A Risk Based Method for Energy Management of Smart EV Parking Lot Equipped with Renewable Energies

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Receive Date: 25June 2024 Accept Date:21August 2024

Abstract

The penetration of electric Vehicles (EVs) to the modern distribution system, has taken place in the last decade. Furthermore, Renewable Energies (RE) play an important role in such Micro-Grids (MG). Several Distributed Energy Resources (DER) including Distributed Generations (DGs) and Demand Response (DR) as well as EVs charge/discharge stations form a typical MG. In this paper, optimal DR-based charging and discharging strategies have been applied on the renewable-energy-based charging station of Electric Vehicles.In order to avoid profit loss due to the uncertainties of renewable energies, Peer to Peer (P2P) energy bartering between EVs charging station as prosumers is suggested in this paper. Therefore, in this paper, the management systems are developed for charge and discharge of EVs and station batteries, as well as Energy Management System (EMS) in order to do so, developed EMS was applied to the individual station in the first step. In the second step, the P2P power transaction was added to the model for the purpose of smoothening volatile uncertain load and renewables. The proposed model is a Mixed-Integer Linear Programming (MILP) and GAMS/CPLEX has been used to solve it. Numerical studies have proved deployment of aggregator is to be more beneficiary for Virtual Power Plant (VPP).

Keywords: Energy Resources, Renewable Energy, Uncertainty, Demand Response, Energy Management System, Peer to Peer.

1. Introduction

1.1 Motivation

Small-scale renewable resources known as Photovoltaics (PVs) and wind had mixed the producers and consumers to form new parties named prosumers who are able to directly participate in their own energy management. These types of consumers may have been coordinated to build larger entity and consequently increase their benefits which are individually unachievable [1]. For example, although DR reduces the grid operation costs, but the incentives may not compensate the dissatisfaction of small prosumers. Besides, the amount of power that can be supplied to the energy markets is significantly larger than the single-family stations who have RE. According to [2], the minimum bid/offer size, simultaneous upwards and downwards bid and activation time are the constraints that should be mitigated as they disable the prosumers to participate in the market. For this purpose, retailers, large consumers, power plants and etc. are the energy markets parties.

The high prices in some periods are caused by the volatile energy prices. The advances in RE technology are also the motives of the aggregated virtual models. These virtual aggregated parties may help decarbonization and local environmental aims by delivering extra energy of REs to the main grid instead of power curtailment [2, 3]. The virtual models can comply national-level market constraints while locally managing prosumers[4, 5]. Therefore,prosumers can also provide opportunity for low carbon policies of current decade paradigm in the energy system, while simultaneously reducing local grid's peak load and contributing to their economic development. So, the local residential entities will have the ability to optimize their Res and EVs as well as the other electric appliances.

A large percent of the overall electricity demand around the world is caused by Residential sector. Thereupon, the Home energy management (HEM) optimization has drawn attentions of many researchers. The changing role of the passive consumers in the electric power system into active is the key idea. Hence, the active participation of customers in energy transactions is done by manipulating the relating patterns of consumption and by optimizing available REs inside them which converts them to prosumers.

However, some reasons such as a sudden need for some appliances and frequent tracking of the order of Demand Response Programs (DRPs), can cause a phenomenon named "response fatigue" [6]. Hence, in the long-run, the return of some consumers to a default consumption pattern is expected.The dissatisfaction index is considered in the proposed Energy Management (EM) system. Which results in response fatigue avoidance. There are lots of research works that have studied the EM byconsidering DR and from different points of view.

1.2 Literature review

The optimization of the energy management of a hybrid green residential complex in [7], which is composed of renewable resources, electric boiler/chiller and electrical storage is done by considering adaptive parking lots, responsive loads and home crypto miners. Since the accurate predictions are the perquisites of reliable operation of such structures, various parameters including solar radiation, local loads, arrival/departure time of vehicles, wind speed, initial charge of batteries and price of markets are modelled via scenario generation procedures firstly. Secondly, the risk analysis of decisions under the desired robustness levelis done using the downside risk method.

A novel framework of energy management for HSS-based IPL is proposed in [8] which considers the risk management approach and demand response programs. The input parameters such as solar irradiation and its temperature, wind speed, energy tariff of the upper grid and IPL's demand, the uncertainties of which, are modelled using two strategies; the stochastic optimization method (SOM) and the stochastic p-robust optimization approach (SPROA). The SPROA is helpfulinmodelling the risk-based form of the IPL in such a way that the total expected expenditure of the IPL and its maximum related regret (MRR) are minimized.

A MG in[9] , is formed by integration of a smart parking lot (SPL), local dispatchable generators (LDG) such as microturbines (MT) and fuel cells (FC) and renewable energy sources (RESs) such as wind turbines (WT) and (PV). Meanwhile, an energy management system considering the uncertainties of solar irradiation, wind speed and load consumption is presented in the study. In order to lower the costs, an optimal operation of the SPL serving as asource for load and energy generation of the distribution network, is done. Cost cutting measures such as time-of-use (TOU)-tariff based DRP is utilized which results in moving a part of load from on-peak to off-peak time intervals which in turn, flattens the load curve. The main purpose is the reduction of operational expenses of the upstream grid (UG), SPL and LDGs while the technical and physical constraints are present. Moreover, the uncertainty modelling method based on Hong's two-point estimate method was adopted for mitigating the uncertainties of load consumption and wind generation.

A real-time energy management strategy based on a deep reinforcement learning (DRL) model was proposed in [10], for controlling power and mass flow of ISPL according to the user's preference parameters, the retail price is set by DRLagent and a fuzzy logic controller of EVs subsystem responds to it. Furthermore, the adoption of detection load vectors which are obtained through interaction, improves the agent's perception of the real-time state of ISPL. Therefore, the system of ISPL is equipped with refined modelling, intelligent decision-making and real-time interactive perception.

The charging and discharging issue of electric vehicles in public parking lots is dealt with in [11] by maximizing the parking's benefit. An algorithm for controlled scheduling of charging/discharging is proposed. The sale (purchase) of energy from (for) electric vehicles at high (low)-price periods is guaranteed by the optimization procedure. By comparing the proposed method with two distinctive uncontrolled strategies including constant power-based scheduling and constant time-based scheduling, the efficiency of the proposed strategy can be achieved. The uncertainty of arrival and departure times and charge state of EVs is considered in the analysis approach. Furthermore, statistical methods have yielded the required data.

According to [12], a suitable model for energy management of the EVPL community is used for the operational scheduling of several PLs. besides the energy trading with each other, the PLs exchange energy with the PDGO for the purpose of maximizing their profit. The mixed-integer linear programming (MILP) problem model is solved via using stochastic programming and a simple additive weighting (SAW) method.

In [13], in order to test and approve the applicability of the proposed method in terms of simplicity, accuracy, independency preservation and not requiring any control or initial parameters, a three-area power network is chosen. The maximum yielded error in the chosen case study is 0.0009 pu. Also, voltage deviation and operation cost are the selected ~~o~~ fundamental objective functions. Their analysis is to be done both multi-objectively and solely. Moreover, distributed generators and soon-to-be-indispensable electric vehicle parking lots are also utilized. The operation cost is optimized up to 49.28% while that of voltage deviation is up to 48.99%.

Theelectricity fluctuation feasible region concept is suggested in [14] and the reliable evaluation of reserve declaration capacity is achieved. The feasibility of EV guidance between different PLs is considered, as well as the reserve the time scale of the market and the asynchronous problem of EV appointment interval. The effectiveness examination of the proposed model is carried out via Simulation verification, which results in the effective relieving of the congestion of PLs after introduction of the guidance model. Besides, the operation profit of PLs and the reserve declaration capacity are accordingly enhanced.

An SPL is proposed in [15] which is equipped with power and heat sources as well as storages, and includes renewable and non-renewable technologies such as micro-turbines, wind turbines, and generating facilities consisting of combined heat and power (CHP) plants which are locally installed SPL operator can supply its electricity for the power market sell and sell the heat which CHP units locally generateto this maximizes the profit. Moreover, the uncertain nature of EV arrivals and departures and the associatedSOC level can be handled by the proposed model for the SPL. Wind-power output management and gauging optimal power prices can be an outcome of the proposed model too. The implementation of the hybrid robust-stochastic programming in a case study,confirms practicality and effectiveness of the model.

A transactive energy management system (EMS) for commercial parking lots is proposed in [16]. These lots possess rooftop PV system and EV charging system the objective of the optimization of the EMS is to balance the charging demand with supply. Factors such as battery degradation cost and photovoltaic levelized cost of energy are considered in order to give the EMS a more realistic look. Then, a communication is established between the EMS of each parking lot and the local trading agent. The data of energy requirement and excess energy initiate the proposed energy transaction mechanism. The flexibility of the double-sided auction bidding mechanism in terms of price and the energy requirement valuation of the parking lots are considered. Implementing the proposed scheme on a system consisting of six parking lots and 25 EVs in each of them results in cost savings in the range of 2% to 7% for different cases of feed-in tariff which is either fixed or variable. The cost savings variety from 2.41% to 12.09% and an average of 6.11% is attained by the uncertainty analysis. The case studies prove the economic benefit of the method that hasbeen proposed.

Public transportation systems which are rail-based, have been integrated with electric vehicle (EV) parking lots in [17]. The new concept of “park and ride” strategy also includes energy production based on renewable resources. Different charging strategies supply the charging power demand of the EV parking lot in this structure. The existing unused energy infrastructure capacity and the regenerative braking energy of the railway system are considered. The design of a renewable energy production unit which is carport type and photovoltaic (PV) based, is also attained in the existing local parking area. Developing an optimal energy management system for the purpose of managing inputs in an effective way, is acquired.The pertaining uncertainties of EVs’ demand are considered too.

A real-time energy management model for an EV parking lot (EVPL) which is based on optimization, is proposed in [18]. Linear programming has been used in the proposed algorithm. A DR program which is oriented at limiting the peak load and provides operational flexibility, is offered the objective of this method is to maximize the load factor of the EVPL on a daily basis operation. The mobility of the EVs results in uncertain arrival/departure times. The generation of the state-of-energy levels upon their arrival is done through considering historical data and providing a more realistic approach.

The coupling relationship among the travel information of EVs and battery status have been considered in carrying out the intelligent grouping method proposed in [19]. The index of charging process contributes to establishing a charging/discharging priority model. At last, for the purpose of maximizing the penetration level of EVs under current conditions, a smart real-time energy management strategy is formed. The proposed strategy yields an increase in the maximum penetration level of EVs from 20% to 60%.

The operation of an integrated system which comprises an electric transportation system possessing a charging station which is battery-powered bus [electric bus (eBus)] and a PV generation based EV parking lot is proposed in [20]. The battery storage system (BSS) is used as a virtual energy hub (VEH). Furthermore, the strategy of ~~a~~ cooperative decision-making (CDM) isused for the VEH. A novel three-stage cooperative control system is used for the active and reactive power flows and the economic operation of the VEH.

A new algorithm based on day-ahead co-optimization is proposed in [21] which mitigates the unwanted effects that PEVs have on the power system. The minimization of cost of energy losses as well as transformer operating cost is done in this algorithm by simultaneousmanagement of active and reactive powers. In addition, the effect of harmonics produced by the PEVs charger, is considered Furthermore, the operating cost of transformer isobtained by a method containing the transformer loss and loading cost as well as its purchase price. Power quality parameters improvement is another upside for this algorithm.

The minimization of micro-grids' operating cost and degradation cost of EV batteries, is the main aim of the proposed method in [22]. Besides, the resulting emission cost from the active and reactive power scheduling of EV parking lots containing photovoltaic (PV) systems and the optimum network configuration acquisition were the other goals. Because of some statistical assumptions, methods which relay on models are not able to appropriately consider uncertainties in EV users' behaviour. Nonetheless, data-driven methods based on generative adversarial networks (GAN) are employed in this paper for representing these uncertainties. The performance evaluation of the proposed method is done via its implementation on a real reconfigurable micro-grid.

This paper introduces an EMS model for the EVs station based on [23]. The EVs station is equipped with renewables and storage, while an aggregator is established for EVs charge/discharge station. The aggregated EMS model and P2P model result in Energy cost reduction of EVs station. Numerical studies with and without aggregator as well as P2P transactions have proved the increase in profit, especially from market balancing point of view.

1.3 Contributions

The optimal operation model of EVs station has been developed in this paper. As for the innovations, the following list is valid.

- Application of EMS for multi-EVs-station~~s~~ system in order to guarantee the procumer benefits in coordinated structure.

- Development of P2P power transaction between EVs stations for uncertainty and variability management of load and renewables.

In the remainder of this paper,Section 2 expresses developed framework of energy management system problem. The coordinated model is given in Section 3. P2P power transaction between stations are expressed in Section 4. Section 5 and section 6 include the Simulation procedure and conclusions, respectively.

2. Energy Management System Framework

For the energy management system, The following decision variables are presented; the transferred power from the grid to 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 and the station battery, $P_{\omega.t}^{S2V}$, $P_{\omega.t}^{V2S}$, $P_{\omega.t}^{S2B}$ and $P_{\omega.t}^{B2S}$, the On/Off state of controllable EVs, $x_{i.\omega.t}^{CEV}$.

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

The selling income and purchasing cost of the station due to the energy trade with the grid, are respectively expressed by the first two terms. While the third term states the aging cost of thebatteries due to their inherent cyclic operation. BAC_{ω}^{B} and BAC_{ω}^{EV} denote the battery costs relating to the battery and EV which are considered as wear for the mentioned modes resulting from the extra cycling nature of the batteries and are calculated by Eq. (2).

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

$Inct_t(P_{\omega.t}^{G2S,after} - P_{\omega.t}^{G2S,befor} + P_{\omega.t}^{S2G})$ presents the incentive income resulting from taking part in an incentive-based DRP. While, $Pen_t(P_{\omega.t}^{G2S.Cont} - P_{\omega.t}^{S2G,after} + P_{\omega.t}^{S2G,befor})$ is the penalty cost for participation in the DRP. $P_{\omega.t}^{G2S,after} - P_{\omega.t}^{G2S,befor}$ is able to shows the energy transferred to the station when implemented tariff has a fixed-rate minus that of the applied incentive-based DRP. The term $Inct_t(P_{\omega.t}^{S2G})$ is used for modelling the customer's incentive-based income (EVs in this paper) resulted from power injection back to the grid. Lastly, $V_{\omega.t}$ is a dissatisfaction modelling function for EVs owner as [23] due to variation from the initial consumption and is given by Eq. (3).

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

where $v_i^{CEV} > 0$ defines the load inelasticity parameter of controllable EVs [24, 25]. The amounts of v_i^{CEV} which are higher, are an indication of the operation of the ith EV at the initial time which is the most convenient time for the consumer.

The demand that contains the charging requirements of the batteries of Station (i.e. $P_{\omega.t}^{S2B}$) and EVs load is shown by Eq. (4). This demand is either supplied by the wind and PV internal generation, or through the grid ($P_{\omega.t}^{G2S}$) or by the battery or Ev's energy.

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

$Y^{B}_{\omega.t}$ and $Z^{B}_{\omega.t}$ are the binary variables to guarantee the disability of a Station battery in simultaneous charging and discharging. Similarly, binary variables $Y^{EV}_{i,\omega.t}$ and $Z^{EV}_{i,\omega.t}$ guarantees the same for each EV as presented in Eq. (5).

$$Y^{X}_{i,\omega.t} + Z^{X}_{i,\omega.t} \leq 1 \qquad \forall t.\forall\omega, x \in \{B.EV\} \quad (5)$$

As in Eq. (6), the controllable part of Station demand is the Total consumption of controllable EVs, each of which's consumption, is considered to be equal to its nominal power. Therefore, each of the single EVs is controlled by determining the relating ON/OFF states, $x^{CEV}_{i.\omega.t}$. It should be mentioned that the EVs' operation is also considered to be a function of scenarios. Simply put, the EVs and operating the Station battery can cover the uncertainty of renewable energies.

$$P^{I/C}_{\omega.t} = \sum_{i}\{x^{CEV}_{i.\omega.t}(Y^{EV}_{\omega.t} - Z^{EV}_{\omega.t})P^{Nom}_{i}\} \quad \forall t.\forall\omega \qquad (6)$$

Inequality (7) states that the daily consumption of each controllable EVs is limited to the required consumption. It is noteworthy that this constraint cannot be extended for more than 24 hours, since the operation of EVs should be some times per day. Besides the considered dissatisfaction function, V_t, an operation time is considered to model the tendency of consumers for preserving the initial consumption pattern. This guarantees the charging of each controllable EVs in a given appropriate period for the inhabitants.

$$P^{Crit}_{i} \leq \sum_{t}\{P^{CEV}_{i.\omega.t}\} t \in T^{CEV}_{i}, \forall i.\forall\omega \qquad (7)$$

The EMS must not switch off some EVs at working period. In other words, the operation period of each EV must be respected by the EMS system. Thereupon, Eq. (8) and Eq. (9) guarantee that all controllable EVs are continuously used in their inhabitant operation period.

$$Y^{EV}_{i,\omega.t} + \sum_{j=1}^{WC_i-1} Z^{EV}_{i,\omega.t+j} \leq 1 \qquad \forall t.\forall i.\forall\omega \qquad (8)$$

$$Z^{EV}_{i,\omega.t} - Y^{EV}_{i,\omega.t} = x^{CEV}_{i.\omega.t} - x^{CEV}_{i.\omega.} \qquad \forall t.\forall i.\forall\omega \qquad (9)$$

The model for the evaluation of the SOC variations in the station and EV batteries is described by Eq. (10).

$$SOC^{X}_{\omega.t} = SOC^{X}_{\omega.t-1} + Z^{X}_{\omega.t}\eta^{ch.X}\left(\frac{P^{S2X}_{\omega.t}}{Cap^{X}}\right) - Y^{X}_{\omega.t}\left(\frac{P^{X2S}_{\omega.t} + P^{X2G}_{\omega.t}}{\eta^{dis.X}Cap^{X}}\right) X \in \{B.EV\} \qquad (10)$$

$$SOC^{min.X} \leq SOC^{X}_{\omega.t} \leq SOC^{max.X} \qquad X \in \{B.EV\} \qquad (11)$$

$$r^{ch.X}_{\omega.t} = \frac{SOC^{X}_{\omega.t} - SOC^{X}_{\omega.t-1}}{\eta^{ch.X}} \qquad \forall t.\forall\omega, X \in \{B.EV\} \qquad (12)$$

$$r^{dis.X}_{\omega.t} = (SOC^{X}_{\omega.t-1} - SOC^{X}_{\omega.t})X \in \{B.EV\} \qquad (13)$$

$$0 \leq r^{ch.X}_{\omega.t} \leq r^{ch.max.X} \qquad \forall t.\forall\omega, X \in \{B.EV \qquad (14)$$

$$0 \leq r^{dis.X}_{\omega.t} \leq r^{dis.max.X} \qquad \forall t.\forall\omega, X \in \{B.EV \qquad (15)$$

As stated by Eq. (10), the SOC at time $t-1$, the injected energy to the battery and back to the grid and station at time t are the input variables of SOC the function of the battery at time t. in Inequality (11), the depth of discharge is limited and no overcharging of the battery is guaranteed. The constraint relating to the charging and discharging rates of Station and EV batteries are presented in Eq. (12) to Eq. (15).

As presented in Eq. (16), the power that is transferred to the grid can be achieved by addition of PV and wind generations as well as battery injections.

$$P^{S2G}_{\omega.t} = P^{wind}_{\omega.t} - P^{wind2S}_{\omega.t} + P^{PV}_{\omega.t} - P^{PV2S}_{\omega.t} + P^{B2S}_{\omega.t} + \sum_{i=1}^{N_{EV}} Y^{EV}_{i,\omega.t}P^{V2S}_{\omega.t} \qquad \forall t.\forall\omega \qquad (16)$$

$$Y^{S}_{\omega.t}P^{G2S}_{\omega.t} + Z^{S}_{\omega.t}P^{S2G}_{\omega.t} \le P^{C.max} \forall t.\forall\omega \quad (17)$$

$$Y^{S}_{\omega.t} + Z^{S}_{\omega.t} = 1 \qquad \forall t.\forall\omega \quad (18)$$

Eq. (17) limits the power transaction between grid and station. Also, equation Eq. (18) describes that the station may choose one direction for power transmission.

Also, in order to model the effect of uncertainty on the problem, the addition of risk index well-known as Conditional Value at Risk (CVaR) was done.

$$OF = (1-\beta) \times EQ(1) + CVaR \quad (19)$$

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

In which α and $\beta$are the level for confidence and risk importance, respectively. Also, decision variables of CVaR,£ and SW_{ω}, are as follows:

$$£ - EQ(1)_{\omega} \le SW_{\omega} \quad (21)$$

$$SW_{\omega} \ge 0 \quad (22)$$

Nomenclature

subscribes	
$after$	After 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 of EVs at 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 EV's
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	Critical working period of the I/C
Inc	Incentive paid for demand curtailment
N	Number
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 of transferred energy
α	Aging coefficient of battery duo to cyclic charge and discharge
η	Battery efficiency for charge and discharge
λ	Tariffs

3. Coordinated EM

The proposed EM model in the previous section can be aggregated in order to apply the proposed EM to multiple procumers. To this end, the profit of each procumersshould be guaranteed in coordinated model due to uncertainty of renewable generation and load of each procumers. It is highly probable that the coordinated EM for multiple stations increases the profit of each station. The schematic of coordinated model for EM is depicted in Fig.1.

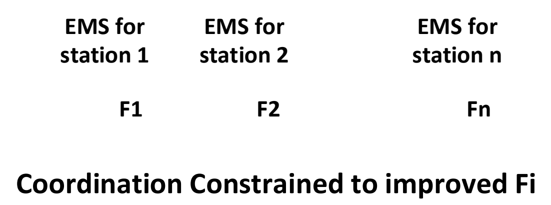


Fig .1. Coordinated EM model for Procumers

Two major matters of aggregation are as follows:

-*Point 1*: reduction of EVs station (as procumer) bill in coordinated model towards each of individual EMs.

- *Point 2*: If the summation of electric energy supply for multiple stations is set as objective function of coordinated model, some of stations are likely to experience an increase in cost and some may face a decrease.To ovoid this, minimum profit insurance as much as the profit of individually EM system application should be modelledas a constraint.

Hence, the coordinated (aggregated) model is developed as:

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

$$S.t: \tag{24}$$

$$Constraints(S)$$

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

Where $Constraints(S)$are Eq. (2) to Eq. (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 the aggregation is dedicated to the aggregator. Hence, the basic concept of aggregation is verified.

4. P2P Power Trading between stations

The main problem in this paper is to enhance EMS using P2P facilities. The addition of P2P energy transaction between stations to the EMS is done in this section. The traded power between the stations is as in [21]. However, other stations are as a black box from point of view of each station.

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

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

$$P_{j.t}^{Sout} = P_{j.t}^{in} \tag{28}$$

$$P_{j.t}^{Sin} = P_{j.t}^{out} \tag{29}$$

The power output and input summation of stations other than *j*th station, is determined by Eq. (26) and Eq. (27). Eq. (28) and Eq. (29) state that these summations are equal to the corresponding station (*j*th one) input/output, respectively. Therefore, the equation for power balance of each station after implementation of P2P transactions between MGs would be as follows:

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

5. Numerical Studies and Discussion

In order to investigate the proposed model, a Station in Italy is considered. All data for the case study is available in [25]. Two types of EVs have been considered as controllable EVs. First groups waiting capacity is three hours in morning and four hours in the evening. On the other hand, second group can wait for two hours. The departure time of these groups floats over a day.

5.1 Case-1

The first case study contains risk analysis for 10 scenarios and study of coordination of EMS considering P2P power transactions.

- *Risk Analysis*

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

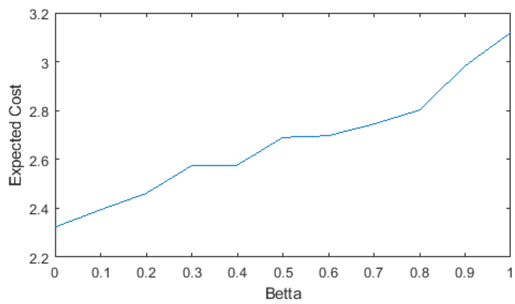
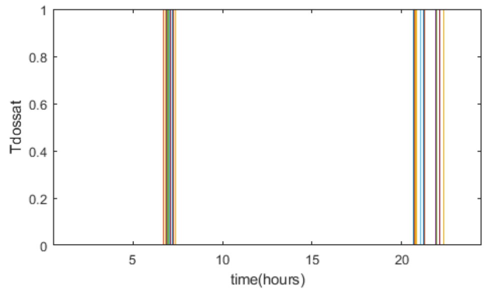
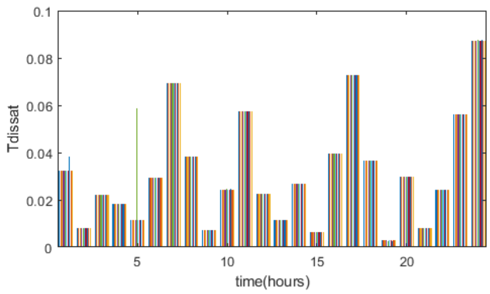


Fig.2. Expected objective VS β[23]



(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 of station using due to participation in the load response program. Fig.3-a and Fig.3-b show this variable for the first and second group of controllable EVs, respectively. For critical EVs, this variable is equal to zero. Although the amount of penalty or inelasticity of critical EV loads is less than that of the controllable EVs, its working hours are limited and specific. Therefore, dissatisfaction cost calculation of the objective function, leads to significant difference in the amount of power consumed by the critical EV loads in case of interruption in the hours of need since its compensation is meaningless in other hours.

Another point in Fig.3 is that even though the dissatisfaction for the first EV group only exists in three hours of the day for some scenarios, its amount is 100%. For the second group of controllable EVs, while this lack of satisfaction was present at all hours and for all scenarios, its value is less than 10%. The first reason is that there are only two consumption periods considered for the first EV group during the 24 hours of the day and night (7-9 and 18-22). Therefore, it cannot be used at periods other than the above, and thereupon, it is possible to have non-zero values. Second, the changes in the common desired pattern for the first group of controllable EVs can be applied for a complete hour, therefore, the changes in its pattern is made as the changes of a complete hour at the desired consumption time. However, for the second group of controllable EVs, it is possible to be changed minutely therefore, the related values are not binary and any value between 0 and 1 is possible. The final point is that there is no difference between the scenarios for second group of controllable EVs, except for the two hours of 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 application of coordinated EM in two cases, where first case contains three stations as an example and the large scale system as the main case study.

Case-1: three station example

Table.1 contains the comparison between the profit increments of the stations in this example.

Table1. Profit enhancement in coordinated model

Station	Individual EM [23]	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.1, it can be concluded that the coordination through aggregation by adding P2P transactions results in a more profitable EMS for consumers. Hence, the tendency of EV stations to take part in DR programs can be increased, as for the EV owners.

5.2 Case-2

In this case three scenarios based on the previous case and some modifications and extension to 30 EV stations, have been considered on a large scale system. Total wind and solar generation of stations are illustrated in Figure.4. Studied scenarios are as follows:

-Scenario 1: without EMS

-Scenario 2: with individual EMS

- Scenario 3: Coordinated EMS

The results of numerical studies consist of load profile and individual cost saving due to participation in EMS in the second and third scenarios. Figure.5 depicts load profile of three scenarios for 30 stations in three scenarios. Note that total EV load is about 3.7 MWh while total renewable generation of stations are about 0.55 MWh. However, there is a strong correlation between them. This may lead to more profitable P2P trading and no subsequent load dissatisfaction due to load shift.

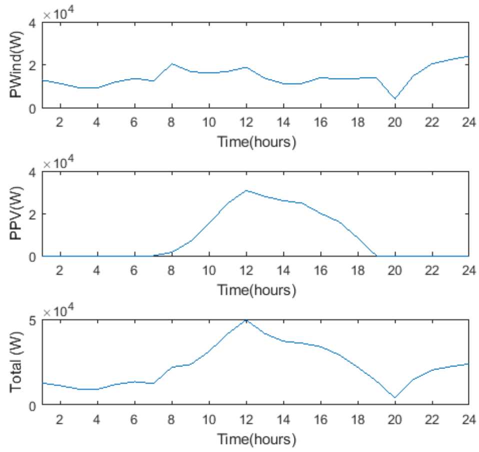
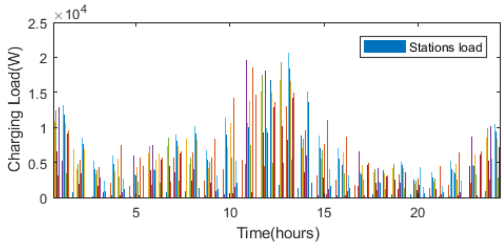
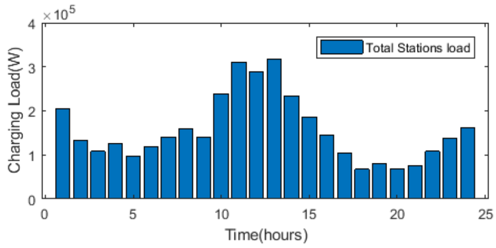


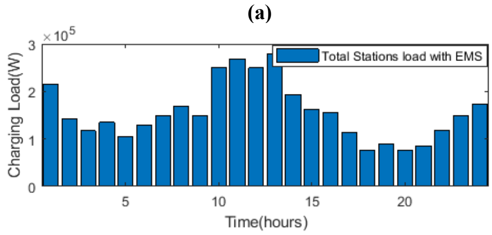
Fig.4. Wind and Solar generation



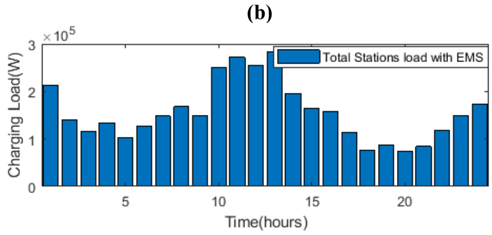
(i)



(a)



(b)



(c)

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

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

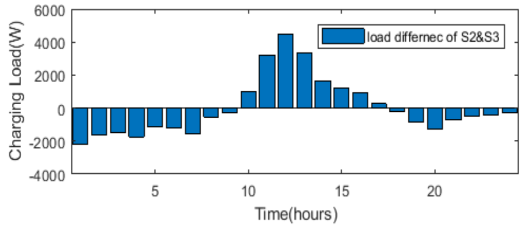


Fig.6. Difference of EV loads between scenarios 3 and 2

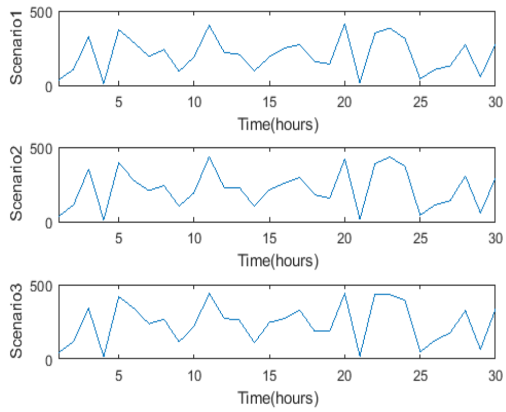


Fig.7. The comparison between income of stations in three scenarios ($)

Figure.7 depicts the comparison between incomes of stations in three scenarios. It can be concluded that the coordinated model is more profitable for entities as well as the operator of grid as it can alter the load more than individually EMS application. Total profit for three scenarios are 6216, 6523 and 7199 $.

6. Conclusion

Besides presenting the basic model of the energy management system, the cost risk modeling by CVaR as well as the coordination method modeling and methods and tools for solving, were proposed in this paper. Numerical studies for different states of the presented model including the basic verification study, increased risk as well as the coordination of the energy management system for several EV stations and studying its effect on the cost of subscribers in individual solution, have been conducted. The most significant outcomes of the paper are as follows:

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

• Coordinated model participation will definitely be attractive for all stations due to the lower total cost ~~for~~ the station brought by this model. However, if the total cost increases by the coordinated application of the energy management system, its implementationwould not be possible.

It is suggested to consider V2G in EMS in order to gain more profit in the stations and lower charging price of EVs.

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