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

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Abstract

This paper presents an innovative method for operational planning of microgrids, focusing on maximizing profitability. The approach addresses key uncertainties, including the probabilistic charging/discharging behavior of EVs and the integration of renewable energy sources like wind and solar. A major challenge with renewables is energy wastage due to storage limitations and grid congestion. EVs offer a solution through Vehicle-to-Grid (V2G) technology, which enables them to supply electricity back to the grid, improving renewable energy utilization. This paper introduces two Energy Management System (EMS) models, with a key innovation being a Coordinated EMS that facilitates peer-to-peer (P2P) power trading between stations and prosumers. The model, evaluated across five stations under ten uncertainty scenarios, is formulated using Mixed-Integer Linear Programming (MILP) and implemented in GAMS/CPLEX. By integrating P2P transactions and organic photovoltaics (OPV) technology, it enables off-grid EV charging and utilizes excess solar energy in remote areas. Results indicate that the Coordinated EMS with P2P trading improves profitability by up to 1.17 times. The findings of this research align with efforts to reduce peak load in distribution grids by reducing reliance on centralized infrastructure, demonstrating the potential benefits of coordinated energy management strategies in microgrids.

Keywords: Energy Management System, Distributed Energy Resources, Electric vehicles, Renewable Energy, Uncertainty, Peer to Peer, Organic Photovoltaics

1. Introduction

1.1 Motivation

Over the past few centuries, renewable energy has been increasingly recognized as a means to alleviate energy shortages [1]. According to the planning by the International Renewable Energy Agency (IRENA), by the year 2050, over two-thirds of energy production will be derived from renewable sources, with contributions from renewable sources such as wind and solar energy reaching 60% [2]. However, both wind and solar energy face significant waste due to energy storage challenges. As the world's largest producer of wind and solar power, China experienced an average wind curtailment rate of 3.2% and a discarded wind power quantity of approximately 6 billion kilowatt-hours in the first quarter of 2022. The solar curtailment rate was2.8%, with a discarded solar power quantity of around 2.4 billion kilowatt-hours[3]. Countries worldwide are also grappling to varying extents with energy storage issues leading to wastage of green energy. The prevailing viewpoint suggests that managing the surplus of wind and solar power is more challenging than addressing their deficiencies [4]. This is attributed to the intricate nature of storing wind and solar energy, where surplus electricity can result in an increased burden on the power grid. Therefore, optimizing electrical energy storage and promptly integrating excess electricity into the grid are crucial measures to enhance the utilization of green energy and achieve sustainable development. EVs are considered a key solution to address energy storage challenges. V2G power technology is one of several storage technologies, enabling vehicles to feed electricity into the grid. Through unified demand control in the power system, V2G can better utilize fluctuating renewable energy. For power companies, V2G offers benefits such as backup power, load balancing, peak load reduction [5, 6], and reduced uncertainty in daily and hourly power load forecasts [7].

Importantly, numerous studies suggest that V2G can effectively enhance the energy efficiency of wind and solar power [3, 8]. Conventional EVs (battery EVs and plug-in hybrid EVs) can contribute to peak shaving by charging in an orderly manner at night, but they cannot feed power back to the grid during the day, offering only limited peak load reduction for fluctuating grids [9]. In contrast, V2G EVs not only contribute to peak shaving at night but can also provide power back to the grid during peak demand hours in the daytime [10], making their advantages more apparent in terms of green energy utilization [11].

Expanding access to reliable, low-cost sustainable energy, such as solar power, can help reduce poverty, inequality, and climate change impacts. The *Charge Around* EVs involves driving an EV powered by portable OPV solar panels, demonstrating the potential of printed solar technology for off-grid charging. These lightweight OPV panels generate renewable energy in remote areas, addressing EV range anxiety and showcasing the feasibility of off-grid solar charging [12].

1.2 Literature Review

Mohamed et al.in [13] designed a fuzzy controller to manage the charging processes of EVs to reduce the overall daily cost and mitigate their impact on the power grid. Tushar et al. in [14] proposed a classification scheme of EVs, such that the PV driven charging station can trade with different energy entities to reduce its total energy cost. Under the Time of Use (TOU) price, Liang et al. in [15] studied the charging/discharging scheme in Vehicle-to-Grid (V2G) system and obtained a state-dependent policy to minimize the charging cost for individual EVs. Considering the battery characteristic and TOU price, Wei et al. in [16] designed an intelligent charging management mechanism to maximize the interests of both the customers and the charging operator.

Considering unpredictable EVs patterns and EV various charging preferences, Wang et al. in [17] designed a Hybrid Centralized-Decentralized (HCD) charging control scheme for EVs to coordinate the EV charging processes, such that the revenues of the whole charging system can be maximized. Kim et al. in [18] developed an algorithm to find the optimal charging scheduling, service pricing and energy storage scheme, such that the profit of charging stations can be maximized. Jin et al. in [19] presented a Lyapunov optimization for EV charging scheduling problems to maximize the utilization of renewable energy and reduce total charging cost. These works typically assumed that the EV charging requirements or the renewable energy can be estimated and do not consider the real time EV charging requirements and renewable energy.

Zhou et al.in [20] achieved the Demand Side Management (DSM) by scheduling intelligent EV charging to relieve the power grid pressure. Wang et al. in [21] designed a novel Two-stage EV charging mechanism to determine the energy generation and charging strategy dynamically, such that the peak-to-average ratio (PAR) and the energy cost can be reduced. Liu et al. in [22]. proposed a leader-follower game model between the EV owners and the distribution service provider, and then designed an optimal pricing based EV charging scheduling scheme to avoid system peak load.

Zhang et al. in [23] proposed a Markov Decision Process (MDP) based charging scheduling scheme to minimize the mean waiting time for EVs. Wang et al. in [24] proposed a mobility-aware coordinated charging strategy for EVs in VANET-Enhanced Smart Grid, which can improve the overall energy utilization, avoid power system overloading, and can address the range anxieties of individual EVs. Farzin et al. in [25] developed a novel framework based on the non-sequential Monte Carlo simulation method to quantify the potential contribution of parking lots to the reliability of PV–Grid charging systems. Yang et al. in [26] proposed a risk-aware day-ahead scheduling and real time dispatch algorithm to minimize the EV charging cost and the risk of the load mismatch. Lee et al. in [27] took into account the competition of neighbouring EV charging stations with renewable energy sources using game theory, and proved that there exists a unique pure Nash equilibrium for best response algorithms with arbitrary initial policy. These works mainly focused on operational efficiency of charging systems and the utilization of renewable energy in long-term, rather than the real time benefit of the parking lot. Also, they lack the quick response abilities to the real time changing information. Sheykhloei et al. optimized the operation of renewable energy resources and a natural gas network to reduce electrical load costs and improve system reliability in in [28] where a 24-bus power system with PV, wind turbines, battery storage, and a 7-node gas network is analyzed over 24 hours to determine optimal resource placement and capacity. This work uses join units combining atural-gas-fired distributed generators and Power to Gas units. By utilizing MILP power and gas fluctuations are managed effectively.

1.3 Contributions

In this paper, an EMS model has been developed based on [29] for the EV station equipped with renewables and storage. 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. By utilizing OPV-based portable solar panels, this study explores the feasibility of off-grid EV charging in remote areas, reducing dependence on traditional charging infrastructure while harvesting and utilizing excess solar energy. This approach not only mitigates range anxiety in long-distance EV travel but also helps address renewable energy wastage by enabling efficient energy use in locations without centralized grid access.

The innovations in model are as follows:

- Application of EMS for multi-EVs-stations system in order to guarantee the procumer benefits in coordinated structure and integration of OPV to provide additional renewable energy

- 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 the proposed model. The numerical studies are provided in section 3. Section 4 represents the conclusions.

2. Proposed Model

2.1. Mathematical Model of Individual EMS

This paper introduces an EMS model for the EVs station based on [29].

Sets:

ω	Scenarios
t	Time
I	Controllable EVs

Parameters and Variables:

α	Aging coefficient of battery duo to cyclic charge and discharge
$Prob_{\omega}$	Probability of scenarios
λ_t	Price of electricity
Inc_t	Incentive paid for demand curtailment
Pen_t	Penalty applied to demand who refuse DR adjustment
v_i^{CEV}	Load inelasticity
P_i^{Nom}	Nominal power of controllable EVs
P_i^{OPV}	Power of organic photovoltaics EVs
$SOC^{min.b}$	Minimum State of charge battery
$SOC^{min,ev}$	Minimum State of charge EV
$SOC^{max.b}$	Maximum State of charge battery
$SOC^{max,ev}$	Maximum State of charge EV
$\eta^{ch.b}$	Charge rate of battery
$\eta^{ch.ev}$	Charge rate of EV
$\eta^{dis.b}$	Discharge rate of battery
$\eta^{dis.ev}$	Discharge rate of EV
Cap^{b}	Capacity of battery
Cap^{ev}	Capacity of EV
$r^{ch.maxb}$	Maximum charge rate of battery
$r^{ch.maxev}$	Maximum charge rate of EV
$r^{dis.maxb}$	Maximum discharge rate of battery
$r^{dis.maxev}$	Maximum discharge rate of EV
$P_{i.\omega.t}^{CEV.ini}$	Initial power of Controllable EV
$P_{\omega.t}^{S2G}$	Power of station to grid
$P_{\omega.t}^{G2S}$	Power of grid to station
$BAC_{t.\omega}^{B}$	Battery Aging Cost
$BAC_{t.\omega}^{EV}$	EV Aging Cost
$P_{\omega.t}^{G2S.ini}$	Initial power of grid to station
$P_{\omega.t}^{S2G,before}$	Power of station to grid before DR application
P_i^{Crit}	Critical demand of EVs at station
$V_{\omega.t}$	Dissatisfaction of EV consumers
$r_{\omega.t}^{ch.X}$	Rate of charge
$r_{\omega.t}^{dis.X}$	Rate of discharge
$P_{i.\omega.t}^{CEV}$	Power of Controllable EV
$P_{\omega.t}^{S2V}$	Power of station to vehicle
$P_{i.\omega.t}^{ini.S2V}$	Initial power of station to Vehicle
$P_{i.\omega.t}^{V2S}$	Power of vehicle to station
$P_{\omega.t}^{wind2S}$	Power of wind to station
$P_{\omega.t}^{PV2S}$	Power of solar to station

$P_{\omega.t}^{B2S}$	Power of battery to station
$P_{\omega.t}^{S2B}$	Power of station to battery
$P_{\omega.t}^{I/C}$	Interruptible curtailable EVs
$SOC_{\omega.t}^{b}$	State of charge / discharge for battery
$SOC_{\omega.t}^{ev}$	State of charge / discharge for EV
$Y_{\omega.t}^{B}$	Binary variable if battery charge set 1
$Z_{\omega.t}^{B}$	Binary variable if battery discharge
$Y_{i,\omega.t}^{EV}$	Binary variable if EV charge set 1
$Z_{i,\omega.t}^{EV}$	Binary variable if EV discharge set 1
$x_{i.\omega.t}^{CEV}$	Binary variable if EV is ON

2.2 System Modelling

The mathematical formulation includes several key equations defining system operations and constraints**.** The objective function (OF) is represented by Equation (1).

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

The first term accounts for the income generated from selling and purchasing power between the grid and the station. The second term represents the costs associated with battery and EV operations. The third term includes incentive income based on the Demand Response Program (DRP), while the fourth term corresponds to the penalty costs incurred for participation in the DRP. Finally, the fifth term models EV owners' dissatisfaction due to deviations from their initial consumption plans.

Equation (2) represents the battery costs related to battery and EV wear, considering the additional cycling nature of the batteries in the given modes.

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

Equation (3) models EV owners' dissatisfaction, while Equation (4) ensures demand balance within the system.

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

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

Equation (5) enforces the constraint that a station battery and EVs cannot charge and discharge simultaneously.

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

Equation (6) defines the controllable portion of station demand, which corresponds to the total consumption of controllable EVs, assuming each EV's consumption is equal to its nominal power. The operation of individual EVs is controlled by determining their ON/OFF states, $x_{i.\omega.t}^{CEV}$. Additionally, EV operations are scenario-dependent, allowing both EVs and station batteries to compensate for renewable energy uncertainties.

$$P_{\omega.t}^{I/C} = \sum_{i}\{x_{i.\omega.t}^{CEV}(Y_{\omega.t}^{EV} - Z_{\omega.t}^{EV})P_i^{Nom}\} \quad \forall t.\forall\omega \tag{6}$$

Equation (7) ensures that the daily consumption of each controllable EV is limited to its required consumption, while Equations (8) and (9) guarantee that all controllable EVs operate continuously within their designated usage periods

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

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

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

Equation (10) describes variations in station and EV battery levels, while Equation (11) defines the charging and discharging limits of both station and EV batteries.

$$SOC_{\omega.t}^X = SOC_{\omega.t-1}^X + Z_{\omega.t}^X \eta^{ch.X}\left(\frac{P_{\omega.t}^{S2X}}{Cap^X}\right) - Y_{\omega.t}^X\left(\frac{P_{\omega.t}^{X2S} + P_{\omega.t}^{X2G}}{\eta^{dis.X} Cap^X}\right) \quad X \in \{B.EV\} \tag{10}$$

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

Equations (12) to (15) specify the constraints on charging and discharging rates for station and EV batteries

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

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

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

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

Equation (16) calculates the station's power balance, considering contributions from wind and solar power, as well as power transfers from the station battery and EVs.

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

$$Y_{\omega.t}^S P_{\omega.t}^{G2S} + Z_{\omega.t}^S P_{\omega.t}^{S2G} \leq P^{C.max} \quad \forall t.\forall \omega \tag{17}$$

$$Y_{\omega.t}^S + Z_{\omega.t}^S = 1 \quad \forall t \tag{18}$$

Power transactions between the grid and the station are limited by Equation (17), and Equation (18) ensures that the station can only transmit power in one direction at any given time.

2.3 Modelling The Effect Of Uncertainty

One of the well-known indicators to measure the financial risk is conditional value at risk (CVaR). CVaR is a risk assessment technique defined as follows:

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

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

Decision variables of CVaR, £ and SW_ω, are as follows:

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

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

In this study, the OF represents a maximization problem, where α and β denote confidence levels ranging between 0 and 1, determined by the decision maker. The positive variable SW_{ω} measures the positive deviation between the value at risk (VaR) and the objective function obtained in each scenario.

Compared to VaR, CVaR offers several advantages that enhance its applicability in risk management. While VaR is only continuous for normal probability distributions, CVaR remains continuous across all probability distributions, addressing this limitation. Additionally, CVaR extends beyond VaR by controlling losses in extreme scenarios, effectively capturing the risk that exceeds the VaR threshold. At the same confidence level, CVaR is considered more conservative than VaR, as it accounts for risks beyond the VaR threshold. However, due to its conservative nature, CVaR may not be a suitable risk measure for highly risk-averse decision-makers. In this paper, CVaR is integrated into the objective function alongside the mean value, ensuring a comprehensive risk-aware optimization approach. This integration enhances the robustness of the model by considering extreme losses while maximizing system profitability.

2.4 Coordinated EMS with P2P Power Trading between Stations

The proposed EM model in the previous section can be aggregated to extend its application across multiple procumers. In this approach, the profitability of each procumer must be ensured within the coordinated model, considering the inherent uncertainties in renewable energy generation and load demand. By implementing a coordinated EM strategy for multipe stations, it is highly probable that the overall profitability of each station will increase due to optimized energy management. The schematic of coordinated model for EM is depicted in Fig.1.

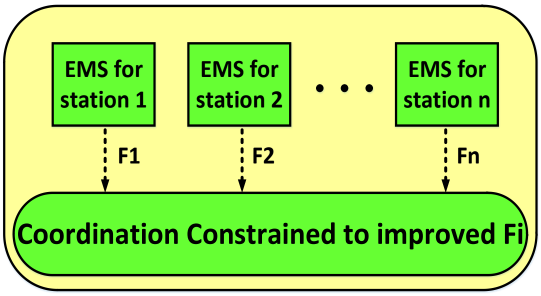


Fig .1. Coordinated EM model for procurers

Coordinated EMS model is same as the introduced model with adding equations (23) to (25) as follows:

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

$S.t:$

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

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

In the above equations, S represents the number of stations, while the constraints are equation (1)-(22) and $OF^{max}(S)$ denotes the maximum objective variable for each station individually.

To further enhance the EMS, P2P facilities are incorporated, allowing energy exchange between stations. The traded power between stations follows the approach outline in [21], while from perspective of each station, other stations are treated as a black box in the optimization process.

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

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

The power output and input summation of stations other than jth station, is determined by Equation (26) and Equation (27).

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

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

Equation (28) and Equation (29) state that these summations are equal to the corresponding station (jth one) input/output, respectively.

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

Equation (30) provides the power balance of each station after implementation of P2P transactions between microgrid and integration of OPV.

3. Numerical Studies

To evaluate the proposed model, a station in Italy is considered as the case study. All relevant data for this study is available in [25]. Fig.2 depicts the correlation expected cost and risk level sensitivity. It can be concluded that increased risk sensitivity results in higher financial impacts, highlighting heightened volatility and financial risk.

Electric vehicles (EVs) are treated as controllable EVs, with a waiting capacity of three hours in the morning and four hours in the evening. The verification of the model has been conducted through the following analyses:

- Risk Analysis
- Comparison between Coordinated EMS and Individual EMS

Two scenarios have been examined for a system consisting of five EV stations:

- Senario 1: Implementation of Individual EMS
- Senario2: Implementation of Coordinated EMS

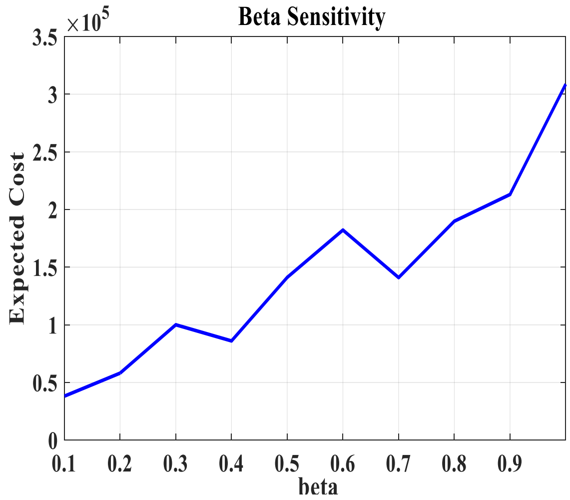


Fig .2. Expected cost changes by β

The income for each station and aggregated income of all stations are shown in Fig.3.

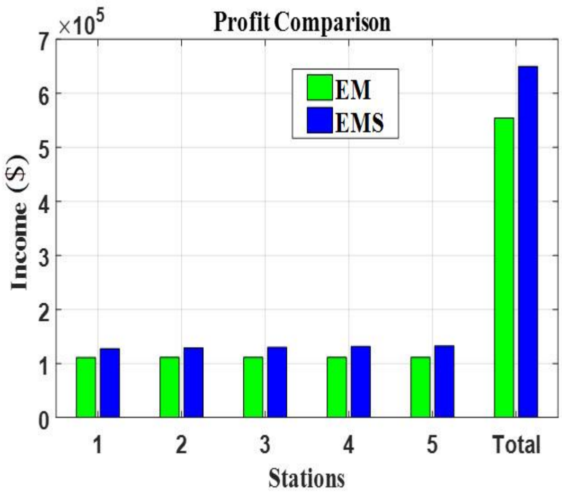


Fig .3. Comparative chart of individual station profits and coordinated profits

The income distribution among these stations, highlights a noticeable improvement in total earnings when a coordinated EMS is implemented. Moreover, Table.1 further quantifies this enhancement, demonstrating the specific financial gains achieved by each station under EMS.

Based on Table 1, the total difference between EM and EMS provides a profit enhancement amounting to $95,044.87, which reflects a 1.17-fold increase in overall profitability.

It can be concluded that coordinating energy management through the integration of P2P transactions leads to a more profitable EMS for consumers.

Table (1). Profit in coordinated model

Station	Individual (EM) ($)	Coordinated (EMS) ($)
1	111024.472	127316.193
2	111145.897	128589.355
3	111186.712	129875.249
4	111320.274	131174.001
5	111430.973	132485.741
Total	554395.666	649440.540

The incorporation of OPV systems further enhances this profitability by enabling decentralized and flexible energy generation. Consequently, the participation of EV stations in demand response (DR) programs can be increased, as OPV technology facilitates more sustainable and efficient energy trading, encouraging greater engagement from EV owners.

The total wind and solar generation across the stations is illustrated in Fig.4.

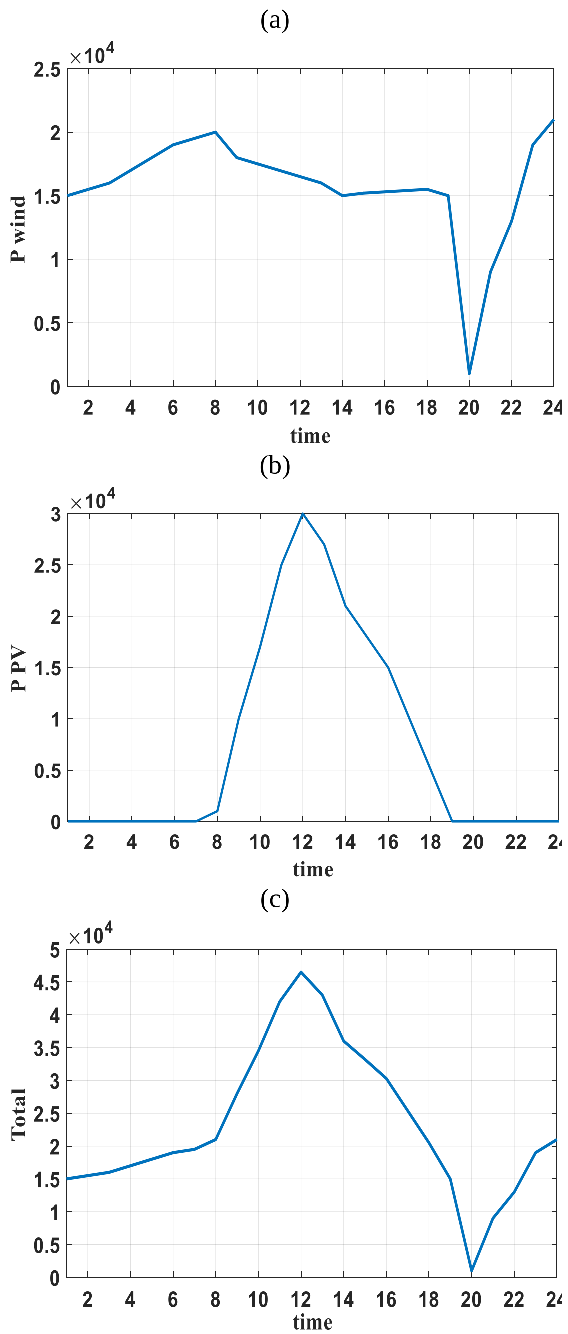


Fig.4. (a)Wind, (b)Solar, (c)Total Renewable Energy Generation (Appendix, Table I)

Fig.5 presents a comparison of load profiles under three different conditions: without EMS, with individual EMS, and with coordinated EMS. The results demonstrate that the DPR effectively reduces energy purchases during peak price periods, leading to cost savings. Furthermore, the coordinated EMS outperforms the individual EM, providing greater efficiency in load shifting and energy cost reduction.

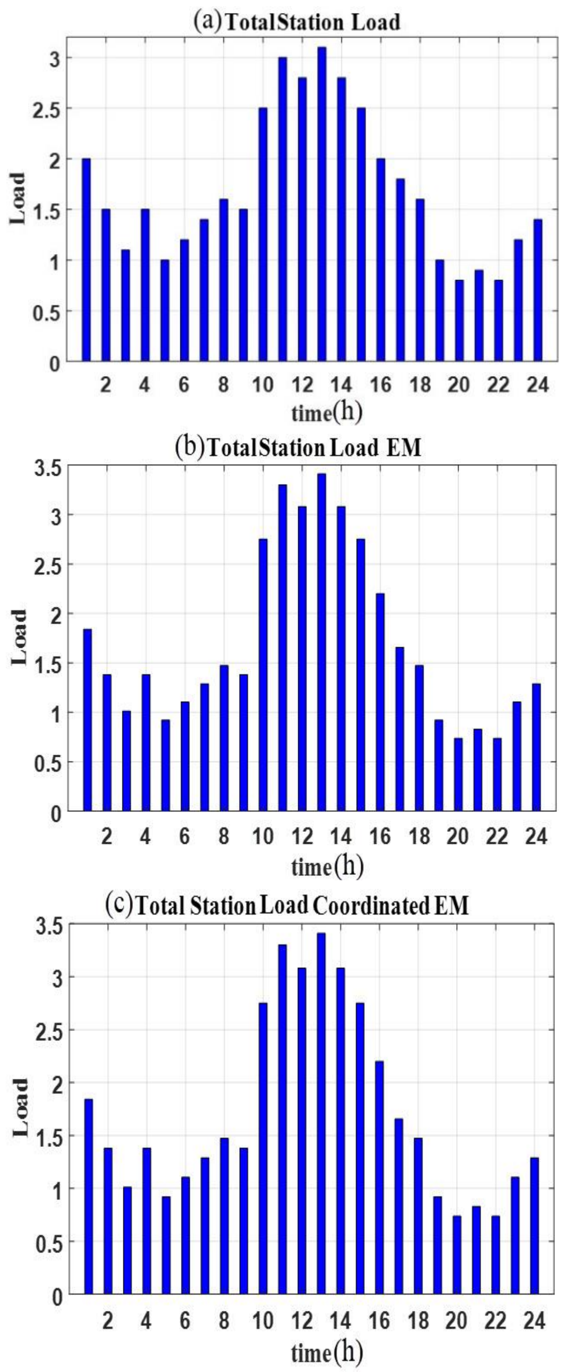


Fig.5. Total station load (a)without use of EMS, (b)with individual EMS and (c)coordinated EMS (Appendix, Table II)

Fig.6depicts the difference in EV loads in scenario 2 and 3. During the 6-hour peak period, the load in scenario 3 is higher, primarily due to the enhanced integration of solar, wind, and OPV energy for EV charging. In contrast, during off-peak periods, scenario 3 shows a lower load, as renewable energy generation does not sufficiently meet the demand, leading to greater reliance on conventional power sources or stored energy. The inclusion of OPV further supports the system by providing additional renewable energy, thus facilitating improved load management and balancing.

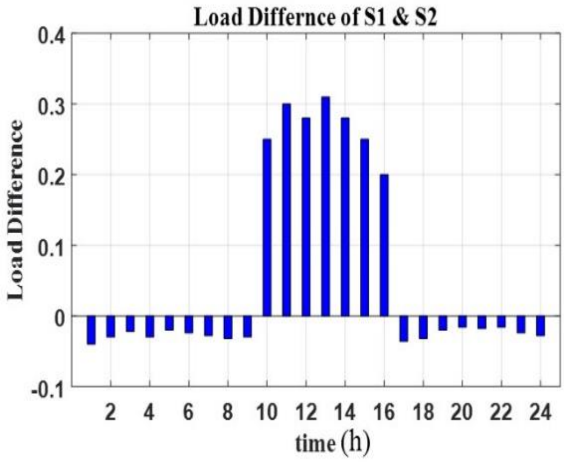
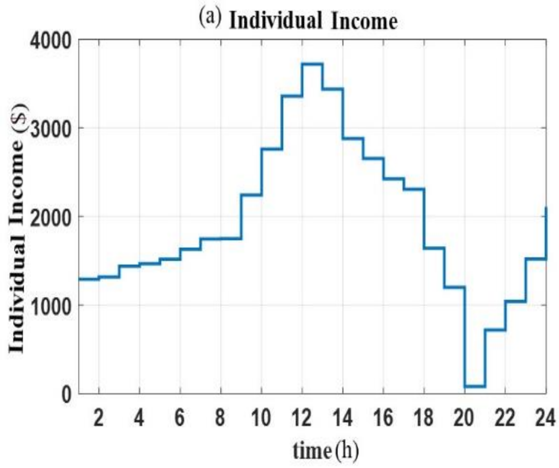


Fig.6. Difference of EV loads between scenarios 3 and 2

Fig.7illustrates the comparison of station income under two different scenarios.



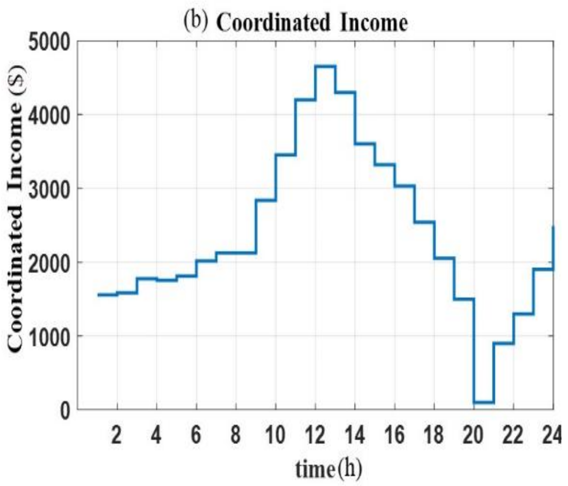


Fig.7. Income of stations (a) Individual and (b) Coordinated two scenarios (Appendix, Table III)

The results indicate that the coordinated model proves to be more profitable not only for individual entities but also for the grid operator. This is primarily due to its ability to effectively manage and shift loads, resulting in improved energy utilization and economic benefits compared to the individual EMS application. Additionally, when incorporating OPV, the coordinated model's efficiency and profitability are further enhanced, as OPV contributes to renewable energy generation, lowering overall energy costs and maximizing grid stability.

4. Conclusion

In this paper, the energy management of the system is analyzed to maximize network profitability by integrating renewable energy sources (wind, solar) and controllable EVs, while incorporating certainty with the conditional risk criterion in two different modes. The results show that the total profit has increased in all stations compared to the other mode. Additionally, both individual station profits and the overall network profit have improved. By utilizing OPV technology, the profitability of both individual stations and the overall network has increased. On a larger scale, this concept can also contribute to reducing peak loads in distribution grids.

5. The use of bi-level optimization could ensure profitability at both upper and lower levels, providing a balanced and efficient approach to energy management. Additionally, integrating V2G technology into EMS could further increase station profits while lowering EV charging costs. Moreover, efforts to develop adoption models for multi-mode transportation patterns could be explored. For future research**,** hub energy systems could be considered as a test model to enhance cooperation between various energy resources.

References

[1] Ramachandran, T.; Mourad , A.H.I.; Hamed , F. A Review on Solar Energy Utilization and Projects: Development in and around the UAE. Energies **2022**, 15, 3754.

[2] IRENA. Power System Flexibility for the Energy Transition-Report. Available online: https://www.irena.org/publications (accessed on 20 September 2022).

[3] National Energy Administration of China. NEA Online Press Conference in the Second Quarter of 2022. Available online:https://www.nea.gov.cn/2022-04/29/c_1310579541.htm (accessed on 29 April 2022).

[4] Lund, H.; Kempton, W. Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy **2008**, 36, 3578–3587.

[5] Kempton, W.; Letendre, S.E. Electric vehicles as a new power source for electric utilities. Transp. Res. Part D Transp. Environ. **1997**,2, 157–175.

[6] Letendre, S.E.; Kempton,W. The V2G concept: A new model for power? Public Util. Fortn. **2001**, 140, 16–27.
[7] Peng, M.; Liu, L.; Jiang, C. A review on the economic dispatch and risk management of the large-scale plug-in electric vehicles (PHEVs)-penetrated power systems. Renew. Sustain. Energy Rev. **2012**, 16, 1508–1515.
[8] Lehtola, T.; Zahedi, A. Solar energy and wind power supply supported by storage technology: A review. Sustain. Energy Technol.Assess. **2019**, 35, 25–31.
[9] Liu, S.; Chen, Y.; Leng, Z.; Su, Y.;Wang, H.; Liu,W. Orderly Charging and Discharging Scheduling Strategy for Electric Vehicles Considering the Demands of Both Users and Power Grid. In Proceedings of the 2021 China Automation Congress (CAC), Beijing,China, 22–24 October 2021; pp. 3434–3439.
[10] Zheng, Y.; Shao, Z.; Jian, L. The peak load shaving assessment of developing a user-oriented vehicle-to-grid scheme with multiple operation modes: The case study of Shenzhen, China. Sustain. Cities Soc. **2021**, 67, 102744.
[11] Dik, A.; Omer, S.; Boukhanouf, R. Electric Vehicles: V2G for Rapid, Safe, and Green EV Penetration. Energies **2022**, 15, 803.
[12] https://chargearoundaustralia.com/
[13] A. Mohamed, V. Salehi, T. Ma, and O. A. Mohammed. Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy. IEEE Trans. Sustain. Energy, 5(2):577–586, 2014.
[14] W. Tushar, C. Yuen, S. Huang, D. B. Smith, and H. V. Poor. Cost minimization of charging stations with photovoltaics: An approach with EV classification. IEEE Trans. Intell. Transp. Syst., 17(1):156–169,2016.
[15] H. Liang, B. J. Choi, W. Zhuang, and X. Shen. Optimizing the energy delivery via V2G systems based on stochastic inventory theory. IEEE Trans. Smart Grid, 4(4):2230–2243, 2013.
[16] Z. Wei, Y. Li, Y. Zhang, and L. Cai. Intelligent parking garage EV charging scheduling considering battery charging characteristic. IEEE Trans. Ind. Electron., 65(3):2806–2816, 2018.
[17] R. Wang, G. Xiao, and P. Wang. Hybrid centralized-decentralized (HCD) charging control of electric vehicles. IEEE Trans. Veh. Technol., 66(8):6728 – 6741, 2017.
[18] Y. Kim, J. Kwak, and S. Chong. Dynamic pricing, scheduling, and energy management for profit maximization in PHEV charging stations. IEEE Trans. Veh. Technol., 66(2):1011–1026, 2017.
[19] C. Jin, X. Sheng, and P. Ghosh. Optimized electric vehicle charging with intermittent renewable energy sources. IEEE J. Sel. Topics Signal Process, 8(6):1063–1072, 2014.
[20] L. Zhou, F. Li, C. Gu, Z. Hu, and S. Le Blond. Cost/benefit assessment of a smart distribution system with intelligent electric vehicle charging. IEEE Trans. Smart Grid, 5(2):839–847, 2014.
[21] R. Wang, P. Wang, and G. Xiao. Two-stage mechanism for massive electric vehicle charging involving renewable energy. IEEE Trans. Veh. Technol., 65(6):4159–4171, 2016.
[22] Y. Liu, R. Deng, and H. Liang. Game-theoretic control of PHEV charging with power flow analysis. AIMS ENERGY, 4(2):379–396, 2016.
[23] T. Zhang, W. Chen, Z. Han, and Z. Cao. Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price. IEEE Trans. Veh. Technol., 63(6):2600–2612, 2014.
[24] M. Wang, H. Liang, R. Zhang, R. Deng, and X. Shen. Mobility-aware coordinated charging for electric vehicles in VANET-enhanced smart grid. IEEE J. Sel. Areas Commun, 32(7):1344–1360, 2014.

[25] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie. Reliability studies of modern distribution systems integrated with renewable generation and parking lots. IEEE Trans. Sustain. Energy, 8(1):431–440, 2017.

[26] L. Liu, F. Kong, X. Liu, Y. Peng, and Q. Wang. A review on electric vehicles interacting with renewable energy in smart grid. Renew. Sustainable Energy Rev., 51:648–661, 2015.2169-3536 (c) 2018 IEEE.

[27] L. Yang, J. Zhang, and H. V. Poor. Risk-aware day-ahead scheduling and real-time dispatch for electric vehicle charging. IEEE Trans. Smart Grid, 5(2):693–702, 2014.

[28] B. Sheykhloei, T. Abedinzadeh, L. Mohammadian, and B. Mohammadi-Ivatloo, "Optimal co-scheduling of distributed generation resources and natural gas network considering uncertainties," *Journal of Energy Storage*, vol. 21, pp. 383-392, 2019.

[29] 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.

Appendix

Table I. Solar, Wind and Total Energy Generation

Hour	P_{wind}	P_{PV}	Total
1	15000		15000
2	15500		15500
3	16000		16000
4	17000		17000
5	18000		18000
6	19000		19000
7	19500		19500
8	20000	1000	21000
9	18000	10000	28000
10	17500	17000	34500
11	17000	25000	42000
12	16500	30000	46500
13	16000	27000	43000
14	15000	21000	36000
15	15200	18000	33200
16	15300	15000	30300
17	15400	10000	25400
18	15500	5000	20500
19	15000		15000
20	1000		1000
21	9000		9000
22	13000		13000
23	19000		19000
24	21000		21000

Table II. Load Distribution

Hour	Load	Individual EMS	Coordinated EMS	Difference
1	2	1.84	1.8	-0.04
2	2	1.38	1.35	-0.03
3	1	1.012	0.99	-0.022
4	2	1.38	1.35	-0.03
5	1	0.92	0.9	-0.02
6	1	1.104	1.08	-0.024
7	1	1.288	1.26	-0.028
8	2	1.472	1.44	-0.032
9	2	1.38	1.35	-0.03
10	3	2.75	3	0.25
11	3	3.3	3.6	0.3
12	3	3.08	3.36	0.28
13	3	3.41	3.72	0.31
14	3	3.08	3.36	0.28
15	3	2.75	3	0.25
16	2	2.2	2.4	0.2
17	2	1.656	1.62	-0.036
18	2	1.472	1.44	-0.032
19	1	0.92	0.9	-0.02
20	1	0.736	0.72	-0.016
21	1	0.828	0.81	-0.018
22	1	0.736	0.72	-0.016
23	1	1.104	1.08	-0.024
24	1	1.288	1.26	-0.028

Table III. Income

Hour	Coordinated Income	Individual Income
1	1555.436	1292.003
2	1584.96	1318.668
3	1774.272	1441.092
4	1754.002	1468.198
5	1811.231	1518.144
6	2015.577	1631.564
7	2127.395	1746.552
8	2124.844	1749.753
9	2838.521	2241.657
10	3450	2760
11	4200	3360
12	4650	3720
13	4300	3440
14	3600	2880
15	3320	2656
16	3030	2424
17	2540	2307.496
18	2050	1640
19	1500	1200
20	100	80
21	900	720
22	1300	1040
23	1900	1520
24	2490.548	2109.046