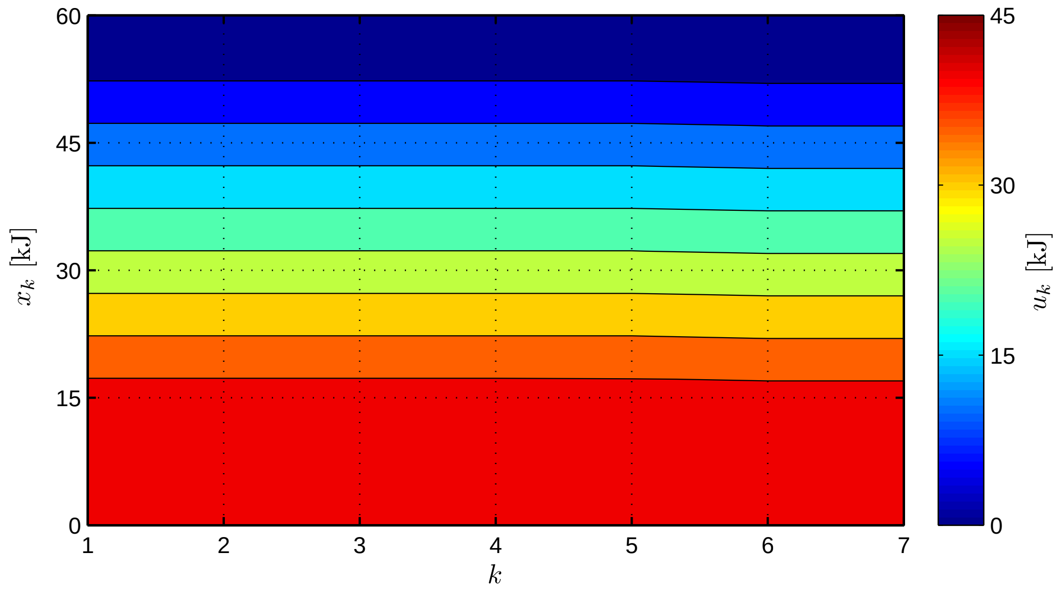


Figure 3.18: Optimized control strategy based on Dynamic Programming for an improved elevation system.

has already been defined in the parameters. If the elevator must be managed in more missions than the decision length (N), the strategy will be applied as a sliding window, repeating the EMS window after (N) missions. This is because the computational cost is exponentially increased for large decisions policies. Applying a sliding window, the obtained results are similar for the whole decision policy and the computational cost is assumable for the considered application.

3.3.3 Rule Based Energy Management Strategy

In order to quantify the behavior of an optimized control strategy based on DP, a non-optimized rule based control strategy has been developed and implemented. The objectives are the same as these defined for the DP based strategy: grid power smoothing and braking resistor energy losses reduction. This control strategy is combinational, i.e., the past and future statistical information are not taken into account. The energy manager make decisions based only on the present mission information.

With regard to the implementation, two terms of the system must be provided to the EMS. On the one hand, the supercapacitors voltage (v_{sc}) in order to estimate their SOC. On the other hand, the power consumed or provided by the electromechanical conversion system (P_e) in order to define the operation mode (traction or regenerative mode) and to know the amount of power consumed by the grid.

Concerning to the SOC of the Scaps, figure 3.19 presents the management of the ESS

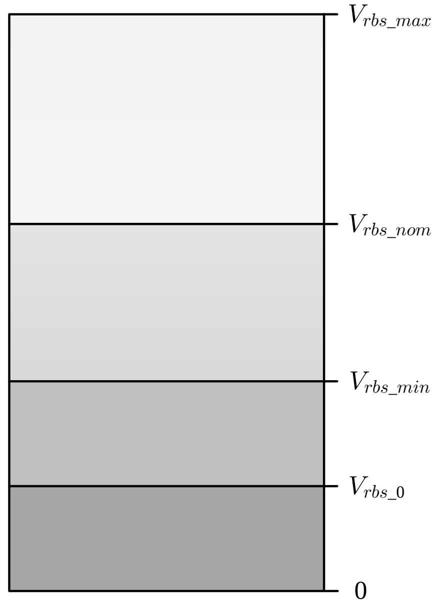


Figure 3.19: Supercapacitors tank division by a non-optimized rule based control strategy.

based on supercapacitors which is divided in four zones of energy, defined by voltage thresholds:

- From ($v_{sc} = 0$) to ($v_{sc} = V_{rbs\_0}$): it is a not-usable energy zone due to the low voltage level.
- From ($v_{sc} = V_{rbs\_0}$) to ($v_{sc} = V_{rbs\_min}$): it is the amount of energy reserved for the automatic rescue mode and it cannot be used during normal operation.
- From ($v_{sc} = V_{rbs\_min}$) to ($v_{sc} = V_{rbs\_nom}$): it is the amount of energy reserved for grid power smoothing. This amount must be enough for the worst case in traction mode.
- From ($v_{sc} = V_{rbs\_nom}$) to ($v_{sc} = V_{rbs\_max}$): it is the amount of energy reserved for regeneration (braking resistor energy losses reduction). This amount must be enough for the worst case in regenerative mode.

Once the information required by the EMS is provided and the energy storage system division is carried out, the control strategy based on rules can be developed. Figure 3.20 presents the flowchart corresponding to this non-optimized control strategy.

The rules are defined depending on the operation mode. In traction mode, if the electromechanical conversion system consumes a power level (P_e) higher than the EMS threshold (P_{grid_rbs}), the energy storage system provides the difference between this

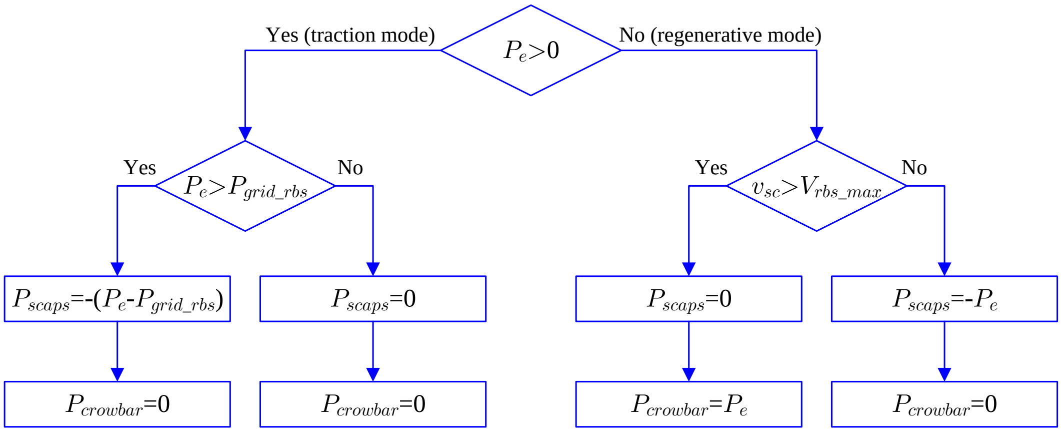


Figure 3.20: Rule based control strategy for the elevation system with energy storing capacity.

threshold and the power required by the application in order to achieve the grid power smoothing goal (P_{scaps}). In regenerative mode, the energy is stored in the supercapacitors tank as long as the ESS is not fully charged, i.e., the voltage (v_{sc}) must be lower than the maximum voltage threshold (V_{rbs_max}). If not, the power is dissipated in the braking resistor ($P_{crowbar}$). Note that the ESS sign criteria is: positive for charging and negative for discharging processes.

It should also be pointed out that when a mission is completed and the supercapacitor voltage is lower than the nominal voltage (V_{rbs_nom}), the Scaps are charged up to their nominal voltage in order to assure the grid power smoothing in the following mission.

3.3.4 Power Management Strategy of the Improved Elevation System

In the introduction chapter, the hierarchical control composed by three levels has been presented (MPEMS), figure 1.14. The energy management level has been developed and implemented in the previous section (DP and RBS). Therefore, the power management level (PMS) must be defined in order to transmit the energy management level commands to the power electronics level.

For the considered case study and in order to define the power management level, the missing terms of the EMS and MCS, (k_d) and (v_{bus_ref}), have to be defined. Following, the power management level is presented.

Distribution factor (k_d)

The distribution factor defines the current through the energy storage system and the braking resistor. The DP based EMS, as well as the rule based EMS, implements the same criteria. When the ($i_{couple\_simp\_ref}$) term is negative because the elevator is working in regenerative mode or some power is being consumed from the grid, the value is ($k_d = 1$) while supercapacitors are not fully charged, otherwise, ($k_d = 0$). In contrast, when the term ($i_{couple\_simp\_ref}$) is positive, the value of the distribution factor is always ($k_d = 1$) because the resistor cannot provide power to the application. The analytical expression is stated in (3.48).

$$k_d = \begin{cases} 0 & \text{if } (i_{couple\_simp\_ref} < 0) \text{ } and \text{ } v_{sc} = v_{sc\_max} \\ 1 & \text{if } (i_{couple\_simp\_ref} < 0) \text{ } and \text{ } v_{sc} < v_{sc\_max} \\ 1 & \text{if } i_{couple\_simp\_ref} \geq 0 \end{cases} \tag{3.48}$$

Dc-link voltage reference (v_{bus_ref})

The dc-link voltage defines how much power is absorbed from the grid. This is because the dc-link is connected to the grid through a non-controllable three-phase rectifier. If the dc-link voltage (v_{bus}) is lower than the average output voltage of the rectifier, the power is absorbed from the grid. In contrast, if this level is higher, no power is absorbed. It is an indirect way to control the power consumption from the grid. For this reason, the EMS block is responsible for controlling the voltage in order to carry out the grid power smoothing objective. Note that between the grid and dc-link there is an equivalent series inductor that limits the current due to the direct connection.

In our case, it will be assumed that the dc-link voltage reference (v_{bus_ref}) is proportional (k_{grid}) to the grid power demand (P_{grid}), implementing an open loop control. The power management layer has been simplified because this thesis is mainly focused on the energy management level. The analytical expression is stated in (3.49).

$$v_{bus\_ref} = P_{grid} \cdot k_{grid} \tag{3.49}$$

3.3.5 Control Strategies Simulation Tests

Once the energy management strategies have been developed, and implemented and the power management level has been defined, these strategies are going to be tested in simulation. For that purpose, they are firstly tested on a single mission in order to verify their correct implementation. Then, both control strategies, the DP based and the RBS based control strategies, are tested on a random sequence of missions for obtaining the first conclusions before their experimental validation in a full-scale elevator. It should be pointed out that cabin and counterweight friction losses have been introduced in order to represent a real elevator.

Term	Value	Term	Value
M_f	$0.5kg/m$	m_{pass}	$78.75kg$
m_c	$1083.5kg$	X_{max_travel}	$18m$
m_e	$800kg$	g	$9.81m/s^2$

Table 3.7: Summary of simulation parameters for the electromechanical conversion system power profile.

One Mission Simulation Tests

Two consecutive missions from a random sequence have been extracted in order to analyze them in simulation. The objective is to check the correct implementation of the control strategies. They are tested with the simulation parameters summarized in table 3.7.

These missions are the second one and the third one from a total sequence of 80 missions. This sequence of missions will be explained in the next section. For the moment, the required information, displacement and number of passengers, is presented in figure 3.24.

Regarding to the non-optimized RBS control strategy, the power profiles are presented in figure 3.21. The top figure shows the electromechanical conversion system power requirements (P_e). The middle figure shows grid power consumption (P_{grid}). Finally, the last figure shows the energy storage system power profile (P_{scaps}).

In the first mission, the elevator is operating in traction mode, from ($t = 5s$) to ($t = t_1$). The grid power threshold has been set to three and a half kilowatts (3.50), and as it can be seen, this power limit is never exceeded. In consequence, the supercapacitors must provide the difference between the elevator power requirements and the defined grid power limit, when that limit is exceeded. Note that the ESS sign criteria is: positive for charging and negative for discharging processes.

$$P_{grid\_rbs} = 3.5kW \tag{3.50}$$

Regarding the second mission and from ($t = 45s$) to ($t = t_2$), the elevator is working on traction mode, and then, it begins to operate on regenerative mode due to the low number of passengers. The grid power threshold is not exceeded, therefore, the energy storage system is not discharged. In contrast, when the power is recovered from ($t = 60s$) to ($t = t_2$), that power is stored in the supercapacitors tank, as it can be appreciated in the bottom figure. It should be noted that it has been supposed that the supercapacitors tank is fully charged. Otherwise, that energy would have been dissipated in the braking

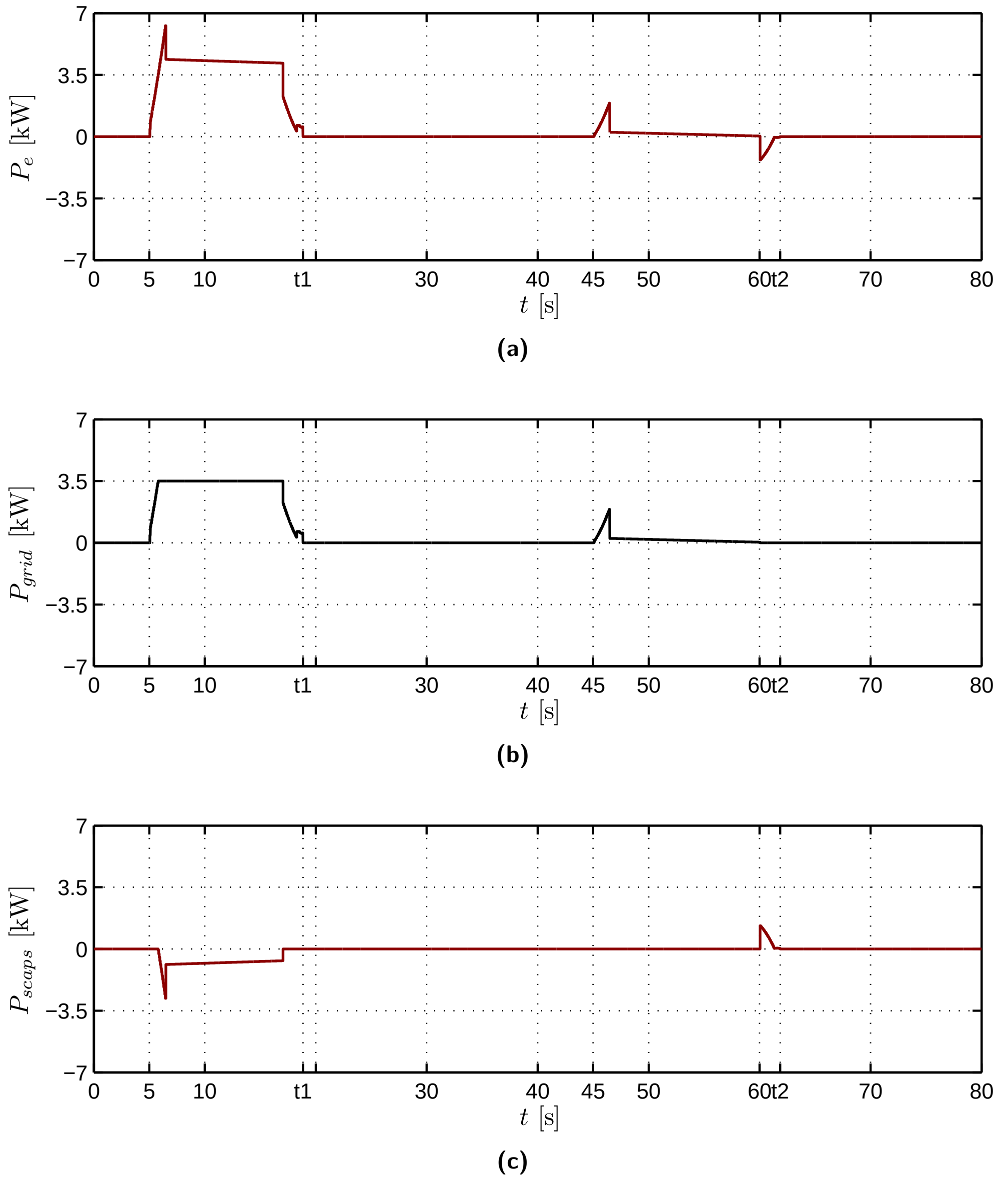
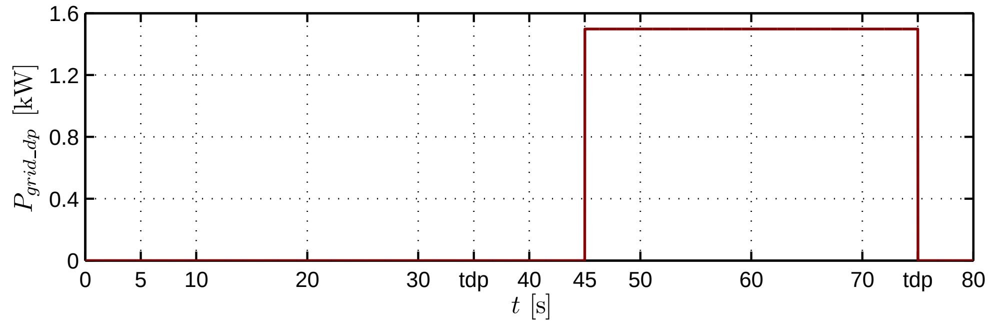


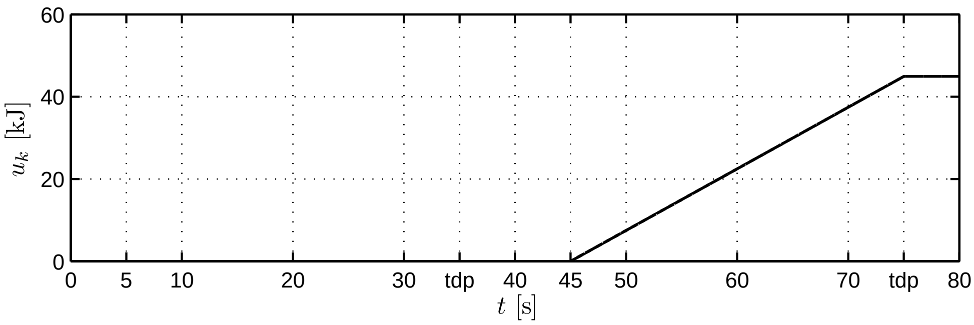
Figure 3.21: Power profiles of two consecutive missions with a RBS strategy: (a) electromechanical conversion system, (b) grid and (c) energy storage system.

resistor in order to protect the system, avoiding the supercapacitors and the dc-link capacitor overloading.

In relation to the DP strategy, it defines the amount of energy that must be introduced in the ESS in each mission (u_k). But, it does not define how to consume this energy. In our case, this energy is consumed in a constant grid power level (P_{grid_dp}) during a fixed period of time (t_{dp}) aimed at reaching the maximum grid power smoothing,



(a)



(b)

Figure 3.22: Power and energy profiles of the Dynamic Programming based control strategy: (a) grid power and (b) grid energy.

expressed in equation (3.51).

$$P_{grid\_dp} = \frac{u_k}{t_{dp}} \tag{3.51}$$

Figure 3.22 presents the power and energy profiles of the DP based control strategy for these two missions. At the top, the grid power reference is applied during a fixed period of time in two consecutive missions, being in both cases ($t_{dp} = 30s$). This power reference is defined by equation (3.51). If these two power profiles are integrated, the DP control strategy references (u_k) are obtained.

These values are expressed in (3.52) and (3.53). For the first mission, the optimized control strategy defines ($u_1 = 0kJ$), and for the second one, the value is ($u_2 = 45kJ$).

$$P_{grid\_dp} = \frac{u_1}{t_{dp}} = \frac{0 \cdot 10^3 J}{30s} = 0kW \tag{3.52}$$

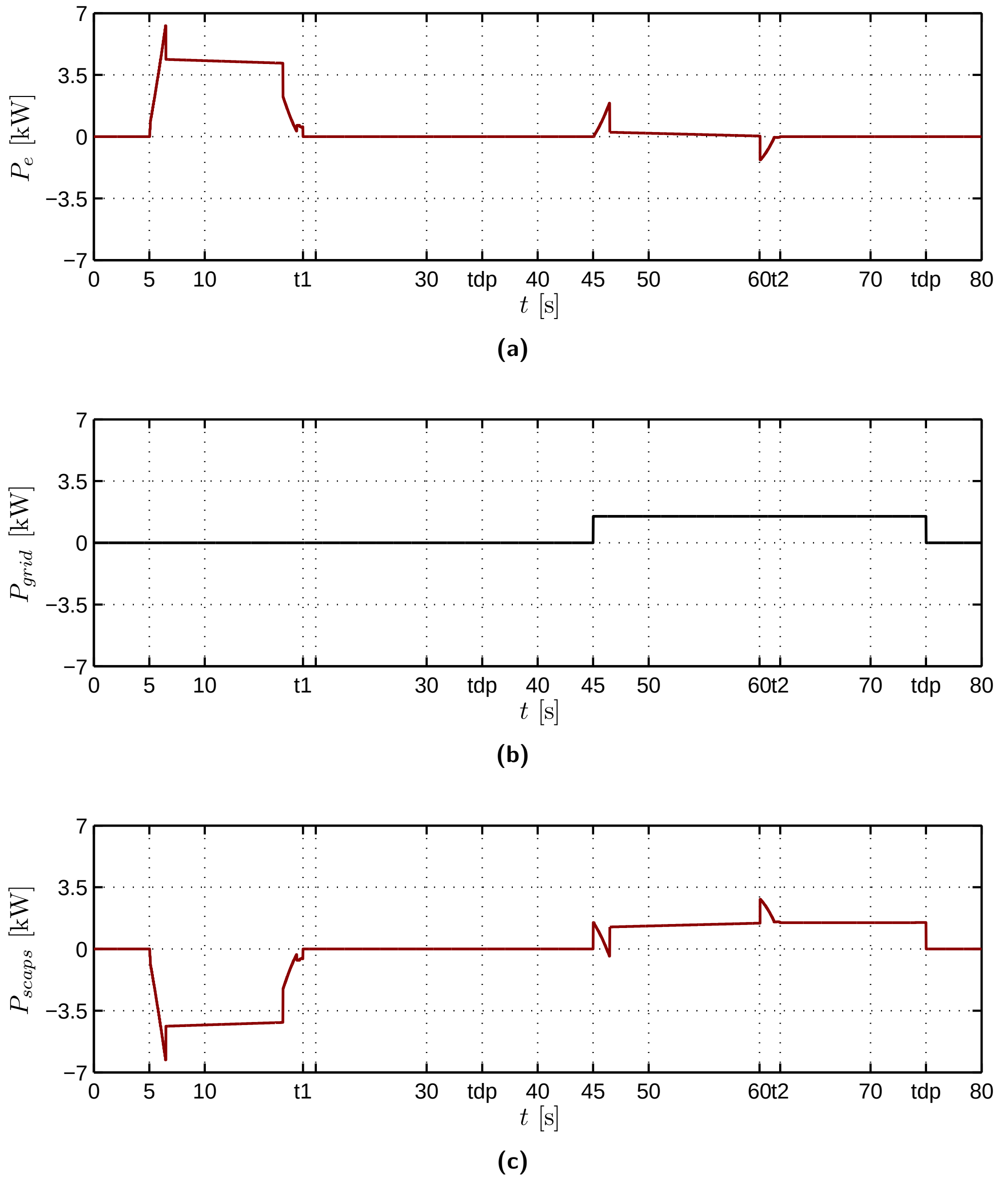


Figure 3.23: Power profiles of two consecutive missions with a DP based control strategy: (a) electromechanical conversion system, (b) grid and (c) energy storage system.

and

$$P_{grid\_dp} = \frac{u_2}{t_{dp}} = \frac{45 \cdot 10^3 J}{30s} = 1.5kW \tag{3.53}$$

The power profiles presented in figure 3.23 are those corresponding to the DP strategy. The electromechanical conversion system power requirements, the grid power consumption and the energy storage system power profile are presented from the top to the bottom, respectively. Note that the top figure is the same as in the rule based control strategy simulation test.

Regarding the first mission, the grid power threshold is equal to zero, from ($t = 5s$) to ($t = 35s$). In consequence, the control strategy fixed period is ($t_{dp} = 30s$). As in the case of RBS strategy, when the electromechanical conversion system power level (P_e) exceeds the energy manager reference (P_{grid_dp}), the ESS provides that power difference (P_{scaps}). In this case, the energy storage system is responsible for providing all the power required by the electromechanical conversion system, because no power is consumed from the grid.

In the second mission, the grid power is steadily consumed, from ($t = 45s$) to ($t = 75s$), applying the energy management strategy in the same period of 30 seconds and being larger than the mission period. In this mission, the ESS must be capable of absorbing the power provided by the elevator in regenerative mode, and also, the power consumed from the grid. As it can be seen, this optimized control strategy prepares the state of charge of Scaps for the following missions in order to assure the grid power smoothing. As in the RBS strategy, it has been supposed that the supercapacitors have not been fully charged, avoiding any energy losses in the braking resistor.

After these simulations tests, it can be concluded that both control strategies have been correctly implemented. Both control strategies, RBS and DP, reduce the short-term power peaks and energy losses in the braking resistor. In addition the DP strategy prepares the SOC of the ESS for upcoming missions in order to achieve these two objectives in a sequence of missions.

In the following section simulations tests are carried out for a random sequence of missions in order to compare both strategies in more realistic conditions.

Sequence of Missions Simulation Tests

The simulations tests of these two control strategies, RBS and DP, have been carried out in a random sequence of missions. In this case the selected sequence of missions represent the behavior of a residential elevation system of five floors elevator shaft and a maximum of eight passengers capacity (Orona M34 - 1 m/s, 5 floors, 8 passengers) in a one day traffic profile. There are 90 different combinations of missions (5 upwards missions, 5 downwards missions and from 0 to 8 passengers) which can also be repeated. Each mission has its probability of occurrence for a one day traffic profile. This information has been provided by the elevators company Orona. This random sequence of mission is illustrated in figure 3.24. Note that the sequence has been developed applying a random function of MATLAB®.

Figure 3.24 shows the cabin position or floor at the beginning of the mission and the bottom figure shows the number of passengers in each mission. Note that the elevator

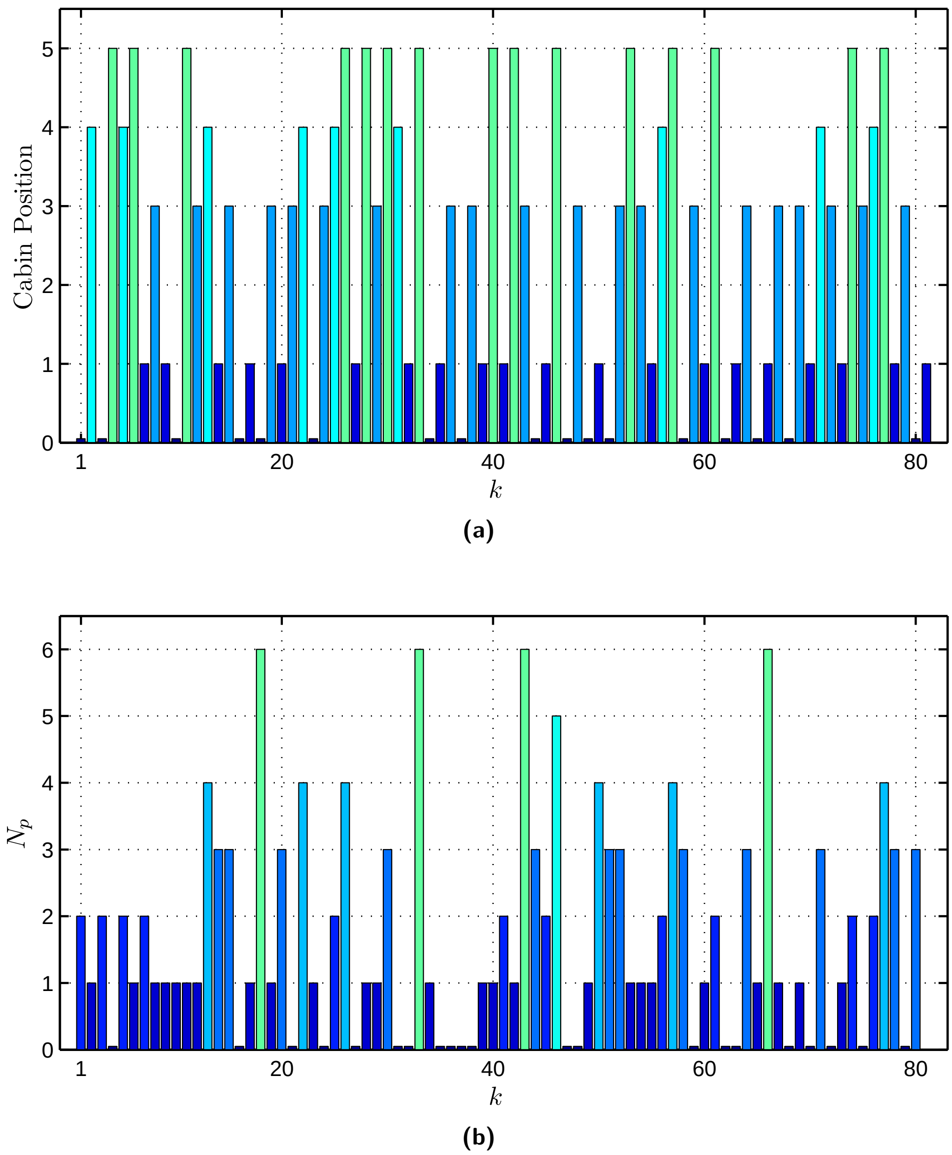


Figure 3.24: Random sequence of 80 missions: (a) cabin starting position and (b) number of passengers.

mission ending floor is represented as the cabin starting position in the following mission. For this purpose, the top figure presents 81 missions in order to contemplate the ending floor of the 80th mission, avoiding a redundant figure for the cabin finishing position in each mission.

In order to develop this sequence, the next three considerations have been taken into account:

- A total of 80 missions is representative of a one day traffic profile. It is more than a 10% of the missions of a day.
- The missions from or to the second floor have been neglected. That floor is inaccessible in the full-scale elevator where the experimental validation of these control strategies will be carried out.
- The missions of seven and eight passengers have been neglected due to their low probability of occurrence compared to the rest of missions, and also because, they generate logistic problems to emulate these loads in the experimental validation.

Once the random sequence of missions has been defined and the control strategies have been developed and implemented, the simulations tests have been carried out. In the following lines, the optimization objectives are presented and analyzed, and then, other parameters are also presented and analyzed in order to get a global vision and to know the boundaries of these energy management strategies.

Regarding the first objective, the grid power smoothing, figure 3.25 shows the grid power profiles corresponding to the defined sequence of missions. The top figure corresponds to an elevator without energy storing capacity (Classic). The middle figure corresponds to an improved elevator with a RBS strategy. The last figure corresponds to an improved elevator with a DP strategy.

As it can be verified, the maximum grid power level has been significantly reduced in the case of both strategies. For a non-improved elevation system the maximum power level consumed from the grid is $7.4kW$. The rule based strategy has been developed and implemented for a maximum level of $3.5kW$. In conclusion, the maximum value has been reduced by 53%. Nevertheless the DP strategy is able to reduce even more this level, down to $1.5kW$, i.e. an 80% of reduction. Therefore, it can be concluded that both control strategies are able to reduce the maximum power level consumed from the grid, but, the DP based strategy achieves a higher level of grid power smoothing.

Concerning the second objective, braking resistor energy losses reduction, figure 3.26 presents the results of simulation tests. The non-improved elevator (Classic) dissipates up to ($188.7kJ$) in the braking resistor. In contrast, the improved elevator can partially reuse this generated energy while the elevator is operating in traction mode. The rule based strategy (RBS) is able to reduce these energy losses by 84% only ($30.1kJ$). In the same way, when a DP based control strategy is implemented, these energy losses are also reduced by 77% ($43.6kJ$). It can be concluded that both control strategies are able to reduce significantly the energy losses in the braking resistor. However in this case, the RBS strategy achieves slightly better results.

It is confirmed that both optimization objectives have been reached in the simulation tests, grid power smoothing and braking resistor energy losses reduction. Nevertheless,

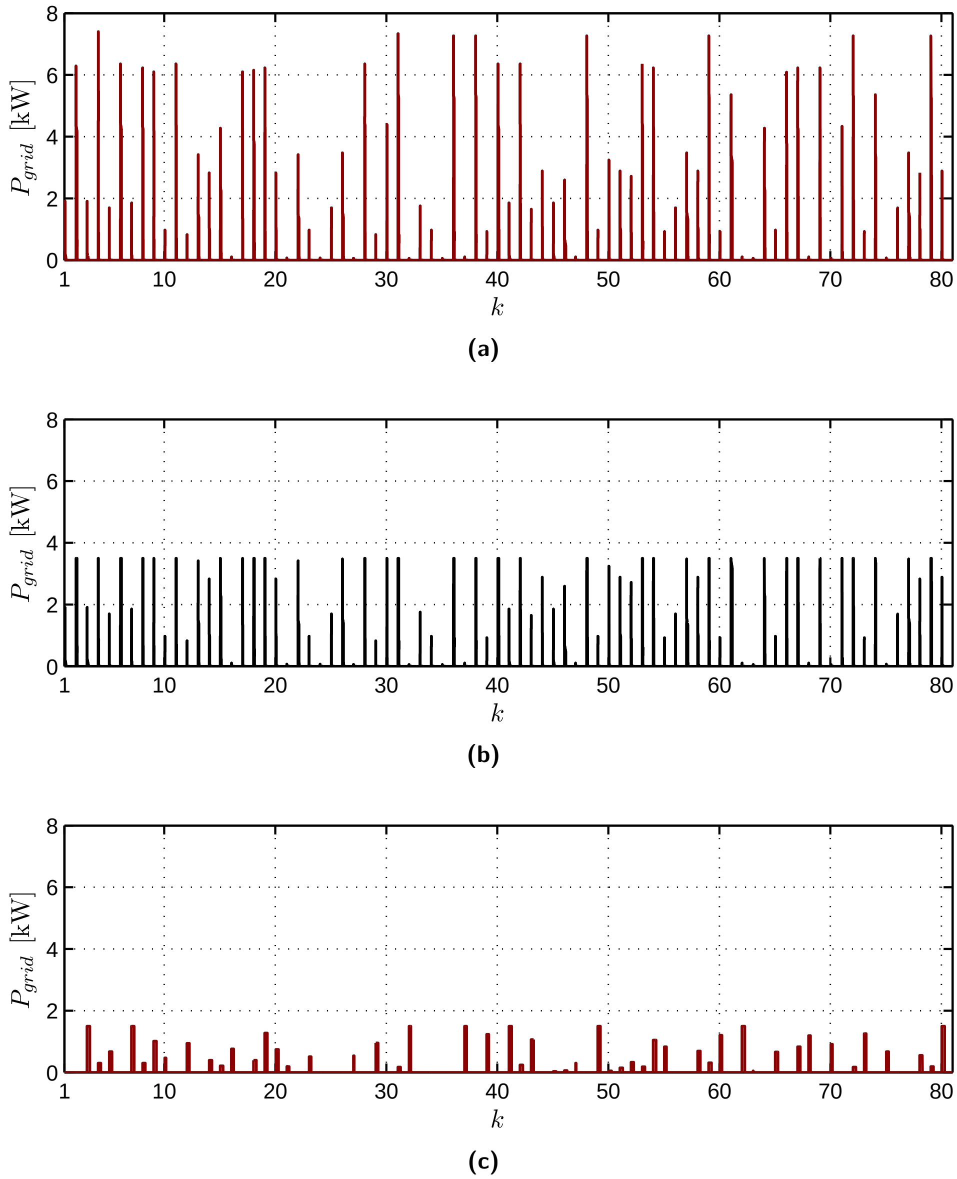


Figure 3.25: Grid power profiles: (a) elevator without energy storing capacity (Classic), (b) improved elevator and rule based control strategy (RBS) and (c) improved elevator and Dynamic Programming based control strategy (DP).

it is also interesting to check the behavior of the rest of non optimized parameters. The objective now is to make a comparison between the developed and implemented energy management strategies taking into account all the optimization objectives from the considered system and to get a global vision of them (table 3.4).

Figure 3.27 presents grid energy profiles. The simulation results show a grid energy consumption reduction. The non-improved elevator consumes ($1119kJ$) (Classic) and the improved elevator reduces the consumption down to ($940kJ$) and ($951kJ$), for the

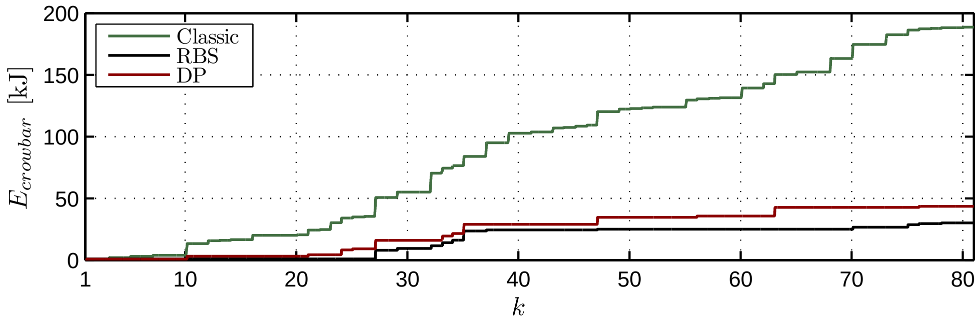


Figure 3.26: Braking resistor energy losses profiles of a non-improved elevator (Classic) and an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

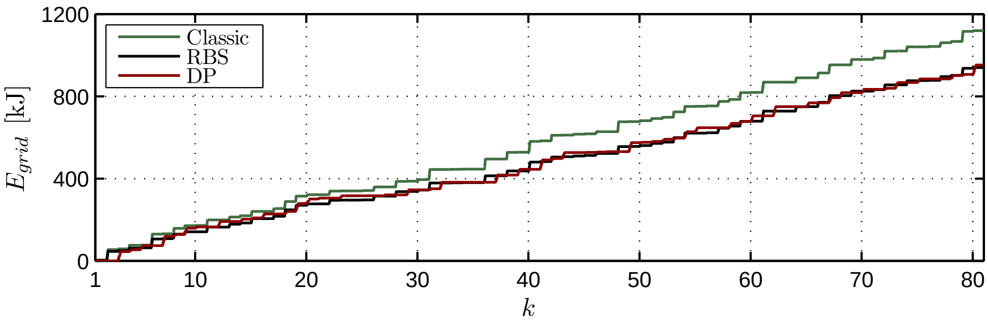


Figure 3.27: Grid energy profiles of a non-improved elevator (Classic) and an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

RBS and the DP strategies, respectively. The reduction is ($179kJ$) and ($168kJ$), i.e., 16% and 15%, respectively. It should be pointed out that the reduction of energy consumption has been higher than the recovered energy. This is due to the fact that the energy storage system starts the simulation test fully charged, and 80 missions later, the state of charge is lower. Therefore, this reduction is a combination between the recovered energy and the stored energy from the scaps.

Regarding to the energy storage systems, there are five terms to be taken into account. First, the amount of energy exchanged between the ESS and the system (figure 3.28). This value represents the energy that has been transferred and consumed from the ESS, reflecting, the use of the energy storage system. It can be remarked that the DP strategy ($2030kJ$) uses six times more the Scaps than the RBS strategy ($338kJ$). There are two possible lectures for this intensive use. On the one hand, the installed ESS has been optimized. On the other hand, the ESS is employed very intensively, and in consequence, it could be prematurely degraded according to its typical lifetime which could be an important drawback in some applications.

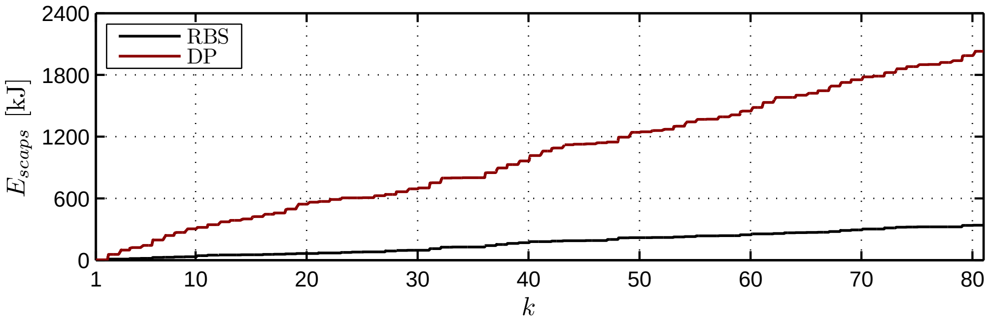


Figure 3.28: Energy storage system energy profiles for an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

Figure 3.29 shows the supercapacitors tank power profiles. Power profiles are higher for the DP based strategy ($7.27kW$) than for the RBS strategy based on rules ($3.9kW$), almost two times higher. These values are partially related to the grid power smoothing level. Therefore, the DP based EMS requires relatively high power levels for the energy storage systems, the supercapacitors and the converter. In addition, system losses would be higher for higher power levels.

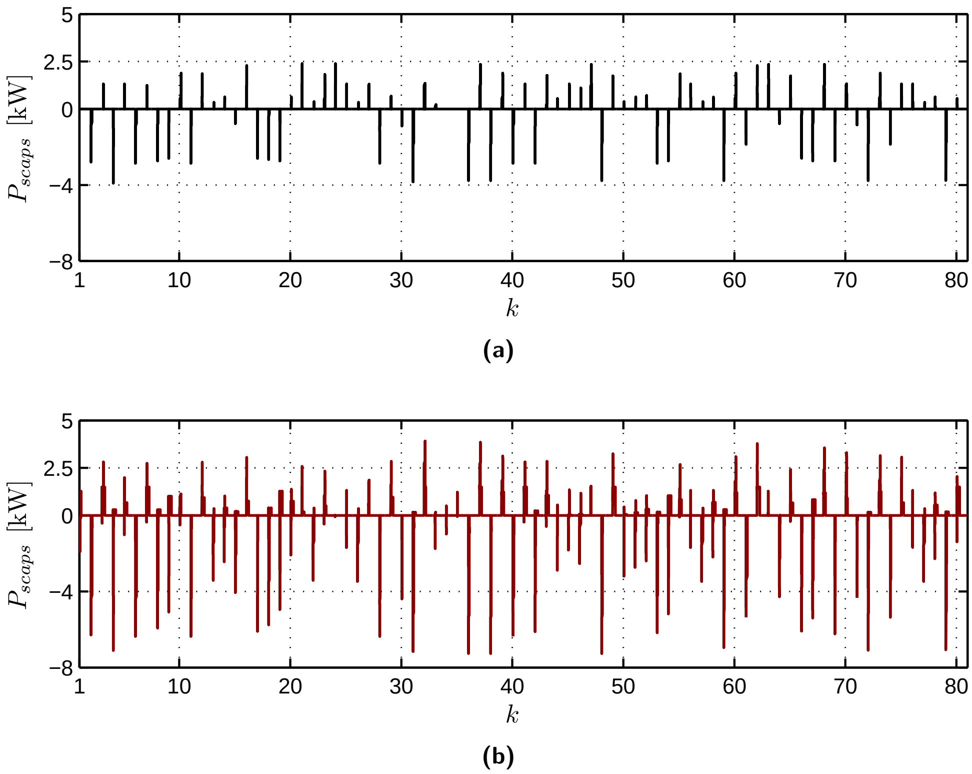


Figure 3.29: Energy storage system power profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

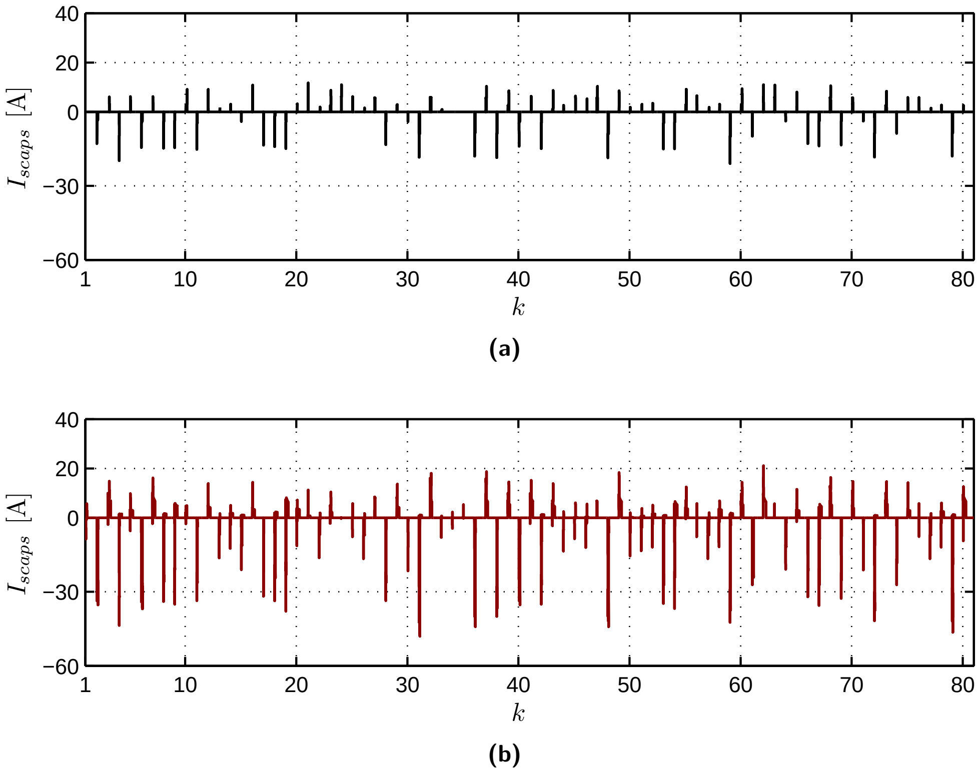


Figure 3.30: Energy storage system current profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

As it can be seen in figure 3.30, energy storage system current levels are also higher, requesting a higher current capability to the supercapacitors and to the converter. When a DP control strategy is implemented, the maximum current is more than twice ($48A$) with respect to the RBS control strategy ($20.95A$). This value is obtained from the ESS power and voltage profiles. An important characteristic of the Scaps is their wide voltage operation range. Therefore, taking as reference the power profile, the current is inversely related to the voltage level.

Figure 3.31 shows the evolution of supercapacitors state of charge over 80 missions, from the energy point of view. Once more, the DP based EMS operates in a wider range than the RBS strategy.

The depth of discharge (DOD) is evaluated taking as reference the state in which the Scaps are fully charged. Therefore, the DOD is equal to 58% for the DP strategy and 40% for the RBS strategy. It should be pointed out that some peaks appear due to the equivalent series resistor of the Scaps, and also, because the ESS voltage is measured in the terminals. When the current is flowing throught the ESS, the output voltage is equivalent to the supercapacitor voltage and the equivalent series resistor voltage, which dissapears for zero-current values. Therefore, these peaks can be neglected.

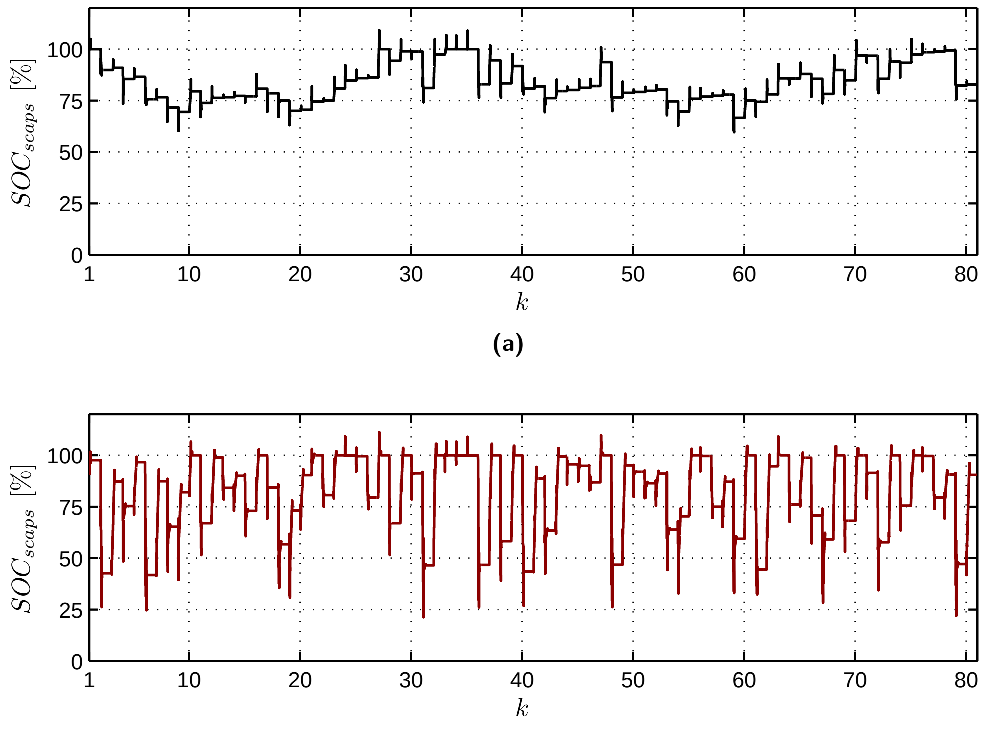


Figure 3.31: Energy storage system state of charge profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

Finally, the evolution of cycles-per-mission (cpm) is presented in figure 3.32. It is a ratio which relates the number of ESS cycles used in each mission, instead of representing the absolute value of the consumed cycles. This factor is useful to evaluate the lifetime of different ESS for the same application. Regarding this value, the factor for the DP control strategy (2.71) is higher than for the RBS (1.23), more than twice. It means that in the DP case the ESS will have be replaced 50% sooner than in the RBS case.

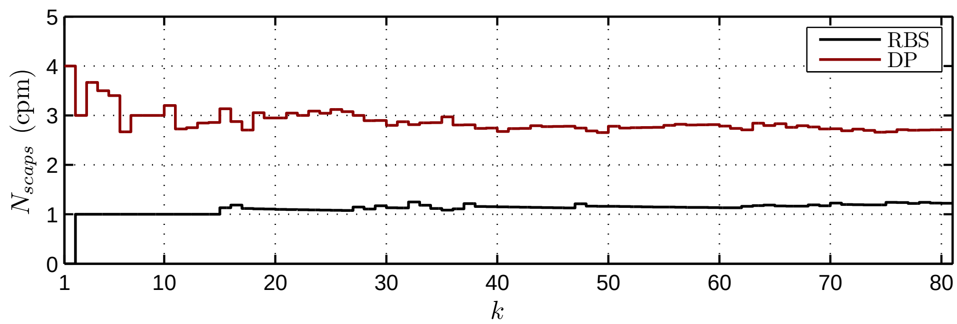


Figure 3.32: Energy storage system lifecycles profiles for an improved elevator with a rule based control strategy (RBS) and a DP based control strategy (DP).

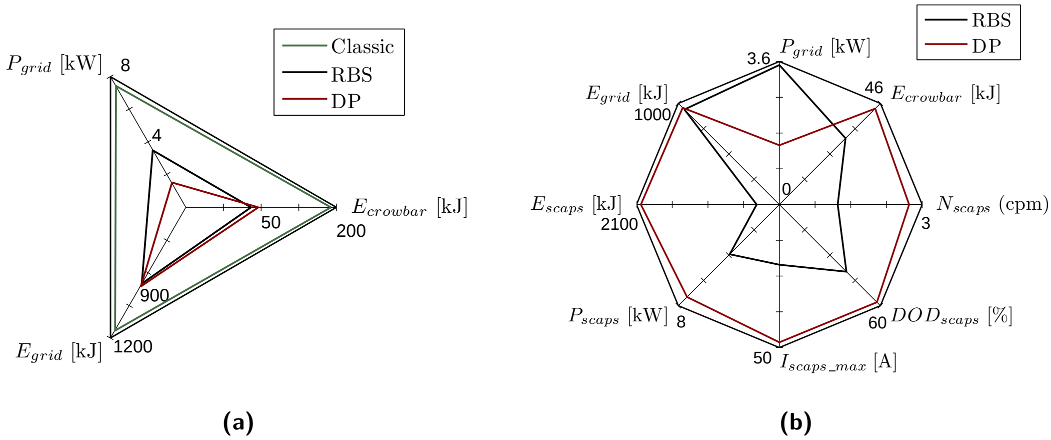


Figure 3.33: Comparison charts of simulations test results: (a) reduced comparison between a non-improved (Classic) and an improved elevator (RBS and DP) and (b) rule based (RBS) and Dynamic Programming based (DP) control strategies comparison chart.

In order to summarize all the simulations tests results, two comparison charts are presented in figure 3.33. On the left, the comparison is carried out between the three terms that can be compared between a non-improved elevator and an improved elevator. On the right, the two developed and implemented control strategies are compared, taking as reference all potential optimization objectives, presented in table 3.4. Note that in both figures, the objective is to get the lowest value as possible in each axis.

Regarding the first comparison, the maximum grid power peak (P_{grid}), the energy consumed from the grid (E_{grid}) and the energy dissipated in the braking resistor ($E_{crowbar}$) are represented. As it can be seen, the improved elevation system with both control strategies is able to reduce the energy consumption from the grid, using the non-dissipated energy in the braking resistor. Besides, the control strategy based on DP reaches a higher level of grid power smoothing.

In the second comparison, it can be appreciated that the terms referred to the ESS (E_{scaps}, P_{scaps}, I_{scaps_max}, DOD_{scaps}, N_{scaps}), are higher for the DP than for the RBS. These values can be interpreted as a better usage of the ESS, but also, as a higher degradation of the ESS. It depends on the safe operating area and the ESS lifetime estimation.

It can be concluded that the defined optimization objectives have been achieved compared to a non-improved elevation system: grid power smoothing and braking resistor energy losses reduction. In addition, the optimized control strategy based on Dynamic Programming reaches better grid power smoothing results. Nevertheless it must be also taken into account that the operating requirements of the energy storage system are higher compared to a non-optimized control strategy.

3.4 Conclusions

In this chapter, the proposed implementation methodology for an optimized DP strategy for energy storing capacity applications has been applied and tested in simulation. The considered case study consists of an improved elevation system with a supercapacitor based energy storage system. First, an introduction to these vertical transport system has been presented in order to know the application more deeply.

Once the case study has been defined and before the energy management strategy implementation, the system modeling has been carried out. Firstly, the Energetic Macroscopic Representation of the system has been obtained by defining the interaction between the power sources (grid, electromechanical conversion system and energy storage system) and the dissipator (braking resistor). Afterwards, this model has been inverted for obtaining the Maximal Control Scheme which defines the inner and outer control loops required by the application, as well as the framework and the required information for the EMS. Then, the electromechanical conversion system has been analyzed and modeled, defining the requirements that must be satisfied by the power source and the energy storage system on a single mission. In our case, the optimized EMS is responsible for controlling the system along several missions, and as this system has a stochastic behavior, the Generalized Energy and Statistical Description has been used. This representation has been developed for a one day traffic profile.

Finally, the proposed methodology has been applied in the improved elevation system. But firstly, the optimization objectives have been analyzed and two objectives have been defined for a multi-objective optimization, grid power smoothing, and the braking resistor energy losses reduction. In order to validate the proposed methodology for an optimized control strategy, a non-optimized Rule Based Strategy has also been developed and implemented. Finally, the simulations tests have been carried out and clarifying results have been obtained, firstly in a single mission, and then, in a random sequence of 80 missions.

4

Implementation and Experimental Validation in a Full-Scale Elevator and Supercapacitors Based Energy Storing System

Summary

In this chapter, the experimental validation of the developed control strategies is presented. Three experimental tests have been carried out in a full-scale elevator with energy storage, including a non-improved elevation scenario and two improved elevation system scenarios. For that purpose, the test bench is presented and described. Then, the experimental validation with one single mission is presented in order to check the correct implementation. Finally, the experimental validation with a random sequence of missions is carried out and the experimental results are presented and analyzed.

4.1 Introduction to the Implementation and Experimental Validation

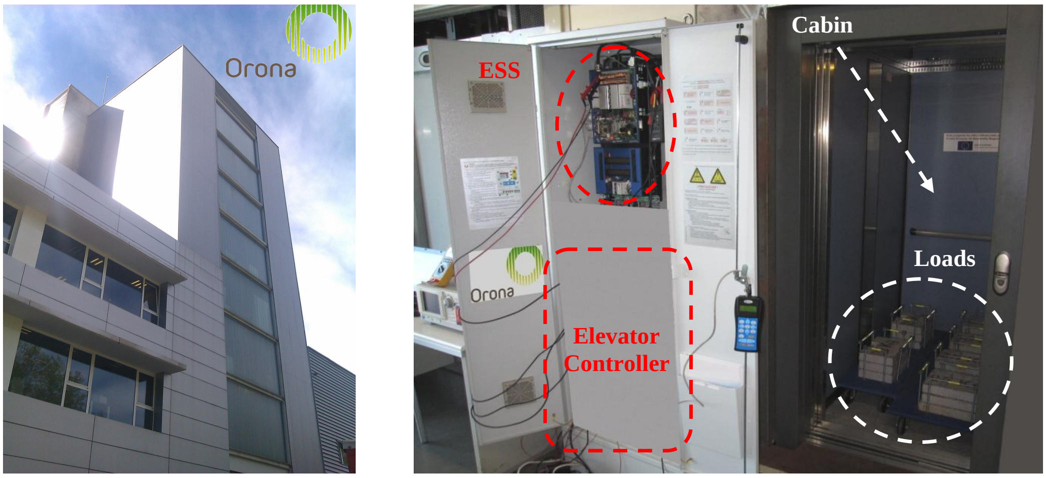
In this chapter the experimental results obtained in three different scenarios are compared based on a random sequence of missions. In the first test, the energy storage system is disabled in order to define the power and energy requirements of a non-improved elevator (Classic). Then in the second test, a rule based control strategy defining new functionalities and improvements is implemented in an improved elevator (RBS). Finally, an optimized control strategy based on Dynamic Programming is tested for the same improved elevator(DP).

Concerning the sequence of missions, it should be noted that the experimental validation has been carried out with the same random sequence of missions defined in the simulation tests, presented in figure 3.24. It consists of 80 missions where the maximum displacement of the elevator car is five floors and the maximum number of passengers is six.

This chapter is divided in four parts. In the first section, the full-scale elevator with energy storing capability (using supercapacitors) is presented and described in detail. Then, the control strategies are validated along one mission in order to check the correct implementation of the control strategies. After that, the experimental results are presented for a random sequence of missions, validating the optimized Dynamic Programming based control strategy and demonstrating its superior features compared to a non-improved elevator, and also, compared to a non-optimized control strategy. Finally, the conclusions of this chapter are presented.

4.2 Test Bench Description

The experimental tests have been carried out in a full-scale elevation system with energy storing capability provided by Orona. The system is composed of a real residential type elevator and an energy storage system prototype based on supercapacitors. Following, the test bench is presented and described.



(a) (b)

Figure 4.1: Full-scale elevator test tower: (a) test tower building and (b) elevation system's main components.

4.2.1 Test Tower

In this section, all the elements of the system are presented in order to introduce the real application of this case study, describing all its different components and defining their parameters. The facility containing the full-scale elevator with energy storing capability and its main components are shown in figure 4.1.

The system can be divided in four main blocks: the electromechanical conversion system, the mechanical system, the elevator controller and the energy storage system based on supercapacitors. Figure 4.2 shows the block diagram of the whole system, showing the interconnection between blocks. The red blocks show the components installed in any residential elevator. While, the blue blocks shows the ESS which provides the energy storing capacity to the elevator.

According to the vertical traveling of the cabin and the counterweight, the elevator shaft is presented in figure 4.2. As it can be seen, there are 5 floors with a height of $5.2m$ for the zero floor and $3.2m$ for the rest of the floors, being the full travel of $18m$ long. Note that there are doors in all the floors except in the second one, being impossible to complete any mission to this floor or from it. In consequence, the random sequence of missions was slightly modified.

4.2.2 Electromechanical Conversion System

The electromechanical conversion system is based on a Permanent Magnet Synchronous Machine (PMSM) developed by Orona. It is a machine especially designed

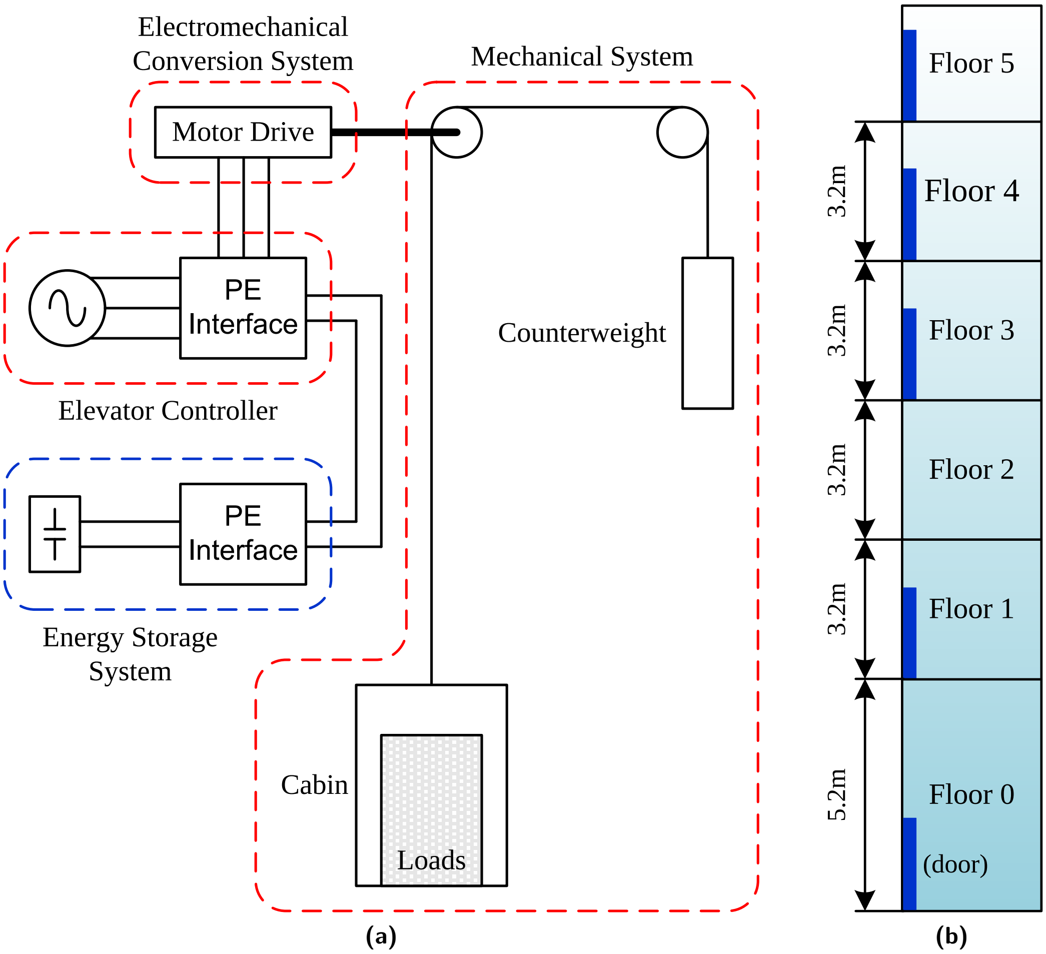


Figure 4.2: Improved elevation system's block diagram: (a) elevation system and (b) elevator shaft.

for vertical transportation applications with a maximum number of passengers of eight (M34-8pax). Orona's PMSM machine is shown in figure 4.3.

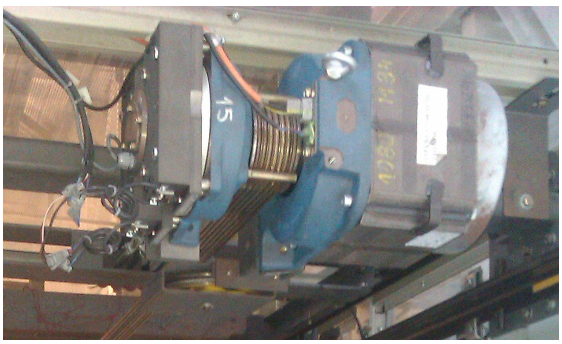


Figure 4.3: Orona's machine (M34-8pax).

(a) (b)

Figure 4.4: Elevator's mechanical system: (a) the cabin and the trolleys with loads used to emulate the mass of passengers and (b) the counterweight.

4.2.3 Mechanical System

The mechanical system is mainly composed by the cabin (with its loads) and the counterweight. Other elements as cables and pulleys have been neglected due to their much less influence on the system's operation.

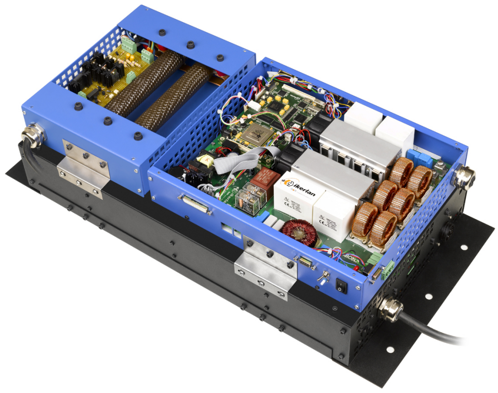
The main characteristics of these elements are presented in table 4.1. Note that the maximum capacity of the cabin is eight passengers and the random sequence of missions only considers a maximum load of six passengers. In order to emulate the mass corresponding to the passengers, six individual trolleys have been used (each with a load of $78.75kg$), combining them according to the passenger requirements defined on the sequence of missions.

The cabin, the trolleys with the loads, and the counterweight are shown in figure 4.4.

Parameter	Value	Term
Cabin mass	$800kg$	m_e
One passenger mass	$78.75kg$	m_{pass}
Maximum number of passengers	8	N_p
Counterweight level	Medium	m_c

Table 4.1: Summary of the mechanical system's characteristics.

(a)



(b)

Figure 4.5: Energy storage system: (a) supercapacitors tank and (b) reversible dc-dc converter.

Parameter	Value
Rated power	$2kW$
Maximum power	$5kW$ @ $10s$
Energy capacity (operational mode)	$16Wh$

Table 4.2: Summary of the energy storage system's specifications.

4.2.4 Elevator Controller

The objective of the elevator controller is to power and to control the electromechanical conversion system in order to carry out the cabin displacement. The cabin is moved using the acceleration, speed and position profiles previously shown in figure 3.10. Note that the duration of those profiles are directly related to the cabin displacement, needing more time for longer distances.

4.2.5 Energy Storage System

The energy storing capability is provided by an energy storage system based on supercapacitors, shown in figure 4.5. A reversible dc-dc converter is also included in order to control the charge and discharge of the Scaps, according to the defined energy management strategies. This equipment is a full-scale demonstrator and its main characteristics are presented in table 4.2.

Regarding to the control strategies implementation, they have been implemented in the energy storage system's control unit. The objective of this energy storage system is to provide energy storing capacity to any conventional elevation system. For that

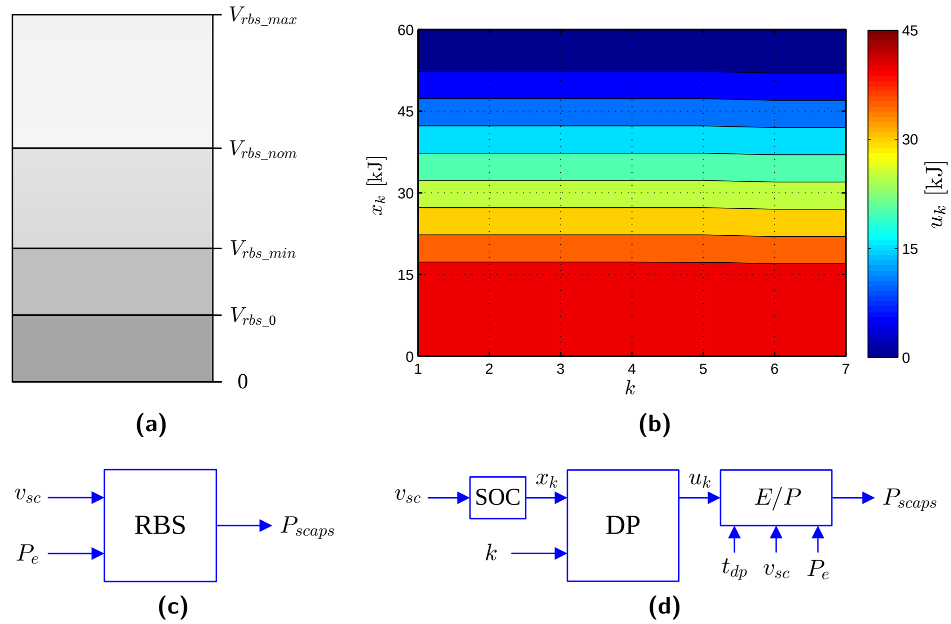


Figure 4.6: Implementation of control strategies for the experimental validation: (a) supercapacitors tank division by the RBS control strategy, (b) lookup table of the DP control strategy, (c) RBS based control strategy implementation and (d) DP based control strategy implementation.

reason, the energy management strategies, the RBS and the DP, must be implemented in the control unit of this system. They have been developed and implemented in C programming language in the DSP and the FPGA of the control unit. Figure 4.6 shows both control strategies and their implementation block diagrams. For the DP based EMS, two additional block have been introduced. The "SOC" block defines the state of charge of Scaps (x_k) from their voltage (v_{sc}) and the "E/P" block converts the energy reference of the DP control strategy (u_k) into the power reference for the ESS (P_{scaps}). It should be pointed out that the DP based EMS has been developed offline.

4.3 Validation of the Operation Along One Mission

In this section, the results of the experimental tests are presented, comparing a DP based EMS (test 3) with a RBS (test 2) and with an elevator without energy storing capacity (test 1). More specifically, a validation along a mission is presented for each of the analyzed configurations, in order to check their correct operation taking as a reference the expected idealized power profiles presented in the previous chapter. The behavior of the analyzed EMS is evaluated along two consecutive missions.

Note that due to the characteristics of the DP, its operation during a particular mission depends not only on the inputs of that mission but also on the inputs of previous

Parameter	Fist Mission	Second Mission
Mission number	2/80	3/80
Initial floor	4	0
Final floor	0	5
Passengers	1	2

Table 4.3: Summary of the main characteristics of the selected single missions for the control strategies implementation validation.

and future expected missions. Therefore, to test properly this behavior it is necessary to check it in the middle of a sequence and to carry out all the previous missions. For instance here missions 2 and 3 out of 80 have been selected (see table 4.3).

From the point of view of energy, the important fact is the moving direction of the heaviest element (the cabin or the counterweight depending on the number of passengers). As a result, the system will be in traction mode if the heaviest element is going up and inversely, it will be in regenerative mode when it goes down. In the case of the first mission, the counterweight is the heaviest element, and it goes up, and therefore it can be considered as a traction mission. On the contrary, the second mission is a regenerative mission, as the heaviest elements is the counterweight and it is going down.

4.3.1 Test 1 - Elevator Without ESS

Figure 4.7 shows all the experimental power profiles corresponding to an elevator without energy storage. As it is shown, the electromechanical conversion system (P_e) is powered by the grid (P_{grid}) in traction mode and the recovered power is dissipated in the braking resistor ($P_{crowbar}$) in regenerative mode.

As it can be seen, there are some variations compared to the simulation tests presented in figure 3.22. Regarding to the first mission, from ($t = 0s$) to ($t = 40s$), the power peak is lower. It means that the cabin cannot be accelerated as required by the acceleration profile. Besides, the first flat zone of the power profile is also lower. Therefore, the cabin displacement has been slower and more time has been required in order to complete the mission. For that reason, the mission has been completed later than in the simulation test. In addition, this flat zone presents some ripple due to the variations of friction losses between the cabin and counterweight with the guide rails. The second flat zone is due to the approximation process to the final floor at a lower speed.

On the contrary, the second mission, from ($t = 40s$) to ($t = 80s$), is similar to the simulation test. Firstly, the power is consumed from the grid in order to accelerate the cabin. And finally, some power is recovered and dissipated in the braking resistor while the cabin is being stopped. The maximum values of the power peaks are different in

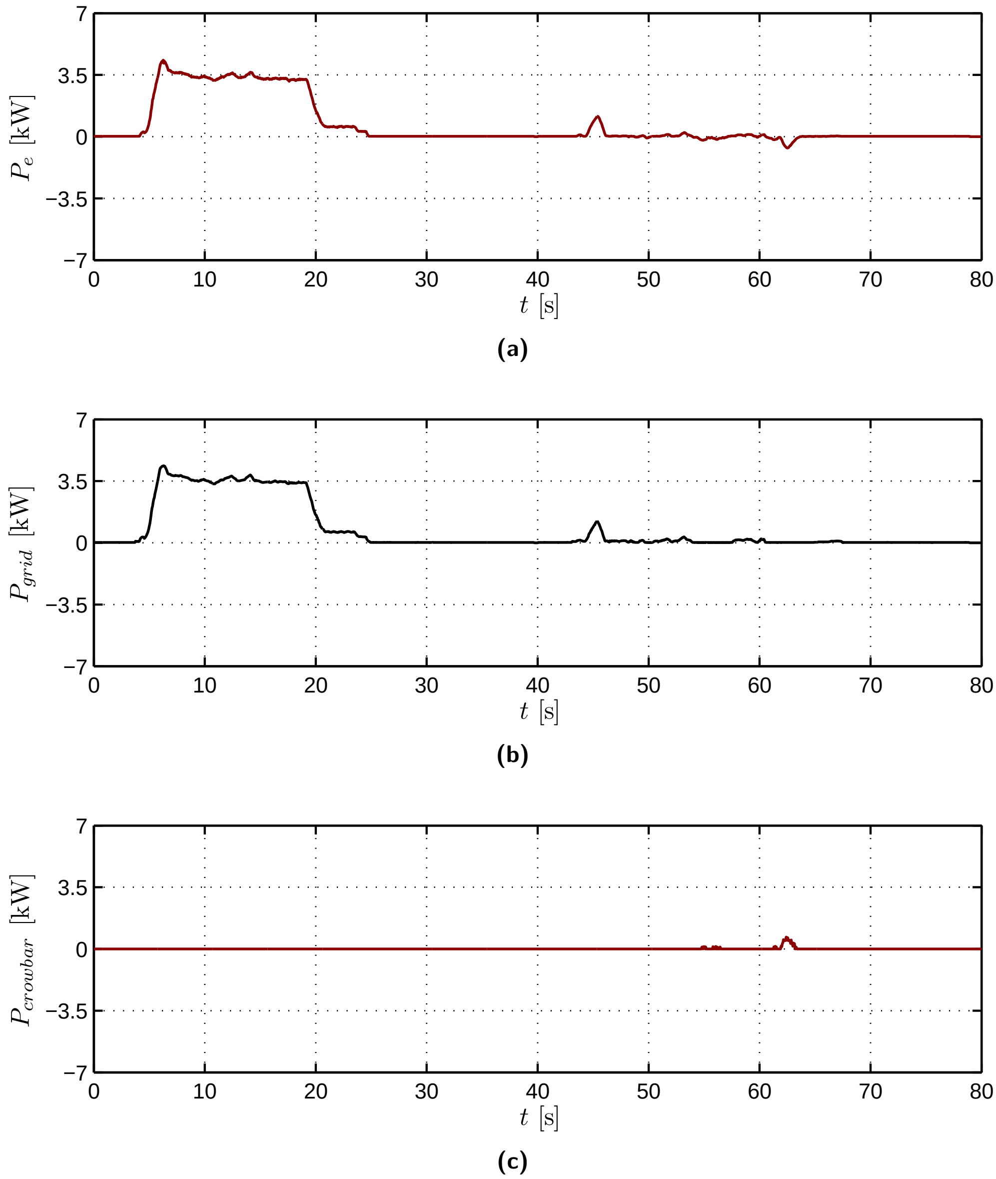
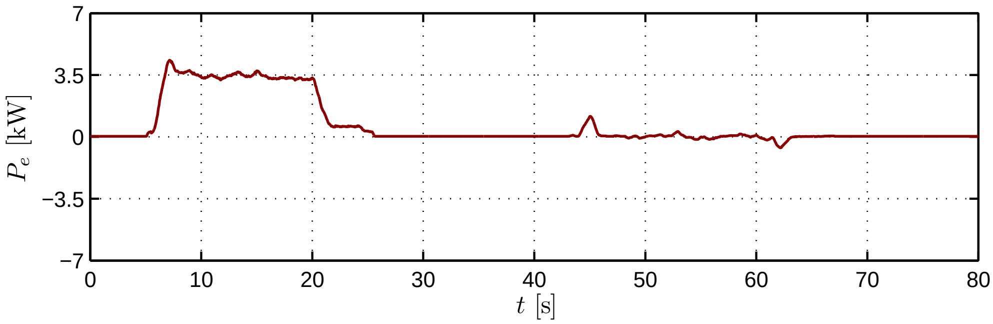


Figure 4.7: Experimental power profiles of a non-improved elevation system for two consecutive missions : (a) power profile of the electromechanical conversion system, (b) power consumed from the grid and (c) power dissipated in the braking resistor.

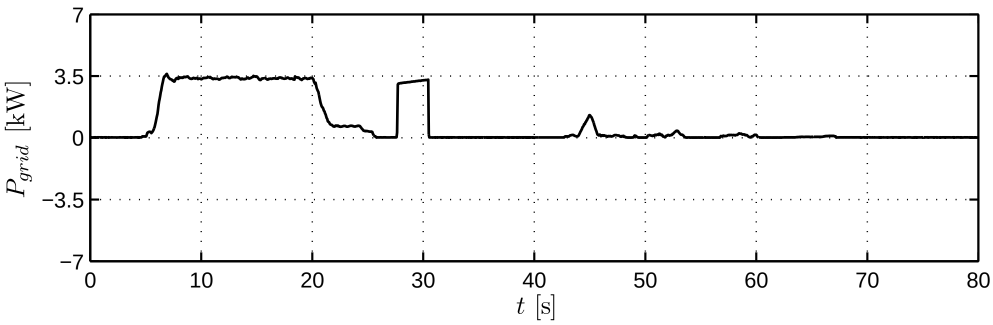
traction and regenerative mode and they are related to the cabin acceleration profiles.

4.3.2 Test 2 - Elevator With ESS and a Rule Based EMS

Figure 4.8 shows all experimental the power profiles corresponding to this case study. As it can be seen in traction mode, the power absorbed from the grid (P_{grid}) is limited to $3.5kW$, as the energy storage system (P_{scaps}) supplies part of the power absorbed by



(a)



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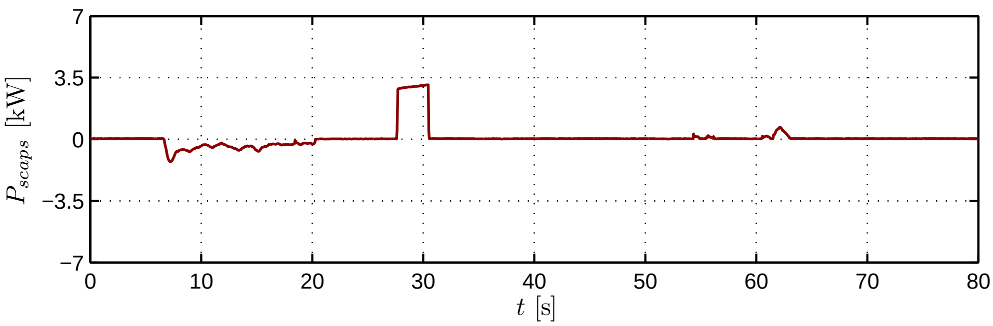
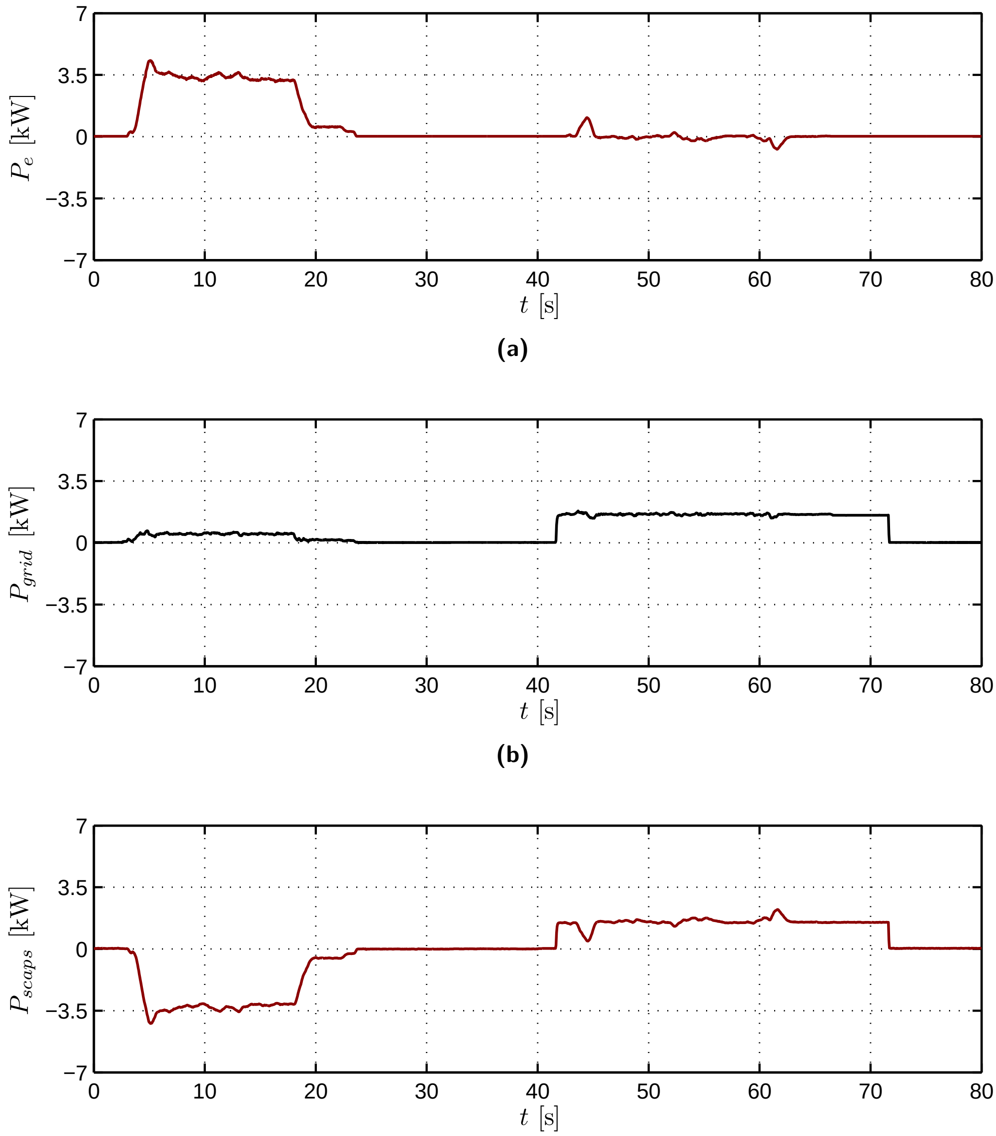


(c)

Figure 4.8: Experimental power profiles of the improved elevation system with a RBS strategy for two consecutive missions: (a) power profile of the electromechanical conversion system, (b) power consumed from grid and (c) power profile of the ESS.

the electromechanical system (P_e). In regenerative mode, the energy is stored in the supercapacitors tank, avoiding energy losses in the braking resistor ($P_{crowbar}$). During the first mission, the maximum grid power has been slightly exceeded. In the execution of that mission, the supercapacitors have been partially discharged, therefore additional power has been absorbed from the grid in ($t = 27s$). In this control strategy when a mission is completed, the energy storage system must be above a voltage threshold, otherwise, it is charged from the end until reaching this voltage level (V_{rbs_nom}).



(a)

(b)

(c)

Figure 4.9: Experimental power profiles of the improved elevation system with a DP strategy for two consecutive missions: (a) power profile of the electromechanical conversion system, (b) power consumed from the grid and (c) power profile of the ESS.

4.3.3 Test 3 - Elevator With ESS and DP Based EMS

Figure 4.9 shows the experimental power profiles corresponding to the DP case study. It must be noted that the DP does not take into account the elevator working mode (traction or regenerative mode) in order to decide the amount of energy to be introduced into the system from the grid (u_k) at each mission (k), (as shown in figure 3.18).

As it can be seen, the power absorbed from the grid (P_{grid}) is constant during both missions, transferring the two flat zones of the first mission to the ESS power profile which is not constant in this case. The energy amount absorbed from the grid during the first mission is different compared to the simulation test. This is because in the previous mission, the supercapacitors tank has finished at a different state of charge, and in consequence, the control strategy has changed for the same mission.

Note that in the second mission the grid supplies power even in regenerative mode in order to optimize the overall objectives defined for the optimization. Finally, the energy losses in the braking resistor ($P_{crowbar}$) are zero also with this EMS, as the ESS is able to store all the regenerative and grid power defined by the EMS.

4.4 Global Validation

In this section the experimental results with a random sequence of 80 missions are presented (figure 3.24).

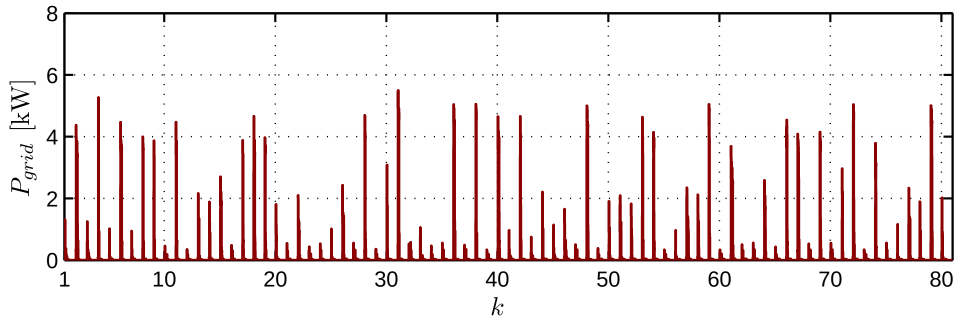
The chapter is divided in three parts: in the first and second parts, the fulfillment of the defined optimization objectives is evaluated (grid power reduction and braking resistor energy losses reduction), while in the third part other system features (such as global system efficiency) are analyzed.

4.4.1 EMS Objective 1: Grid Power Smoothing

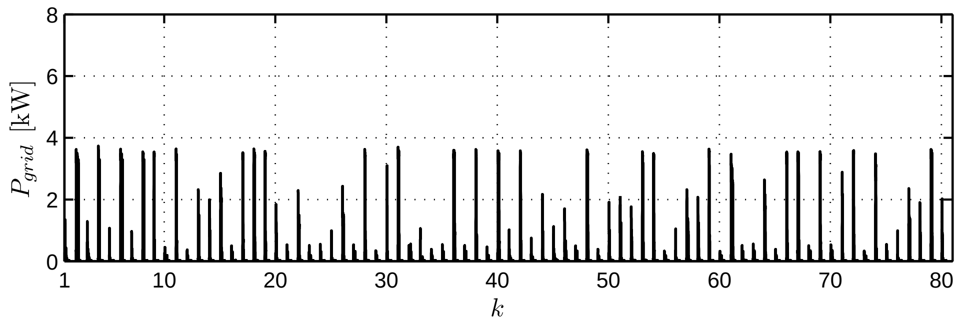
Figure 4.10 shows the complete grid power (P_{grid}) profile for the three considered systems (each bar corresponds to a mission). While the rule based strategy (RBS) reduces power peaks to a certain pre-established limit ($3.5kW$), the DP based EMS reduces power peaks even more, below $2kW$ (DP).

It must be noted that the SOC of the Scaps is correctly controlled, and consequently the stored energy can be used to successfully reduce the grid power absorption during all the missions. A summary grid power smoothing values are presented in table 4.4 and the main conclusions are:

- Grid power peaks can be reduced introducing an ESS and implementing an optimized control strategy (as much as a 64% power reduction).
- The Dynamic Programming control strategy achieves a better power smoothing than the rule based one.
- The ESS must be charged before the power peaks in order to guarantee that the system is under control (SOC successfully controlled).



(a)



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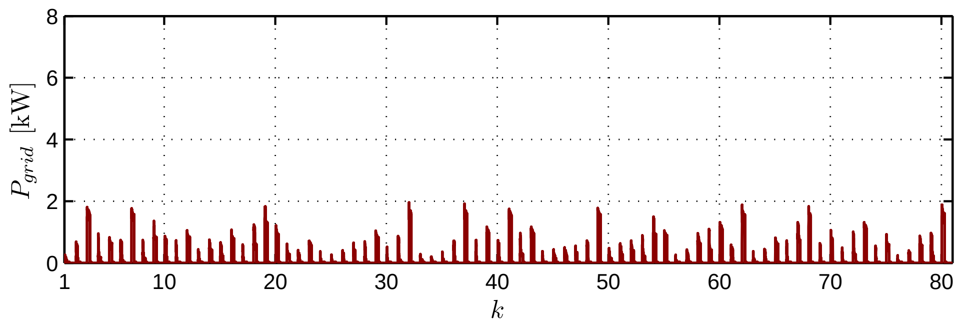


(c)

Figure 4.10: Experimental grid power profiles for a random sequence of 80 missions: (a) elevator without energy storing capacity (Classic), (b) improved elevator and rule based control strategy (RBS) and (c) improved elevator and Dynamic Programming based control strategy (DP).

Parameter	Classic	RBS	DP
Maximum power	$5.5kW$	$3.73kW$	$1.96kW$
Smoothing level	$0kW/0\%$	$1.77kW/32\%$	$3.54kW/64\%$

Table 4.4: Grid power smoothing experimental results.

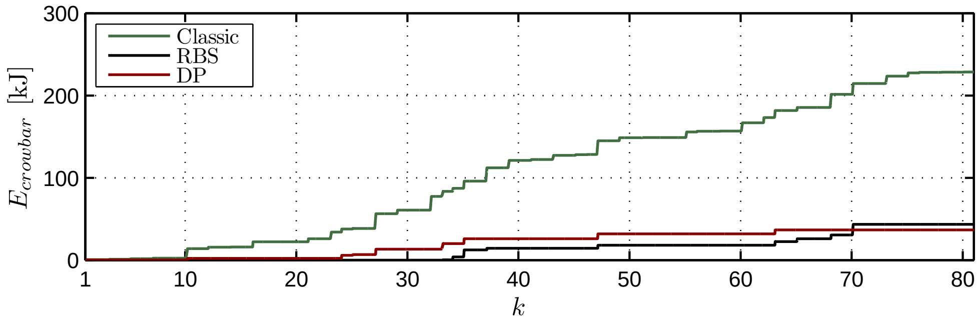


Figure 4.11: Experimental braking resistor energy losses profiles of a non-improved elevator (Classic) and an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

4.4.2 EMS Objective 2: Braking Resistor Energy Losses Minimization

The accumulated energy losses in the braking resistor ($E_{crowbar}$) are shown in figure 4.11 while the instantaneous power profiles ($P_{crowbar}$) are presented in figure 4.12.

The experimental results demonstrate that the energy losses in the braking resistor can be significantly reduced by using an ESS. Furthermore, the optimized control strategy based on Dynamic Programming (DP) improves slightly the results compared to a rule based one (RBS), achieving both algorithms a very similar behavior.

It can be observed that energy losses cannot be completely eliminated along the sequence of missions. This phenomena occurs when the ESS is fully charged and the electromechanical conversion unit is regenerating electric power. As it can be seen in figure 4.13 (a zoom of figure 4.12 during the mission 37) and 4.14 and taking as a reference the regenerative power profile of the conventional system (Classic), the rule based control strategy (RBS) decides to store this energy in the Scaps until they are fully charged, and then, the rest of the energy is dissipated in the braking resistor. This strategy is not able to predict this situation in this case and it does not prepare correctly the SOC of the Scaps for the upcoming regenerative mission.

In contrast, in this particular case the optimized DP strategy (DP) starts this mission with a lower SOC, and therefore, it is able to store all the energy regenerated from the electromechanical conversion system and additionally some more energy from the grid (defined by the control strategy in order to improve the system efficiency and prepare the SOC of Scaps for upcoming missions).

The total amount of energy dissipated in the braking resistor in experimental tests is presented in table 4.5. Regarding the objective of energy losses minimization in the braking resistor, the main conclusions are:

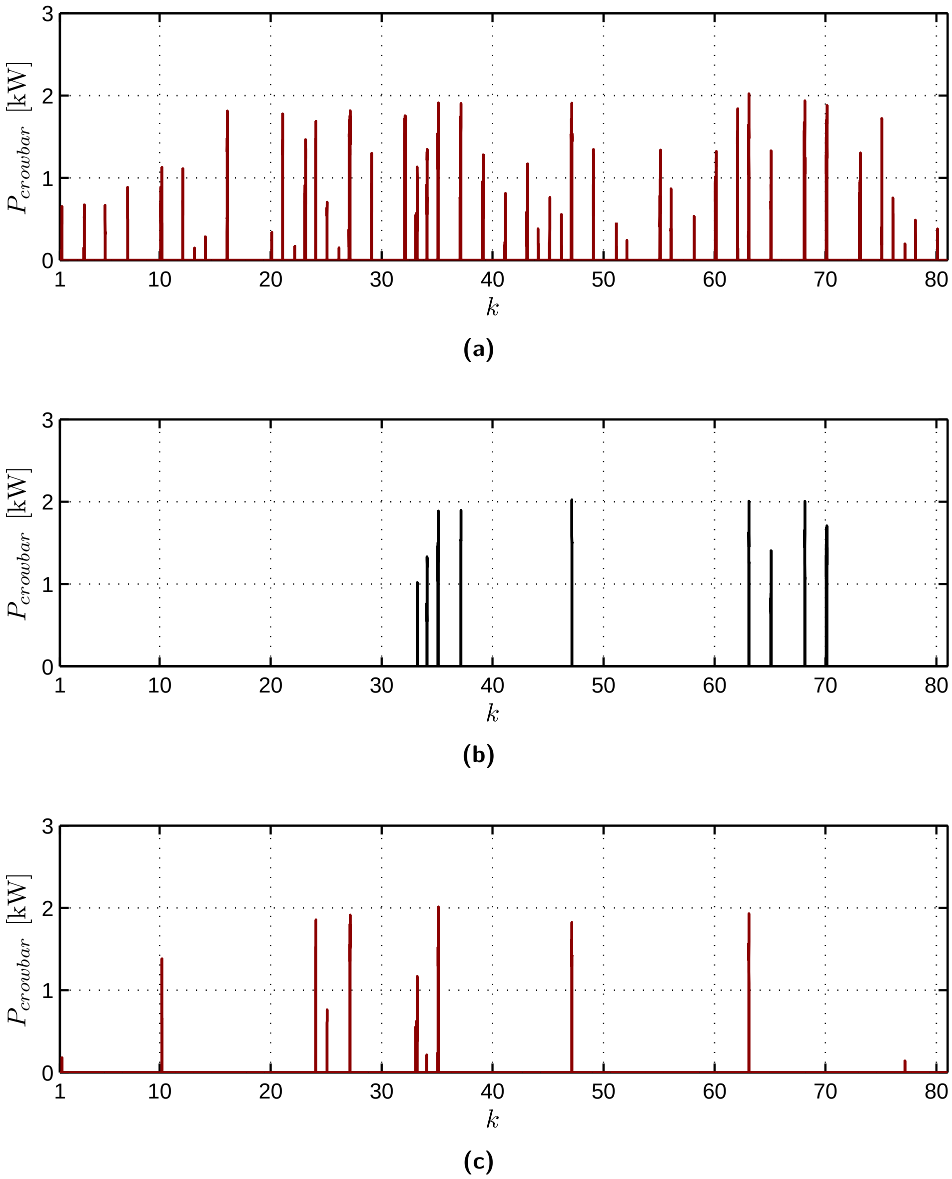
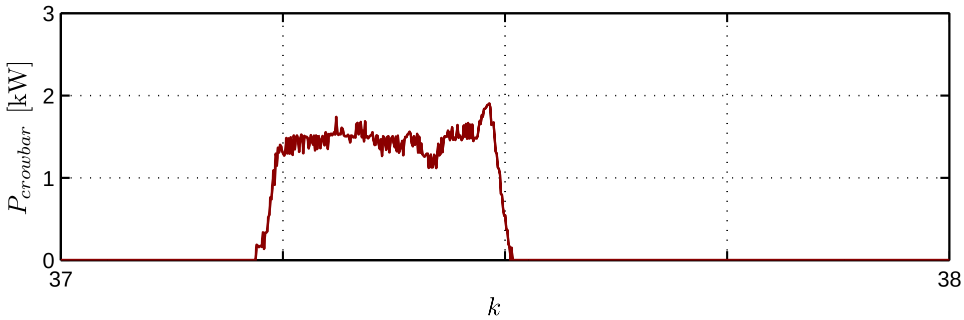


Figure 4.12: Experimental braking resistor's power profiles for a sequence of 80 missions: (a) elevator without energy storing capacity (Classic), (b) improved elevator and rule based control strategy (RBS) and (c) improved elevator and Dynamic Programming based control strategy (DP).

Parameter	Classic	RBS	DP
Energy losses	$228.54kJ$	$43.48kJ$	$36.76kJ$
Reduction level	$0kJ/0\%$	$185.06kJ/81\%$	$191.78kJ/84\%$

Table 4.5: Total braking resistor energy losses minimization experimental results.



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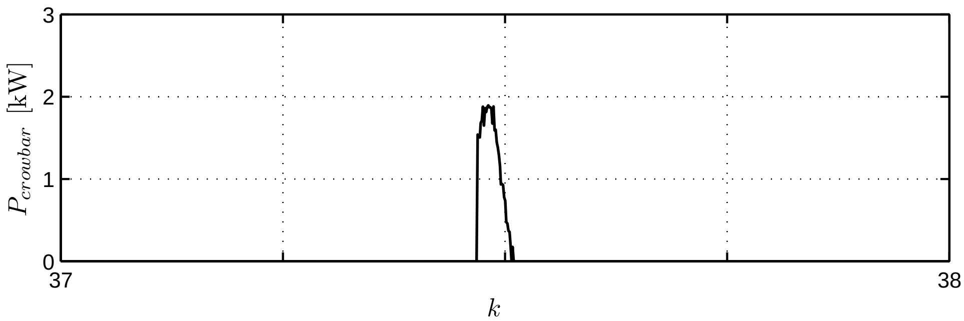

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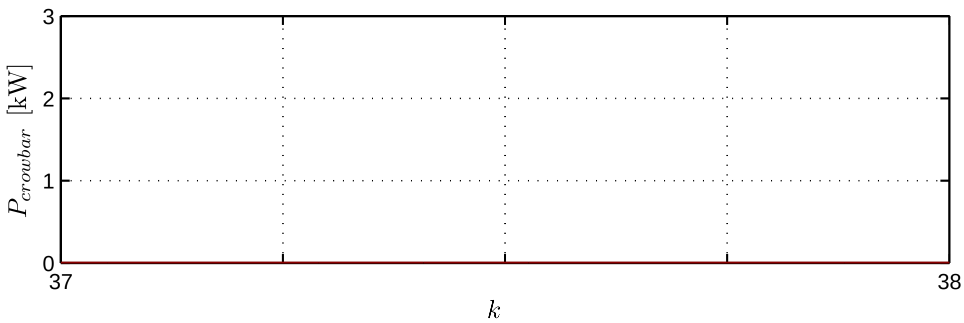

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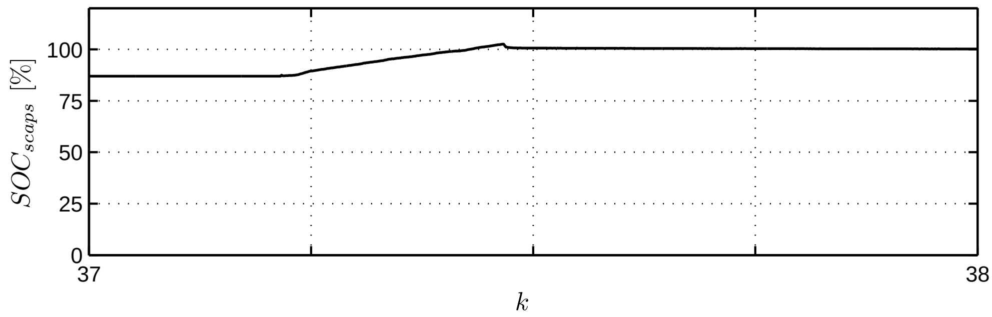
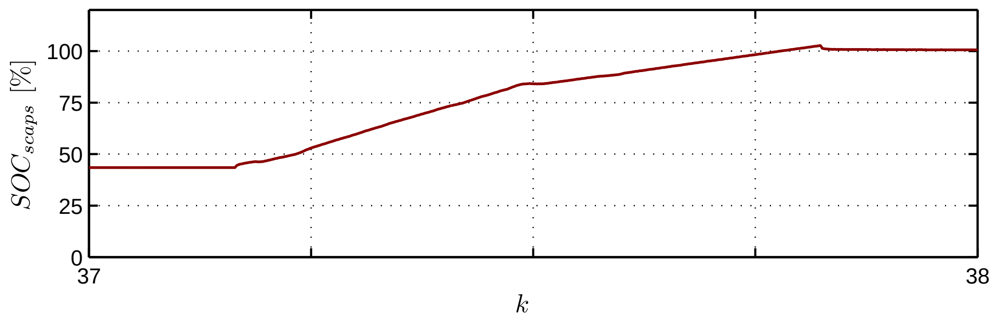
Figure 4.13: Experimental Braking resistor's power profile along one mission in regenerative mode: (a) elevator without energy storing capacity (Classic), (b) improved elevator and rule based control strategy (RBS) and (c) improved elevator and Dynamic Programming based strategy (DP).

- The energy losses in the braking resistor can be reduced by introducing an ESS and implementing an optimized control strategy.
- The DP control strategy achieves slightly better results than the RBS one.
- The braking resistor cannot be removed from the system because the ESS does not guarantee a complete regeneration in all possible cases.



(a)



(b)

Figure 4.14: Experimental energy storage system's SOC profile along one mission the same figure as in 4.13: (a) rule based control strategy (RBS) and (b) DP based control strategy (DP).

4.4.3 Experimental Results Analysis of Additional Parameters

Although the main objectives of the optimization are correctly achieved by the analyzed EMS strategies, it is important to analyze additional system parameters in order

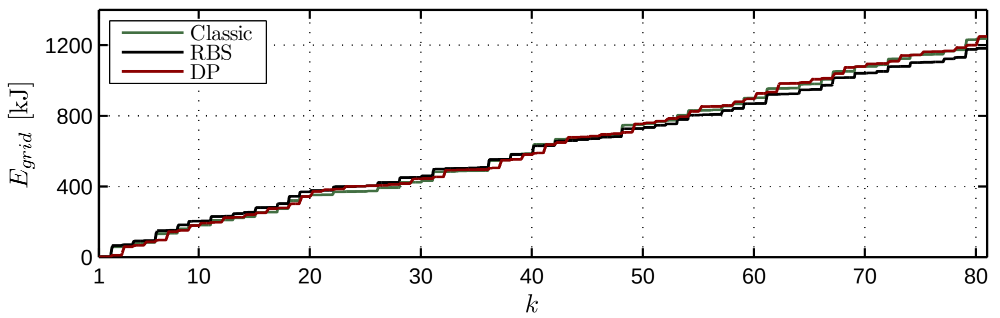


Figure 4.15: Experimental grid energy profiles of a non-improved elevator (Classic) and an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

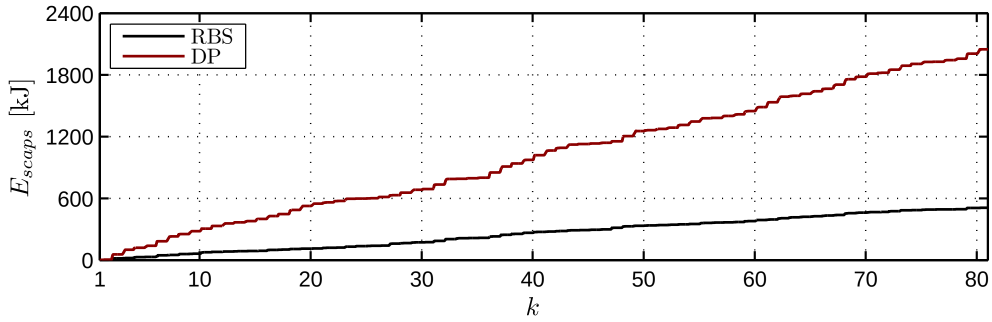


Figure 4.16: Experimental energy storage system's energy profiles of an improved elevator with a rule based control strategy (RBS) and a Dynamic Programming based control strategy (DP).

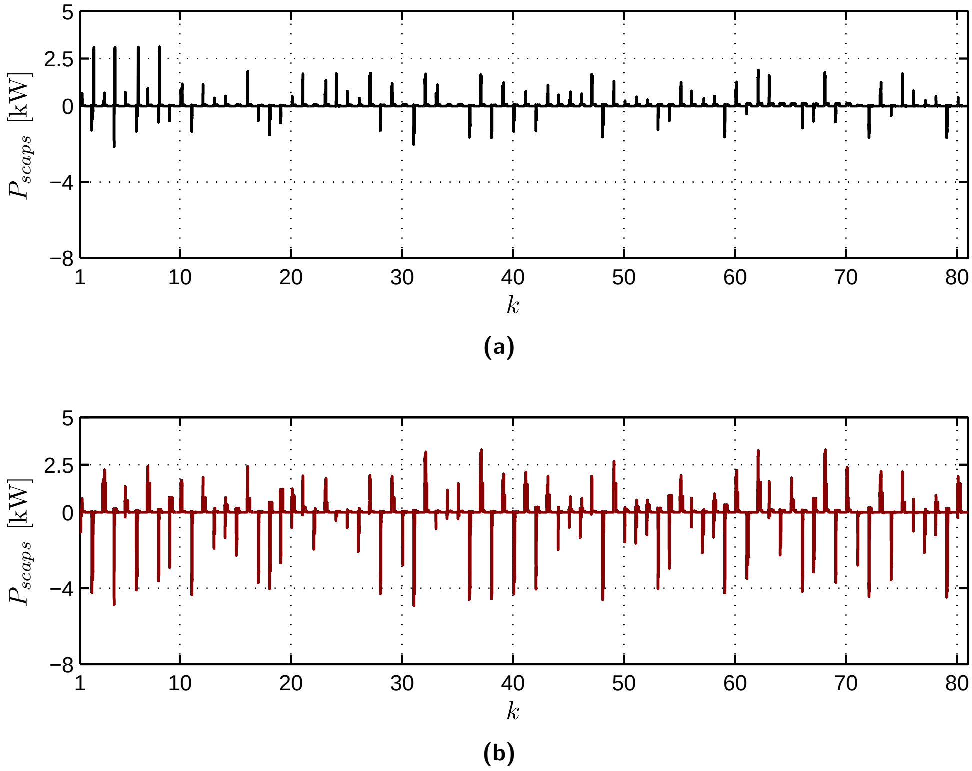
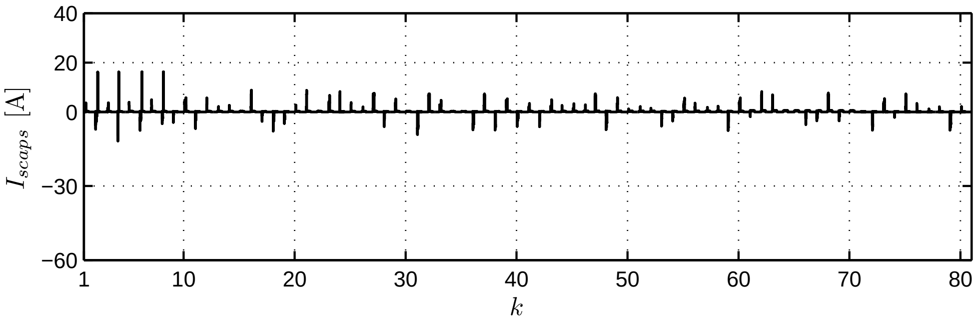


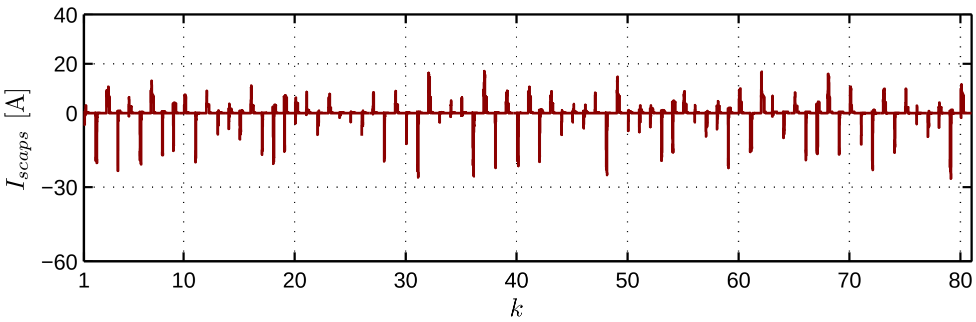
Figure 4.17: Experimental energy storage system power profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

to have a more accurate vision of each of the proposed EMS strategies.

The whole system efficiency is estimated by using the accumulated energy consumed from the grid and taking as a reference the elevator without energy storing capability (Classic) ($1237kJ$). As it is shown in figure 4.15, the efficiency is slightly improved by the rule based control strategy (RBS) ($1182kJ$). In contrast, the Dynamic Programming



(a)



(b)

Figure 4.18: Experimental energy storage system current profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

strategy (DP) does not improve the global system efficiency ($1249kJ$). This is due to the fact of the limited efficiency of the mechanical system and the higher cycles-per-mission ratio of the DP strategy. As a result, there are more energy exchanges between the Scaps and the electromechanical conversion system, and in consequence, more energy losses in the mechanical system. Consequently, it can be concluded that it is not possible to improve the whole system efficiency using a DP based strategy when the grid power smoothing is carried out.

The amount of energy exchanged between the energy storage system and the application is shown in figure 4.16. This value represents the energy that has been transferred to and from the ESS, reflecting the use of the energy storage system. As it can be seen, the DP strategy ($2048kJ$) uses four times more the Scaps than the RBS strategy ($508kJ$), confirming the results obtained in simulation (figure 3.28).

Another important parameter of the ESS is its power profile, presented in Figure 4.17. Power levels are higher for the DP based strategy ($4.91kW$) than for the control strategies based on rules ($3.11kW$).

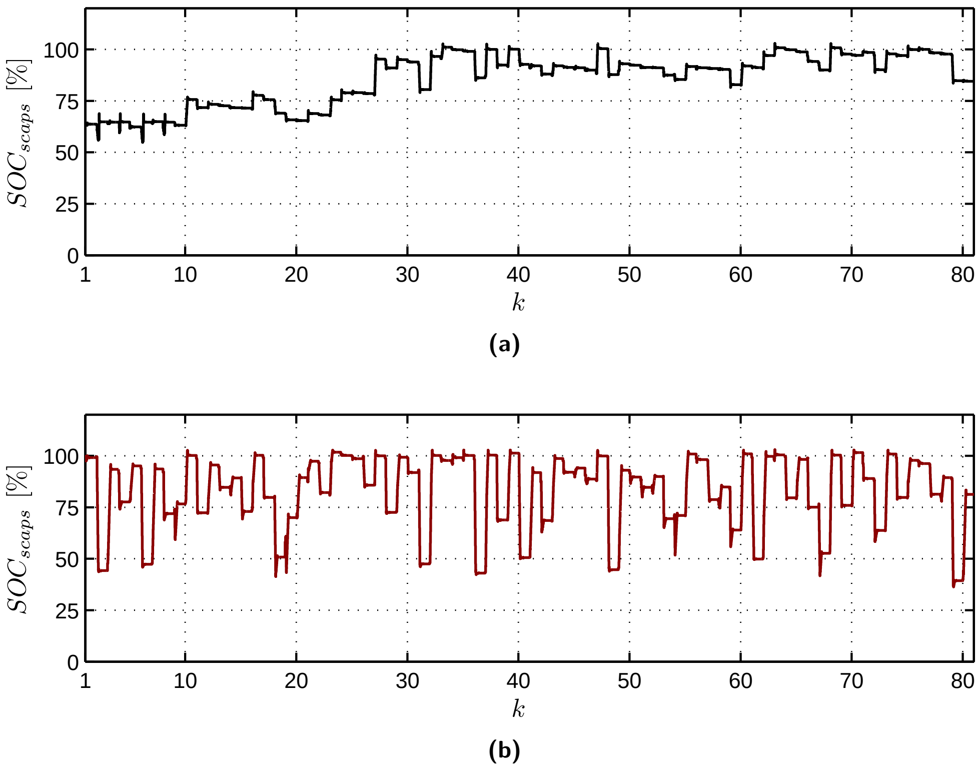


Figure 4.19: Experimental energy storage system's state of charge profiles: (a) rule based control strategy (RBS) and (b) Dynamic Programming based control strategy (DP).

The energy storage system's current profiles have also been obtained and presented in figure 4.18. The DP based control strategies requires a higher current capability ($26.48A$) compared to the rule based control strategy ($16.25A$). Note that the current profiles are obtained from the ESS voltage profiles, and in the case of the DP the supercapacitors based energy storage system works in a wider operation range, increasing consequently the ESS current levels.

From point of view the ESS state of charge, the Scaps are discharged more deeply with the DP based control strategy (DP) compared to the rule based one (RBS), taking further advantage of the energy storage system (figure 4.19). This is due to the fact that the DP injects a higher power than the rule based strategy in order to achieve a higher grid power smoothing.

The depth of discharge is evaluated taking as reference an imaginary axis corresponding to a state of full charge of the Scaps. Therefore, the DOD is equal to 60% for the DP strategy and 45% for the RBS strategy. It should be pointed out that same peaks as the ones found in simulation appear also here, confirming the simulation results.

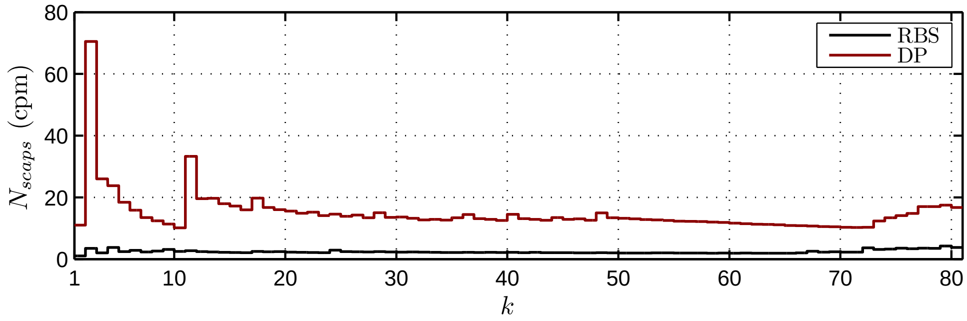


Figure 4.20: Experimental energy storage system's cycles profiles of an improved elevator with a rule based control strategy (RBS) and a DP based control strategy (DP).

Finally, the evolution of cycles is presented in figure 4.20. This factor is useful to evaluate the lifetime of different ESS for the same application. Regarding to this value, the factor for the DP control strategy (16.7) is much higher than for the RBS (3.76), almost five times higher. A higher number of charging and discharging cycles are required by the DP, because it smooths the grid power and it prepares the ESS for upcoming missions. Therefore, the DP presents a higher cycles-per-mission ratio (cpm).

In order to summarize the experimental results, two comparison charts are presented in figure 4.21, the same ones as in the simulation tests. Concerning the first comparison, the maximum grid power peak (P_{grid}), the energy consumed from the grid (E_{grid}) and the energy losses in the braking resistor ($E_{crowbar}$) are represented during the random sequence of 80 mission. As predicted by the simulations, the energy losses in the braking resistor have been reduced implementing both control strategies. Besides, the EMS based

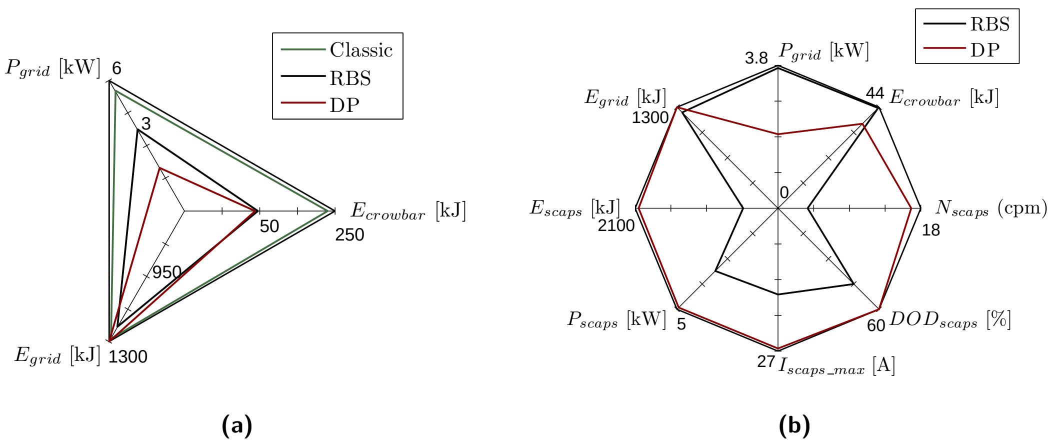


Figure 4.21: Comparison charts of experimental validation: (a) reduced comparison between a non-improved (Classic) and an improved elevator (RBS and DP) and (b) rule based (RBS) and Dynamic Programming based (DP) control strategies comparison chart.

on DP reaches a higher level of grid power smoothing (almost twice compared to the RBS control strategy). It should be pointed out that the energy consumption from the grid is similar in the three experimental tests due to the low mechanical efficiency.

In the second comparison, it can be appreciated how the values achieved with the DP based control strategy which are related to the ESS (E_{scaps}, P_{scaps}, I_{scaps_max}, DOD_{scaps}, N_{scaps}), are higher than the ones obtained with the rules based control strategy. These values can be interpreted as a better usage of the ESS, but also, as a higher degradation of the ESS. Regarding these additional parameters analysis, the conclusions are:

- The energy storage system is used in a wider operation range by the DP based control strategy in order to achieve better results compared to a non-optimized EMS based on rules.
- The energy losses reduction in the braking resistor is not directly related to the reduction of the energy consumption from the grid.
- The whole system efficiency is directly related to the cycles-per-mission ratio, achieving a higher efficiency for a lower cpm value.

4.5 Conclusions

In this chapter the experimental validation of control strategies for an improved elevation system have been carried out in a full-scale residential type elevator and an energy storage system prototype based on supercapacitors. The passengers have been emulated with trolleys and the control strategies have been implemented in the DSP and FPGA based control unit of the energy storage system. Three experimental tests have been completed in a random sequence of 80 missions.

First, the control strategies have been validated along one mission in order to check the correct implementation and operation taking as a reference the simulated power profiles. Afterwards, the global validation of the control strategies have been presented in order to evaluate the real application of these EMS.

It has been demonstrated that, both energy management strategies, rule based and Dynamic Programming based EMS, are capable of reducing the grid power peaks, by 32% and 64%, compared to a non-improved elevator, respectively. Moreover, the braking resistor energy losses are also reduced, by 81% and 84%, respectively. Therefore, the objectives have been achieved and the optimized control strategy based on DP reaches a superior behavior compared to a non-improved elevator, and also, compared to a non-optimized EMS based on rules.

If other operational parameters are considered, it can be concluded that the Dynamic Programming based control strategy works in a wider operation range of the ESS to reach a higher grid power smoothing level. In contrast, the system efficiency cannot be increased because it is directly related to the cycle-per-mission ratio, which is higher for the DP as the grid power smoothing level is also increased. Therefore, the braking resistor energy losses reduction cannot be translated into a system efficiency improvement.

5 Conclusions

5.1 Summary

The use of energy storage systems is being extended to new applications, both stationary and mobile. They can be used in applications where an isolated power source is required, or also, in applications in which a system behavior improvement is desired. There are many different energy storing technologies such as the mechanical, electrical and electrochemical technologies.

When an energy storage system is introduced in any application, two main issues must be solved. On the one hand, the energy storage system must be rated in order to satisfy the application requirements. On the other hand, the energy storage system must be managed as the amount of energy to be charged and discharged, as well as the appropriate instants must be decided. In addition, these two issues are strongly coupled. In this thesis, it has been proposed a solution, to address the management problem first, and then the ESS rating. This is the reason why this thesis is focused on energy management strategies for applications with energy storing capacity.

In this context, a new implementation methodology has been proposed for the development and implementation of these kinds of optimized control strategies. This methodology is able to solve the management problem of deterministic and stochastic applications with energy storing capacity, getting a control strategy based on Dynamic Programming. It should be pointed out that the cost function evaluated by the optimization technique is based on the stock management theory. In addition, a new representation of stochastic applications has also been proposed, relating the energy requirements of an application and their probabilities of occurrence.

This methodology has been applied to an improved elevation system with a supercapacitors based energy storage system aimed at reducing grid power peaks and the braking resistor energy losses. Furthermore, a non-optimized but conventional control strategy based on rules has also been implemented in order to make a comparison. These control strategies have been tested in simulation and experimentally validated in a full-scale elevation system. In addition, these two configurations have also been compared to a non-improved elevator. As it has been demonstrated, both control strategies are able to reduce the braking resistor energy losses, but in addition, the Dynamic Programming based control strategy presents a superior behavior in relation to the grid power smoothing.

5.2 Contributions

The main contributions of this thesis are:

Demonstration of the Potential of the Dynamic Programming Principle in Energy Management Applications

The applications with energy storing capacity can be represented as a general block diagram composed of three elements (the power source, the energy storage system and the application). In these systems, an energy management strategy is requested in order to control the power source and the energy storage system for satisfying the application requirements.

In this context, the Dynamic Programming principle presents several advantages. The global optimization of the energy management strategy can be carried out, obtaining optimal large decisions policies, while the computational cost is reduced. It can be developed for deterministic as well as for stochastic systems, depending on the application. In addition, this energy management strategy can also be implemented online or offline.

Adaptation and Implementation of the Cost Function Based on the Stock Management Theory to Energy Storage Applications

The optimization techniques require a cost function in order to quantify the optimization results. This thesis is focused on the Dynamic Programming techniques which request a cost function in order to optimize use of the energy storage system used as a decoupling element between the power source and the application.

The stock management theory defines a cost function which is able to evaluate the profits of a warehouse from the economic point of view. Due to the similarity between a warehouse and an energy storage system, the cost function has been adapted and implemented to energy storage applications from an energy point of view. In addition, this cost function has also been formulated for stochastic applications, introducing the statistical terms into the expression.

Proposal of an Implementation Methodology for DP Based EMS in Applications with Energy Storing Capacity

The implementation of this kind of DP control strategies has not been sufficiently explained in the literature. For that reason, it has been proposed and developed a new methodology for implementing energy management strategies based on Dynamic Programming in applications with energy storing capacity (deterministic or stochastic) with multiple degrees of freedom. This methodology is divided in five steps, enabling a systematical development and implementation of the DP method in these applications.

These five steps can be divided in two groups. The first three steps consist of adapting the energy management problem to the Dynamic Programming principle. And then, the last two steps carry out the analytical resolution of the problem obtaining the optimized control strategy. This methodology is entirely valid both for deterministic and stochastic applications, where the graphical representation is one-dimensional for the first ones and multi-dimensional for the second ones.

Proposal and Introduction of a New Multi-Dimensional Representation of Cost Maps for Stochastic Systems

Deterministic problems are represented in one dimensional cost maps, where all possible decisions, their associated costs and the evolution of the system are entirely represented. In the case of stochastic applications, this representation is not enough due to the uncertainty in the evolution of the system. For that reason in this thesis, it has been proposed and introduced a new multi-dimensional representation of cost maps in order to solve this drawback, representing in each map one possible decision and representing all possible evolutions of the system and their associated costs.

Proposal of a New Representation of Stochastic Systems in Energy Management Applications - GESD

A new kind of representation for stochastic applications called GESD (Generalized Energy and Statistical Description) has been introduced, where the energy requirements are related to the probability of occurrence. Two parameters are taken into account for the representation. On the one hand, all possible values of energy requirements of the system (w_k) are considered. On the other hand, the probabilities of occurrence for each energy requirement (P_{wk}) are defined.

$$w_k \quad vs. \quad P_{wk}$$

As the behavior of a stochastic system cannot be specified exactly, this representation can be used to model their behavior. Besides, this information is required for DP based EMS in order to solve the optimization problem. In addition, if the behavior of the system is modified, the representation can be updated online in the control unit (monitoring the system energy consumption), and in consequence, the optimized control strategy can be reevaluated online, improving the energy manager and incorporating a self learning ability.

Implementation and Experimental Validation of the Energy Manager Based on DP in an Improved Full-Scale Elevator with Supercapacitors

It has been developed, implemented, tested in simulation and validated experimentally an optimized energy management strategy based on DP in an improved elevator with supercapacitors based energy storage system. The correlation between the simulation tests and the experimental results has validated the modeling of the elevator with energy storing capacity (EMR and MCS, electromechanical analysis and GESD). In addition, the implementation of the DP based EMS in a control unit has demonstrated the interest of DP based EMS for real industry applications.

5.3 Future Work

The work presented in this thesis provides different possibilities for further work which are proposed as follows:

- Optimal rating of the ESS. At the beginning of this thesis, it has been presented the dilemma of an energy storage system. The need to rate and manage an ESS, and the couple between these actions. In this thesis, it has been addressed that problem opening that close loop and solving the management problem first. Therefore, it would be very interesting to solve the rating problem too once the optimal EMS has been obtained. The objective is to close that loop and to reach an integral solution for these kinds of applications, i.e., the optimal rating and management of an energy storage system.

- Online implementation of the DP energy management strategy. The objective is to carry out the industrial implementation of these optimized control strategies for different elevation systems where the EMS will be evaluated in each elevator, achieving a customization of these control strategies.

- Addition of a self learning ability to the DP control strategy. For that, it is proposed to develop an online monitoring and updating of the Generalized Energy and Statistical Description (GESD) of the application, in this case the electromechanical conversion system energy requirements of elevators and their occurrence in a period of time. Once the new representation is obtained and the EMS is reevaluated online, the optimized control strategy is adapted to new requirements of the application, incorporating the self learning ability.

- Extension to a complete building scenario. Nowadays, new scenarios are emerging such as nanogrids for sustainable buildings composed by programmable power sources, renewables and energy storage systems in order to satisfy the building power and energy requirements. Therefore, it is proposed to apply this implementation methodology in new potential scenarios where an energy management strategy is clearly needed and DP techniques could be well-suited.

A

Dynamic Programming Mathematical Developments

A.1 Principle of Optimality

Theorem (Principle of Optimality). *Let $\pi^* = \{\mu_0^*, \mu_1^*, \ldots, \mu_{N-1}^*\}$ be an optimal policy for the basic problem, and assume then when using π^*, a given state x_i occurs at time i with positive probability. Consider the subproblem whereby we are at x_i at time i and wish to minimize the "cost-to-go" form i to time N.*

$$E\left\{g_N(x_N) + \sum_{k=i}^{N-1} g_k(x_k, \mu_k(x_k), w_k)\right\} \tag{A.1}$$

Then the truncated policy $\{\mu_i^*, \mu_{i+1}^*, \ldots, \mu_{N-I}^*\}$ is optimal for this subproblem.

A.2 Dynamic Programming Algorithm

Theorem (Dynamic Programming Algorithm). *For every initial state X_0, the optimal cost $J^*(x_0)$ of the basic problem is equal to $J_0(x_0)$, given by the last step of the following algorithm, which proceeds backward in time from period $N-1$ to period 0:*

$$J_N(x_N = g_N(x_N), \tag{A.2}$$

and for $k = 0, 1, \ldots, N-1$

$$J_k(x_k) = \min_{u_k \in U_k(x_k) w_k} E\left\{g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k))\right\} \tag{A.3}$$

where the expectation is taken with respect to the probability distribution of w_k, which depends on X_k and u_k. Furthermore, if $u_k^* = \mu_k^*(x_k)$ minimizes the right side of equation (A.3) *for each X_k and k, the policy $\pi^* = \{\mu_0^*, \ldots, \mu_{N-1}^*\}$ is optimal.*

Bibliography

[1] B. Scrosati and J. Garche. Lithium batteries: Status, prospects and future. *Journal of Power Sources*, 195(9):2419–2430, 2010.

[2] D.W. Gao, C. Mi, and A. Emadi. Modeling and simulation of electric and hybrid vehicles. *Proceedings of the IEEE*, 95(4):729–745, 2007.

[3] L. Mir, I. Etxeberria-Otadui, I.P. de Arenaza, I. Sarasola, and T. Nieva. A supercapacitor based light rail vehicle: system design and operations modes. In *Proc. IEEE Energy Conversion Congress and Exposition ECCE 2009*, pages 1632–1639, 2009.

[4] Tesla Roadster. http://www.teslamotors.com/roadster.

[5] L. Gaillac, J. Castaneda, A. Edris, D. Elizondo, C. Wilkins, C. Vartanian, and D. Mendelsohn. Tehachapi wind energy storage project: description of operational uses, system components, and testing plans. In *Transmission and Distribution Conference and Exposition (T&D), 2012 IEEE PES*, pages 1–6, 2012.

[6] Xtreme Power Company Solar Projects. http://www.xtremepower.com/projects/solar.php.

[7] BYD Li ion batteries for RES integration (36MWh). http://www.sustainablebusiness.com/index.cfm/go/news.display/id/23281.

[8] L. Barote, R. Weissbach, R. Teodorescu, C. Marinescu, and M. Cirstea. Stand-alone wind system with vanadium redox battery energy storage. In *Proc. 11th Int. Conf. Optimization of Electrical and Electronic Equipment OPTIM 2008*, pages 407–412, 2008.

[9] H. Beltran, E. Bilbao, E. Belenguer, I. Etxeberria-Otadui, and P. Rodriguez. Evaluation of storage energy requirements for constant production in pv power plants. *IEEE Transactions on Industrial Electronics*, 60(3):1225–1234, 2013.

[10] R.S. Srinivasan, W.W Braham, D.P. Campbell, and C.D. Curcija. Energy balance framework for net zero energy buildings. In *Proc. Winter Simulation Conf. (WSC)*, pages 3360–3372, 2011.

[11] A. Molderink, V. Bakker, M.G.C. Bosman, J.L. Hurink, and G.J.M. Smit. Management and control of domestic smart grid technology. *IEEE Transactions on Smart Grid*, 1(2):109–119, 2010.

[12] F. Mangiatordi, E. Pallotti, P. Del Vecchio, and F. Leccese. Power consumption scheduling for residential buildings. In *Proc. 11th Int Environment and Electrical Engineering (EEEIC) Conf*, pages 926–930, 2012.

[13] C.C. Chan. The state of the art of electric, hybrid, and fuel cell vehicles. *Proceedings of the IEEE*, 95(4):704–718, 2007.

[14] A. Rufer and P. Barrade. A supercapacitor-based energy-storage system for elevators with soft commutated interface. *IEEE Transactions on Industry Applications*, 38(5):1151–1159, 2002.

[15] Grid Energy Storage. http://energyinformative.org/.

[16] Beacon Power. http://www.beaconpower.com/.

[17] Euskal Herriko Unibertsitatea. http://www.sc.ehu.es/sbweb/energias-renovables/.

[18] J.M. Miller. How to size ultracapacitors. http://www.eetimes.com/design/automotive-design/4011062/How-to-size-ultracapacitors, 2006.

[19] M.G. Molina. *Dynamic Modelling*, chapter Dynamic Modelling and Control Design of Advanced Energy Storage for Power System Applications, pages 49–92. InTech, 2010.

[20] D.D. Banham-Hall, G.A. Taylor, C.A. Smith, and M.R. Irving. Frequency control using vanadium redox flow batteries on wind farms. In *Proc. IEEE Power and Energy Society General Meeting*, pages 1–8, 2011.

[21] Saft Batteries. http://www.saftbatteries.com/.

[22] C. Blanc. *Modeling of a vanadium redox flow battery electricity storage system.* PhD thesis, Laboratoire d'Électronique Industrielle (LEI) - Ecole Polytechnique Fédérale de Lausanne (EPFL), 2009.

[23] Renewable Energy UK. http://www.reuk.co.uk/.

[24] Climatelab. http://climatelab.org/plug-in-hybrid-electric-vehicles.

[25] S. Luri, I. Etxeberria-Otadui, A. Rujas, E. Bilbao, and A. González. Design of a supercapacitor based storage system for improved elevator applications. In *Proc. IEEE Energy Conversion Congress and Exposition (ECCE)*, pages 4534–4539, 2010.

[26] EBR Energy. http://www.ebr-energy.com/en/solar/.

[27] S. Mariethoz and P. Barrade. Design methodology of an electric vehicle hybrid energy storage unit for improved energy efficiency. In *Proc. IEEE Vehicle Power and Propulsion Conf. (VPPC)*, pages 1–6, 2010.

[28] P. Barrade and A. Rufer. Current capability and power density of supercapacitors: Considerations on energy efficiency. In *Proc. 10th European Conference on Power Electronics and Applications, EPE*, pages 1–10, 2003.

[29] F.R. Salmasi. Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends. *IEEE Transactions on Vehicular Technology*, 56(5):2393–2404, 2007.

[30] S.G. Wirasingha and A. Emadi. Classification and review of control strategies for plug-in hybrid electric vehicles. *IEEE Transactions on Vehicular Technology*, 60(1):111–122, 2011.

[31] L. Rosario. *Power and Energy Management of Multiple Energy Storage Systems in Electric Vehicles.* PhD thesis, Defence College of Management and Technology - Cranfield University, 2007.

[32] L. Rosario and P.C.K. Luk. Applying management methodology to electric vehicles with multiple energy storage systems. In *Machine Learning and Cybernetics, 2007 International Conference on*, volume 7, pages 4223 –4230, 2007.

[33] M.E. Glavin, P.K.W. Chan, S. Armstrong, and W.G. Hurley. A stand-alone photovoltaic supercapacitor battery hybrid energy storage system. In *Proc. 13th Power Electronics and Motion Control Conf. EPE-PEMC 2008*, pages 1688–1695, 2008.

[34] T.A. Singo, A. Martinez, S. Saadate, and S. Rael. An optimized photovoltaic system using an effective energy conversion. In *Proc. 8th Int. Symp. Advanced Electromechanical Motion Systems & Electric Drives Joint Symp. ELECTROMOTION 2009*, pages 1–6, 2009.

[35] W. Lhomme, P. Delarue, P. Barrade, A. Bouscayrol, and A. Rufer. Design and control of a supercapacitor storage system for traction applications. In *Proc. Fourtieth IAS Annual Meeting Industry Applications Conf. Conf. Record of the 2005*, volume 3, pages 2013–2020, 2005.

[36] J. Cao and A. Emadi. A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles. *IEEE Transactions on Power Electronics*, 27(1):122–132, 2012.

[37] B. Chen, Y. Gao, M. Ehsani, and J.M. Miller. Design and control of a ultracapacitor boosted hybrid fuel cell vehicle. In *Proc. IEEE Vehicle Power and Propulsion Conf. VPPC '09*, pages 696–703, 2009.

[38] J. Bauman and M. Kazerani. A comparative study of fuel-cell–battery, fuel-cell–ultracapacitor, and fuel-cell–battery–ultracapacitor vehicles. *IEEE Transactions on Vehicular Technology*, 57(2):760–769, 2008.

[39] Y. Cheng, M. Van Joeri, and P. Lataire. Research and test platform for hybrid electric vehicle with the super capacitor based energy storage. In *2007 European Conference on Power Electronics and Applications, EPE*, 2007.

[40] P. Thounthong, P. Sethakul, S. Rael, and B. Davat. Control of fuel cell/battery/-supercapacitor hybrid source for vehicle applications. In *Proc. IEEE Int. Conf. Industrial Technology ICIT 2009*, pages 1–6, 2009.

[41] W. Li and G. Joos. A power electronic interface for a battery supercapacitor hybrid energy storage system for wind applications. In *Proc. IEEE Power Electronics Specialists Conf. PESC 2008*, pages 1762–1768, 2008.

[42] A.A. Ferreira, J.A. Pomilio, G. Spiazzi, and L. de Araujo Silva. Energy management fuzzy logic supervisory for electric vehicle power supplies system. *IEEE Transactions on Power Electronics*, 23(1):107–115, 2008.

[43] D. Gao, Z. Jin, and Q. Lu. Energy management strategy based on fuzzy logic for a fuel cell hybrid bus. *Journal of Power Sources*, 185(1):311–317, 2008.

[44] O. Erdinc, B. Vural, and M. Uzunoglu. A wavelet-fuzzy logic based energy management strategy for a fuel cell/battery/ultra-capacitor hybrid vehicular power system. *Journal of Power Sources*, 194(1):369–380, 2009.

[45] C. Abbey and G. Joos. Supercapacitor energy storage for wind energy applications. *IEEE Transactions on Industry Applications*, 43(3):769–776, 2007.

[46] M. Dondas, F. Alkhalil, P. Degobert, F. Colas, and B. Robyns. Supervision of a hybrid system based on photovoltaic arrays and supercapacitors. In *POWERENG 2009 - 2nd International Conference on Power Engineering, Energy and Electrical Drives Proceedings*, pages 342–347, 2009.

[47] M.U.D. Mufti, S.A. Lone, S.J. Iqbal, M. Ahmad, and M. Ismail. Super-capacitor based energy storage system for improved load frequency control. *Electric Power Systems Research*, 79(1):226–233, 2009.

[48] P.L. Bartlett. The sample complexity of pattern classification with neural networks: the size of the weights is more important than the size of the network. *IEEE Transactions on Information Theory*, 44(2):525–536, 1998.

[49] S. Li, D.C. Wunsch, E.A. O'Hair, and M.G. Giesselmann. Using neural networks to estimate wind turbine power generation. *IEEE Transactions on Energy Conversion*, 16(3):276–282, 2001.

[50] R. Fierro and F.L. Lewis. Control of a nonholonomic mobile robot using neural networks. *IEEE Transactions on Neural Networks*, 9(4):589–600, 1998.

[51] Y. Ates, O. Erdinc, M. Uzunoglu, and B. Vural. Energy management of an fc/uc hybrid vehicular power system using a combined neural network-wavelet transform based strategy. *International Journal of Hydrogen Energy*, 35(2):774 – 783, 2010.

[52] M. Ortuzar, J. Moreno, and J. Dixon. Ultracapacitor-based auxiliary energy system for an electric vehicle: implementation and evaluation. *IEEE Transactions on Industrial Electronics*, 54(4):2147–2156, 2007.

[53] M. Cavalletti, J. Piovesan, C.T. Abdallah, S. Longhi, P. Dorato, and G. Ippoliti. Statistical learning controller for the energy management in a fuel cell electric vehicle. In *2008 47th IEEE Conference on Decision and Control*, pages 2481–2486, 2008.

[54] F.M.F. Mascioli, A. Rizzi, M. Panella, and C. Bettiol. Optimization of hybrid electric cars by neuro-fuzzy networks. In *Applications of Fuzzy Sets Theory*, pages 253–260, 2007.

[55] E.D. Tate and S.P. Boyd. Finding ultimate limits of performance for hybrid electric vehicles. In *Proc. of the SAE Future Transportation Technology Conference*, pages 1–12, 2000.

[56] H. Morais, P. Kadar, P. Faria, Z.A. Vale, and H.M. Khodr. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. *Renewable Energy*, 35(1):151–156, 2010.

[57] M.C. Bozchalui, S.A. Hashmi, H. Hassen, C.A. Canizares, and K. Bhattacharya. Optimal operation of residential energy hubs in smart grids. *IEEE Transactions on Smart Grid*, 3(4):1755–1766, 2012.

[58] M. Ramamoorty and J. Gopala Rao. Load scheduling of hydroelectric/thermal generating systems using nonlinear programming techniques. *Proceedings of the Institution of Electrical Engineers*, 117(4):794–798, 1970.

[59] I.G. Moghaddam and A. Saeidian. Self scheduling program for a vrb energy storage in a competitive electricity market. In *Proc. Int Power System Technology (POWERCON) Conf*, pages 1–6, 2010.

[60] A. Korpela, J. Lehtonen, R. Mikkonen, and J. Paasi. Optimization of smes magnet volume with electromagnetic and mechanical constraints. *IEEE Transactions on Applied Superconductivity*, 10(1):780–783, 2000.

[61] M. Koot, J.T.B.A. Kessels, B. de Jager, W.P.M.H. Heemels, P.P.J. van den Bosch, and M. Steinbuch. Energy management strategies for vehicular electric power systems. *IEEE Transactions on Vehicular Technology*, 54(3):771–782, 2005.

[62] S. Teleke, M.E. Baran, S. Bhattacharya, and A.Q. Huang. Optimal control of battery energy storage for wind farm dispatching. *IEEE Transactions on Energy Conversion*, 25(3):787–794, 2010.

[63] Y. Xu and C. Singh. Adequacy and economy analysis of distribution systems integrated with electric energy storage and renewable energy resources. *IEEE Transactions on Power Systems*, 27(4):2332–2341, 2012.

[64] Y. Riffonneau, S. Bacha, F. Barruel, and S. Ploix. Optimal power flow management for grid connected pv systems with batteries. *IEEE Transactions on Sustainable Energy*, 2(3):309–320, 2011.

[65] S. Grillo, M. Marinelli, S. Massucco, and F. Silvestro. Optimal management strategy of a battery-based storage system to improve renewable energy integration in distribution networks. *IEEE Transactions on Smart Grid*, 3(2):950–958, 2012.

[66] C. Romaus, K. Gathmann, and J. Böcker. Optimal energy management for a hybrid energy storage system for electric vehicles based on stochastic dynamic programming. In *Proc. IEEE Vehicle Power and Propulsion Conf. (VPPC)*, pages 1–6, 2010.

[67] C. Mansour and D. Clodic. Optimized energy management control for the toyota hybrid system using dynamic programming on a predicted route with short computation time. *International Journal of Automotive Technology*, 13(2):309–324, 2012.

[68] S. Mei, Y. Wang, F. Liu, X. Zhang, and Z. Sun. Game approaches for hybrid power system planning. *IEEE Transactions on Sustainable Energy*, 3(3):506–517, 2012.

[69] D. Grosu and A.T. Chronopoulos. Algorithmic mechanism design for load balancing in distributed systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 34(1):77–84, 2004.

[70] J.A. Momoh and A.R. Ofoli. Load management and control of the photovoltaic (pv) system using fuzzy logic. In *Proc. Large Engineering Systems Conf. Power Engineering LESCOPE '01*, pages 184–188, 2001.

[71] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu. Smart energy management system for optimal microgrid economic operation. *IET Renewable Power Generation*, 5(3):258–267, 2011.

[72] F.H.F. Leung, H.K. Lam, S.H. Ling, and P.K.S. Tam. Tuning of the structure and parameters of a neural network using an improved genetic algorithm. *IEEE Transactions on Neural Networks*, 14(1):79–88, 2003.

[73] R. Bellman. On the theory of dynamic programming. In *Proceedings of the National Academy of Sciences of the United States of America*, volume 38, pages 716–719, 1952.

[74] R. Bellman. Bottleneck problems and dynamic programming. In *Proceedings of the National Academy of Sciences of the United States of America*, volume 39, pages 947–951, 1953.

[75] R. Bellman. *Dynamic Programming.* Princeton University Press, 1957.

[76] R. Larson. A survey of dynamic programming computational procedures. *IEEE Transactions on Automatic Control*, 12(6):767–774, 1967.

[77] R. Giegerich, C. Meyer, and P. Steffen. A discipline of dynamic programming over sequence data. *Science of Computer Programming*, 51(3):215–263, 2004.

[78] J. Rust. Chapter 14 numerical dynamic programming in economics. In *Handbook of Computational Economics*, volume 1, pages 619–729. Elsevier, 1996.

[79] L. Grüne and W. Semmler. Using dynamic programming with adaptive grid scheme for optimal control problems in economics. *Journal of Economic Dynamics and Control*, 28(12):2427–2456, 2004.

[80] A.A. Amini, T.E. Weymouth, and R.C. Jain. Using dynamic programming for solving variational problems in vision. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(9):855–867, 1990.

[81] H. Sakoe and S. Chiba. Dynamic programming algorithm optimization for spoken word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 26(1):43–49, 1978.

[82] M. Sniedovich. *Dynamic Programming: Foundations and Principles.* CRC Press, 2010.

[83] K.J. Arrow, T. Harris, and J. Marschak. Optimal inventory policy. *Econometrica*, 19(3):250–272, 1951.

[84] J.F. Hêche, T.M. Liebling, and D. de Werra. *Recherche opérationnelle pour ingénieurs II.* Presses Polytechniques et Universitaires Romandes, 2003.

[85] Pneumatic Vacuum Elevators. http://www.pneumaticelevator.com/techinfo.html.

[86] Orona Elevators. http://www.orona.es/.

[87] How stuff works. http://science.howstuffworks.com/transport/engines-equipment/elevator1.htm.

[88] H. Yang, W. Sun, and B. Xu. New investigation in energy regeneration of hydraulic elevators. *IEEE/ASME Transactions on Mechatronics*, 12(5):519–526, 2007.

[89] C. Attaianese, V. Nardi, F. Parillo, and G. Tomasso. High performances supercapacitor recovery system including power factor correction (pfc) for elevators. In *2007 European Conference on Power Electronics and Applications, EPE*, pages 1–10, 2007.

[90] L.W. White, S.M. Lukic, and S. Bhattacharya. Investigations into the minimization of electrical costs for traction-type elevators. In *Proc. IEEE Energy Conversion Congress and Exposition (ECCE)*, pages 4285–4292, 2010.

[91] C. Attaianese, V. Nardi, and G. Tomasso. A high efficiency conversion system for elevators. In *2007 International Conference on Clean Electrical Power, ICCEP '07*, pages 236–242, 2007.

[92] A. Bouscayrol, X. Guillaud, and P. Delarue B. Lemaire-Semail. Energetic macroscopic representation and inversion-based control illustrated on a wind-energy-conversion system using hardware-in-the-loop simulation. *IEEE Transactions on Industrial Electronics*, 56(12):4826–4835, 2009.

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E. Bilbao, P. Barrade, I. Etxeberria-Otadui, A. Rufer, S. Luri and I. Gil "Optimal Energy Management of an Improved Elevator with Energy Storage Capacity based on Dynamic Programming" IEEE Transactions on Industry Applications (Submitted on 2012).

E. Bilbao, P. Barrade, I. Etxeberria-Otadui, A. Rufer, S. Luri and I. Gil, "Optimal Energy Management of an Improved Elevator with Energy Storage Capacity based on Dynamic Programming" in Proc. IEEE Energy Conversion Congress and Exposition (ECCE), 2012.

S.Luri, I. Etxeberria-Otadui, A. Rujas, **E. Bilbao** and A. Gonzalez “Design of a Supercapacitor Based Storage System for Improved Elevator Applications” in Proc. IEEE Energy Conversion Congress and Exposition (ECCE), 2010.

E. Bilbao, H. Gaztañaga, L. Mir, I. Etxeberria-Otadui and A. Milo “Design and Development of a Supercapacitor-Based Microgrid Dynamic Support System” in Proc. 13th European Power Electronics Conference (EPE), 2009.

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