Towards Smart Railways: A Charging Strategy for On-Board Energy Storage Systems

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Abstract. The huge power requirements of future railway transportation systems require the usage of energy efficient strategies towards a more intelligent railway system. With the usage of on-board energy storage systems, it is possible to increase the energy efficiency of railways. In this paper, a top-level charging controller for the on-board energy storage system is proposed based on a fuzzy logic controller. As an optimization procedure to increase the energy efficiency of such charging controller, a genetic algorithm meta-heuristic is used to automatically tune the fuzzy rules weight. To validate the proposed controller, two sets of rules were defined, one considering only known rules and the other also considering all possible combinations of rules. As global results, the reduction of regenerated energy reached 30%, and the net energy consumption reduction is near 10%.

Keywords: Railway power systems · On-board energy storage systems · Fuzzy Logic Controllers · Genetic algorithms Meta-heuristics · Energy efficiency

1 Introduction

1.1 Railway Power Systems

The railway system has huge power requirements, which leads the railway operators to focus their efforts to increase the energy efficiency and reduce the energy consumption bill. Modern trains have the possibility to enhance the energy consumption with the usage of power electronic devices, which allows bi-directional power flow and, as ultimate goal, the regeneration of energy due to the braking [1].

From the data from [2], a typical train power consumption has the profile presented in Fig. 1a. In Fig. 1b, it is possible to see a huge dispersion of the power consumption/regeneration, which is caused mostly due to the needs to guarantee a given journey timetable, and in this case, stop in every passenger station. In certain countries, the regenerated energy cannot be "returned" to the Transmission/Distribution System Operator TSO/DSO. Therefore, in these cases, most of the regenerated energy must be burn in the train rheostatic system and the billed energy will not be the blue graph of Fig. 1c, being the red graph. According to [3], in the worst case where the headway between trains is big, almost all of the regenerated energy will not be absorbed by another train,

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and it will result in around 60% of energy losses. Therefore, there is a need to minimize the regenerated energy without affecting the train dynamic characteristics. One way to achieve this is with the use of railway Energy Storage Systems (ESS).

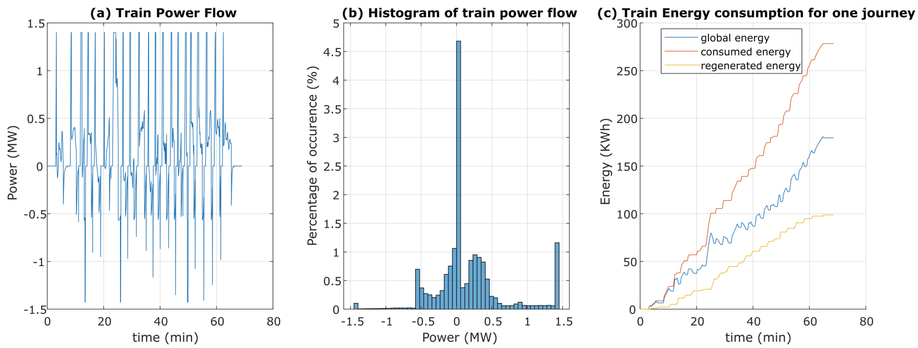

Fig. 1. Details on a train journey power flow: (a) Power consumption/regeneration for a sub-urban train journey; (b) Histogram of train power flow; (c) Train energy consumption.

1.2 Railway Energy Storage Systems

Ideally, the most effective way to increase the global efficiency of traction systems is to use the regenerative braking energy to feed another train in traction mode (and absorbing the totality of the braking energy) [4]. However, this solution requires an excellent synchronism and a small distance between "in traction mode" and "in braking mode" trains. Therefore, in the occurrence of small delays, the regenerative energy cannot be used by another train and can be burned in the train rheostatic system or, if possible, can be returned to the DSO [5].

The usage of regenerative braking energy to charge Energy Storage Systems (ESSs) is one effective way to increase the global efficiency of traction systems [1, 5]. However, due to the high cost of ESSs, alternatives such as reversible Traction Power Substation (TPS) result in a better cost-effective solution [6].

Nevertheless, on-board ESS are the only solution for a catenary-free system [7]. In addition, to the better knowledge of the authors, wayside ESS study only considers the acquisition cost of an infrastructure having the totality of ESS, without considering the possibility of not including batteries (or other storage technology).

In the future, it is possible and needed to have Electric Vehicles (EVs) charging stations located at passenger stations. Therefore, in theory, it is possible to connect the charging stations to the catenary and increase the degree of freedom in the EVs charging strategy. This way, having this possibility, the wayside ESS can now be a cost-effective solution, having multiple charging objectives.

In this paper, an ESS multiple-objective charging strategy is proposed based on Fuzzy Logic Controllers (FLC). This charging controller considers on-board ESS, as a case study, but it can be extended to wayside ESS.

1.3 Optimal Charging Strategy of ESS

The management of ESS charging system is a research topic in smart grids. Usually, the optimal charging strategy is based on scheduling of charging profiles, using the knowledge of a predicted load profile [8].

However, due to the high-variation of the railway energy consumption resulting in a difficult task for energy consumption prediction, the scheduling of the charging profile is not an option. In this work, optimal charging strategies without scheduling are explored to be implemented in a ESS system, where the charging controller decides in real-time the energy flow.

A multi-objective system using a FLC for energy management, as proposed in [9] and extended in [10] and in [11], is a real-time charging strategy, with the rule weights and membership function parameters being the search space of the optimization algorithm.

Since the performance of a fuzzy system is more dependent on rule weights rather than membership function parameters [12], in this work the MF parameters are fixed and were defined upon the authors knowledge of the system. The search space of the Genetic Algorithm is, therefore, the adjustment of the rule weights.

Based on [10], there are two possible objectives for the charging strategy: (i) the financial objective function, purely on the cost of buying/selling energy in different times; and (ii) the battery stress, to represent the physical degradation of the battery. In this work, the financial objective is related to the energy consumption/regenerated, whereas the battery stress is purely on the *di/dt* of the ESS charging converter (later called converter temperature).

1.4 Structure of the Paper

This paper is structured in five sections. The first section covers the need for ESS. The second section presents the proposed charging optimization strategy, based on FLC. Later in third section, is shown the meta-heuristic strategy to optimize the behavior of FLC, by adjusting the fuzzy rule weights. The case study to illustrate this optimization strategy is presented in Sect. 4, as well as a discussion. In Sect. 5, the conclusions of this work are presented.

2 Proposed Fuzzy-Based Charging Optimization Strategy

In this section, the proposed fuzzy-based charging strategy is presented. The main core of the energy storage control system is a Mamdani Fuzzy Logic Controller (FLC), proposed in [13], having the structure illustrated in the Fig. 2a.

The FLC has multiple inputs (the train power flow value, the ESS SOC and a variable representing the temperature of the ESS) and one output (the set point for the ESS power flow). In Fig. 2b, c, d, e is illustrated the FLC Membership Functions (MF) for the input and output variables.

The first input is the power consumption of the train and it can be categorized as consumption (if the train is in the traction mode and the energy flows from the catenary to the wheels) or categorized as regeneration (if the train is in braking mode and the

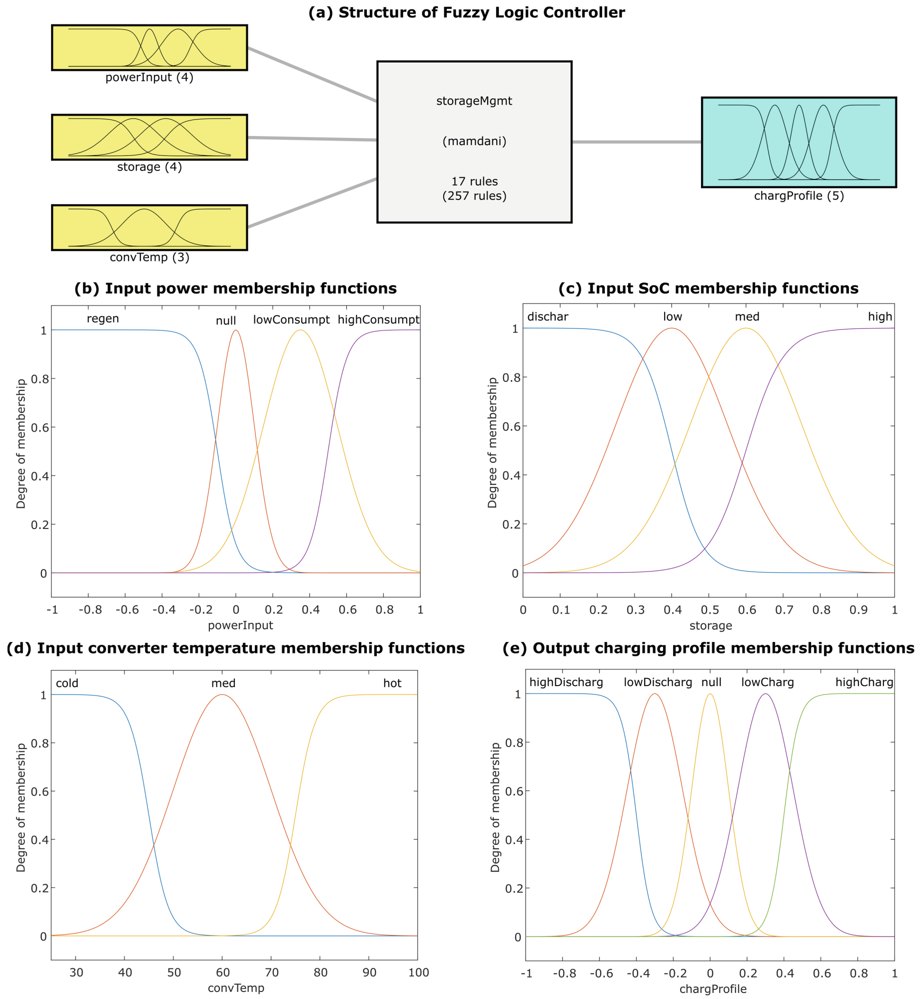

Fig. 2. Implemented Fuzzy Logic Controller (FLC): (a) Structure of controller; (b) Membership Function (MF) of train power consumption input variable; (c) MF of ESS state of charge input variable; (d) MF of converter temperature input variable; (e) MF of charging percentage of the ESS output variable.

regenerated energy from the motors flows back to the catenary). The second input is the on-board ESS State of Charging (SoC) and corresponds to 100% if the system is fully charged or 0% if the system is fully discharged (considering those values the absolute maximum/minimum voltage values, and considering that reaching SoC values above 80% and below 20% should be avoided by the controller). To promote a reasonable usage of the ESS, a third variable is proposed. This variable mimics the semiconductors heating and the battery state of health, and it is a quadratic function of the charging power.

On the FLC output, a variable is proposed to define the ESS charging profile, in an absolute per-unit (p.u.) value. In this work, a hypothetical ESS hardware was arbitrarily chosen. Specifically, the power capabilities of the ESS was set to have 350 kW of charging/discharging maximum power (25% of the train power consumption) and 35 kWh of stored energy (6 min to fully charge the ESS when the charging profile is constant and 1 p.u.).

In this work, the FLC is tested with a test bed in which a near 70-min train journey is considered. The train power consumption presented in Fig. 1a is the independent input of the test bed. The SoC and the converter temperature depends on the previous result of the FLC output variable. Iteratively for each time instant, the stored energy and the ESS temperature variables are calculated from previous values, as follows:

```
REPEAT
    CharProfile[n] = FUZZY(power[n-1], SoC[n-1], ConvTemp[n-1])
    SOC[n] = SOC[n-1] + K_ESS×CharProfile[n]
    ConvTemp[n] = ConvTemp[n-1] + K_temp×(power[n-1])^2- K_dissip
UNTIL all time instants [n] are calculated
Compute objective function metrics
```

The K_{ESS} constant defines the storage capacity and the charger design limitations. The K_{temp} and the K_{dissip} represents the temperature increase of the ESS, as quadratic function of the power, and a dissipation factor to promote the temperature reduction. In this work, no effort was made to use a specific ESS system and these values were arbitrary chosen.

To ensure the physical limits, the input variables are limited by its admissible maximum and minimum values and, in the case of the occurrence of over-temperature, over-charge or over-discharge events, the charging profile value is changed to avoid those events.

In this work, two possible sets of rules were defined:

(a) 17 rules were defined, considering the expected behavior of the system, as shown in the Table 1.
(b) 17 + 240 rules, where the first 17 rules were defined based on the expected behavior of the system and the remaining rules corresponds to all possible combinations of rules.

Regarding the fuzzy rule weights, in Sect. 3 of this work is presented an iterative approach to adapt the weights, towards the fulfillment of optimization objectives. As initial values, in the sets of rules presented in (a), all the weights were chosen to be 0.5. In the second set of rules, the “known rules” have an initial value of 0.9 and the remaining 240 rules starts with a weight of 0.1.

Table 1. List of fuzzy rules with the initial weights.

	Rule	Weight
1	If (powerInput is regen) then (chargProfile is highCharg)	0.5
2	If (powerInput is highConsumpt) then (chargProfile is highDischarg)	0.5
3	If (storage is high) then (chargProfile is highDischarg)	0.5
4	If (storage is dischar) then (chargProfile is highCharg)	0.5
5	If (powerInput is null) and (storage is high) then (chargProfile is lowDischarg)	0.5
6	If (powerInput is null) and (storage is med) then (chargProfile is null)	0.5
7	If (powerInput is null) and (storage is low) then (chargProfile is lowCharg)	0.5
8	If (powerInput is lowConsumpt) and (storage is high) then (chargProfile is null)	0.5
9	If (powerInput is lowConsumpt) and (storage is med) then (chargProfile is null)	0.5
10	If (powerInput is lowConsumpt) and (storage is low) then (chargProfile is lowCharg)	0.5
11	If (convTemp is hot) then (chargProfile is null)	0.5
12	If (powerInput is regen) and (convTemp is cold) then (chargProfile is highCharg)	0.5
13	If (powerInput is highConsumpt) and (convTemp is cold) then (chargProfile is highDischarg)	0.5
14	If (storage is high) and (convTemp is cold) then (chargProfile is highDischarg)	0.5
15	If (storage is dischar) and (convTemp is cold) then (chargProfile is lowCharg)	0.5
16	If (convTemp is med) then (chargProfile is lowDischarg)	0.5
17	If (convTemp is med) then (chargProfile is lowCharg)	0.5

3 Meta-heuristic Rule Weight Adjustment

As a way to define the fuzzy rules, the human knowledge is a good starting point to obtain a charging strategy for the FLC. In this section is proposed a genetic algorithm (GA) as a meta-heuristic to define the weights of the fuzzy rules, having an objective function as the optimization criteria.

Therefore, each individual of the GA population will have an array of 17 weights (genes) and a value for its objective function that will be obtained in the FLC for a given test bed. The crossover process considers the best individuals and, a new individual is generated having part of the genetic material from the parent individuals. The mutation considers the random increase/decrease of certain genes. If a gene from previous generation has changed, in the mutation, it has higher probability to increase/decrease accordingly. The algorithm for the implemented GA is presented as follows:

```
START
Generate the initial population
RUN test bed for all individuals
REPEAT
```

```
        Selection
        Crossover
        Mutation
        RUN test bed for all individuals
UNTIL population has converged OR max generations
STOP
```

The initial population is generated from five individuals having the weights defined from the human knowledge in the previous section. In addition, 30 new individuals were generated as mutations from those individuals. Then the FLC is tested for all the new rule weights, and the objective function is calculated from the results of the FLC test bed.

In this work, the objective function values were calculated based on four metrics:

(a) The RMS value of the graph of converter temperature;
(b) The RMS value of the resultant charging profile;
(c) The final value of the ESS SoC;
(d) The final value of the regenerated energy.

It is considered, as optimization criteria objective, to avoid peak values in the first two metrics (avoiding high *di/dt* on the ESS). In the remaining metrics, the optimization objective is to minimize the difference between final and initial values of SoC and to minimize the difference between the regenerated energy without and with the ESS.

In the design of the global objective function metric, all four metrics are considered, having arbitrarily defined weights to better fulfil the expected behavior of the system (in terms of convergence speed, stability of the GA, intuition, etc.). Therefore, to obtain the results presented in Sect. 4, the converter temperature and charging profile metrics, has receive small weights, and the SoC variation and global energy reduction has received a higher weight (with the global energy reduction tuned to rapidly reduce this metric).

4 Results

In this section, two sets of rules were considered to illustrate the evolution of the optimization algorithm. Later, the two cases results are compared and a discussion is presented.

4.1 Preliminary Knowledge of System Behavior

The following results present the testbed evaluated with the 17 known rules. For different generations and the same independent power consumption input (Fig. 3a), in Fig. 3b is illustrated the evolution of stored energy; in Fig. 3c is presented the evolution of the charging profile and in Fig. 3d is visible the evolution of the converter temperature.

At each generation, 40 new individuals are generated from previous population, where 25 of the individuals results of crossing the genetic material (the weight of FLC

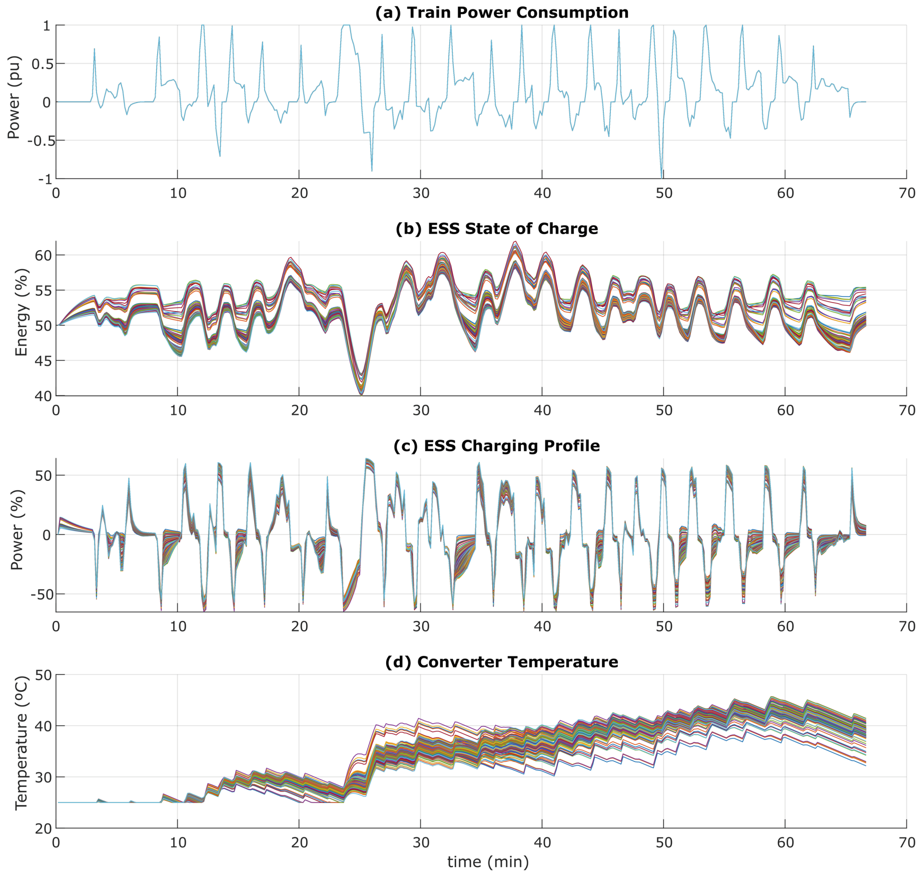

Fig. 3. Evolution of testbed variables, in order of time, for different meta-heuristic generations of fuzzy rule weights: (a) Power consumption for one journey; (b) Stored energy; (c) Charging profile; and (d) Converter temperature.

rules) from previous generation and the other 15 results of mutations on the population. Between generations, only the five best individuals are eligible to pass to the next generation. The evolution of the objective function is presented in Fig. 4.

Figure 4a shows the evolution of individual objective functions. Each of the individual objective functions was adapted to result in a near-unitary value. By providing different weights for each of the metrics, a global objective function is presented in Fig. 4b. Specifically, Fig. 4 illustrates the weights of all individuals of the same generation, plotted with "+" in the graphs, having the best individual of a generation highlighted with a square (in Fig. 4b).

For each rule, the FLC rule weights evolution for 200 generations are presented in the heat map graph of Fig. 5.

From the previous heat map result, certain rules will contribute more to the expected optimality. As example, the heuristic algorithm will increase the weight of rules 1, 3, 6,

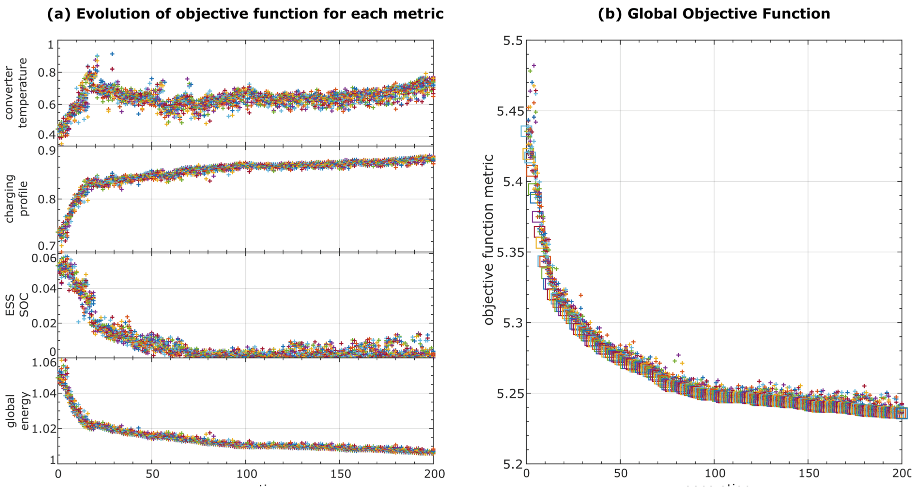

Fig. 4. Evaluation of objective function: (a) Individual evaluation of each metric for all generations; (b) Global objective function as dependent of the generation.

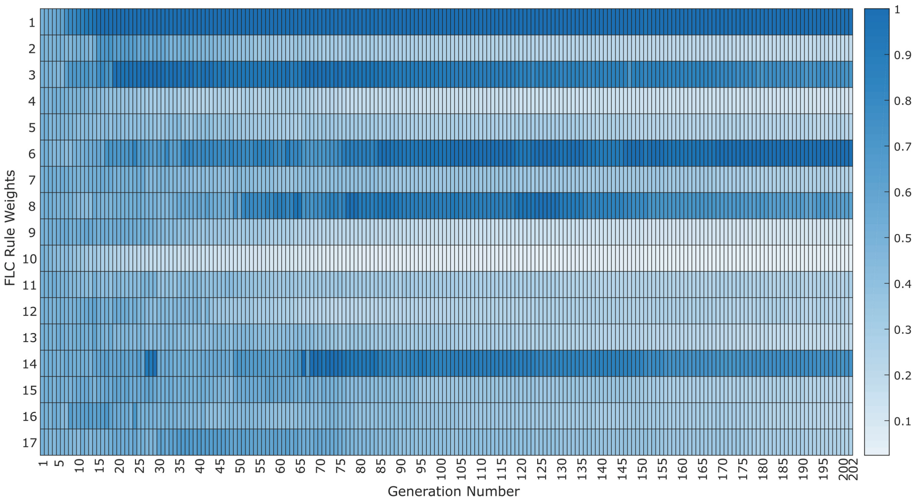

Fig. 5. Heat map of the best FLC rule weights for each generation.

8 and 14, and reduce the weight of remaining rules, in order to achieve lower value of the objective function.

4.2 Extended Optimization of ESS Charging Controller

The following results present the testbed evaluated with the 17 known rules, having an initial weight of 0.9, and the 240 possible combinations for fuzzy rules, with an initial weight of 0.1. For different generations and the same independent power consumption

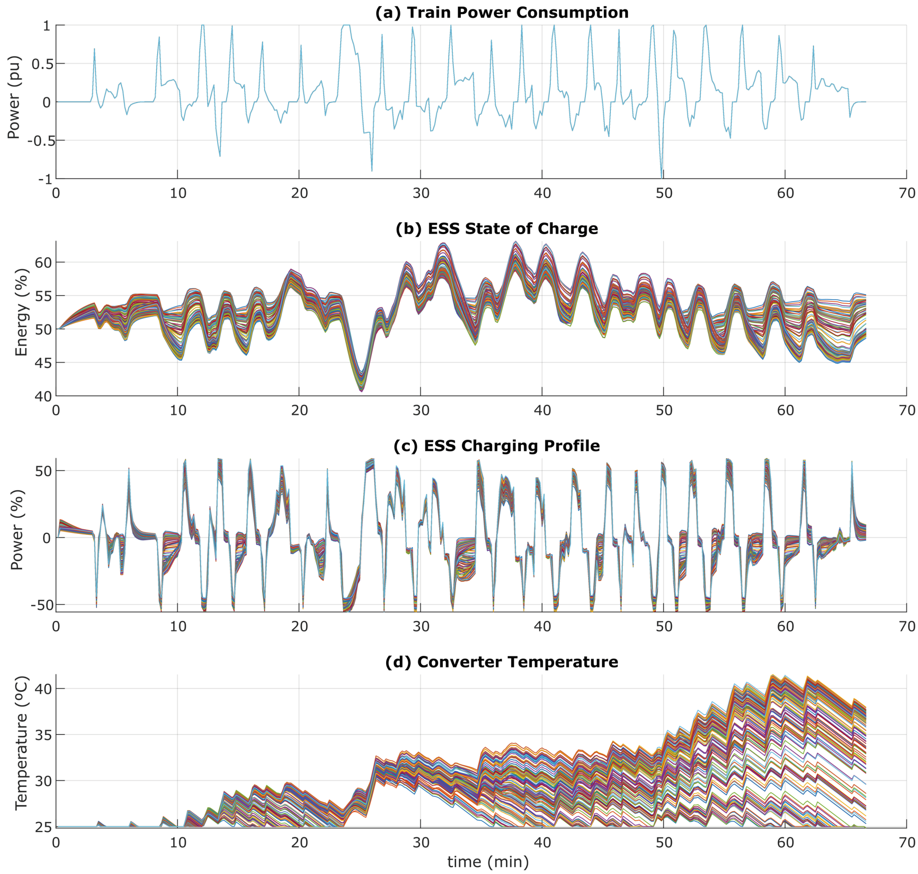

Fig. 6. Evolution of testbed variables, in order of time, for different meta-heuristic generations of fuzzy rule weights: (a) Power consumption for one journey; (b) Stored energy; (c) Charging profile; and (d) Converter temperature.

input, present in Fig. 6a, in Fig. 6b is illustrated the evolution of stored energy; in Fig. 6c is presented the evolution of the charging profile and in Fig. 6d is visible the evolution of the converter temperature.

The metaheuristic algorithm used for this set of rules is the same from the "known-only" rules. The evolution of the objective function for different generations is presented in Fig. 7.

Figure 7a shows similar results from the ones present in Fig. 4, in terms of convergence of the objective function values.

For each rule, the FLC rule weights evolution for 200 generations are presented in the heat map graph of Fig. 8.

From the previous heat map result, the first 17 known rules has a higher prevalence in the final result than the unknown combinations of rules. It is visible that, the unknown rules do not increase inversely proportional to the decrease of the known rules which its

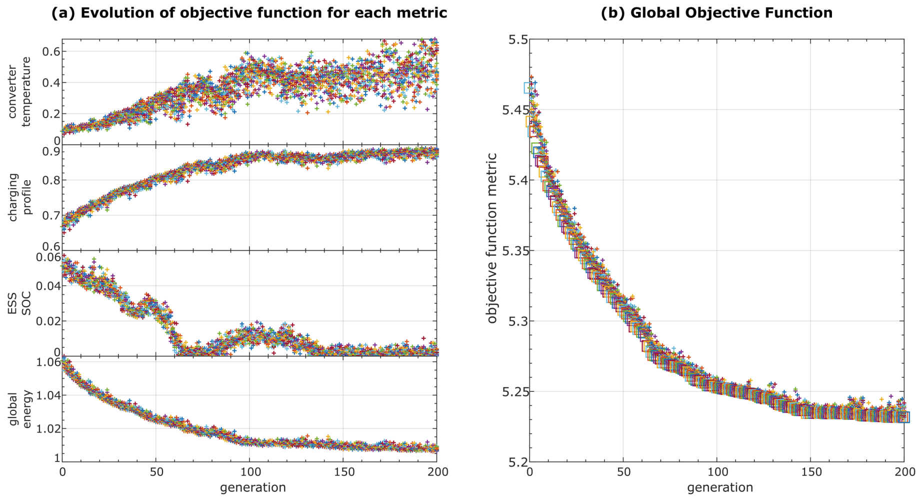

Fig. 7. Evaluation of objective function: (a) Individual evaluation of each metric for all generations; (b) Global objective function as dependent of the generation.

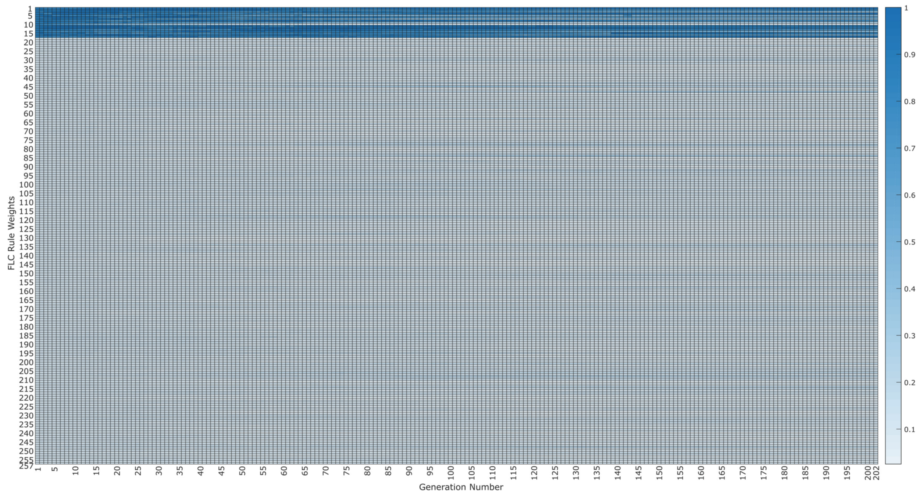

Fig. 8. Heat map of the best FLC rule weights for each generation.

weight is reduced by the GA. Specifically, with this results, it is visible that there is no unknown rule that was "forgotten" in the rule specification stage of the FLC controller design. It is more visible that the known rules are more eligible by the GA to be reduced (or eliminated).

4.3 Evaluation of Energy Optimization

In Fig. 9 is presented the comparison of the train journey energy consumption/regeneration for the four possible cases in study:

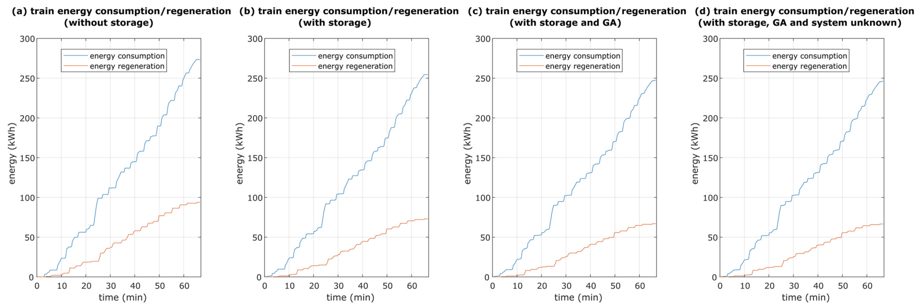

Fig. 9. Comparison of train energy consumption/regeneration graphs.

- A train without on-board ESS, in Fig. 9a;
- A train with ESS, with a FLC charging controller but without fuzzy weights optimization (only with the known rules having the same weights), in Fig. 9b;
- A train with on-board ESS, with the charging controller based on FLC, using the GA optimization criteria over the known rules, in Fig. 9c;
- A train with on-board ESS, with the charging controller based on FLC, using the GA optimization over either the known rules and all possible combinations of unknown rules, in Fig. 9d.

In Table 2 is summarized the comparison of the train energy for the four cases in study: the inclusion or not of the on-board ESS, the inclusion or not of the optimization procedure, and the consideration or not of the unknown rules.

Table 2. Energy optimization results.

	Train energy			
	Consumption		Regeneration	
	kWh	%	kWh	%
Without ESS	273.5	100	93.9	100
With ESS, with known rules, without GA optimization	254.4	93.0	73.0	77.7
With ESS, with GA, only known rules	247.4	90.5	67.0	71.3
With ESS, with GA, with all possible rules	246.1	90.0	66.6	70.9

From the results of the Table 2, a maximum near 30% of reduction on the regenerated energy is achieved, as well as a reduction of 10% of energy consumption. Later, if the on-board charging strategy uses a GA meta-heuristic to increase the energy efficiency, in the case study considered, the reduction of regenerated energy is around 5% and the reduction of the train energy consumption is more than 2%.

4.4 Discussion

The previously presented reduction is of advanced interest since the energy consumption/regeneration reduction is achieved only with the adaptation of the charging strategy and without the adaptation of the ESS hardware. In addition, the FLC is an algorithm with low execution time and, therefore, it can be implemented in to a real-time charging controller for on-board ESS.

The fuzzy rules weights can be adjusted with offline calculation, using the meta-heuristic genetic algorithm presented in this work, or alternative adjustment strategy. By using the knowledge extracted from the operation of other trains and/or from the state of the railway power system, it is possible to better control multiple on-board ESS accordingly.

Therefore, this approach of having a multi-criteria charging strategy is of advanced interest since it has a big level of flexibility in the development of this kind of systems. As example, it is possible that all trains are equipped with ESS, with the FLC structure as the main control strategy and this structure being the same for all the railway ESS. Later, the rule weight adjustment confers each of the trains different behavior towards a better usage of the railway energy, which is essential to have smart railways.

Future research directions of this work will be in the extension of the presented charging strategy to a multi-train simulator system, where each of the trains are supposed to have an on-board ESS. Each of the ESS charging controller complies a FLC with the rule weights being defined by the GA, towards further optimization.

5 Conclusions

The initial approach of a storage charging controller, focused in multiple optimization criteria, and applied to railway transportation systems, is presented here. This optimization strategy combines the knowledge of the expected behavior of the system, by manually defining the rules of a fuzzy logic controller, and later, a meta-heuristic is used to adjust the weight of the fuzzy rules.

The focus of this work is to validate that a feasible charging solution having multiple input variables can be easily implemented with a FLC. This charging solution can result in high reduction of the regenerated energy (near 23%). Later, as an optimization strategy, a meta-heuristic can achieve 5% to 7% of regenerated energy reduction.

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