

Cloud-based Optimal Energy Scheduling of Photovoltaics and Electric Vehicle-integrated Community Microgrids

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Abstract—Community microgrid is one of the promising pathways to achieve higher levels of penetration of distributed generation from intermittent renewables and energy storage, further electrify heat and transport and enable active energy customers. Optimal energy scheduling of wide range and large number of flexible asset, using operational information from stakeholders (such dynamic pricing rates) and relying on customer preferences has been a processing power intensive major challenge. The inconsistencies between the common assumptions, simplifications in modeling, scenario determination and observations gained from field pilots require design and investigation of improved models and scenarios that can better represent reality. This study presents a cloud-based optimal energy scheduling approach for community microgrids with large penetration of photovoltaics and electric vehicle chargers. A case study for an urban energy community is explored highlighting the promising flexibility potential of EV charging coordination of wide range of car models and charger options.

Keywords—community microgrid, community energy system, electric vehicle charging, energy management, local energy communities.

I. INTRODUCTION

Power systems are facing bottom-up transformation, with massive deployment of photovoltaics, distributed energy storage and electrified heat and transport. Distributed generation from PV is expected to be more than doubled in residential, commercial and off-grid applications by 2024, compared to 2019 [1]. The annual sale of EVs is more than doubled in every two years from 2010 to 2020, which is followed by record breaking annual sales in 2020 and 2021 (3 million and 6.6 million cars respectively) even in the challenging market environment due to pandemic, reaching around 9% of the global car market [2]. Until 2030, 130 to 250 million EVs are expected be on roads. There are over 180 car models in the market in addition to 36 announced models upcoming in the near future [3].

Despite massive efforts, fossil fuels are in dominance in global electricity generation mix (by over 60%) and in world total energy supply (by over 80%) [1]. Contrary to national and international promising roadmaps, targets and incentives driving renewables deployment, there are social, economic,

technological and regulatory barriers on the path to achieving near- and mid-future objectives. Technical issues such as under/overvoltages especially in rural networks and overloading in urban distribution grids, in addition to challenges in financing high investment need for the integration of new technologies have led to adoption of novel approaches and business models.

Community microgrid is one of the pioneering and promising approaches to integrate and coordinate renewable energy technologies and low-carbon solutions into existing infrastructure. A group of customers, (not always necessarily have to be located next to each other or belong to same MV/LV transformer) can be coordinated to act together to financially and operationally match their energy profiles with PV panels and storage options. Due to challenges in motivating and convincing all the customers in a specific distribution region to participate in community microgrids, virtual formations that coordinate the voluntary customers from different locations is also becoming a common practice. Non-place-based communities mainly have the purpose of producing, managing or purchasing energy based on shared rules. There are increasing number of pioneering community microgrid applications. Clean Coalition deploys community microgrids across the US, with usually above 100 kW to hundreds of MWs of PV installed capacity and above 200 kWh to hundreds of MWhs of installed battery energy storage capability, serving tens to thousands of customers [4]. Brooklyn Microgrid is another exemplary success, providing a marketplace for locally generated energy from PVs [5]. Community microgrid is considered as a viable non-wires alternative for improving the reliability and energy security of customers and reduce vulnerability of local energy systems to natural disasters and regional blackouts, compared to costly infrastructure upgrades. Moreover, large number of photovoltaics and energy storage can be connected to the technically most suitable points in the considered regions, providing higher operational effectiveness compared to discrete and dedicated installation per customer.

There is also increasing interest and efforts in the literature on community microgrids. The number of publications have significantly been escalated from 2020 to 2022, representing more than half of the currently available works. A day-ahead

scheduling approach for the battery energy considering degradation costs using particle swarm optimization is presented in [6]. Scheduling of fuel cell electric vehicles in a community microgrid is studied in [7]. [8] investigated community microgrid scheduling considering building thermal dynamics and HVAC control. Another study considered management of centralized storage and PV systems in a rural community microgrid [9]. EV charging management in a community microgrid for 4 types of EVs, random initial SoC values and 3.3 kW charger is studied in [10]. 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. 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 the 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. One of the common assumptions in the literature is consideration of EV charging sessions in particular time periods of a day. On the other hand, field pilots proved that EV charging takes place at any time period in a day based on different probabilities [11]. Another wide assumption present in the literature is reaching to full SoC level by the end of every charging session, while in the field demonstration, 30 to 50% of the customers interrupt charging activities and start their trips with 50 to 90% SoC levels. Contrary to studies that consider single charging throughout a day, 20% of the customers is observed to be charging twice daily. Another common assumption is consideration of same or a limited range of initial SoC levels in the beginning of charging events, while in reality EVs start charging with any initial SoC level inside their operational range with 9 to 13% probability. The inconsistencies between the common assumptions in the literature and the field applications require adoption of more detailed approaches in modelling daily EV charging behavior, utilizing realistic statistics and probabilities.

Contrary to the simplifications summarized in the previous paragraph, there are several real measurement data and detailed models about the individual charging behavior of EVs in reliable resources. Moreover, statistics are available in different resources about the technical parameters of EV brands and models, driving times, distances, parking times and charging habits [3].

The studies in the literature and the preliminary field applications have not extensively investigated coordination of electric vehicle charging sessions under dynamic price and detailed EV owner preferences. Moreover, the majority of the studies have not considered cloud processing to overcome the challenges of optimal energy scheduling of large number of flexible assets.

This study proposes a cloud-based optimal energy scheduling approach investigated in a realistic scenario for community microgrids with photovoltaics and electric

vehicles. Section 2 describes the developed and adopted modelling, scenario determination and optimization methodologies, while section 3 presents a case study for an urban community microgrid with 90 customers and large penetration of photovoltaics and EV chargers. Section 4 discusses the findings and provides directions for future research.

II. METHODOLOGY

The methodology developed and adopted in this study is described under three subsections: EV charging behavior and charger modelling, community microgrid daily operation scenario development and optimization.

A. Charging Station and EV Charging Behavior Modelling

Each of the constraints in the model are defined for all members of the corresponding sets, except (10), (12) and (13). Hence, additional explanations are given for these three constraints to detail the indices they are defined for.

In order to prevent the simultaneity of charging and discharging sessions for the same EV the constraint in (1) is determined. $I_{Vc}(t, v)$ is the charging status of vehicle v from a vehicle cluster of V during period t of a planning horizon of T , while $I_{Vd}(t, v)$ is the discharging status for the same vehicle and time period. Each took the value 1 if the related activity is taking place and 0 in case of no activity.

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

The charged energy and discharged energy by the vehicle v during period t is represented by $E_{Vc}(t, v)$ and $E_{Vd}(t, v)$ respectively, in equation (2) and (3). M is a big number. 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 cannot discharge more than the energy stored in its battery. Here, energy storage capability of the battery is considered as the limited capacity, specified by the battery manufacturer as a safe operation region preventing deep discharging and overcharging that can vitally damage the battery.

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

(5) is the calculation of the energy stored in vehicle v at period t (denoted by $E_V(t, v)$), by taking the sum of the initial energy stored in the battery with the difference of charged and discharged energy, then subtracting the energy spent outside until period t (denoted by $E_{Vout}(t', v, n(v))$) from it.

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

(6) is to limit the energy level of a car to the maximum storage capability of its battery (denoted by $E_{Vmax}(v)$).

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

(7) and (8) represents that if the car is charged or discharged in a different charging station respectively, during a specific trip $n(v)$ of a large set of trips for that vehicle $N_V(v)$ when it is used outside the considered charging station. $bV(v, n(v))$ and $eV(v, n(v))$ denote beginning and ending periods of trip $n(v)$, respectively. Detailed information about constraints (1) to (8) is available in [12].

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

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

(9) forces charging stations to charge at most one vehicle in a given period, where $I_{CS}(cs, v, t)$ is the binary variable denoting the usage of charging station cs by vehicle v at period t .

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

(10) is defined for all $t \in T, cs \in CS, v \in V: CR(v) \notin CR(cs)$, where $CR(v)$ is a specific charging rate for vehicle v , while $CR(cs)$ is set of charging rates for charging station cs . It ensures that a vehicle cannot be charged at a charge station if its rate is not included in charge rate set of the charging station.

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

In (11), energy charged by a vehicle at a period must be equal to the total of charged energy by the vehicle at all charge stations at that period. $VC(v)$ is the consumption of vehicle v and $CE(t, v)$ is the energy charged by vehicle v at period t .

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

(12) and (13) ensure that in a charging activity of a vehicle, charging periods must be consecutive. t' is alias for t . These set of constraints are defined for all $v \in V, t \in T: bV(v, h(v)) \leq t \leq eV(v, h(v)), h(v) \in H_V(v)$, where $bV(v, h(v))$ and $eV(v, h(v))$ denote beginning and ending periods of interval $h(v)$, respectively. $h(v)$ is an idle waiting time (of vehicle v) from a set of $H_V(v)$. $I_{Vb}(t, v)$ and $I_{Ve}(t, v)$ are the binary variables denoting respectively the beginning and ending of an idle waiting time for vehicle v at period t .

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

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

(14) and (15) determines that for an interval when vehicle is not in use, at most one charging can begin or end.

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

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

(16) and (17) are used to determine, only one charge station can be used by a vehicle for a given interval when the vehicle is not in use. $I_{CSu}(cs, v, h(v))$ is an auxiliary binary variable that relates two constraints.

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

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

(18) relates two type of variables (for the usage of charging stations and vehicles) for feasibility.

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

B. Community Microgrid Daily Operation Scenario Development

Daily operation scenario consists of generation or adoption and use of a desired number of residential energy consumption, PV production depending on solar irradiance, EV model and charger allocation and dynamic pricing rates for each hour. Residential energy demand profiles are generated using a widely preferred open source high-resolution stochastic demand profile generator (CREST Demad Model) developed by a research group at Loughborough University [13]. 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 with 1-min resolution from individual device operation schedules, matching annual household appliance consumption statistics in the UK. The tool has been cited in over 1000 studies so far, ranging from future distribution grid planning to distributed energy resources integration, microgrid energy management to demand response applications. Further details of the tool can be found in [13]. An example stochastically generated daily demand profile with 1-min resolution for a house with 3 people during a weekday by the tool is shown in Figure 1.

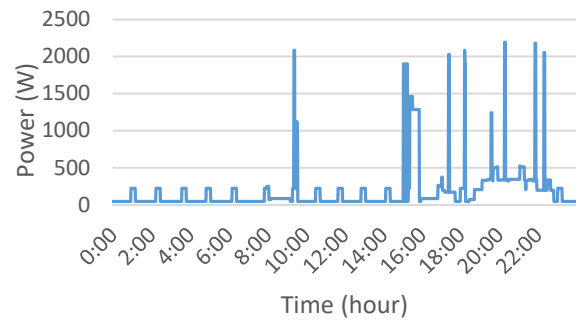


Figure 1. An example daily residential demand profile with 1-min resolution generated by CREST tool

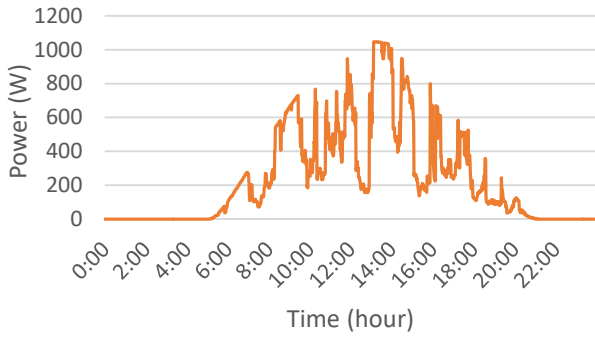


Figure 2. An example daily PV generation profile for a 1kWp PV panel with 1-min resolution generated by CREST tool

Daily solar irradiance profiles including cloudiness impact and related PV panel energy production efficiency is stochastically generated using an advanced version of CREST tool details of which are available in [14]. The tool uses meteorological information and stochastic cloudiness ratios, generating stochastic daily solar irradiance and PV panel production profiles with 1-min resolution. Among 60 stochastically generated daily PV generation profiles (30 for winter and 30 for summer days), using a modified version of the hourly clearness index methodology presented in [15], characteristically different 2 days are selected. The modified index (K_t) is formulated as in (19). The adopted modified hourly clearness index methodology takes the sum of the ratios of average generation of each hour ($E_{ave,i}$) to the overall average hourly demand of the whole day ($E_{ave,day}$).

$$K_t = \frac{\sum_{i=1}^{24} E_{ave,i}}{E_{ave,day}} \quad (19)$$

Calculating the modified hourly clearness index for each of the 60 days generation data, a day with the highest clearness index (representing a clear sky scenario) and a day with the lowest hourly clearness index (representing a cloudy day scenario) are selected. The selected daily PV generation profiles with 30-min resolution (to comply with the case study optimization resolution) are shown in Figure 3 and 4.

EV model technical characteristics of 23 cars commonly available in the US market in the last ten years are used from [3] and [16]. Normal and fast charging powers (in kW), charging speed (as mileage equivalent of energy stored per hour, km/hour), battery energy storage capacity (in kWh) and energy consumption per km (in Wh/km) specific for each car model are considered. The charging power of the considered cars range from 3.6 to 16.5 kW for normal charging and 22 to 100 kW for fast charging, while battery energy storage capacity is from 16 to 95 kWh and full charging time is from 3 to 14 hours for normal charging to below 40 minutes for fast charging. Based on the specified number of EVs in a scenario, a random cluster of cars is assigned to a determined number of customers. In the next step, probabilities for charging session starting time and initial SoC levels from [11] are used to stochastically specify the charging starting time and initial SoC level for each single charging session. After that, the desired mileage to become possible by the end of charging is specified based on realistic trip statistics from [17] are used to determine final SoC levels that need to be reached by the end of each charging session.

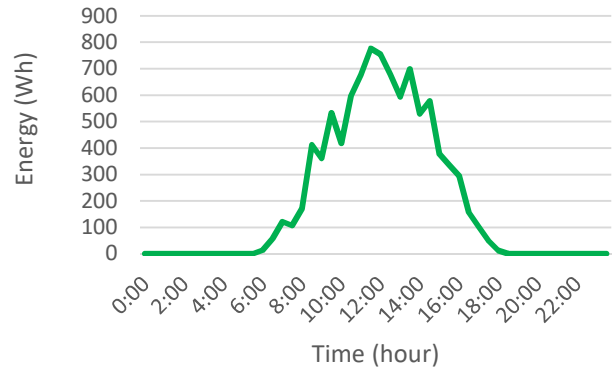


Figure 3. The daily PV generation profile with the highest modified clearness index

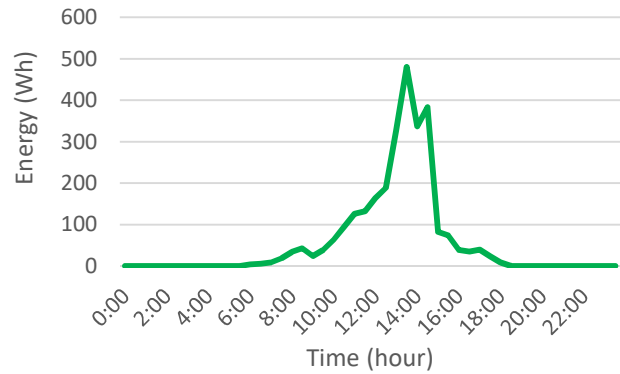


Figure 4. The daily PV generation profile with the lowest modified clearness index

SoC and energy needed for charging. Charging duration is derived from these parameters and scheduling of each charging session is done by the optimization approach explained in the next subsection. Dynamic pricing rates are obtained from ComEd's hourly pricing program in use in the US [18]. The predicted and actual prices of the days with one of the highest average hourly prices in 2021 are selected to be used in the case study presented in Section 3. The prices of the selected days are shown in Figure 5.

C. Energy Scheduling Optimization

A widely preferred commercial exact solver with proven effectiveness, ILOG CPLEX (version 12.6.1) is used as the optimization engine. For a decision horizon of 24 hours, day-ahead scheduling of electric vehicle charging sessions is done based on EV owner preferences, the residential consumption, PV production and hourly dynamic prices.

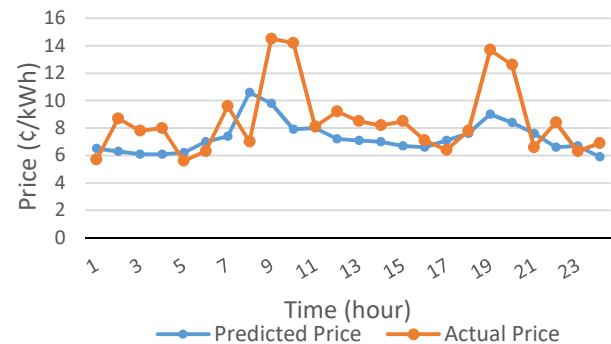


Figure 5. Hourly prices for a day with one of the highest average price in 2021

The objective function for scenario s , based on minimization of the net energy purchase cost from grid and depreciation cost of assets (based on $m_{vc}(v)$, $m_{vd}(v)$ and $m_p(p)$ as depreciation cost per unit charge, discharge of EV and generation from PV respectively) is provided in (20). $PP(s, t)$ is the forecasted purchase price and $E_{purchase}(s, t)$ is the amount of energy purchased, while $SP(s, t)$ is the forecasted sale price and $E_{sell}(s, t)$ is the amount of energy sold in period t of scenario s . $E_p(s, t, p)$ and $I_p(s, t, p)$ are energy generation rate and binary variable (on/off status) for PV p at period t in scenario s . (21) ensures that the total of sold and used energy cannot exceed the total of purchased, stored and generated energy, while (22) and (23) declare limits on the purchased and sold amounts by parameters $E_{pmax}(t)$, $E_{smax}(t)$ and allow either purchasing or selling at a period t by variable $I_{sp}(t)$. $n_{vd}(v)$ and $n_p(p)$ are the efficiency parameters for charge and discharge activities of vehicle and for PV.

$$c_T(s) = \sum_{t \in T} PP(s, t) \times E_{purchase}(s, t) - SP(s, t) \times E_{sell}(s, t) + \sum_{v \in V} \sum_{t \in T} m_{vc}(v) \times E_{vc}(t, v) + \sum_{v \in V} \sum_{t \in T} m_{vd}(v) \times E_{vd}(t, v) + \sum_{p \in P} \sum_{t \in T} m_p(p) \times E_p(s, t, p) \times I_p(s, t, p) \quad (20)$$

$$E_{sell}(s, t) + \sum_{v \in V} E_{vc}(t, v) \leq E_{purchase}(s, t) + \sum_{v \in V} n_{vd}(v) \times E_{vd}(t, v) + \sum_{p \in P} n_p(p) \times E_p(s, t, p) \times I_p(s, t, p) \quad (21)$$

$$E_{purchase}(s, t) \leq (1 - I_{sp}(t)) \times E_{pmax}(t) \quad (22)$$

$$E_{sell}(s, t) \leq I_{sp}(t) \times E_{smax}(t) \quad (23)$$

III. CASE STUDY

Two daily operation scenarios for an urban community microgrid with 200 residential customers and high penetration of PV and EV is investigated. Scenario-1 includes the daily PV generation profile with the highest clearness index, presented in Section 2 and shown in Figure 3. Scenario-2 considers the daily PV generation profile with the lowest clearness index, shown in Figure 4. For both scenarios, 200 daily residential demand profiles are stochastically generated and used. The overall daily demand profile with 30-min resolution for the 200 residential customers is provided in Figure 6. Considering a community-owned 20 kWp PV panel group and daily PV generation profile (the two generation profiles selected for Scenario-1 and Scenario-2) the net energy demand excluding EVs are shown in Figure 7 and 8, representing duck-curve challenge in daily supply/demand balance, with very low net demand in midday and steep ramps before reaching the daily peak in the evening hours.

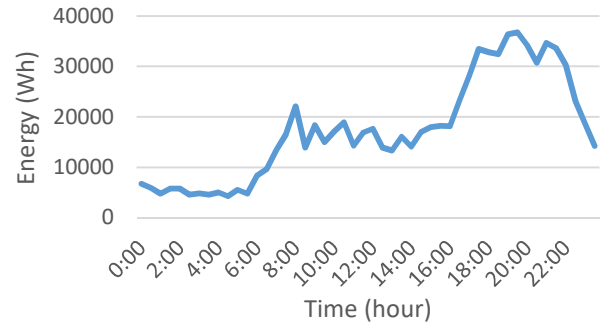


Figure 6. The overall daily demand profile of 200 residential customers based on stochastically generated data using CREST tool

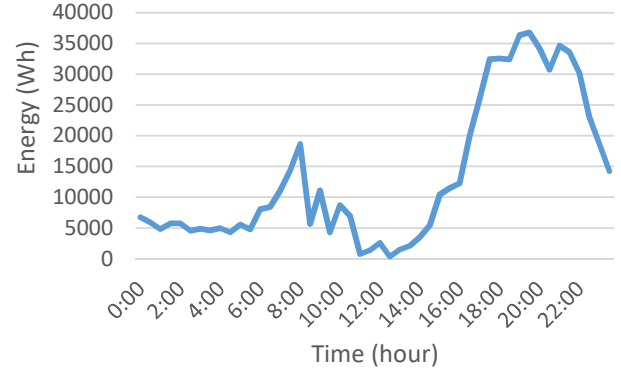


Figure 7. The net energy demand of the houses and the community-owned PV for a clear sky day in Scenario-1

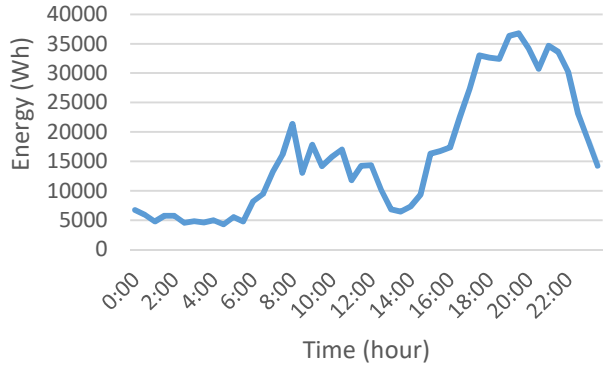


Figure 8. The net energy demand of the houses and the community-owned PV for a cloudy day in Scenario-2

Daily EV charging profiles are stochastically generated for 90 EVs based on realistic trip, charging and parking statistics explained in Section 2. In the uncoordinated scenario, only 14 EVs are charged simultaneously, thus a community-owned EV park with 14 chargers are enough to serve a fleet of 90 EVs. The overall daily EV demand with 1-min resolutions (later transformed into 30-min resolution to comply with optimization resolution) for the whole EV fleet is shown in Figure 9. Considering the residential demand and generation from PV panels uncontrollable, EV charging stations are coordinated, scheduling EV charging times by the cloud-based optimization tool based on the hourly dynamic pricing rates provided in Figure 5 in section 2, to minimize the daily energy costs. Due to difference in day-ahead predicted hourly prices and the actual prices for the related hours (shown in Figure 5) the expected and actual costs are calculated for the optimized schedules. The results are provided in Table 1.

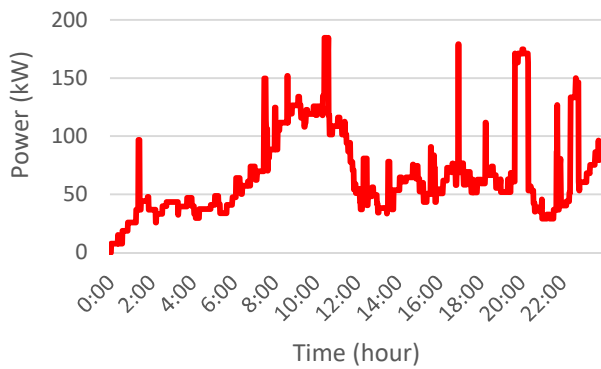


Figure 9. The aggregate EV demand of 90 EVs throughout a day, based on the stochastically generated individual profiles using realistic statistics

TABLE I. THE DAILY ENERGY COSTS FOR THE OPTIMUM SCHEDULES

Scenarios	Expected Cost (\$)	Actual Cost (\$)
Scenario-1 no coordination	4884	4289
Scenario-1 optimized	2955	3477
Scenario-2 no coordination	3658	4414
Scenario-2 optimized	3173	3879

The analysis showed that, cloud-based optimization tool can reduce actual costs by 12% and 18% in Scenario-1 and Scenario-2 respectively. In case of reduced uncertainty between the expected and actual hourly pricing rates in the considered dynamic hourly pricing program, a further 12% to 16% cost savings can be achieved by the optimization tool.

IV. CONCLUSION

This study presented a cloud-based energy scheduling optimization solution for community microgrids with large penetration of PV and EV. Two scenarios based on real hourly pricing data and stochastically generated realistic PV generation, residential demand and EV charging profiles based on statistics are explored to highlight achievable saving through EV charging coordination and scheduling. The study showed that the cloud-based optimization tool is capable of optimizing very large clusters of flexible assets, achieving 12% to 18% actual savings considering uncertainty in dynamic prices, which can be nearly doubled in case of reduced uncertainty. The findings of the study highlights the promising potential and importance of EV charging coordination in urban community microgrid systems and significant additional savings potential in case of reducing price uncertainties. The future work will be on optimization including demand response, CHP units, stationary battery energy storage, wind turbines, diesel generators, co-generation plants and HVAC systems, covering commercial and industrial microgrids. Uncertainty considered optimization methodologies will be focused on too.

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