

# Financial Risk-Based Scheduling of Microgrids Accompanied by Surveying the Influence of the Demand Response Program

Tohid Khalili, *Student Member, IEEE*, Hamed Ganjeh Ganjehlou, Ali Bidram, *Senior Member, IEEE*, Sayyad Nojavan, Somayeh Asadi

**Abstract**—This paper presents an optimization approach based on mixed-integer programming (MIP) to maximize the profit of the Microgrid (MG) while minimizing the risk in profit (RIP) in the presence of demand response program (DRP). RIP is defined as the risk of gaining less profit from the desired profit values. The uncertainties associated with the RESs and loads are modeled using normal, Beta, and Weibull distribution functions. The simulation studies are performed in GAMS and MATLAB for 5 random days of a year. Although DRP increases the total profit of the MG, it can also increase the risk. The simulation results show that RIP is reduced when downside risk constraint (DRC) is considered along with DRP implementation. Considering DRC significantly reduces the percentage of the risk while slightly decreasing the profit.

**Index Terms**—Demand response program, microgrid, optimization, profit, risk assessment.

## NOMENCLATURE

### Indices and Sets

$bat$	Battery
$ch$	Charge
$disch$	Discharge
$g$	Index of DGRs
$i$	Counter of PVs number
$j$	Counter of WT's number
$p$	Profit
$r$	Risk
$RIP$	Risk in profit
$s$	Index of scenario
$t$	Index of hour
$w$	Counter of buses number

### Parameters and Constants

$\alpha, \beta$	Beta's parameters
$\eta^a$	Charging efficiency
$\eta^{dis}$	Discharging efficiency
$\mu$	Average value
$\sigma^2$	Variance value
$a$	Lower limit
$b$	Upper limit
$b_g$	Coefficient of DGRs' cost function [\$/kW]
$c_g$	Coefficient of DGRs' cost function [\$/]

Tohid Khalili and Ali Bidram are supported by the National Science Foundation EPSCoR Program under Award #OIA-1757207.

Tohid Khalili and Ali Bidram are with the Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, USA. (e-mails: {khalili, bidram}@unm.edu). Hamed Ganjeh Ganjehlou is with the Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran. e-mail: (hamed.ganjehlo@aut.ac.ir). Sayyad Nojavan is with the Department of Electrical Engineering, University of Bonab, Bonab, Iran. e-mail: (sayyad.nojavan@ubonab.ac.ir). Somayeh Asadi is with the Department of Architectural Engineering, Pennsylvania State University, University Park, USA. e-mail: (xa511@psu.edu).

$c_1, k_1$	Weibull's parameters
$down\ rate_g$	Minimum rate of decrease in the DGRs power [kW]
$M_p$	A large and positive number
$P_g^{max}$	Maximum generation capacity of the $g^{th}$ DGR [kW]
$P_g^{min}$	Minimum generation capacity of the $g^{th}$ DGR [kW]
$P_{min}^{ch, bat}$	Minimum charging power of the BESS [kW]
$P_{max}^{disch, bat}$	Maximum discharging power of the BESS [kW]
$PV_{i,t,s}^{max}$	Maximum generation capacity of the $i^{th}$ PV [kW]
$q$	A real number
$shut_g$	Shutdown cost of DGRs [\$/]
$SOC_{min}$	Minimum permissible value of the BESS SOC
$SOC_{max}$	Maximum permissible value of the BESS SOC
$start\ up_g$	Startup cost of DGRs [\$/]
$up\ rate_g$	Maximum rate of increase in the DGRs power [kW]
$WT_{j,t,s}^{max}$	Maximum generation capacity of the $j^{th}$ WT [kW]

### Functions and Variables

$\lambda_p$	A number between 0 and 1
$\rho(t), \rho(k)$	Power price at $t^{th}$ and $k^{th}$ hours [\$/]
$\rho_0(t), \rho_0(k)$	Initial power price at $t^{th}$ and $k^{th}$ hours [\$/]
$A(t), A(k)$	Customer incentive at $t^{th}$ and $k^{th}$ hours [\$/]
$b_{i,s}^{ba}$	Binary variable
$C_{i,s}^{sell}$	Selling price of the electricity [\$/]
$C_{i,s}^{buy}$	Purchase price of the electricity [\$/]
$Cost_{DRP}$	Total cost paid as an incentive [\$/]
$EDR_p$	Expected downside risk (EDR) of the system
$E(t, t)$	Self-elasticity at $t^{th}$ hour
$E(t, k)$	Cross elasticity between $t^{th}$ and $k^{th}$ hours
$f(v)$	Weibull distribution function
$g(y')$	Beta distribution function
$h(q, \mu, \sigma^2)$	Normal distribution
$P_{g,t,s}$	$g^{th}$ DGR's generated power at $t^{th}$ hour and $s^{th}$ scenario [kW]
$P_{trans,t,s}$	Transmission line power [kW]
$P_{i,s}^{ch, bat}$	BESS charged power [kW]

$P_{i,s}^{disch,bat}$	BESS discharged power [kW]
$P_{i,s}^{bu}$	Purchased power from the main grid [kW]
$P_{i,s}^{sell}$	Sold power to the main grid [kW]
$Pb_{w,j,s}$	Injected power to $W^{th}$ bus [kW]
$pen(t),$ $pen(k)$	Consumer penalties at $t^{th}$ and $k^{th}$ hours [\$]
$PL_{p,t,s}$	Demanded load [kW]
$PL_{p,t,s}^D$	Reduced/increased load by the consumer [kW]
$PL_{p,t,s}^{LD}$	Load after the implementation of the DRP [kW]
$PL_{p,t,s}^{LD}$	Reduced load by the customer [kW]
$prob_s$	Possibility of each scenario
$prob_{p,s}$	Probability of the $s^{th}$ scenario
$profit_s$	Profit at the $s^{th}$ scenario [\$]
$PV_{i,t,s}$	Generated power of the $i^{th}$ PV [kW]
$risk_{p,s}$	Risk value at the $s^{th}$ scenario
$shut_{g,t}^{cost}$	Shutdown cost of $g^{th}$ DGR [\$]
$SOC_{i,s}$	SOC of the BESS at $t^{th}$ hour and $s^{th}$ scenario
$SS_{g,t,s}$	Binary index
$start\ up_{g,t}^{cost}$	Startup cost of $g^{th}$ DGR [\$]
$target_{p,s}$	Target value at the $s^{th}$ scenario
$v'_{g,t,s}$	Binary index of the UC status
$W_{p,s}$	Binary index
$W_{z,p}$	Profit value without considering downside risk [\$]
$WT_{j,t,s}$	Generated power of the $j^{th}$ WT
$X_{i,t,s}^{grid}$	Binary variable
$y_{g,t,s}$	Binary index
$\bar{Z}_{profit}$	Average profit of the MG [\$]
$\bar{Z}_{profit}^{DRP}$	Average profit of the MG by considering the DRP [\$]
$ZZ_s^{profit}$	Profit of each scenario [\$]
$ZZ_s^{profit, DRP}$	Profit of each scenario in this specific case [\$]

## I. INTRODUCTION

MICROGRIDS (MGs) have gained much attention due to their improved reliability and resilience. Moreover, they facilitate the integration of renewable energy sources (RESs) and energy storage systems (ESS) [1]. The optimized operation and energy management of microgrids are of particular importance which have been widely investigated in the literature. The control and operation of MGs are investigated in [2]. In [3], an MG energy management scheme is proposed. In some studies, a single objective is considered to accommodate the optimized operation of MGs. For example, in [4], the performance of the energy management of an MG is optimized. Scheduling of an MG integrating battery energy storage systems (BESSs), fuel cells, wind turbine (WTs), photovoltaics (PVs), and micro-turbines (MTs) is investigated in [5]. The impact of reconfiguration on the reliability of distribution systems is analyzed in [6]. In [7], power scheduling considering

economic and environmental aspects is performed in an MG with the goal of minimizing MG's total operational costs. Also, a hierarchical framework for the optimal operation of MGs is presented in [8]. In [9], a scheduling model for MG's generation is suggested in which the cuckoo-search optimization algorithm is utilized with the aim of minimizing operating costs with or without the demand response program (DRP). In [10], a novel method is presented for stochastic optimal power flow with DRP and considering the quality of service. The multi-objective performance optimization of MGs is investigated in [11]–[12]. The impact of the incentive-based DRP on the MG's operation is analyzed in [11]. Reference [12] shows that DRP increases the quality of service delivered to customers. Despite the several advantages of utilizing RESs in MGs, the price of the power purchased from the utility is usually lower than the RESs' power price. Additionally, the intermittent nature of RESs imposes more risk in profit (RIP) from the MG operator's point of view. RIP is defined as the risk of gaining less profit from the desired profit values. The risks associated with the different uncertain parameters of the power system, including the scheduling and price uncertainties, are studied in [13]. In another research, the effect of the DRP and risk are considered, but BESSs are not taken into account [14]. Also, sensitivity analysis is not implemented in [14]. Also, a stochastic risk-aware model considering profit and risk is presented in [15].

In this paper, optimal power scheduling of RESs, BESSs, and diesel generators (DGRs) in an MG is implemented to minimize RIP while maximizing the MG profit by optimizing the purchased/sold power from/to the main grid. Moreover, DRP is utilized to maximize the MG profit. The uncertainties associated with the RESs and loads are modeled using normal, Beta, and Weibull distribution functions. With the proposed approach, the MG operator can maximize its profit by performing optimal scheduling of different resources as well as optimizing the traded power. The optimization is performed using mixed-integer programming (MIP). In the MIP problem, DGRs are dispatched using unit commitment (UC). The simulations are done for five random days of a year using GAMS and MATLAB. Although DRP increases the profit of the MG, it also notably increases the risk. RIP is reduced when downside risk constraint (DRC) is considered along with DRP implementation. DRC significantly reduces the percentage of the risk with a slight decrease in profit. The novelty and contributions of this research are briefly described as follows:

- An optimization framework is presented which accounts for the risk-based scheduling of a grid-connected MG with high penetration of RESs, BESSs, and DGRs.
- The probabilistic nature of the load, PVs, and WTs are considered for assessing the risk of the MG's operation. Moreover, the power price uncertainty is considered.
- The effect of the DRP on the risk of the trade between the MG and the main grid is taken into consideration. This will help the MG's owner either minimize its risk or maximize its profit. Also, a sensitivity analysis is performed to examine the impact of the participation rate of DRP on the RIP.

The structure of this paper is organized as follows: Section II describes the MG architecture, components, and parameters.



Section III discusses the constraints and objective functions. The proposed optimization method is formulated in Section IV. In Section V, the simulation results are analyzed and presented. Finally, the main conclusions are summarized in Section VI.

## II. MG MODEL

In this section, first, the structure of MG is described. Then, the models and input of RESs, loads, and price are elaborated.

### A. Structure of MG

The considered MG consists of six buses. This MG is operating in the grid-connected mode. Including a total number of six PV systems, four of them are installed on the first bus and the other two are installed on the second bus. WTs are located on the third bus, and the DGRs are installed at the fourth, fifth, and sixth buses. Also, there are BESSs in the mentioned MG which support the MG in the case of power shortage or overage. BESS and load are installed in the sixth bus. It is assumed that MG's load can participate in DRP. The discussed MG's schematic is illustrated in Fig. 1.

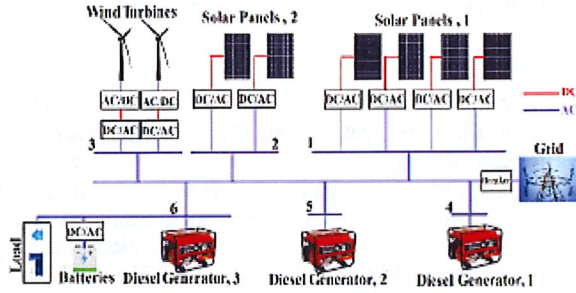


Fig. 1. Schematic of the considered MG system.

### B. Modeling of the RESs

Due to the variable generation of the RESs and their probabilistic nature, Weibull and Beta functions are used for the modeling of WTs and PVs power generation, respectively [16]-[17]. First, the average and variance of input data are calculated by using mean and variance in the MATLAB environment [18]; then, the generation of the RESs are produced, using Weibull and Beta distribution functions for five different days. It should be noted that the output of the distribution functions for each RES in a specific hour is the maximum predicted generation capacity of that source in that hour. The Weibull and Beta functions can be formulated as follows [19]-[20]:

$$g(y') = \frac{1}{B(\alpha, \beta)} \frac{(y'-a)^{\alpha-1} (b-y')^{\beta-1}}{(b-a)^{\alpha+\beta-1}} \quad (1)$$

$$B(\alpha, \beta) = \int_0^1 y'^{\alpha-1} (1-y')^{\beta-1} dy' \quad (2)$$

$$f(v) = \frac{k_1}{c_1} \left(\frac{v}{c_1}\right)^{k_1-1} \exp\left\{-\left(\frac{v}{c_1}\right)^{k_1}\right\} \quad (3)$$

Equations (1) and (2) are related to the Beta distribution function and (3) is related to the Weibull distribution function. Also,  $k_1$  and  $c_1$  are the Weibull's parameters as well as  $\alpha$  and  $\beta$  are Beta's parameters. Moreover,  $y'$  and  $v$  are the input of

the functions.  $a$  and  $b$  are lower and upper limits, respectively.

### C. Load and Price Modeling

Load's accurate forecasting is a challenging task due to the stochastic behavior of the consumers. On the other hand, the energy price in the energy market varies according to the consumer's demand. Hence, in this paper, the normal distribution function is used to model the load and energy price uncertainties. To this end, the average and variance of the consumer's demanded load [18] and the energy price [18] are calculated. Then, by using the normal distribution function [21], the hourly load and the price of electricity are created for five different days. The normal distribution is defined as follows:

$$h(q, \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(q-\mu)^2}{2\sigma^2}\right) \quad (4)$$

## III. PROBLEM FORMULATION

In this section, first, the problem constraints are discussed. Then, the objective functions are formulated.

### A. Constraints

As shown in Fig. 1, the intended system consists of several types of equipment with specific constraints. These constraints are classified as follows:

**Constraint 1: Transmission line constraints:** The main grid is connected to the MG through a transmission line. It is obvious that each transmission line is not able to transmit more than a certain amount of power. Therefore, in this work, a maximum value is considered for transmission line capacity. The maximum capacity of the transmission line (MCTL) is selected with respect to the base value of the power ( $S_{base}$ ), i.e.

$$P_{trans,t} \leq MCTL \quad (5)$$

**Constraint 2: DGRs constraints:** DGRs are used to generate power in the MG. For optimal utilization of DGRs, UC is implemented, and shutdown and startup costs are considered. These concepts are mathematically formulated as [22]:

$$y_{g,t,s} - SS_{g,t,s} = v'_{g,t,s} - v'_{g,t-1,s} \quad (6)$$

$$start\ up_{g,t,s}^{cost} \geq start\ up_g [v'_{g,t,s} - v'_{g,t-1,s}] \quad (7)$$

$$start\ up_{g,t,s}^{cost} \geq 0 \text{ for } g=1,2,3 \text{ and } t=1,\dots,24$$

$$shut\ down_{g,t,s}^{cost} \geq shut\ down_g [v'_{g,t-1,s} - v'_{g,t,s}] \quad (8)$$

$$shut\ down_{g,t,s}^{cost} \geq 0, \text{ for } g=1,2,3 \text{ and } t=1,\dots,24$$

The maximum increase rate and minimum decrease rate of the DGRs' power are denoted as up rate and down rate, respectively. Up rate and down rate can be mathematically expressed by [22]

$$P_{g,t,s} - P_{g,t-1,s} \leq up\ rate_g \quad (9)$$

$$P_{g,t-1,s} - P_{g,t,s} \leq down\ rate_g \quad (10)$$

According to UC, the minimum and maximum power generation of DGRs are expressed as [22]

$$P_{g,t,s} \leq P_g^{max} \times v'_{g,t,s} \quad (11)$$

$$P_{g,t,s} \geq P_g^{min} \times v'_{g,t,s} \quad (12)$$

**Constraint 3: BESS constraints:** BESSs have a minimum and maximum state of charge (SOC) as well as minimum and maximum rate of charge or discharge; accordingly, the constraints for the BESSs are as follows [20]:

$$SOC_{\min} \leq SOC_{i,t} \leq SOC_{\max} \quad (13)$$

$$0 \leq P_{i,t}^{ch,bat} \leq P_{\max}^{ch,bat} b_{i,t}^{bat} \quad (14)$$

$$0 \leq P_{i,t}^{disch,bat} \leq P_{\max}^{disch,bat} (1 - b_{i,t}^{bat}) \quad (15)$$

Furthermore, the mathematical expressions of the other constraints of the BESS are presented in (16) and (17). Equation (16) determines how the current SOC is calculated with respect to the previous hour's SOC. Equation (17) guarantees that, in one day, the summation of the hourly SOC change (i.e., the difference between the SOC at the end of hour  $t$  and SOC at the end of hour  $t-1$ ) is greater than or equal to zero [12].

$$SOC_{i,t} = SOC_{i,t-1} + \eta^{ch} \frac{P_{i,t}^{ch,bat}}{S_{base}} - \frac{P_{i,t}^{disch,bat}}{\eta^{disch} S_{base}} \quad (16)$$

$$\sum_{t=1}^{T=24} (SOC_{i,t} - SOC_{i,t-1}) \geq 0 \quad (17)$$

**Constraint 4: Constraints of the power exchange:** The maximum power which can be traded between the main grid and MG is set to the maximum capacity of the transmission line (MCTL). Therefore:

$$P_{i,t}^{buy} \leq MCTL \times X_{i,t}^{grid} \quad (18)$$

$$P_{i,t}^{sell} \leq MCTL \times (1 - X_{i,t}^{grid}) \quad (19)$$

**Constraint 5: Constraints of the injected power to each bus:** The total generation of the sources connected to each of the buses follows the following constraints:

$$Pb_{w,t,s} = \sum_{i=1}^4 PV_{i,t,s}, \quad (w=1) \quad (20)$$

$$Pb_{w,t,s} = \sum_{i=3}^6 PV_{i,t,s}, \quad (w=2) \quad (21)$$

$$Pb_{w,t,s} = \sum_{j=1}^2 WT_{j,t,s}, \quad (w=3) \quad (22)$$

$$Pb_{w,t,s} = P_{g,t,s}, \quad (w=4, g=1) \quad (23)$$

$$Pb_{w,t,s} = P_{g,t,s}, \quad (w=5, g=2) \quad (24)$$

$$Pb_{w,t,s} = P_{g,t,s} - P_{i,t}^{ch,bat} + P_{i,t}^{disch,bat} - PL_{i,t,s} \quad (w=6, g=3) \quad (25)$$

Equations (20) and (21) indicate that four of the PVs are installed on the first bus and two of the PVs are installed on the second bus, respectively. Equation (22) shows that there are two installed WTs on the third bus. Furthermore, (23), (24), and (25) demonstrate the DGRs-related buses.

**Constraint 6: Constraints of power balance without DRP:** The power balance equation without DRP is formulated as

$$\sum_{g=1}^3 P_{g,t,s} + P_{i,t}^{buy} - P_{i,t}^{sell} + \sum_{i=1}^4 PV_{i,t,s} + \sum_{j=1}^2 WT_{j,t,s} - P_{i,t}^{ch,bat} + P_{i,t}^{disch,bat} = PL_{p,t,s} \quad (26)$$

**Constraint 7: Constraints of the RESs:** WTs and PVs have a minimum and maximum generation capacity which are indicated as follows [23]:

$$0 \leq PV_{i,t,s} \leq PV_{i,t,s}^{\max}, \quad i \in \{1, \dots, 6\} \quad (27)$$

$$0 \leq WT_{j,t,s} \leq WT_{j,t,s}^{\max}, \quad j \in \{1, 2\} \quad (28)$$

**Constraint 8: Risk assessment constraints:** Risk assessment constraints describe the relation between RIP and MG's profit. The MG operators tend to have more profit than a determined lower limit. The  $target_p$  is the desired lower limit for the profit of the MG. When the MG's profit is more than  $target_p$ , it makes the operator satisfied. Otherwise, it is considered a downside risk. Thus, the DRCs for the profit are as follows [13]: if  $profit_s < target_{p,s}$ ,  $risk_{p,s} = target_{p,s} - profit_s$ ; otherwise,  $risk_{p,s} = 0$ .

Equation (29) can be expressed as (30) [13]:

$$0 \leq risk_{p,s} - (target_{p,s} - profit_s) \leq M_p \cdot (1 - W_{p,s}) \quad (30)$$

$$0 \leq risk_{p,s} \leq M_p \cdot W_{p,s}$$

$W_{p,s}$  is set equal to 1 when  $profit_s < target_{p,s}$ . According to the above description, the expected downside risk (EDR) for the profit objective function is defined as follows [24]:

$$\sum_{s=1}^S prob_{p,s} \times risk_{p,s} \leq \lambda_p (w_{r,p} - target_p) = \overline{EDR}_p \quad (31)$$

In (31),  $prob_{p,s}$  is set to 0.2.

**Constraint 9: DRP constraints:** DRP denotes the consumers' role in controlling and management of the power system. MG's operator can obtain the satisfaction of the consumers by implementing DRP. With DRP, the system load at a specific time may depend on the load and system's condition during other periods. To this end, in addition to self-elasticity, the cross elasticity is also considered in this paper [25]. The DRP can be formulated as:

$$PL_{p,t,s}^{LD} = PL_{p,t,s} \times \left[ \frac{1 + E(t,t) \cdot \frac{[\rho(t) - \rho_0(t) + A(t) + pen(t)]}{\rho_0(t)}}{1 + \sum_{k=1}^T E(t,k) \cdot \frac{[\rho(k) - \rho_0(k) + A(k) + pen(k)]}{\rho_0(k)}} \right] \quad (32)$$

$pen(t)$  denotes the customer's penalty at time  $t$  if the customer consumes more power than its contract. In this paper, the amount of penalty is assumed to be zero without loss of generality. The customers' participated power limitations and their new demanded load after the implementation of DRP are as follows [23]:

$$-0.25 PL_{p,t,s} \leq PL_{p,t,s}^D \leq 0.25 PL_{p,t,s} \quad (33)$$

$$PL_{p,t,s}^{LD} = PL_{p,t,s} + PL_{p,t,s}^D \quad (34)$$

The consumers do not eliminate the load; they just transfer it from one period to another. So, one can have [23]:

$$\sum_{t=1}^T PL_{p,t,s}^D = 0 \quad (35)$$

The DRP cost function is given as follows [23]:

$$Cost_{DRP} = \sum_{t=1}^T (PL_{p,t,s}^D \cdot A_t), \quad PL_{p,t,s}^D = |PL_{p,t,s}^D| \quad (36)$$

**Constraint 10: Constraints of power balance with DRP:** Due to the DRP in the considered MG, the power balance equation in this state differs from the previous one. Thus, the power balance equation with DRP's effect on the RIP is as follows:

$$\sum_{g=1}^3 P_{g,t,s} + P_{i,t}^{buy} - P_{i,t}^{sell} + \sum_{i=1}^4 PV_{i,t,s} + \sum_{j=1}^2 WT_{j,t,s} - P_{i,t}^{ch,bat} + P_{i,t}^{disch,bat} = PL_{p,t,s}^{LD} \quad (37)$$



### B. Objective Functions

This paper focuses on assessing the effect of DRC on profit and surveying the impact of DRP on the RIP. To determine the effect of the downside risk constraints and DRP on the defined parameters, the results with considering DRC (CDRC) and without considering DRC (WCDRC) will be compared. To this end, the following objective functions are defined:

-*Objective function without DRP*: This objective function is used to investigate the MG's profit in the CDRC and WCDRC cases which can be formulated as:

$$ZZ_s^{profit} = \sum_{t=1}^{24} P_{t,s}^{sell} \times C_{t,s}^{sell} - \sum_{t=1}^{24} P_{t,s}^{buy} \times C_{t,s}^{buy} - \sum_{t=1}^{24} \sum_{g=1}^3 (b_g \times P_{g,t,s} + V'_{g,t,s} \times c_g) \quad (38)$$

$$- \sum_{t=1}^{24} \sum_{g=1}^3 shut_g \times SS_{g,t,s} - \sum_{t=1}^{24} \sum_{g=1}^3 start_{up_g} \times y_{g,t,s} \quad (39)$$

$$\bar{Z}_{profit} = \sum_{s=1}^5 prob_s \times ZZ_s^{profit}$$

-*Objective function with DRP*: This objective function is utilized to investigate the impact of DRP on WCDRC and CDRC cases. This objective function can be formulated as:

$$ZZ_s^{profit,DRP} = \sum_{t=1}^{24} P_{t,s}^{sell} \times C_{t,s}^{sell} - \sum_{t=1}^{24} P_{t,s}^{buy} \times C_{t,s}^{buy} - \sum_{t=1}^{24} \sum_{g=1}^3 (b_g \times P_{g,t,s} + V'_{g,t,s} \times c_g) \quad (40)$$

$$- \sum_{t=1}^{24} \sum_{g=1}^3 shut_g \times SS_{g,t,s} - \sum_{t=1}^{24} \sum_{g=1}^3 start_{up_g} \times y_{g,t,s} - \sum_{t=1}^{24} (PL_{p,t,s}^D \times A_s) \quad (41)$$

$$\bar{Z}_{profit}^{DRP} = \sum_{s=1}^5 prob_s \times ZZ_s^{profit,DRP}$$

### IV. PROPOSED OPTIMIZATION METHOD

The presented optimization model for this study is a MIP problem. GAMS CPLEX solver and MATLAB are utilized to solve this problem. The optimization algorithm is briefly described in the following steps:

*Step 1*: Import the initial data independent of the scenarios and the considered objective functions.

*Step 2*: Stochastically generate MG's load, purchasing and selling price of the electricity, and power of RESs using MATLAB. The study is implemented for 5 days to make a proper assessment of the proposed model. Thus, five groups of data are produced in MATLAB and sent to GAMS as initial data. Each group is called a scenario. The purpose of creating several scenarios is to perform stochastic scheduling.

*Step 3*: Calculate MG's profit in the WCDRC case. In this step, Constraints 1 to 7 in Section III.A and the first objective function, in (38) and (39), are used. Note that the objective function, initial data, and constraints are considered for each of the five scenarios. Then, the MG's profit is calculated.

*Step 4*: Calculate MG's profit in the CDRC case. Constraints 1 to 8 and the first objective function, in (38) and (39), are utilized in this step. Similar to Step 3, the studies are conducted for 5 scenarios and the profit of MG is calculated for the CDRC case. This step's results are compared with the results of step 3.

*Step 5*: Analyze the impact of DRP on MGs' profit values in the WCDRC case. To this end, Constraints 1, 2, 3, 4, 5, 7, 9, and 10 with the second objective function, in (40) and (41), are utilized to calculate the MG's profit for each scenario.

*Step 6*: Analyze the impact of DRP on both the MGs' risk and profit values in the CDRC case. Constraints 1 to 5, and 7 to 10 with the second objective function, in (40) and (41), are used in this step. The amount of risk and profit is calculated for each of the scenarios. The results of this step are compared with the

results of Step 5. After the completion of this step, the results of Steps 3 to 6 are compared.

*Step 7*: Analyze the MG's robustness and efficiency of the proposed model with DRP considering the sensitivity analysis in the WCDRC case and CDRC case. All constraints in Section III.A and both objective functions are used. The results are compared against the results of the other steps.

## V. RESULTS AND DISCUSSION

### A. Initial Data and Generation of Stochastic Input

As discussed in Section IV, the first step in the proposed optimization framework is to import the system initial data. To this end, the following assumptions are made for the parameters of the MG system shown in Fig.1: The maximum generation capacity for all of WTs is 42 kW and the maximum generation capacity for the PVs connected to the first and second buses are 32 kW and 16 kW, respectively. These generation capacities are selected according to the MG's demanded load. The base value of the power ( $S_{base}$ ) and the maximum capacity of the transmission line (MCTL) is set to 50 kW and 37.5 kW (0.75 per-unit (p.u.)), respectively. The initial SOC of the BESSs is assumed to be 70%. The values of  $SOC_{min}$ ,  $SOC_{max}$ ,  $P_{min}^{bat}$ , and  $P_{max}^{bat}$  are 20%, 100%, -50 kW, and 50 kW, respectively. The charge efficiency and discharge efficiency of the BESS are set equal to 100%. The characteristics of the three DGRs are summarized in Table I. These values are extracted from [22]. Since the DGRs' capacity is low, a linear cost function is used. Table I lists the coefficient of DGRs' cost function, minimum and maximum power generation of each DGR, and their up rate and down rate.  $c_g$ , the coefficient of DGRs' cost function, is set to zero. It should be noted that all the studies are performed on 5 random days of a year. All the studies in this article have been done for a short period, which does not include costs including initial investments and periodic repairs. However, fuel costs of the DGRs are considered.

TABLE I  
CHARACTERISTICS OF THE DGRs

$g$	$b_g$	$P_g^{min}$ [kW]	$P_g^{max}$ [kW]	down rate <sub><math>g</math></sub> [kW]	up rate <sub><math>g</math></sub> [kW]
1	0.7	0	4	3	3
2	0.25	0	6	5	5
3	0.5	0	9	8	8

In Step 2, the power of RESs, MG's load, and energy price are stochastically created using Beta, Weibull, and Normal probabilistic distributions [18]. The MG's created loads on 5 random days of the year are illustrated in Fig. 2.

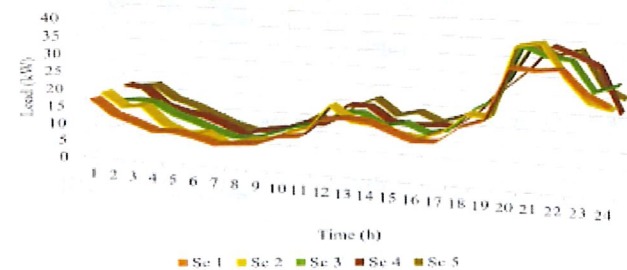


Fig. 2. MG's load.



## B. Profit Maximization

In Step 3, the MG's profit in the WCDRC case is calculated. The amount of the profit, RIP for each scenario, and the average profit and RIP are shown in Table II. The average profit for the five scenarios is \$72.6946 and the average RIP is \$0.5979. The target value for Steps 4 and 5 is set to \$72.6946 based on the average profit in Step 3. In Step 4, the optimization is performed to maximize the MG's profit in the CDRC case. The results are shown in Table III and Table IV.

The profits for each scenario with different  $\lambda_p$  in (31) are illustrated in Table III. Table IV shows the average profit, total RIP, average RIP, average profit's reduction, and average RIP's reduction in comparison to the WCDRC case for each  $\lambda_p$  value. Comparing Tables II, III, and IV, one can see that the risk is reduced significantly even though the profit slightly decreases. For example, Table IV shows that for  $\lambda_p = 0.7$  the RIP is reduced by 29.9987% in comparison to the WCDRC; while the reduction of the profit is only 0.2462%. Moreover, increasing the value of  $\lambda_p$  leads to an increase in the average profit and RIP reduction, but the reduction rate of RIP is more than the rate of the average profit reduction. For instance, considering  $\lambda_p = 0.99$  as well as  $\lambda_p = 0.7$  in Table IV, it is observed that the average RIP is reduced by 29.0011% against 0.2445% reduction of the average profit. The comparison schematics of the average RIP and average profit for different  $\lambda_p$ s as well as CDRC case versus WCDRC case are shown in Figs. 3 and 4.

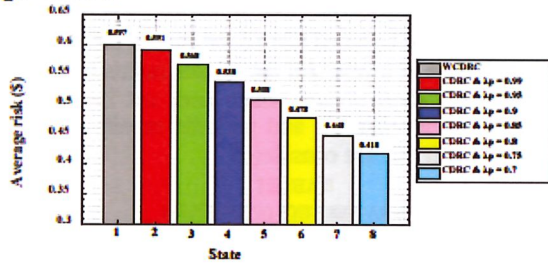


Fig. 3. Comparison schematic between RIP with various  $\lambda_p$  values.

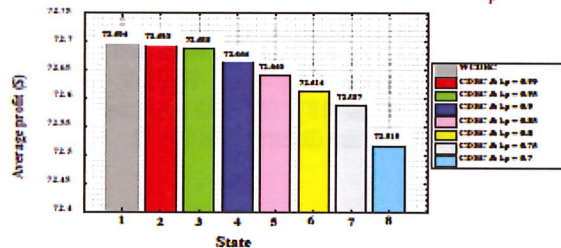


Fig. 4. Comparison schematic between average profit with various  $\lambda_p$  values.

TABLE II  
RESULTS OF THE PROFIT MAXIMIZATION IN THE WCDRC CASE [\$]

Scenario	Profit	RIP
1	72.10782	0.5868
2	73.42139	0
3	70.29204	2.4026
4	74.01032	0
5	73.64145	0
Average	72.69460	0.5979

TABLE III  
EACH OF THE SCENARIO'S PROFIT WITH DIFFERENT  $\lambda_p$  VALUES FOR CDRC

CASE [\$]					
$\lambda_p$	Sc 1	Sc 2	Sc 3	Sc 4	Sc 5
0.99	72.1078	73.3854	70.3219	74.0103	73.6414
0.95	72.1078	73.2413	70.4414	74.0103	73.6414
0.9	72.1078	72.9739	70.5910	74.0103	73.6414
0.85	72.1078	72.7035	70.7404	74.0103	73.6414
0.8	72.1078	72.6947	70.8899	73.7362	73.6414
0.75	72.1085	72.6947	71.0386	73.4518	73.6414
0.7	72.2581	72.6947	71.0386	72.9453	73.6414

TABLE IV  
RESULTS OF THE MG'S PROFIT MAXIMIZATION IN THE CDRC CASE AS WELL AS COMPARISON WITH WCDRC CASE

$\lambda_p$	Average profit [\$]	Total RIP [\$]	Average RIP [\$]	Average profit reduction [%]	Average RIP reduction [%]
0.99	72.6934	2.9596	0.5919	0.0017	0.9976
0.95	72.6885	2.8401	0.5680	0.0085	4.9940
0.9	72.6649	2.6906	0.5381	0.0409	9.9969
0.85	72.6407	2.5411	0.5082	0.0741	14.9949
0.8	72.6140	2.3916	0.4783	0.1109	19.9978
0.75	72.5870	2.2422	0.4484	0.1480	24.9958
0.7	72.5156	2.0926	0.4185	0.2462	29.9987

## C. Impact of DRP

The effect of DRP on profit and RIP is investigated using Steps 5 and 6 of the proposed optimization method in Section IV, respectively. In Step 5, the goal is to maximize the profit of the MG by considering DRP and without considering the risk. The results of this section are shown in Table V. In Steps 5 and 6, the maximum rate of consumer participation in DRP is assumed to be 25%. Table V shows the profit and risk values in each scenario and the average profit and RIP. Also, the target value for Steps 5 and 6 is \$75.1807.

TABLE V  
SURVEY RESULTS OF THE MG'S PROFIT CONSIDERING DRP AND WCDRC [\$]

Scenario	Profit	RIP
1	74.1715	1.0093
2	77.4795	0
3	72.5267	2.6541
4	75.7385	0
5	75.9878	0
Average	75.1807	0.7326

To perform a detailed assessment, Step 6 is conducted, and the results are compared with Step 5 and Table V. In Step 6, the goal is to examine the MG's profit with DRP and risk constraints. The results are shown in Tables VI and VII. Table VI indicates the profit of the MG for different scenarios and different  $\lambda_p$  values. For achieving a more accurate comparison, the average profit, total RIP, average RIP, percentage of RIP reduction, and the percentage of profit reduction for various  $\lambda_p$  values are shown in Table VII. Comparison of the results of Tables V, VI, and VII show that by decreasing  $\lambda_p$ , RIP significantly reduced, and profit value has slightly decreased. According to Table VII, the rate of RIP reduction is much faster than the rate of reduction in profit (e.g., consider these values



when  $\lambda_p = 0.99$  and when  $\lambda_p = 0.7$ ). As seen in Table VII, although there is a 29.0485% reduction in RIP, the profit value has only decreased by 0.0493%. The schematic representation of the comparison between the average profit and the average RIP for Step 6 is shown in Figs. 5 and 6, respectively. As shown, by decreasing  $\lambda_p$ , the slope of risk reduction is faster than the rate of decline in profit. According to Figs. 5 and 6, for  $\lambda_p$  greater than 0.8, no significant changes are observed in the average profit, but the RIP is changing. The goal of this work is the maximization of the MG's profit and minimization of the RIP. There is an intrinsic direct relationship between RIP and profit. For this reason, it is not possible to reach the ideal point, but it is possible to find points in which the changes in the profit reduction are very low and the RIP reduction is so high, and these points are important for the MG's operator. Similarly, for  $\lambda_p$  less than 0.8, the reduction in profit is faster while the slope of RIP changes has maintained a downward trend (for larger  $\lambda_p$  s). Therefore, the most reasonable result that can be achieved is that the MG's operator considers points above 0.8. On the other hand, sometimes the MG's operator decides to minimize the RIP and operate its MG with a  $\lambda_p$  below 0.8 point in which it should pay the cost of reducing the MG's profit. Meanwhile, this reduction in profit is not so high, therefore the MG's operator is always interested in reducing the risk in the MGs.

The schematic comparison of the results of steps 3 and 5 is shown in Figs. 7 and 8. These figures show changes in average profit and average RIP of implementing and not implementing the DRP without considering risk, respectively.

TABLE VI  
SCENARIOS' PROFIT WITH DIFFERENT  $\lambda_p$  VALUES IN THE CDRC CASE WITH DRP [\$]

$\lambda_p$	Sc 1	Sc 2	Sc 3	Sc 4	Sc 5
0.99	74.1715	76.8600	72.5633	76.3213	75.9878
0.95	74.1715	76.8600	72.7100	76.1747	75.9878
0.9	74.1715	76.8600	72.8933	75.9913	75.9878
0.85	74.1715	76.8600	73.0768	75.8079	75.9878
0.8	74.1715	76.7696	73.2602	75.7097	75.9878
0.75	74.1715	76.6167	73.4436	75.5907	75.9878
0.7	74.1715	76.3416	73.6269	75.5907	75.9878

TABLE VII  
MG'S PROFIT IN CDRC CASE AND COMPARISON OF WCDRC CASE WITH DRP

$\lambda_p$	Average profit [\$]	Total RIP [\$]	Average RIP [\$]	Average profit reduction [%]	Average RIP reduction [%]
0.99	75.1808	3.6272	0.7254	0	0.9868
0.95	75.1808	3.4800	0.6960	0	5.0049
0.9	75.1808	3.2967	0.6593	0	10.0093
0.85	75.1808	3.1132	0.6226	0	15.0178
0.8	75.1797	2.9299	0.5859	0.0014	20.0223
0.75	75.1620	2.7464	0.5493	0.0249	25.0308
0.7	75.1437	2.5631	0.5126	0.0493	30.0353

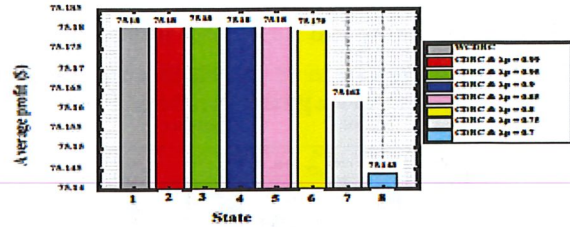


Fig. 5. Average profit with and without considering risk constraint and with DRP.

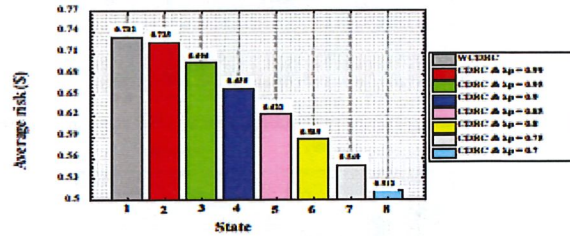


Fig. 6. RIP with and without considering risk constraint and with DRP.

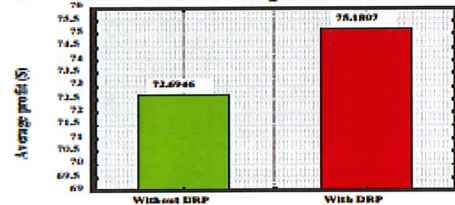


Fig. 7. Average profit with and without DRP and WCDRC.

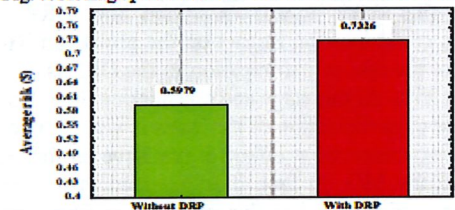


Fig. 8. RIP with and without considering DRP and WCDRC.

As shown in Figs. 7 and 8, by applying DRP without risk, the average profit of the MG and the average risk rate increase compared to the without DRP and without the risk cases. Also, according to Figs. 7 and 8, by applying the DRP, the rate of RIP increase is higher than the rate of profit increase. The increase rate in RIP is 22.5288% while the increase rate in profit is 3.4199% according to Figs. 7 and 8, respectively. This means that the sensitivity of the RIP is greater than the MG's profit, due to the implementation of DRP. The schematic of the compared results of Steps 4 and 6 is also shown in Figs. 9 and 10. These figures show, respectively, average changes in profit and average RIP changes for performing and not performing the DRP by considering the risk for different  $\lambda_p$  s. According to Figs. 9 and 10, similar to WCDRC scenarios, when applying DRP by considering risk, the average profit of the MG and the average RIP increase as compared to the without DRPs and CDRC cases. According to Fig. 10, for high values of  $\lambda_p$  s, the average increase in the RIP is higher than  $\lambda_p$  s with low values while these sensible changes are not seen in the profit. According to Figs. 7-10, RIP sensitivity to with and without the implementation of DRP is higher than the profit sensitivity. So



that by changing the  $\lambda_p$  and rate of loads participation in the DRP, the RIP changes are more sensible than the changes in profit. Also, RIP changes are greater than the profit changes.

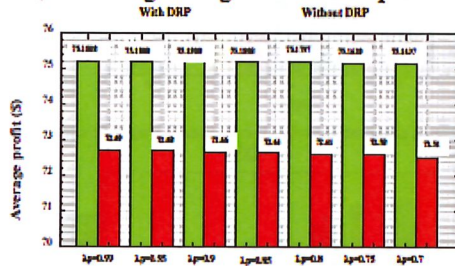


Fig. 9. Average profit's with and without considering DRP states and CDRC.

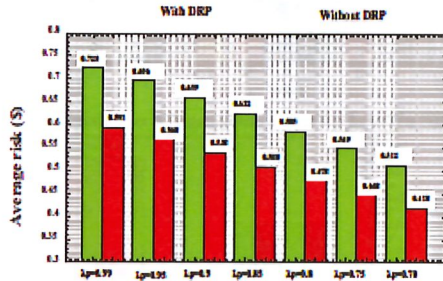


Fig. 10. RIP with and without considering DRP states and CDRC.

#### D. Sensitivity Analysis

Up to this stage, it was examined how DRP and risk constraints could have an impact on the profit and RIP of the MGs. Also, the rate of participation in the DRP is assumed to be fixed at 25%. At this stage and considering Step 7 in Section IV, the rate of participation of the loads is also changed, and it should be examined what effects it can have on the profit and the RIP of the MG. In fact, it is intended that a sensitivity analysis is carried out. For this purpose, in three completely separate modes, it is assumed that the rate of participation in the DRP is 20%, 25%, and 30%, and for each one, it is examined which results will be in the presence and absence of downside risk constraints. It should be noted that the target value was \$73,9981, \$75.1808, and \$76.4125, respectively, when loads participation in the DRP are 20%, 25%, and 30%, respectively. In Step 7, it is assumed that the risk constraints in the modeling of the problem are not considered and the rate of participation is changed. The results of this study are schematically shown in Figs. 11 and 12. Figs. 11 and 12 show changes in average RIP and changes in profit according to the rate of the load's participation percentage in DRP, respectively. Based on Figs. 11 and 12, by increasing the participation of loads in DRP, the average profit, and average RIP increase. It is also observed that with the same change in the participation rate (5%), the slope of the average profit changes is regular and almost linearly changed, but average RIP changes are irregular and nonlinear, but their changes have always been ascending. Thus, Figs. 11 and 12 represent that load's participation in DRP should not be high. For example, when the value of the participation varies from 25% to 30%, the profit value is approximately the same as the previous step (between 20% and 25%), but the RIP has increased. Operator uses these choices to achieve higher profit.

In the next step, the risk constraints are considered in the modeling of the problem and the rate of participation is changed

to investigating the changes in the MG's profit and RIP. The results of this study are schematically shown in Figs. 13 and 14.

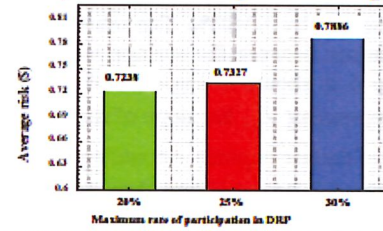


Fig. 11. Average RIP in WCDRC considering loads participation with DRP.

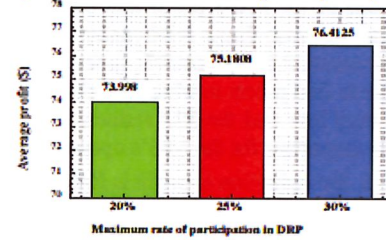


Fig. 12. Average profit in WCDRC considering loads participation with DRP.

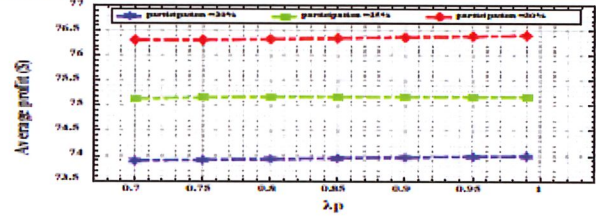


Fig. 13. Average profit in CDRC for loads participation and changing  $\lambda_p$ .

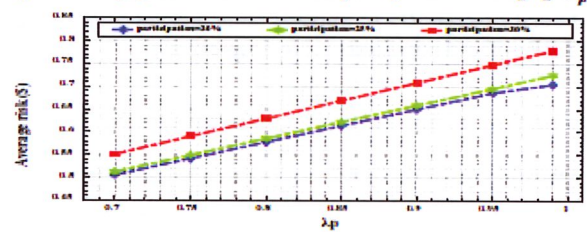


Fig. 14. Average RIP in CDRC for loads participation and changing  $\lambda_p$ .

These figures show, respectively, changes in average profit and average risk according to the changes in the rate of the load's participation in DRP and the variations in the  $\lambda_p$ . It should be noted that in Figs. 13 and 14, the word participation is the maximum permitted rate of participation of loads in DRP. Based on Figs. 13 and 14, increasing the participation rate in DRP increases the average profit and average RIP. Also, with the increase of  $\lambda_p$ , the average profit and average RIP will increase. Also, with the same change in the participation rates, the slope of the average profit changes is slower than the slope of RIP changes, but the trend of these changes has been almost upward. Regarding Figs. 13 and 14, when the value of the load's participation varies from 25% to 30%, the profit changes have roughly regulated. These changes are nearly the same as the previous step (between 20% and 25%). Also, these changes are incremental, but the changes in RIP have increased a lot.

#### E. Discussion of the Paper Results

The goal of this study is to examine the parameters in which their changes are effective in profit and RIP changes, and this



analysis and sensitivity analysis is carried out in 7 steps. The first and second steps are obtaining the initial data, and the next five steps are the main steps. In the third and fourth steps, it is examined that the presence of or non-presence of risk constraints could have any effect on the profit and RIP when the MGs loads not participating in the DRP. In the fifth and sixth steps, the purpose of the study is to investigate the profit and RIP changes with the participation of loads in DRP and in the presence or non-presence of risk constraints. In the seventh step, sensitivity analysis is also carried out in which how by changing the value of the load's participation rate and the presence and non-presence of risk constraints the profit of the MG and RIP change. In this survey, it is found that generally there is always a direct relationship between RIP and profit. Of course, their relationship is not linear, and the value of their changes is not related to each other, but their manner is similar. For example, both are incremental, but their increase is not the same. Applying the risk constraints always reduces the profit and RIP, and this expression exists for both DRP and without DRP modes. Studies have also shown that by implementing the DRP, profit and RIP are increased. Also, when the participation of loads in DRP is increased, the profit and RIP are increased. Generally, these surveys help the MG's operator and improve the profit and minimize the RIP in different states.

## VI. CONCLUSION

The optimal power scheduling of the resources in an MG is performed to minimize the risk. The main objectives of this work are profit maximization as well as investigating the effect of the DRP on the risk and the profit of the MGs. The secondary goals are risk minimization and optimal scheduling of the energy sources. UC is performed on the DGRs. First, the profit of the MGs for both WCDRC and the CDRC is investigated. The results of this MIP problem show that for the CDRC case the profit is slightly reduced, but RIP is reduced significantly; in one of the cases, RIP is reduced by 29.9987%; whereas the average profit is only reduced by 0.2462%. Without considering DRC, the simulation results show that DRP has significant impacts on the risk and the profit of the MGs. Then, the DRCs are added to the problem, and the optimization is performed. The comparison between WCDRC and CDRC cases shows that the average profit slightly decreases while the average RIP significantly decreases. Therefore, CDRC and applying DRP at the same time led to a dramatic reduction of RIP. After sensitivity analysis, results confirm the proper performance of the model. Thus, some constraints and techniques are suggested which led to a significant reduction in the risk and a notable increment in the profit of the MGs.

## REFERENCES

- [1] J. A. Aguado, S. de la Torre, and A. Triviño, "Battery energy storage systems in transmission network expansion planning," *Electr. Power Syst. Res.*, vol. 145, pp. 63–72, Apr. 2017.
- [2] F. Katiraei, R. Iravani, N. Hatzargyriou, and A. Dimeas, "Microgrids management," *IEEE Power Energy Mag.*, vol. 6, no. 3, pp. 54–65, May 2008.
- [3] W. Su and J. Wang, "Energy management systems in microgrid operations," *Electr. J.*, vol. 25, no. 8, pp. 45–60, 2012.
- [4] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET Renew. Power Gener.*, vol. 5, no. 3, p. 258, 2011.
- [5] M. Izadbakhsh, M. Gandomkar, A. Rezvani, and A. Ahmadi, "Short-term resource scheduling of a renewable energy based micro grid," *Renew. Energy*, vol. 75, pp. 598–606, 2015.
- [6] A. Jafari, H. Ganjeh Ganjehlou, F. Baghal Darbandi, B. Mohammadi-Ivatloo, and M. Abapour, "Dynamic and multi-objective reconfiguration of distribution network using a novel hybrid algorithm with parallel processing capability," *Appl. Soft Comput.*, vol. 90, p. 106146, May 2020.
- [7] A. Rezvani, M. Gandomkar, M. Izadbakhsh, and A. Ahmadi, "Environmental/economic scheduling of a micro-grid with renewable energy resources," *J. Clean. Prod.*, vol. 87, pp. 216–226, 2015.
- [8] M. S. Misaghian *et al.*, "Hierarchical framework for optimal operation of multiple microgrids considering demand response programs," *Electr. Power Syst. Res.*, vol. 165, pp. 199–213, Dec. 2018.
- [9] M. De, G. Das, S. Mandal, and K. K. Mandal, "A reliable energy management and generation scheduling model in microgrids using modified cuckoo search algorithm," in *2018 Emerging Trends in Electronic Devices and Computational Techniques (EDCT)*, 2018, pp. 1–6.
- [10] M. B. Wafaa and L.-A. Dessaint, "Multi-objective stochastic optimal power flow considering voltage stability and demand response with significant wind penetration," *IET Gener. Transm. Distrib.*, vol. 11, no. 14, pp. 3499–3509, Sep. 2017.
- [11] T. Khalili, S. Nojavan, and K. Zare, "Optimal performance of microgrid in the presence of demand response exchange: A stochastic multi-objective model," *Comput. Electr. Eng.*, vol. 74, pp. 429–450, Mar. 2019.
- [12] T. Khalili, A. Jafari, M. Abapour, and B. Mohammadi-Ivatloo, "Optimal battery technology selection and incentive-based demand response program utilization for reliability improvement of an insular microgrid," *Energy*, vol. 169, pp. 92–104, Feb. 2019.
- [13] L. Wu, M. Shahidehpour, and T. Li, "GENCO's risk-based maintenance outage scheduling," *IEEE Trans. Power Syst.*, vol. 23, no. 1, pp. 127–136, 2008.
- [14] M. Vahedipour-Dahraie, H. Rashidizadeh-Kermani, M. Shafie-Khah, M. Loffi and J. P. S. Catalão, "Economic-Reliability Risk-Constrained Scheduling for Resilient-Microgrids Considering Demand Response Actions," *IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society*, Lisbon, Portugal, 2019, pp. 4139–4144.
- [15] J. J. Chen, Y. B. Zhuang, Y. Z. Li, P. Wang, Y. L. Zhao, and C. S. Zhang, "Risk-aware short term hydro-wind-thermal scheduling using a probability interval optimization model," *Appl. Energy*, vol. 189, pp. 534–554, 2017.
- [16] H. Cherif and J. Belhadi, "Energy output estimation of hybrid wind-photovoltaic power system using statistical distributions," *J. Electr. Syst.*, vol. 10, no. 2, pp. 117–132, 2014.
- [17] C. Novoa and T. Jin, "Reliability centered planning for distributed generation considering wind power volatility," *Electr. Power Syst. Res.*, vol. 81, no. 8, pp. 1654–1661, 2011.
- [18] A. Luna *et al.*, "Optimal power scheduling for a grid-connected hybrid PV-wind-battery microgrid system," in *2016 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2016, pp. 1227–1234.
- [19] A. Jafari, H. Ganjeh Ganjehlou, T. Khalili, and A. Bidram, "A fair electricity market strategy for energy management and reliability enhancement of islanded multi-microgrids," *Appl. Energy*, vol. 270, p. 115170, Jul. 2020.
- [20] H. Ganjeh Ganjehlou, H. Niazee, A. Jafari, D. O. Aroko, M. Marzband, and T. Fernando, "A novel techno-economic multi-level optimization in home-microgrids with coalition formation capability," *Sustain. Cities Soc.*, vol. 60, p. 102241, Sep. 2020.
- [21] A. Jafari, H. Ganjeh Ganjehlou, T. Khalili, B. Mohammadi-Ivatloo, A. Bidram, and P. Siano, "A Two-Loop Hybrid Method for Optimal Placement and Scheduling of Switched Capacitors in Distribution Networks," *IEEE Access*, vol. 8, pp. 38892–38906, 2020.
- [22] N. I. Nwulu and X. Xia, "Optimal dispatch for a microgrid incorporating renewables and demand response," *Renew. Energy*, vol. 101, pp. 16–28, Feb. 2017.
- [23] A. Jafari, T. Khalili, H. G. Ganjehlou, and A. Bidram, "Optimal integration of renewable energy sources, diesel generators, and demand response program from pollution, financial, and reliability viewpoints: A multi-objective approach," *J. Clean. Prod.*, vol. 247, p. 119100, Feb. 2020.
- [24] L. Wu, M. Shahidehpour, and Z. Li, "GENCO's Risk-Constrained Hydrothermal Scheduling," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1847–1858, Nov. 2008.
- [25] M. P. Moghaddam, A. Abdollahi, and M. Rashidinejad, "Flexible demand response programs modeling in competitive electricity markets," *Appl. Energy*, vol. 88, no. 9, pp. 3257–3269, Sep. 2011.



