IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 1, 2016, accepted March 31, 2016, date of publication April 25, 2016, date of current version June 3, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2555926

A Microgrid Energy Management System and Risk Management Under an Electricity Market Environment

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ABSTRACT This paper presents a novel energy-management method for a microgrid that includes renewable energy, diesel generators, battery storage, and various loads. We assume that the microgrid takes part in a pool market and responds actively to the electricity price to maximize its profit by scheduling its controllable resources. To address various uncertainties, a risk-constrained scenario-based stochastic programming framework is proposed using the conditional value at risk method. The designed model is solved by two levels of stochastic optimization methods. One level of optimization is to submit optimal hourly bids to the day-ahead market under the forecast data. The other level of optimization is to determine the optimal scheduling using the scenario-based stochastic data of the uncertain resources. The proposed energy management system is not only beneficial for the microgrid and customers, but also applies the microgrid aggregator and virtual power plant. The results are shown to prove the validity of the proposed framework.

INDEX TERMS Controllable load, smart grid, energy management, electricity market, microgrid, renewable energy, risk management, stochastic optimization.

I. INTRODUCTION

In recent years, the microgrid has been growing dramatically due to its potential benefits to provide reliable, secure, efficient, environmentally friendly, and sustainable electricity from renewable energy sources [1], [2]. A microgrid consists of distributed energy sources, such as micro turbines, wind turbines, fuel cells and photovoltaic system (PVs), storage devices and a group of radial load feeders [3]. In the grid-connected mode, a microgrid is connected to the grid through a point of common coupling in a low-voltage distribution network. With the development of smart grid technologies, more and more controllable resources in the microgrid can exchange information with the higher-level power system [4], [5]. Hence a microgrid can respond actively to the electricity price to maximize its profit by scheduling its controllable resources. In [6], a price-incentive model was utilized to generate a management strategy to coordinate the charging of electric vehicles (EVs) and battery swap stations (BSSs) to minimize the total cost of the EVs and maximize the profit from the BSS in grid-connected mode. In [7], the author designed an objective to determine the optimal hourly bids that the microgrid aggregator should submit to the day-ahead market to maximize its profit. In [8], two market bidding techniques, single bidding and discriminatory bidding, were proposed for the microgrid to participate in the bidding process. Much work has been carried out on bidding and auction theory in the competitive electricity market. However, the energy management and optimal operation for the microgrid under the electricity market environment face challenges.

As it is an important research field of smart power, several approaches have been reported in the literature in relation to microgrid smart energy management applicable within the smart grid system. In [9], the authors proposed multi-objective intelligent energy management to minimize the operation cost and the environmental impact of a microgrid. In [10], a novel double-layer coordinated control approach for microgrid energy management was proposed, including a schedule layer obtaining an economic operation scheme based on forecasting data and a dispatch layer providing power to controllable units based on real-time data. In [11], three-level hierarchical energy management strategies were presented for multi-microgrids. Demand response and demand side management have also been considered in the microgrid energy management system [12], [13]. Overall, most existing works have not roundly considered the uncertainties of elements in the microgrid system. Renewable energy, such as wind and photovoltaic generation, customer loads and market electricity prices are uncertain and random in real time. Although some works considered the uncertainties of renewable energy [10], [11], the uncertainties of market electricity prices have seldom been considered.

In this paper, we present a microgrid energy management system that considers the uncertainties of renewable resources, customer loads and electricity prices. To address various uncertainties, we propose a double-layer scenario-based stochastic optimization approach. The first layer obtains an economic operation scheme based on forecasting data, while the second layer provides the power to controllable units based on real-time data. The microgrid schedules the controllable resources to maximize its profit. However, the profit may be at risk due to the uncertain resources in scenario-based stochastic programs. To constrain the risk, risk management is also proposed in the objective function using the conditional value at risk method.

The remainder of this paper is organized as follows. Section II describes the system model. Section III describes the solution approach. A detailed problem formulation is presented in Section IV. Several case studies and numerical results are provided in Section V. Finally, Section VI states the concluding remarks and discusses some directions for future works.

II. MICROGRID COMPONENT MODELING

A. PRICE MODELING

We assume that a microgrid is connected to the main grid and the grid supplies power to the microgrid to balance the microgrid demand. A two-way communication network is available for a microgrid management center to control the controllable units. We assume that the microgrid possesses a few diesel generators, storage batteries, wind turbines, PV panels, and controllable loads. The microgrid can procure energy from the wholesale electricity market and can also sell energy back to the market when the local generation is surplus. Under the electric power pool mode, the microgrid is a price-taker. It submits the hourly power quantities that it commits to buy/sell in the day-ahead (DA) energy market to the market operator before the operating day. During the operating day, the microgrid participates in the real-time energy market to compensate for the deviation from the day-ahead schedule. The market electricity price and quantity are formulated as

$$\mathrm{pr}_{B,t} = \mathrm{pr}_{BP,t} + \triangle\, \mathrm{pr}_{BP,t} \tag{1}$$

$$Q_{B,t} = Q_{BF,t} + \triangle\, Q_{BF,t} \tag{2}$$

where $\mathrm{pr}_{B,t}$ represents the market electricity price, $\mathrm{pr}_{BP,t}$ and $\triangle\, \mathrm{pr}_{BP,t}$ represent the forecast electricity price and forecast error, respectively, $Q_{B,t}$ represents the electricity quantity that the microgrid buys from the electricity market, and $Q_{BF,t}$ and $\triangle\, Q_{BF,t}$ represent the planning purchase quantity and real-time variation, respectively. The forecast error includes the active variation and passive variation. The active variation represents the variation that the microgrid dispatches actively to maximize its profit when the supply is abundant within the microgrid. The passive variation represents the variation by which the microgrid must purchase energy from the main grid when the supply is not enough due to forecast error. The mathematical formula is

$$\triangle\, \mathrm{pr}_{BP,t} = \triangle\, \mathrm{pr}_{BAC,t} + \triangle\, \mathrm{pr}_{BPC,t} \tag{3}$$

where $\triangle\, \mathrm{pr}_{BAC,t}$ and $\triangle\, \mathrm{pr}_{BPC,t}$ represent the active variation and passive variation, respectively.

B. DEMAND RESPONSE

We assume that the controllable loads are effective controllable units that respond actively to the electricity price. There are two types of controllable loads within the microgrid. One type of is passive such as refrigerators, freezers, air conditioners, water heaters and heat pumps, which can be controlled by direct load control (DLC) and interruptible load management (ILM).The other type is active, such as vehicle-to-grid (V2G) and heat storage, which not only can be controlled like the first type but can also supply energy to the main grid. This type can more effectively take part in load management programs. In the electricity market, the controllable loads respond actively to the electricity price as

$$P'_{LD,t} = P_{LD,t} + k \cdot (\mathrm{pr}'_{B,t} - \mathrm{pr}_{B,t}) \tag{4}$$

where $\mathrm{pr}'_{B,t}$ and $\mathrm{pr}_{B,t}$ represent the electricity price in real time and the reference price, respectively, $P'_{LD,t}$ and $P_{LD,t}$ represent controllable loads under $\mathrm{pr}'_{B,t}$ and $\mathrm{pr}_{B,t}$, respectively, and k represents the price elastic coefficient. As the electricity prices are fluctuant and uncertain, the controllable loads are also stochastic.

C. RENEWABLE ENERGY

Renewable resource generation such as wind turbines and PV panels is uncertain. For example, the output of wind turbines depends on the wind speed, and the output of PV panels depends on the irradiance and temperature.

1) WIND TURBINES

The output power of the wind turbines is described by

$$P_{WT} = \begin{cases} 0 & V \le V_{ci} \text{ or } V > V_{co} \\ a \cdot V^3 - b \cdot P_{rate} & V_{ci} < V \le V_r \\ P_{rate} & V_r < V \le V_{co} \end{cases} \tag{5}$$

where P_{WT} and P_{rate} represent the output power and rated output power of the wind turbine, respectively; V, V_{ci}, V_r and V_{co} represent the wind speed, cut-in speed, rated speed and cut-off speed of the wind turbine, respectively; and a and b are fitting parameters of the wind turbine power curve.

As shown in Eq. (5), the output of the wind turbines is dependent on the wind speed, which is obtained by the forecast in the energy-management system, but is unpredictable.

2) PV PANELS

The output of a PV generator is a function of the irradiance and temperature, which is provided by a confirmed formula,

$$P_{PV} = P_{STC,max} \cdot \frac{G_{AC}}{G_{STC}} \cdot (1 + k(T_e - T_{STC})) \tag{6}$$

where $P_{STC,max}$ represents the maximum output under standard test conditions; G_{AC} and G_{STC} represent the current irradiance and standard irradiance, respectively; T_e and T_{STC} represent the current temperature and standard temperature, respectively; and k is a temperature coefficient.

III. MODELING APPROACH

A. STOCHASTIC OPTIMIZATION APPROACH

In this paper, we propose a two-stage scenario-based stochastic programming approach to address the uncertainties in the microgrid. In the first stage, the forecast data of the uncertainties such as the wind speed, PV power, loads and electricity prices can be obtained by traditional forecasting techniques. Then, a Monte Carlo simulation with the Latin hypercube sampling technique is implemented to generate a large number of scenarios representing values of the uncertain parameters. Forecasting errors are always present. For simplicity, the forecasting errors of the wind speed, PV power, loads and electricity prices are assumed to follow normal distributions in this paper.

It is desirable to generate a large number of scenarios to increase the accuracy of the results. However, the number of generated scenarios directly impacts the computational complexity. To address this tradeoff, 2000 scenarios are generated using a Monte Carlo simulation with the Latin hypercube sampling(LHS) technique in this paper. A fast-forward reduction method such as The general algebraic modeling system (GAMS)/ scenario reduction (SCENRED) is implemented to reduce the computation time from 2000 scenarios to 200 scenarios without affecting the accuracy of the optimization results.

B. RISK MANAGEMENT

As data such as the wind speed, PV power, loads and electricity prices are produced randomly in the scenario-based stochastic optimization programming, the profit of the microgrid in the proposed model is indeed uncertain. The optimal expected profit under some scenarios may be very low or even negative. As a result, the expected profit may be variable and faces a high level of risk. In this paper, we propose a risk management scheme, namely, conditional value at risk (CVaR), to control the trade-off between the expected profit and its variability.

Several risk measures have been introduced to quantify risk [14], and one of the most popular is Value-at-Risk (VaR). However, it has undesirable mathematical characteristics such as a lack of subadditivity and convexity. VaR is also difficult to optimize when it is calculated from scenarios. As an alternative measure of risk, CVaR is known to have advantages over VaR in that it is transition-equivariant, positively homogeneous, convex, and has a stochastic dominance of order 1. In the scenario-based stochastic optimization method, the conditional value at risk at the α confidence level (α-CVaR) can be defined as the expected profit in the $(1-\alpha) \times 100\%$ worst scenarios, which is expressed as [14]

$$\text{Prob}\left(\xi \geq \text{VaR}_\alpha [\xi]\right) = \alpha \tag{7}$$

$$\text{CVaR}_\alpha [\xi] = E(\xi | \xi \leq \text{VaR}_\alpha [\xi]) \tag{8}$$

Where ξ represents a random variable and α represents a confidence level.

In [7], the author supplies a CVaR solving method, which is represented as

$$\max \delta, \eta S \quad \text{CVaR} = \delta - \frac{1}{1-\alpha} \sum_{s=1}^{NS} \rho_S \lambda_s \tag{9}$$

$$\lambda_s \geq \delta - \text{profit}_S, \quad \forall S \tag{10}$$

$$\lambda_s \geq 0, \quad \forall S \tag{11}$$

where N_S represents the number of Monte Carlo scenarios; ρ_s represents the probability of scenario s, δ represents the VaR, and λ_s represents an auxiliary nonnegative variable equal to the difference between the VaR and profit_S if profit_S is smaller than VaR and equal to zero otherwise.

IV. PROBLEM FORMULATION

A. OBJECTIVE FUNCTION

In this paper, we propose a double-level stochastic optimization method to maximize the profit of the microgrid. We assume that the microgrid always operates in grid-connected mode. The objective of the model is to maximize the profit of the microgrid over a given time period together with achieving risk management. Normally, the operation costs of renewable energy and energy storage such as batteries are minimal. Therefore, renewable energy and battery operation costs are not considered in this paper. The objective function is given as

$$\text{Max} \sum_{s=1}^{NS} \rho_S \text{profit}_s + \varphi \text{CVaR} \tag{12}$$

where N_S represents the number of Monte Carlo scenarios; ρ_s represents the probability of scenario s; profit_s represents the profit of the microgrid in scenario s; and φ represents the risk aversion parameter. When φ is equal to zero, the microgrid is a risk-neutral decision maker. With φ increasing, the microgrid becomes more risk-averse.

The profit of the microgrid in scenario s is

$$\text{profit}_s = \sum_{t=1}^{NT} \Delta T \left(G_{s,t} - F_{s,t}^{DG}\right) \tag{13}$$

$$G_{s,t} = P_{s,t}^{sell} \times \pi_{s,t}^{sell} - P_{s,t}^{buy} \times \pi_{s,t}^{buy} - P_{s,t}^{pen} \times \pi_{s,t}^{pen} \tag{14}$$

$$F_{s,t}^{DG} = \sum_{i=1}^{N_G} \left[C_{F,i} P_{s,t}^{G,i} + C_{M,i} P_{s,t}^{G,i} + C_{G,i} U_{s,t}^{G,i}\right] \tag{15}$$

where $G_{s,t}$ represents the profit of the microgrid obtained from the main grid; $F_{s,t}^{DG}$ represents the cost of the distributed generation (DG) in the microgrid; $P_{s,t}^{sell}$ and $P_{s,t}^{buy}$ represent the electrical energy sold and bought from the grid tie line in scenario s, respectively; $\pi_{s,t}^{sell}$ and $\pi_{s,t}^{buy}$ represent the sell and buy electricity prices in scenario s, respectively; $P^{pen}_{s,t}$ and $\pi^{pen}_{s,t}$ represent the penalty amount and penalty price when the actual power is not equal to the plan exchange power in the tie line and scenario s; $C_{F,i}$ represents the i^{th} generator cost of fuel; $C_{M,i}$ represents the i^{th} generator maintenance cost; N_G represents the total number of diesel generators; $P^{G,i}_{s,t}$ represents the i^{th} generator power in period t and scenario s; $C_{G,i}$ represents the i^{th} generator start-up cost; and $U^{G,i}_{s,t}$ represents the i^{th} generator status in period t and scenario s.

The system constraints are given in the following.

Active Power Balancing Constraint:

$$\sum_{i=1}^{N_G} P^{G,i}_{s,t} + \sum_{i=1}^{N_B} P^{B,i+}_{s,t} - \sum_{i=1}^{N_B} P^{B,i-}_{s,t} + \sum_{i=1}^{N_{WT}} P^{WT,i}_{s,t} + \sum_{i=1}^{N_{PV}} P^{PV,i}_{s,t} + P^{TL}_{s,t} = \sum_{i=1}^{N_D} P^{LD,i}_{s,t} \tag{16}$$

where N_B, N_{WT}, N_{PV} and N_D represent the numbers of batteries, wind turbines, photovoltaic generators and loads, respectively. $P^{G,i}_{s,t}, P^{B,i+}_{s,t}, P^{B,i-}_{s,t}, P^{WT,i}_{s,t}, P^{PV,i}_{s,t}, P^{TL}_{s,t}$, and $P^{LD,i}_{s,t}$ represent the power of the DG, batteries discharging, batteries charging, wind, photovoltaic generators, tie line, and controllable loads in scenario s, respectively.

Power Exchange With Main Grid:

$$-P_{TL,max} \le P^{TL}_{s,t} \le P_{TL,max} \tag{17}$$
$$0 \le P^{sell}_{s,t} \le g_{s,t} P_{TL,max} \tag{18}$$
$$0 \le P^{buy}_{s,t} \le (1 - g_{s,t}) P_{TL,max} \tag{19}$$
$$P^{TL}_{s,t} = P^{buy}_{s,t} - P^{sell}_{s,t} \tag{20}$$

where $P_{TL,max}$ represents the maximum power of the grid tie-line, $P^{buy}_{s,t}$ and $P^{sell}_{s,t}$ represent the amount of energy that the microgrid buys and sells from the tie line in period t under scenario s, respectively, and $g_{s,t}$ is a Boolean variable that is equal to 1 when the microgrid sells energy to the main grid and equal to 0 when the microgrid buys energy from the main grid.

Diesel Generator Output Limits:

$$U^{G,i}_{s,t} P_{G,i,min} \le P^{G,i}_{s,t} \le U^{G,i}_{s,t} P_{G,i,max} \tag{21}$$
$$-R_{down,i}\Delta T \le P^{G,i}_{s,t} - P^{G,i}_{s,t-1} \le R_{up,i}\Delta T \tag{22}$$

where $P_{G,i,min}$ and $P_{G,i,max}$ represent the i^{th} generator minimum and maximum power, respectively, $U^{G,i}_{s,t}$ represents the i^{th} generator status at time t in scenario s, and $R_{up,i}$ and $R_{down,i}$ represent the i^{th} generator ramp-up and ramp-down rate, respectively.

Battery Models and Limits: In this paper, lead-acid batteries are implemented to compensate for the differences between energy supply and demand. The following constraint should be considered for the scheduling program of the batteries [11]

$$SOC_{min} \le SOC_{s,t} \le SOC_{max} \tag{23}$$
$$SOC_{s,t+1} = SOC_{s,t} + \eta_c P^{B,-}_{s,t} - P^{B,+}_{s,t}/\eta_d \tag{24}$$

where $SOC_{s,t}$ and $SOC_{s,t+1}$ represent the capacity energy state of the batteries in periods t and t + 1, respectively; SOC_{min} and SOC_{max} represent the minimum and maximum capacities of the batteries, respectively; $P^{B,-}_{s,t}$ and $P^{B,+}_{s,t}$ represent the battery charge and discharge power in period t, respectively; and η_c and η_d represent the battery efficiencies during the charging and discharging processes, respectively.

When the battery is charging or discharging, the power should be limited as

$$0 \le P^{B,-}_{s,t} \le P^{B,-}_{max} \tag{25}$$
$$0 \le P^{B,+}_{s,t} \le P^{B,+}_{max} \tag{26}$$
$$P^{B}_{s,t} = P^{B,+}_{s,t} - P^{B,-}_{s,t} \tag{27}$$

where $P^{B,-}_{max}$ and $P^{B,+}_{max}$ represent the maximum charging and discharging power, respectively and $P^{B}_{s,t}$ represents the battery output power in scenario s.

In this paper, we assume that the energy of the batteries at the end of the dispatch period is more than SOC^{end} to ensure that the batteries are available the next day. The limit is given as

$$SOC^{NT} \ge SOC^{end} \tag{28}$$

where SOC^{NT} represents the energy of the batteries at the end of the dispatch period and SOC^{end} represents the minimum required dispatched energy of the batteries.

B. CONTROLLABLE LOADS

We assume that the passive controllable loads such as water heaters and heat pumps can participate in demand response programs with interruptible load management (ILM). The constraints and limitations of an interruptible load are given as

$$P_{LD,min} \le P^{LD}_{s,t} \le P_{LD,max} \tag{29}$$
$$P^{IL}_{s,t} \le \alpha P^{LD}_{s,t} \tag{30}$$

where $P^{LD}_{s,t}$ and $P^{IL}_{s,t}$ represent the load power and interruptible load power in period t under scenario s, respectively; $P_{LD,min}$ and $P_{LD,max}$ represent the minimum and maximum load power, respectively; and α is an interruptible load coefficient.

The electric vehicles are assumed to be in charging mode from time 1 to time T_{ev} and in travelling mode from time T_{ev} to NT. The constraints and limitations are given as

$$0 \le P^{ev,ch}_{s,t} \le P^{ev,ch}_{max} \quad t \text{ in } 1 \ldots T_{ev} \tag{31}$$
$$P^{ev,ch}_{s,t} = 0 \quad t \text{ in } T_{ev} + 1 \ldots NT \tag{32}$$
$$SOC^{ev}_{s,t} = SOC^{ev}_{s,t-1} + P^{ev,ch}_{s,t} \times \eta^{ev} \quad t \text{ in } 1 \ldots T_{ev} \tag{33}$$
$$SOC^{ev}_{s,t} \le SOC^{ev,max} \quad t \text{ in } 1 \ldots T_{ev} \tag{34}$$
$$SOC^{ev}_{s,T_{ev}} \ge SOC^{ev,end} \tag{35}$$

where $P^{ev,ch}_{s,t}$ represents the charging power of the electric vehicles, $P^{ev,ch}_{max}$ represents the maximum charging power, η^{ev} represents the electric vehicle efficiency during the charging processes, $SOC^{ev}_{s,t}$ represents the capacity of the electric

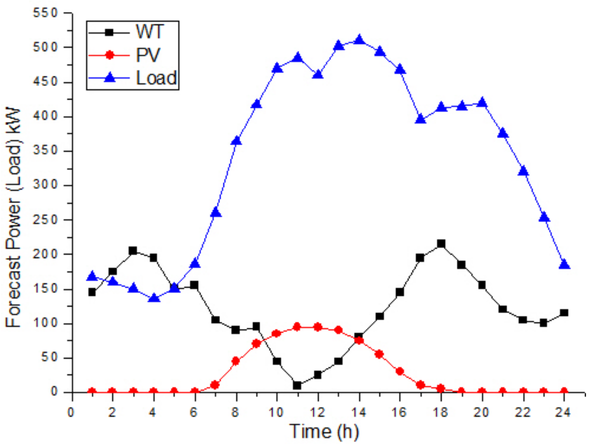

FIGURE 1. Forecast output power for WT and PV and load.

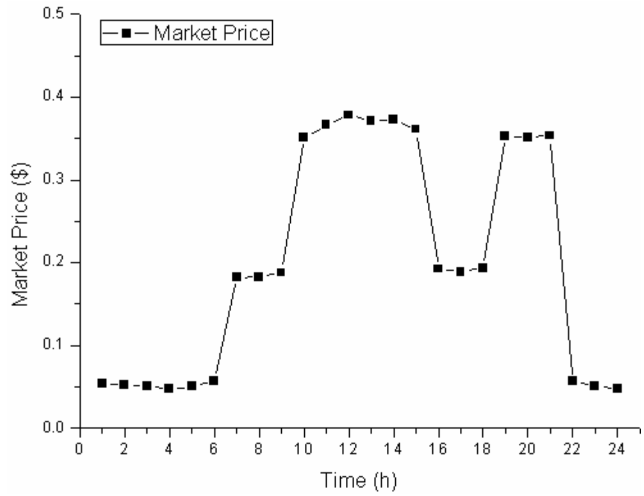

FIGURE 2. Day-ahead forecast output for market prices.

vehicles, and $SOC^{ev,max}$ and $SOC^{ev,end}$ represent the maximum and end time capacities, respectively.

C. OTHER LIMITS

The market electricity price and quantity are shown in Eq. (1) and Eq. (2). The demand response of the controllable loads is shown in Eq. (4). The output power limits of the wind turbines and PV generators are shown in Eq. (5) and Eq. (6). The risk management limits are shown in Eq. (7)- Eq. (11).

V. CASE STUDY

The microgrid is operating in grid-connected mode by a single tie-line. The maximum exchange power limit of the grid tie-line is 800 kW. The scheduling period is assumed to be 24 equal time slots in one day. The microgrid has non-dispatchable distributed generation units consisting of a wind turbine (WT) unit and a photovoltaic (PV) panel unit. One industrial customer, two commercial, and one-hundred residential customers are considered in the microgrid. In this paper, we assume that the loads have a common characteristic and can be considered as critical and interruptible loads. Therefore, the loads can be added together and considered the total load. The output of the WT unit, the PV panel unit, and the total load are obtained by forecast-based historical data, weather forecast data, and the forecast method of the Autoregressive Integrated Moving Average Model (ARIMA). Using a single day as an example, the forecast power for the WT and PV units and the total load were obtained from [11] and are shown in Fig. 1.

The energy-storage system consists of lead-acid battery units with a capacity of 200 kWh. The charging and discharging ramp-rate limits are 50 kW for each hour. The battery efficiency during the charging and discharging processes is 0.9 at any time step [15].

In this paper, we assume that the electricity price is fluctuant. The sample day-ahead forecast electricity market price is obtained from the PJM market, which is shown in Fig. 2 [16].

TABLE 1. Technical and economic features of diesel generators.

Unit	Cost coefficients		
	a ($)	b ($/kWh)	c ($/kWh^2)
DG1	0.18	0.09	0.01
DG2	0.22	0.14	0.01
Unit	Technical constraints		
	Startup ($)	Pmin (kW)	Pmax (kW)
DG1	0.15	30.00	300.00
DG2	0.21	40.00	400.00

The shiftable load is the controllable load that participates in the demand response. We assume that the controllable load is no more than 50% of the total load at any time [16].

Two diesel generators are considered in the microgrid. Because small DG units have negligible start-up times, the start-up cost can be simplified as a constant for each unit. The technical aspects and cost functions of the two diesel generators installed in the microgrid were obtained from [17] and are given in Table 1.

By the piecewise linearization of the dispatchable DG units' fuel and maintenance costs in Eq. (15), the multi-objective optimization problem (shown in Eq. (12)) can be formulated as a mixed-integer linear problem (MILP) [18], which can be solved by IBM CPLEX12.4.

A. DAY-AHEAD SCHEDULED POWER RESULT WITH FORECAST DATA.

In this case, we do not consider stochastic optimization or risk management. The day-ahead scheduled result uses confirmed forecast data, including the WT, PV, load and market price, as is shown in Fig. 3. The result shows that the grid tie-line power fluctuates severely. During the periods of 6 AM-10 AM and 4 PM-6 PM, the grid tie-line power is much greater than that in the other periods, and the microgrid

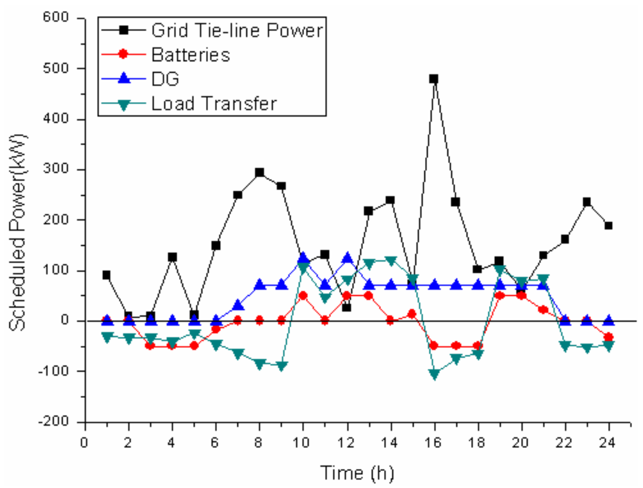

FIGURE 3. Day-ahead scheduled power with forecast data.

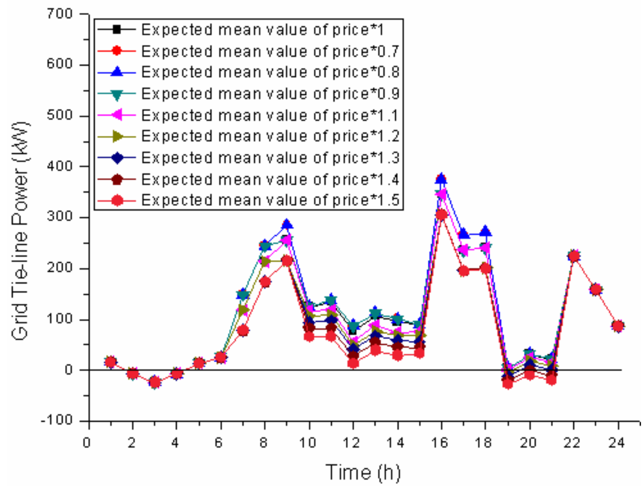

FIGURE 5. Effect of price expected mean value on energy purchase and sale plan.

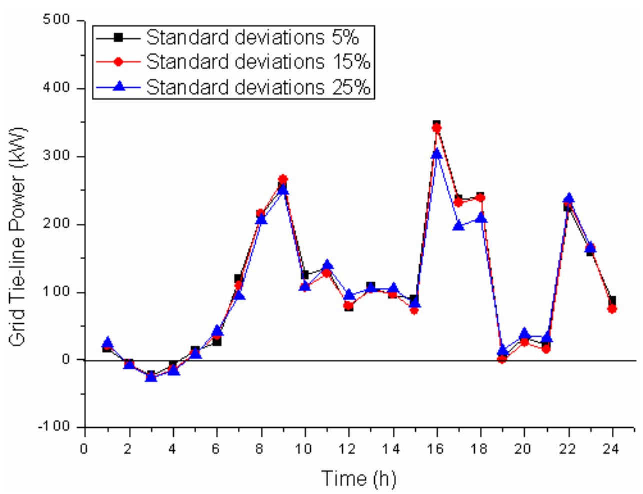

FIGURE 4. Effect of price standard deviation on energy purchase and sale plan.

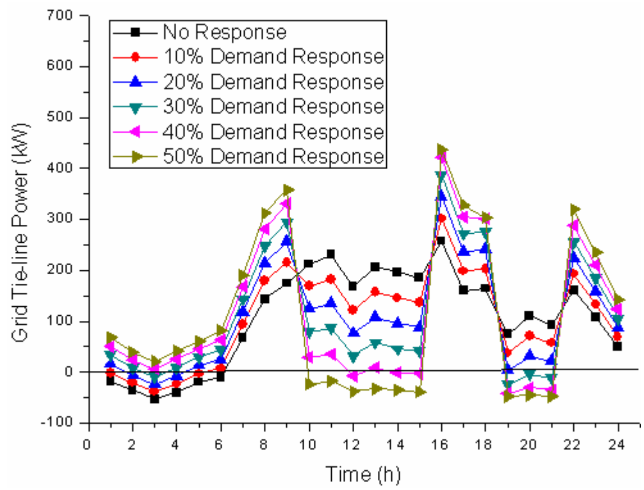

FIGURE 6. Effect of demand response on energy purchase and sale plan.

buys much energy from the main grid then as the market price is lower. Many more loads are transferred during this period to maintain the system balance. The result shows that the model proposed in this paper is effective.

B. EFFECT OF VARIOUS PRICES ON POWER PURCHASE AND SALE STRATEGIES.

Having obtained the forecast data for the uncertainties such as the market price, wind speed, PV power and loads, we use the Monte Carlo simulation to generate a large number of scenarios representing the uncertain parameters. 2000 scenarios are generated using a Monte Carlo simulation with the LHS technique in this paper. In this case, we propose a scenario-based stochastic programming approach to address the uncertainties in the microgrid. We assume that the forecast errors of the market prices are normally distributed with a zero mean and their standard deviations are 5%, 15% and 25% of the forecasted values. The result of the grid tie-line power is shown in Figure 4. The grid tie-line power fluctuates less when the standard deviations are less than 15%. As the standard deviation increases (for example, to 25%), the grid tie-line power significantly decreases in the period of 4 PM - 6 PM. Figure 5 shows the effect of the expected mean value of the price on the energy purchase and sale plan. During the periods of 1 AM - 6 AM and 9 PM - 12 AM, the grid tie-line power fluctuates negligibly, whether the price's expected mean value increases or decreases. During other periods, the grid tie-line power decreases as the price's expected mean value increases. Table 2 shows the profit and CVaR with various price standard deviations.

C. EFFECT OF DEMAND RESPONSE ON ENERGY MANAGEMENT STRATEGIES.

The effect of the demand response on the energy purchase and sale plan is shown in Figure 6. As the demand response increases, the grid tie-line power fluctuates regularly,

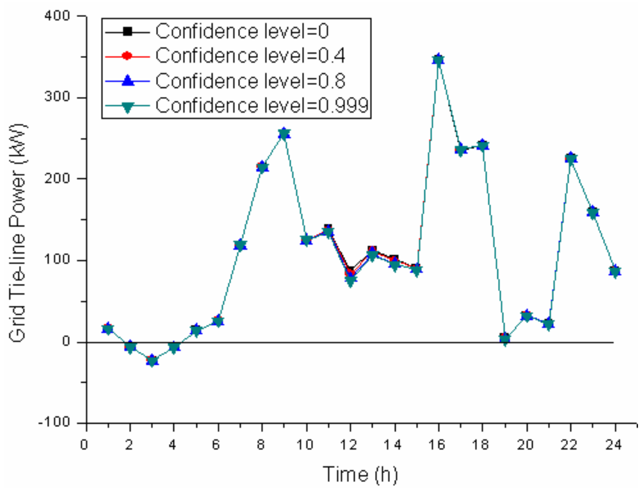

FIGURE 7. Effect of confidence level on energy purchase and sale plan.

TABLE 2. Profit and CVaR with various Price Standard Deviations.

Price Standard Deviations	Profit ($)	CVaR ($)
0.05	690.315	352.358
0.1	706.962	352.257
0.15	728.549	341.205
0.2	749.174	352.43
0.25	767.696	331.996

TABLE 3. Microgrid Profit and CVaR variations with demand response.

Demand Response	Profit ($)	CVaR ($)
0	653.397	314.631
10%	672.204	333.55
20%	690.315	352.358
30%	707.22	370.927
40%	720.678	389.034
50%	731.084	405.337

decreasing during the peak hours (for example, 10 AM - 3 PM) and increasing during the valley hours (for example, 1 AM - 6 AM). When the demand response level is greater than 40%, which means that more than 40% of controllable loads can participate in demand response, the grid tie-line power is negative, so the microgrid may sell energy to the grid during the peak hours (10 AM - 3 PM and 7 PM - 9 PM). Because the market prices are high during these periods, the microgrid may use the most demand response to achieve the maximum profit. Table 3 shows the microgrid profit and CVaR along with the change in the demand response. Both the microgrid profit and the CVaR are proportional to the demand response. This proves that the optimization strategy proposed in this paper is reasonable.

TABLE 4. Results with confidence levels.

Confidence level	Grid_profit _sum($)	CVaR($)	fuel_cost_ sum($)	grid_cost _sum($)
a=0	679.467	419.088	260.379	793.414
a=0.1	680.255	412.107	261.9	792.641
a=0.2	681.057	406.239	263.473	791.825
a=0.3	682.138	400.755	265.566	790.758
a=0.4	683.455	395.135	268.136	789.441
a=0.5	684.424	389.490	270.024	788.472
a=0.6	685.881	383.226	272.851	787.015
a=0.7	686.782	375.632	274.599	786.114
a=0.8	688.778	365.688	278.507	784.103
a=0.9	690.315	352.358	281.531	782.567
a=0.95	690.968	339.413	282.816	781.913
a=0.97	691.419	330.381	283.706	781.462
a=0.98	691.671	323.894	284.202	781.211
a=0.99	691.879	315.575	284.609	781.003
a=0.995	691.983	309.963	284.811	780.898
a=0.999	692.059	309.507	284.962	780.823

D. RISK MANAGEMENT ANALYSIS

In this paper, the risk management for CVaR is considered in the objective function. We change the confidence level from 0 to 1, and a series of optimal results are obtained. The grid tie-line power is obtained with different confidence levels (shown in Figure 7). The grid tie-line power is the same at different confidence levels, except for some minor fluctuation during the period of 12 PM- 3 PM. The expected total microgrid profit, CVaR, total fuel cost and microgrid cost are shown in Table 4. The expected total microgrid profit and the total fuel cost increase together as the confidence level increases, while the CVaR and the expected microgrid cost decrease together. In engineering practice, an appropriate value for the confidence level will be selected considering the total microgrid profit and cost.

VI. CONCLUSIONS

In this paper, a novel energy management strategy for a microgrid is proposed under an electricity market environment. A risk-constrained scenario-based stochastic programming framework is implemented to address the uncertainties in the WT, PV and loads. Stochastic electricity prices are also considered in the model. The effect of demand response on the energy management model is discussed. The risk management for CVaR is considered in the objective function, and the risk management analysis is also proposed in this paper. As a result, the proposed energy management system is effective in engineering practice and beneficial for both the microgrid and the customers. In future work, the energy management system for the microgrid aggregator and virtual power plant (VPP) will be studied under the electricity market environment.

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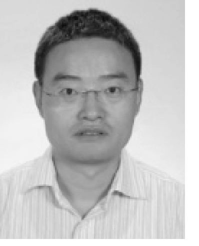

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