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EV-integrated Community Microgrid Scheduling considering Distributed Generation, Non-flexible Load and Dynamic Pricing Uncertainties[#]

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ABSTRACT

Flexible devices with remote monitoring and control availabilities, integrated behind-the-meter or last mile of electricity (grid edge) have significantly become widespread in the past decade. There are emerging distributed energy resource (DER) management solutions that give DER more active roles in power system and energy market operation. DER coordination incorporates inherent uncertainties related to distributed generation from intermittent renewables, non-flexible loads and dynamic prices. Consideration of uncertainties in optimum energy scheduling in community microgrids with a large number of electric vehicles can provide considerable benefits. This study presents a cloud-based optimal energy scheduling approach that considers diverse uncertainties in EV charging coordination as part of community microgrid energy scheduling. A case study is conducted for a representative community microgrid to investigate the benefits and challenges in uncertainty considered optimal energy scheduling.

Keywords: community microgrid, distributed generation, dynamic pricing, electric vehicle charging, energy management, uncertainty

NONMENCLATURE

Abbreviations	
CREST	Centre for Renewable Energy Systems Technology
DER	Distributed Energy Resource
EV	Electric Vehicle
GW	Gigawatt
kW	Kilowatt
kWh	Kilowatt-hour
MW	Megawatt
MWh	Megawatt-hour
PV	Photovoltaic panel
SoC	State of Charge
U.S.	United States
Symbols	
bV	Beginning period of a trip
cs	Charging station index
c_T	Overall costs
CE	Energy charged by a vehicle
CI	Confidence interval
CR	Charging rate
CS	A set of charging stations
eV	Ending period of a trip
E_p	Energy generation rate for PV
E_{Pmax}	Maximum energy purchase limit
$E_{purchase}$	The amount of energy purchased
E_{sell}	The amount of energy sold
E_{Smax}	Maximum energy sale limit
E_V	The energy stored in a vehicle
E_{Vc}	The charged energy
E_{Vd}	The discharged energy
E_{Vmax}	The maximum storage capability of a vehicle
E_{Vout}	The energy spent outside
h	Idle waiting time index
H_V	A set of idle waiting times
I_{CS}	Binary variable for the usage of charging station
I_{CSu}	Auxiliary binary variable for use of a single charger for a given interval
I_p	Binary variable for PV on/off status
I_{sp}	Binary variable for energy sale to grid
I_{Vb}	Idle waiting time starting period binary variable
I_{Ve}	Idle waiting time ending period binary variable
I_{Vc}	The charging status of a vehicle

I_{Vd}	The discharging status of a vehicle
m_{Vc}	Cost of energy purchased from grid
m_{Vd}	Depreciation cost of vehicle
m_p	Depreciation cost per unit charge, discharge of EV and generation from PV
m_{pi}	The mean value of a parameter of interest at a given time
M	A big number
n	Trip index
n_{Vd}	Vehicle charge/discharge efficiency
n_p	PV efficiency
N_V	A set of trips
p_s	Parameter of interest
PP	Forecasted energy purchase price
s	Scenario index
s_{pi}	The standard deviation of a parameter of interest at a given time
S	The number of considered scenarios
SP	Forecasted energy sale price
t	Time period index
t'	Alias for the time period index
T	Planning horizon
v	Vehicle index
V	A set of vehicles
VC	Energy consumption of vehicle during charging
z	Confidence level value

1. INTRODUCTION

Decarbonizatio n of the energy industry takes place at a fast pace considerably through the wide deployment of distributed generation from renewables and record-braking sales of EVs [1-2]. Combined with advanced remote monitoring and control availabilities, behind-the-meter and grid-edge flexible devices take an increasingly active role in power system and energy market operation. There are products and solutions currently available in the market that can coordinate up to 1000 EVs on-premise [3], have remote control over several GW-scale portfolios [4] and can provide hundreds of MW-scale flexibilities coordinating hundreds to thousands of grid edge assets [5].

The mentioned applications that can even significantly impact the frequency stability of the interconnected power systems heavily depend on the voluntary participation of a large number of small customers through aggregators and coordinators providing monetary incentives with rare reflection of the penalties incurred at the wholesale market level due to unmet targets. The annual demand response statistics in the US could be given as an example, with 11 million participants, around 96% of which are residential. Moreover, there are several inevitable uncertainties due to forecasting errors in distributed generation, non-flexible load and dynamic prices. Therefore, it is a major challenge for DER management solution providers to determine optimal energy scheduling plans in a highly dynamic environment.

Community energy system is an emerging concept with different configurations ranging from shared residential resources in a premise to shared local resources in a specific distribution region and shared virtual resources located at different locations forming a virtual energy pool [6].

There are several deployments of community energy systems based on shared local resources in a specific region in the US. Clean Coalition establishes pioneering community microgrids in different areas from hundreds of kWs to MWs scale distributed generation from PV and from a couple of hundreds of kWh to hundreds of MWh of battery energy storage capacity, providing service to tens to thousands of end-users [7]. There is also increasing interest in establishing virtual formations to coordinate remotely located assets, without requiring consent and active participation of all the customers located in a specific region. Non-place-based communities share common rules for producing, managing or purchasing energy, benefiting from their aggregated flexibilities and synergies.

As of May 2022, there are 202 available EV models on roads and 38 announced models upcoming in the near future [8]. Battery capacities of the available EVs range from 16.7 to over 100 kWh providing a driving range from 95 to 640 km. There are several types of electric vehicle battery chargers (EVBCs) in the market and the field. Charging systems are mainly categorized as on-board and off-board with unidirectional or/and bidirectional power flow [9]. The chargers are divided into three groups according to their power levels. Level 1 single-phase onboard chargers have rates usually from 3 to 7 kW, allowing supply using a normal power outlet, taking 4 to tens of hours for full charging, depending on 5 to 50 kWh energy storage capacity of EVs. Level 2 on-board chargers can be 1- or 3-phase with a 7-22 kW charging rate, usually requiring dedicated supply equipment, with a charging period of 1 to 6 hours. It is the most widely used charger type on private and public premises. The last category is Level 3 off-board, 3-phase, fast chargers preferred for only commercial uses so far, reaching 50 to 100 kW, and rapid chargers reaching even 350 kW charging rates with a charging duration from 15 min to 1 hour.

There are a number of common assumptions and oversimplifications in EV charging studies in the literature. While many studies consider that EV charging takes place in limited deterministic time periods of a day, field pilots proved that EV charging can take place at any time period in a day with different probabilities [10]. Although it is widely assumed that cars are fully charged by the end of each charging session, 30% to 50% of customers that participate in field pilots leave charging spots and start their trips with 50% to 90% SoC. Despite many studies considering single charging in a day, 20% of the customers charge their car more than once. Another conflicting assumption is deterministic specification of initial SoC levels from a limited range in the beginning of charging sessions, while in the field, EVs start charging with any initial SoC level covering their whole operational range with 9% to 13% probabilities. The number of car models in the explored scenarios are highly limited, belonging to a couple of brands, while there are hundreds of model available globally, and tens of models that became widespread in national markets. These inconsistencies require development of more detailed modelling and analysis approaches to represent and investigate EV charging behavior, benefiting from realistic statistics, characteristics and probabilities.

There are real measurements, detailed statistics, probabilities and characteristics available in different resources, comprising EV brands and models, driving times, trip distances, overall parking times and charging habits that could be used in stochastic generation of more realistic charging sessions [8].

A study explored minimization of overall operating costs in microgrids considering PV output uncertainty [11]. Another study considered both generation from wind output and load uncertainty [12]. A different study considers uncertainty of failures caused by extreme environmental conditions in microgrid energy management [13]. A comprehensive review study highlights common use of uniform error distribution around forecasted points in different studies [14]. Uncertainty oriented studies have not considerably investigated EV charging-included energy scheduling in community microgrids under several uncertainties.

The studies based on uncertainty consideration in microgrid scheduling usually considers deterministic probability distribution functions [15], while in this study the probability distribution is based on historical data and realistic estimation accuracies. While PV generation and customer load forecast uncertainties are commonly considered in past studies, dynamic pricing rate uncertainties and particularly EV charging related uncertainties are usually not taken into account [16-19]. Although some studies considered single or a couple of uncertainties [20-21], their combined consideration in energy scheduling can reveal new synergies and represent a more realistic case.

This study presents a cloud-based energy optimization approach that takes into account diverse uncertainties inherent in distributed generation from PV, non-flexible aggregate residential demand and dynamic hourly prices, for scheduling large number of EV charging sessions in community microgrids. Section 2 describes the developed and utilized EV charging and behavior model, uncertainties and energy optimization approaches. Section 3 presents a case study for an urban community microgrid with large number of customers and high penetration of PVs and EVs. Section 4 discusses the findings and provides directions for future works.

2. METHODOLOGY

This section describes the modelling of EV charger and daily charging behavior, uncertainty representation of distributed PV, non-flexible residential demand and dynamic prices; and energy scheduling optimization under dedicated subsections.

2.1 EV Charger and Charging Behavior Modelling

All the constraints except (10), (12) and (13) are specified for all members of the corresponding sets. Additional explanations are given next to these three constraints to elaborate more about the indices they are determined for.

Simultaneity of charging and discharging sessions for the same EV for a given time period is prevented by the constraint (1). The charging/discharging statuses are represented by 0 in case of no activity, and 1 if the related activity takes places.

$$I_{Vd}(t,v) + I_{Vc}(t,v) \leq 1 \quad (1)$$

(2) and (3) determine the constraints for the amount of energy that can be charged/discharged by a vehicle at a time period, based on vehicle model and charging station capabilities. Each of these constraints relates the decision variables for feasibility.

$$I_{Vc}(t,v) \times \frac{1}{M} \leq E_{Vc}(t,v) \leq I_{Vc}(t,v) \times M \quad (2)$$

$$I_{Vd}(t,v) \times \frac{1}{M} \leq E_{Vd}(t,v) \leq I_{Vd}(t,v) \times M \quad (3)$$

(4) ensures that a car can not discharge energy more than the amount available in its batteries by the previous time period. When specifying (4), the energy storage capability of the batteries is considered as the limited capacity, specified by the battery manufacturer for safe operation preventing deep discharging and overcharging that can criticially and irreversibly damage the battery.

$$E_{Vd}(t,v) \leq E_V(t-1,v) \quad (4)$$

(5) calculates the energy stored in the vehicle, by adding the difference of the amount of the energy charged and discharged, to the initial energy stored in vehicle's batteries and subtracting the amount of energy spent outside until the related period.

$$E_V(t,v) = E_V(0,v) + \sum_{t' \le t} E_{Vc}(t',v) - E_{Vd}(t',v) - \sum_{t' \le t} \sum_{n(v) \in N_V(v)} E_{Vout}(t',v,n(v)) \quad (5)$$

(6) limits the energy storage level of a car at any time period to the maximum storage capability of its batteries.

$$E_V(t,v) \le E_{Vmax}(v) \quad (6)$$

(7) and (8) are determined to represent if the car is charged or discharged in another charging station respectively, when it is away from the considered charging area, during a trip that spans a number of time periods. More detailed information about constraints (1) to (8) is provided in [22].

$$\sum_{bV(v,n(v)) \le t \le eV(v,n(v))} I_{Vc}(t,v) = 0 \quad (7)$$

$$\sum_{bV(v,n(v)) \le t \le eV(v,n(v))} I_{Vd}(t,v) = 0 \quad (8)$$

(9) is used to prevent charging stations from charging more than one vehicle at any time period.

$$\sum_{v \in V} I_{CS}(cs,v,t) \le 1 \quad (9)$$

(10) is determined for $t \in T, cs \in CS, v \in V: CR(v) \notin CR(cs)$, ensuring that a vehicle cannot be charged at a charging station, which does not support its charging protocol.

$$I_{CS}(cs,v,t) = 0 \quad (10)$$

(11) is used to guarantee that the amount of energy charged by a vehicle at a period must be equal to the total amount of energy charged by the vehicle at all the charging stations at that period.

$$\sum_{cs \in CS: CR(v) \in CR(cs)} CR(cs) \times VC(v) \times I_{CS}(cs,v,t) = CE(t,v) \quad (11)$$

(12) and (13) are specified to ensure that a charging session can take place only in consecutive time periods. These set of constraints are defined for all $v \in V$, $t \in T: bV(v,h(v)) \le t \le eV(v,h(v))$, $h(v) \in H_V(v)$.

$$\sum_{t' \in T: t' > 0 \wedge t' \le t} I_{Ve}(t'-1,v) - I_{Vc}(t',v) - I_{Vc}(t'-1,v) - I_{Vb}(t',v) = 0 \quad (12)$$

$$\sum_{t' \in T: t' = 0 \wedge t' = t} I_{Vc}(t',v) - I_{Vb}(t',v) = 0 \quad (13)$$

(14) and (15) ensure that, for a time period when vehicle is not outside, not more than one charging session can begin or end.

$$\sum_{bV(v,h(v)) \le t \le eV(v,h(v))} I_{Vb}(t,v) \le 1 \quad (14)$$

$$\sum_{bV(v,h(v)) \le t \le eV(v,h(v))} I_{Ve}(t,v) \le 1 \quad (15)$$

(16) and (17) prevents any vehicle from using more than one charging station at a time period when it is not on a trip outside.

$$\sum_{bV(v,h(v)) \le t < eV(v,h(v))} I_{CS}(cs,v,t) \le M \times I_{CSu}(cs,v,h(v)) \quad (16)$$

$$\sum_{cs \in CS} I_{CSu}(cs,v,h(v)) \le 1 \quad (17)$$

(18) is defined to relate the usage of charging stations with charging status of vehicles for feasibility.

$$\sum_{cs \in CS} I_{CS}(cs,v,t) = I_{Vc}(t,v) \quad (18)$$

2.2 Distributed PV, Non-flexible Residential Demand and Dynamic Price Uncertainty Determination

Univariate normal distribution is used to determine local generation, non-managable demand and price uncertainties. The planning horizon (24 hours) is divided into a desired number of periods, for each of which mean value and standard deviation parameters are derived from stochastically generated closely related scenarios or historical real data that belong to similar days, to represent uncertainty using uniform distribution functions. The mean value of parameter of interest for a considered time interval can be derived as in (19).

$$m_{pi}(t) = \sum_{s \in S} \frac{p_s(t)}{S} \quad (19)$$

The standard deviation of a parameter of interest for a considered time interval can be derived as formulated in (20).

$$s_{pi}(t) = \sqrt{\frac{\sum_{s \in S} \left(p_s(t) - m_{pi}(t)\right)^2}{S}} \quad (20)$$

Using mean and standard deviation values and a specified confidence level value, confidence interval of a parameter of interest for a considered time interval can be calculated as in (21).

$$CI(t) = m_{pi}(t) \pm z\frac{s_{pi}(t)}{\sqrt{S}} \tag{21}$$

In (19), (20) and (21), parameter of interest can be obtained from a set of distributed PV generation daily scenarios, overall daily residential demand scenarios of a number of houses or dynamic pricing scenarios, as presented in section 3.

2.3 Energy Scheduling Optimization

IBM ILOG CPLEX Optimizer (version 12.6.1) is used as the optimization engine, as a high-performance mathematical programming solver for mixed integer programming.

For the purpose of day-ahead energy optimization, for a decision horizon of 24 hours, electric vehicle charging sessions scheduling is made based on EV owner preferences (tripping periods, charging outside the considered area and mileage), the residential non-flexible consumption, distributed generation from PV and hourly dynamic prices.

The objective function for each considered scenario, aims to minimize of the cost of net energy purchased from grid and depreciation cost of assets (in this study, EV and PV) as formulated in (22). (23) is used to guarantee that the total of amount of energy sold to grid and charged by vehicles does not exceed the total amount of energy purchased from the grid, discharged by vehicles and generated from PV. (24) and (25) are used to limit the amounts of purchased and sold energy and allow either purchasing or selling at any time period.

The objective function of stochastic optimization can be represented as in (26), aiming to select a schedule that will minimize the overall cost of the considered stochastic scenarios based on the uncertainty ranges of parameters as explained in section 2.2.

3. CASE STUDY

A case study is explored for a representative community microgrid with 50 residential customers, 50 kWp PV cluster and 10 electric vehicle charging stations providing normal and fast charging services. Among a large dataset of individual daily stochastic residential demand profiles for each house, aggregate demand profiles are obtained for several days. The individual residential demand profiles are generated using CREST Demand Model of Loughborough University [12]. Using macro codes in Excel, depending on the specified occupants in a house, weekday or weekend and allocated individual home appliances from a database of 34 types of appliance, a bottom-up approach is followed to generate the aggregate household energy demand up to 1-min resolution from individual device operation schedules, matching annual household appliance consumption statistics in the UK.

$$\begin{aligned} c_T(s) = \sum_{t\in T} PP(s,t) \times E_{purchase}(s,t) \\ - SP(s,t) \times E_{sell}(s,t) \\ + \sum_{v\in V}\sum_{t\in T} m_{Vc}(v) \\ \times E_{Vc}(t,v) \\ + \sum_{v\in V}\sum_{t\in T} m_{Vd}(v) \\ \times E_{Vd}(t,v) \\ + \sum_{p\in P}\sum_{t\in T} m_p(p) \\ \times E_p(s,t,p) \times I_p(s,t,p) \end{aligned} \tag{22}$$

$$\begin{aligned} E_{sell}(s,t) + \sum_{v\in V} E_{Vc}(t,v) \\ \le E_{purchase}(s,t) \\ + \sum_{v\in V} n_{Vd}(v) \times E_{Vd}(t,v) \\ + \sum_{p\in P} n_p(p) \times E_p(s,t,p) \\ \times I_p(s,t,p) \end{aligned} \tag{23}$$

$$E_{purchase}(s,t) \le (1 - I_{sp}(t)) \times E_{Pmax}(t) \tag{24}$$

$$E_{sell}(s,t) \le I_{sp}(t) \times E_{Smax}(t) \tag{25}$$

$$minimize \sum_{s\in S} c_T(s) \tag{26}$$

The tool has been cited in over 1000 studies so far, ranging from future distribution grid planning to distributed energy resources integration, from microgrid energy management to demand response applications. Further details of the tool can be found in [23].

The uncertainty range of aggregate residential demand is shown in Figure 1. Following the methodology presented in section 2.2, half-hourly demand uncertainties are specified to the optimization engine.

A set of daily solar irradiance profiles including cloudiness impact and related PV panel energy production efficiency is stochastically generated for summer using an advanced version of CREST tool details which are available in [24].

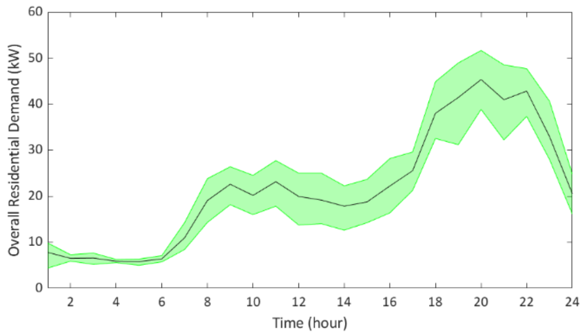

Fig. 1 Uncertainty range of aggregate residential demand of 50 houses

The uncertainty factor is represented using 80% confidence interval as stated in [25] (Figure 2).

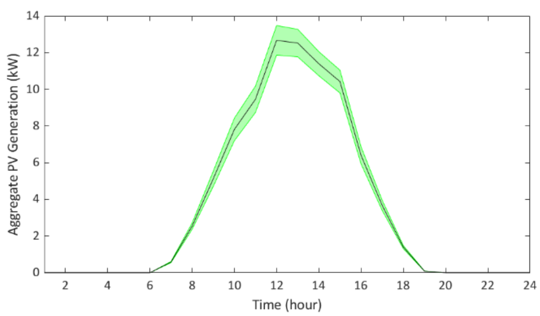

Fig. 2 Uncertainty range of aggregate PV generation with 80% confidence interval

The tool uses meteorological information and stochastic cloudiness ratios, generating stochastic daily solar irradiance and PV panel production profiles up to 1-min resolution. Price uncertainties are determined based on the forecasted and actual prices in a selected set of similar summer days of ComEd Hourly Pricing Program in use in the US [26] (Figure 3). The uncertainties are represented based on 95% confidence interval as stated in [27].

44 EV charging sessions with different available time durations are stochastically generated and used as part of the analysis, based on the explanations provided in section 2.2 and more details available in [28]. The time periods the cars are present near compatible chargers are shown in Figure 4.

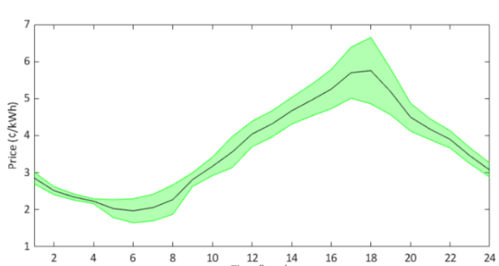

Fig. 3 Uncertainty range of hourly prices with 95% confidence interval

Each charging session is represented with a unique ID number on the vertical axis to better distinguish the sessions with overlapping time periods. The time periods are generally comparably longer than the minimum required time to charge each car to meet the energy need of users in their next trip. Inside these time periods, the optimization algorithm selects the most suitable, time windows to charger the cars.

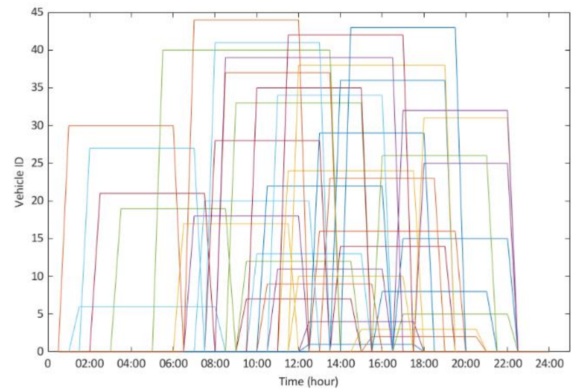

Fig. 4 The time periods the cars are available near compatible chargers and can be charged based on the optimization process results

Different number of stochastic runs are explored to determine the optimum schedule. In the explored scenario, better schedules with considerable additional cost savings were observed up to 100 runs, while beyond that level, negligibly minor changes in energy costs noted.

Table 1 comparatively presents single run, 20-run and 100-run results in overall energy costs. Exploration of high number stochastics runs in the range of considered uncertainties statistically makes the optimization solution closer to highly likely actual results, while a low number or single stochastic run may not cause determination of schedules based on less likely results.

Table 1. Comparison of overall costs per different number of runs

Number of considered stochastic scenarios	Resulting overall costs ($)	Savings compared to single run
Single run	1711	-
20 runs	1623	5.14%
100 runs	1604	6.29%

4. CONCLUSION

This study presented several uncertainties considered optimum energy scheduling in community microgrids with large penetration of PV and wide availability of EV coordination. Uncertainties in distributed generation from PV, non-manageable load and dynamic prices are taken into account when determining the optimum schedule.

The case study showed that, EV charging coordination considering uncertainties and running several stochastic scenarios can provide around 6% additional savings, by planning closer to highly likely cases. Future studies will consider further uncertainties related to end-user and other stakeholder behavior, including different types of flexible assets such as demand response and stationary batteries.

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