Optimizing Energy Efficiency for Train Operation Constrained to Scheduling

Thesis Work Plan

Agostinho Manuel Afonso da Rocha

Supervisor: Prof. Armando Luís Sousa Araújo
Co-Supervisor: Prof. Manuel João Sepúlveda Mesquita Freitas

Doctoral Program in Electrical and Computer Engineering,
Department of Electrical and Computer Engineering
Faculty of Engineering, University of Porto
11th July, 2017

Contents

List of Figures

List of Tables

Acronyms

AC	Alternating Current
ACO	Ants Colony Optimization
ANN	Artificial Neural Network
ATO	Automatic Train Operation
BMS	Battery Management System
DAS	Driving Assistant System
DC	Direct Current
DG	Distributed Generation
DP	Dynamic Programming
EA	Evolutionary Algorithm
EDLC	Electric Double-Layer Capacitors
EMS	Energy Management System
ESS	Energy Storage System
GA	Genetic Algorithms
HGA	Hierarchical Genetic Algorithm
IBEA	Indicator - Based Evolutionary Algorithm
IDE	Immune Differential Evolutionary
MARK	Minimum-Allele-Reserve-Keeper
PCC	Point of Common Coupling
PSO	Particle Swarm Optimization
PWM	Pulse Width Modulation
SA	Simulated Annealing
SC	Super-Capacitors
SOH	State of Health
SQP	Sequential Quadratic Programming

CHAPTER 1
Introduction

The Railway system is widely used for freight and passenger transportation. Its popularity derives mainly from being a reliable and secure transportation system.

Unfortunately, operation and maintenance costs associated to railways have increased over the years. On the other hand, due to the high traffic, some infrastructures are near to its maximum capacity, debilitating their ability to respond to all costumers/system needs.

So, inserted in the iRail Program framework, and with the purpose of accomplishing modern railway system needs, it is intended to develop a thesis focused in research systems to improve trains energy efficiency.

The iRail program - Innovation in Railway Systems and Technologies - has the objective to respond to the actual concerns related with railway systems, achieving a high capacity, cost-efficient and sustainable rail transportation system. The Thesis work covers the innovation program IP3 – Cost-Efficient, Sustainable and Reliable High Capacity Infrastructures, exploring how power electronics can contribute for the iRail program objectives [1].

The proposed work will focus in ways to reduce energy consumption during trains operation. Reducing the energy in each train appears an opportunity to increase the system capacity.

The starting point will be the study of a typical train driving cycle in order to identify the amount of energy involved on a railway system and understand the system dynamics. The following study will be done in order to develop a Driving Assistant System (DAS) to advice the driver about how the train must be driven between two consecutive stations. The DAS will include an optimization algorithm to reduce the energy consumption, maximize the use of regenerative energy, constraint to the system schedules and velocity limits on the line.

This document presents the thesis main objectives and the expected contributions. The literature review to start the developments will be also presented followed by a short description about the methodology to be adopted. A work plan, based on thesis objectives is also proposed. In the end, the actual research statement is presented and preliminary results obtained are discussed.

CHAPTER 2

Objectives and Contributions

The current chapter presents the objectives proposed for the doctoral thesis. The expected contributions are also enumerated in Section 2.2.

2.1 Objectives

The aim of this work is focused on the development of systems and tools with the purpose to improve the energy efficiency in railways. This objective will be met by developing solutions that allow both minimization of energy consumption and maximization of regenerative energy.

To reach these objectives, a research in DAS is proposed. As the name suggests, a DAS is a system that advices the train driver how to operate the train in order to meet a specific purpose. These systems are typically installed in the cabin and, through a display, information about velocity, acceleration and breaking phases are displayed. The velocities profiles generated by DAS can be determined by considering energy consumption and/or time delays reduction [2].

Based on this thesis proposal, inserted on Shift2Rail program, the defined objectives are:

1. Research on train models;
2. Implementation and Development of a train model for simulation purpose;
3. Research and development of a DAS;
4. Algorithm implementation on a portable platform;
5. Validation through real tests.

2.2 Contributions

Based on the thesis main objectives inserted in the Shift2Rail scope, the contributions identified for this thesis work are:

1. Increase system capacity by reducing energy consumption in each train;
2. Optimisation of timetables by reducing time delays;
3. System stabilization by reducing the peak power asks.

CHAPTER 3

State of the Art

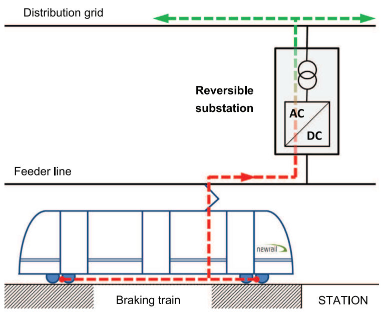
The present chapter shows the state of the art related with thesis research subjects. The study starts with a brief description about regenerative energy flow in railways, Section 3.1. After, an introduction about microgrids is done in Section 3.2. Some microgrids configurations and control strategies are the main topics discussed. The next section, Section 3.3, a mathematical model for the dynamic behaviour of the train is described and recent work in energy efficiency for railways is also presented. The state of the art continues with Energy Storage System (ESS), Section 3.4. This section includes a description about ESS technologies and topologies. The railways actual systems available in the market and in research works are also presented. Before the end of the chapter, Section 3.5, some optimization algorithms are presented as a tool that can be followed in future developments.

3.1 Regenerative Energy Flow

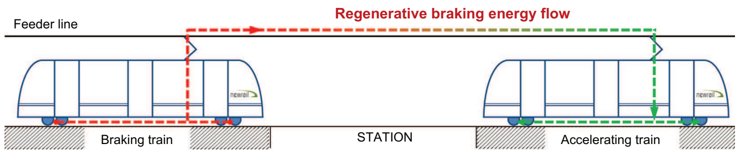
Regenerative breaking is frequently used as a technique to generate energy. As another system, in railways this technique makes use of train breakings and decelerations to generate energy. The resulting recovered energy can be again used in the system or stored properly [3].

The recovered energy in railway system has three possible outcomes has described in [4–6]:

- Auxiliary systems power supply: feeding auxiliary systems (air conditioner or door opening system, etc) installed on the train;
- Sent back to catenary: Typically happen when the amount of energy is higher than internal consumption and the catenary is available to receive. Once on the catenary side, energy can be delivered to two different destinations:
    - Grid injection, Fig. 3.1a. The energy can only be injected into the grid if a bidirectional power flow in the substation is allowed;
    - Reused by the catenary in another train that is accelerating at same line section, Fig. 3.1b. This application requires trains departures and arrives synchronization to allow energy changes between two line "dead zones".
- Dissipated on breaking resistors installed in the train.



(a) Grid injection



(b) Between trains

Figure 3.1: Regenerative energy flow in railways [5]

To maximize the regenerative energy and efficiency in railway system, some developments on integration of ESS are being made. Later, Section 3.4.4, some solutions presented in the literature will be described.

3.2 MicroGrids

During the past few years, microgrids have received special attention as research area. One of the main research objectives is related with development of new control strategies, in order increase microgrids accuracy and robustness.

Microgrids are defined in [7] as a multi-source bus that can operate in two possible modes: grid connected and grid disconnected, also known as island mode. Although the number of microgrids structures and scenarios in use is large, a group of basic components is common in all microgrid systems. Those components can be defined as being fundamental to microgrids and they can be seen in Fig. 3.2, where a general structure is presented.

As mentioned before, a microgrid must operate autonomously in two different modes, grid connected or island mode. As such, a physical component that allows the connection and/or disconnection of the grid must be a part of the structure. This connection is done in a region of the microgrid called Point of Common Coupling (PCC). The next basic component is the Distributed Generation (DG), that consists in all generation units connected to the main bus. The DG are responsible to keep the microgrid operation during the island mode and can contribute for frequency, active and reactive power control when connected to the utility.

For energy management purposes and to easily manage the energy flow in the microgrid, an ESS is commonly used. The last basic component is the controller that is responsible for defining the operation mode in the microgrid; the controller must also keep the nominal voltage and frequency in the grid.

The power electronics converters, associated with each system and with the purpose to

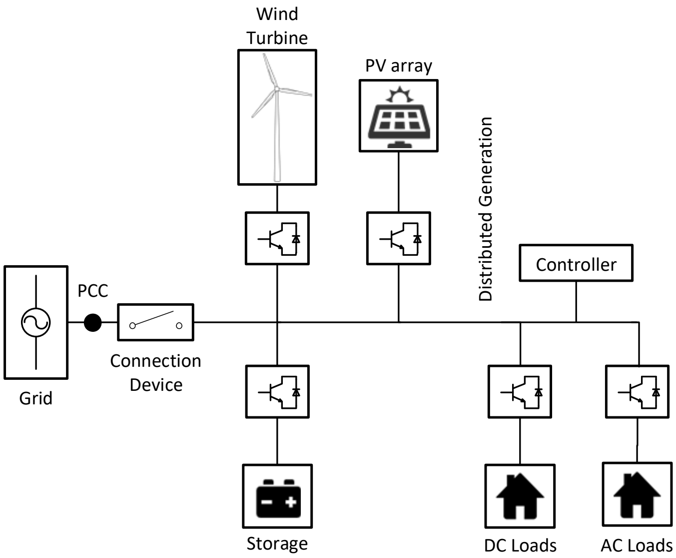


Figure 3.2: Microgrid basic components (adapted from [8])

connect each component to the main bus, are also considered microgrid basic components. They must adapt the voltage and current values of each output to the main bus.

As mentioned before, microgrids have two operations modes. A detailed description of each mode is presented:

- **Grid Connected:** During grid connected mode, the microgrid can be absorbing or providing energy to the grid. This operation point depends on the amount of energy that is consumed and generated. The grid can get some advantages during this mode, since microgrid can contribute for frequency, active and reactive power. The voltage magnitude and frequency in the microgrid is controlled by the grid.

- **Island Mode:** Microgrid during island mode has the purpose of provide energy locally. The grid operates autonomously, managing the energy flow between generation and load. The voltage amplitude and frequency is controlled by the microgrid controller.

In both modes, some maintenance and diagnosis functions must be implemented in order to keep the network safe. In some cases, the transition states between the two previously presented modes are also considered as additional operation modes.

Related with microgid control, two classes of control strategies for Alternating Current (AC) and Direct Current (DC) microgrids are nowadays implemented. The control strategies are:

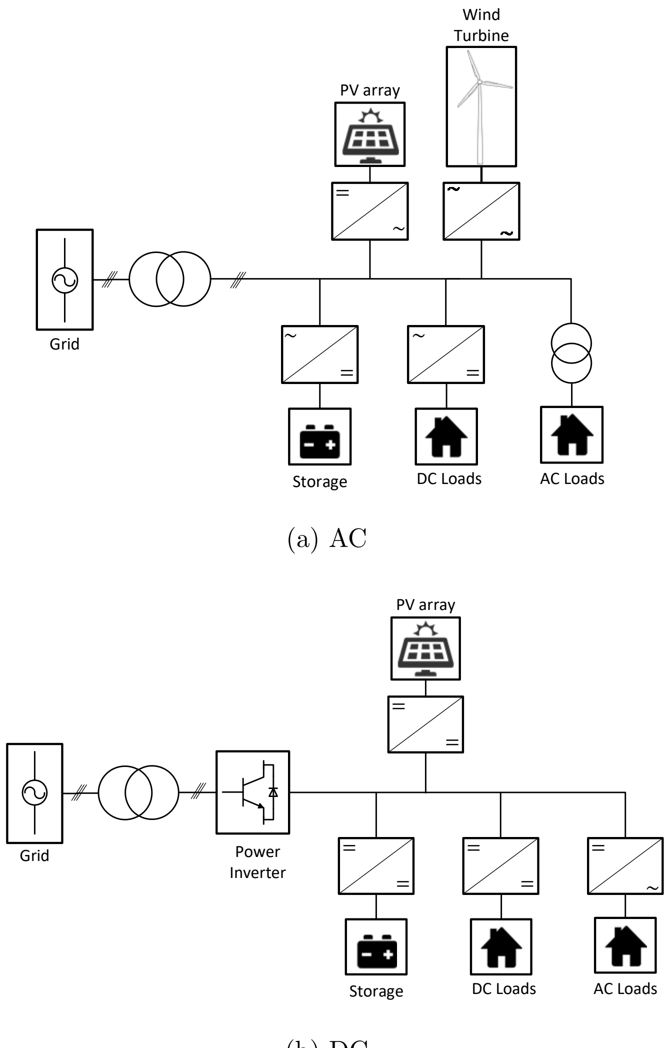
- **Centralized:** As the name suggests, the power flow over the microgrid is controlled in a central point. This class of control relies on communication that is made between the central controller and each subsystem. The biggest drawback of this scheme is the difficulty of introducing new sources and/or loads.

- **Decentralized:** The control is done in each grid component. This scheme is the most appropriate for microgrids, since is more robust to grid expansion. Besides, since every component terminal determines their own actions, the decentralized scheme gives some redundancy to the control, which is an advantage. With this scheme, the introduction or disconnection of new loads and/or DG units does not compromise the system's stability.

As with any other system, microgrids also have requirements: be compatible with the introduction and/or exclusion of new power sources and/or loads without compromise the system's stability is one example. Besides, it must be also prepared to be plugged or unplugged from the grid autonomously [8–10].

3.2.1 Configurations

Microgrids can be AC or DC systems. The classification is established by the way that the grid components are connected and integrated. The basic structure of AC and DC microgrids are presented in Fig. 3.3.



(a) AC

(b) DC

Figure 3.3: Microgrid structures (adapted from [11])

The first structure presented, Fig. 3.3a, is an AC microgrid. All the DG units, loads and ESS are connected to a common AC bus. This AC bus can be considered a small grid that must be synchronized with a controller to the main utility for voltage amplitude and frequency control purposes. For the island operation mode, it is common for a converter to generate for the grid, supported by the remaining ones. In some applications, AC microgrids are developed under standards used by the grid operator.

The other microgrid structure presented is the DC, Fig. 3.3b. DC microgrids are composed by power sources and/or loads that shared a common bus. The interest of research in DC microgrids has grown up with the increase of research in renewable energy. The main reason is the fact that it is easier to integrate with storage systems and renewable energy sources in a DC microgrid (when compared with an AC). At same time, grid efficiency can increase, since it is not necessary to introduce additional AC/DC or DC/AC converters to connect the sources and/or loads.

Additionally, in a DC microgrid, the power flow control development is relatively simple, since there is no needed to implement functions for synchronization and reactive power compensation. Although, the controller's complexity comes with the sources and loads behaviour, which is typically unpredictable [9]. As a solution, stated in [7], an ESS can give stability to the grid by absorbing or injecting power into the grid during load changes, caused by the unpredictable power flow. With this solution, the grid stabilization increases with the need of a controller over the storage. This controller, called Energy Management System (EMS), is responsible for keeping the storage working without being damaged [7, 9, 11].

The most common control topologies applied in microgrids are going to be presented next section.

3.2.2 Control Strategies

The operation modes of microgrids have an important role in the design of control strategies. These control strategies aim in microgirds is to ensure the proper operation of the system. Apart from this, microgrids must be prepared to change from the grid connected mode to island mode autonomously when a fault happens in the grid. With this, the microgrid must feed continuously the local loads uninterruptedly, if the load demand does not exceed the generated energy. In the event that this happens, the microgrid must be prepared to characterize the loads and be able to disconnect the least priority loads [8].

In microgrids, a controller with hierarchical approach is implemented. Typically, 3 levels are defined: level 1 is on bottom and level 3 is on top of this hierarchy, and can be seen as a control topology with three loops. As expected, the control levels do not operate isolated and all contribute for system stabilization. The three levels can be described as [12]:

- Level 1: The first level is responsible for voltage and current control at converter level. This level also contains a droop control loop with the purpose of defining the contribution of each converter in the microgrid. This level can include a controller with two loops, an inner loop that controls the voltage at the converters terminals, by regulating the current, and an outer loop, that manages the energy through all microgrids DG.

- Level 2: It is known as secondary control in the literature. At this level, functions with the purpose to keep microgrid voltage and frequency in nominal values are implemented. In other words, the second level restores the voltage and frequency after deviations caused by load changes. For AC microgrids, the grid synchronization is given by this secondary control.

- Level 3: The highest level in hierarchy known as tertiary control. This level is responsible for power flow control between the microgrid and the grid. In some cases, optimization algorithms are included at this level. The idea is determining the best operation for the microgrid, with energy consumption cost minimization or reduction of the high power peaks.

In grid connected mode, the most known control strategy applied is the power flow control. The aim of this strategy is to generate an output with controlled active and reactive power. To achieve the desired output, the power flow control can be implemented in two different ways:

Current Regulation:

This control strategy makes use of a reference frame transformation from natural coordinates *abc* to a rotating reference frame $d-q$. For that, some measurements in the grid must be done in order to determine the phase angle to synchronize both power sources.

In the rotating reference frame, the 3 phase grid is represented by two DC components. Those components can be controlled separately through a linear PI controller and a vector control can generate Pulse Width Modulation (PWM) signals to be applied in a power converter as a voltage source inverter. The current regulation for power flow control is based on the current control in the line, where the active and reactive power can be controlled by managing the d an q component of the current [8, 13].

Fig. 3.4 shows a block diagram that represents the control topology.

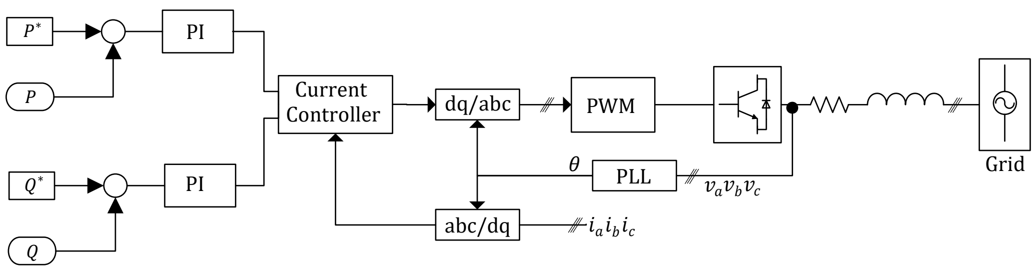


Figure 3.4: Power flow control through current regulation (adapted from [13])

Voltage Regulation:

The other way to implement the power flow control is by voltage regulation. Fig. 3.5 shows a block diagram that represents this control strategy.

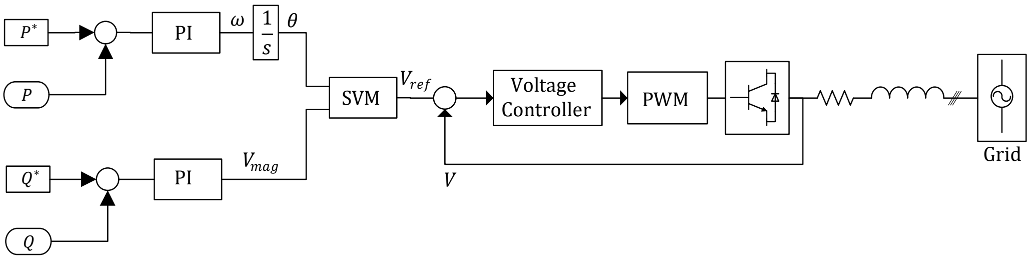


Figure 3.5: Power flow control through voltage regulation (adapted from [13])

The voltage regulation controls the line power by managing the voltage amplitude and phase difference at the converter output. The scheme makes uses of line characteristics between the source and the controlled output terminals, which can be a disadvantage, since the controller's gains are determined for a specific connection. This connection can be the line between the grid terminal and the converter output. The scheme does not need a phase lock loop synchronizer and the loop is closed by the measurement of the converter output voltage.

The active power control is achieved by defining the phase angle difference between the converter output and the grid. The reactive power is dependent on the voltage difference between the two points [8, 13].

The biggest challenge in microgrids control is the automatic switch between grid connected to island mode, when required by the system. All the systems connected to microgrid must be able to determine when an operation mode change occurs in order to change each local control mode.

Between both microgrids structures presented, the controller development for DC is easier when compared with AC. This is due to the fact of having no need of controlling frequency and/or phase deviations caused by load changes [11, 13].

Microgrids controllers in island mode operation must be implemented with the aim of accomplishing grid requirements as voltage and frequency control. Besides, power quality and balance over the bus must also be a requirement for the controller [8]. Some controller strategies are being developed, such as the load shedding algorithm, commonly used when changing modes (to disable some load before starting a voltage control mode) [13]. The main idea is, before establishing the island mode, it guarantees the power balance between the generation and consumption. The power flow control by voltage regulation, presented as a strategy for grid connected mode, can be also used in AC microgrids when is in isolated operation.

For DC microgrids control, some published works have been analysed in order to understand the achieved developments. From that analysis, it was noticed that DC the proposed microgrids controllers are all very similar and generally have the same principles. The main monitored variable is the voltage over the main DC link and, in some works, it is presented as a communication channel between the primary control. Based on DC link voltage, some states and possible operations points take into account microgrids definition and balance of power between generation and load. In conclusion, the power flow management is made by a state machine that determines the microgrid operation point based on DC voltage bus. Besides, since it is a requirement, the state machines also contains the island and grid connected modes and ESS supervision. As an example, [14] presents a DC microgrid with ESS and renewable energy sources with a similar structure for the power flow control [9, 11].

3.3 Energy Efficiency in Railways

Energy efficiency in railways is a research topic where the first developments were made around the 1970s. Recently, the interest of research in this area has grown and new developments aimed at reducing energy consumption during train operation are being done [15, 16].

Developments in power electronics and ESS are being done in order to achieve an operation costs reduction without compromising the system reliability. Furthermore, new controllers and optimization algorithms are being implemented for trip planning. The purpose is to give to the driver some accelerations and/or decelerations advices for the actual trip.

3.3.1 Train Dynamic Model

The energy determination, due to train operation, can be done by real data measurements or through a dynamic model. Although real data measurements is the most interesting approach as analyses tool, the acquisition system costs and data processing time needed makes it an unpopular method. As alternative, dynamic models are developed in order to describe and estimate a real systems behaviour. In some works, related with energy-efficiency, as example in [15,17–19], dynamic motion equations to represent the train behaviour are used. The purpose of the model is to estimate the energy consumption, and regenerated, if considered. Some equations variations are presented, but they are based in the same physical principles. In [20] the model is presented and a briefly description will be given during this section.

Train motion equation, described by (3.1) is based on Lomonossoff principle. The equation can be used to describe the dynamic behaviour of any vehicle. In the case of a train, the forces that the vehicle is subject during a normal operation are represented in Fig. 3.6. Those forces are traction force, F_t, motion resistance, F_r and gravity resistance, F_g. Considering the case presented in the figure, to have a forward movement, traction force must be higher than the sum of both resistance forces.

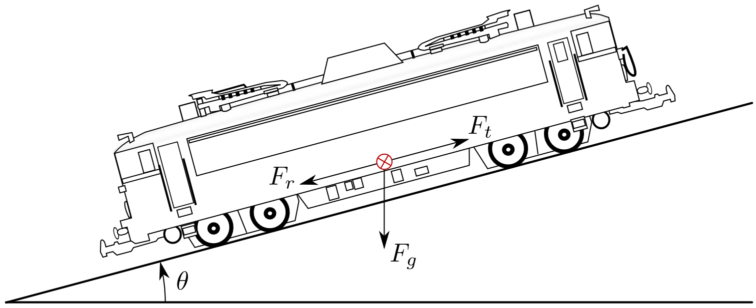


Figure 3.6: Forces scheme for a train

$$M_e \frac{\partial v}{\partial t} = F - W \tag{3.1}$$

Analysing (3.1) can be concluded that the train motion equation is written based on Newton's second law. v represents train velocity, F the resultant force and W the resistance to movement. M_e is the train mass that can be considered equal to the total mass, M, when there are no rotating parts in the vehicle. When it happens, the total should be affected by a rotary allowance, λ, added to the equation, to include the rotating parts influence in the total mass. This factor can be determined by the moment of inertia of each part, I as shown in (3.2). In the end, in (3.1) M_e must be substituted by $(1 + \lambda)M$.

$$\lambda = \frac{\sum \frac{w}{v} \frac{\partial w}{\partial v}}{M} \tag{3.2}$$

In (3.1) W represents the motion resistance composed by three resistance components. Those components are caused by the straight and horizontal travelling, gradient and curvature of the rails. In other words, the resistance forces applied is reduced to the gravity, F_g, and motion resistance, F_r. Motion resistance can be solved by applying Davis equation as presented in (3.3).

$$F_r = a + bv + cv^2 \tag{3.3}$$

The coefficients, a, b and c characterize the simulated vehicle and therefore can be determined based on real data, acquired on a train. Coefficients a and b are related with train mass, representing the mechanical resistance and c introduces the influence of air resistance in the model [21].

Additionally to train resistance, the second force opposite to train movement is the gravity resistance (3.4). F_g appears in line sections with slopes, and it is proportional to vehicle total mass, M, and the track inclination or angle θ.

$$F_g = Mgsin(\theta) \tag{3.4}$$

Combining all the equations into one, the final motion equation of the dynamic model of the train is (3.5). This model will be used considering a pathway length larger than the train, making possible to consider the train as a point of mass that moves in a plan.

$$(1 + \lambda)M \frac{\partial v}{\partial t} = F - \left(a + bv + cv^2 + Mgsin(\theta)\right) \tag{3.5}$$

(3.5) allow the determination of total force felt by the train as respective acceleration. With this, the traction force needed can be determined to estimate the amount of traction power (3.6) and the energy (3.6) needed for train movement.

$$P = Fv \tag{3.6}$$

$$E = \int Fv\partial t \tag{3.7}$$

3.3.2 Trajectory Planning

Concerning with energy consumption reduction, some developments are being done in trajectory planning for railways. After a state of the art analyses, some approaches were identified. The first examples were based on algorithms developments used to determine coast point position in a train pathway, once during coasting phase no traction force is applied to have a train movement. Following the previous statement, energy consumed by a train can be reduced by increasing coast points number in a train pathway. As results, algorithms that produces velocity references as output that avoids unnecessary accelerations and/or decelerations are being developed. Some examples are going to be presented in a next section. The second approach is related with schedules synchronization. As explained before, regenerative energy generated by trains breaking can be applied in another accelerating train. Under this approach, algorithms to synchronize trains departures and arrivals are being developed with the purpose to maximize the use of regenerative energy. This last approach was not explored once the objective of this work is to develop on-board solutions.

Returning to the first approach, DAS are being developed with the purpose to reduce the energy bill. A DAS determines speed profiles to advice the driver about how the actual journey can be done. The most common algorithm structure that can be found in the literature uses energy consumption reduce as main objective. In other hand, DAS can also be developed to reduce time delays in the journey. To accomplish the objectives, the solutions presented must satisfy some real constrains as line velocity limits and slope gradients.

Concerning with regenerative energy, most of the papers studied are not considering an ESS, and as consequence, the recovered energy is delivered to the catenary. As referred before, once delivered to the catenary, the energy can be applied in another vehicle or be injected on the grid. After a briefly analyses, an ESS is considered an improvement to contribute for the system efficiency. With this improvement, the regenerative energy flow will not be only dependent on the catenary availability. Besides, power losses in the line can be reduce and peak shaving functionalities can be implemented [6].

3.3.2.1 Optimal Speed Profile

The velocity profile of a train, between two consecutive stations, was governed by similar patterns. This pattern, Fig. 3.7, consists in a sequence of four different traction profiles.

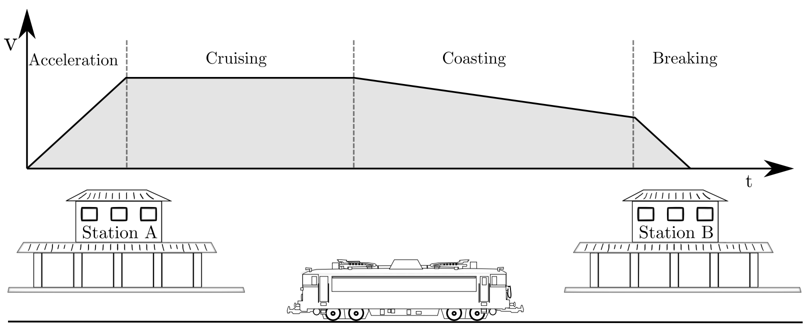


Figure 3.7: Train Trajectory

The sequence of traction regimes are a result of application of optimal control theory to speed profile determination. In [15–17, 22–24] is described how the velocity profile can be determined by applying the maximum principle. The profile is determined through the dynamic model equations, considering the velocity and time constraints. As objective function, the energy consumption minimization is set as the desired output of the algorithm. The main results of the algorithm is a set of four traction regimes characterize as:

- Acceleration with maximum traction force - Applied at the beginning with the purpose to reach the cruising velocity. The use of maximum force has the aim to reduce the time and space needed to reach desired velocity;
- Cruising - After reached a predefined velocity, preciously determined as the cruising optimal velocity, the train must maintain that velocity by applying a traction force that maintains movement. The cruising phase is used to accomplish the total distance;
- Coasting - Characterized by train movement due to inertia, it means, there is no traction force needed;
- Full breaking - Used to reduce the train velocity against a speed limit or stop the train in a station. Has happen in acceleration, breaking phase can also be done to reduce the time and space needed.

The traction regime sequence, in train operation can be defined in another order and/or some could be not applied. There are some reasons as not enough space between stations or line profile characteristics that affect the optimal operation point [25]. As conclusion, it is not mandatory the application of traction regimes as presented. The most appropriate sequence and duration time of each regime has been determined through some optimization algorithm. Next section, some examples will be presented.

3.3.3 Driving Assistant Profiles

A Genetic Algorithms (GA) based algorithm is presented in [26] which determines coast point in train pathway. At each station, before train's departures, a new solution is determined and a coast control table is produce. The algorithm output can be used with an Automatic Train Operation (ATO) system. Considering a multi-objective function, each coast profile is determined concerning time punctuality, passenger's comfort and energy consumption. The algorithm was tested in two different cases, based on schedules definition and the algorithms results were compared with a fuzzy logic control ATO. Another GA based algorithm to locate coast points in a train pathway is presented in [27]. In each stop, a new profile for the travelling distance between two consecutive stations is determined. A binary string, whit a length dependent on the total travelling distance, is used to represent the coast point's position, and on this, mutation and crossover operations are applied. In this same work, an optimization for multiple railways stations is also considered. For this, an implementation based on a Hierarchical Genetic Algorithm (HGA) is presented where the previous string were used with an addiction of a number which represents the total coast point needed. A Minimum-Allele-Reserve-Keeper (MARK) mutation scheme is used in the algorithm, to reduce the processing time and the solution is evaluated by a cost function based in two parameters: schedule time and energy consumption. [28] searches for speed profiles with an algorithm based on GA together with an Artificial Neural Network (ANN), to minimize energy consumption. The ANN was trained with the purpose to substitute a train dynamic model, as inputs receives a coast points sequence and at output the total time and energy consumption are determined. GA is used to determine the best option of coast point sequence based on a cost function defined as a weighed sum of travelling time with energy consumption. In the end, the algorithm has been tested in a Turkish metro line with 5 stations with two lines on a multi-train situation. As last example with GA, [29] presents an speed profile determination based in a multi-population GA. The speed profile determination is done in two phases. The first one determines the most economical scenario considering the travelling distance between two consecutive stations, and the second one is considering the full trip. The searching process is done by considering a multi-population with the purpose to reduce the time needed and to avoid the algorithm be stuck in a local minima. Real data from a subway line section, more precisely in Beijing, with a total distance of 21 km was used to test he algorithm. In the test, line gradients, curves radios and velocity limits were considered.

Besides GA, others searching algorithms are also being applied. As another example, in [23] Simulated Annealing (SA) based algorithm is presented to reduce energy consumption in a metro line between New York and Connecticut. The algorithm considers line gradients and velocity limits during searching process. Energy consumption of each solution generated is determined throw a dynamic model of the train following a cost function defined to minimize the energy consumption and penalize higher travelling times than the previous defined on the schedule. The SA algorithm searches for maximum velocity, coast position and time space for each travelling regime.

A comparison between three methods is presented in [30]. The research proposes to search for speed values for each point in the journey. The points identified as points where the velocity must be determined are stops, speed limits changes and kilometres points multiples of total travelling distance. The algorithms subject to study and posteriorly compared are GA, Ants Colony Optimization (ACO) and Dynamic Programming (DP). These algorithms were studied in two different situations, different trip times, and in both situations DP showed a better performance. Another example where ACO was applied as searching algorithms for speed profiles is presented in [31], and the algorithm was tested in real data acquired from a subway line in Beijing.

[32] presents an algorithm that results from a combination between GA and SA, called as a Genetic Simulated Annealing Algorithm. The objective of joining both algorithms is to eliminate the weaknesses of each one of them and to enhance the advantages. By this, GA is used to create a good solution to be a good initial value for SA while it produces outputs that avoid local minimums in GA. The algorithm performance was tested in some stations of Eskisehir light rail.

Evolutionary Algorithm (EA) are another example of algorithm applied in railways as presented in [33]. The paper presents a multi-objective algorithm for velocity profile determination focused on energy consumption, total travelling time and delays reduction. The speed profiles determination is done per section and for each is defined a group of 5 values for velocities. The output produce by the algorithm was tested in two different lines in France.

Particle Swarm Optimization (PSO) is the algorithm chosen in [34]. An algorithm with a multi-objective function was implemented to find the best velocity profile. The research works considers a train equipped with an automatic train operator and the algorithm generates random commands sequences. Some tests in a line without slopes have been done to validate and tune the algorithm before being applied in a real line section of Madrid subway.

[35] presents a speed profile determination based in a multi-objective evolutionary algorithm. The algorithm proposed is Indicator - Based Evolutionary Algorithm (IBEA) with the purpose to minimize the energy consumption and travelling time. The train pathway, limited by the distance between two consecutive stations, is divided by several section defined by velocity limits. Since the total distance is divided, the velocity profile is determined for each space interval. In each interval, the entrance and output velocity are defined as well the maximum and the desired one, without ignoring the next section limit.

3.4 Energy Storage Systems

In a railway system without an ESS, the regenerated energy by trains operation can be easily wasted. With energy losses reduction as main objective, some research groups and railways manufacturers are presenting innovative solutions with ESS. The introduction of an ESS in railways can bring huge advantages for the system. The biggest advantage is concerned with the increase of the power flow control in train. This advantage conduces to improvements in energy efficiency since the train has more autonomy over the energy that flows in the train main circuit. Besides, in [36] some possible advantages about ESS in railways are mentioned. Those advantages are generated energy storage, reduce the peak power consumption on the line and ability to operate as a free-catenary train.

An ESS is typically composed by three main functions. The first main function is the energy storage technology that depends on the application requirements. The actual technologies available are going to be present on Section 3.4.1. To connect a storage technology to main bus, a power converter is needed. The power converter purpose is to adapt the voltage and current values of the ESS to the main bus and at same time provide a controlled charge and discharge current. As a typical power electronics system, a controller for the power converter is needed. Another functionalities as power flow management and monitoring critical variable on the systems are also implemented on an ESS microcontroller. The last functions are crucial to keep the system working in a safe zone, improving the operation safety for the system as for user.

3.4.1 Energy Storage Systems Technologies

Nowadays, the available number of options in ESS technologies is high. As expected, the characteristics changes with the ESS technology so it makes highly important define the systems requirements before select it.

From all ESS characteristics, the most important ones when a system is designed are the energy and power density and specific energy and power. The energy density gives the amount of energy that can be stored per unit volume (Wh/L) while the specific energy is per mass (Wh/kg). In power density and specific power, the first one characterizes the rate at which energy can be taken from the ESS per unit volume (W/L) and per unit mass (W/kg). Beyond these, number of life cycles, working temperature and cost are characteristics that should be considered at the choosing mode of the ESS technology [37].

A possible ESS classification is present in Fig. 3.8. The classification presented is based on the energy conversion. This means, the classification is done taking in account the type of energy used to store the electrical energy [38]. The classification results in 5 groups known as mechanical, electrochemical, chemical, electrical and thermal.

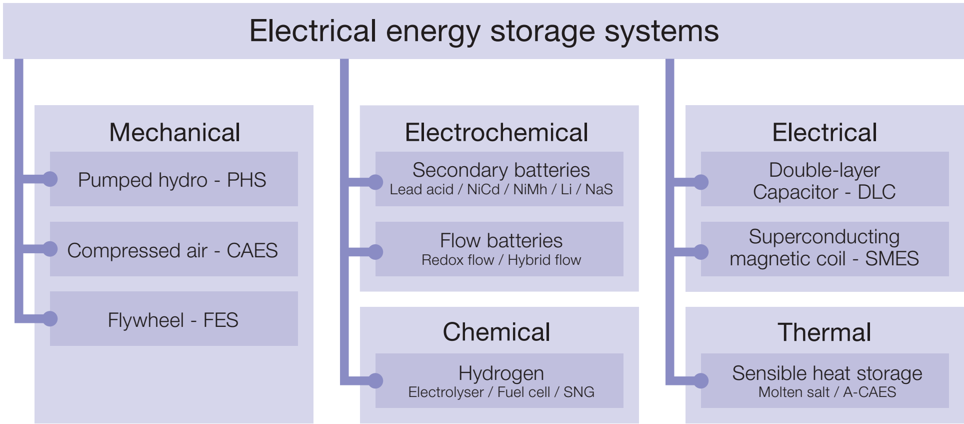


Figure 3.8: Energy storage systems classification [38]

Once the available ESS technologies are quite large, for this work has only be considered for study batteries and Super-Capacitors (SC). This decision lies with the application where is considered that those type of ESS are the more appropriated.

3.4.1.1 Batteries

Batteries are one of the most known and used technology in ESS. The application range nowadays is quite large including renewable energy systems and electric mobility.

They are commonly characterized by high energy density, that defines the energy capacity by unit weight. A battery is an electrochemical device that is able to store electric energy as chemical. Because of that, batteries are classified as Electrochemical ESS as can be seen in Fig. 3.8.

The energy conversion in a battery can be in both directions. When the battery is charging, the electric energy injected is converted in chemical to be stored. The reverse operation happens when the battery is discharging.

Typically, the voltage of a single battery cell is low when compared with the power electronics requirements. Therefore, the word battery is commonly referred to a group of several cells. The cells are connected in series and/or in parallel and the number of elements in use highly depends on the system requirements. These requirements are output voltage in the battery terminals and the amount of energy that must be stored. For the same energy and voltage requirements, the number of cells in use changes with the battery technology.

Once a battery is composed by several cells the energy stored when it is used requires some control and management. An uncontrolled use can lead to cells degradation and posteriorly reduction of the battery State of Health (SOH). The reduction of SOH results in a decreasing of battery life cycle. To avoid that, batteries packs needs a system based in a control algorithm that manages the charge and discharge avoiding over charging and/or deep discharging. Furthermore, critical variable as temperature and current can be also monitored in order to be keep an operation inside recommended values. This system is known as Battery Management System (BMS). Depending on the application, the functions offered by a BMS can change. As example, in some application a charge equalizer to maximize the energy stored in the pack can be interesting since small variations during the cells manufacturing process can happen, maximazing with this the system energy storage capacity [39–42].

Before selecting the right technology, it must be known the available ones and the advantages and/or disadvantages offered. Here, some of well known technologies in the market will be briefly described.

Lead-Acid

Lead – acid batteries have been used over the past years. They are still used in vehicles and in other systems as back-up power supplies. This application is due to the characteristics of this type of batteries that are design to have a fast response and they are not suitable to be discharged over 20 % of the total capacity. They are built with a lead dioxide cathode, a lead anode and a sulfuric acid electrolyte.

The advantages of this type of batteries are, small rate of small self-discharge, low acquisition costs and high efficiency. The disadvantages are related with the low number of life cycles and low performance with low temperatures. As characteristics, they present an energy density in a range between $50 - 90$ Wh/L and a specific energy from 25 up to 50 Wh/kg [39, 41].

Nickel Based Batteries

Nickel-Metal Hydride:

Built by a nickel hydroxide cathode and an alloy of vanadium, nickel and titanium. The specific energy of this type of battery is around 70 to 100 Wh/kg and the energy density between 170 up to 420 Wh/kg.

As advantages, the number of life cycles is high, the range of operating temperatures is also wide and the possibility of being recyclable. If compared with the lead-acid technology, the memory effect was reduced. The disadvantages the self-discharge rate is high and presents a high life cycles degradation when exposed to high discharge currents [39, 41].

Nickel-Cadmium:

In a Nickel-Cadmium battery the electrodes are made by nickel hydroxide and metallic cadmium. The electrolyte is based in an aqueous alkaline solution. These batteries are characterized by an energy density in range $30 - 75$ Wh/kg.

The main advantages of these batteries is related with the long lifetime and the low self-discharge rate. Besides that, a precise controller for the discharge is not need since they can be fully discharged without causing damage. On the other hand, the materials used for the electrodes are known as toxic heavy metals making the batteries not so recyclable. The memory effect and the high acquisition cost are the main disadvantages.

An application example where these batteries can be found is in utility-scale ESS as power supply in remote areas [39, 41, 43].

Lithium-Ion Based Batteries

Lithium-ion based batteries are one of the most promising technologies in use in actual applications. This battery technology is known as being light weight, high energy density and long life cycle. Because of that, they are selected for most of the applications where the space requirements are slightly tight.

Besides, lithium batteries present a high cycle efficiency and no memory effect. In other hand, the influence of a depth charge over the battery lifetime, the control and management issues as the initial cost, are presented as the main drawbacks of this technology.

In terms of research and development, this battery technology is one of the highest areas.The research objectives are focused on battery power capability and specific energy improvements by development new materials for electrodes and electrolyte. The most known are the lithium-ion and the lithium-polymer and the main difference is in the electrolyte, it can be an organic solvent or held in a solid polymer composite, respectively.

Actually, exists many variations of lithium batteries with different materials in the positive electrode. As examples, lithium cobalt oxide, lithium iron phosphate and lithium nickel cobalt aluminium oxide. These batteries have typically a negative electrolyte made by graphite with lithium. Although, some variation for the anode materials as lithium titanate. These lithium batteries variations are all developed in order to improve the characteristics of the lithium-ion based batteries. The lithium iron phosphate was developed to improve the temperature operation range while the lithium-titanate can be charged with high currents rates [5, 39, 43].

3.4.1.2 Super-Capacitors

SC, also known as Electric Double-Layer Capacitors (EDLC), have been increasingly used in several applications namely in electric mobility. They are characterized by high energy density, when compared with other type of capacitors. Physically, SC are built by two electrodes, an electrolyte and a separator that is typically a porous membrane.

Comparing this technology with batteries, SC have higher power density but lower energy density. Because of that, they are chosen to support a primary energy source, being responsible in absorb and/or provide energy when high power fluctuations occur.

The advantages of SC are related with the possibility of being able to deal with high current variations. Besides, the high number of life cycles is also viewed as a good characteristic. The disadvantages are related with the acquisition cost of the storage elements and the self-discharge rates.

As happen with the batteries, the nominal voltage of elements available in the market is quite low ($2.7\ V$ up to $3.0\ V$) when compared with the required for high power applications. For that reason, the super-capacitors are assembled in series in order to increase the voltage at output terminals. Once again, a charge equalizer must be added to the pack in order to maximize the energy stored and to protect it against possible deviations caused by the production process. Also, a management system must be used in order to supervise and control some variables on system as temperatures, voltages and currents [41, 44–46].

Actually, some solutions are available in the market for single cells and/or modules. As an example Maxwell [46], a well known SC manufacture, presents a set of solutions for railway systems prepared for handle with peak currents, high duty cycles and harsh charge/discharge profiles. Those solutions are orientated for rail voltage stabilization, rail propulsion and locomotive engine starting.

Table 3.1 resumes the main characteristics of some known manufacturers.

Table 3.1: Super-Capacitors Characteristics [44, 46]

	Capacitance (F)	Voltages (V)	Internal Resistance (Ω)	Energy Density (Wh/kg)	Power Density (W/kg)
Maxwell	310-350	2.7	2.2-3.2	5.2-5.9	9500-14000
	650-3.400	2.7-2.85	0.28-0.8	4.1-7.4	12000-14000
Nesscap	650-3000	2.7	0.26-0.60	3.2-5.6	6200-7100

3.4.2 Technologies Comparison

This section presents an ESS technologies comparison. The purpose of this comparison is to be helpful in future developments, more precisely during the deciding process about which technology should be used in trains as an on-board ESS.

The comparison starts with Table 3.2 where the main characteristics of each ESS are listed. The comparison relies on energy and power density, specific power and energy, lifetime, cycle numbers and energy efficiency.

Table 3.2: Energy storage technologies comparison [38, 39, 42, 45, 47]

ESS Technology	Energy Density (Wh/L)	Power Density (W/L)	Specific Energy (Wh/kg)	Specific Power (W/kg)	Lifetime years	Cycle numbers	Efficiency (/%)
Lead Acid	50 – 90	10 – 400	30 – 50	75 – 300	5 – 15	1000	80 – 90
Nickel Metal Hydrid	180 – 220	500 – 3000	70 – 95	200 – 300	2 – 10	< 3000	60 – 70
Nickel Cadmium	60 – 150	80 – 600	30 – 75	150 – 300	5 – 20	1500 – 3000	60 – 80
Lithium-ion	200 – 500	1500 – 10000	75 – 200	150 – 315	5 – 15	2000	90 – 100
Lithium polymer	130 – 225	–	130 – 225	150 – 450	–	> 1200	90 – 100
Lithium-titanate	–	–	80 – 100	4000	–	18000	90 – 100
Supercapacitors	10 – 30	100000	2.5 – 15	10000	10 – 40	100000	90 – 100

Complementing the information presented in Table 3.2, a graphical comparison is showed in Fig. 3.9. The ESS are displaced in function of power density and energy density. Some technologies presented in figure are not discussed on the report.

From a briefly image analyses, a conclusion can be taken. Once the y-axis is the power density and along x-axis appears the energy density, the technologies that appears in the lower left corner can be selected for applications without space requirements and/or constraints. In other hand, for slightly tight space requirements, as happens with mobile applications, the upper right corner technologies are the most appropriated [39].

Following this conclusion, the lithium-ion batteries are the most promising technology for being applied in an on-board ESS for railways.

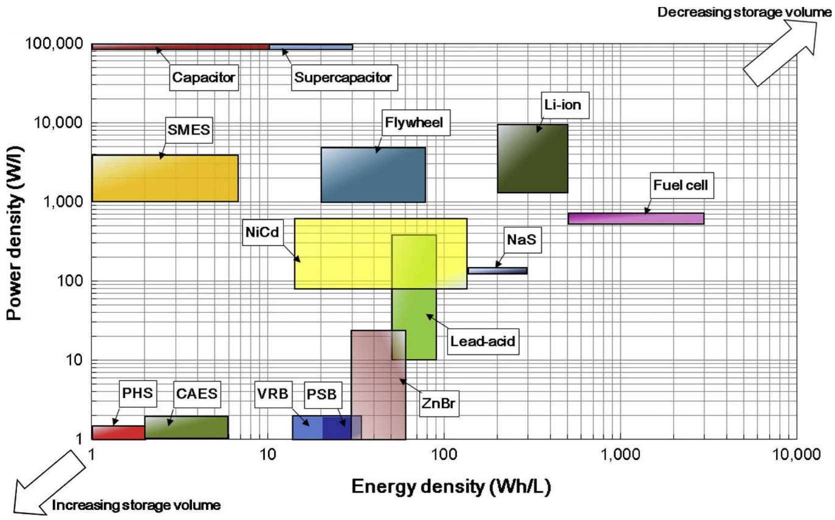


Figure 3.9: Energy storage systems comparison [39]

3.4.3 Energy Storage Systems Topologies

During ESS development and implementation, the technology choice, as presented before, is the first and a critical step. After deciding the technology, a topology for the system must be defined in order to get the maximum benefits of the ESS without compromise the system and user's safety.

Depending on the technologies number and type, the ESS can have several topologies. As expected the right topology depends on the application requirements and characteristics. In this report, battery based, SC and hybrid storage systems will be presented.

3.4.3.1 Battery Based Storage System

A Battery based storage system only uses batteries as storage element to support voltage and power needs of the DC Bus. The most common way to connect batteries to the DC-bus is made through a bidirectional DC/DC that allow a controlled charge and the discharge. The power electronics converter needs is related with voltage levels typically in use. In a real application the DC Bus voltage is higher when compared with batteries terminals, so the power converter is responsible for adapted the respective values. An example of the structure for the battery based storage system is presented in Fig. 3.10.

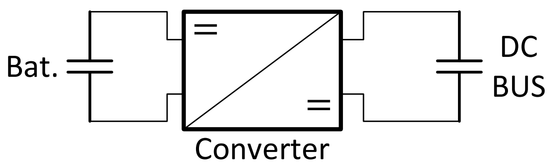


Figure 3.10: Battery based storage system

The battery based storage system is a simple topology that requires some control over charge and discharge current. It is important to keep a constant current reference for batteries ensuring low degradation. This topology is recommended to be used in applications where the load has small power variations [48].

3.4.3.2 Super-Capacitor Based Storage System

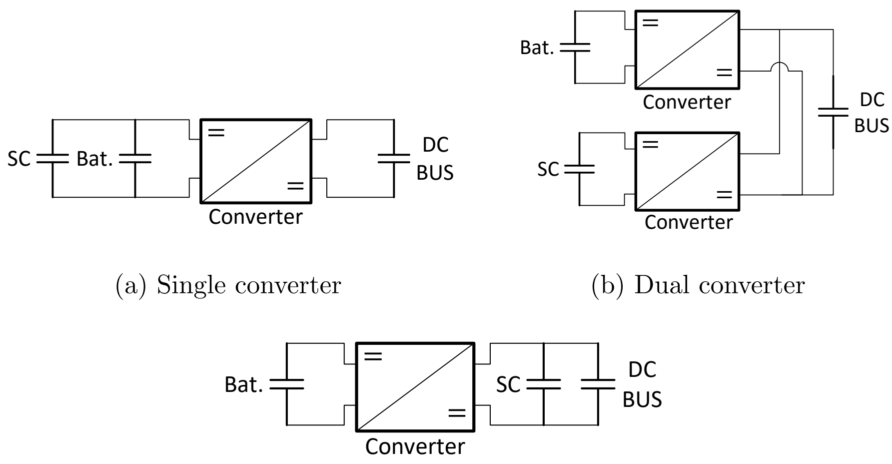
SC are able to store or deliver high amount of energy in a small time. Typically, SC is used as a secondary energy source, responding to fast load changes. Although, in some cases, they are used as a primary source using a similar topology as batteries, Fig. 3.10. They are connected in series and/or in parallel in order to accomplish energy and power requirements of the system, and a bidirectional converter to connect the SC to the main DC-Bus is also used [46, 49].

An example of applications in railway system with super-capacitor based storage system as primary source is in free-catenary trains [36]. In this application, an electric locomotive must have some ESS on-board that allows train movements between stations without being connected to the line. The energy is obtained while the train is stopped and by this reason, an ESS technology that support fast charging must be used.

3.4.3.3 Hybrid Storage System

A hybrid storage system contains more than one ESS technology, for example, a combination of a battery pack with a SC array. The main idea of combining more than one ESS is to get more benefits to the system. In the case of being used batteries and SC, the ESS can store or deliver fast current references from super-capacitors and keep a constant charge/discharge rate with batteries. Applied in an electric vehicle or in a train, fast changes in current reference can be absorbed by the SC and it can be delivered to the batteries after. The batteries will be protected to the high current charges and/or discharges improving this way the ESS lifetime.

There are several ways to connect the ESS to the main bus. Three possible topologies are presented in Fig. 3.11.



(a) Single converter (b) Dual converter

(c) Single series converter

Figure 3.11: Hybrid Storage Systems

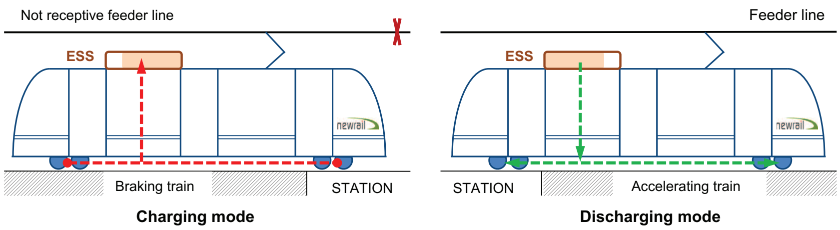
The simplest approach is a parallel connection between batteries and SC, where the SC act as a high filter for current, Fig. 3.11a. The single converter topology, or passive hybrid as known in literature, the energy management is made by the internal resistance of each ESS technology. This topology is considered inefficiency since the total energy of the SC is not completely used.

The second way, storage elements are connected to the DC-bus through a converter, Fig. 3.11b. With this, the ESS charge and discharge is performed separately. Based on load needs, different current references can be generated by the current controllers. This new current reference values are determined based on the characteristics of each ESS technology. The drawbacks of this topology are the increase of complexity of the controller, but have the advantage of increase the efficiency and performance of the system.

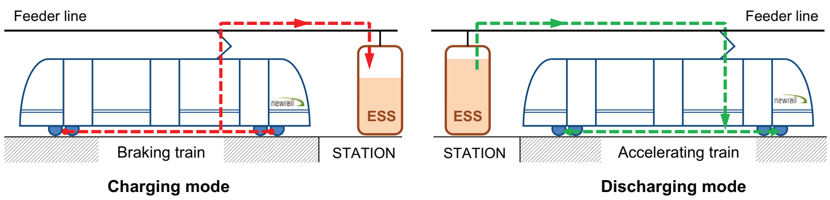
The last topology presented, Fig. 3.11c, called single series converter a single bidirectional converter is used to connect both technologies. The ESS technologies can be placed as presented in figure or in a reverse order, connecting batteries directly to the main DC bus. The problem of this topology is related with the efficiency of the converter with a variable voltage on the DC bus caused by the SC. In other way, fixing the voltage at DC bus with batteries, requires a high number of elements [42, 48].

3.4.4 Railways Systems

In literature, several proposed systems are presented to store the regenerative energy resulted by trains operation. Those solutions can be divided into two categories, on-board, Fig. 3.12a, and stationary ESS, Fig. 3.12b [50].



(a) Onboard



(b) Stationary

Figure 3.12: Energy storage systems solutions for railway systems [5]

On-board ESS are presented as a promising systems to store regenerative energy on trains. This category has as advantage a line independent control. Since regenerative energy is generated by the vehicle where the ESS technology is installed, the controller does not depend directly on line availability/receptively to define where energy must be used. Besides, energy losses, when compared with the case where energy is sent back to the line, will be lower. In [5] is considered that on-board ESS can contribute for actual railway system problems as peak power consume reduce, stabilization of the line voltage and provide a catenary-free operation.

In on-board systems, development restrictions are mostly related with space requirements. A precise algorithm to determine the number of elements is needed in order to avoid an oversizing of the ESS. The algorithm purpose is the overweight reduction of the ESS which results in power losses. In [50] some approaches to size the ESS with different purposes as maximum energy regenerated by the train, line voltage stabilization and free-catenary operation.

The stationary ESS systems, when compared with on-board, are easier to develop since there are not space restriction and weight concerns. Although, the ESS location must be carefully defined to reduce line losses and maximize the energy store. A good location example is near to a station where deceleration/acceleration are more frequent. Another possible location for stationary ESS is on line substations. The energy stored by stationary ESS is the energy that is not consumed at the train during the service.

The most common control scheme in use for this ESS category is based on line voltage. It means, when a voltage rise is detected, the controller starts a charging process while when voltage drops a minimum value, ESS starts to feed the line. As a consequence, each ESS can receive or deliver at same time energy from/to different vehicles that are located at same line section.

The stationary ESS systems are implemented in the railway system with the aim to contribute for line voltage stabilization and peak power reduction [5, 50].

Actually, some research work in ESS for railway system have been done. Some manufacturers as simenens, bombardier and toshiba are developing options for on-board and stationary solutions.

In [5] a review through the actual systems developed under research and to be available in market are presented. Related with on-board ESS in research area, most of them uses SC as ESS technology. The purpose is mostly concerned with energy consumption reduction, peak shaving and free catenary operation. Beyond research, some manufacturers as simenens, bombardier and toshiba are developing options for on-board and stationary solutions with same purposes. Table 3.3 shows some available systems on market showing some characteristics.

Table 3.3: On-board available systems [5, 51–54]

Manufacter	**Product**	**ESS Technology**	**Power (kW)**	**Weight (kg)**
Bombardier	Mitrac Energy Saver	SC	100 - 300	428 - 477
Siemens	Sitras MES	SC	288	820
	Sitras HES	SC	288	820
		Nickel-Metal Hydride	105	826
Toshiba	SCiB Battery System	Lithium titanate	60	1850
Alstom	STEEM	SC	-	-
Saft	Ion-OnBoard	Super-Phosphate Lithium	83-304	-

Related with stationary ESS, the available systems developed under research works or available at the market is also high. Starting with systems developed under research works and described in [5], SC are the technology mostly used in line voltage stabilization and energy consumption reduction.

The stationary systems available at the market have more ESS technologies offer when compared with systems developed under research works. Some examples of systems available are described in Table 3.4.

Table 3.4: Stationary available systems [5, 55–60]

Manufacter	Product	ESS Technology	Power (kW)
ABB	Enviline ESS	SC (expansible with batteries)	4500
Toshiba	Traction Energy Storage System with SCiB	Lithium Titanate Oxide	500 - 2000
Saft	Intensium-max	Lithium Ion	420-1020
Siemens	Sitras SES	SC	700
Bombardier	Energstor	SC	650
Kawasaki	Battery Power System (BPS)	Nickel-Metal Hydride	110

3.5 Optimization

The optimal speed profile for trains can be determined by developing algorithms with the purpose to determine traction regimes sequence, time duration and respective velocities values. Concerning with thesis's objectives, an optimization algorithm is going to be developed to obtain an optimal speed profile that allows the maximum advantage of regenerative breaking and reduce system energy consumption. The algorithm must be developed and integrated with trains without compromising the passenger's safety. Time and space limits, as schedule and velocity limits must be set as constraints ensuring their accomplishment. Besides, acceleration limits must also be considered to ensure passenger's comfort.

This section presents some algorithms as possible tools to be used in future developments. Some of the algorithms presented here were being selected once they were already used in some referenced works.

3.5.1 Optimization Algorithms

Optimization algorithms are implemented in real problems with the purpose to find a solution that fits systems requirements. These problems are defined by a set of constraints and at least one objective function. The variables on the objective functions are known as design variables an it is formulated in order to maximize or minimize an objective. The optimal solution is considered found when a set of values for design variables are determined and all or most of the constraints are accomplished. Another requeriment is the objective function value must be the best one achived [61].

Since one of the thesis's objectives is related with energy efficiency optimization, some algorithms were studied to be applied in future developments. During this section, some of them will be presented.

The optimal solution searching process in optimization algorithms are commonly based in real principals and/or natural behaviours that can be found on nature. These behaviours are presented in some algorithms as linear programming, GA, SA, PSO and ACO and will be presented in this section.

3.5.1.1 Linear Programming

Linear programming, as the name suggests, is a technique used in linear problems with the purpose to find the optimal solution. Linear problems are defined by linear objective functions and constraints dependent on design variables.

When the problem is defined by a low number of design variables (between 2 and 4), the optimal solution can be determined through a graphic method. The optimal solution is obtained by a graphical visualization of the problem, by using a 2-D or 3-D reference frame.

To increase applications range of linear programming, a standard form can be used in order to convert a non-linear problem into a linear. In the standard form the restrictions are reformulated as equalities and the problem is converted into a minimization one. To rewrite the problem in the standard form, some transformations must be done, and they can be found in the literature. As example, [61] presents the necessary steps that must be followed during problem transformation.

Another well known linear programming technique is the simplex method. This method is applied in problems with high number of design variables. This is a method that searches for the optimal solution by moving from each feasible solution to another iteratively. Feasible solutions are the solutions that accomplish all the constraints imposed by the problem formulation [61].

3.5.1.2 Genetic Algorithms

Based on evolutionary theory, GA are searching algorithms that looks through the solutions space in order to find the optimal solution. The optimal solution searching process is done in group of points, instead of a single one, and because of that reason GA are also known as a global optimal searching algorithm. The searching group of points is called population. Iteratively, the fitness value for each individual is determined with the purpose to see if it is inserted in the population. This can be seen as a disadvantage since the process time increases with the number of individuals. Furthermore, the group search does not avoid the algorithm be stagnant in a local solution instead of searching for the optimal one [62].

Before start the algorithm description, some definitions must be given. The algorithm search, as referenced before, occurs based on a population. Each population is composed by several individuals and each individual is structured by genes. Genes are considered the most basic elements in the algorithm. In GA, before running the algorithm, an assumption for the population must be done. This assumption defines the population codification, process that is realised during population construction. Each individual is codified, converting each individual in a string of bits. This makes easier some operations that must be done during the searching process as mutation and gene crossover.

The GA algorithm flowchart is presented in Fig. 3.14.

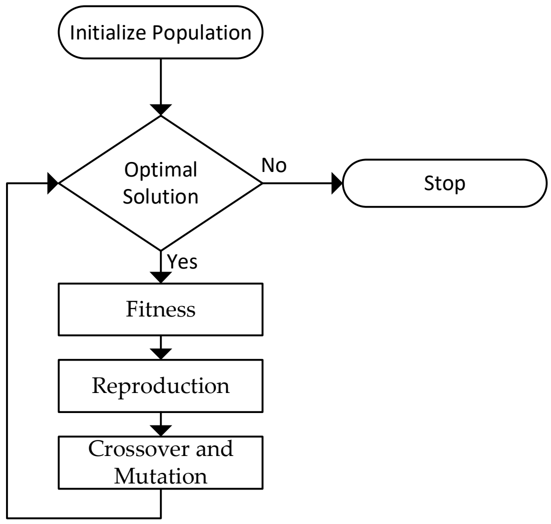


Figure 3.13: Genetic algorithm flowchart (adapted from [61])

GA is a hierarchical algorithm where, as happens at evolutionary principal, the best information, selected at each iteration, pass through generations. During the searching process, the population suffers some mutations based on best individuals, defined by the best fitness value. The purpose is generate the next population, used in the following iteration, based on the best individual characteristics.

The algorithm starts with population initialization and the respective fitness value is determined. Based on fitness values obtained, good individuals are identified and posteriorly selected while bad ones are dropped away. The next step is reproduction where a new generation is determined by copping the best individual's genes. To create changes in new generations, some genes exchanges must be done. This happens in the step called crossover where individuals are randomly selected to cross genes. As result of these operations, a new population is generated and it will be used at next algorithm iteration.

The SA algorithm admits that the best population is generated by the best individuals. So, the algorithm evolves by continuously mutation over best individuals. The optimal solution is found when there are almost no variations between several individuals of the population [61, 62].

3.5.1.3 Simulated Annealing

SA is another optimization algorithm based in a physical principle used in crystallizes formation, where the material is heated up in a first stage followed by a slowly cooling.

The SA algorithm searches for optimal solutions in an iteratively process. The searching process makes use of a control variable, called temperature T, defined to avoid the algorithm being stuck in minimum local. Besides, the control variable can also limit the searching boundaries. For these reasons, the control variable must be carefully defined since it is highly important on the SA algorithm.

In each iteration, the control variable values decreases according $T_{i+1} = \alpha T_i$, where α is the cooling factor and typically assumes a value equal to 0.8. The initial value of T, T_0, is determined by (3.8).

$$T_0 = \frac{F_{obj} - F_{ds}}{ln(\alpha)} \tag{3.8}$$

To understand the SA algorithm, Fig. 3.14 shows the flowchart.

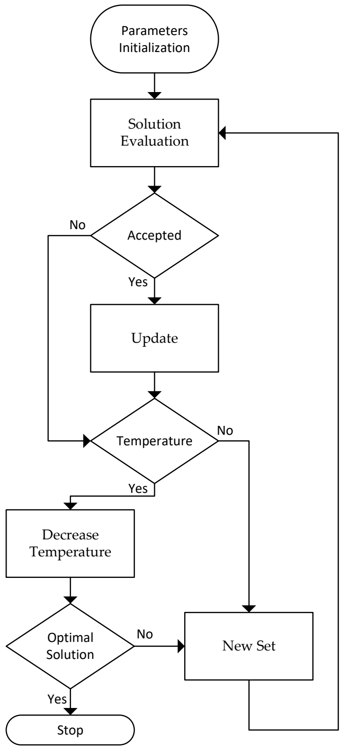


Figure 3.14: Simulated Annealing flowchart (adapted from [63])

Since SA is an iterative algorithm, in each iteration a new solution is determined. Before start the algorithm, stop criteria must be defined. The possible options can be:

- Maximum number of iterations;
- Minimum value of temperature;
- Optimal solution found.

The first two options are easy to define. The last one, at each iteration the new solution must be analysed in order to define if presents a better result, concerning with the objective function.

The acceptance mechanism of the algorithm can be done divided into two stages. At first stage, the solution is acepted when improvements happend at cost function. If the new solution is worst than the previous one, two ways can happen. The first one, the new solution is accepted as a better than the last one, or can be accepted if the result of (3.9) is high than a value generated randomly [63].

$$e^{-\frac{S_{new}-S_{old}}{T}} \tag{3.9}$$

3.5.1.4 Particle Swarm Optimization

PSO is an optimization algorithm that searches for optimal solution in space. This algorithm is inspired in animals group movement, searching for solutions inside the search area. This searching process is done in swarm and the algorithm keeps tracking the best individual position and the population.

As another algorithm, PSO starts with initialization of some variables. In this case, the definition of best individual position and a first population is the initial point of the algorithm. The next step is the evaluation of the new solution. If it is better than the previous, it must be updated and saved. After, new particles velocity and positions determination must be done. Since PSO algorithm is an iterative searching process, new solutions evaluation and new particles definition is repeated until the objective function, or another initial statement, be accomplished.

At the beginning, it is necessary to determine initial position $x_{i,k}$ of each individual on population, (3.10).

$$x_{i,k} = x_{i,min} + (x_{i,max} - x_{i,min})\, u_i \tag{3.10}$$

At each iteration, the position of each individual changes and it can be updated by (3.11). In the case of the new position exceeds the search boundaries, a new position for the individual is determined by (3.10), forcing the searching process to be inside of the limits.

$$x_{i+1,k} = x_{i,k} + v_{i+1,k} \tag{3.11}$$

In (3.11), $v_{i+1,k}$ represents the velocity of the individual that must updated in each iteration. The individual velocity is characterized by three components: inertia, personal and social influence. Those components can be seen in (3.12).

$$v_{i+1,k} = w_1 v_{i,k} + \phi_1 (p_{xik} - x_{i,k})\, u_i + \phi_2 (g_{xi} - x_{i,k})\, u_i \tag{3.12}$$

In (3.12) p_{xik} is determined by (3.13) and g_{xik} following (3.14) respectively. p_{xik} is the best individual and g_{xik} the global fitness [61].

$$p_{i+1,k} = f(x_{i+1,k}) \tag{3.13}$$

$$g_{i+1} = min(p_{i+1,k}) \tag{3.14}$$

3.5.1.5 Ant Colony Optimization

As happen with other algorithms, ACO also has a physical analogy. Ant's natural behaviour is the inspiration of the present algorithm.

The number of ants, layers and nodes must be defined at algorithm initialization. The number of layers are correspondents with the design variables while nodes are related with correspondent values. As happen in an ant colony, when ants are searching for food, they must pass through all the nodes searching for the best solution, defined by the objective function.

During the searching process, the best solutions tends to get more ants. As happen in the nature, when ants are searching for food, they left a trail with the purpose to guide the others. So, in the algorithm, the same happens by updating a variable called pheromone with the purpose to guide all the ants to the best solution.

Defining N as the number of ants, the probability of node j be selected is determined by (3.15):

$$p_{ij}^{k} = \frac{\tau_{ij}}{\sum_{j \epsilon N_i^k} \tau_{ij}} \tag{3.15}$$

In (3.15) τ_{ij} represents the trail. It can be determined by (3.16).

$$\tau_{ij} = \tau_{ij} + \Delta\tau^{k} \tag{3.16}$$

The trail must be updated during the searching process by (3.17). In expression (3.17) ρ is known as evaporation rate (typically equal to 0.5), f_b the best and f_w the worst value of the objective function.

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{N} \frac{\phi f_b}{f_w} \tag{3.17}$$

ACO has several applications as optimal vehicle routes and project scheduling [30, 61].

3.5.2 MultiObjective Optimization

A problem is classified as a multiobjective when, during the formulation, more than one objective function are defined. It can happen on a same problem, maximize one objective function while one is minimizing. As example, related with thesis's objectives, can be defined an optimization problem with several objective functions as maximize regenerative energy while consumption is minimized.

The solution of those type of problems can be sometimes difficult to determine due to computational effort required or complexity. Actually, some techniques are being used to find the optimal solution of a multiobjective optimization problem. The points set that make up the solution of the problem are known as Pareto Optimal Solutions. The techniques presented in the literature are [61].

3.5.2.1 Sum Approach

This technique converts a multiobjective optimization problem into a single objective one. It is reached by organizing all the objective function into one by adding weights. With this, the multiobjective problem can be solved by the same methods as the single ones.

The simplicity of this technique is presented as main advantage. Besides, this method is not so robust, since different weights can reach the same solution. As result, the effort applied to weights tunning is higher than the expectable one [61].

3.5.2.2 ε-Constraints Technique

The ε-constraints is a technique also used for multiobjective optimization. From the all objective functions, a minimization one is kept and the others are converted into constraints. During this conversion, a target value for constraints must be defined, and it is going to influence the solution. Because of that, the target value choice is considered a critical aspect, presented in some books as a disadvantage. This technique shows that some apriori information must be taken before problem definition [61].

3.5.2.3 Goal Programming

Goal Programming is a technique that converts a multiobjective problem into a single objective. This algorithm, starts with a target definition for each objective function and the aim is to find the optimal solution by minimizing the target deviations. With this, it is possible to conclude that the objectives functions are converted into constraints [61].

3.5.2.4 Multi-level Programming

Technique where the problems objectives are organized, ordered hierarchly. After thiis organization, the optimization problem consists in a minimization of each objective following the previous hierarchy. As expected, the solution obtained is highly dependent on the hierarchy, previouly defined. At same time, once more, shows that some apriori knowledge about the problem must be on the table during the hierarchy definition. In the case of a bad definition, the lowest objectives at hierarchy can significantly change the optimal solution of the problem [64].

CHAPTER 4

Methodology and Work Plan

This chapter presents the methodology that is going to be adopted for this thesis' development. Based on the methodology presented and in focus with the thesis main objectives and expected contributions (both presented in Chapter 2), a work plan for the following years has been made and will be presented, at the end of the chapter.

4.1 Methodology

Energy efficiency on trains has received some attention as a research topic during last years. The main reason is the amount of energy that is consumed during trains operation. After studying and analysing the state of the art related with energy efficiency, it was clear that some issues are not solved. Therefore, during the thesis, solutions to this issue will surface, focusing on reducing energy consumption in railways, with highly satisfying results.

The thesis' main work is concerned with development of a DAS for trains to increase energy efficiency. To reach all the objectives, a dynamic model of a real train and an algorithm able to determine speed profiles will be implemented.

As starting point, a dynamic train model will be studied and then simulated to understand the system behaviour. Besides, those simulations will be also helpful to evaluate the amount of energy involved during trains operation. The following step will be the development of an algorithm to determine speed profiles, also known as DAS. For the algorithm, some objectives must be defined as optimization target, type of service in studied and programming language to use.

The DAS algorithm will be developed with constant growth of complexity. It will start with constant acceleration, without considering velocity limits or line gradients. Gradually, a real world approximation will be done by introducing acceleration and breaking curves characteristics. Velocity limits and gradients influence on train dynamics will be also included to determine speed profiles. As last step, it is expected to validate the algorithm potential by introduction real data related with real railway lines. Real trains characteristics as traction curve, breaking behaviour and resistance forces will be considered.

As will happen with DAS algorithm, the optimization one will also be a target of continuous improvement. The searching algorithm and optimization mechanism will be implemented by successive improvements at cost function level. It is proposed to start with a simple scheme and later, progress to a multiobjective function.

Another point in study, during thesis work, will be the process of generating new solutions. After simple cases implementation, as random generation, it is expected to introduce some knowledge. By introducing some knowledge, new solutions can be generated by taking the maximum advantage on line characteristics.

Regardless of the algorithm implemented and respective changes, the DAS developed must determines a velocity profile that allows the minimum energy consumption for the actual line and train characteristics.

After validation with real data, in a simulation tool, the algorithm will be implemented in portable platform to be tested in real cases.

4.2 Software

To achieve the proposed objectives, the appropriate software and tools must be selected. The software identified here must be capable of computational analysis and enable algorithm implementations. The software and tools considered appropriate for further development are:

- Matlab/Simulink - for dynamic computational analysis of the system;
- Matlab - for development of optimization algorithms, making use of the provided optimization tool;
- Mobile platform - Algorithm implementation.

4.3 Work Plan

Based on the before-mentioned objectives, an annual planning for future developments was built for the next three years. The work plan is presented in Table 4.1. It is expected that all the main tasks will be accomplished, in order to be able to spent more time for system implementation, thus making possible to obtain better conclusions about the developed work.

Table 4.1: Thesis work plan

Year	Semester	Task	
1	1st	Train model development	Computational analyses
		Speed profile determination	Dynamic model implementation
			Optimization algorithm implementation
	2nd		Velocity limits and grades influence
			Cost function and searching process tunning
2	1st		Real Data Validation
	2nd	System Implementation	Platform definition
			Algorithm implementation in a compatible language
3	1st		Algorithm optimization: reduce time processing and other features
			Systems tests and Results analyses
	2nd	Thesis Delivery	Document Writing
			Public Presentation

CHAPTER 5

Actual Developments

5.1 System Overview

During the past year, some research work orientated to thesis objectives was developed. The work development was focused on DAS, starting with implementation of a train dynamic model and an optimization algorithm to determine speed profiles. The system overview can be seen in Fig. 5.1.

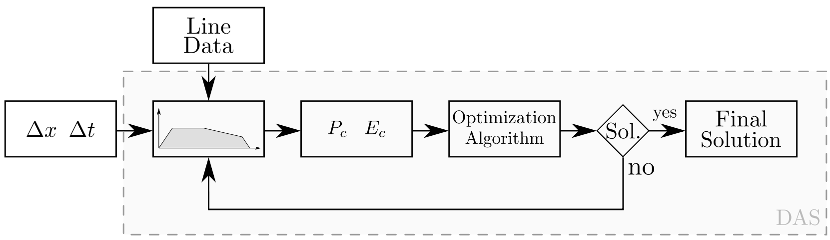


Figure 5.1: System Overview

As inputs, the algorithm receives the space between two consecutive stations and the respective time available from the timetable. Line characteristics as velocity constraints and slopes values are also considerate during speed profile determination.

After state of the art analyses, the optimal speed profile shape was defined as a reference to determine new profiles. Based on that, the algorithm starts with a random generation of values that characterize the profile, more precisely, values for cruising and breaking velocities. Considering train traction characteristics, time and space needed to accomplish each traction regime are determined based in an ideal situation. The ideal situation, in this case, is a railway line without any velocity limits either slopes. Once determined a speed profile, the next stage is a dynamic train model which follows the velocity reference. In a time based simulation, train's acceleration, velocity and distance are updated to verify if exists any velocity limit or gradient that requires a profile shape change. The time step used, at train simulator, is very small with the purpose to consider constant accelerations in each interval. In each run, and for each velocity values generated, the output of this stage is a speed profile, power and energy needed to accomplish the journey.

The consumed energy is considered, together with time spent and distance travelled to determine the cost value of the purposed solution. After that, the solution is evaluated by an optimization algorithm. For this purpose, SA algorithm was selected to evaluate each solution generated. The acceptance mechanism was developed by considering the original algorithm and new values generation is done randomly. During new velocities generation, it is considered the maximum value allowed by train as well as the braking speed generated is always less than the cruising. In the end, the algorithm identifies the best option from the generated set and presents the solution.

5.2 Research Progress

Since the beginning, the algorithm implemented has suffered several changes, increasing the system complexity. This section intends to show an algorithm time line by describing the most important changes. Fig. 5.2 shows the speed profile determination progress.

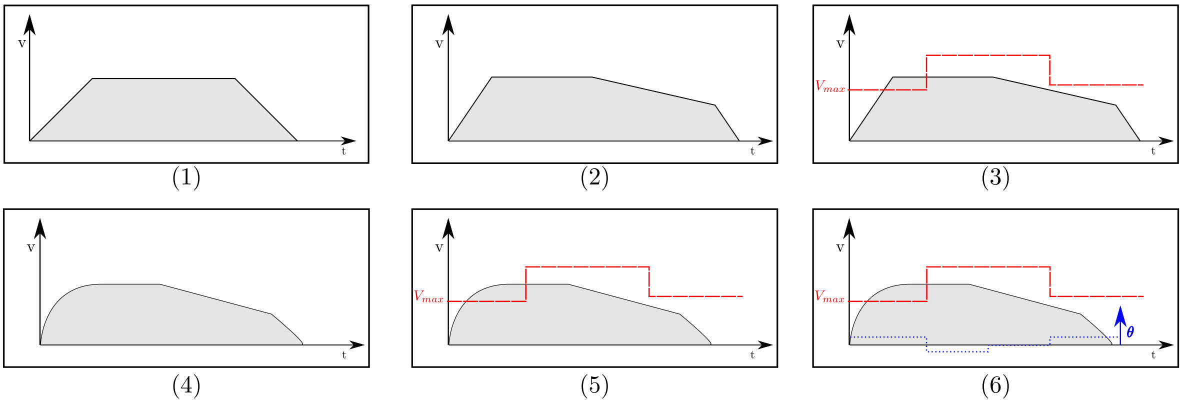


Figure 5.2: Algorithm Progress

The starting point was the determination of a speed profile where constant accelerations were considered with three in possible four traction regimes, (1). In this stage of development was mandatory to reduce the algorithm complexity providing a better understanding of the system. The optimization algorithm was also implemented and used to define accelerations and velocities, generated randomly, that characterize the profile. The output, as expected, was a speed profile with minimum energy consumption for the journey.

The second stage of development, (2) was the addition of a fourth traction regime. The traction regime added was the cruising phase and to the searching process, breaking velocity was added. The coasting phase acceleration was approximated by the maximum value possible, it means, at the beginning. By this, constant accelerations were considered and the optimization algorithm was responsible to return a speed profile with minimum energy consumption.

In real situations, some velocity constraints can appear on the line. They can be temporary, caused by works, or limited by line characteristics. By this reason, it was added to the algorithm some velocity constraints, (3). Initially, the algorithm's structure has not changed. The optimal speed profile was considered, as happen previously, to be followed as a reference but expecting in the end, a different sequence of traction regimes. As example, if a velocity constraint appear at the beginning of the journey, an acceleration phase must be interrupted by a cruising or breaking one. To solve the speed profile changes on the appearance of a speed limitation, a state machine was implemented as train simulator, changing the algorithm structure. Each traction regime is defined as a state and transitions are based on train position, velocity and line characteristics. By this reason, train position is determined at each time interval in order to define the state machine flow. As a brief description, it starts with a determination of an ideal speed profile, considering the generated values for velocities. After the first profile determination, train simulator updates the velocity and position by considering velocity limits drawing the final speed profile. In the end, energy consumption is analysed, together with the travelling time, in a multi-objective function.

The use of constant accelerations in the algorithm is a good approximation when low velocities are considered. As velocity values increases, the error between the model response and the reference also increases. In this perspective, a few steps back on algorithm development have been taken. Train traction and breaking characteristics were considered and the results was non-constant acceleration during acceleration, cruising and breaking phase,(4).

Since train dynamics changed, the equations to determine travelling time and distance necessary for each traction regime had to be deduced again. The train motion simulation, was defined with a small time interval with the purpose to consider a constant acceleration in each run. The following developments, identified with (4), (5) and (6) followed the same principal as happen with constant accelerations. It started with the most basic case (4), and gradually velocity limits, (5) and the influence of line slopes,(6) were added step by step.

The developments made in the optimization algorithm were largely made at cost function level. The searching process started by a random search of acceleration and velocity values. With the change from constant accelerations to non constant, only velocity values are being searched for. At new solutions generation level, the algorithm uses some knowledge to limit the range of new values. For the cruising velocity generation, any value between 0 and the maximum velocity allowed by the train is considered. The breaking velocity is limited from 0 up to v_{cru} (value generated to cruising velocity). At cost function level, the algorithm started with a single objective defined as reduction of energy consumption. As the complexity of the system increased, the cost function changed to a multi-objective one where the cost value is determined by using a sum approach. Thus, the cost value associated with each solution is the weighted sum of consumed energy combined with time, velocity and distance error. During the cost function definition the weights and penalization factors used were also a tuning target.

5.3 Preliminary Results

The developed algorithm searches for velocity profiles to be applied between two stations by advising the driver. Fig. 5.3 represents in a simple way the problem.

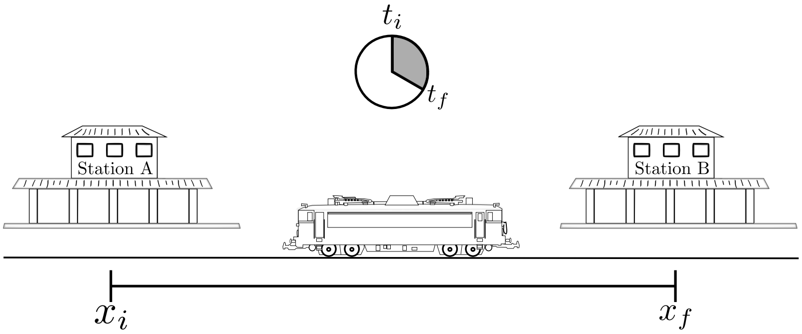


Figure 5.3: Problem description

Considering Station A as the starting point and Station B as the ending, the algorithm must determine a speed profile which accomplish the total distance in the required time. The speed profile must ensure the minimum energy consumption for the actual journey.

After tests on random lines, the algorithm started to be tested using data acquired in real railways lines. With this data, the algorithm output is compared with real velocity measurement. Velocity limits and gradients values are also being considered. To get coherent results, speed profiles are determined by using parameters that defines the real train were the measurements were made.

Until the moment, two cases are being analysed and the will be present during this section. Table 5.1 presents two study cases where the algorithm has been tested. Due to confidentiality issues, no information about the stations, line gradients or train characteristics are going to be presented. As relevant information, velocity limit on those section is much higher than the required speed. Both lines have positive and negative slopes, which influences energy consumption.

Table 5.1: Study cases

Case	**Distance (m)**		**Time (s)**		**Ec (kWh)**	
1	Real	DAS	Real	DAS	Real	DAS
	1710	1766.29	120	117	17	15.07
2	Real	DAS	Real	DAS	Real	DAS
	2000	2035.81	120	120	8	6.80

Case 1:

The first case considers a total travelling distance of 1710 m and a required travelling time of 120 s. The algorithm was defined to run 100 iterations and at the end, a solution is given as the most economical for the required time and travelling distance.

Fig. 5.4 and Fig. 5.5 shows the algorithm searching mechanism which generates several speed profiles. The first picture shows all the speed profiles while the second presents the values generated for each velocity.

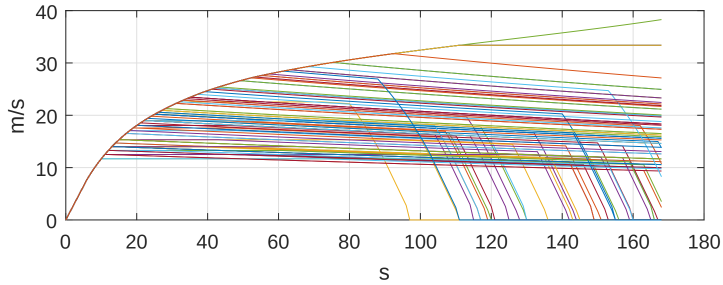


Figure 5.4: Searching process: candidat profiles

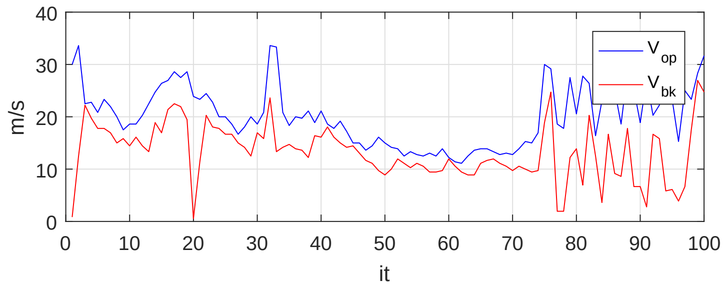


Figure 5.5: Searching process: velocity values

The velocity profile generated by the algorithm is presented in Fig. 5.6 where the x label represents the travelling time. The same result is presented in Fig. 5.7 but the speed profile was drawn with distance at x-label. The velocity limit of the line is also shown.

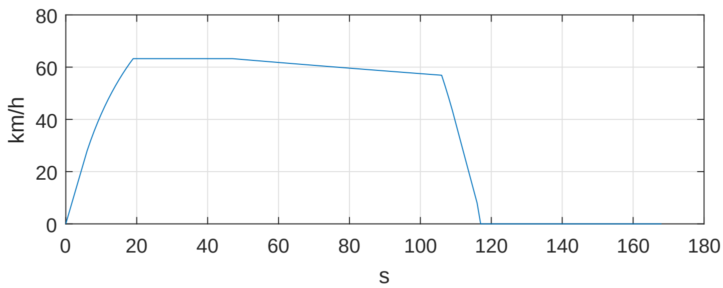


Figure 5.6: Final Result: velocity vs time

From the data received, it was analysed the velocity profile accomplish between both stations. The profile is presented in Fig.5.8 and as can be seen, the train arrived also a little early than the expected on the timetable.

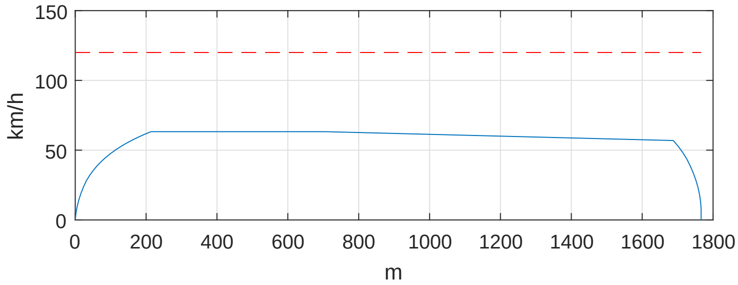


Figure 5.7: Final Result: velocity vs distance

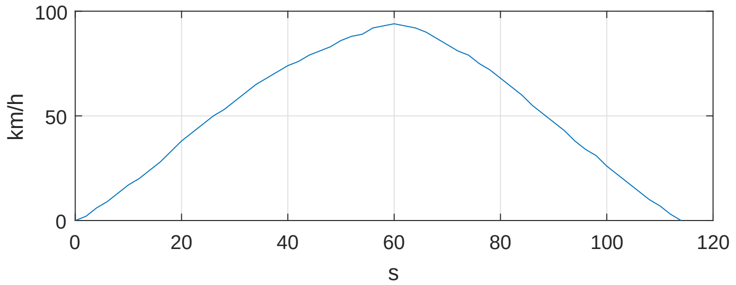


Figure 5.8: Real velocity

Comparing the algorithm results with the measurements, Table 5.1, it shows a promising reduction on energy consumption. Another conclusion about the results is the fact of the speed profile generated by the algorithm, Fig. 5.6, advices a velocity near to the average one. This follows the idea of the minimum energy consumption is achieved by travelling at average velocity. Once the real velocity, Fig. 5.8, is much higher than the average velocity, is expected an improvement by following the generated one.

Case 2:

The second case considers a total travelling distance of 2000 m and a required travelling time of 120 s. The algorithm was defined to run 100 iterations and at the end, a solution is given as the most economical for the required time and travelling distance.

Once the algorithm structure is the same, only the results are going to be presented. Fig. 5.9 and Fig. 5.10 shows the result of the algorithm after running 100 iterations for the actual profile.

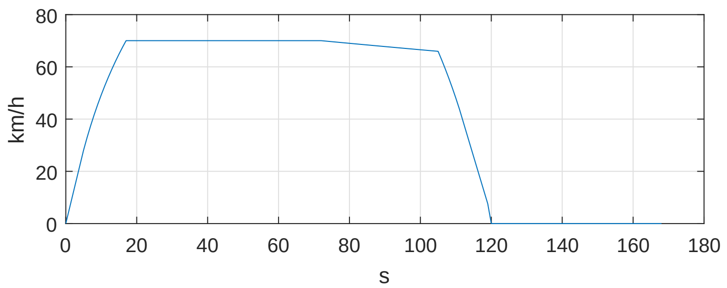


Figure 5.9: Final Result: velocity vs time

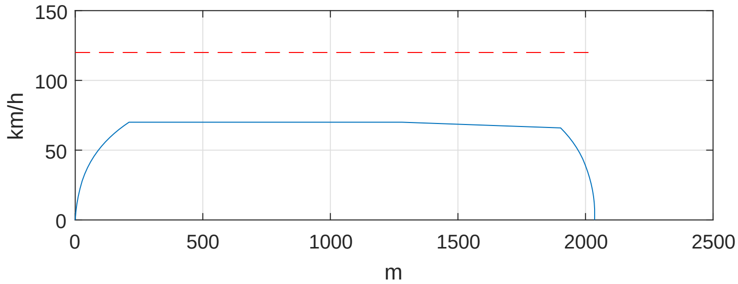


Figure 5.10: Final Result: velocity vs distance

Comparing the algorithm results, Table 5.1, and the speed profiles with the real one, Fig. 5.11 can be concluded that the algorithm output once again produced a energy consumption lower than the real.

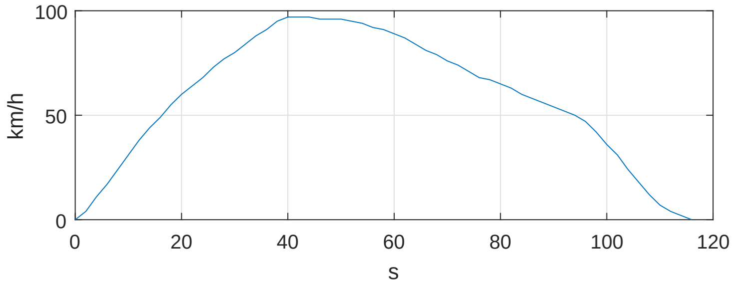


Figure 5.11: Real velocity

Case 3:

To evaluate the algorithm robustness, a special case was created to test speed profile generation in a case where a velocity limit appear. The situation can be compared with a real situation when works are being done in the line. The efficiency of the algorithm output was not analysed since there were no data to analyse the situation. The idea of present here the results is to show the algorithm response.

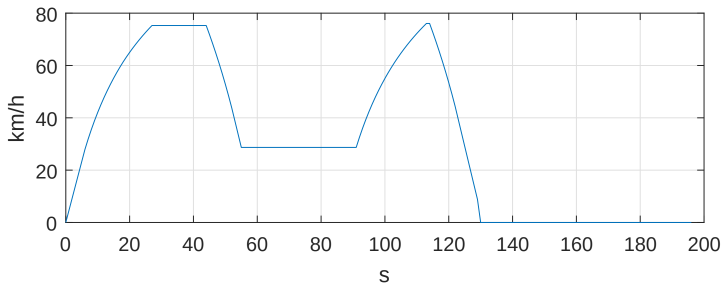


Figure 5.12: Final Result: velocity vs time

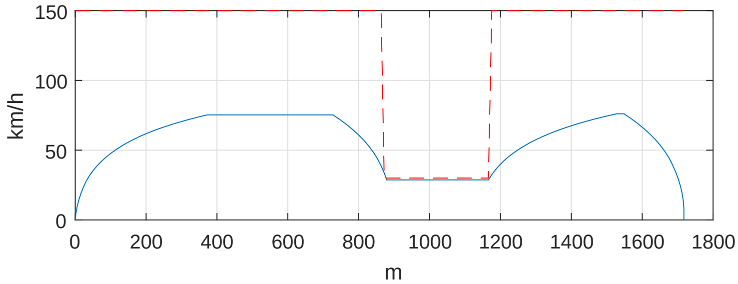


Figure 5.13: Final Result: velocity vs distance

5.4 Conclusion

Analysing the results obtained until now, the algorithm reveals to improve the railway systems for reducing energy consumption. Thus, it shows that all the research work developed is in the fed of the proposed objectives.

Now, it is necessary to validate the algorithm in new sections to evaluate the robustness and response to new and different situations. Also, train parameters must be also confirmed to despite false results. The need to implement the system on a mobile platform grows with the purpose to receive improvement by real train drivers to understand what can be done or which improvements can be made.

Bibliography

[1] shift2rail.org, "Infrastructure innovation programme 3 shift2rail," June 2016. [Online]. Available: http://shift2rail.org/research-development/ip3/

[2] A. Fernández-Rodríguez, A. Fernández-Cardador, and A. P. Cucala, "Energy efficiency in high speed railway traffic operation: a real-time ecodriving algorithm," in *IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*, June 2015, pp. 325–330.

[3] Y. Jiang, J. Liu, W. Tian, M. Shahidehpour, and M. Krishnamurthy, "Energy harvesting for the electrification of railway stations: Getting a charge from the regenerative braking of trains.a," *IEEE Electrification Magazine*, vol. 2, no. 3, pp. 39–48, Sept 2014.

[4] S. de la Torre, A. J. Sánchez-Racero, J. A. Aguado, M. Reyes, and O. Martínez, "Optimal sizing of energy storage for regenerative braking in electric railway systems," *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1492–1500, May 2015.

[5] A. Gonzalez-Gil, R. Palacin, and P. Batty, "Sustainable urban rail systems: Strategies and technologies for optimal management of regenerative braking energy," *Energy Conversion and Management*, vol. 75, pp. 374 – 388, 2013.

[6] M. Dominguez, A. Fernandez-Cardador, A. P. Cucala, and R. R. Pecharroman, "Energy savings in metropolitan railway substations through regenerative energy recovery and optimal design of ato speed profiles," *IEEE Transactions on Automation Science and Engineering*, vol. 9, no. 3, pp. 496–504, July 2012.

[7] L. E. Zubieta, "Power management and optimization concept for dc microgrids," in *DC Microgrids (ICDCM), 2015 IEEE First International Conference on*, June 2015, pp. 81–85.

[8] M. Mahmoud, S. A. Hussain, and M. Abido, "Modeling and control of microgrid: An overview," *Journal of the Franklin Institute*, vol. 351, no. 5, pp. 2822 – 2859, 2014.

[9] Y. Gu, X. Xiang, W. Li, and X. He, "Mode-adaptive decentralized control for renewable dc microgrid with enhanced reliability and flexibility," *IEEE Transactions on Power Electronics*, vol. 29, no. 9, pp. 5072–5080, Sept 2014.

[10] X. Yu, A. Huang, R. Burgos, J. Li, and Y. Du, "A fully autonomous power management strategy for dc microgrid bus voltages," in *Applied Power Electronics Conference and Exposition (APEC), 2013 Twenty-Eighth Annual IEEE*, March 2013, pp. 2876–2881.

[11] J. J. Justo, F. Mwasilu, J. Lee, and J.-W. Jung, "Ac-microgrids versus dc-microgrids with distributed energy resources: A review," *Renewable and Sustainable Energy Reviews*, 2013.

[12] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna, and M. Castilla, "Hierarchical control of droop-controlled ac and dc microgrids - a general approach toward standardization," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 1, pp. 158–172, Jan 2011.

[13] F. Z. Peng, Y. W. Li, and L. M. Tolbert, "Control and protection of power electronics interfaced distributed generation systems in a customer-driven microgrid," in *2009 IEEE Power Energy Society General Meeting*, July 2009, pp. 1–8.

[14] S. Kotra and M. K. Mishra, "Control algorithm for a pv based hybrid microgrid," in *2015 Annual IEEE India Conference (INDICON)*, Dec 2015, pp. 1–6.

[15] R. R. Liu and I. M. Golovitcher, "Energy-efficient operation of rail vehicles," *Transportation Research Part A: Policy and Practice*, vol. 37, no. 10, pp. 917 – 932, 2003.

[16] T. Albrecht, C. Gassel, A. Binder, and J. van Luipen, "Dealing with operational constraints in energy efficient driving," in *Railway Traction Systems (RTS 2010), IET Conference on*, April 2010, pp. 1–7.

[17] J. Qu, X. Feng, and Q. Wang, "Real-time trajectory planning for rail transit train considering regenerative energy," in *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, Oct 2014, pp. 2738–2742.

[18] Q. Gu, T. Tang, F. Cao, and Y. d. Song, "Energy-efficient train operation in urban rail transit using real-time traffic information," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 3, pp. 1216–1233, June 2014.

[19] X. H. Yan, B. G. Cai, B. Ning, and W. ShangGuan, "Moving horizon optimization of dynamic trajectory planning for high-speed train operation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1258–1270, May 2016.

[20] H. Douglas, P. Weston, D. Kirkwood, S. Hillmansen, and C. Roberts, "Method for validating the train motion equations used for passenger rail vehicle simulation," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, p. 0954409716631784, 2016.

[21] B. P. Rochard and F. Schmid, "A review of methods to measure and calculate train resistances," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, vol. 214, no. 4, pp. 185–199, 2000.

[22] G. M. Scheepmaker, R. M. Goverde, and L. G. Kroon, "Review of energy-efficient train control and timetabling," *European Journal of Operational Research*, vol. 257, no. 2, pp. 355 – 376, 2017.

[23] K. Kim and S. I.-J. Chien, "Optimal train operation for minimum energy consumption considering track alignment, speed limit, and schedule adherence," *Journal of Transportation Engineering*, vol. 137, no. 9, pp. 665–674, 2011.

[24] P. Howlett, I. Milroy, and P. Pudney, "Energy-efficient train control," *Control Engineering Practice*, vol. 2, no. 2, pp. 193 – 200, 1994.

[25] J.-C. JONG and S. CHANG, "Algorithms for generating train speed profiles," *Journal of the Eastern Asia Society for Transportation Studies*, vol. 6, pp. 356–371, 2005.

[26] C. S. Chang and S. S. Sim, "Optimising train movements through coast control using genetic algorithms," *IEE Proceedings - Electric Power Applications*, vol. 144, no. 1, pp. 65–73, Jan 1997.

[27] K. K. Wong and T. K. Ho, "Dynamic coast control of train movement with genetic algorithm," *International Journal of Systems Science*, vol. 35, no. 13-14, pp. 835–846, 2004.

[28] S. Acikbas and M. T. Soylemez, "Coasting point optimisation for mass rail transit lines using artificial neural networks and genetic algorithms," *IET Electric Power Applications*, vol. 2, no. 3, pp. 172–182, May 2008.

[29] Y. Huang, X. Ma, S. Su, and T. Tang, "Optimization of train operation in multiple interstations with multi-population genetic algorithm," *Energies*, vol. 8, no. 12, pp. 14 311–14 329, 2015.

[30] S. Lu, S. Hillmansen, T. K. Ho, and C. Roberts, "Single-train trajectory optimization," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 743–750, June 2013.

[31] Y. Huang, C. Yang, and S. Gong, "Energy optimization for train operation based on an improved ant colony optimization methodology," *Energies*, vol. 9, no. 8, 2016.

[32] K. Keskin and A. Karamancioglu, "Energy-efficient train operation using nature-inspired algorithms," *Journal of Advanced Transportation*, vol. 2017, 2017.

[33] R. Chevrier, G. Marliere, B. Vulturescu, and J. Rodriguez, "Multi-objective evolutionary algorithm for speed tuning optimization with energy saving in railway: Application and case study," in *RailRome 2011*, 2011.

[34] M. Domínguez, A. Fernández-Cardador, A. P. Cucala, T. Gonsalves, and A. Fernández, "Multi objective particle swarm optimization algorithm for the design of efficient ATO speed profiles in metro lines," *Engineering Applications of Artificial Intelligence*, vol. 29, pp. 43 – 53, 2014.

[35] R. Chevrier, P. Pellegrini, and J. Rodriguez, "Energy saving in railway timetabling: A bi-objective evolutionary approach for computing alternative running times," *Transportation Research Part C: Emerging Technologies*, vol. 37, pp. 20 – 41, 2013.

[36] A. D. Pizzo, L. Fratelli, D. Perna, and C. Nappo, "A method for "design to range" energy storage systems in catenary free operations of light railway vehicles," in *Clean Electrical Power (ICCEP), 2015 International Conference on*, June 2015, pp. 761–766.

[37] A. Emadi, *Advanced electric drive vehicles.* CRC Press, 2014.

[38] IEC, "Electrical energy storage," *White Paper*, vol. 39, 2011.

[39] X. Luo, J. Wang, M. Dooner, and J. Clarke, "Overview of current development in electrical energy storage technologies and the application potential in power system operation," *Applied Energy*, vol. 137, pp. 511 – 536, 2015.

[40] J. Cao and A. Emadi, "Batteries need electronics," *IEEE Industrial Electronics Magazine*, vol. 5, no. 1, pp. 27–35, March 2011.

[41] A. Khaligh and Z. Li, "Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: State of the art," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 6, pp. 2806–2814, July 2010.

[42] S. F. Tie and C. W. Tan, "A review of energy sources and energy management system in electric vehicles," *Renewable and Sustainable Energy Reviews*, vol. 20, pp. 82 – 102, 2013.

[43] M. Ehsani, Y. Gao, and A. Emadi, *Modern electric, hybrid electric, and fuel cell vehicles: fundamentals, theory, and design.* CRC press, 2009.

[44] L. Nesscap Co., "Nesscap ultracapacitors, supercapacitors & modules," June 2016. [Online]. Available: http://www.nesscap.com/ultracapacitor/EDLC/Supercapacitor/family.jsp

[45] J. C. Beardsall, C. A. Gould, and M. Al-Tai, "Energy storage systems: A review of the technology and its application in power systems," in *Power Engineering Conference (UPEC), 2015 50th International Universities*, Sept 2015, pp. 1–6.

[46] I. MAXWELL TECHNOLOGIES, "Maxwell technologies transportation solutions: Rail," June 2016. [Online]. Available: http://www.maxwell.com/solutions/transportation/rail

[47] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Progress in Natural Science*, vol. 19, no. 3, pp. 291 – 312, 2009.

[48] M. A. Silva, H. N. de Melo, J. P. Trovao, P. G. Pereirinha, and H. M. Jorge, "Hybrid topologies comparison for electric vehicles with multiple energy storage systems," in *Electric Vehicle Symposium and Exhibition (EVS27), 2013 World*, Nov 2013, pp. 1–8.

[49] R. Carbone, *Energy storage in the emerging era of smart grids.* InTech, 2011.

[50] A. Gonzalez-Gil, R. Palacin, P. Batty, and J. P. Powell, "Energy-efficient urban rail systems: strategies for an optimal management of regenerative braking energy," *Transport Research Arena*, 2014.

[51] Bombardier, "Mitrac energy saver - eco4 technologies - bombardier," August 2016. [Online]. Available: http://www.bombardier.com/en/transportation/products-services/innovation-driver/eco4-technologies/mitrac-energy-saver.html

[52] Siemens, "Mobile energy storage - mobility - siemens," August 2016. [Online]. Available: http://www.mobility.siemens.com/mobility/global/en/rail-solutions/rail-electrification/dc-traction-power-supply/energy-storage-solutions/pages/mobile-energy-storage.aspx

[53] Toshiba, "Energy storage applications system : Railway systems : Toshiba," August 2016. [Online]. Available: http://www.toshiba.co.jp/sis/railwaysystem/en/solution/eco/storage.htm

[54] Saft, "Ion-onboard li-ion regenerative hybrid traction battery system — saft," August 2016. [Online]. Available: http://www.saftbatteries.com/battery-search/ion-onboard%C2%AE-li-ion-regenerative-hybrid-traction-battery-system

[55] ABB, "Enviline- ess - energy management (dc wayside power solutions) — abb," August 2016. [Online]. Available: http://new.abb.com/power-electronics/dc-wayside-power-solutions/energy-management/enviline-ess

[56] Toshiba, "Traction energy storage system with scib : Railway systems : Toshiba," August 2016. [Online]. Available: http://www.toshiba.co.jp/sis/railwaysystem/en/products/power/tess.htm

[57] Saft, "Intensium max - saft," August 2016. [Online]. Available: http://www.saftbatteries.com/battery-search/intensium-max

[58] Siemens, "Stationary energy storage - mobility - siemens," August 2016. [Online]. Available: http://www.mobility.siemens.com/mobility/global/en/rail-solutions/rail-electrification/dc-traction-power-supply/energy-storage-solutions/pages/stationary-energy-storage.aspx

[59] Bombardier, "Energstor wayside energy storage - eco4 technologies - bombardier," August 2016. [Online]. Available: http://www.bombardier.com/en/transportation/products-services/innovation-driver/eco4-technologies/energstor-wayside-energy-storage.html

[60] Kawasaki, "Battery power system (bps) for railways — kawasaki heavy industries," August 2016. [Online]. Available: https://global.kawasaki.com/en/energy/solutions/battery_energy/applications/bps.html

[61] R. K. Arora, *OPTIMIZATION - Algorithms and Applications*, 2015.

[62] B. Wang, Z. Yang, F. Lin, and W. Zhao, "An improved genetic algorithm for optimal stationary energy storage system locating and sizing," *Energies*, vol. 7, no. 10, p. 6434, 2014.

[63] R. Chibante, A. Carvalho, and A. Araujo, *Parameter identification of power semiconductor device models using metaheuristics.* INTECH Open Access Publisher, 2010.

[64] M. Caramia and P. Dell'Olmo, *Multi-objective management in freight logistics: Increasing capacity, service level and safety with optimization algorithms.* Springer Science & Business Media, 2008.