LOAD SHIFTING POTENTIAL OF ELECTRIC VEHICLES USING MANAGEMENT SYSTEMS FOR INCREASING RENEWABLE ENERGY SHARE IN SMART GRIDS

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ABSTRACT
A decarbonisation of the energy system is necessary to reduce greenhouse gas emissions and thus achieve the climate protection goals. For this reason, the renewable energy share in the power grids of many countries is increasing. In order to stabilize the energy system and increase its flexibility, energy management systems are needed. This paper offers a model of energy management system which starts from the network operator and ends at the consumer (an electric vehicle). Firstly, a controllable local system signal, which is sent through a smart meter gateway from the grid operator to the consumer, has been developed. The signal is based on the renewable energy share in the local grid, on the electricity exchange price and on a defined profile. Then, different charging modes, which regulate the energy consumption based on the signal, have been developed and field tested. Finally, the charging modes have been simulated in order to better compare the data. The results show that with smart charging, 90% of the energy demand can be rescheduled. In view of the load shifting, greenhouse gas emissions and energy costs can be reduced.
Keywords: electric vehicles, energy management systems, load shifting, renewable energy, smart grids.

1 INTRODUCTION

The Paris Agreement on climate change confirmed the need to reach close to zero greenhouse gas (GHG) emissions by the second half of the century [1]. To achieve these goals, a rapid, almost full-scale decarbonisation of the power supply is required [2, 3]. Therefore, many countries have planned to cover the energy demand with renewable energy (RE) [4–7]. In Germany, the official target is to provide more than 50% of electricity from RE sources by 2030 and at least 80% by 2050 [8]. However, introducing RE in large amounts to the power system presents some challenges. In traditional power systems, the balance between power demand and supply at each point of time is maintained through fossil-fuel power plants. REs such as wind and solar instead are variable, consequently there can be a mismatch of power supply and demand and this can lead to an unstable power network [9, 10]. Furthermore, there can be an imbalance between the locations of power supply and demand. In Germany, for example, wind farms are mostly installed in the northern part of the country and on the coast, but the biggest industry is in the southern and western part of the country [11]. To balance the supply/demand mismatches and overcome energy distribution issues, the energy system flexibility has to increase. An important approach to increase energy system flexibility is considering the energy system as a whole and thus integrating the electricity, the heat and the mobility sectors together. Moreover, sector coupling has to be supported by energy management systems (EMS), which can provide the required stability [12, 13].

EMS comprise a broad set of means to affect the patterns and magnitude of energy supply and demand. An application of EMS is demand-side management (DSM) system, which controls the end-use electricity consumption, reducing (peak shaving), increasing (load growth) or rescheduling (load shifting) energy demand. DSM allows ample flexibility and can be 100% efficient, as no energy conversion to and from an intermediate storable form is

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required [14]. The application of DSM, as a form of standing reserve could improve the system performance by increasing the amount of power from RE, which can be absorbed. This is particularly relevant when high RE conditions coincide with low demand. In this context, DSM would allow more RE to be absorbed and would, therefore, reduce the GHG emissions [15]. DSM systems and smart appliances can facilitate the user to shift electricity demand of devices in domestic area. A study shows that smart appliances are a promising strategy for households to shift their electricity demand depending on price signals [16]. However, before demand systems can be effectively deployed on a wide scale in the residential sector, a number of technical challenges need to be resolved (infrastructure of communications, metering infrastructure, etc.). House DSM can rely on technologies which automatically respond to signals and taken into consideration the homeowner's preferences and expectation [14]. This work gives a model of house DSM, which automatically responds to a signal transmitted from the grid operator. The house DSM system can control the electricity consumption of electric vehicles (EVs) or of electric heating systems such as heat pump, hybrid heating or thermal storage heating.

Prior research demonstrates that EVs have a great shifting potential since the charging process can be curtailed for significant periods of time (e.g., several hours) without impact on end-use function [17, 18]. Load shifting is particularly important for EVs as they are greatly dependent on the electricity generation mix, which is used for charging them [19]. Many charging systems have been already developed [20–23] and it is proved that with smart charging, the consumption of RE can be more than doubled compared to uncoordinated charging [24]. Consequently, charging management systems contribute to balancing the generation and consumption of electricity from RE sources and help to avoid peak demand and thus stress the grid [25, 26].

In this work, firstly a special signal for the communication between grid operator and end-user through the metering infrastructure has been created. Secondly, different charging managements that respond to the signal have been developed and field tested at a Wallbe charging station with an electric car BMW i3 (22 kWh). Then the relevant data have been recorded and analysed. Finally, each charging process has been simulated with the different charging modes, in order to better compare their distinctions. The procedure and the results will be dealt with in this paper.

2 CLS SIGNAL

A controllable local system (CLS) signal has been developed for the communication between a local grid operator and the house DSM. The CLS signal is sent from the local grid operator and is designed to be transmitted through a smart meter gateway (SMGW) to the end consumer. The SMGW is connected to a CLS control box. On this control box, there are several relays, which can be switched according to the transmitted CLS signal. These kinds of devices are currently under development and for this work, it was possible to use a CLS control box with four relays. These four relays are switched according to the current CLS signal, which is in this way transmitted to the consumer. This type of SMGW can transmit only the current CLS signal and not its forecast. Thus, it can be used only by simple consumers, which use controlling algorithms without forecast. Smart consumers need the forecast of the CLS signal also to better program their energy consumption. Since the SMGW used in this work is not able to transmit the forecast of the CLS signal, this is transmitted directly through the Internet. However, in the future, with further developed devices, the CLS signal will be transmitted only through the SMGW. Both transmission paths were established and operated in cooperation with the local grid operator.

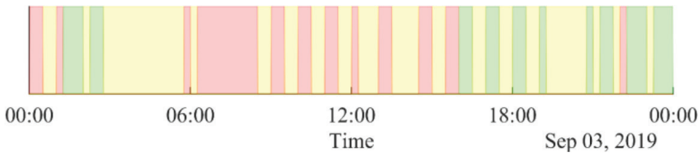

Figure 1: CLS signal.

The CLS signal is based on three parameters:

- the consumer profile, which depends on the type of the consumer (EV, heat pump, hybrid heating, thermal storage heating, etc.)
- the share of RE in the power system [27–29], which also depends on the consumption [30, 31]
- the electricity price at the European Energy Exchange [32, 33].

These three parameters can be different for every consumer and they can have the value one or zero. Every consumer can have a different profile, which indicates in which hours of the day it should better consume energy. This profile allows the grid operator to schedule the consumption hours of the different consumers in order to avoid peak demand. The parameter of the consumer's profile has the value one if the appliance should consume energy and the value zero if it should not. For the tested EV, this parameter has the value one mostly during the night since the EV is usually plugged in after the working time (between 7 p.m. and 5 a.m.). The parameter of the percentage of RE in the power system has the value one if more than a defined percentage (e.g. 60%) of the electricity is generated from renewable sources. The parameter of the price has the value one when the intraday price is lower than the daily average price. During the development of this work, it has been proved that the exchange electricity price is correlated to the percentage of RE in the power system. Due to this correlation, the parameter of the price contributes to the consumption of RE. The CLS signal is based on the combination of these three parameters and it works like a traffic light. If all the three parameters have the value one, the CLS signal is green. If at least two parameters have the value zero, the CLS signal is red and if some have the value one and some have the value zero, the CLS signal is yellow. In the case the special regulation (§14a EnWG [34]) of the grid operator occurs, the CLS signal is black. An example of CLS signal for one day is illustrated in Fig. 1.

3 CHARGING MANAGEMENT SYSTEM

The CLS signal is sent to the end device of the house EMS, which regulates the energy consumption. In this paper, an EV is taken as an example of end device. Therefore, different algorithms for the charging process of the EV have been developed. In this chapter, the three charging modes, which can regulate the electricity consumption of the EV, are described.

3.1 Charging mode Normal

The simplest charging mode is the charging mode Normal. This corresponds to the unmanaged charging, which is currently used for charging most EVs. The charge starts as soon as the EV is plugged in. At the beginning, the EV is charged constantly with the maximum current power. When a certain voltage limit is reached, the charge continues with decreasing current until the battery is fully charged. For this charging mode grid load, electricity costs and share of RE in the power grid are not considered.

3.2 Charging mode Simple

The charging mode Simple has been developed for simple devices. For this charging mode, the current CLS signal is transmitted to the end device, namely the charging station, through the SMGW. According to the CLS signal, the charging station or the heating system regulates the power intensity with which the EV is charged or the house is heated. Considering the EV, if the CLS signal is green, the EV is charged with the maximum allowed power. If the CLS signal is yellow, the current power is reduced to 60% of the maximum power. If the CLS signal is red, the EV is charged with 30% of the maximum power. In case the CLS signal is black, the charging process is stopped, as shown in Fig. 2. A similar process is applicable to heating systems.

With the charging mode Simple, the charging process is not scheduled according to the forecast of the CLS signal, but it starts directly when the EV is plugged in. Additionally, there is a risk that the EV is not charged enough by the departure time. To better explain this issue, an example can be taken of an EV which is just for a short period of time at the charging station (referring to Fig. 2 from 5 p.m. until 9 p.m.) and during this period, the CLS signal is red or yellow. In this case, the EV is charged with a low power and thus it can happen that it will not be charged enough for the next drive.

3.3 Charging mode Smart

The charging mode Smart has been developed in order to increase the energy demand, namely to charge the EV as much as possible when the CLS signal is green, consume less when it is yellow and possibly decrease the demand when it is red. If the CLS signal is black, no electricity can be consumed, consequently the charging process is stopped. Moreover, with this charging mode, there is a guarantee that the EV is charged enough by the time of departure.

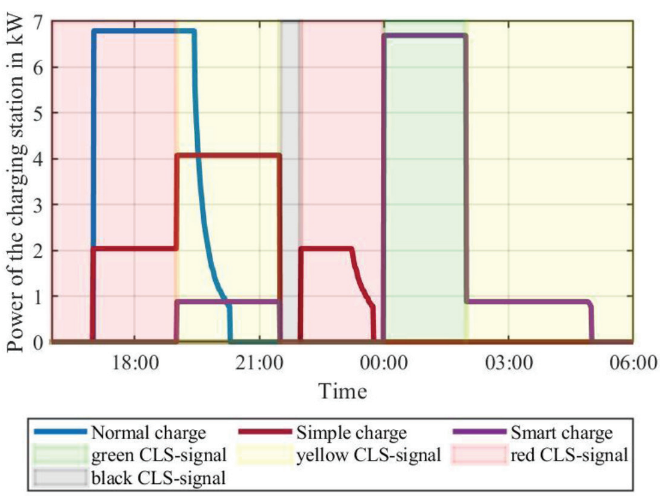

Figure 2: Charging mode Normal, Simple and Smart.

To achieve this purpose, data such as departure time, current state of charge and desired minimum range are needed. These data have to be provided by the user, who has to enter them on a webpage before plugging the EV. The webpage has been developed for this work and it has been specially designed for the data input purpose. Additionally, previous data from the charging process and the CLS signal forecast are needed. With the current state of charge and the desired minimum range, the algorithms calculate first of all how much energy has to be charged, considering previous data of the charging process. Then, the charging schedule can be computed. If the CLS signal is green from the time of arrival until the time or departure, the EV is charged with the maximum power until the battery is fully charged. If this cannot be achieved, at least the desired minimum range is charged. If the time when the CLS signal is green is not enough even to charge the minimum range, the EV has to be charged also when the CLS signal is yellow. The power of the charging station when the CLS signal is yellow is the minimum power necessary to charge the minimum range by the departure time, as shown in Fig. 2. If this one is still not enough, according to the same principle as before, the EV is charged also when the CLS signal is red.

The three charging modes have been field tested on a Wallbe-Wallbox charging station for 9 months. During this period, 2.5 MWh of electricity have been consumed to charge the EV, which has covered around 15,000 km. During the first two months of the test phase, the charging station has been managed with the charging mode Normal. Later, the charging mode Simple has been tested for two months and in the last five months of the test, the charging station has been managed with the charging mode Smart. Each charging mode has been tested in different periods of the year. However, in every season, the weather conditions change and, as a consequence, the share of RE in the network, the energy consumption and the energy price are different. Hence it is not possible to compare the measured data of the charging mode Normal, which has been tested in summer with those of the charging mode Smart, which has been tested in winter, because the results would be imprecise. Therefore, a method for comparing the charging process of the three different charging modes is needed.

4 METHOD FOR COMPARISON

For a better comparison of the data of the three different charging modes, a simulation of the charging process has been developed. The simulation is based on the collected data of the charging station and on the data obtained by the user from the website. There are no data collected through communication with the EV. This is important because the charging modes should work for any kind of EV and any charging station. During the first two months, the charging mode Normal has been tested and its data were recorded. Consequently, for these months, a simulation of the charging modes Simple and Smart is needed. According to the same principle, when the charging mode Simple has been tested, the mode Normal and Smart have been simulated. In the last five months, the mode Smart has been tested and the Normal and Simple mode have been simulated. To prove the validity of the simulations, the measured data of each charging mode have been compared with the corresponding simulated data, as shown in Fig. 3. For the comparison, firstly the absolute error, i.e. the difference between the measured and the simulated data, has been calculated.

Secondly, with these data the relative error has been determined and it was possible to estimate the mean relative error of every single charge. Finally, the mean of the relative error of each charge has been determined and its value is 2%. From this result, it can be concluded that the error of the simulation is negligible, thus the simulation can be validated and used for further data processing.

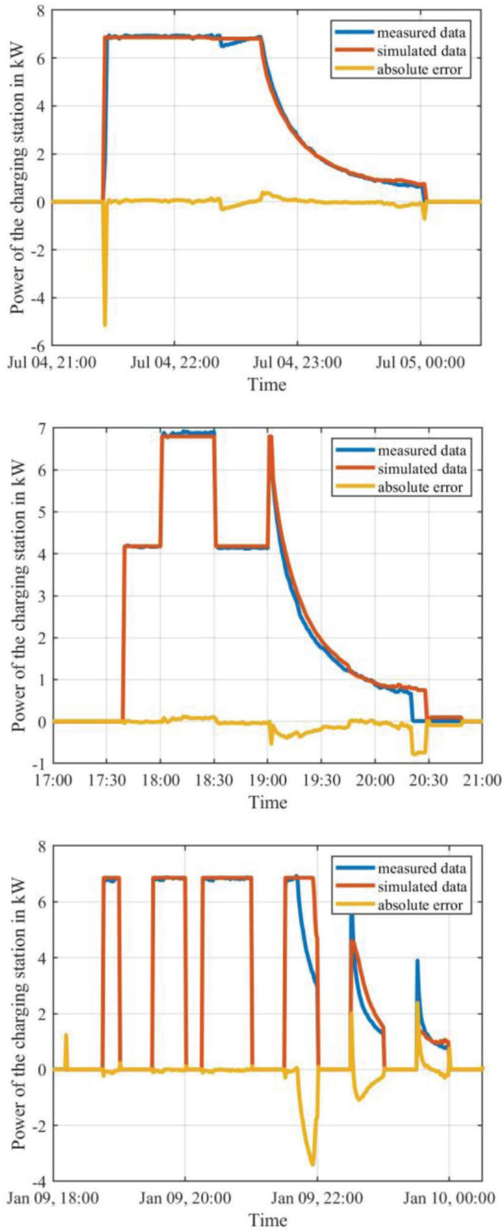

Figure 3: Measured data, simulated data and absolute error of the three charging modes.

5 RESULTS

In this section, the results of the measured and simulated data are explained.

5.1 Load shifting

The three charging modes Normal, Simple and Smart have been simulated for each charge of the EV. With the simulation of every charging mode, it can be determined how much energy has

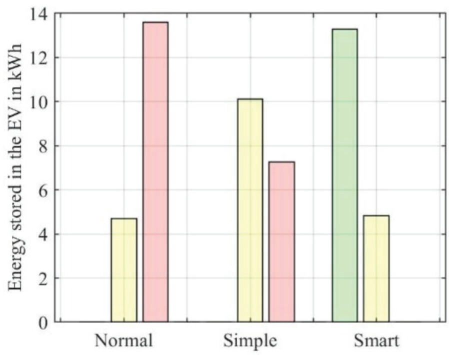

Figure 4: Load shifting of the three charging modes for the charge of Fig. 2.

been charged when the CLS signal is green, yellow and red. As explained in Section 3: Charging management system, and as shown in Fig. 2, the charging process of the EV can be regulated and scheduled. This means that the load, which would be charged directly after the EV is plugged in without charging management, can be rescheduled to another period of time with the developed charging management systems. In this way, the load shifting can be calculated. Referring to the example in Fig. 2 of Section 3: Charging management system, Fig. 4 shows how much electricity has been consumed during this single charge when the CLS signal is green, yellow and red with the three different charging modes. With this kind of calculation, it is possible to evaluate the amount of load, which can be shifted for each charging mode. With the mode Normal, the EV is charged 13.6 kWh when the CLS signal is red and 4.7 kWh when it is yellow. With the mode Simple, the energy charged when the CLS signal is red was reduced to 7.2 kWh and the energy charged when the CLS signal is yellow was increased to 10.1 kWh. This means, that 5.4 kWh of the total 18.3 kWh have been shifted from the time when the CLS signal is red to the time when the CLS signal is yellow. Consequently, the load shifting with the charging mode Simple is 31%. With the charging mode Smart, better results can be achieved. The EV, in this case, is charged only when the CLS signal is green or yellow and not at all when it is red. The amount of energy charged when the CLS signal is yellow has almost not changed.

However, 13.3 kWh of the energy charged when the CLS signal is red have been shifted to a period of time when the CLS signal is green. This corresponds to 73% of the whole charge.

The same calculation can also be done for the simulated charges with the three charging modes during the 9 months of the test phase. The load shifting during this whole period is shown in Fig. 5. There are slight differences comparing the charging mode Simple with the mode Normal. About 225 kWh of the energy charged when the CLS signal is red or yellow have been shifted to the period of time when the CLS signal is green. Thereby, the load shifting with this charging mode is 9%. However, the EV is still mostly charged when the CLS signal is yellow. Differently, with the charging mode Smart, the EV is charged more than 90% when the CLS signal is green, less than 8% when it is yellow and not even 1% when it is red. About 1833 kWh have been shifted to the period of time when the CLS signal is green. This corresponds to a load shifting of over 90%.

5.2 Greenhouse gas emissions

An important aim of this work is to reduce significantly the GHG emissions. The GHG emissions of an EV depend on the electricity generation, which is used to charge it [17]. In this

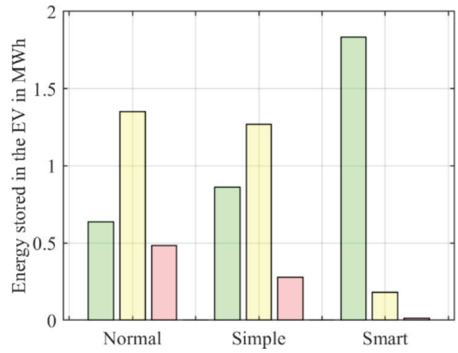

Figure 5: Load shifting of the three charging modes during the 9 test months.

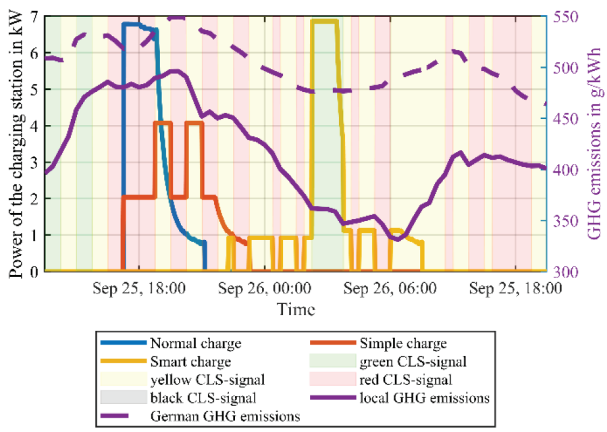

Figure 6: Simulation of the three charging modes and of the trend of the greenhouse gas emissions in the German and local electricity grid.

paper, two different electricity generations have been considered. One is the electricity generation in Germany [31] and the other one is an electricity generation of a local energy network operator [35]. With these two different electricity generations and the emission factors of the different energy sources [2, 31], the GHG emissions of the EV's charges can be calculated.

Figure 6 shows the simulation of the charging process with the three charging modes and the trend of the GHG emissions in the German and in the local grid. It is noticeable that there is a correlation between the GHG emissions of the two grids.

For this charge with the charging mode Simple, the GHG emissions are not reduced. With the charging mode Smart instead, if the German electricity generation is considered, there is a reduction of more than 7%. If, for the Smart charge, the local energy generation is being used, there is a reduction of almost 22% of the GHG emissions.

Figure 7 shows the amount of the GHG emissions, considering the whole test phase with the different charging modes and electricity grid. With the charging mode Simple, the GHG

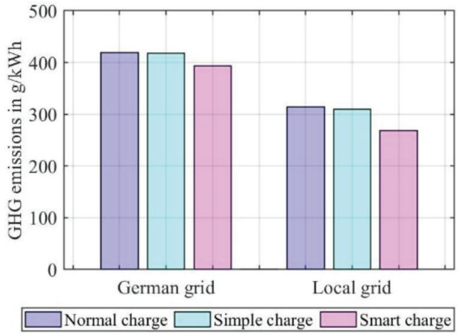

Figure 7: GHG emissions of the three charging modes with the German and local electricity grid for the 9 test months.

are slightly reduced. With the charging mode Smart, they are reduced by over 5%, considering the German electricity generation and almost 15% considering the local electricity generation.

As can be observed in Fig. 6, the fluctuation of the GHG emissions of the German grid is not very high since in Germany, the percentage of RE in the grid is lower than 40% [35]. This means that 60% of the GHG emissions are produced from fossil fuels, which have a big influence because of their high emissions factors, which are up to 20 times higher than the one of the RE sources [2, 31].

The percentage of RE in the local grid is around 50% [35]. Consequently, the GHG emissions of the local grid fluctuate more than those of the German grid since there is a higher percentage of fluctuating energy sources. For this reason, using the local grid electricity, the reduction of GHG emissions with the developed charging management systems is higher. This means that the higher the share of RE in the power grid is, the better results in terms of GHG emissions reduction can be achieved.

5.3 Charging costs

A similar evaluation can be performed for the costs of the EV's charges. Figure 8 shows an example of the trend of the German electricity exchange price and the simulation of a charge with the three charging modes. Comparing Fig. 8 with Fig. 6, it is noticeable that there is a correlation between the GHG emissions and the electricity exchange price in Germany. Since the CLS signal is also correlated to the electricity exchange price, with the charging modes Simple and Smart, the cost of the charge is reduced.

As Fig. 9 shows, for the charge of the example in Fig. 8, with the charging modes Simple, there is a reduction of more than 20% of the electricity exchange price and with the mode Smart, the reduction rises to 38%.

Considering the whole test period with the charging mode Smart, there is a reduction of 3% and with the mode Smart of over 12%. Actually, the electricity price in Germany is not directly correlated to the electricity exchange price but, in the future, there will be electricity tariffs based on variable electricity prices [36]. This will contribute to a reduction of the charging costs and to a stabilisation of the grid.

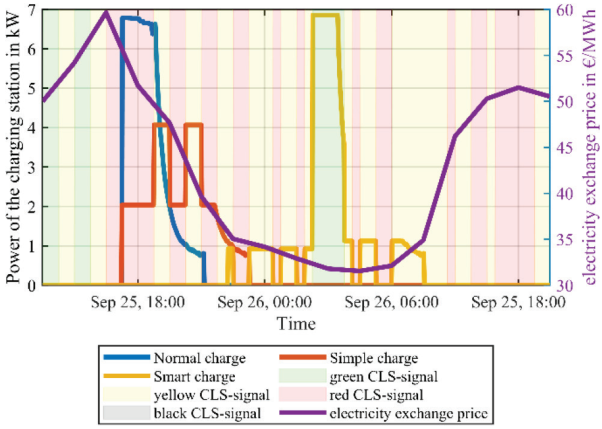

Figure 8: Simulation of the three charging modes and of the trend of German electricity exchange price.

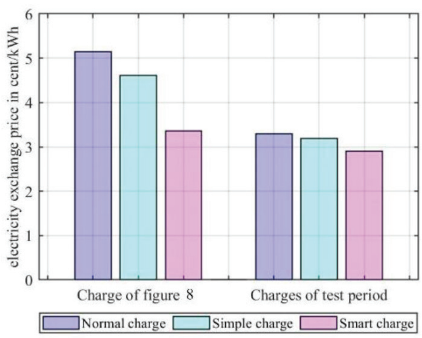

Figure 9: Cost of charges with the German electricity exchange price.

6 CONCLUSIONS

In this paper, a model of EMS for sector coupling has been developed. A special signal, based on the share of RE in the grid, the electricity exchange price and the grid load, is sent from the local grid operator to the end user (EV or heating system). The end user then regulates through smart algorithms the energy demand. This paper focuses on flexible charging management which has been simulated and field tested for many months. The results show that the goal of charging the EV mostly when the CLS signal is green, and not when it is yellow or even worse red, has been achieved. The charging mode Simple has a low load shifting but with the charging mode Smart, 90% of the load can be rescheduled.

Furthermore, considering the whole test period, with this house DSM, there is a reduction of GHG emissions of 15% and of electricity costs of 12%.

The reduction of the GHG emission will be stronger, when the share of RE in the grid will be higher. In this case, the fluctuation of the GHG emissions will be broader and consequently the charging management system will be more efficient. Besides, variable electricity tariffs which are based on electricity exchange prices will be available in the future. This will contribute to reducing the charging costs, balancing energy supply and demand and avoiding overloading the power grid.

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