Weather-Aware Data-Driven Microgrid Energy Management Using Deep Reinforcement Learning

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***Abstract*—In this paper, we develop a deep reinforcement learning (DRL) framework to manage distributed energy resources (DER) in a prosumer-centric microgrid under *generation uncertainties*. The uncertainty stems from varying weather conditions (i.e., sunny versus cloudy days) that impact the power generation of the residential solar photo-voltaic (PV) panels. In our proposed system model, the microgrid consists of traditional power consumers, prosumers with local battery storage, and the distributor. The prosumers and distributor are equipped with artificial intelligence (AI) agents that interact with each other to maximize their long-term reward. We investigate the impact of weather conditions on the energy storage charging/discharging, as well as the amount of power injected into the microgrid by the prosumers. To show the efficacy of the proposed approach, we implement the DRL framework using Deep-Q Network (DQN). Our numerical results demonstrate that the proposed distributed energy management algorithm can efficiently cope with the generation uncertainties, and it is robust to weather prediction errors. Finally, our results show that adopting energy storage systems on the residential side can alleviate the power curtailment during generation surplus.**

***Index Terms*—Reinforcement Learning, Microgrid Energy Management, Weather Forecast, Demand Response.**

I. Introduction

In the U.S., heating and cooling account for more than 40% of end-users energy demand [1]. Climate change and global warming are likely to increase the electricity demand for cooling/heating in the summer/winter as reported by the U.S. National Climate Assessment over the past few years [2]. The rising and falling of extreme weather temperatures is also expected to increase the peak electricity demand, which exacerbates the stress on the power grid [3]. Meeting this peak demand requires a new energy generation infrastructure and more advanced energy management mechanisms. Renewable energy resources play an important role for the U.S. electricity production industry in order to move toward clean energy and reduce the carbon footprint [4]. As such, financial incentives and environmental benefits encourage users to install distributed energy resources (DERs), such as solar photo-voltaic panels (PV) and energy storage systems, on the residential customer side, which led to the advent of prosumers [5]–[8].

A microgrid consists of a group of DERs, loads, and energy storage units, and it can operate in both grid-connected or island-mode [9], [10]. In the grid-connected mode, the microgrid is connected to the upstream main grid in case of power deficiency or surplus exchange. In both scenarios, energy management and planning are considered as the key objectives that have recently attracted the attention of the research community [11], [12]. Still, accurate analysis, modeling, and optimization of the microgrid operation and energy management are challenging tasks leading to various intrinsic and extrinsic *uncertainties* in the system [13]. In particular, load, renewable generation, and weather forecast are the main sources of uncertainty on the demand side. Some types of loads, e.g. flexible loads, cannot be easily forecasted since they depend on several factors such as the end-user behavior, weather condition, and electricity prices [14]. Renewable generation by the distributed PV panels in residential settings constitutes another major source of uncertainty.

Higher penetrations of DERs introduce more uncertainty on the supply side due to inherent volatility and the unpredictable power generation. The intermittent output of PV systems causes fluctuation in the overall power of the microgrid, which can lead to a generation and consumption mismatch. To handle these types of uncertainties, an accurate day-ahead or hourly renewable generation forecast becomes critical for microgrid planners [15]. For instance, PV output power is strongly correlated with solar irradiation such that the irradiation peak in cloudy days is less than half of that in clear days [16]. This example illustrates the importance of investigating weather-related uncertainty in micro-grid energy management.

In addition to the higher uncertainty introduced by increased DER deployment, the rapid rise of renewable resources has led to generating excess power during off-peak hours. Under such scenarios, power curtailment is regarded as a popular solution to keep the power system in balance. One of the main reasons for renewable energy curtailment is a system-wide oversupply during low-load periods that could lead base-load generations to reach the minimum, and thus causing voltage or interconnection issues [17]. As an example, power curtailment frequently happens in California during the Spring months [18]. Energy storage systems are contemplated as a potential solution to mitigate the power curtailment issue.

This paper aims to fill the gap in the literature concerning microgrid energy management and demand response. Specifically, we aim to develop a *weather-aware* data-driven deep reinforcement learning (DRL) framework that properly reacts to generation uncertainty on the one hand, and alleviates the power curtailment on the other hand. Other works also focused on weather forecasting [19]. Our goal is to neither replicate nor expand those results. Instead, this paper aims to integrate weather information with distributed energy management for microgrids. As such, any type of weather forecasting algorithm introduced in the literature can be integrated into our framework. Overall, the main contributions of this paper are as follows:

- We investigate the impact of day-ahead weather information on dispatching DERs and demonstrate that this information significantly improves microgrid energy management.
- We illustrate that using an energy storage system as a dispatchable asset can be an effective solution to alleviate PV power curtailment while considering the microgrid economic benefits.
- We implement the proposed weather-aware DRL method using Deep-Q Network (DQN). Our numerical results show that the proposed framework can operate effectively even with a 20% error rate in the weather forecasting system.

In our previous works ([20], [21]) a multi-agent reinforcement learning framework was proposed in order to implement dynamic pricing and demand response programs for the microgrid. This paper integrates weather forecasting with the proposed energy management framework and investigates the impact of weather dynamicity and uncertainty.

II. Related Work

Most studies on energy management and demand response (DR) are based on deterministic renewable generation (RG) profiles [22], [23]. There are also several works that use RG forecast in their energy planning. For instance, a methodology is proposed in [24] to predict energy consumption and renewable generation in the presence of prosumers. The authors in [25] propose an ensemble learning method to realize the short-term prediction of prosumers' air-conditioning load in order to establish an energy management system for smart grids. The work in [26] proposes a stochastic energy scheduling for two cooperative microgrids where the forecast error of RG was modeled over time. Nonetheless, none of these works consider the impact of weather conditions on power generation by distributed renewable energy resources.

There is also a multitude of prior works on demand-side management that take the weather condition into account. For example, [27] considers the weather forecast to predict the indoor temperature for smart buildings. In [28], consumption scheduling of HVAC while considering weather forecasting errors and predicting the outdoor temperature is addressed. Likewise, in [29], the authors model the energy management problem in a microgrid as a Markov decision process with considering generation and a load model, which is constructed based on weather data. A model predictive control (MPC) framework is used in [30], [31] for energy management. Silva *et al.* [30] proposed a hybrid MPC to investigate the energy exchange between the grid and a microgrid by converting weather data forecast to PV and wind power forecast. Although the aforementioned works consider the weather conditions for the demand-side management, our main goal is to develop weather-aware control of distributed energy resources such as residential PV deployments.

A weather-based stochastic renewable generation prediction method is proposed in [32] in which a game theory-based

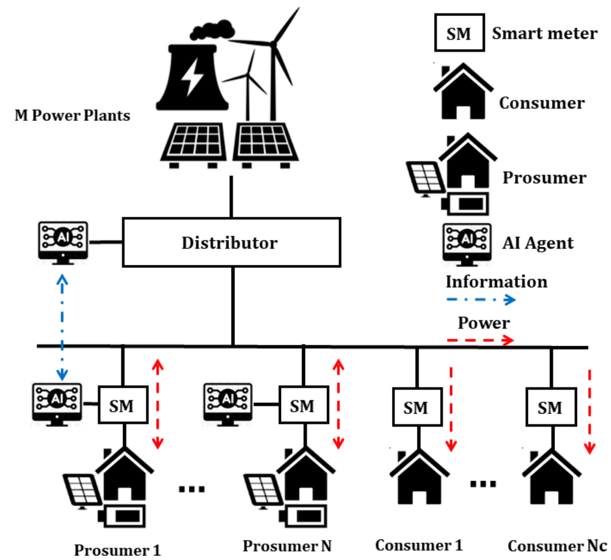

Fig. 1. A microgrid system architecture that consists of consumers, prosumers, distributor, and generation facilities. The distributor and prosumers are equipped with artificial intelligence agents for autonomous decision-making.

approach is used for power scheduling in a microgrid. This work is quite different from our proposed DRL-based framework that leverages generation, consumption, and weather data for energy management across DERs. Khodaei *et al.* [15] proposed an energy management framework for a prosumer-centric microgrid by considering neural networks for short-term load and weather prediction. However, they use the time-of-use (TOU) pricing scheme and they did not investigate the prosumers participation in a demand-response program, which we cover in this paper.

The remainder of this paper is structured as follows. Section III provides details about the system model and problem formulation. The proposed framework implementation in a small sample microgrid is introduced in Section IV, while Section V concludes the paper.

III. System Model and Problem Formulation

In this study, we consider a microgrid that consists of residential prosumers and consumers connected to the upstream grid. The microgrid is managed by a distributor that is responsible for energy management and sets the electricity price. The architecture of this microgrid is captured in Fig.1. It consists of N prosumers, N_c consumers, and the main grid, which ensures to meet the local demand in case of a deficiency i.e., the sum of all power consumption should be equal to generation power at each time slot. Also, there is no direct energy sharing or communication link between users, but there is a bidirectional communication and energy sharing link between the distributor and users, which enables the distributor to optimize the energy management in the microgrid. It is also worth mentioning that our framework provides additional flexibility by charging the battery either from PV generation or by buying electricity from the grid. In our model, one day has been divided into T time slots. We denote $g_i = [g_i^1, g_i^2, \ldots, g_i^T]$ as the vector of generation of the i^{th} prosumer, while b_i and c_i are the vectors of energy storage and consumption for the i^{th} prosumer. Thus, the power balance for the prosumer at time slot t will be:

$$D_i^t = c_i^t + b_i^t - g_i^t, \tag{1}$$

where D_i^t is the total load of the i^{th} prosumer or consumer at time slot t, which can be positive or negative. Positive means the prosumer has demand, and negative means the prosumer would inject the excess power into the grid. The PV generation on the prosumer side has an upper limit as follows:

$$0 \leq \; g_i^t \leq \; g_i^{\max}, \tag{2}$$

where $g_i^{\max}$ is the maximum solar panel capacity installed on the prosumer side. The rate of charging and discharging the battery is illustrated in (3), which limits the maximum amount of energy that battery can be charged or discharged with during one time slot. As such, $b_i^{\text{discharge}}$ and b_i^{charge} indicate the maximum discharging and charging rates, respectively.

$$b_i^{\text{discharge}} \leq \; b_i^t \leq \; b_i^{\text{charge}}. \tag{3}$$

In this case, each prosumer is considered to reduce their electricity bill by maximizing the following profit function.

$$C_{P_i} = \sum_{t=1}^{T} (\lambda - 1) \times D_i^t . \rho_{buy}^t - \sum_{t=1}^{T} \lambda \times D_i^t . \rho_{sell}^t, \tag{4}$$

where C_{P_i} denotes the profit of the i^{th} prosumer in one day. $\lambda \in \{0, 1\}$, in which $\lambda = 0$ is for the case that D_i^t is negative and prosumer has excess power that it needs to sell back to the distributor, and $\lambda = 1$ is for the case that D_i^t is positive and prosumer needs to buy electricity from the distributor. ρ_{buy}^t is the electricity buy price from the prosumer, and ρ_{sell}^t is the electricity sell price to the prosumer.

On the grid side, the power balance must be maintained at any given time slot t, which is defined as,

$$\sum_{i=1}^{N+N_c} D_i^t - \sum_{j=1}^{M} G_j^t = 0, \tag{5}$$

where G_j^t is the generation for the j^{th} generation facility out of all M power plants. D_i^t for consumer is defined as its consumption. The distributor aims to increase its profit, while the power balance in (5) is satisfied. The distributor profit is calculated as,

$$U_{Dist} = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N+N_c} D_i^t \rho_{sell}^t - \sum_{i=1}^{N} F(H_i^t) - \sum_{j=1}^{M} F(G_j^t) \right\}, \tag{6}$$

where $F(G_j^t)$ and $F(H_i^t)$ are the costs of buying electricity from the j^{th} generation facility and i^{th} prosumer, respectively. In (6), the distributor utility function is derived by subtracting the electricity generation cost from the revenue of selling electricity to the end-users.

As mentioned, both prosumers and the distributor are interested to maximize their total profit. For prosumers, this appears in minimizing their overall electricity bill, and meanwhile, the distributor handles the total energy provided in the microgrid by dynamically determining the buy price and dispatching the DERs. To solve these optimization problems in real-time, a decision-making process has been developed as a multi-agent system by embedding RL agents in the microgrid, as shown in Fig. 1. In this model, an autonomous agent interacts with the distributor agent and makes decisions for each prosumer. Agents are interacting in the same environment by making the decision a^t based on their observations of the environment at any time slot t. The agents then will receive a reward for their decision. The ultimate goal of the RL agents is to learn a policy to maximize their accumulative rewards in an iterative process. This means minimizing the electricity bill for the prosumers and increase the profit of the distributor. Next, we provide details on the observations, actions, and rewards for each agent.

A. Distributor Agent

Action: In (6), the control variable is the retail buy price. Unlike most of the previous works, which executed the dynamic pricing with the selling price [33], in this work we formulate the demand-response framework by dynamically changing the buy price. This approach does not lead to customer dissatisfaction because end-users do not need to shift their loads based on the selling price. Conversely, we only manage the extra energy provided by the PV rooftop panels and dispatching the battery storage by adjusting the electricity buy price from the prosumers. Therefore, the action of the distributor agent can be characterized as:

$$a^t = \rho_{buy}^t \in \mathcal{A}, \tag{7}$$

in which $\mathcal{A}$ is the distributor agent feasible action set. In this work, ρ_{sell}^t assumes to be deterministic during the day.

Observation: The distributor agent needs to have information of energy injected/purchased by the end-users, as well as the energy purchase costs from the main grid. Hence, at any time slot t, the distributor observes:

$$s^t = \left\{ F(G_j^t), \; \Omega^t, \; D_i^t \right\} \in \mathcal{S} \;, \tag{8}$$

where $\mathcal{S}$ is the observation set, $F(G_j^t)$ is the cost of buying electricity from the j^{th} generation facility, Ω^t is the total cost of injected power to the grid from prosumers and D^t is the total demand.

Reward: In RL, the goal of an agent is to maximize the accumulative reward. By considering U_{Dist}^t as the immediate reward at time slot t, the cumulative reward over the infinite time horizon is given by:

$$R_{Dist}^t = \sum_{k=0}^{\infty} \gamma^k U_{Dist}^{t+k+1}, \tag{9}$$

where $0 \leq \gamma \leq 1$ is the discount factor and R_{Dist}^t is the cumulative reward for the distributor agent.

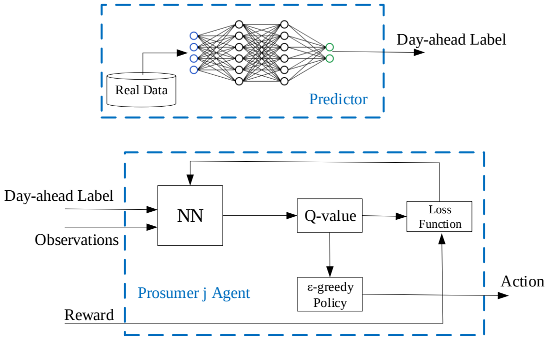

Fig. 2. Prosumer agent diagram consists of weather forecast data and a deep-Q network (DQN).

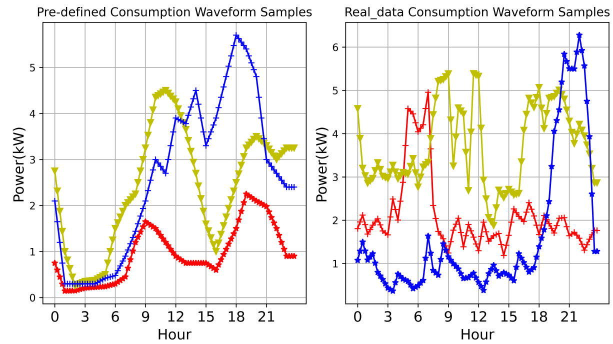

Fig. 3. Several sample paths of pre-defined and real-world data consumption waveforms used in training and testing episodes.

B. Prosumer Agents

Action: In the proposed model, the prosumer agent decides whether to charge, discharge, or take no action on the battery. This determines the amount of power demand or injection from/to the grid.

Observation: Each prosumer agent is assumed to have information of the local real-time consumption, PV generation, and battery State of Charge (SoC). In addition, prosumer agents need to have information about the retail price at any time slot t. Furthermore, to incorporate the weather conditions in the energy management of the microgrid, the prosumer agent utilizes a prediction framework based on weather real-data, which outputs the day-ahead label as $W = \{Sunny : w_1, \ \ Cloudy : w_2\}$. It should be noted that the day-ahead renewable prediction is out of the scope of this work. Hence, the observation vector for the prosumer agent is defined as:

$$s^t = \left\{ b_i^t, \ \rho_{buy}^t, \ g_i^t, \ c_i^t, \ W \right\} \in \mathcal{S}. \tag{10}$$

Reward: The goal of the prosumer agent is to minimize the daily electricity bill by minimizing their utility function, which is denoted as C_{P_i}. Assuming that $C_{P_i}^t$ is the immediate reward of the prosumer agent at the time slot t, the cumulative reward is defined as follows:

$$R_P^t = \sum_{k=0}^{\infty} \gamma^k C_{P_i}^{t+k+1}, \tag{11}$$

where $0 \leq \gamma \leq 1$ is the discount rate and R_P^t is the total reward of the prosumer.

IV. Case Study and Numerical Results

In this section, we present numerical results for a small-scale residential microgrid that consists of five prosumers each equipped with PV rooftop panels and battery storage, five consumers, one distributor, and two generation facilities connected to the microgrid. One of the generation facilities is referred to as the base generation facility that has 45kW maximum capacity to meet the microgrid demand. If the demand exceeds the defined capacity, a more costly generation facility (i.e., reserve plant) is deployed to meet the extra demand. In the simulations, the maximum capacity for the reserve generation is set to 100kW. Without loss of generality, this effort forgoes the ramp rate constraints of this generation facility. The distributor is equipped with a DRL agent for microgrid energy management, which is achieved by dispatching battery storage as well as electricity purchases from the base and reserve generation facilities. Likewise, each prosumer has a DRL agent that collects local observations such as amount of PV generation, electricity consumption, and battery SoC.

To investigate the weather condition effects on the distribution of energy in the microgrid, we assume that the prosumer agents can use a weather forecast system that provides a label for the day ahead. This label could be either "sunny" or "cloudy" (i.e., a binary classification problem). As shown in Fig.2, the day-ahead label is then provided to the prosumer agent as an observation.

The simulations are carried out via episodic iterations for 9500 episodes where each episode represents a 24-hours cycle. Therefore, the sample time is considered as 15 minutes, which means 96 iterations per episode. Fig. 3 demonstrates several sample paths of our pre-defined and real-world consumption waveforms that are used for training and testing, respectively. The pre-defined PV generation and consumption waveforms are constructed to be representative of real data from California ISO [18]. Then, the fully-trained agents are tested with a real-world consumption dataset from UK households for 500 episodes (days) [34].

First, we examine the convergence of the proposed algorithm as the simulation episodes evolve. Fig. 4 shows the cumulative rewards collected by five prosumers and distributor agents during iterative training episodes. From the results, the cumulative reward gradually increases and converges to maximum values. However, it should be noted that the initial fluctuations can be attributed to two reasons: (i) we use an ϵ-greedy policy that selects a random action to balance between exploration and exploitation during the training phase, and (ii) the generation and consumption waveforms and their maximum values are selected randomly from a set of values. Still, even with the initial fluctuations, the reward functions converge to their corresponding maximum values.

The energy management over the microgrid with the real consumption dataset is shown in Fig.5. In particular, Fig.5 (a) represents the comparison of the total power pur-

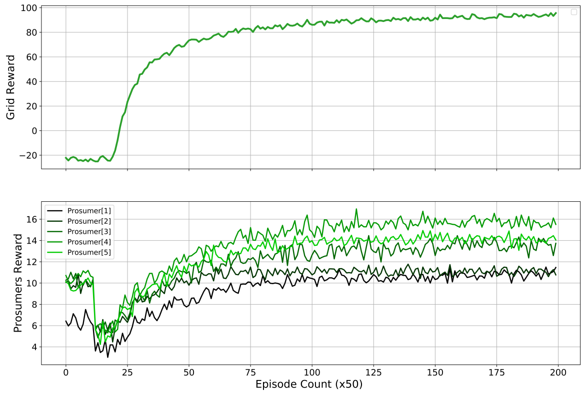

Fig. 4. Accumulative rewards for the distributor and prosumer agents.

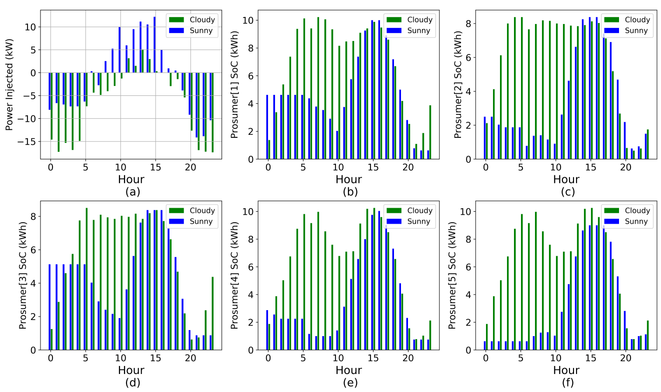

Fig. 5. (a) Comparing power injection into the grid on sunny vs. cloudy days. (b)-(f) Prosumers' battery SoC in sunny and cloudy days.

chased/injected from/to the grid by five prosumers for sunny and cloudy weather. As demonstrated in Fig. 5 (a)-(f), in cloudy days, during the off-peak hours when the price is relatively low, the prosumers prefer to fully charge their battery by purchasing more power from the grid at the beginning of the day to support the grid and sell more power back to the grid during the peak hours (i.e., after 5 p.m.). This behavior proves highly rational especially during cloudy days when a small amount of excess PV generation power is discernible. Thus, purchasing power from the grid to charge the battery at the beginning of the day yields higher battery SoC, which ensures grid support during peak-demand hours. However, in case it is sunny, the prosumer agent prefers to wait for PV excess energy to charge the battery and then discharge it during peak-demand hours. Since the prosumers have extra generated power to sell back to the grid, charging the battery with PV excess energy has higher benefits than purchasing from the grid to store in battery during sunny days. While the prosumers' consumption profile and battery capacity are different, Fig. 5 shows all prosumer agents can learn the optimal charge and discharge actions under different weather conditions.

As discussed, high penetration of PV generation in residential microgrids could generate surplus power during off-peak hours that leads to an increase in the voltage level and micro-

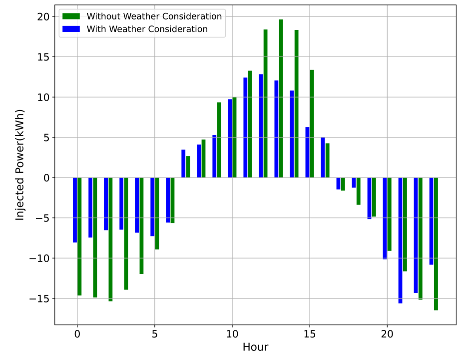

Fig. 6. Comparing power injection into the grid with and without considering the weather conditions.

grid instability. To mitigate this issue, PV inverters reduce their power output, and in some extreme cases, even shut down the inverter. This behavior is known as PV curtailment. Energy storage is known as a potential solution to help alleviate curtailment and efficiently use surplus energy. In this context, Fig. 6 compares the power injected by five prosumers for a given sunny day and under two cases of with and without weather and PV prediction. On a sunny day, most likely there is excess power during sun peak hours. In real-time optimization, dispatching battery storage regardless of weather and PV output prediction can lead to more power injection during sun peak hours, which increases the need for a curtailment system, especially when the number of prosumers increases in the microgrid. However, with the proposed weather-aware DRL agents, we achieve around 33% and 45% reduction in power injected/purchased to/from the grid during sun-peak/off-peak hours, respectively. Thus far, we demonstrated that if our proposed energy management and demand response framework utilizes a weather forecast system to acquire the knowledge of day-ahead prediction as a sunny or cloudy day, the DERs dispatching procedure provides performance improvements, compared to not considering weather data.

Next, we consider the scenario that the weather forecast system outputs the day-ahead labels with some errors. In this context, we are interested to examine the robustness of the proposed weather-aware algorithm to weather forecasting errors. Fig. 7 illustrates the total injected/purchased power to/from the grid for a given sunny day in four cases with different percentages of error in labeling the day-ahead weather condition. From the results, we note that there is a significant difference in power purchased and injected from/to the grid at the beginning of the day and during peak sun hours, respectively. With a 20% error in labeling, the algorithm is still able to effectively dispatch the battery storage. However, if the error percentage increases to 30%, the agent's performance degrades compared with the 0 and 20% error rates.

V. Conclusion

In this paper, we investigated the impact of the day-ahead weather prediction on the proposed weather-aware distributed energy management in microgrids. Our simulation results

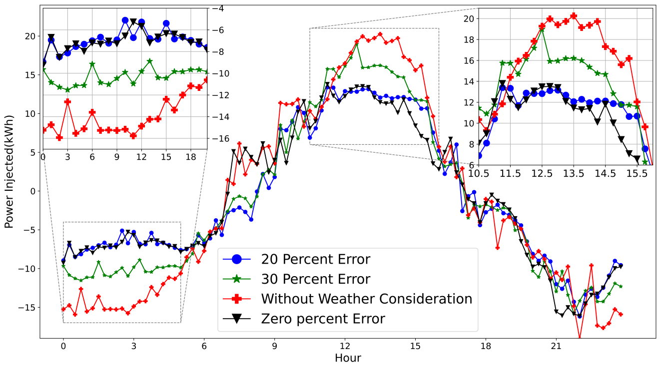

Fig. 7. Power purchased/injected from/into the grid in the presence of day-ahead labeling errors.

demonstrate that with the knowledge of day-ahead weather as a binary flag (i.e., sunny or cloudy day), the optimal battery storage dispatch leads to (i) improved grid support during peak demand hours and higher economic benefits by leveraging the surplus PV generation on sunny days, and (ii) decreased power curtailment in case of excess power generation. Overall, this paper integrates the PV generation uncertainty into microgrid energy management systems. The proposed framework can be improved by leveraging a more granular weather forecast system with a higher fidelity/accuracy (beyond binary a classification as sunny and cloudy days).

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