Economic-Reliability Risk-Constrained Scheduling for Resilient-Microgrids Considering Demand Response Actions

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***Abstract*--In this paper, a risk-constrained optimal scheduling framework is proposed for an economic and reliable operation of microgrids. The framework is developed based on a scenario-based optimization technique, to schedule the microgrid operation both in normal and islanding modes. The prevailing uncertainties of islanding duration as well as prediction errors of loads, market prices and renewable power generation are addressed in the scheduling problem. The effect of participation of customers in demand response (DR) programs is investigated on economic-reliable operating solutions. Also, the uncertainties associated with wind power, loads and electricity prices as well as the uncertainties of islanding duration events of the microgrid are modeled, properly. The optimal scheduling carried out through a unit commitment algorithm and an AC power flow procedure by considering system's objectives and constraints. Moreover, to adequately handle the uncertainties of the problem, conditional value-at-risk (CVaR) metric is incorporated into the optimization model to evaluate the profit risk associated with operator's decisions in different conditions. With the proposed model, the impacts of DR actions, in terms of economy and reliability, are investigated with a 400 V microgrid system.**

Keywords—Optimal scheduling, demand response (DR), reliability, microgrid, conditional value-at-risk (CVaR).

I. Introduction

Microgrids, as small-scale power systems, are self-controlled entities which facilitate the penetration of renewable generation and distributed energy resources (DERs) for economic and reliability purposes [1].

Microgrid reliability reflects the ability of microgrid to withstand severe disturbances without experiencing any major disruption and supply customers at the required amount and power quality [2]. In fact, by deploying microgrids with self-supply and islanding capabilities, they have the potential for improving system reliability and resiliency and are considered as one of the most effective ways for supplying local loads in the bulk transmission systems [3].

Meanwhile, into a smart active network, demand response (DR) management is a critical mechanism to balance power demand and supply and to make microgrids more flexible and reliable [4], [5].

Most of the existing publications on the topic of microgrid reliability have mainly focused on reliability evaluation of grid-connected or isolated microgrids [6], weather dependent microsources [7] and operational strategies [8].

In [9], a two-stage adaptive robust optimization model has been proposed for scheduling of microgrids in both grid-connected and islanded modes. The objective is minimizing operating cost of microgrid under the worst-case scenarios associated with RESs generation and islanding events.

In [10], an optimal scheduling framework has been presented for minimizing the load curtailment of microgrids during extended islanded periods considering uncertainties in islanding duration, loads and generations.

Moreover, a risk-constrained stochastic framework has been proposed in [11] for scheduling of microgrids over unscheduled islanding periods. In that work the risk caused by uncertainties in islanding duration, loads and renewable generation was addressed via conditional value-at-risk (CVaR) index. However, the impact of risk aversion on decision-making of the operator has not been analyzed properly.

The authors in [12] have presented a risk-constrained two-stage stochastic framework for joint energy and reserve scheduling of islanded microgrids where risk of profit variability is considered using CVaR.

Moreover, in [13], a risk-constrained stochastic programming approach is presented for optimal scheduling of a microgrid under uncertainty.

This paper developed a risk-constrained framework for optimal scheduling of microgrids considering DR action. This model addresses the economic-reliability indices of microgrid considering its resilience issues.

The framework is formulated as a stochastic optimization problem and the objective is to maximize the expected profit of the operator. As the uncertainties of islanding duration have a significant effect on the microgrid operation, they have to be addressed in the scheduling process. Moreover, the impact of risk aversion on decision-making of the operator and on reliability indices is discussed for normal and resilient operations of microgrids.

The rest of this paper is arranged as follows. Description of the proposed optimal scheduling method is introduced in Section II. The mathematical problem formulation is presented in Section III. Case studies together with simulation results are discussed in section IV. Finally, the major findings of the paper are concluded in Section V.

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II. DESCRIPTION OF THE PROPOSED SCHEDULING STRATEGY

This paper presents a stochastic framework for scheduling of microgrid by implementing time-based rate DR scheme under uncertainties. Microgrid consists of several controllable DG (CDG) units, renewable generation units such as wind turbine (WT), responsive and non-responsive loads and can operate both of normal and emergency modes. At the normal operation, microgrid is connected to the main grid, thus the operator schedules the local generating units and energy trading with the main grid to maximize its profit while considering a possible islanding event.

However, when a severe disturbance event occurs in the main grid, microgrid can switch into resilient operation, i.e., the islanded mode. In this mode, the operator should schedule available energy and reserve resources to supply demand with the lowest load shedding. In this scheme, customers participate in DR actions and adjust their consumption based on the hourly price signal.

Moreover, two categories of uncertainties i.e. normal operation uncertainties and contingency-based uncertainties are modeled by traditional forecasting techniques. In this study, the uncertainties associated with wind power, loads and electricity prices are considered as normal operation uncertainties while the uncertainties of islanding duration events are deemed as contingency-based ones.

Monte Carlo approach is adopted to calculate the microgrid islanding duration after an extreme event. The optimal power flow (OPF) is performed to calculated load curtailment in the microgrid. Also, Monte Carlo simulation (MCS) with the Latin hypercube sampling technique is applied for scenarios generation.

For simplicity, forecasting errors of all uncertain parameters are assumed to follow normal distributions in this study. A fast-forward reduction method such as the general algebraic modeling system (GAMS)/ scenario reduction (SCENRED) is employed to decrease computation time by limiting the amount of scenarios [13], [14].

The input data that is produced randomly in the proposed scenario-based model causes the microgrid operator encounter with uncertainties in its profit.

In order to control the trade-off between the expected profit and its variability, CVaR as a risk management tool is incorporated into the model to control the trade-off between the expected profit and its variability.

In the scenario-based model, CVaR measure at the α confidence level (α-CVaR) can be defined as the expected profit in the (1- α)×100% worst scenarios, given by [15]:

$$\Pr ob\ \ [\xi \geq VaR(\xi)] \tag{1}$$

$$CVaR_{\alpha}(\xi) = E[\xi | \xi \leq VaR_{\alpha}(\xi)] \tag{2}$$

where Value-at-Risk (VaR) is one of the most popular risk measures to quantify risk, ξ is a random variable and α represents a confidence level.

Therefore, CVaR method is applied in the proposed model as follow [15]:

$$\max_{\delta,\lambda_s} =[\delta-(1-\alpha)^{-1}\sum_{s=1}^{N_S}\rho_s.\lambda_s] \tag{3}$$

$$\eta_s \geq \delta - profit_s, and \qquad \lambda_s \geq 0; \qquad \forall s \tag{4}$$

where N_S denotes the number of scenarios, ρ_s is the probability of scenario s, $profit_s$ denotes the profit in scenario *s*, δ characterizes the VaR and λ_s is an auxiliary nonnegative variable equals to the difference between auxiliary variable δ and $profit_s$ when the $profit_s$ is smaller than δ .

III. PROBLEM FORMULATION

A. Objective Function

The objective of the proposed stochastic optimization problem is to maximize the profit of the microgrid together with achieving risk management. The objective function is given as:

$$Max \ \sum_{s=1}^{N_S}\rho_s profit_s + \beta CVaR_{\alpha}(\xi) \tag{5}$$

where β is the risk aversion parameter. When β is equal to zero, the operator is a risk-neutral decision maker and when it is increasing, the operator becomes more risk-averse. The profit in scenario *s* of the microgrid is:

$$profit_s = \sum_{t=1}^{N_T}\Delta t.[F_{s,t}^{C} + F_{s,t}^{M} - F_{s,t}^{R} - F_{s,t}^{CDGs}] \tag{6}$$

$$F_{s,t}^{C} = \sum_{j=1}^{N_J}\pi_{s,j,t}.D_{s,j,t} - VOLL \times EENS_t \tag{7}$$

$$F_{s,t}^{M} = \pi_{s,t}^{sell}.P_{s,t}^{sell} - \pi_{s,t}^{buy}.P_{s,t}^{buy} \tag{8}$$

$$\begin{aligned} F_{s,t}^{R} &= \pi_{s,t}^{up}R_{t,s}^{up} - \pi_{s,t}^{dn}R_{s,t}^{dn} + \sum_{j=1}^{N_J}[(\pi_{s,j,t}^{up}R_{s,j,t}^{up} - \pi_{s,j,t}^{dn}R_{s,j,t}^{dn}) \\ &+ \sum_{g=1}^{N_G}[(\pi_{s,g,t}^{up}R_{s,g,t}^{up} - \pi_{s,g,t}^{dn}R_{s,g,t}^{dn} + \pi_{s,g,t}^{non}R_{s,g,t}^{non}) \end{aligned} \tag{9}$$

$$F_{s,t}^{CDGs} = \sum_{i=1}^{N_G}[C_g(P_g) + SU_{s,g,t} + SD_{s,g,t}] \tag{10}$$

where *t, j* and *g* represent the index of time, index of loads and index of CDGs, respectively. Also, N_T, N_J and N_G represent the numbers of time slots, number of customers and number of CDGs, respectively. Δt is duration of interval *t*, which can be 5 minutes or more. $F_{s,t}^{C}$ and $F_{s,t}^{M}$ represent the profit obtained from customers and main grid, respectively. $\pi_{s,j,t}$ and $D_{s,j,t}$ stand for demand and electricity price offered to customers at time *t* in scenario *s*, respectively. The term of $VOLL \times EENS_T$ in (7) represents the cost of mandatory load shedding at time *t*. $F_{s,t}^{R}$ represents the cost of the required reserve that provided by main grid, responsive loads and CDGs. Moreover, $F_{s,t}^{R}$ is the operation cost of the CDGs. $P_{s,t}^{sell}$ and $P_{s,t}^{buy}$ indicate the energy sold and bought from main grid at time *t* and in scenario *s*, respectively. $\pi_{s,t}^{sell}$ and $\pi_{s,t}^{buy}$ represent the sell and buy electricity prices, respectively. Also, $\pi_{s,g,t}^{up}$, $\pi_{s,g,t}^{dn}$ and $\pi_{s,g,t}^{non}$ represent the bid of up-, down- and non-spinning reserve submitted by CDG unit g at time t. $\pi^{up}_{s,j,s}$ and $\pi^{dn}_{s,j,s}$ indicate bid of up (down)-spinning reserve submitted by customer j, and $\pi^{up}_{s,t}$ and $\pi^{dn}_{s,t}$ represent up (down)-regulation market prices. Likewise, R represents the allocated reserve and $C_g(P_g)$ refers to generation cost of CDG unit g, $SU_{s,g,t}$ and $SD_{s,g,t}$ are start-up and shut-down cost of CDG unit g.

B. The Problem Constraints

Active power (P) balancing constraint for each scenario and at each time slot t and at bus n is presented as:

$$P^n_{g,t,s} + P^n_{w,t,s} - D^n_{j,t,s} + MLS^n_{j,t,s} = \sum_{r=1}^{N_B} fl^P_{(n,r),t,s} \tag{11}$$

where, $MLS^n_{j,t,s}$ represents mandatory load shedding at bus n and at time t and in scenario s, and $fl^P_{(n,r),t,s}$ represents the active power flowing between bus n and r at time t and scenario s, and is represented as:

$$\begin{aligned} fl^P_{(n,r),t,s} &= G^l_{(n,r)}[V^2_{n,t,s} - V_{n,t,s}V_{r,t,s}\cos(\theta_{n,t,s} - \theta_{r,t,s})] \\ &\quad - B^l_{(n,r)}[V_{n,t}V_{r,t,s}\sin(\theta_{n,t,s} - \theta_{r,t,s})] \end{aligned} \tag{12}$$

Where, V and $\theta_{n,t,s}$ are voltage magnitude and voltage angle at node n, respectively. $G^l_{(n,r)}$ and $B^l_{(n,r)}$ represent conductance and susceptance of line l, respectively.

Limits of power exchanges between the microgrid and main grid are given as below:

$$-P^{TL,\max}_{s,t} \le P^{TL}_{s,t} \le P^{TL,\max}_{s,t} \tag{13}$$

$$P^{TL}_{t,s} = P^{buy}_{t,s} - P^{sell}_{t,s} \tag{14}$$

$$0 \le P^{buy}_{t,s} \le P^{TL,\max}_{s,t}.\upsilon_{t,s} \tag{15}$$

$$0 \le P^{sell}_{m,t,s} \le P^{TL,\max}_{s,t}(1-\upsilon_{t,s}) \tag{16}$$

where $P^{TL,\max}_{s,t}$ is the maximum power of the main grid tie-line, and $\upsilon_{t,s}$ is a binary 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.

The output power of wind turbine w in scenario s and at time t ($P_{w,t,s}$) is limited with its maximum capacity ($P^{\max}_w$).

$$0 \le P_{w,t,s} \le P^{\max}_w \tag{17}$$

The limits of reserve services allocated by the CDGs and responsive loads are determined by constraints (18)-(22)

$$0 \le R^{up}_{g,t,s} \le P^{\max}_g u_{g,t,s} - P_{g,t,s} \tag{18}$$

$$0 \le R^{dn}_{g,t,s} \le P_{g,t,s} - P^{\min}_g u_{g,t,s} \tag{19}$$

$$0 \le R^{non}_{g,t,s} \le P^{\max}_g (1-u_{g,t,s}) \tag{20}$$

$$0 \le R^{up}_{j,t,s} \le D_{j,t} - D^{\min}_{j,t} \tag{21}$$

$$0 \le R^{dn}_{j,t,s} \le D^{\max}_{j,t} - D_{j,t} \tag{22}$$

where, $u_{g,t,s}$ is commitment status of CDG unit g, and it is 1 when unit g is committed, else it is 0.

The conventional reliability indices such as expected load not served (ELNS) and expected energy not supplied (EENS) are usually used to assess long-term security of energy supply [16]. These indices have been redefined here to evaluate the reliability of microgrid in one day.

Therefore, the ELNS_t and EENS_t are defined as the expected load not served and the expected energy not supplied, respectively. These indices can be calculated as follows [16]:

$$ELNS_t = \sum_{s=1}^{N_S}\sum_{j=1}^{N_J} \rho_s.MLS_{j,t,s}.\Delta t \tag{23}$$

$$EENS = \sum_{s=1}^{N_S}\sum_{j=1}^{N_J} \rho_s.MLS_{j,t,s}.\Delta t \tag{24}$$

Also, one another index for EENS (IEENS) is defined that represents the percentage of EENS per sum of expected energy supplied over the scheduling horizon. Therefore, this index is provided as follow:

$$IEENS = \frac{EENS}{\sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\sum_{s=0}^{N_S} p_s.D_{s,j,t}.\Delta t} \times \%100$$

IV. Simulation and Numerical Results

A. Test System and Main Assumptions

The proposed framework is performed on a low voltage microgrid test case with 5 CDGs and 3 wind turbines to carry out the economy and the reliability assessment. The load and wind generation profiles as well as electricity price signal are given in Fig. 1, [17], [18].

The data of CDGs are given in Table I (FC, MT and DE represent fuel cell, micro-turbine and diesel engine, respectively) [19]. In addition, forecasted errors of load, wind power and energy price are assumed to follow normal distributions with standard deviations equal to 8%, 5% and 10%, respectively [17], [20].

Moreover, it is assumed that islanding durations of the microgrid follow a normal distribution with mean of 12 hours and different values of standard deviations. This distribution of islanding durations of the microgrid during the scheduling horizon is approximated as shown in Fig 2 [11].

In order to carefully investigate different aspects of the proposed framework, four cases are defined as follow:

Case I: Optimal scheduling of microgrid in normal condition without considering DR actions. In this case, there are no islanding events and as the result the islanding duration scenarios are not considered.

Case II: Similar to Case I, but DR actions are considered.

Case III: Optimal scheduling of microgrid with considering islanding duration scenarios. In this case, DR actions are not considered.

Case IV: Similar to Case 3, but DR actions are considered.

It should be noted that the scheduling horizon is considered one day which is divided into 24 time slots. Also, all calculations were implemented in MATLAB and GAMS [21] and solved by CPLEX on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor.

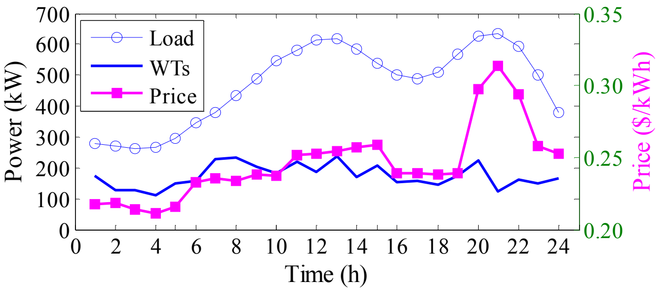

Fig. 1. The forecasted values of load, wind power and electricity price.

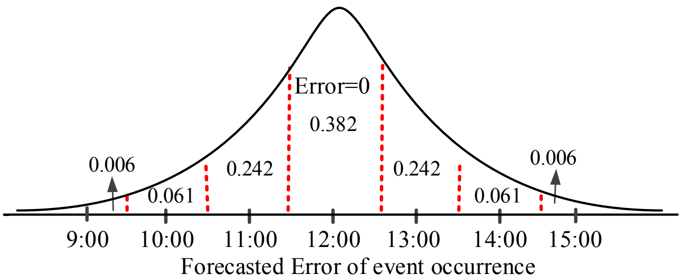

Fig. 2. Islanding durations of the microgrid during the scheduling horizon.

TABLE I
CHARACTERISTICS OF THE CDG UNITS

CDGs Type	P^{min} (kW)	P^{max} (kW)	Operation Cost ($/kWh)	Start-up Cost ($)	Shat-down Cost ($)
MT_1	25	150	0.9	0.09	0.08
MT_2	25	150	1	0.09	0.08
FC_1	20	100	2.4	0.16	0.09
FC_2	20	100	2.6	0.16	0.09
GE	35	150	3.1	0.12	0.08

B. *Results and Analysis*

The effect of risk aversion parameter on the expected profit, VaR and CVaR terms in different Cases are compared in Table II. Here, the values of lost load (VOLL) and confidence level, α , are considered 0.5 $/kWh and 0.95, respectively.

As expected, in Case I, the solution achieved for β = 0 (risk-natural case) attains the highest expected profit and when β increases from 0 to 20, the expected profit decreases 28.2%, from $517 to $371. Decrement of the profit in Cases II, III and IV is equal to 18.7%, 18% and 15.4%, respectively.

However, CVaR increases 30.1%, 88.5%, 19.7% and 80.6% in Cases I, II, III and IV, if risk is accounted for β = 20. Therefore, the expected profit is highly dependent on the risk-aversion of the operator, especially in Case I that DR action is not considered.

Moreover, in Cases III and IV that islanding duration scenarios are considered in the scheduling, the expected profit decreases compared with the normal operations, i.e. Cases I and II.

When customers participate in DR, the number of scenarios with negative profits decreases and consequently the values of VaR and CVaR in cases II and IV are higher than those in cases I and III, respectively.

Moreover, in such condition, the expected profit of the worst 5% scenarios becomes higher when DR action is not considered. Moreover, the result in table III shows that by increasing β from 0 to 20, the cost of CDG increases and hence the operator imports more energy from the main-grid.

In fact, in lower levels of β, the operator tries to provide more energy from the local CDG units with low uncertain resources compared with DA market.

Also, the results show that in cases of with DR, the customers adjust their consumption and as the result, the provided power from CDGs reduces at peak hours and consequently, the total cost of CDGs decreases.

TABLE II
THE EFFECTS OF RISK AVERSION ON THE PROFIT, VAR AND CVAR IN DIFFERENT CASES

β	**Expected Profit ($)**				**VaR ($)**				**CVaR ($)**			
	Case I	Case II	Case III	Case IV	Case I	Case II	Case III	Case IV	Case I	Case II	Case III	Case IV
0	517	629	444	585	-192	-155	-169	-97	-200	-157	-178	-98
1	507	595	442	563	-153	-34	-154	-32	-162	-35	-163	-33
2	495	592	433	561	-144	-29	-146	-29	-154	-30	-155	-31
5	472	562	411	543	-140	-22	-142	-24	-143	-25	-148	-26
20	371	511	364	495	-137	-14	-132	-16	-140	-18	-146	-19

TABLE III
EFFECTS OF RISK AVERSION ON THE COST OF CDGs OPERATION, RESERVE AND TREADING ENERGY WITH MAIN GRID IN DIFFERENT CASES

β	**Cost of CDGs ($)**				**Total energy (kwh) bought from the main grid**				**Cost of scheduled reserve ($)**			
	Case I	Case II	Case III	Case IV	Case I	Case II	Case III	Case IV	Case I	Case II	Case III	Case IV
0	1712	1556	1980	1903	365	610	174	268	225	185	444	585
1	1865	2043	2039	2057	210	-102	103	111	206	117	442	563
2	1895	2044	2964	2047	127	-305	-50	-120	200	112	433	561
5	1926	2017	2091	2150	-11	-430	-102	-341	194	105	411	543
20	1986	2093	2093	2189	-170	-568	-159	-574	180	97	402	495

Moreover, the cost of scheduled reserves decreases by increasing risk aversion parameter. This observation can be justified as follows. In higher values of β, generating units are scheduled such a way that the probability of mismatch between supply and demand mitigates and as a result the required reserve decreases.

In fact, when the operator becomes more risk-averse, it is willing to sacrifice high profits in the best scenarios in the hope of avoiding low profits or even losses in the worst scenarios. Therefore, by decreasing the number of worst scenarios, the amount of reserve scheduled in the electricity market increases and so its associated cost would augment.

To quantify and evaluate the system reliability under different risk levels, the ELNS, IELNS and the cost of EENS are illustrated in Fig. 3. Observe that when the operator becomes more risk-averse, the amount of three mentioned indices increase in all cases, non-monotonically. However, comparing different cases shows that by implementing DR, the amount of load shedding decreases. Moreover, cost of EENS decreases during unscheduled islanding periods, due to higher reserve capacities allocated in these cases in comparison with normal operation cases.

Fig. 4 shows hourly trading energy between the microgrid and main grid and its total amount over the scheduling horizon in different cases.

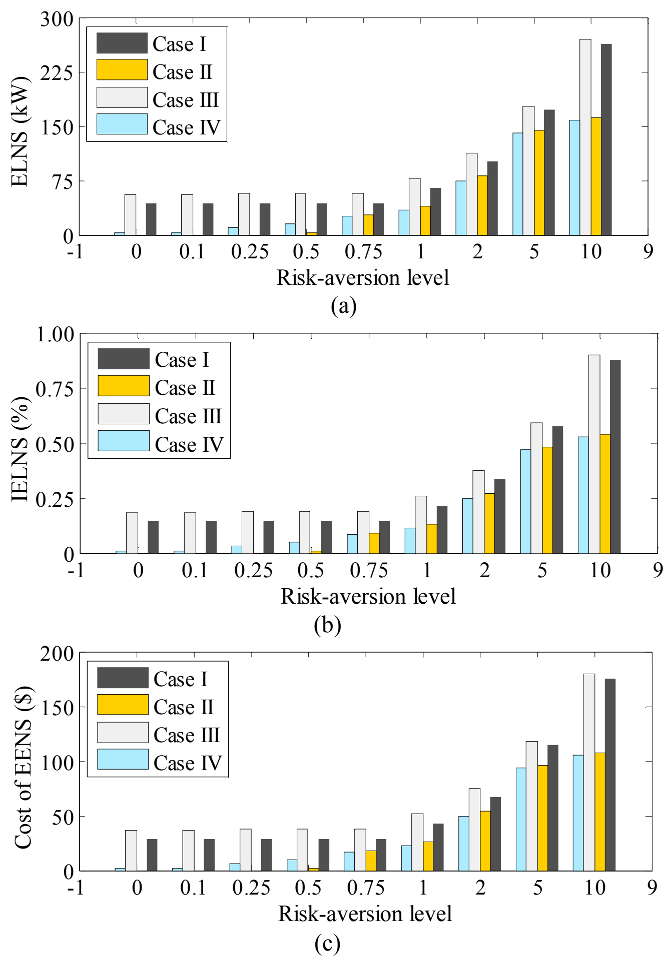

Fig. 3. Reliability indices, (a) ELNS, (b) IELNS, and (c) cost of EENS.

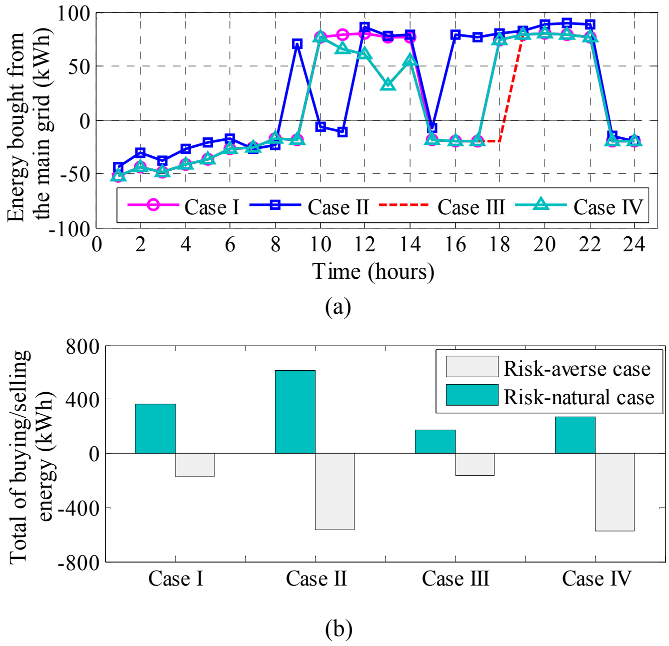

Fig. 4. Hourly exchange energy between the microgrid and the main grid.

Observe that by participation of customers in DR programs in Cases II and IV, the energy bought from the main grid declines and the energy sold to the main grid increases. The reason is that the DR utilization would reduce hourly peak loads and/or fill the valley periods when energy supplement from the main grid is cheaper.

Therefore, in a risk-neutral case ($\beta = 0$), the operator tends to buy more energy blocks from main grid. In contrast, by increasing the risk aversion level, the operator tends to supply microgrid loads from more reliable CDGs rather than the main grid.

V. Conclusions

This paper developed an economic-reliability risk-constrained scheduling for microgrids by considering demand response actions. The expected profit of the operator was maximized through a stochastic optimization model and the risk imposed by uncertainties in islanding duration, microgrid load, and electricity price as well as wind power generation was addressed via CVaR. The proposed evaluation framework was applied to a test microgrid and the simulation results have been presented for several cases. When islanding contingencies are considered, the expected profit decreases significantly compared to a normal operating condition. Moreover, in a resilient microgrid, the value of CVaR in a certain risk aversion is higher than the one in normal condition. In a risk-neutral case, the operator tends to buy more energy from the main grid. However, by increasing risk aversion, the operator tends to supply microgrid loads from more reliable CDG units rather than the main grid. Furthermore, the results show when the operator becomes more risk-averse, the amount of ELNS, IELNS and the cost of EENS increase in all cases. However, these indices in cases with DR are lower than in cases without DR actions.

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