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Short-term reliability and economic evaluation of resilient microgrids under incentive-based demand response programs

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ABSTRACT

In this paper, a flexibility oriented stochastic scheduling framework is presented to evaluate short-term reliability and economic of islanded microgrids (MGs) under different incentive-based DR (IBDR) programs. A multi-period islanding constraint is considered to prepare the MG for a resilient response once a disturbance occurs in the main grid. Also, a multi-segment optimal power flow (OPF) approach is used to model the IBDR actions and reserve resources. Moreover, uncertainties associated with electricity prices, loads, renewable generation, calls for reserve as well as uncertainties of islanding duration of the MG are considered. The ultimate goal of the MG operator is to maximize its expected profit under a certain level of security and reliability in conjunction with the minimization of energy procurement costs of customers. The MG's economy and reliability indices are studied considering normal operation and resilient condition based on appliances characteristics, customers' and operator's behaviors. The proposed model can effectively manage MGs operation in both normal and resilient conditions in order to improve economic and reliability indices. Numerical results demonstrate that by implementing IBDR, in cases of normal and resilient operation, the expected profit of the MG operator increases about 4% and 2.7% and reliability indicator improved 60% and 56%, respectively.

1. Introduction

Over the past years and as a response to climate changes and energy crisis, utilization of renewable energy resources (RESs) has been widely increased around the world [1]. In a power system with a high penetration of renewable generation, power mismatch between supply and demand increases due to the intermittent nature of such uncertain resources. In traditional power systems, some solutions such as backup generation, energy storage systems (ESSs), or curtailment (in part) of wind and solar power have been employed to mitigate supply–demand imbalance [1,2].

However, in smart modern power systems, in addition to conventional solutions for power mismatch compensation, demand side management (DSM) techniques are frequently used as they can provide a great opportunity for power/energy regulation and relieve risks associated with operation of renewable-based energy systems[3,4]. DSM provides several financial and technical benefits for power system operators by improving the operation of RESs and enabling cost saving for end-use customers [5]. In this regard, demand response (DR) as a main option of DSM strategy is recognized to mitigate the imbalance by stimulating consumers to modify their demand profile through varying electricity prices or incentive payments in order to reduce their electricity bills [6,7].

Implementing of DR programs can also play an important role in reliable operation of microgrids (MGs) where the uncertainties of RESs and stochastic behaviors of customers have a significant impact on the reliability and security, especially when MGs enter to islanded operation [8]. This subject has been investigated in several literatures and the results have confirm that the implementation of DR programs not only brings great profits to MGs, but also enhance their reliability through mitigating peak demand and proper management of renewable generation units [8–10]. Therefore, DR is known as a system reliability resource that can procure spinning reserve for system reliability

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Nomenclature

Indices and sets

t, h Index of time slot, $t = 1, 2, \ldots, N_T$.
s Index of scenario, $s = 1, 2, \ldots, N_S$.
g Index of DG units, $g = 1, 2, \ldots, N_G$.
w Index of wind turbines, $w = 1, 2, \ldots, N_W$.
k Index of energy storage system, $k = 1, 2, \ldots, N_K$.
j Index of load groups, $k = 1, 2, \ldots, N_J$.
n, r Indices of buses
$\alpha_{1,t}, \alpha_{2,t}$ Cost coefficients of DG unit g.
$(.)_{t,s}$ At time t in scenario s.
$(.)^{max}, (.)^{min}$ Upper and lower limits of variable $(.)$.

Parameters and constants

$D^S_{j,t}$, $(D_{j,t,s})$ Scheduled demand (power consumption) of the j-th group of customer (kW).
$P^S_{g,t}$, $(P_{g,t,s})$ Scheduled power (power generation) of DG unit g (kW).
$Pr^{DA}_t (Pr^{RT}_{t,s})$ Day-ahead (real-time) market prices ($/kWh).
$\rho_{j,t}$ Total rate of electricity ($/kWh).
β Risk-aversion parameter.
α Per unit confidence level.
$Pr^{up}_{g,t} (Pr^{dn}_{g,t})$ Bid of up (down)-spinning reserve submitted by DG unit g at time t ($/kWh).
$Pr^{up}_{j,t} (Pr^{dn}_{j,t})$ Bid of up (down)-spinning reserve submitted by the j-th group of customer at time t ($/kWh).
$Pr^{non}_{g,t}$ Bid of non-spinning reserve submitted by DG unit g at time t ($/kWh).
$inc_{j,t}, (pen_{j,t})$ Incentive (penalty) rate considered in IBDR program ($/kWh).
$Pr^{Voll}_{j,t}$ Value of lost load ($/kWh).
$E_{j,t,t}$, $(E_{j,t,h})$ Self (cross) demand elasticity.
$\lambda^{SU}_{g,t}, (\lambda^{SD}_{g,t})$ Start-up (Shut-down) cost of DG unit g at time t ($).
$RU_g, (RD_g)$ Ramp-up (ramp-down) rates of DG unit g.
UT_g, (DT_g) Minimum up (down) time of DG unit g.
$G^l, (B^l)$ Conductance (Susceptance) of line l.
π_s Probability of scenario s.

Variables

$p^{DA}_{t,s}$ Exchange power between the MG and the main grid in the DA market (kW).
$p^{shed}_{j,t,s} (q^{shed}_{j,t,s})$ Active (reactive) power of load shedding of customers in group j (kW).
$R^{up}_{g,t} (R^{dn}_{g,t})$ Reserve up/down service provided by DG unit g (kW).
$R^{up}_{j,t} (R^{dn}_{j,t})$ Reserve up/down service provided by customers in group j (kW).
$R^{non}_{g,t}$ Non-spinning reserve provided by DG unit g (kW).
$r^{up}_{g,t,s} (r^{dn}_{g,t,s})$ Up- and down spinning reserves deployed by DG g (kW).
$r^{up}_{j,t,s} (r^{dn}_{j,t,s})$ Up- and down spinning reserves deployed by customers in group j (kW).
$\theta_{t,s}$ $(V_{t,s})$ Voltage angle and amplitude.
η_s Auxiliary variable for calculating the CVaR ($).
ξ Value-at-risk ($).
$u_{g,t,s}$ Commitment status of DG unit g, {0, 1}.
$y_{g,t,s} (z_{g,t,s})$ Start-up (shutdown) indicator of DG g, {0, 1}.
$INC(\Delta D_{j,t})$ Total incentive payment for load reduction of customer j participated in IBDR program ($)
$PEN(\Delta D_{j,t})$ Total penalty charge of customer j ($)
$B(D_{j,t})$ Income of customer j when participate in IDBR program during *t-th* hour ($)
$S^c_{j,t}$ Benefit of customer j when participate in IDBR program ($)
$LOL_{j,t,s}$ Loss of load of customer j at time t and scenario s (kW).
EIR_t Energy index of reliability.
$EDNS_t$ Expected demand not served at time t.
VLR (IVLR) Value of voluntary (involuntary) load reduction.
$EDNS^{VLR}_t$ Expected demand not served stemmed from *VLR*.
$EDNS^{IVLR}_t$ Expected demand not served stemmed from *IVLR*.

enhancement [11].

Some studies have attempted to model the effects of DR participants on network reliability. DR participants and dynamic line ratings (DLR) for optimum power network reliability and ageing have been addressed in [12]. When expected energy not supplied (EENS) and expected total network ageing (ETNA) are considered together, the reliability model is more cost-effective [12]. In [13], the effects of network ageing towards its reliability have been modelled considering wind integration plants. These studies modelled the effects of network ageing towards its reliability and mainly applied for real-time operation management of overhead lines at transmission level.

The ability to operate in islanded mode is the most salient feature of MGs when a disturbance occurs in the upstream grid. The impact of prevailing uncertainty of islanding events on optimal scheduling of MGs has been studied in a significant number of literatures [14–16]. In [14], a resiliency-oriented MG optimal scheduling model has been presented aiming to minimize the MG load curtailment by efficiently scheduling available resources when supply of power from the main grid is interrupted for an extended period of time. Prevailing operational uncertainties in load, RESs power, and the main grid supply interruption time and duration are considered and captured using a robust optimization method. In [15], a two-stage stochastic problem has been modeled for optimal scheduling of resilient MGs. In that model, the operation cost of MGs is minimized while taking into account the prevailing uncertainties associated with wind power, electric vehicles (EVs), and real-time market prices are also taken into account in that work. A two-stage adaptive robust optimization model has been proposed in [16] for scheduling of MGs considering islanding operation mode. In that model, operating cost of MG is minimized under the worst-case scenarios associated with RESs generation and islanding durations. In [17], a resiliency-oriented stochastic framework has been presented for MG scheduling to minimize the operation cost and reduce the mandatory load shedding under the weather-related incidents. In the mentioned studies, reliability issues are not considered when islanding events occur. Moreover, the impact of uncertain factors such as islanding events and DR participants on system reliability are not addressed.

This paper presents a flexibility-oriented stochastic framework for joint energy and reserve scheduling of resilient MGs considering incentive-based DR (IBDR) programs. Risk constraints are added to the mathematical scheduling formulation to control the uncertainties associated with electricity prices, loads, renewable generation, calls for reserve and islanding duration of the MG. The impacts of the operator behavior and also incentive price factor are studied on short-term reliability of the MG in different cases. The existing reliability evaluation techniques are more focused on steady-state (time-independent) reliability evaluation and have been successfully applied in power system planning and expansion [18,19]. In this paper, short-term reliability of resilient MGs is studied considering islanding duration of the MG in the short term scheduling. The proposed method provides an accurate model for the MG operator to evaluate the reliability and arrange reserve for maintaining secure operation of MG considering islanding duration in the short terms. The proposed method can provide some references for short-term dispatching and operation of resilient MG and the effect of DR programs for its reliability improvement. To evaluate the true effects of IBDR programs on the MG reliability, optimal power flow (OPF) approach is employed to the problem formulation. The careful evaluation of reliability and economic indices of MGs considering emergency conditions is very important. In this way, the MG operator can effectively check the status of reliability indicators in different situations and make necessary decisions.

Various sensitivity analyses on the risk parameters and incentive factors in both normal and resiliency conditions are carried out to validate the short-term reliability of the MG in different states. The results of this research demonstrate that the proposed scheduling and pricing schemes can effectively manage opportunistic demand and enhance system reliability, thus have the potential to improve the penetration of wind generation. Also, the results confirm that the proposed stochastic strategy can help to the operators to effectively manage the MGs operation in the unscheduled island mode.

The novel contributions of this paper are threefold:

- A flexibility-oriented stochastic framework is proposed for joint energy and reserve scheduling of resilient MGs. The proposed model handles the prevailing uncertainties of islanding duration, component contingency as well as prediction errors of loads, day-ahead (DA) and real time (RT) market prices, renewable power generation and reserve provision.
- To assess the effect of DR on the reliability, two new reliability-based indices are defined to compare the MG operation in normal operation and resilient condition.
- The impacts of the operator behavior and incentive price factor on economy and reliability indices are investigated via a sensitivity analysis.

The rest of the paper is organized as follows. Section 2 describes the proposed stochastic scheduling framework. In Section 3, mathematical formulations are presented. Numerical analysis and results are given in Section 4 and Section 5 concludes the paper.

2. Flexibility-oriented stochastic scheduling framework

In this study, a flexibility-oriented stochastic framework is presented for MG scheduling, in which, the main objective is maximizing the expected profit of the MG operator by optimal scheduling of both demand and supply side resources. The MG includes a few dispatchable DGs and RESs that supply number of local customers. It is assumed that the MG has the capability of communicating with the end-users and controlling their responsive loads when it is needed. Each customer has a number of electrical devices which some of them are essential and some others are flexible and manageable. The MG operates normally in grid-connected mode and goes to islanding mode when a disturbance occurs in the upstream. A reconnection to the main grid is established once the disturbance is cleared.

However, the disturbance occurring time and period are not predetermined for the MG operator. During islanding duration, the MG's resources should be scheduled in such a way that the loads be supplied with minimum interruption. Therefore, a realistic islanding constraint should be implemented in scheduling problem to consider all probable disturbances in any time. In other words, a resilient operation with adequate online generation resources would be performed for all 24 h of a scheduling horizon. Moreover, the operator should try to anticipate unbalanced power of the MG by implementing IBDR program and providing required balancing power during all time periods. Based on this program, when the MG reliability encounters high-risk operation or in the periods with higher energy prices, the proposed method relies on providing incentive prices to the customers in order to reduce their energy procurement costs. Meanwhile, the customers participate in IBDR programs and reduced their consumption to achieve more incentives or energy credits.

In this study, the customers can participate in two different IBDR plans including interruptible/curtailable (I/C) programs and capacity market programs (CAP). In I/C programs, customers receive a rate discount or bill credit to reduce their demand when contingencies are triggered. Also, the customers will be penalized if they do not commit themselves to the agreement. Moreover, in CAP, customers should supply pre-determined load reductions on demand and are subjected to penalties if they do not respond properly to load reduction commands.

In smart grids, in addition to DG units, responsive loads can provide spinning reserve to improve the system reliability. Customers' energy bills decrease when they provide reserve services, because reserve generation would be freed up to supply energy. When responsive loads allocate reserve, they should be able to rapidly curtail a part of their demand in response to an event or contingency. This option requires responsive loads with storage and control capability, a communication system that tells the loads when to respond, and monitoring to ensure that the load response is obtained.

The MG operator clears DA, RT and spinning reserve (SR) markets using a market-clearing procedure to obtain the share of providing balancing power of each customer and the reserve services in each time slot. In the decision-making process, the operator may face sources of uncertainty including RESs power generation, load demand, availability of responsive loads, calls for reserve, DA, RT and SR market prices and also the MG islanding durations. An optimal power flow (OPF) model is implemented in the market clearing program to consider network constraints, properly, to determine energy credit earned by customers, values of voluntary load reductions (VLR), involuntary load reductions (IVLR), EENS and other economy and reliability indicators. After determining the incentive prices of the MG, the optimal balancing power of consumers in response to these prices and their reserve provision capacity are also determined such a way that to maximize benefits of consumers.

3. Mathematical formulation

3.1. Uncertainties characterization and modeling procedure

Two major classes of uncertainties are considered in this study. The first class that is called normal operation uncertainty including uncertainties associated with prediction errors of loads, electricity price, renewable power generation and call for reserve. The values of stochastic variables at each hour would be equal to the forecasted value at that hour plus an error that is randomly generated based on the distributions obtained from historical data [20]. At first, normal probability distribution functions (PDFs) are used to model prediction errors of the first class uncertainties, and then Monte-Carlo simulation (MCS) [20] is applied to generate numerous scenarios based on random sampling from related PDFs.

In this study, DG units and DR can provide reserve services to the MG operator. Such reserve services are traded by purchasing options to buy reserves at predetermined prices by paying premiums. These reserves include call and deploy options to address underproduction and overproduction. To estimate the possible call for reserve, normal distribution function is considered in this study. Forecasting errors of this stochastic variable is modeled with PDF for each interval (in this case 24 PDF) with a zero-mean normal distribution and different standard deviations. The MG operator may call the responsive loads and DG units for providing reserve, when it required reserve services. If the MG operator accepts the bid of reserves submitted by each of the units and DR, the mentioned units and DR receive a capacity payment for being on stand-by. If that unit or DR is called to deploy their services, they will receive in payment in real time. This behavior of unit and DR is uncertain and its distribution are modelled with normal PDF as shown in Fig. 1 that each PDF is divided into seven discrete intervals with different probability levels. As observe, the mean values are equivalent to the forecasted values of the

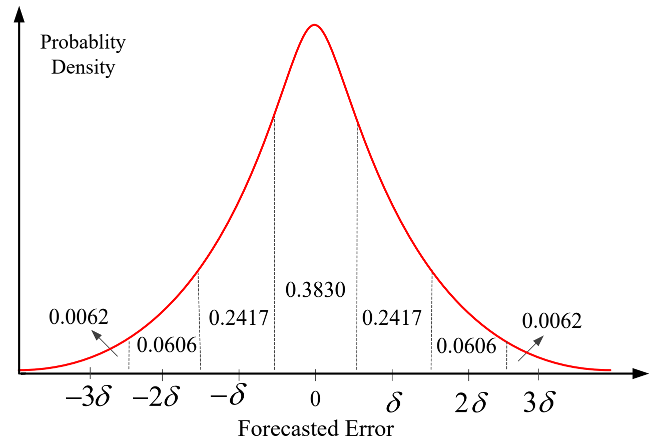

Fig. 1. Discretization of the probability distribution of the call for reserves.

reserve provided by reserve resources in each time period. MCS method is used to generate a large number of scenarios indicating the uncertain parameters based on hourly PDFs of call for reserve.

The second class of uncertainties, which deemed as contingency-based uncertainties, include two groups: uncertainty of islanding duration events and contingency of the MG's components, such as DG units. Islanding duration is unknown in case of unscheduled islanding events and may not be determined with certainty. However, the associated probability distribution can be estimated from historical data, Monte Carlo simulations or any credible source of information [9]. The uncertainties of islanding duration are represented via an appropriate scenario set that are extracted from historical data. This scenario set has different possibilities of unscheduled islanding duration and the estimated probability of occurrence. In this study, normal PDF is considered to model the associated randomness of unscheduled islanding durations. For example, normal PDF for modeling forecasting errors of unscheduled islanding durations with mean of 12:00 h and standard deviation of one hour [9].

The second group of the contingency-based uncertainties is considered with a two state reliability model. In this model random forced outages of DG units as contingency of the MG's components is considered based on the 2-state Markov model {0, 1}, in which 0 represents the working state and 1 shows the fault state. Assuming that λ (fault rate) and the μ (repair rate) of the two state components are constant, and then the working time and fault repairing time of the components are exponentially distributed [21]. Assuming also that the component is in the working state initially ($t = 0$), the component probability of each state at time t,$\boldsymbol{\rho}(\boldsymbol{t})$, is [21]:

$$\boldsymbol{\pi}_h(t) = [1 - \pi_h(t), \pi_h(t)] = \left[\frac{\mu}{\lambda+\mu} + \frac{\lambda}{\lambda+\mu} e^{-(\lambda+\mu)t}, \frac{\lambda}{\lambda+\mu}\left(1 - e^{-(\lambda+\mu)t}\right)\right] \quad (1)$$

where 1-$\pi_h(t)$ is the working condition probability of the component at t, $\pi_h(t)$ is the probability of fault state of the component at t.

Based on the above discussion, a set of N_A scenarios is created for normal operation uncertainties (i.e. uncertainties of RESs generation, demand load, call for reserve and energy prices) and a set of N_B scenarios is created for contingency-based uncertainties (i.e, uncertainties of islanding duration events and random forced outages of DG units). These two groups of scenarios are combined based on the scenario tree [22]. The probability of the corresponding combined scenario would be determined based on the multiplication of the probability related to the scenario of the two groups assuming that the two uncertainties are independent. The total number of scenarios considering all uncertain parameters would equal to $\mathrm{N} = \mathrm{N_A} \times \mathrm{N_B}$ with occurrence probability of $\pi_s = \pi_{nor}.\pi_{con}$, where, π_{nor} and π_{con} are occurrence probability of normal scenario s and occurrence probability of contingency-based, respectively.

3.2. Model of IBDR programs

Participation of responsive loads in IBDR programs is modeled based on the incentives and penalties imposed to the customers. When customer j participates in IBDR program, its hourly demand changes from initial value ($D^{int}_{j,t}$) to a modified level ($D_{j,t}$), as:

$$D_{j,t} = D^{int}_{j,t} + \Delta D_{j,t} \quad (2)$$

In this case, the total revenue of customer j participated in IBDR based on the hourly incentive rate, $inc_{j,t}$, is calculated as:

$$INC(\Delta D_{j,t}) = inc_{j,t} \times (D^{int}_{j,t} - D_{j,t}) \quad (3)$$

Also, the penalty payments of customer j who (that) do not respond or satisfy its pre-defined contract is obtained as follows:

$$PEN(\Delta D_{j,t}) = pen_{j,t} \times [L^c_{j,t} - (D^{int}_{j,t} - D_{j,t})] \quad (4)$$

where, $L^c_{j,t}$ and $pen_{j,t}$ are respectively predetermined level of contract of customer j and penalty factor at time period t. As mentioned before, customer j changes demand to maximize its total benefits which are difference between incomes from consuming electricity and incurred costs. By assuming $B(D_{j,t})$ be the income of customer j during t-th hour, the benefit of customer j, $S^c_{j,t}$, at time t will be as follows:

$$S^c_{j,t} = B(D_{j,t}) - Pr_{j,t}D_{j,t} + INC(\Delta D_{j,t}) - PEN(\Delta D_{j,t}) \quad (5)$$

To maximize the benefit of customer j, $\frac{\partial S^c_{j,t}}{\partial D_{j,t}}$ should be equal to zero, therefore:

$$\frac{\partial B(D_{j,t})}{\partial D_{j,t}} - Pr_{j,t} + \frac{\partial INC(\Delta D_{j,t})}{\partial D_{j,t}} - \frac{\partial PEN(\Delta D_{j,t})}{\partial D_{j,t}} = 0 \quad (6)$$

By replacing the (3) and (4) into (6) and differentiating the equation and moving the last three terms to the right side of the equality, Eq. (7) is obtained.

$$\frac{\partial B(D_{j,t})}{\partial D_{j,t}} = Pr_{j,t} + inc_{j,t} + pen_{j,t} \quad (7)$$

The customer marginal benefit from the use of $D_{j,t}$ kWh of electrical energy can be calculated as follows [23]:

$$B(D_{j,t}) = \int_0^{D_{j,t}} \rho_{j,t} \partial d \quad (8)$$

where, $\rho_{j,t}$ is the total rate of electricity. By comparing (7) and (8), the below equality should be satisfied:

$$\rho_{j,t} = Pr_{j,t} + inc_{j,t} + pen_{j,t} \quad (9)$$

Based on economics theory, the demand-rate elasticity at time t is defined as the demand sensitivity with respect to the price at time [24].

$$E_{j,t,t} = \frac{\rho^{int}_{j,t}}{D^{int}_{j,t}} \frac{\partial D_{j,t}}{\partial \rho_{j,t}} \quad (10)$$

where $E_{t,t}$ is self-elasticity coefficient, which shows the effect of price change in time period t on demand change at the same time. For time varying loads, cross-time elasticity relates the effect of price change at one point in time to consumptions at other time periods and it defined by following relation [24]:

$$E_{j,t,h} = \frac{\rho^{int}_{j,h}}{D^{int}_{j,t}} \frac{\partial D_{j,t}}{\partial \rho_{j,h}} \quad (11)$$

By substituting (9) to (10) and (11), the following relation is obtained based on self and cross elasticity coefficients.

$$\frac{\partial D_{j,t}}{D_{j,t}^{int}} = E_{j,t,h}\frac{\partial Pr_{j,h} + \partial inc_{j,h} + \partial pen_{j,h}}{Pr_{j,h} + inc_{j,h} + pen_{j,h}} \tag{12}$$

By integrating of (12) over the scheduling horizon, the following equations are obtained as:

$$\int_{D_{j,t}^{int}}^{D_{j,t}} \frac{\partial D_{j,t}}{D_{j,t}} = \sum_{h=1}^{N_T} E_{j,t,h}\left[\int_{Pr_{j,t}^{int}}^{Pr_{j,t}} \frac{\partial Pr_{j,h}}{Pr_{j,h} + inc_{j,h} + pen_{j,h}} + \int_0^{inc_{j,h}} \frac{\partial inc_{j,h}}{Pr_{j,h} + inc_{j,hx} + pen_{j,h}} + \int_0^{pen_{j,h}} \frac{\partial pen_{j,h}}{Pr_{j,h} + inc_{j,h} + pen_{j,h}}\right] \tag{13}$$

$$ln\left(\frac{D_{j,t}}{D_{j,t}^{int}}\right) = \sum_{h=1}^{N_T} E_{j,t,h}\left[ln\left(\frac{Pr_{j,h} + inc_{j,h} + pen_{j,h}}{Pr_{j,h}^{int} + inc_{j,h} + pen_{j,h}}\right) + ln\left(\frac{Pr_{j,h} + inc_{j,h} + pen_{j,h}}{Pr_{j,h} + inc_{j,h}}\right) + ln\left(\frac{Pr_{j,h} + inc_{j,h} + pen_{j,h}}{Pr_{j,h} + pen_{j,h}}\right)\right] \tag{14}$$

By simplification of (10), the level of responsive loads after participating in IBDR programs is calculated as follow:

$$D_{j,t} = D_{j,t}^{int}\left\{\prod_{h=1}^{N_T}\left[\frac{(Pr_{j,h} + inc_{j,h} + pen_{j,h})^3}{(Pr_{j,h}^{int} + inc_{j,h} + pen_{j,h})(Pr_{j,h} + inc_{j,h})(Pr_{j,h} + pen_{j,h})}\right]^{E_{j,t,h}}\right\} \tag{15}$$

3.3. Short-term reliability evaluation procedures

To evaluate short-term operating reliability of the MG, the indices of expected demand not served at time t ($EDNS_t$) and the energy index of reliability (EIR_t) are implemented that are defined as follow:

$$EDNS_t = \sum_{j=1}^{N_J}\sum_{s=1}^{N_S} \pi_s LOL_{j,t,s} \tag{16}$$

$$EIR_t = 1 - EDNS_t/(\sum_{j=1}^{N_J}\sum_{s=1}^{N_S} D_{j,t,s}) \tag{17}$$

Here, the index of $EDNS_t$ is redefined as expected demand not served stemmed from VLR ($EDNS_t^{VLR}$) and as expected demand not served stemmed from $IVLR$ ($EDNS_t^{IVLR}$). These two indices are defined as follow:

$$EDNS_t^{VLR} = \sum_{j=1}^{N_J}\sum_{s=1}^{N_S} \pi_s VLR_{j,t,s} \tag{18}$$

$$EDNS_t^{IVLR} = \sum_{j=1}^{N_J}\sum_{s=1}^{N_S} \pi_s IVLR_{j,t,s} \tag{19}$$

To get more insight into the MG reliability, indices of DR are defined to improve VLR (DRS_t^{VLR}) and $IVLR$ (DRS_t^{IVLR}) as follows:

$$DRS_t^{VLR} = (EDNS_t^{VLR,No-DR} - EDNS_t^{VLR,DR})/\sum_{j=1}^{N_J}\sum_{s=1}^{N_S} D_{j,t,s} \tag{20}$$

$$DRS_t^{IVLR} = (EDNS_t^{IVLR,No-DR} - EDNS_t^{IVLR,DR})/\sum_{j=1}^{N_J}\sum_{s=1}^{N_S} D_{j,t,s} \tag{21}$$

Superscripts of DR and No-DR in $EDNS_t$ denote the state of with and without applying DR programs, respectively. These indices can give a clear picture of the share of DR participants to provide ancillary services and assess the ability of applying DR on the MG reliability improvement. Higher values of DRS_t^{VLR} and DRS_t^{IVLR} shows a significant impact of DR participant on the decrement of voluntary and involuntary load reduction, and as the result, causes more improvement of the system reliability operation.

3.4. Objective function (OF)

The objective is maximizing expected profit of the MG operator (EP) considering the conditional value at risk (CVaR) under different levels of risk aversion as follow:

$$Max: OF = EP + \beta CVaR \tag{22}$$

$$\begin{aligned}
EP = & \sum_{t=1}^{N_T}\sum_{s=1}^{N_S}\sum_{j=1}^{N_J} \pi_s\left(D_{j,t,s} - VLR_{j,t,s} - IVLR_{j,t,s}\right)Pr_{j,t,s} \\
& - \sum_{t=1}^{N_T}\sum_{s=1}^{N_S} \pi_s[P_t^{DA}Pr_{t,s}^{DA} + (P_{t,s}^{RT} - P_t^{DA})Pr_{t,s}^{RT} - \lambda_{t,s}] \\
& - \sum_{t=1}^{N_T}\sum_{g=1}^{N_G}\sum_{s=1}^{N_S} \pi_s[C_{g,t,s}^{DG} + SUC_{g,t,s}y_{t,s} + SDC_{g,t,s}z_{g,t,s}] \\
& - \sum_{t=1}^{N_T}\sum_{g=1}^{N_G} \pi_s(R_{g,t}^{up}Pr_{g,t}^{up} + R_{g,t}^{dn}Pr_{g,t}^{dn}) \\
& - \sum_{t=1}^{N_T}\sum_{j=1}^{N_J} \pi_s(R_{j,t}^{up}Pr_{j,t}^{up} + R_{j,t}^{dn}Pr_{j,t}^{dn}) \\
& - \sum_{t=1}^{N_T}\sum_{j=1}^{N_J}\sum_{s=1}^{N_S} \pi_s(Pr_{j,t}^{VLR}VLR_{j,t,s} + Pr_{j,t}^{IVLR}IVLR_{j,t,s})
\end{aligned} \tag{23}$$

The first term of (22) represents the revenue by selling energy to local customers, the second term represents the revenue of the bids in the electricity market, the third term denotes the operation costs of conventional DG units and their start-up and shut down costs, the fourth and the fifth terms represent the spinning reserve costs of DGs and DR, respectively. Finally, the sixth term denotes the expected cost of voluntary and involuntary load shedding during time scheduling. The VLR and $IVLR$ are valued at $Pr_{j,t}^{VLR}$ and $Pr_{j,t}^{IVLR}$ that are dependent on the general load type and the point of connection. It should be noted that, in the second term of (22) when P_t^{DA} is positive/negative, the MG is selling/buying power to/from the DA market, and $P_t^{DA}Pr_{t,s}^{DA}$ denotes the MG's revenue/cost by selling/buying electricity to/from the DA market at time t and scenario s. Similarly, when $P_{t,s}^{RT} - P_t^{DA}$ is positive/negative, the MG is selling/purchasing power to/from the RT market, and $(P_{t,s}^{RT} - P_t^{DA})Pr_{t,s}^{RT}$ shows the MG's revenue/cost by selling/purchasing electricity to/from the RT market at time t and scenario s. Here, auxiliary variable $\lambda_{t,s}$ is used to denote the penalty that occurs when the RT power exchange deviates from the DA power scheduling, i.e. $(P_t^{DA} - P_{t,s}^{RT})Pr_{t,s}^{RT}$ [25].

As presented in (22), risk-averse parameter β is introduced to construct risk aversion model to minimize the uncertainty influence on the decision-making problem. The mathematical definition of CVaR for a discrete distribution and at a certain confidence level $\alpha \in (0,1)$ is given as [22]:

$$CVaR = \xi + \frac{1}{1-\alpha}\sum_{s=1}^{N_S} \pi_s \eta_s \tag{24}$$

$$Subject\ to: EP + \xi \geqslant \eta_s; \quad \forall s \tag{25}$$

CVaR represents the expected cost of a predetermined portion of the worst (in our case most costly) possible scenarios. On these bases, CVaR is applied to measure the risk of different candidate schedules in this paper. Based on the behavior of the MG operator, parameter β is chosen that allows it to make a balance between the expected cost and CVaR, and made optimal decision making strategy under different conditions. When $\beta = 0$ (risk-neutral case), the expected cost is minimized ignoring the risk of cost. As the value of β increases, the operator becomes more risk-averse, in the sense that it minimizes both the expected cost and CVaR.

3.5. Network and market constraints

The presented optimization problem is subject to the following network and market constraints:

1) Constraints of active and reactive power balance: Equations (26) and (27) present respectively limits of active and reactive power balance in node n at time t and scenario s.

$$P^n_{g,t,s} + P^n_{w,t,s} - D^n_{j,t,s} + VLR^n_{j,t,s} + IVLR^n_{j,t,s} = \sum_{r=1}^{N_B} \left\{ G^L_{n,r}\left[V^2_{n,t,s} - V_{n,t,s}V_{r,t,s}cos(\theta_{n,t,s} - \theta_{r,t,s})\right] - B^L_{n,r}V_{n,t,s}V_{r,t,s}sin(\theta_{n,t,s} - \theta_{r,t,s}) \right\} \quad (26)$$

$$Q^n_{g,t,s} + Q^n_{w,t,s} - Q^n_{j,t,s} + VQR^n_{j,t,s} + IVQR^n_{j,t,s} = \sum_{r=1}^{N_B} \left\{ -B^L_{n,r}\left[V^2_{n,t,s} - V_{n,t,s}V_{r,t,s}cos(\theta_{n,t,s} - \theta_{r,t,s})\right] - G^L_{n,r}V_{n,t,s}V_{r,t,s}sin(\theta_{n,t,s} - \theta_{r,t,s}) \right\} \quad (27)$$

2) Constraints of responsive loads: These constraints include limits of scheduled demand (28), scheduled upward spinning reserve (29) and scheduled downward spinning reserve (30), actual demand loads (31), as well as limits of deployed upward reserve (32) and deployed downward reserve (33).

$$D^{min}_{j,t} \leqslant D^S_{j,t} \leqslant D^{max}_{j,t} \quad (28)$$

$$0 \leqslant R^{up}_{j,t} \leqslant D^S_{j,t} - D^{min}_{j,t} \quad (29)$$

$$0 \leqslant R^{dn}_{j,t} \leqslant D^{max}_{j,t} - D^S_{j,t} \quad (30)$$

$$0 \leqslant r^{up}_{j,t,s} \leqslant R^{up}_{j,t} \quad (31)$$

$$0 \leqslant r^{dn}_{j,t,s} \leqslant R^{dn}_{j,t} \quad (32)$$

$$D^S_{j,t} = D_{j,t,s} - r^{up}_{j,t,s} + r^{dn}_{j,t,s} \quad (33)$$

3) Constraints of operating of dispatchable DG units: These constraints include limits of power capacity of DG g (34), start-up cost limit (35), shut-down cost limit (36) as well as ramping up limit (37) and ramping down limit (38), [26,27].

$$P^{min}_g u_{g,t,s} \leqslant P_{g,t,s} \leqslant P^{max}_g u_{g,t,s} \quad (34)$$

$$SUC_{g,t,s} \geqslant \lambda^{SU}_{g,t}(u_{g,t,s} - u_{g,t-1,s}) \quad (35)$$

$$SDC_{g,t,s} \geqslant \lambda^{SD}_{g,t}(u_{g,t-1,s} - u_{g,t,s}) \quad (36)$$

$$P_{g,t,s} - P_{g,t-1,s} \leqslant RU_g(1 - y_{g,t,s}) + P^{min}_g y_{g,t,s} \quad (37)$$

$$P_{g,t-1,s} - P_{g,t,s} \leqslant RD_g(1 - z_{g,t,s}) + P^{min}_g z_{g,t,s} \quad (38)$$

Constraint (35) denotes $SUC_{g,t,s}$ is equal to $\lambda^{SU}_{g,t}$ if$u_{g,t,s} = 1$ and$u_{g,t-1,s} = 0$, i.e., if unit g is started up in period t, and 0 otherwise. Moreover, (36) represents $SDC_{g,t,s}$ is equal to $\lambda^{SD}_{g,t}$ if$u_{g,t-1,s} = 1$ and$u_{g,t,s} = 0$, i.e., if unit g is shut-down in period t, and 0 otherwise. Start-up and shut-down binary variables related to the commitment status of unit g as follows:

$$y_{g,t,s} - z_{g,t,s} = u_{g,t,s} - u_{g,t-1,s} \quad (39)$$

$$y_{g,t,s} + z_{g,t,s} \leqslant 0 \quad (40)$$

In addition, up and down services allocated by unit g are limited by (41) and (42), respectively. Also, limits of deployed upward and downward reserves are presented by (43) and (44), respectively. Finally, the decomposition of DGs output power is determined as (45).

$$0 \leqslant R^{up}_{g,t} \leqslant P^{max}_g u_{i,t} - P^S_{g,t} \quad (41)$$

$$0 \leqslant R^{dn}_{g,t} \leqslant P^S_{g,t} - P^{min}_g u_{i,t} \quad (42)$$

$$0 \leqslant r^{Up}_{g,t,s} \leqslant R^{Up}_{g,t} \quad (43)$$

$$0 \leqslant r^{Dn}_{g,t,s} \leqslant R^{Dn}_{g,t} \quad (44)$$

$$P_{g,t,s} = P^S_{g,t} + r^{Up}_{g,t,s} - r^{Dn}_{g,t,s} \quad (45)$$

3.6. Solution methodology

Fig. 2 represents the solution methodology of the proposed flexibility-oriented scheduling problem. First of all, historical data of loads, market prices, RESs and calls for reserves are collected and a numerous scenarios are generated based on their prediction errors. Also, another set of scenarios are generated based on contingencies of DG units and islanding durations of the MG. In this study, MCS is applied to generate the scenarios that represent the mentioned uncertain parameters based on the corresponding distribution functions [20].

The obtained scenarios of different parameters are combined to provide the completed set of uncertain inputs. Moreover, some certain inputs such as DGs' data, MG's topology and limits of DR and RESs should be determined by the MG operator as an input data. These certain and uncertain inputs are simultaneously given to the optimization scheduling problem. Before running the scheduling problem, the risk-averse parameter and incentive price factor should be set on the desirable value to manage the uncertainties and demand side resources, respectively. Selection of these parameters depends on the operator behavior and the customers characteristics. As it can be observed, the scheduling process includes two stages. In the first stage, decisions related to the units commitment and reserve capacity and trading energy from the electricity market are made for DA. In the second stage, decisions associated with the economic dispatch of DG units, IBDR implementation, deployed reserves of DGs and DR as well as VLR and IVLR are determined.

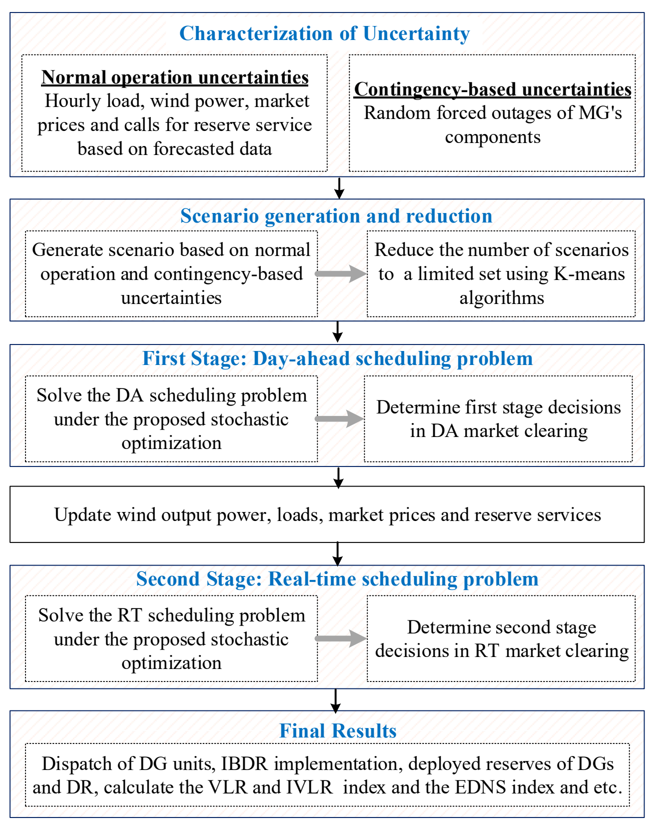

Fig. 2. Solution methodology of the proposed two-stage flexibility-oriented scheduling problem.

4. Case study and test results

4.1. Case study description

The presented approach is implemented to do the scheduling of the test MG shown in Fig. 3, [28] over a daily time horizon. The MG comprises of five controllable DG units including two micro turbines (MT1 and MT2), two fuel cells (FC1 and FC2) and one diesel engine (DE) that their technical data are presented in Table 1 [28]. As shown in Fig. 2, the MG supplies 200 aggregated residential loads within eight groups of customers that are equipped with house energy management and controllers (Hex MCs) to enable automated connectivity to end-use customers' control systems. The forecasted values of total demand of eight groups of customers, output power of wind turbines (WTs) as well as DA electricity price is considered as shown in Fig. 4. The hourly DA electricity price extracted from the Nordpool market [29]. The forecast errors related to load, wind power, electricity price and call for reserve are assumed to be 10%, and the positive and the negative balancing prices are assumed to be 0.9 $Pr_{t,s}^{DA}$ and 1.1 $Pr_{t,s}^{DA}$, respectively. Furthermore, the price of up/down spinning reserve services of DGs and DR resources in time t are considered to be 0.2 $Pr_{t,s}^{DA}$ and 0.15 $Pr_{t,s}^{DA}$, respectively.

The optimization problem is investigated for two different operation conditions of the MG, namely normal condition (without considering islanding contingencies of the MG), and resilient condition (considering islanding contingencies).

In this paper, each uncertain parameter is modelled with 100 scenarios, and the result total number of combined scenarios is 10^8 scenarios. Then, these original scenarios are reduced to 200 scenarios by using K-means algorithm [30] for computational tractability. The results

Table 1
Technical data of dispatchable dg units.

SD Cost ($)	SU Cost ($)	Operation Cost ($/kWh)	P^{max} (kW)	P^{min} (kW)	DGs Type
0.08	0.09	0.9	150	25	MT_1
0.08	0.09	1	150	25	MT_2
0.09	0.16	2.4	100	20	FC_1
0.09	0.16	2.6	100	20	FC_2
0.08	0.12	3.1	150	35	GE

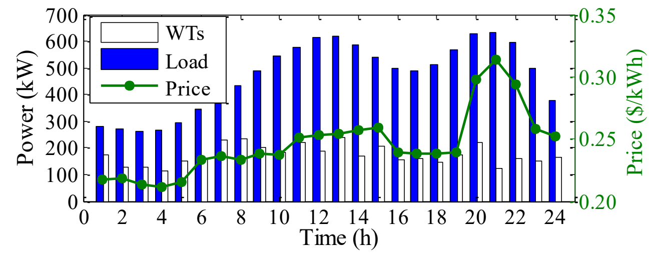

Fig. 4. The hourly forecasted values of aggregated loads, wind power and electricity price.

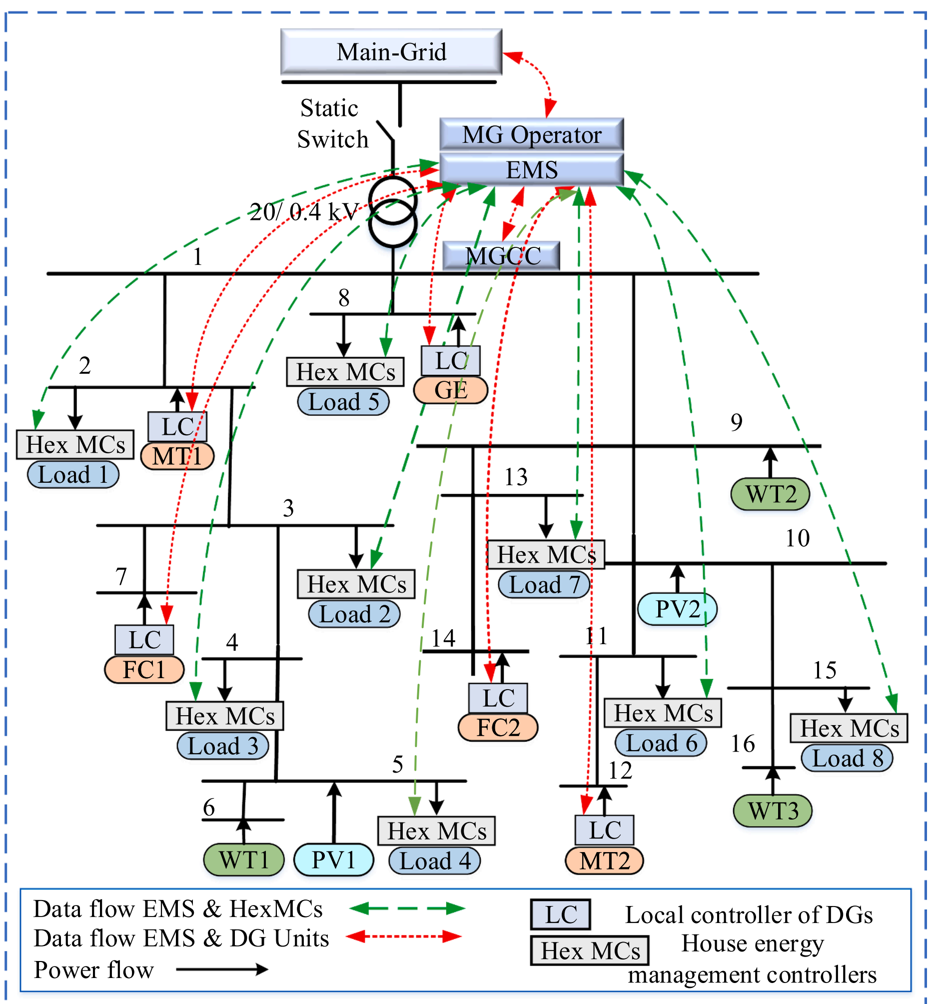

Fig. 3. Structure of the studied MG.

are obtained on a PC with 4 GB of RAM and Intel Core i7@2.60 GHz processor with GAMS software and CPLEX solver [31]. The relative gap is set to be 10^{-4}. The computation time in different cases is less than 5 min.

4.2. Results and discussions

This section analyzes the impact of implementing IBDR programs on the normal and resilient MG based on the economy and reliability indices.

Expected profit, payment cost of customers, reserve costs of DGs and DR as well as reliability indices with and without considering resiliency conditions in different incentive factor η_{INC} are presented in Table 2. It is assumed that η_{INC} varies from 0 to 50% of the DA price. In higher incentive prices, the customers' power consumption profile is better adjusted and the expensive DG units are not committed and therefore the operating costs of DGs decrease and then expected profit increases.

When incentive price grows, the customers receive more incentives and so their payment costs as electricity bills decrease, substantially. In higher η_{INC}, both DGs and DR resources allocate more reserve capacity and so cost of reserve provision increases. In fact, when η_{INC} increases, generation of DGs reduces and therefore they can allocate more spinning reserve capacities. The result of this table shows that when the resiliency is taken into account, the expected profit is decreased mainly due to higher operation cost of DG units. Considering the resiliency condition, there is a higher probability of mismatch between supply and demand, which in turn necessitates more reserve capacity.

The efficient frontiers in normal condition and with considering resiliency for cases$\eta_{INC} = 0$ and$\eta_{INC} = 0.5$ are depicted in Fig. 5. As it can be observed, when incentive is considered, both the expected profit and the CVaR decrease in all risk-averse conditions. When a resilient scheduling according to the credible islanding contingencies is considered (Fig. 5 (b)), the expected profit decreases and the CVaR increases in comparison with the normal operations (Fig. 5 (a)). Comparing the results in different risk-aversion parameter β, it is understood that the risk seeking degree of operator has different effects on the profit and the CVaR. It means that by applying invective prices in risk-neutral case (i.e. $\beta = 0$) the profit and the CVaR have less variation rather than those of in risk-averse case (i.e. $\beta = 20$).

Fig. 6 shows hourly DRS^{VLR} and DRS^{IVLR} in different incentive prices. As it can be seen from Fig. 6 (a), with choosing higher incentive prices, more customers participate in IBDR program and more voluntary load reductions occurs in peak periods, where the reliability of the MG endangers. As shown in Fig. 6 (b), when MG offers higher incentive prices, values of involuntary load reductions decrease, and consequently, the values of DRS^{IVLR} decrease and the reliability of the MG improves. Also, for almost all cases, DRS^{IVLR} experiences less variation during peak periods of the day, where DRS^{VLR} faces more changes.

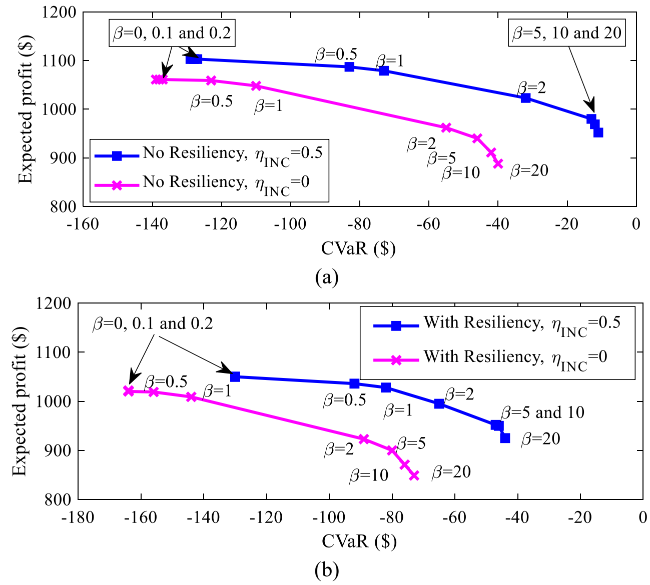

Fig. 5. Efficient frontier, (a) without resiliency, and (b) with resiliency.

Fig. 7 shows the role of π^{IVLR} on the IVLR index in both normal and resiliency conditions. Noted that π^{IVLR} is defined as the average constant cost value that customers will lose due to the loss of one kWh of energy for one hour [32].

As it can be seen, almost during all hours of the day, by increasing π^{IVLR} much more load reduction occurs. However, during peak hours (i.e. 11:00–14:000 and 20:00–22:00) that the customers reduce their demand under incentive prices, values of DRS_t^{IVLR} index has lower values. High IVLR during peak hours imposes extreme costs on the MG operator, who can use IBDR programs to mitigate such excessive costs through incentive payments. As observed in resilient condition, values of DRS_t^{IVLR} index are less than those in normal operation in most periods that the main grid connection is lost.

5. Conclusions

In this paper, a flexibility-oriented stochastic model was presented for scheduling of MGs to address the effect of IBDR programs on the economy and reliability indices, simultaneously. Uncertainties associated with loads, renewables, electricity prices, calls for reserve, as well as uncertainties of islanding duration of the MG were addressed, and their effects were controlled by the CVaR tool. The uncertain behavior of the customers on different reliability indices in both normal operation and resiliency condition were investigated. The proposed model was

Table 2
Economic indexes of the MG in different incentive prices.

η_{INC}	Resilience condition	Indexes					
0.5	0.4	0.3	0.2	0.1	0		
1103	1095	1085	1078	1068	1062	No resiliency	Expected profit ($)
1050	1047	1042	1037	1032	1022	With resiliency	
1339	1572	1863	2152	2441	2728	No resiliency	Payment of customers ($)
1358	1593	1883	2178	2451	2742	With resiliency	
1256	1273	1292	1312	1330	1351	No resiliency	Cost of DGs ($)
1380	1393	1405	1421	1437	1461	With resiliency	
122	119	115	109	105	102	No resiliency	Cost of DGs reserve ($)
139	134	129	124	119	115	With resiliency	
32	29	27	25	23	21	No resiliency	Cost of DR reserve ($)
37	33	30	29	27	25	With resiliency	
738	649	560	471	343	0	No resiliency	VLR (kW)
738	649	560	471	343	0	With resiliency	
11.5	12.8	14.1	16.4	18.7	29.2	No resiliency	EDNS (kW)
16.4	17.8	19.7	22.2	24.5	37.1	With resiliency	

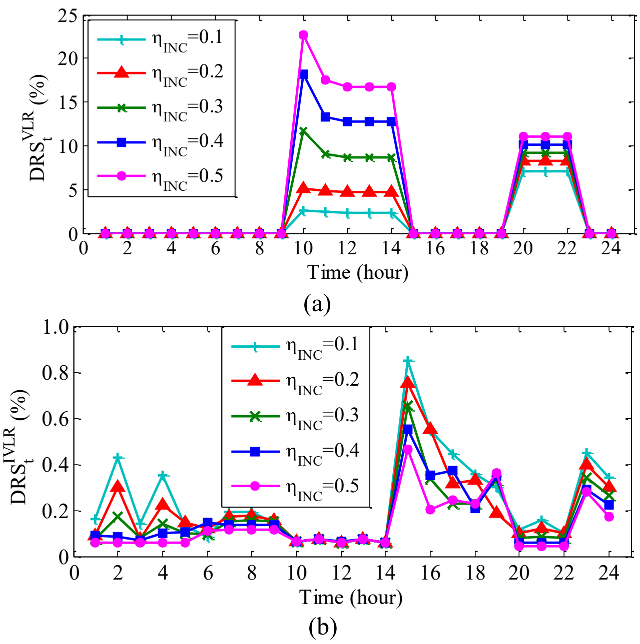

Fig. 6. Effect of different incentive prices on hourly DRS^{VLR} and DRS^{IVLR}.

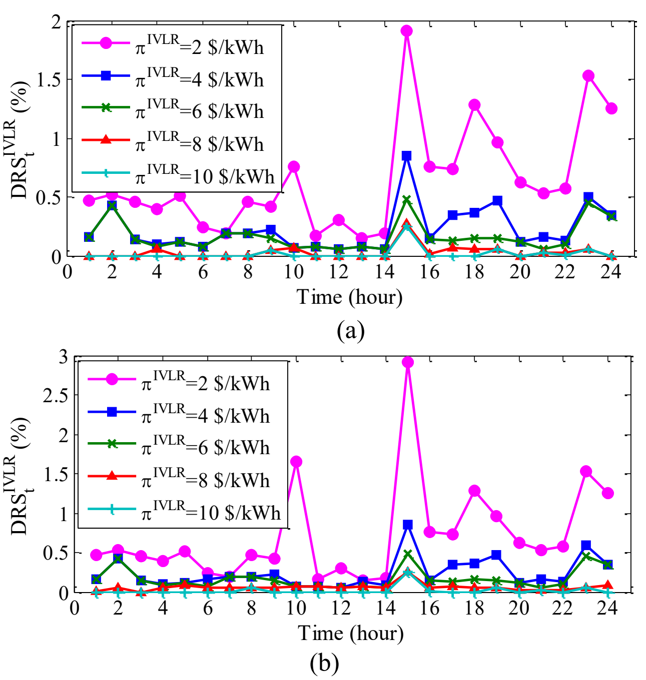

Fig. 7. Effect of π^{IVLR} on hourly DRS_t^{IVLR} index, (a) in normal condition, and (b) in resiliency condition.

applied to a typical MG and various sensitivity analyses on the incentive prices and reliability indices were carried out to validate the model in different states. Numerical results showed that by increasing incentive rate η_{INC} to 0.5, the expected profit of the MG operator could increase about 4%, and reliability index of EDNS could improve 60% in case of no resiliency condition. When the resiliency condition was taken into account, the expected profit and EDNS improved 2.7% and 56%, respectively. Improvements in other reliability indices by increasing incentive rate in both normal and resilient operation of the MG were also achieved. Also, in most time periods the values of reliability index DRS_t^{IVLR} in normal operation were less than those of in resilient operation.

In further research, the presented model will be extended to investigate reliability and resiliency of multi-MGs and will focused on the coordination method of different responsive load models with different time scales on resiliency of multi-MGs. Also, coordination schemes at transmission and distribution levels will be elaborated in further works, e.g., through leveraging DLR mechanism, for better system operation management and facilitating reliable distributed resources integration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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