Risk Based Energy Management of Renewable Based Smart EV Parking Lot

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***Abstract*— Electric Vehicles (EVs) have penetrated the modern distribution system in the last decade. On the other hand, Renewable Energies (RE) play a serious task in such Micro-Grids (MG). A typical MG consists of several Distributed Energy Resources (DER) including Distributed Generations (DGs) and Demand Response (DR) as well as EV charge/discharge stations. In this paper, optimal charging and discharging strategies based on DR programs are applied to Electric Vehicle charging stations equipped with renewable energies. To avoid profit loss due to renewable uncertainties, Peer-to-peer (P2P) energy bartering between EV charging stations as prosumers are suggested in this paper. Hence the management system for the charge and discharge of EVs and station batteries, as well as the Energy Management System (EMS) are developed in this paper. To this end firstly developed EMS applied to the individual station. Secondly, the P2P power transaction was added to the model in order to smoothen volatile uncertain load and renewables. The proposed model is a Mixed-Integer Linear Programming (MILP) and has been solved by GAMS/CPLEX. Numerical studies have shown that aggregator deployment is more beneficiary for Virtual Power Plant (VPP).**

***Index Terms*— Demand Energy Resources, Renewable Energy, Uncertainty, Demand Response, Energy Management System, Peer to Peer.**

I. INTRODUCTION

Small - scale renewable resources such as Photovoltaics (PVs) and wind have mixed the producers and consumers to form new parties named prosumers who can participate directly in the energy management of their own. These type of consumers may have coordinated to build larger entity to increase their benefits that could not be achieved individually [1]. In example, although DR is reduces the grid operation costs, the incentives may not compensate for the dissatisfaction of small prosumers. Besides, the amount of power that can be supplied to the energy markets is too large for the single-family stations that have RE. According to [2] "simultaneous upwards and downwards bid. This means that prosumers need to be able to both buy and sell energy at the same time, the minimum bid/offer size, simultaneous upwards and downwards bid, and activation time are constraints that should be mitigated while these constraints disable the prosumers to participate in the market. For this sake, the energy market parties are large consumers, retailers, power plants, etc. The second constraint mentioned is "activation time." This refers to the time required for prosumers to start buying or selling energy in response to market signals or their preferences.

The volatile energy prices that cause high prices in some periods, and the RE technology advances i.e. decreasing capital costs are also motivations for the aggregated virtual models. These virtual aggregated parties may help decarburization and local environmental goals with the delivery of extra energy of REs to the main grid instead of power curtailment [2], [3]. The virtual models can comply with national-level market constraints while local prosumers management [4], [5]. The line implies that virtual models—that is, software- or digital-based representations of energy systems—can manage local prosumers more easily while still adhering to national-level market restrictions. Therefore prosumers also can provide an opportunity for low carbon policies of the current decade paradigm in the energy system, simultaneously reducing the peak load of the local grid and contributing to their economic development. In this way, the local residential entities will be able to optimize their Res as well as EVs and also other electric appliances.

The residential sector contributes a large percentage of global electricity demand. Researchers are focusing on optimizing Home Energy Management (HEM) due to the changing role of consumers in the power system. Customers can now actively participate in energy transactions by adjusting their consumption patterns and even utilizing their renewable energy sources, turning them into prosumers.

However, some reasons like a sudden need to some appliances and frequent tracking of Demand Response Programs (DRPs) orders cause a phenomenon named “response fatigue” [6]. Hence in long-run, it is expected that some consumers may return to a default pattern of consumption. To avoid response fatigue, the proposed Energy Management (EM) system has considered the dissatisfaction index.

There are lots of research works that have studied the EM from different points of view, considering DR strategies that can be summarized as Residential electric appliances [7], Residential energy objectives [7], and Uncertainty characteristics of Stations [8].

In [9], energy scheduling is presented based on incentives. The objective is to minimize the energy consumption costs, increasing load factor considering consumer satisfaction. However, the main disadvantage of [9] is the assumption that all equipment has the same properties. In [10] and [11], a smart electric equipment operation has been optimized considering dynamic tariffs. In [12] and [13], the EM limits the station’s

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peak load. Pipattanasomporn et al. [12] presented the priority of appliance consumption by DR programs and proved that it can keep the total power consumption below a predetermined level. Note that the [12] does not include the price-based DR (PBDR). An optimal appliance scheduling to minimize the monthly electricity bill through a PBDR has been explained in [14].

The summary of EM and HEM coordination-related research studies is illustrated in Table I at the top of the next page.

In this paper, an EMS model has been developed based on [28] for the EV station equipped with renewables and storage, and then an aggregator for the EV charge/discharge station is established in a way that applies the aggregated EMS model and P2P model to reduce the Energy cost of EVs station. numerical studies with and without aggregators as well as P2P transactions have explained profit increase, especially from a balancing market point of view.

Contributions

The developed model in this paper accounts for the optimal operation of EV stations. The innovations of the paper based on literature reviews can be listed as follows:

- Application of EMS for multi EVs stations system in order to guarantee the prosumer benefits in coordinated structure.
- Development of P2P power transactions between EV stations for uncertainty and variability management of load and renewables.

The rest of the paper is organized as follows. Section II expresses the developed energy management system. The coordinated model is given in Section III. P2P power transactions between stations are expressed in Section IV. The simulation procedure is represented in section V and finally, conclusions are given in section VI.

II. ENERGY MANAGEMENT SYSTEM

The decision variables are the transferred power from the grid to the station, $P_{\omega.t}^{G2S}$, the transferred power from the station to the grid, $P_{\omega.t}^{S2G}$, the charging and discharging powers of the EV, $P_{\omega.t}^{S2V}$ and $P_{\omega.t}^{V2S}$ the charging and discharging power of the station battery, $P_{\omega.t}^{S2B}$ and $P_{\omega.t}^{B2S}$, the On/Off state of controllable EVs, $x_{i.\omega.t}^{CEV}$.

TABLE I
HEMS Coordination in Literature

Ref	Context	Coordinated	Individual	Decentralized	Centralized	HEMS application	Other application	Uncertainty	Decomposition
[15]	**Coordinated HEMS**	*	*	*	*	*	-	-	-
[16]	**Coordinated HEMS**	*	*	*	-	*	-	-	-
[17]	**Coordinated HEMS**	*	*	*	*	*	-	-	-
[18]	**Energy Hub**	*	*	-	*	-	hub	-	-
[19]	**Coordinated HEMS**	*	-	*	-	*	-	*	-
[20-21]	**Combined gas and electric system**	*	-	-	*	*	P2G	-	-
[22]	**Coordinated HEMS**	*	-	-	*	*	-	*	-
[23]	**Power dispatch**	*	-	-	*	*	P2G	-	-
[24-25]	**Coordinated OPF**	*	-	*	-	-	OPF	-	*
[26]	**Energy hub**	*	*	*	*	*	hub	-	*
[27]	**Coordinated HEMS**	*	*	*	*	*	-	-	*
paper	**Coordinated EMS**	*	*	*	*	*	-	*	*

$$\sum_{\omega} Prob_{\omega} \sum_{t=1}^{T} \{P_{\omega.t}^{S2G}\lambda_t - P_{\omega.t}^{G2S}\lambda_t - (BAC_{t.\omega}^{B} + BAC_{t.\omega}^{EV}) + Inc_t(P_{\omega.t}^{G2S} - P_{\omega.t}^{G2S.ini} + P_{\omega.t}^{S2G}) - Pen_t(P_{\omega.t}^{G2S.ini} - P_{\omega.t}^{S2G} + P_{\omega.t}^{S2G,before}) - V_{\omega.t}\} \tag{1}$$

The first two terms represent the income from selling energy and the cost of purchasing energy from the grid. The third term accounts for battery aging costs due to cyclic operation.

〖BAC〗 _ω^B and 〖BAC〗 _ω^EV are battery and EV battery costs, respectively, which consider wear from extra cycling of batteries. They are calculated using equation (2).

$$BAC_{t.\omega}^{X} = \alpha \cdot \left(r_{\omega.t}^{ch.X} + r_{\omega.t}^{dis.X}\right) \quad X \in \{B.EV\} \tag{2}$$

$$Inct_t\left(P_{\omega.t}^{G2S,after} - P_{\omega.t}^{G2S,befor} + P_{\omega.t}^{S2G}\right)$$

represents the incentive income for participation in an incentive-based DRP. While, $Pen_t\left(P_{\omega.t}^{G2S.Cont} - P_{\omega.t}^{S2G,after} + P_{\omega.t}^{S2G,befor}\right)$ is the penalty cost resulting from taking part in the DRP. $P_{\omega.t}^{G2S,after} - P_{\omega.t}^{G2S,befor}$ shows the transferred energy to the station when a fixed-rate tariff is implemented minus the one when an incentive-based DRP is applied. It should be mentioned that the term $Inct_t(P_{\omega.t}^{S2G})$ models the incentive-based income of customers (EVs in this paper) from injecting the power back into the grid. Lastly, $V_{\omega.t}$ shows a function that models the dissatisfaction of EV owners as [28] due to variation from the initial consumption and is given by (3).

$$V_{\omega.t} = \sum_i v_i^{CEV}\left(P_{i.\omega.t}^{CEV} - P_{i.\omega.t}^{CEV.ini}\right) + v^{EV}\left[\left(P_{\omega.t}^{S2V} - P_{i.\omega.t}^{ini.S2V}\right) + \left(P_{i.\omega.t}^{ini.V2S} - P_{i.\omega.t}^{V2S}\right)\right] \tag{3}$$

where $v_i^{CEV} > 0$ is defined as the controllable EV load inelasticity parameter [29]. The higher amounts of v_i^{CEV} indicate that the operation of the EV at the initial time is the most convenient time for the consumer.

Eq. (4) shows that the demand containing the EVs load and the charging requirements of the batteries of Station (i.e., $P_{\omega.t}^{S2B}$) is either supplied through the grid ($P_{\omega.t}^{G2S}$) or by the internal generation of wind and PV, or by the energy from the battery or the EV.

$$P_{\omega.t}^{G2S} + P_{\omega.t}^{wind2S} + P_{\omega.t}^{PV2S} + Y_{\omega.t}^{B}P_{\omega.t}^{B2S} + \sum_{i=1}^{N_{EV}} Y_{i,\omega.t}^{EV}P_{\omega.t}^{V2S} = \sum_{i=1}^{N_{EV}} Z_{i,\omega.t}^{EV}P_{\omega.t}^{S2V} + Z_{\omega.t}^{B}P_{\omega.t}^{S2B} \tag{4}$$

$Y_{\omega.t}^{B}$ and $Z_{\omega.t}^{B}$ show binary variables to guarantee that a Station battery cannot be charged and discharged simultaneously. Similarly, binary variables $Y_{i,\omega.t}^{EV}$and $Z_{i,\omega.t}^{EV}$ guarantee that each EV (i.e. ith EV) battery cannot be charged and discharged concurrently as presented in (5).

$$Y_{i,\omega.t}^{X} + Z_{i,\omega.t}^{X} \le 1 \quad \forall t.\forall\omega, x \in \{B\,.EV\} \tag{5}$$

The total consumption of controllable EVs determines the controllable part of Station demand (as in (6)). Each controllable EV consumes its nominal power, and the EM controls each EV by determining its ON/OFF states, x_(i.ω.t)^CEV. The operation of EVs is also influenced by scenarios, covering the uncertainty of renewable energies and operating the Station battery.

$$P_{\omega.t}^{\frac{I}{C}} = \sum_i\{x_{i.\omega.t}^{CEV}(Y_{\omega.t}^{EV} - Z_{\omega.t}^{EV})P_i^{Nom}\} \quad \forall t.\forall\omega \qquad £ - EQ(1)_\omega \le SW_\omega \tag{6}$$

Inequality (7) limits the daily consumption of each controllable EV to the required amount. This constraint cannot exceed 24 hours since EVs need to operate multiple times a day. In addition to the dissatisfaction function V_t, which models consumers' preference for maintaining their initial consumption pattern, an operation time ensures that each controllable EV is charged within a suitable period for the occupants.

$$P_i^{Crit} \le \sum_t\{P_{i.\omega.t}^{CEV}\} \qquad t \in T_i^{CEV}, \forall i\,.\forall\omega \tag{7}$$

The EMS must not switch off some EVs when they are working. This means that the EMS system respects the operation period of each EV. On this basis, (8) to (9) are considered to assure that all controllable EVs are ceaselessly used in their inhabitant operation period.

$$Y_{i,\omega.t}^{EV} + \sum_{j=1}^{WC_i-1} Z_{i,\omega.t+j}^{EV} \le 1 \qquad \forall t.\forall i.\forall\omega \tag{8}$$

$$Z_{i,\omega.t}^{EV} - Y_{i,\omega.t}^{EV} = x_{i.\omega.t}^{CEV} - x_{i.\omega.t-1}^{CEV} \quad \forall t.\forall i.\forall\omega \tag{9}$$

Eq. (10) describes the model considered to evaluate the SOC variations for the station and EV batteries.

$$SOC_{\omega.t}^{X} = SOC_{\omega.t-1}^{X} + Z_{\omega.t}^{X}\eta^{ch.X}\left(\frac{P_{\omega.t}^{S2X}}{Cap^X}\right) - Y_{\omega.t}^{X} \qquad X \in \{B.EV\} \tag{10}$$

$$SOC^{min\,.X} \le SOC_{\omega.t}^{X} \le SOC^{max.X} \qquad X \in \{B.EV\} \tag{11}$$

$$r_{\omega.t}^{ch.X} = \frac{SOC_{\omega.t}^{X} - SOC_{\omega.t-1}^{X}}{\eta^{ch.X}} \qquad \forall t.\forall\omega, X \in \{B.EV\} \tag{12}$$

$$r_{\omega.t}^{dis.X} = (SOC_{\omega.t-1}^{X} - SOC_{\omega.t}^{X}) \qquad X \in \{B.EV\} \tag{13}$$

$$0 \le r_{\omega.t}^{ch.X} \le r^{ch.max.X} \qquad \forall t.\forall\omega, X \in \{B.EV\} \tag{14}$$

$$0 \le r_{\omega.t}^{dis.X} \le r^{dis.max.X} \qquad \forall t.\forall\omega, X \in \{B.EV\} \tag{15}$$

Based on (10), the battery's SOC at time t depends on the SOC at time t-1, injected energy to the battery, and injected energy back to the grid and station at time t. Inequality (11) limits the depth of discharge to prevent overcharging. The charging and discharging rates for Station and EV batteries are limited as shown in (12) to (15). Power transferred to the grid is determined by surplus wind and PV generation, along with battery injection, as in (16).

$$P_{\omega.t}^{S2G} = P_{\omega.t}^{wind} - P_{\omega.t}^{wind2S} + P_{\omega.t}^{PV} - P_{\omega.t}^{PV2S} + P_{\omega.t}^{B2S} + \sum_{i=1}^{N_{EV}} Y_{i,\omega.t}^{EV}P_{\omega.t}^{V2S} \qquad \forall t.\forall\omega \tag{16}$$

$$\mathrm{Y}_{\omega.t}^{S}P_{\omega.t}^{G2S} + \mathrm{Z}_{\omega.t}^{S}P_{\omega.t}^{S2G} \le P^{C.max} \qquad \forall t.\forall\omega \tag{17}$$

$$\mathrm{Y}_{\omega.t}^{S} + \mathrm{Z}_{\omega.t}^{S} = 1 \qquad \forall t.\forall\omega \tag{18}$$

limits the power transaction between the grid and the station. Also, equation (18) describes that the station may choose one direction for power transmission.

Also to model the uncertainty effect on the problem, the well-known risk index of Conditional Value at Risk (CVaR) has been added to the problem.

$$OF = (1-\beta) \times EQ(1) + CVaR \tag{19}$$

$$CVaR = \beta \times \left(£ - \frac{1}{1-\alpha} \sum_{\omega} \pi_{\omega} \times SW_{\omega} \right) \tag{20}$$

In which α and β are confidence level and risk importance level. Also £ and SW_{ω} are decision variables of CVaR and are as follows:

$$£ - EQ(1)\omega \leq SW\omega \tag{21}$$

$$SW\omega \geq 0 \tag{22}$$

III. COORDINATED EM

The proposed EM model in the previous section can be aggregated by an aggregator in order to apply the proposed EM to multiple prosumers. To this end, the profit of each prosumer should be guaranteed in a coordinated model due to the uncertainty of renewable generation and the load of each prosumer, it seems that the coordinated EM for multiple stations may increase the profit of each station. The schematic of the coordinated model for EM is depicted in Fig. 1.

Two major matters of aggregation are as follows:

-Point 1: reduction of EVs station (as prosumer) bill in coordinated model toward individual EM for each of them.

- Point 2: If the summation of electric energy supply for multiple stations, is set as an objective function of the coordinated model, some of the stations probably experience a cost increase and some may face a decrement. To avoid this challenge, minimum profit insurance as much as the profit of individual EM system applications should be modeled as a constraint.

Hence the coordinated (aggregated) model is developed as:

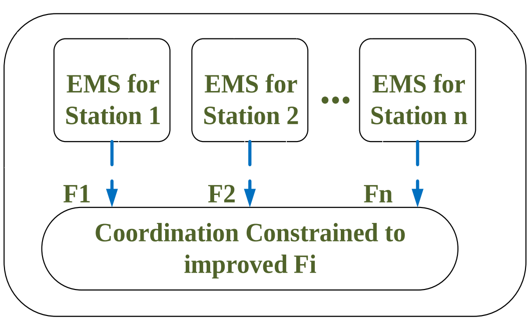


Fig. 1. coordinated EM model for Prosumers

$$Min: \sum_{H=1}^{N_S} OF(S) \tag{23}$$
$$S.t:$$

$$Constraints(S) \tag{24}$$

$$OF(S) \leq OF^{min}(S) \tag{25}$$

where $Constraints(S)$ are (2)-(22) for each station. And $OF^{max}(S)$ is the optimal cost of each station in the individual EM application. Note that the added value of profit due to aggregation is dedicated to the aggregator. Hence the basic concept of aggregation is verified.

IV. P2P POWER TRADING BETWEEN STATIONS

The main problem in this paper is to enhance EMS using P2P facilities. In this section, P2P energy transactions between stations are added to the EMS. To this end, the proposed method in [21] is used to model the power traded between stations. Hence from each station's point of view, other stations are as a black box.

$$P_{j.k.t}^{Sout} = \sum_{l=1.l\neq j}^{N_S} P_{l.t}^{out} \ \forall j.t.k \tag{26}$$

$$P_{j.k.t}^{Sin} = \sum_{l=1.l\neq j}^{N_S} P_{l.t}^{in} \ \forall j.t.k \tag{27}$$

$$P_{j.t}^{Sin} = P_{j.t}^{out} \tag{28}$$

$$P_{j.t}^{Sout} = P_{j.t}^{in} \tag{29}$$

(27) and (29) determine the summation of output and input power of stations other than *j*th one. Also (30) explains that the sum of stations other than *j*th one input/output power is equal to the corresponding station (*j*th one) output/input. Simply power balance equation for each station Eq (6) after the application of P2P transactions between MGs would be as follows:

$$\begin{aligned} P_{\omega.t}^{G2S} + P_{\omega.t}^{wind2S} + P_{\omega.t}^{PV2S} + Y_{\omega.t}^{B} P_{\omega.t}^{B2S} \\ + \sum_{i=1}^{N_{EV}} Y_{i.\omega.t}^{EV} P_{\omega.t}^{V2S} + P_{S.\omega.t}^{in} \\ = \sum_{i=1}^{N_{EV}} Z_{i,\omega.t}^{EV} P_{\omega.t}^{S2V} + Z_{\omega.t}^{B} P_{\omega.t}^{S2B} \\ + P_{S.\omega.t}^{out} \end{aligned} \tag{30}$$

V. NUMERICAL STUDIES AND DISCUSSION

A Station in Italy is considered to investigate the proposed model. All data for the case study is available in [30,31]. Two types of EVs have been considered as controllable EVs. The first group can wait for just three hours in the morning and four hours in the evening. While second group can wait for two hours and their departure time is floating in a day.

A. Case-1

The first case study is risk analysis for 10 scenario numbers and then coordination of EMS considering P2P power transactions has been studied.

- *Risk Analysis*

Firstly, to validate the model and GAMS codes the objective function has been depicted for different values of β in Fig. 2.

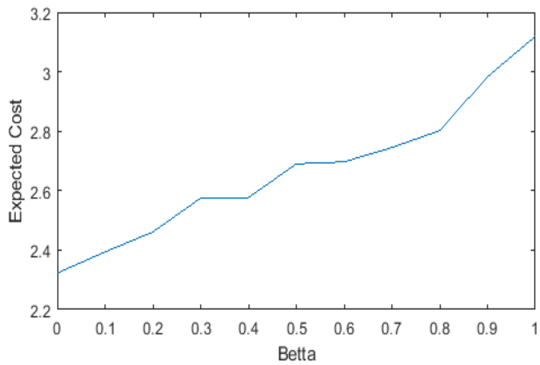
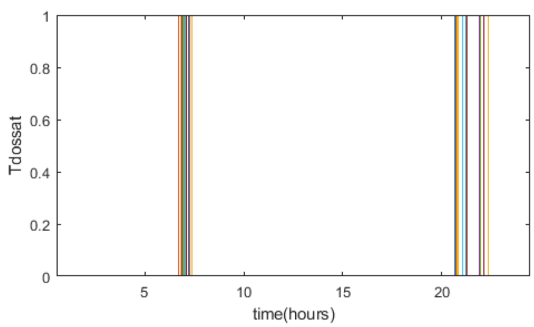
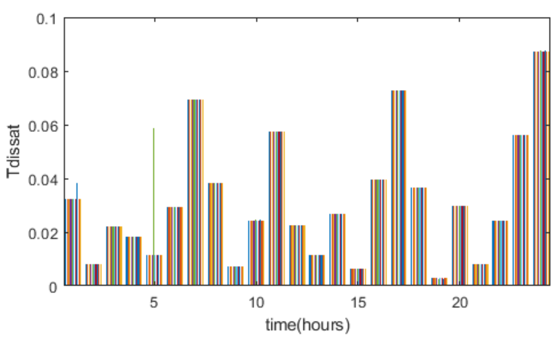


Fig. 2. Expected objective VS β



(a): First group of controllable EVs



(b): Second group of controllable EVs

Fig. 3. Dissatisfaction time due to change in EV consumption pattern

Fig. 3 shows the waiting time for using the station due to participation in the load response program. Fig. 3-a. shows this variable for the first group of controllable EVs and Fig. 3-b. shows this variable for the second group of controllable EVs. For critical EVs, this variable is zero. Although the amount of penalty or inelasticity of critical EV loads is less than the controllable EVs, its working hours are limited and specific, and therefore, in the calculation of the cost of dissatisfaction in the objective function, the difference in the amount of power consumed by the critical EV loads in case of interruption will be large in the hours of need because its compensation is meaningless in other hours.

Another point in Fig. 3. is that the amount of dissatisfaction for the first EV group only exists in three hours of the day for some scenarios, but this amount of dissatisfaction is 100%. For the second group of controllable EVs, this lack of satisfaction was present at all hours for all scenarios, but its value is less than 10%. The reason is that, first of all, there are only two usage periods for the first EV group during the 24 hours of the day and night (7-9 and 18-22), so it is not possible to use at all outside these periods, and therefore it is possible to become non-zero. Secondly, the change in the common desired pattern for the first group of controllable EVs can be applied for 1 full hour, and therefore the change of its pattern is made as a change of 1 full hour at the desired consumption time. However, the values associated with the second group of modifiable EVs are not binary and can take any value between 0 and 1. This is because it is possible to change it minutely. The last point is that there is no difference between the scenarios for the second group of controllable EVs, except for two hours 1 and 5, which shows the independence of the performance of this system from the change in scenarios of uncertain parameters.

- *coordination of EMS considering P2P transactions*

The coordinated model verification has been done through the application of coordinated EM to two cases, a first case containing three stations as an example and the large-scale system as the main case study.

Case-1: three station example

In this example case, the comparison between the station's profit increments is illustrated in Table II.

TABLE II
Profit Enhancement in a Coordinated Model

station	Individual EM	Aggregated EM	Profit enhancement
1	2.444	2.445	0.199
2	2.692	2.716	0.024
3	2.747	2.784	0.037
total	7.883	7.945	0.26

From Table II it can be concluded that the coordination through aggregation by adding P2P transactions makes the EMS more profitable for consumers. Hence the EV stations' tendency to take part in DR programs can be increased, either do EV owners.

B. *Case-2*

In this case, three scenarios have been done on a large-scale system with the base of the previous case with some modifications and extension to 30 EV stations. The total wind and solar generation of stations are illustrated in Fig. 4. The studied scenarios are as follows:

-Scenario 1: without EMS

-Scenario 2: with individual EMS

-Scenario 3: Coordinated EMS

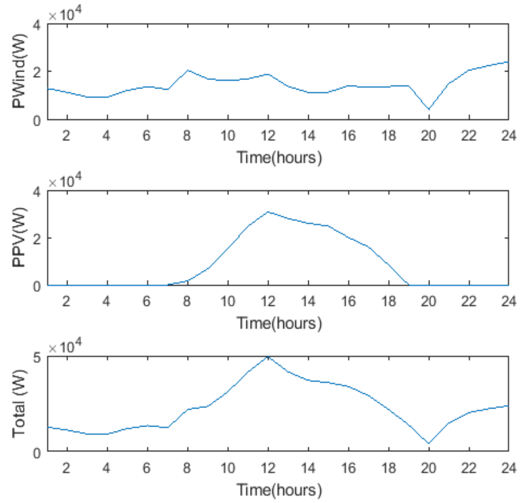
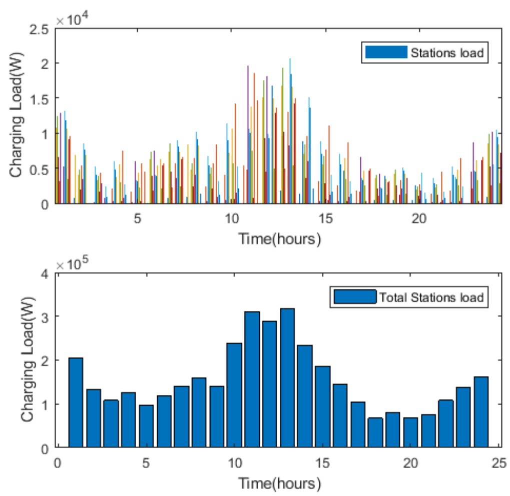
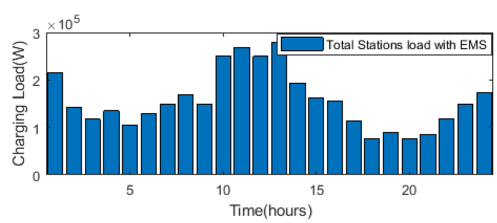


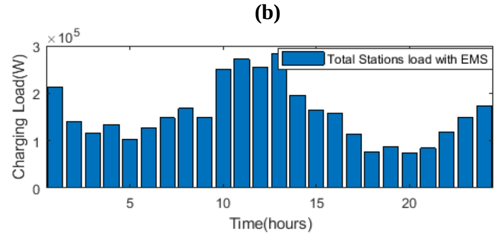
Fig. 4. Wind and Solar generation



(a)



(b)



(c)

Fig. 5. Load profile of three scenarios for 30 stations in three scenarios, (a): First scenario, (b): Second scenario, (c): Third scenario

The results of numerical studies consist of load profile, and individual cost savings due to participation in EMS in scenarios 2 and 3. Fig. 5. depicts the load profile of three scenarios for 30 stations in three scenarios. Note that the total EV load is about 3.7 MWh while the total renewable generation of stations is about 0.55 MWh, but there is a good correlation between them. This may cause the P2P trading more profitable without any load dissatisfaction due to load shift.

As can be seen from Fig. 5., in the second scenario the load is adapted to the electric price bought by stations with manipulated tariffs and EMS application in comparison to scenario 1, while in the third scenario because of P2P power trading more flexibility is achieved by stations despite the equal price manipulation in comparison to the second scenario. It is noticeable that although there is little difference between the charging load of scenarios 3 and 2 (see Fig. 6) the following valuable effect of this much difference will be shown.

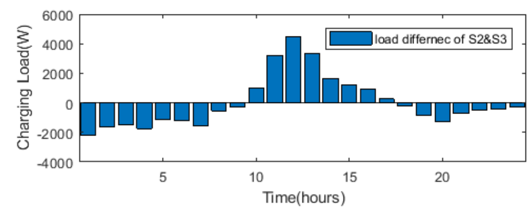


Fig. 6. Difference of EV loads between scenarios 3 and 2

Fig. 7. gives the comparison of the incomes of stations in three scenarios. It can be concluded that the coordinated model is more profitable for entities as well as operators of the grid as it can alter the load more than individual EMS applications. The total profit for the three scenarios is 6216, 6523, and 7199 $.

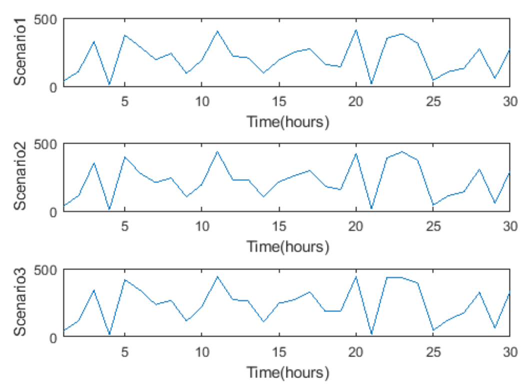


Fig. 7. The comparison between the income of stations in three scenarios ($)

VI. CONCLUSION

In this paper besides presenting the basic model of the energy management system according to the existing article, cost risk modeling by CVaR, proposed coordination method modeling, solution methods, and tools were proposed. Next, numerical studies for various states of the model that was presented were carried out. These included the basic study for verification, increased risk, the coordination of the energy management system for multiple EV stations, and the study of how coordination affected the cost of subscribers in separate solutions. The most significant outcomes of the paper are as follows:

• The reason that coordination leads to the reduction of the total energy supply cost is to cover the unevenness and uncertainties of the load curve and the production of renewable resources. For example, the intensity of load changes in the distribution network is greater than in the transmission networks, while the load of the transmission network is the sum of these highly variable loads, but this aggregation leads to a smoother load curve.

• A coordinated model will be attractive for all stations to participate due to the lower total cost for the station. If the total cost increases with the coordinated application of the energy management system, it would not be possible to implement this energy management system.

It is suggested to consider V2G in EMS for more profit for stations and lower charging prices for EVs.

Nomenclature

$after$	After the DR application.
B	Battery.
BAC	Battery Aging Cost.
$before$	Before DR application.
$B2G$	Battery to grid.
$B2S$	Battery to station.
CEV	Controllable EV
ch	Charge.
Cont	Contracted
$Crit$	Critical demand for EVs at the station.
dis	Discharge.
EV	Electric vehicle.
$G2S$	Grid to station.
$G2V$	*Grid to vehicle.*
I/C	Interruptible curtailable EVs.
Nom	Nominal power of controllable EVs.
PV	Photovoltaic.
Req	Requisite power of controllable EVs.
S	Station.
$S2B$	Station to batteries.
$S2G$	Station to grid.
$S2V$	Station to vehicle.
$V2G$	Vehicle to the grid.
$V2S$	Vehicle to the Station.
indices	
i	Controllable EVs.
t	Time.
ω	Scenarios.
Variables and parameters	
Cap	Battery capacity.
CW	The critical working period of the I/C.
Inc	Incentive paid for demand curtailment.
N	
P	Power.
Pen	Penalty applied to demand who refuse DR adjustment.
$Prob$	Probability of scenario.
r	Charging/discharging rates of battery.
SOC	State of charge.
v	Inelasticity of demand.
V	Dissatisfaction of EV consumers.
WC	Working Cycle of EVs.
x	Binary variable for controllable EVs.
Y,Z	Binary variables for direct transferred energy.
α	Aging coefficient of battery duo to cyclic charge and discharge.
η	Battery efficiency for charge and discharge.
λ	Tariffs.

VII. REFERENCES

[1] S. Hunkin and K. Krell. Renewable energy communities, policy brief from the policy learning platform on low-carbon economy, Aug. 2018. [Online]. Available: https://interregeurope.eu/

[2] S. Minniti, N. Haque, P. Nguyen, and G. Pemen, "Local markets for flexibility trading: Key stages and enablers," Energies, vol. 11, no. 11, Nov. 2018.

[3] I. Baäekovi and P. A. Østergaard, "Local smart energy systems and cross-system integration," Energy, vol. 151, pp. 812-825, May 2018.

[4] G. Raveduto, V. Croce, M. Antal, C. Pop, I. Anghel, and T. Cioara, "Dynamic coalitions of prosumers in virtual power plants for energy trading and profit optimization," IEEE 20th Mediterranean Electrotechnical Conference (MELECON), pp. 541-546, Jun. 2020.

[5] M. Yazdanie, M. Densing, and A.Wokaun, "The nationwide characterization and modeling of local energy systems: Quantifying the role of decentralized generation and energy resources in future communities," Energy Policy, vol. 118, pp. 516-533, Jul. 2018.

[6] J.-H. Kim and A. Shcherbakova, "Common failures of demand response," Energy, vol. 36, no. 2, pp. 873-880, Feb. 2011.

[7] M. Beaudin and H. Zareipour, "Home energy management systems: A review of modelling and complexity," Renewable and Sustainable Energy Reviews, vol. 45, pp. 318-335, May 2015.

[8] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "A distributed algorithm for managing residential demand response in smart grids," IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2385-2393, Nov. 2014.

[9] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," IEEE Transactions on Smart Grid, vol. 1, no. 2, pp. 120-133, Sep. 2010.

[10] F. D. Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints," IEEE Transactions on Industrial Informatics, vol. 9, no. 3, pp. 1518-1527, Aug. 2013.

[11] A. Soares, A. Gomes, C. H. Antunes, and C. Oliveira, "A customized evolutionary algorithm for multi-objective management of residential energy resources," IEEE Transactions on Industrial Informatics, vol. 13, no. 2, pp. 492-501, Apr. 2017.

[12] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 2166-2173, Dec. 2012.

[13] N. G. Paterakis, A. Tackaraolu, O. Erdin, A. G. Bakirtzis, and J. P. S. Catalo, "Assessment of demand-response-driven load pattern elasticity using a combined approach for smart households," IEEE Transactions on Industrial Informatics, vol. 12, no. 4, pp. 1529-1539, Aug. 2016.

[14] I. Y. Joo and D. H. Choi, "Optimal household appliance scheduling considering consumer's electricity bill target," IEEE Transactions on Consumer Electronics, vol. 63, no. 1, pp. 19-27, Feb. 2017.

[15] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Optimal residential load management in smart grids: A decentralized framework," IEEE Transactions on Smart Grid, vol. 7, no. 4, pp. 1836-1845, Jul. 2016.

[16] B. Celik, R. Roche, D. Bouquain, and A. Miraoui, "Decentralized neighborhood energy management with coordinated smart home energy sharing," IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 6387-6397, Nov. 2018.

[17] B. Celik, R. Roche, D. Bouquain, A. Miraoui, T. Hansen, and S. Suryanarayanan, "Increasing local renewable energy use in smart neighborhoods through coordinated trading," Cyber-Physical-Social Systems and Constructs in Electric Power Engineering. Edison, NJ, USA: Institution of Engineering and Technology, Oct. 2016, ch. 9.

[18] M. Jadidbonab, B. Mohammadi-Ivatloo, M. Marzband, and P. Siano, "Short-term self-scheduling of virtual energy hub plant within thermal energy market," IEEE Transactions on Industrial Electronics, vol. 68, no. 4, pp. 3124-3136, Apr. 2021.

[19] H. R. Gholinejad, A. Loni, J. Adabi, and M. Marzband, “A hierarchical energy management system for multiple home energy hubs in neighborhood grids,” Journal of Building Engineering, vol. 28, Mar. 2020, Art. no. 101028.

[20] M. Nazari-Heris, M. A. Mirzaei, B. Mohammadi-Ivatloo, M. Marzband, and S. Asadi, “Economic-environmental effect of power to gas technology in coupled electricity and gas systems with price-responsive shiftable loads,” Journal of Cleaner Production, vol. 244, Jan. 2020, Art. no. 118769.

[21] M. A. Mirzaei, A. Sadeghi-Yazdankhah, B. Mohammadi-Ivatloo, M. Marzband, M. Shafie-khah, and J. P. S. Catalão, “Integration of emerging resources in IGDT-based robust scheduling of combined power and natural gas systems considering _exible ramping products,” Energy, vol. 189, Dec. 2019, Art. no. 116195.

[22] M. A. Mirzaei, M. Hemmati, K. Zare, M. Abapour, B. Mohammadi-Ivatloo, M. Marzband, and A. Anvari-Moghaddam, “A novel hybrid two-stage framework for flexible bidding strategy of reconfigurable micro-grid in day-ahead and real-time markets,” International Journal of Electrical Power & Energy Systems, vol. 123, Dec. 2020, Art. no. 106293.

[23] M. A. Mirzaei, M. Nazari-Heris, K. Zare, B. Mohammadi-Ivatloo, M. Marzband, S. Asadi, and A. Anvari-Moghaddam, “Evaluating the impact of multi-carrier energy storage systems in optimal operation of integrated electricity, gas and district heating networks,” Applied Thermal Engineering, vol. 176, Jul. 2020, Art. no. 115413.

[24] F. Safdarian, O. Ciftci, and A. Kargarian, “A time decomposition and coordination strategy for power system multi-interval operation,” IEEE Power & Energy Society General Meeting (PESGM), pp. 1-5, Aug. 2018.

[25] A. Engelmann, Y. Jiang, T. Muhlpfordt, B. Houska, and T. Faulwasser, “Toward distributed OPF using ALADIN,” IEEE Transactions on Power Systems, vol. 34, no. 1, pp. 584-594, Jan. 2019..

[26] S. Fan, Z. Li, J. Wang, L. Piao, and Q. Ai, “Cooperative economic scheduling for multiple energy hubs: A bargaining game theoretic perspective,” IEEE Access, vol. 6, pp. 27777-27789, May. 2018.

[27] Z. Tan, P. Yang, and A. Nehorai, “An optimal and distributed demand response strategy with electric vehicles in the smart grid,” IEEE Transactions on Smart Grid, vol. 5, no. 2, pp. 861-869, Jan. 2014.

[28] M. shafie-khah, and P. Siano, “A stochastic home energy management system considering satisfaction cost and response fatigue,” IEEE Transactions on Industrial Informatics, vol.14, no.2, pp.629-638, Feb.2018.

[29] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, “The role of aggregators in smart grid demand response markets,” IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1247-1257, Jun. 2013.

[30] The italian electricity market - gestore dei mercati energetici (GME), 2016. [Online]. Available: http://www.mercatoelettrico.org.

[31] Salman Habib , Sina Aghakhani , Mobin GhasempourNejati , Mahdi Azimian , Youwei Jia , EmadM. Ahmed , ‘Energy management of an intelligent parking lot equipped with hydrogen storage systems and renewable energy sources using the stochastic p-robust optimization approach’, 1 September 2023, 1278.