DEMAND-SIDE MANAGEMENT STRATEGY FOR ELECTRIC VEHICLES AND ELECTRIC WATER HEATERS CONNECTED TO DISTRIBUTION GRIDS

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Abstract. *The growing integration of renewable energy production and important loads such as electric vehicles bring a lot of challenges to today's electric systems. Demand-side management strategies are often presented as one of the solutions to these problems. In this study, a fuzzy logic supervision system is proposed to minimize energy transmission costs in distribution grids by controlling electric vehicle charging and electric water heater activation. The supervision system takes into account the production of renewable energy within the grid, the load consumption and other parameters including user's constraints. A genetic algorithm is used to optimize the supervisor's parameters. Finally, the system's performance is confirmed through simulation by testing it on real distribution grid data.*

Keywords: *Demand-side management; Electric vehicles; Electric water heaters; Renewable energy; Distribution grids.*

Nomenclature

DSM	Demand-Side Management
DSO	Distribution System Operator
ETC	Energy Transmission Cost
EV	Electric Vehicle
EWH	Electric Water Heater
GA	Genetic Algorithm
PV	Photovoltaic

1. Introduction

Due to recent energy transition policies trying to limit the alarming effects of global warming, the use of renewable energy instead of fossil fuels is very encouraged alongside other green technologies such as electric vehicles.

According to the French General Commissariat for Sustainable Development, renewable energy constitutes 16.3% of the gross final energy consumption in France in 2017 [1]. These numbers have been growing steadily in the past ten years, and significant growth of 62% in primary renewable energy production has been recorded between 2005 and 2017. This growth is mainly related to the growth of biofuels, heat pumps and the wind energy sector.

On the other hand, the global stock of electric cars surpassed the 3 million mark in 2017 [2] according to the International Energy Agency, with a similar growth of the charging infrastructure worldwide. This massive EV integration aggravates the electricity peak loads noticed during the day, leaving night hours with relatively low electricity demand.

This significant increase in renewable energy production on one side, and the growing integration of EVs on the other side can cause many problems on the distribution network mainly because of their stochastic nature. The electrical grid will have a higher risk of having overloading problems for example, which may require expensive reinforcements for equipment such as transformers and cables. The impact of EV integration has been broadly studied in the literature, showing that problems like congestions and voltage problems may appear [3] if there is no proper charging strategy for EVs and that the reliability of distribution systems may become compromised [4] [5]. However, the author of [6] showed that the use of decentralized photovoltaic generation in distribution networks could alleviate the impacts of uncontrolled EV charging on transformer and cable loading, the voltage profile and daily energy losses.

Another way to remedy previous problems is to use demand-side management strategies. A review of the DSM framework and methods is presented in [7]. Among previous studies involving EV load control, [8] used a multi-energy scheduling strategy to minimize the grid power fluctuation, [9] used an optimal load management strategy based on quadratic programming to schedule EV charging, and [10] used dynamic programming to reduce power losses and improve the voltage profile within the grid.

DSM strategies for home applications also control electric water heaters, heating, air conditioning, and other home appliances generally using dynamic pricing strategies [11]. These methods try to encourage users to avoid using all their appliances in peak times and shift demand towards less busy hours or periods when renewable energy production is abundant. The acceptance and involvement of consumers and energy producers to participate in these DSM methods were also studied recently in [12].

In this paper, an energy management strategy is proposed to monitor EVs and EWHs within the distribution network, with a primary goal of minimizing the energy transmission cost for the distribution system operator. A fuzzy logic supervision system is used to generate reference power signals for EV charging and EWH activation. Fuzzy logic was particularly chosen for its effectiveness in managing complex systems such as electrical distributions grids without the necessity to model all their components. The proposed supervisor's parameters are determined first empirically and then optimized using a genetic algorithm for better performance. The paper is structured as follows: First, the adopted EV and EWH load models are presented. Then, the proposed energy management strategy is explained, starting with ETC calculation since it's the objective to minimize, and going through the different components of the supervision system that are presented alongside the operating rules. The system's performance is finally evaluated through simulation results, and some perspectives are given in the last section.

2. Load Modeling

This section presents the proposed load models for EVs and EWHs that are used in the distribution grid's energy management system.

Electric Vehicles. The load profile and energy requirements of EVs are determined using deterministic and probabilistic parameters that define their charging process:

- *Battery specifications:* especially the battery capacity (kWh) and the standard consumption (kWh/km) of the EV. In this study, all EVs are considered to have the same characteristics as the Renault ZOE [13].
- *Charging mode:* since the EVs can charge at home and at the workplace, the normal charging mode (16A/230V) is considered for its versatility. Faster charging modes could be considered in places where the necessary infrastructure (charging stations) is available.
- *Daily travel distance:* the average travel distance recorded in France in 2017 is around 35km per day [14].
- *Arrival/departure times:* based on the traffic habits of French department Deux-Sèvres [15] in which this study is conducted, the home to office journey takes place around 08:00 and the return journey is around 17:00.

The heterogeneity between EV users is represented by a normal distribution, which characterizes a random variable x by its average value μ and its standard deviation σ, as expressed in (1). The chosen values in this study are given in Table 1.

$$f(x) = \frac{1}{\sigma\sqrt{2\cdot\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} . \quad (1)$$

Table 1. Arrival/departure times to home/office.

	Daily travel distance, km	Office arrival, hh:mm	Office departure, hh:mm	Home arrival, hh:mm	Home departure, hh:mm
μ	35	08:15	16:45	17:15	07:45
σ	5	00:30	00:30	00:30	00:30

These arrival/departure times vary on weekends since people have different dynamics. Traffic-based modeling of working days and weekends was proposed in [16], where probability distribution functions were fitted to real traffic data through a linear optimization problem. In this study, simpler assumptions are used: the office charging is not considered on weekends, and the home arrival and departure times are shifted two hours forward since people do not wake up early for work and return home later in the evening.

Electric Water Heaters. The load profile and energy requirements of EWHs are determined using a single element thermal model inspired by [17] and depend mainly on the users' hot water demand which is determined statistically.

The incoming cold water enters the EWH at the temperature T_{in} = 15°C, is heated through an electric resistance, and the outgoing hot water is delivered at the temperature T_{out} = 60°C as explained in Fig. 1. The water temperature is considered uniform in the entire EWH.

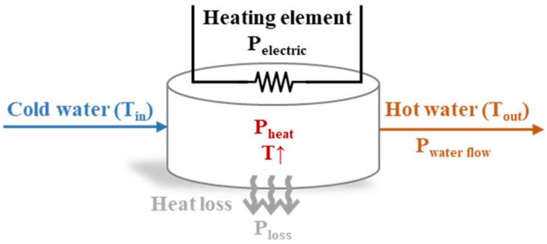

Fig. 1. Operating diagram of an EWH

The energy exchanges in the EWH are expressed in the equations (2-5). The energy given by the heating element ($P_{electric}$) is used to raise the temperature T of the water (P_{heat}), a part is lost due to the consumption of hot water ($P_{water\ flow}$), and another one is lost as heat exchanges with the outside environment through the tank (P_{loss}).

$$P_{electric}(t) = P_{heat}(t) + P_{water\ flow}(t) + P_{loss}(t) . \quad (2)$$

$$P_{heat}(t) = \rho c_p V \frac{dT(t)}{dt} . \quad (3)$$

$$P_{water\ flow}(t) = \rho c_p W_{flow}(t)(T(t) - T_{in}) . \quad (4)$$

$$P_{loss}(t) = \frac{S}{R}(T(t) - T_{out}) . \quad (5)$$

where:

- ρ and c_p are respectively the mass density (kg/m^3) and the specific heat (J/(kg.°C)) of water.
- V, S, and R are respectively the volume (m^3), the surface (m^2) and the thermal resistance (m^2.°C/W) of the tank.
- W_{flow} is the outgoing water flow (m^3/s).

The EWH is switched on or off by a thermostat, which means $P_{electric}$ is either null or equal to the nominal power P_{nom} of the EWH. The only remaining parameter that varies through time is the hot water demand (W_{flow}).

The hot water usage in France has been determined with a one-hour step by a study [18] conducted by the French environmental and energy efficiency agency (ADEME). An average household of three people consumes around 150±50 L of water at 40°C daily, which corresponds to 83±28 L at 60°C. The hot water consumption profile is then obtained by modulating this average daily consumption ($W_{cons\ day\ average}$) with hourly (α_{hour}), daily (α_{day}) and monthly (α_{month}) coefficients, as expressed in (6). The water flow is considered constant within every hour as it is suggested in Fig. 2.

$$W_{flow} = W_{cons\ day\ average} * \alpha_{hour} * \alpha_{day} * \alpha_{month} . \quad (6)$$

Finally, taking into account all the elements of (2) and knowing that $P_{electric}$ and W_{flow} are considered constant during every hour, the temperature evolution is calculated in (7).

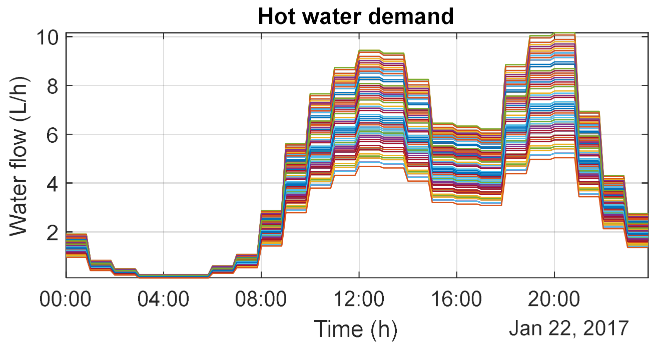

Fig. 2. Hourly hot water demand of 100 EWHs

$$T(t) = K + (T(t_0) - K)e^{-\frac{t-t_0}{\tau}} \text{, where:} \quad (7)$$

$$\tau = \frac{\rho c_p V R}{S + \rho c_p W_{flow} R}. \quad (8)$$

$$K = \frac{PR + ST_{out} + \rho c_p W_{flow} R T_{in}}{S + \rho c_p W_{flow} R}. \quad (9)$$

To obtain the temperature evolution on a long period, t_0 is reset every hour, $T(t_0)$ gets the final value of the previous hour, and the temperature evolution within the hour is determined using (7).

3. Energy management strategy

This section starts by presenting the computation of the energy transmission cost aimed to be minimized in this study, then describes the specifications of the proposed energy management system, its structure, and implementation.

Energy transmission cost computation. As users of the electricity transport network operated by RTE, the French Transport System Operator, Distribution System Operators like GEREDIS pay an annual Energy Transmission Cost that represents an important financial expense. The computation of this cost is set by the public electricity network user tariff (TURPE 5) [19], which is regulated by CRE, the French energy regulatory commission, to guarantee economic and secure access to electricity within the network. The considered components of the energy transmission cost are mainly related to the energy extracted by the DSO, and the periods where the subscribed power with the TSO is exceeded. The cost computation (10) is done for each High Voltage / Medium Voltage (HV/MV) substation.

$$ETC = b_1\, P_{sc\,1} + \sum_{i=2}^{5} b_i\,(P_{sc\,i} - P_{sc\,i-1}) + \sum_{i=1}^{5} c_i\, E_i + \sum_{12\,mois} \sum_{i=1}^{5} \alpha\, b_i \sqrt{\sum_j \left(P_j - P_{sc\,i}\right)^2}\,. \quad (10)$$

where:

- $P_{sc\,i}$ is the subscribed power (in kW) at the i[th] time frame (each time frame corresponds to peak or off-peak hours during different seasons, as defined in [19]).
- E_i is the extracted energy (in kWh) during the i[th] time frame.
- P_j is the measured power (in kW) exceeding the subscribed power.
- b_i and c_i are weighting coefficients for power and energy respectively. They depend on the voltage range on the substation and tariff version considered.
- α is a weighting coefficient for the exceeding power that also depends on the voltage range on the substation.

System specifications. The supervision system aims to control EV charging and EWH activation within a distribution network. Its objectives, constraints, means of actions and performance indicators are presented in Table 2.

Table 2. Supervision system specifications.

Objectives	Reduce the DSO's energy transmission bill by promoting local consumption of renewable energy through EV charging and EWH activation.
Constraints	- Renewable power intermittency. - Availability of EVs at home/office. - Full charging of EVs before departure. - Complete heating of EWHs before the end of the day.
Means of action	Load shifting.
Performance indicators	Energy transmission cost reduction.

Supervisor structure. The energy management strategy aims to supervise EV charging and EWH activation in a real distribution network operated by GEREDIS. Real power flow data is collected every 10 minutes from HV/MV substations through telemetry devices.

As shown in Fig. 3, the supervision system takes two main inputs. First, there is the measured power at the substation (P_{sub}) expressed in (11) that includes PV and wind energy producers (P_{PV}, P_{wind}), EVs and EWHs, and other consumers (P_{cons}) connected to the HV/MV substation.

$$P_{sub} = (P_{EV} + P_{EWH} + P_{cons}) - (P_{PV} + P_{wind})\,. \quad (11)$$

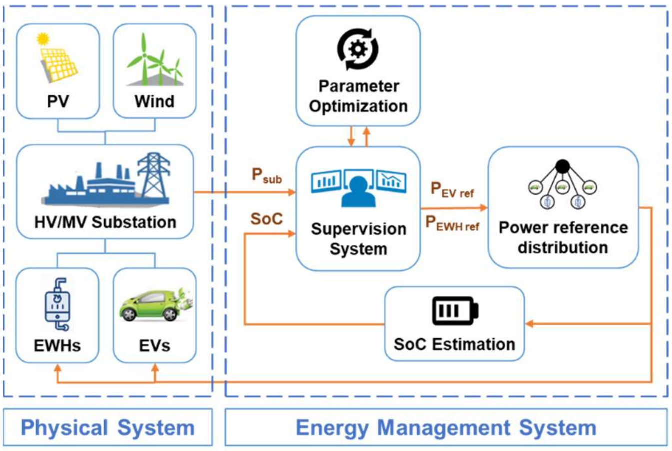

Fig. 3. Structure of the supervision system

The measured power can be positive in case the consumption within the substation is greater than the local production and can be negative in the opposite case.

The second input is the State of Charge (SoC) of EVs and EWHs, which is estimated at each time step within the system. The system output is the global power reference for charging EVs and EWHs, which is finally distributed into individual references for EVs and EWHs. It should be noted that in the entire supervision strategy, EWHs are treated the same way as EVs by reasoning on their daily energetic needs instead of thermodynamic parameters such as temperature.

Supervision strategy. The supervision system includes two stages, as illustrated in the functional graph in Fig. 4 [20]:

- A "Fuzzy Mode" that aims to maximize EV and EWH charging during the periods of excess PV/Wind production, and limit it in the opposite case.
- A "Boolean Mode" that guarantees the fulfillment of EVs and EWHs daily energy requirements by forcing the charging power reference if necessary.

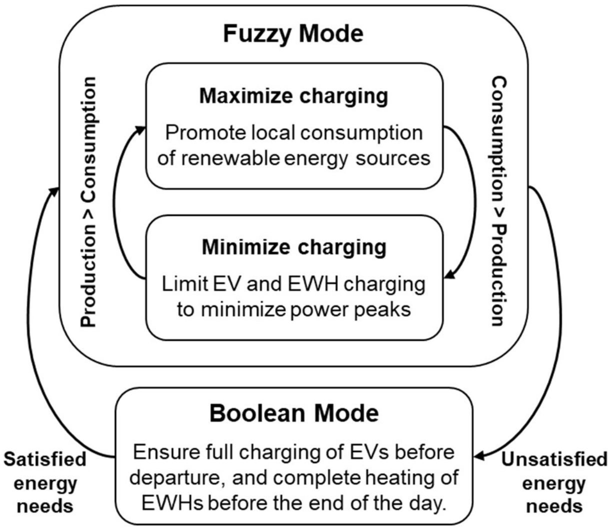

Fig. 4. Functional graph of the supervision system

The supervision system generates the charging power references for EVs at home/office and EWHs depending on P_{sub}, which can be Negative (N) or Positive (P), and the SoC of EVs and EWHs, which can be Small (S), Mean (M) or Big (B). The proposed operating rules are illustrated in Fig. 5.

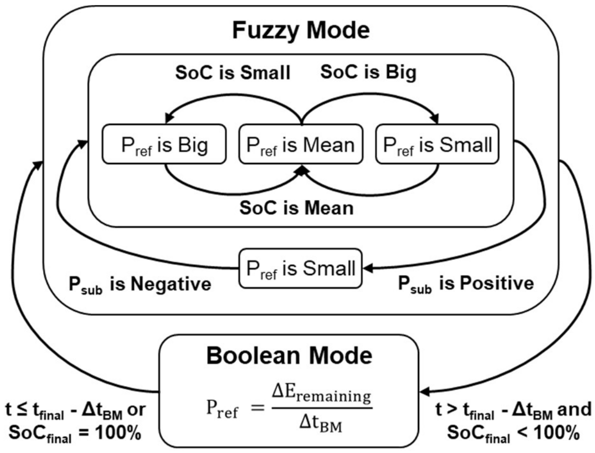

Fig. 5. Operational graph of the supervision system [20]

The Fuzzy Mode's inputs and outputs are described using membership functions (Fig. 6) that are determined empirically at first. On the other hand, the Boolean Mode duration was also fixed empirically at 3 hours for EVs and EWHs.

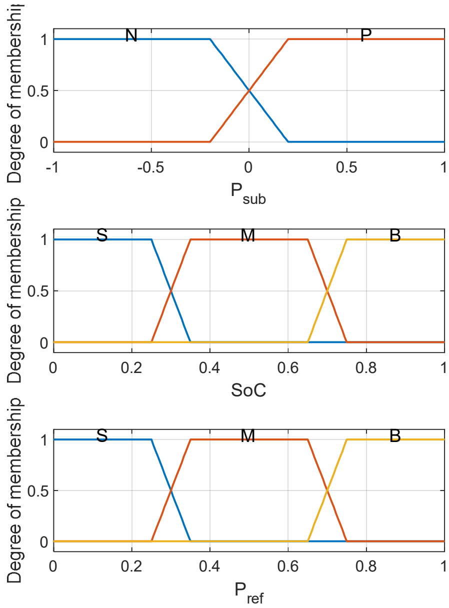

Fig. 6. Membership functions of the empirical fuzzy supervisor

Optimization of supervisor parameters. The supervision system's performance depends directly on the parameters of the Fuzzy Mode and the Boolean Mode. In this study, these parameters are optimized using a Genetic Algorithm (GA) as presented in [21]. The objective function to minimize is the annual energy transmission cost and the parameters are the membership functions (MF) limits and the duration of the Boolean Mode for EVs and EWHs. The optimized MFs are represented in Fig. 7, and the optimized Boolean Mode durations for EVs at home/office and EWHs are $\Delta t_{BM\ EV\ office} = \Delta t_{BM\ EV\ home} = 3h10$ and $\Delta t_{BM\ EWH} = 4h30$.

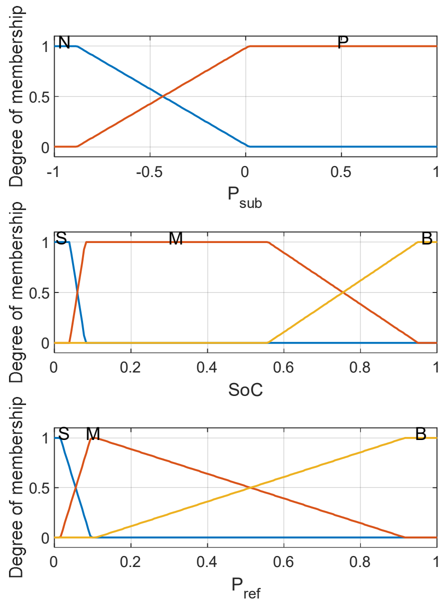

Fig. 7. Membership functions of the optimized fuzzy supervisor

4. Results and Discussion

The energy management strategy is tested using data from an HV/MV substation operated by GEREDIS that contains 2 90/20 kV transformers of 36 MVA and a 225/20 kV transformer of 40 MVA. Around 5000 customers and six energy producers (PV and wind) with a total power of 83 MW are connected to this substation. The controllable loads considered in this study are 2700 EVs (according to the 2030 scenario in the department of Deux-Sèvres [22]), and approximately 3400 EWHs that are identified from the global load profile in the substation. The total energy flow is recorded every 10min using telemetry devices and communicated to the supervision system.

The load profile of EVs and EWHs, as well as the resulting power profile at the HV/MV substation, are represented in Fig. 8 and 9 respectively for a day where renewable energy is available and another one when it is not.

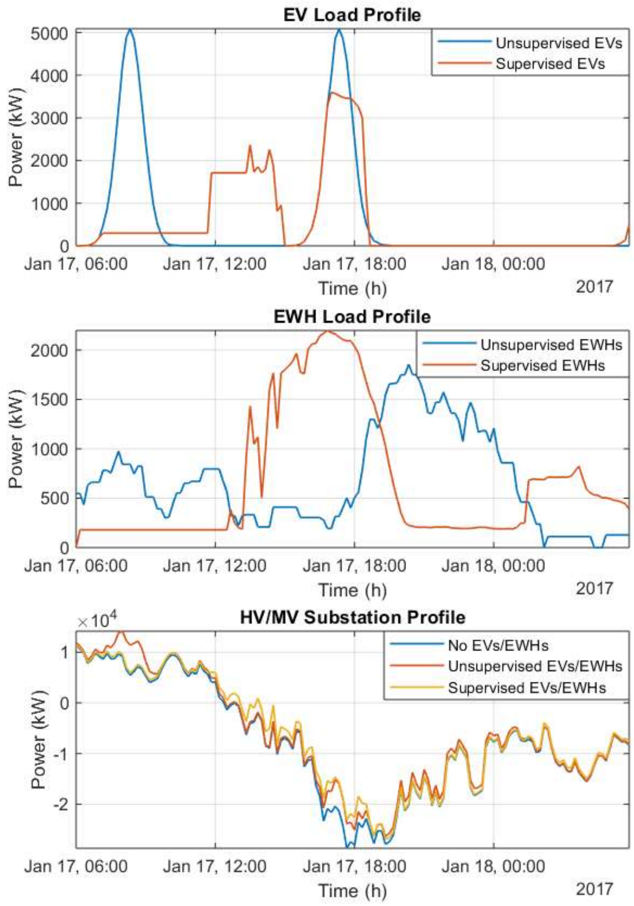

Fig. 8. Simulation results on a day with available renewable energy

In the first case illustrated in Fig. 8, the supervisor shifts most of the EV and EWH load to the time when an excess of renewable energy is detected in the substation ($P_{sub} < 0$). In the second case illustrated in Fig. 9, there is no excess production that appears throughout the day, therefore EVs are activated only by the Boolean Mode in the last hours before their departure, and the same thing happens for EWHs at the end of the day.

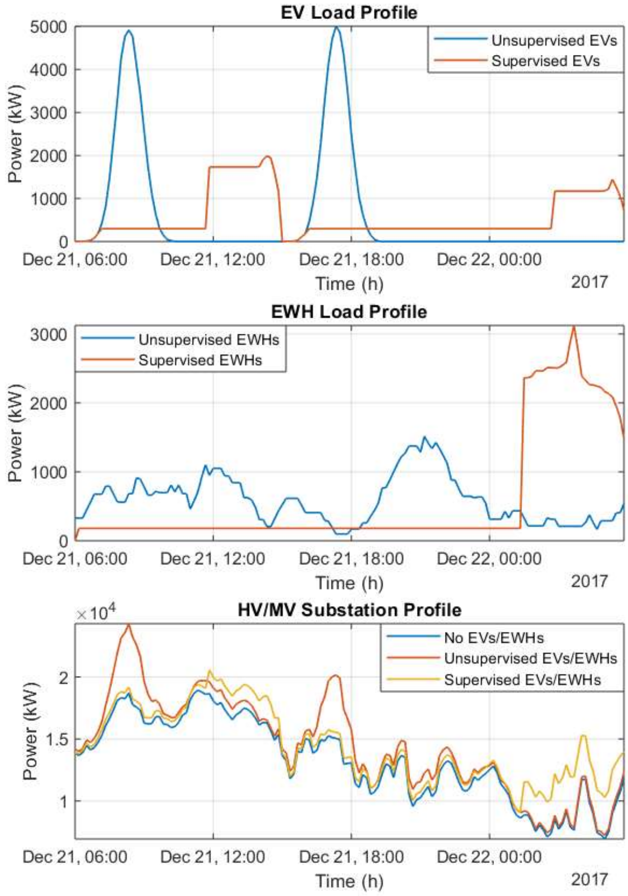

Fig. 9. Simulation results on a day with no available renewable energy

The annual results of the simulation are used to calculate the optimal subscribed power with the TSO and the resulting annual energy transmission cost shown in Table 3. The introduction of EVs and EWHs into the grid without any supervision increases the ETC by approximately 13.1%. The energy management system reduces this percentage to only 8.6% of the original cost.

Table 3. Performance indicators.

	Subscribed Power, kW	Energy Transmission Cost, k€	Energy Transmission Cost, pu
No EVs/EWHs	21738	786	1.000
Unsupervised EVs/EWHs	24351	889	1.131
Supervised EVs/EWHs	22438	853	1.086

5. Conclusion and Perspectives

This paper proposed a supervision strategy to manage EV charging and EWH activation in a distribution grid, with a particular goal of minimizing the energy transmission cost. The performance of the system was confirmed through simulation by testing it on real power flow data from an

HV/MV substation and showed that proper supervision of EVs and EWHs leads to an important reduction of the energy transmission cost. However, some additional improvements are expected to be introduced in future work. The integration of production and consumption forecasting into the supervision strategy can greatly improve the system since it adds the possibility to use optimization methods to calculate the best load profile for EVs and EWHs one day ahead. Another phenomenon to be considered is the impact of these strategies on electrical grid parameters like voltage and loading. Therefore, another important perspective of this work is to integrate the electrical constraints in the supervision strategy and modify the outputs accordingly. Finally, these strategies will be implemented in a real supervision system to test their performance and evaluate their acceptability by users that are participating in a demonstrator project in the Nouvelle-Aquitaine region in France.

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