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CVaR-based Energy Management Scheme for Optimal Resilience and Operational Cost in Commercial Building Microgrids

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Abstract—**This paper aims at enhancing the resilience of a photovoltaic-based microgrid equipped with battery storage, supplying a typical commercial building. When extreme weather conditions such as hurricane, tsunami and similar events occur, leading to islanding of the microgrid from the main power grid, it is not expected that the microgrid would be taken out of service for a long time. At the same time, it is not cost effective to make the electrical system to be absolutely reliable to provide service for the customers. The main contribution of this paper lies in its ability to determine the optimal point between the operational cost and grid resilience. In other words, this work proposes an optimal management system of battery energy storage in a way to enhance the resilience of the proposed microgrid while maintaining its operational cost at a minimum level. The optimization is achieved by solving a linear optimization programming problem while the Conditional Value at Risk (CVaR) is incorporated in the objective function. The CVaR is used to account for the uncertainty in the intermittent PV system generated power and that in the electricity price. Simulation analyses are carried out in MATLAB to evaluate the performance of the proposed method. Results reveal that the commercial building microgrid resilience is improved remarkably at a slight increase in the operational cost.**

Key words—**Commercial buildings, resilience, Conditional Value at Risk (CVaR), energy management, microgrid.**

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I.   Nomenclature

Indices		P_t^{PV}	Total generated power by PV at the tth step time
t	Index of time step	P_t^{ij}	the power transfered from unit i to unit j at the tth step time
Abbreviations		***Parameters***	
SOC	State of charge	ΔS^C	maximum amount for charging rate
VaR	Value at risk	ΔS^D	Maximum amount for discharging rate
CVaR	Conditional Value at Risk	SOC_{min}	Minimum SOC of battery
RERs	Renewable energy resources	SOC_{max}	Maximum SOC of a battery
SARIMA	Seasonal autoregressive integrated moving average	$S_{Battery}$	Battery Capacity
Variables		η^C	charging efficiency of the battery
S_t	The charging level of battery at the tth step time	η^D	discharging efficiency of the battery
C_t^{GD}	Cost of energy transferred from grid to load	w	weighting factor for the price risk consideration
C_t^{GS}	Cost of energy transferred from grid to battery at the tth step time	S_{min}	minimum allowable charge level of the battery storage
C_t^{SG}	Cost of energy transferred from battery to grid at the tth step time	S_{max}	maximum allowable charge level of the battery storage
C_t^{PVG}	Cost of energy transferred from PV to grid at the tth step time	P_{STG}	the maximum power of module at standard test condition
$\mathrm{Cost}_t(X_t^{ij},C_t)$	Total operational cost of the commerial bulding microgrid	G_{STG}	irradiance at STC 1000 W/m^2
B	Confidence level	G_{ING}	incident irradiance
P_{PV}	The output power of PV module at irradiance G_{ING}	k	temperature coefficient of PV power
T_c	Cell temperature	T_r	reference temperature
D_t	The load of commercial building microgrid at the tth step time	T_N	Number of step time

II.   Introduction

Nowadays, the number of events related to severe weather conditions such as hurricanes, sandy storms, tsunami, blizzards and similar incidents which affect the operation of the power grid has increased significantly. This problem is linked to power systems resilience, which simply means the capability of the grid to resist, recover and minimize the undesirable effects from unfavorable accidents, attacks, or natural events that occur erratically [1]. It should be noted that the concept of power system resilience is different from reliability. A reliable system is essentially one that functions as desired and expected to, while resilience is the ability of the system to withstand certain types of failure and yet remains functional from the customer's point of view. In other words, reliability is

the outcome and resilience is the way to achieve it. While reliability generally affected by events with high possibility but a fairly small effect e.g., different faults in power system, resilience is associated to low probability events with large influence such as thunderstorm, hurricanes, floods, blizzards, etc.

The main features and differences between resilience and reliability as applied to power grid are shown in Table 1 [2]. The benefits of resilience as it applies to power grids have been investigated in [3]. The coordination approach proposed by the authors demonstrate that it is capable of exchanging power once a microgrid experiences a power shortage and at the same time keep their frequency and voltage at the rated values. In [4], a design and configuration for a resilience power grid is presented and discussed. Nevertheless, there are some physical limitations such as voltage and power generation limits that must be considered in resilience studies.

Table 1. Main features of resilience compared to reliability

Resilience	Reliability
Reaction to unfavorable events which affect the system	Response to frequency and duration of faults
Affected by power grid design, operational circumstances and control actions	Capability of distribution systems to supply the load demand
Has no evaluation metrics yet	It is generally measured by interruption indices such as SAIFI, SAIDI, ENS, CAIDI and CAIFI
Usually calculated before or after an event	Often calculated over a specified length of time
Focuses mainly on critical loads	All load demands are regarded
All power outages, regardless of time and duration, is necessary to study resilience assessment	Small interval of power outages (usually lasting less than 5 minutes) are ignored

Traditional power grids were designed in a way to allow only unidirectional power flow from the generation units to the load centers. However, in recent years, the need for a flexible power system which could be expanded and that is able to use renewable energy resources (RERs) in an effective way, has necessitated the development of microgrids to enable a bi-directional power flow between generation and consumers [5]. Microgrids are usually operated in a small geographical zone and may be integrated to the main grid. Because it is more stable and resilient, it usually decreases the power outages or demand curtailments remarkably. For this reason, using microgrids where the power generation units are close to the customers is one of the most practical options to enhance the resilience of the power grid [6]. In [7], a policy based on managing the accessible resources in an effective way is suggested in order to reduce load shedding during islanded mode. The study uses mixed integer linear programming to model the normal and resilient modes. Similarly, the merits of hierarchical DC control system in microgrids to enhance resilience and economic performance compared to AC microgrids are investigated in [8]. Three types of control including primary, secondary and tertiary are used and studied for DC microgrids. In addition, it is demonstrated that when there are outages, the operation of a power grid is improved by using a number of microgrids located in places precisely calculated. A novel restoration service plan for the distribution power system is presented in [9] while there is a big insertion of dispersed generation. It is shown that the requirement for more equipment of remotely controlled switches which is contingent on the dispersed generation

capacity and its location will be beneficial in reconfiguration and restoration of service after a significant incident in the main grid.

In [10], a two-stage algorithm which models predictive control in the first stage with the aim of planning the existing resources and power from unexploited capacities of microgrids is exchanged among different microgrids in the second stage to supply the rest of the demands, is proposed. In the same vein, ref [11], a self-healing strategy is used to improve the resilience of overloading microgrids using centralized and decentralized method. The frequency of each migrogrid is used in the decentralized stage in order to specify the requirement or probability for interconnection of different microgrids. Generation of power by all microgrids is also calculated in the centralized stage. To describe the behavior of the PV generation, joint predictive distributions based on marginal densities was proposed in [12] and space-time trajectories of the PV generation assessment was modelled. It is verified in the work that when historical data is not available, it is possible to regard covariance matrix recursively as an alternative approach to determine the PV generation.

In [13], the wind power generation is explained at several locations from space-time trajectories including paths sampled from high-dimensional joint predictive densities. In [14], a multi-objective optimization programming is employed in an integrated building and microgrid system. The proposed control scheme in the study is able to preserve energy in sustainable homes and microgrid system in order to reduce operational costs and satisfy consumers. In [15], networked microgrids are considered for a study and the optimal planning approach is examined with respect to the unpredictable nature of the generating units and load demand. In [16], in order to minimize the system risk against incident occasions, new hybrid market framework involving emergency transactions and a bilateral contract is suggested in a multi-microgrid system to parameterize the emergency energy transactions.

In [17], a comprehensive operational approach is proposed for optimal self-restoration via assignment of energy storage devices and distributed reactive sources to a distribution system split into several microgrids. The interaction of microgrids is presented in some literature to improve the resilience of microgrids [18] - [19]. In [18], an agreement is reached to transmit power from operating microgrids so as to back-up for the microgrids having problems to operate due to unforeseen events. This is usually done while the privacy of each microgrid is preserved. In [19], an innovative coordinated control of interconnected microgrids is offered in a way that each microgrid and distribution system operator establishes a separate unit with different objective to reduce the working costs. It is equally proposed that either the dispatchable or non-dispatchable distributed generators be present in the interconnected microgrids.

Although using microgrid technology to increase resilience in power systems is a reasonable solution as proposed by different researches, some of which were mentioned in the previous paragraphs, none of these works considered the uncertainty in the renewable generation units. The only uncertainty considered is that of electricity price as it supplies the microgrids. Recently, risk-based management methods such as value at risk (VaR) was presented in some literature. Nevertheless, VaR is a non-coherent risk measure that has some drawbacks such as

lack of convexity and coherency which makes it undesirable in practice [20]. In contrast, Conditional Value at Risk (CVaR) is a coherent risk measure that was recently applied to some problems related to the power grid for optimum energy control.

Robust optimization is a field focusing on the traditional optimization concepts, particularly algorithms, geometry, and tractability, in addition to modeling of power and structural results which are more generically prevalent for robustness. In contrast to robust optimization, CVaR assumes that there is distribution data for the uncertain parameter. CVaR is a risk assessment technique often used to reduce the probability that a portfolio will incur large losses. This is performed by assessing the likelihood (at a specific confidence level β) that a specific loss will exceed the value at risk. Mathematically speaking, CVaR is derived by taking a weighted average between the value at risk and losses exceeding the value at risk. In addition, CVaR is capable of choosing the objective function more flexibly than the traditional robust optimization.

A CVaR based optimal offering approach is presented in power market for a hybrid power system including wind farm and demand response in [21]. Again, ref [22] presents an optimal management of day-ahead planning under risk measurement where a stochastic programming approach is applied in the management. A domestic case study comprising electric vehicle, electric water heater, clothes dryer, air conditioner, photovoltaic system and battery is considered for a real-time planning in [23] where CVaR is proposed to compromise between the operational cost and uncertainty in electricity price.

However, none of the aforementioned works considered the fact that an islanded microgrid should able to supply its load demand for a long time in the event of a transient event. It should be noted that when a microgrid is islanded for a long time due to adverse weather conditions such as hurricanes or faults, it may take a long time for the power system operator to remove the problem and reconnect the microgrid to the main gird. In this situation, the microgrid should be controlled in a way to supply itself as long as possible, especially as most microgrids today, comprise renewable energy resources (RERs) such as PV or wind as the main power sources. Because RERs suffer from uncertainty and unpredictability, they aggravate the situation whenever an incident occurs in the system. For this reason, a real-time optimal energy management for a finite time horizon is proposed in this paper for a PV-based microgrid equipped with battery storage so as to extend the time that the microgrid can survive without support from the main grid. The microgrid considered in this paper is a small-to-medium size commercial building. Such a microgrid typically use low voltage distribution system and has approximately 1 MW under its peak demand. This type of microgrid is typical in commercial building sector [24].

The first contribution of this work is consideration of uncertainty in PV power generation and electricity price as it manages the battery storage in such a way to increase the resilience of the commercial building microgrid while minimizing its operational costs. Accordingly, CVaR is introduced for risk consideration in the objective function of the optimal management procedure. In addition, the operational constraints of the battery energy storage system such as the storage level limitation so as not to exceed the up and down limit of the storage level, as well as maximizing the rate of charging and discharging, are considered in this paper.

Consider the system depicted in Fig. 1, which comprises a commercial building, PV system and battery energy storage system connected to the power grid where there is a bidirectional flow of power. The PV system, battery energy storage and power grid are responsible for the power supply of the commercial building load demand. The time horizon considered for the simulation in this study is one week (i.e. 168 hours). Each hour is regarded as one step time. Priority to supply power to the commercial building is given to the PV system and battery energy storage system. In addition, they are legally empowered to sell excess power to the grid. Otherwise, if the generated power from PV and storage power in battery are not sufficient for the commercial building demand, the grid injects the shortage power into the commercial building. This problem is formulated in a linear programming incorporated with the CVaR to manage the energy in order to minimize its operational cost and uncertainty related to PV power generation and electricity price. This way, the battery storage level is increased remarkably while the operational cost shows a trivial rise (see Figures 5-8 and Tables 3-6). Therefore, when the commercial building microgrid is isolated from the main grid, the battery can power the load for an extended time and this means the system's resilience has improved.

The rest of this paper is organized as follows. System description of the case study is presented in Section III. Risk measurement and scenario generation description are explained in Section IV. Section V describes the proposed management of a commercial building microgrid considering risk. Simulation results are presented and discussed in Section VI to evaluate the performance of the proposed approach. Finally, the paper is concluded in Section VII.

III.   The Description of the Proposed Scheme

Commercial building microgrids are typically small microgrids with approximately 1 MW for its peak load which use low voltage distribution system. In most metropolises or even in the medium size cities, commercial buildings are increasing, which constitute a major share of the load demand. A few examples of this setting are a hyper market, an institutional building, a shopping center, and so on. Using RERs like solar PV and wind is a desirable solution for supplying these microgrids. However, the power generated from these kinds of energy is unpredictable and oscillates greatly. Therefore, they need energy storage devices for this purpose to flatten their fluctuated power generation.

The case study considered in this paper is a PV-based commercial building with battery energy storage as shown in Fig. 1. It has a power system which provides support for a bidirectional flow of power for economic, reliability and stability purposes. The hypothetical microgrid considered for the commercial building, such as a hyper market having about 100 stores, has approximately 450 kW peak load demand. The voltage of operation is considered as three-phase 400 volts.
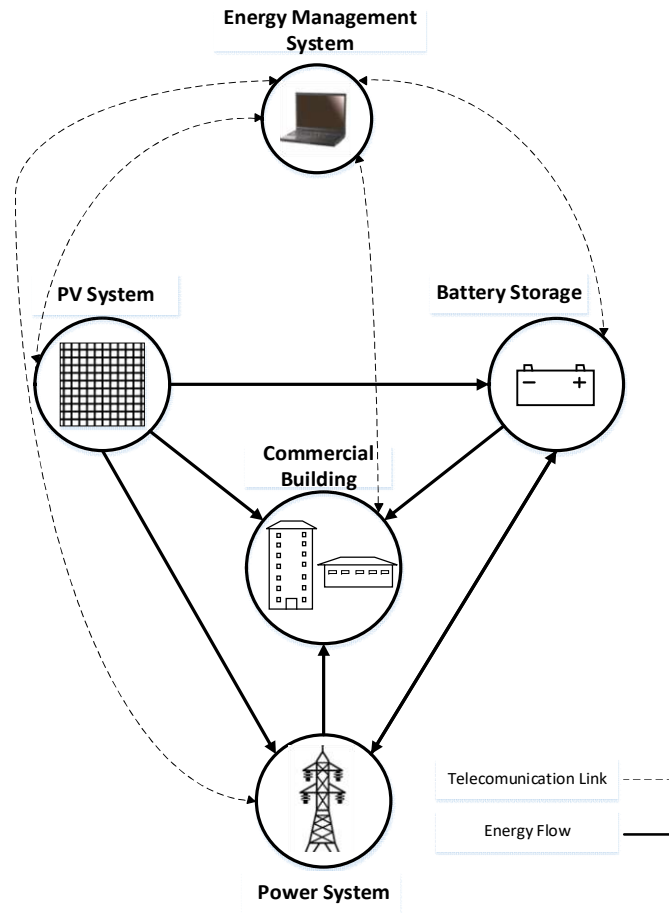
Fig. 1. The proposed PV-based model for commercial buildings.

The PV system contains many cells connected in parallel and series configuration to provide the desired voltage and current. The relationship between the voltage and current of a PV module is non-linear naturally. The power generated by PV array depends on three factors: temperature, irradiation and output voltage (or current). Simply, the output power delivered by the PV system can be expressed by:

$$P_{PV} = P_{STG} \times \frac{G_{ING}}{G_{STG}} \times (1 + k.(T_C - T_r)) \tag{1}$$

IV.   Risk Measurement and Scenario Generation

A. Risk Measurement

Assuming that $f(x,y)$ is the loss associated with a set of decision variables x , to be chosen from a certain subset X of R^n and the random variable y in R^m. The vector x can be interpreted as the set of available portfolios, while vector y indicates the uncertainty set. The target is to reach a value for the decision vector x which could minimize the cost function subject to the uncertainty in vector y. One of the most commonly used risk measurement is VaR, which is especially suitable for loss distributions function with fat tail manners [25]. For a specified confidence level β, the VaR has the smallest loss over the rolling horizon time which is exceeded with probability 1-β according to following equation:

$$VaR_\beta = \min\{\alpha \in R : P\{f(x,y) \le \alpha\} \ge \beta\} \quad \text{for} \quad 0 \le \beta \le 1 \tag{2}$$

Although VaR is a well-known risk measure used in economic problems, it is a non-coherent risk measure suffering from non-convexity, non-smoothness, subadditivity, etc., which makes it undesirable in optimization programming. To avoid this problem, there is an attractive alternative risk measure identified as CVaR also known as average value at risk or mean shortfall. For a given confidence level β, CVaR is defined as [26, 28]:

$$\beta - CVaR = E_y(f(x,y)\,|\,f(x,y) \ge \beta - VaR) \tag{3}$$

Eq (3) indicates the expected conditional value of the cost function, subject to its value greater than β-percentile. On the contrary to traditional robust optimization methods, minimization of CVaR is a flexible option for choosing the objective function. It is capable of enhancing the optimization performance considerably because distributional data on the parameter of y is uncertain. Indeed, the risk of system being exposed to high losses will be minimized when the CVaR of the cost is minimized [26]. In addition, for linear cost function problems, minimizing CVaR can be formulated as a linear programming problem which is an attractive choice in practical applications [27]. Using sample generated from distribution of the uncertain parameter y, the CVaR can be approximated by:

$$CVaR_\beta = \min(\alpha + \frac{1}{M.(1-\beta)}\sum_{i=1}^{M}[f(x,y_i)-\alpha]^+) \tag{4}$$

where, z^+ indicates the positive elements of z, α is the β-VaR, M is the number of Monte Carlo paths to estimate the expected value of β-CVaR in the cost function, and y_i indicates the ith generated path of the uncertain variable.

To solve this problem, it is normally suggested to replace 0^+ with a set of constraints. So the corresponding equation for minimizing CVaR is formulated as follows:

$$CVaR_\beta = \min(\alpha + \frac{1}{M.(1-\beta)}\sum_{i=1}^{M} z_i) \tag{5}$$

Subject to: $z_i \geq 0, z_i \geq f(x, y_i) - \alpha$

B. Scenario Generation using Seasonal Arima Model

The probabilistic arrangement of stochastic process Y can be defined by finding the joint distribution of its random variables that describes both the probabilistic manner of each random variable on its marginal distributions and the interrelations which exists among all variables (statistical dependencies). In real conditions, the definition of joint distribution is often a difficult and cumbersome work. However, this can be done under the following assumptions [28]:

1) The joint distribution considered is a multivariate Gaussian distribution and hence it is determined by specifying the mean vector and the variance-covariance matrix of the random variables which generate the stochastic process.

2) The stochastic process is a stationary means that neither the mean vector nor the variance-covariance matrix is contingent on time t.

The autoregressive moving average (ARMA) model relies on these two principles. However, these properties do not hold in some stochastic processes. Hence it is needed to create some changes to the process in order to achieve the desired characteristics. In addition, numerous time series events periodically (e.g., monthly) show a seasonal trend, which means there is a relationship between observations made during the similar period in successive periods. Besides the seasonal link, there is also a relationship between the observations made during sequential periods. This fact can be observed, for example, in load demand in a month which shows a similar behavior every day and every week, thereby establishing an instance of both daily and weekly seasonality.

In this example, the daily seasonality indicates that a seasonal pattern of order equal to 24 can be recognized as the series of hourly load demand. This means that the load at hour h on day d is approximately similar to the demand at hour h on day d-1. This matter can also be explained for weekly seasonality, where the seasonality order is equal to $24 \times 7 = 168$. In these situations, seasonal autoregressive integrated moving average model, also known as SARIMA, which considers seasonality and potential seasonal unit roots, an extension of the ARMA model, is required [29].

Let us consider a stochastic process with seasonality of order S. The general expression of a seasonal ARIMA model with parameters $(p,d,q) \times (P,D,Q)_S$ can be expressed as:

$$(1 - \sum_{j=1}^{P} \phi_j.B^j)(1 - \sum_{j=1}^{P} \varphi_j.B^{jS}).(1-B)^d.(1-B^S)^D.y_t = (1 - \sum_{j=1}^{q} \theta_j.B^j).(1 - \sum_{j=1}^{Q} \vartheta_j.B^{jS}).\varepsilon_t \tag{6}$$

with a seasonal component of P autoregressive parameters $\varphi_1, \varphi_2, ..., \varphi_P$, Q moving average parameters $\vartheta_1, \vartheta_2, ..., \vartheta_Q$ and a differentiation order D. In this paper, photovoltaic system power generation and load power demand which have a time-varying nature are characterized by seasonal ARIMA model. The forecasted value for commercial building load demand, PV generated power and electricity price are predicted by SARIMA model which is accurate in describing the tail fatness and seasonality effects.

V. CVaR Based Energy Management to Maximize Resilience and Minimize Operational Cost

Consider the case study system depicted in Fig. 1 where the PV system, battery energy storage and power grid are responsible to supply the commercial building for a finite time horizon. The time horizon considered could be discretized into N interval of length Δt and the power demand of commercial building is met by either the PV, battery or from the grid at each step time. The time horizon for simulation in this study is considered for one week equal to 168 hours, as reported previously. Each hour is regarded as one step time. For $t = 1, 2, ..., T_N$, there are eight decision variables as follows:

$$P_t = (P_t^{GD}, P_t^{GS}, P_t^{PVD}, P_t^{PVS}, P_t^{PVG}, P_t^{SG}, P_t^{SD}, S_t) \tag{7}$$

where, P_t^{ij} indicates the amount of power transferred from unit i to unit j in the specified time step t. The superscripts *G, PV, S,* and *D* denote grid, Photovoltaic, battery storage and the load demand of the commercial building respectively. Consider S_t as the proportion of battery storage at the tth step time, S_{t+1} which is equal to:

$$S_{t+1} = S_t + \frac{\eta^C.(P_t^{GS} + P_t^{PVS}) - (P_t^{SD} + P_t^{SG})}{S_{Battery}} \tag{8}$$

Taking into account the stated assumptions and the fact that PV and battery belong to the commercial building, the cost in each time step, imposed on the commercial building owner while exchanging power with the power grid is equal to:

$$\text{Cos} t_t(P_t, C_t) = (P_t^{GD}.C_t^{GD} + P_t^{GS}.C_t^{GS}) - (\eta^D.P_t^{SG}.C_t^{SG} + P_t^{PVG}.C_t^{PVG}) \tag{9}$$

For the sake of simplicity, identical values are considered for prices i.e. $C_t^{GD} = C_t^{GS} = C_t^{SG} = C_t^{PVG} = C_t$, which is acceptable in most energy markets. So the cost function will be equal to:

$$\text{Cos} t_t(P_t, C_t) = [(P_t^{GD} + P_t^{GS}) - (\eta^D.P_t^{SG} + P_t^{PVG})].C_t \tag{10}$$

In fact, the operational cost of the commercial building owner is equal to the profit obtained from the power sent to the grid by the battery and RER minus the cost of power that supplies the commercial building from the

power grid. At each time step, a simple policy for optimal operation is to minimize the tth stage cost by solving the following linear programming:

$$\text{Min} \quad \text{Cost}_t(P_t, C_t) \tag{11}$$

This strategy is known afterwards by a simple policy in this paper. Although this policy is direct, it does not consider the impacts of decisions on the future conditions of the battery storage level. In addition, the uncertainty in electricity price and PV power generation is not considered. So it cannot be an interesting method practically. An alternative to the above strategy is risk neutral policy which considers the overall cost over the planning time horizon and it is obtained by solving the following problem:

$$\text{Min} \quad \sum_{T=1}^{N} \text{Cost}_t(P_t, C_t) \tag{12}$$

Due to volatility and unpredictable nature of electricity price and PV generated power; neutral policy cannot also be a suitable approach for optimal management of energy. This is because it ignores the uncertainty in the electricity price and PV power generation. For this reason, it is essential to consider risk and uncertainty while seeking an optimal approach for energy management. Additionally, there is another alternative for neutral and simple policy known as risk averse policy which is made in this paper by incorporating the cost function represented in eq. (9) into the minimization of conditional value at risk formulation in eq. (4). Consideration of risk averse policy without considering battery limitations and constraints, leads to a linear programming problem as follows:

$$\text{Min} \quad \left[\sum_{T=1}^{N} (\text{Cost}_t(P_t, C_t)) + (w.CVaR_\beta)\right] \tag{13}$$

Subject to:

$$[(P_t^{GD} + P_t^{GS}) - (\eta^D.P_t^{SG} + P_t^{PVG})].C_t \leq z_i + \alpha \tag{14}$$

$$z_i \geq 0, \tag{15}$$

$$P_t^{PVD} = \min\{D_t, P_t^{PV}\}, \tag{16}$$

$$P_t^{PV} = P_t^{PVS} + P_t^{PVD} + P_t^{PVG}, \tag{17}$$

$$D_t = P_t^{GD} + \eta^D.P_t^{SD} + P_t^{PVD}, \tag{18}$$

$$(P_t^{SD} + P_t^{SG}) - \eta^C.(P_t^{GS} + P_t^{PVS}) \leq [S_t - S_{\min}].S_{Battery}, \tag{19}$$

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$$\eta^C . (P_t^{GS} + P_t^{PVS}) - (P_t^{SD} + P_t^{SG}) \leq [S_{\max} - S_t].S_{Battery}, \qquad (20)$$

$$\eta^C . (P_t^{GS} + P_t^{PVS}) \leq \Delta S^C . S_{Battery}, \qquad (21)$$

$$(P_t^{SD} + P_t^{SG}) \leq \Delta S^D . S_{Battery}, \qquad (22)$$

where, w which indicates the weighting factor for the price risk consideration is considered 50 in this paper. Constraint (16) indicates that the whole power generated by the PV is sent to the load demand when the PV power is less than the need of the commercial building. When the power generated by the PV is more than the commercial building demand, the excess power will be sent to the battery energy storage or power grid. Constraint (18) shows that the power demand of the commercial building is completely supplied by the grid, battery storage or PV power generation. Constraints (19) and (20) imply that the storage level of the battery in the next step time remains greater than S_{min} but less than S_{max} respectively. Moreover, constraints (21) and (22) prevent the battery to charge or discharge faster than the acceptable rates during each time step. The simulation is done in MATLAB.

VI. Results and Discussions

In order to examine the accuracy of the proposed method, simulation results are provided in this section. For this reason, a case study introduced in section III (Fig. 1) is used to investigate the suggested strategy. The data of electricity prices are available in [30] and the data related to irradiation of PV systems is also provided from National Renewable Energy Laboratory (NREL) [31]. In addition, the assumed load demand is typical of commercial buildings. The parameters of the battery energy storage are shown in Table 2. In order to have a reasonable approximation for the commercial building load demand, electricity price and PV power generation, SARIMA model are used for the forecasting to consider seasonality effect in their modeling. We consider two scenarios for the load demand and PV power generation.

In the first scenario, we assume that we have a PV system with a rated power of 1000 kW. The power demand of commercial building, power generation from PV and electricity price are shown over the time horizon of 168 hours in Fig. 2, Fig. 3 and Fig. 4 respectively. The simulation is carried out under two situations. In the first situation, the uncertainty in electricity price is considered while the second situation considers the uncertainty in the PV power generation.
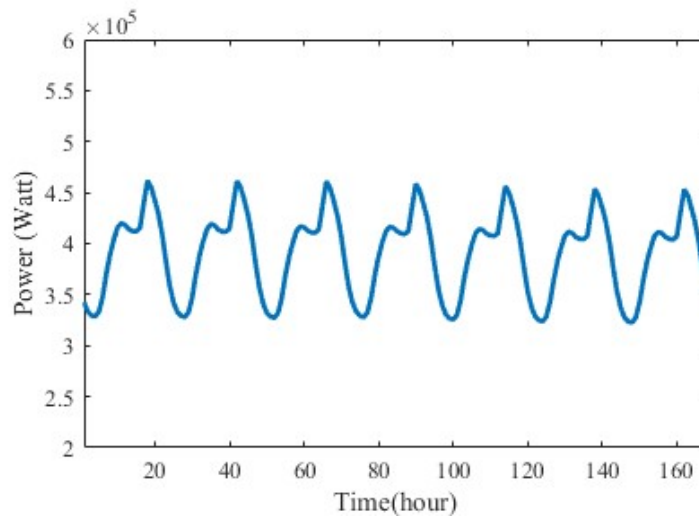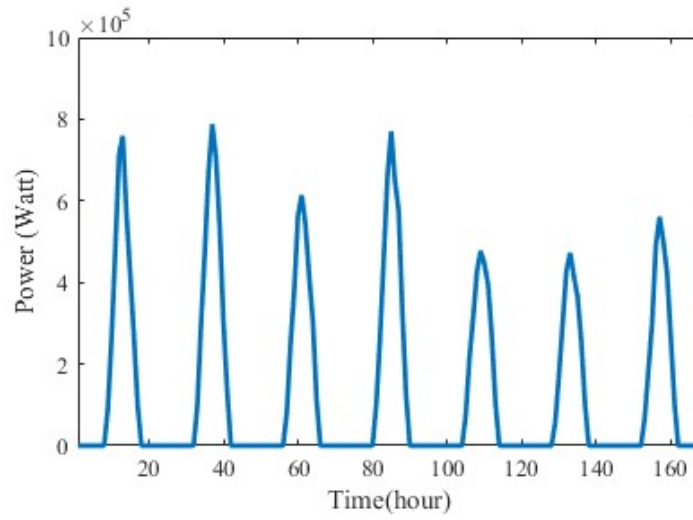
Fig. 2. Power demand over the time horizon.

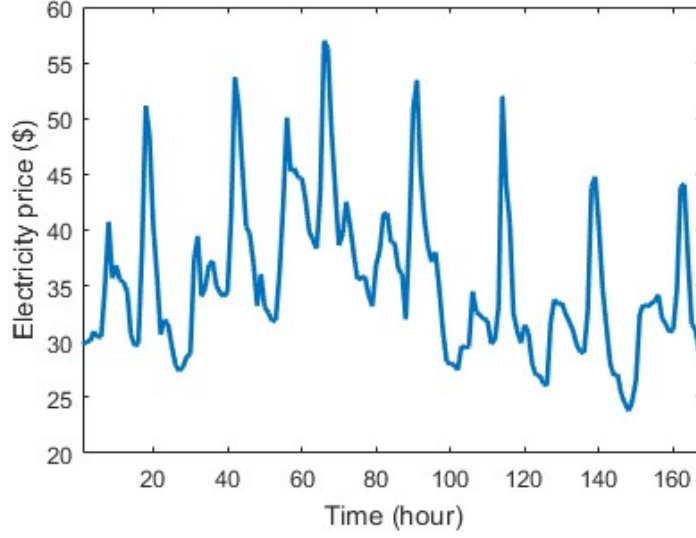Fig. 3. Photovoltaic power generation (average of 500 paths).

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Fig. 4. Electricity price over time.

Table 2. Parameters for battery energy storage

ΔS^D = 0.15	ΔS^C = 0.1	η^C = 0.95	η^D = 0.9
S_{min} = 0.15	S_{max} = 0.85	$S_{Battery}$ = 350 (KWh)	S_0 = 0.85

A. Uncertainty in Electricity Price

SARIMA model is used in order to predict the electricity price based on historical data. However, day-ahead electricity price is generally accompanied with some uncertainty which causes a large effect on the energy management strategy and makes it more complex. Disregarding this uncertainty may lead to a non-optimal management. For this reason, in order to increase the resilience of the system and reduce the risk associated with day-ahead electricity price, CVaR is introduced in this paper. Fig. 5, Fig. 6, and Fig. 7 illustrate the battery storage level for different kinds of energy management strategy (risk averse, neutral risk and simple policy) and under 3 confidence level β=0.9, 0.95 and 0.99.

It is obvious from these figures that a simple policy makes the battery discharge to the minimum level as fast as possible and maintains it in this condition for the rest of time horizon. On the other hand, risk neutral policy charges and discharges the battery when the expected price is increasing and decreasing respectively and it does not consider the fluctuations in the electricity price. This switching between minimum and maximum charge level depends on ΔS^C and ΔS^D. In contrast, risk averse policy does not have a similar pattern for all horizon time as it considers the uncertainty in electricity price in the optimal planning. This policy is dependent on the confidence

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level β such that higher amount for *β* results in more different behavior than neutral risk policy in order to yield an optimal management for battery energy storage. This is due to the risk related to electricity price.

Tables 3, 4 and 5 indicate the total operational cost and battery energy storage level of the commercial building for neutral risk and risk averse policy for different confidence levels. Here, the battery storage level could be interpreted as resilience of the commercial building microgrid. Because when a severe event occurs in the system, which isolates the commercial building from the main power grid, the only stable source which supplies the commercial building load demand is the battery energy storage. The average battery storage in both policies is provided in the Tables 3, 4 and 5. In addition, the battery level at 1 P.M. every day is considered in these tables. It is the time when PV generates its maximum power and the difference between the battery storage level risk averse and neutral risk policy is maximum. According to Tables 3, 4 and 5, as the confidence level increases, the operational cost of the commercial grid rises a little bit but the resilience of the commercial building microgrid increases significantly.

According to Table 3, the whole operational cost of the commercial building in 168 hours is increased by only 0.19% when the risk averse policy with confidence level of 0.90 is used rather than neutral risk policy. However, the resilience of the commercial building microgrid has improved to about 41.1% on the average and 183.3%, maximum (on day 7). In Tables 4 and 5, for the confidence level of 0.95 and 0.99, the operational cost is increased by 0.21% and 0.28% respectively using risk averse policy instead of neutral risk strategy. However, the
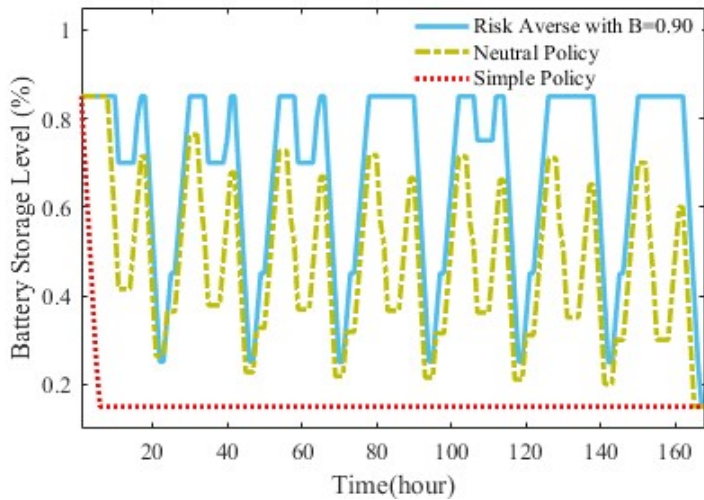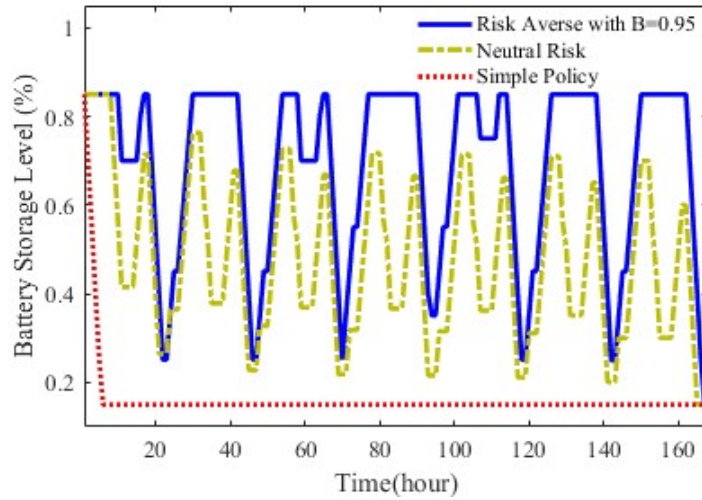

Fig. 5. Battery storage level.
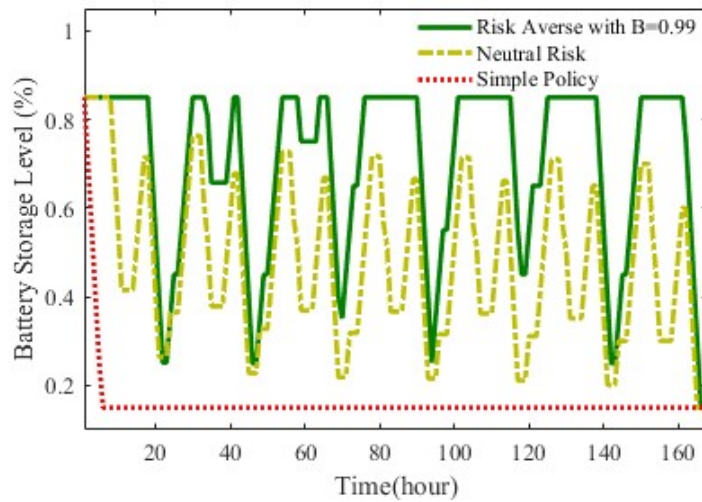
Fig. 6. Battery storage level.

Fig. 7. Battery storage level.

resilience of the commercial building microgrid has improved to about 44% on the average and 183.3% maximum (day 7) for confidence level equal to 0.95. Similarly, it is 46.9 on the average and 183.3% maximum (day 7) for the confidence level equal to 0.99. Consequently, using the risk averse policy may impose a little bit higher operational cost on the commercial building rather than neutral risk management, but it enhances the resilience of the system when an extreme incident, which leads to islanding of the commercial building from the power grid, occurs.

Table 3. Comparison of the operational cost and resilience in neutral risk and risk averse policy with B=0.9

policy index	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Cost (for 7days)	1178900000	1181200000	+ 0.19 (%)
Resilience	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Day 1	0.41	0.70	+70.7 (%)
Day 2	0.38	0.70	+84.2 (%)
Day 3	0.37	0.70	+89.2 (%)
Day 4	0.37	0.85	+129.7 (%)
Day 5	0.36	0.75	+108.3 (%)
Day 6	0.35	0.85	+142.8 (%)
Day 7	0.30	0.85	+183.3 (%)
Average for 7 days	0.4768	0.6726	+41.1 (%)

Table 4. Operational cost and resilience comparison in neutral risk and risk averse policy with B=0.95

policy index	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Cost (for 7days)	1178900000	1181400000	+ 0.21 (%)
Resilience	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Day 1	0.41	0.70	+70.7 (%)
Day 2	0.38	0.85	+123.7 (%)
Day 3	0.37	0.70	+89.2 (%)
Day 4	0.37	0.85	+129.7 (%)
Day 5	0.36	0.75	+108.3 (%)
Day 6	0.35	0.85	+142.8 (%)
Day 7	0.30	0.85	+183.3 (%)
Average for 7 days	0.4768	0.6865	+44 (%)

Table 5. Operational cost and resilience comparison between neutral risk and risk averse policy with B=0.99

policy index	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Cost (for 7days)	1178900000	1182200000	+ 0.28 (%)
Resilience	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Day 1	0.41	0.85	+107.3 (%)
Day 2	0.38	0.66	+73.7 (%)
Day 3	0.37	0.76	+105.4 (%)
Day 4	0.37	0.85	+129.7 (%)
Day 5	0.36	0.85	+136.1 (%)
Day 6	0.35	0.85	+142.8 (%)
Day 7	0.30	0.85	+183.3 (%)
Average for 7 days	0.4768	0.7004	+46.9 (%)

B. Uncertainty in PV Power Generation

SARIMA model is used to forecast PV power generation for one week based on historical data. However, the forecasted power generation may have variations according to the weather conditions. Because RERs, like PV, are uncertain in power generation, it causes a great impact on power management for the day-ahead scheduling. Ignoring this uncertainty may cause some errors in the management, which could render the decision non-optimal. Therefore, to increase the resilience of the commercial building considered in this paper, CVaR is introduced to account for uncertainty in the PV power generation.

Fig. 8 shows the battery storage level for different kinds of energy management strategy (risk Averse only for confidence level of 0.99, neutral risk and simple policy). In simple policy, battery is discharged to the minimum level immediately and stays in that situation for the next few hours. On the other hand, in risk neutral policy, the battery is charged and discharged when the expected price is increasing and decreasing respectively and does not depend on the uncertainty in the PV generation unit. This switching between minimum and maximum charge level is contingent on ΔS^C and ΔS^D. Finally in the risk averse policy, the energy management is done under risk consideration in PV generated power. The confidence level here is considered equal to 0.99. As it is evident from Fig. 8, the peak and the average level of the battery storage is at a higher level using risk averse policy rather than neutral risk strategy due to the uncertainty in the PV generation power. This causes improvement in the commercial building microgrid resilience while an extreme event causes the commercial building to be isolated from the main power grid.
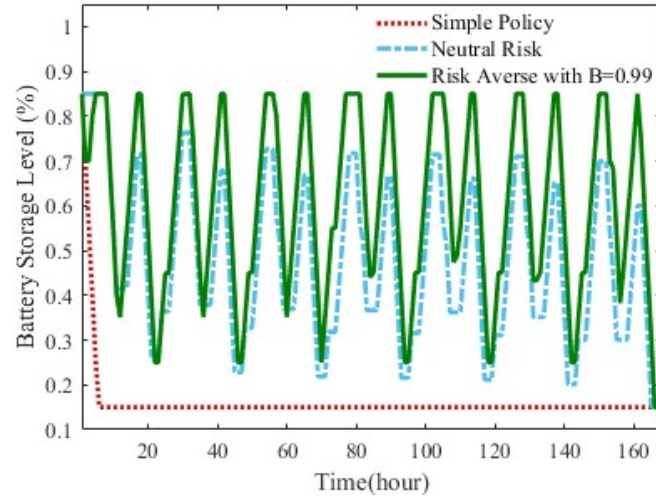
Fig. 8. Battery storage level.

Table 6. Operational cost and resilience comparison between neutral risk and risk averse policy with B=0.99

policy index	Neutral Risk	Risk Averse	$\frac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Cost (for 7days)	1178900000	1182700000	+ 0.32 (%)
Resilience	Neutral Risk	Risk Averse	$\frac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Day 1	0.71	0.85	+19.7 (%)
Day 2	0.68	0.85	+25.0 (%)
Day 3	0.67	0.85	+26.8 (%)
Day 4	0.66	0.85	+28.8 (%)
Day 5	0.66	0.85	+28.8 (%)
Day 6	0.65	0.85	+30.8 (%)
Day 7	0.60	0.85	+41.7 (%)
Average for 7 days	0.6024	0.4768	+26.34 (%)

Table 6 shows the total operational cost for 7 days and battery energy storage level of the commercial building for neutral risk and risk averse policy. Similar to the previous section, the battery storage level is taken as an index to show the resilience of the commercial building microgrid. Because the only stable source for commercial building after isolation from the power grid is battery storage, the average level of battery storage and the battery level at 5 P.M. every day is considered in these tables. Within the time period when the differences between battery storage level in risk averse and in neutral risk policy is maximum, the average level of battery storage in 168 hours

is about 0.6024 using risk averse strategy compared to 0.4768 in neutral risk policy which shows a 26.34% increase.

Accordingly, it is reasonable to mention that the resilience of the commercial building microgrid is improved by about 26.34% on average and 41.7% maximum (in day 7) as presented in Table 6. On the other hand, the total operational cost of the commercial building during the 7-day period has increased slightly by about 0.32%. As a result, using the risk averse policy, the resilience of the commercial building microgrid during extreme events and with uncertainty in PV power generation has improved significantly whereas the increase in system operational cost in the neutral risk policy is negligible.

In the second scenario, a new case study with new load demand (3.5 times scenario 1) and PV power generation (2 times scenario 1) is considered. The value of load demand and PV power generation comparing to scenario 1 are depicted in the Fig.9 and Fig.10.
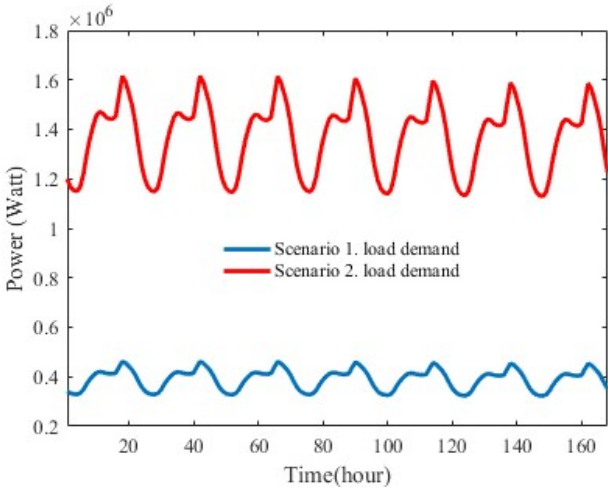

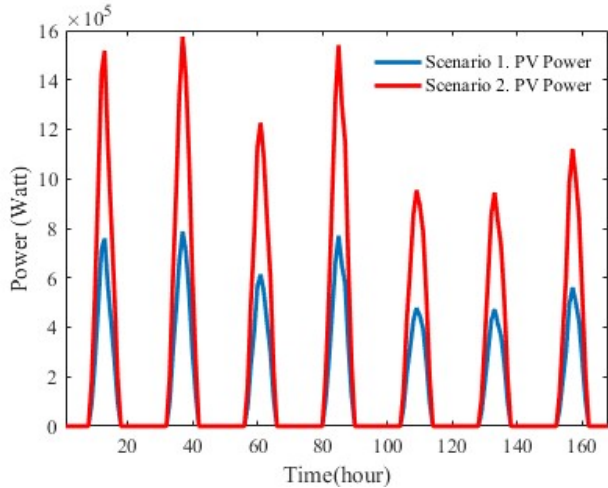Fig. 9. Load demand profile
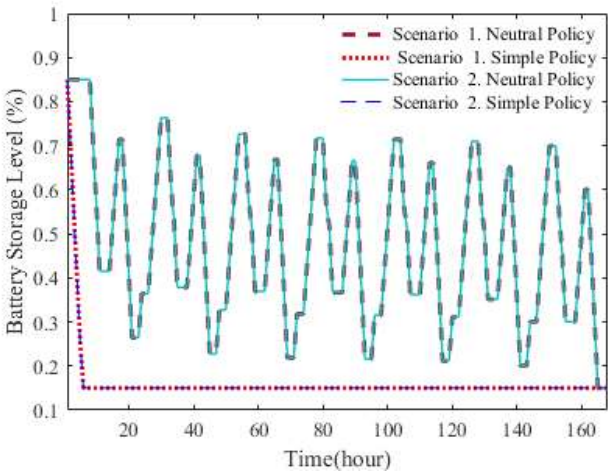

Fig. 10. PV power generation
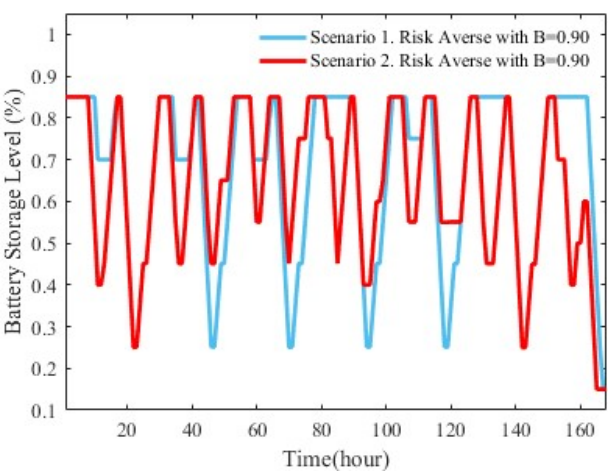

Fig. 11. Battery storage level

Fig. 12. Battery storage level

According to Fig. 11, there is no change in the battery storage level when using simple policy and neutral risk policy. However, the battery storage level has changed due to variability in the load demand and PV power generation as shown in Fig .12. This means that the proposed energy management based on CVaR is working properly. Table 7 illustrates the operational cost for the two policies. Here, only the average level of battery storage in 7 days is considered for the comparison. As evident from this table, not only the average level of battery storage level has increased by about 29.2% (which indicates improvement in the system resilience), the operational cost has also reduced by about 0.4 %. It should be noted that, these two scenarios are just taken as examples of the many possible scenarios that could be defined for the proposed approach.

Table 7. The operational cost for the two policies.

policy index	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Cost (for 7days)	5159700000	5139800000	+ 0.19 (%)
Resilience	Neutral Risk	Risk Averse	$\dfrac{\text{Risk Averse} - \text{Neutral Risk}}{\text{Neutral Risk}}$
Average for 7 days	0.5001	0.6460	+29.2 (%)

VII.   Conclusion

Severe events such as thunderstorms, blizzards, floods, hurricanes and other incidents, which could impose big challenges on the power grid resilience, are increasingly widespread all over the world. Microgrids are generally a desirable solution in power system to improve resilience. This paper has presented an optimal management of battery energy storage in a PV-based commercial building to increase its resilience as it minimizes its operational cost. CVaR was used to account for the uncertainties in both the day-ahead electricity price and PV power generation. Simulation results revealed that the commercial building microgrid resilience was improved remarkably with a slight increase in the commercial building operational cost, though. For example, considering the uncertainty in the day-ahead electricity price of the case study, the risk averse policy with confidence levels of 0.90, 0.95 and 0.99 had a slight increase in the operational cost by about 0.19%, 0.21% and 0.28% respectively, whereas the resilience of the commercial building microgrid increased by about 41.1%, 44% and 46.9% respectively.

Considering the uncertainty in the PV power generation, the resilience of the commercial building microgrid using the risk averse policy with the confidence level of 0.99 increased by about 26.34% while its operational cost was just about 0.32% higher compared to the neutral risk strategy. For the battery storage level, at 5 P.M. daily for example, when the difference between the battery storage level in the risk averse and neutral risk policy is maximum, the average battery storage level in 168 hours, which is about 0.6024 using risk averse strategy compared to 0.4768 in neutral risk policy, which is about 26.34% increase.

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