Flexibility-Oriented Scheduling of Microgrids Considering the Risk of Uncertainties

Mohammad MansourLakouraj [1], Mohammad Sadegh Javadi [2] and João P. S. Catalão [2,3]

[1] Department of Electrical and Computer Engineering, Babol Noshirvani University of Technology, Babol, Iran

[2] Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), 4200-465 Porto, Portugal

[3] Faculty of Engineering, University of Porto (FEUP), 4200-465 Porto, Portugal

Emails: m.mansour349@gmail.com (M.M.L.), msjavadi@gmail.com (M.S.J.), catalao@fe.up.pt (J.P.S.C.)

***Abstract*— Increasing the penetration of renewable resources has aggravated the operational flexibility at distribution level. In this study, a flexibility-oriented scheduling of microgrids (MGs) is suggested to reduce the power fluctuations in distribution feeders caused by the high penetration of wind turbines (WTs) in MGs. A flexibility constraint as viable and practical solution is used in MG scheduling to address this challenge. The presented scheduling model, implemented using mixed integer linear programming (MILP) and a stochastic framework, exercises risk constraints to capture the uncertainties associated with wind turbines, loads and market prices. The effectiveness of the model is investigated on a MG with high penetration of WTs in the presence of demand response (DR) and energy storage systems (ESSs). Numerical studies show the influence of risk parameters' changing on operation costs. In addition, the flexibility constraint mitigates the sharp variation of the net load at distribution level, which improves the flexibility of the distribution system.**

Keywords—Microgrids (MGs), Flexibility, Stochastic scheduling, Risk constraints, Wind.

NOMENCLATURE

Acronyms

DA, RT	Day ahead and real time
ESS, WT	Energy storage system and wind turbine
DU, DR	Dispatchable unit and demand response
VOLL, LC	Value of lost load and load curtailment
CVaR, VaR	Conditional value at risk, Value at risk

Indices

t, s	Index for time and scenarios
b, m	Index for energy storage and dispatchable units
e, c	Index for responsive loads and steps

Parameters

$\pi^t_{DA}, \pi^t_{RT,s}$	Day-ahead and real-time markets' price
α, β	Confidence level and Risk parameter
μ^t_s	Probability of scenario
l	Accepted amount for power reduction by load

Variables

$P^t_{DA}, P^t_{RT,s}$	Day-ahead and real-time markets' power
$P^t_{DU,m,s}$	Dispatchable unit's power
$P^t_{WT,s}$	Wind turbines' generated power
$\eta_{t,s}, \zeta_t$	Auxiliary variable and Value at risk
LC^t_s	Load curtailment
$P^{t,dis}_b, P^{t,ch}_b$	Discharging/charging power of ESS
SOC^t_b	State of charge
MD_b, MC_b	Minimum discharging/charging hours of ESS
$T^{dis}_{b,t}, T^{ch}_{b,t}$	Successive time of discharging/charging
$u^{t,ch}_b, u^{t,dis}_b$	Statues of charging /discharging (1means charging/discharging, 0 otherwise)
$P^t_{l,s}$	Aggregated load
$IP^t_{e,s}, IC^t_{e,s}$	Reduced power by load and its cost
o	Financial offered by load

I. Introduction

A) Motivation and background: The application of renewable energy resources has intensified during the recent decades in power system due to the environmental concerns and depletion of fossil fuels. In addition, operation cost reduction and increment of power system reliability have been the other reasons of this widespread usage [1]. Despite the benefits of renewables, there exists some challenges that should be considered. To be more specific, increasing wind energy deployment besides conventional resources and consumers has modified the net load (i.e. the difference between aggregated energy generation and consumption), profile pattern [2]. Considering the variable behavior of wind power, the net load has significant fluctuations and changes, so the upstream grid operator faces a sharp ramping in load profile during a day [3]. In addition, unlike the conventional generation resources, renewable generation is uncertain, so the remarkable

978-1-7281-4701-7/20/$31.00 ©2020 IEEE

penetration of renewable generation aggravates the system uncertainty which brings about new hurdles in power system operation and control [4].

B) Relevant literatures: To circumvent the challenges associated with fluctuation and uncertainties in power system, several methods are available. Utilizing dispatchable units (DUs) with the fast ramping capacity is one of the traditional solution for keeping the supply-demand balance in power systems [1]. Energy storage system (ESS) can be utilized to arrest the uncertainties associated with renewables [5] and [6]. Moreover, Demand response (DR) is another practical solution to increase the system flexibility and reliability by modifying the net load pattern [7]. Hence, an efficient method is needed to optimally employ these resources.

In [8], a stochastic scheduling of multi energy carrier MGs is proposed to minimize the operation cost using the DR resources; however, the risk of uncertainties is neglected. A stochastic optimal coordination between the ESS, DR resources and renewables in a MG is presented in [5] and [9], while an efficient tool is not used to capture the uncertainties. A stochastic framework is presented in [10] to manage the MG's resources during unscheduled islanding period. However, the role of DR is not studied. A risk-based energy management of dependent MGs is investigated in [11] to satisfy both resilient and economic operations, while the flexibility of distribution system is not analyzed.

In the context of flexibility, a day-ahead scheduling of power system hosting high penetration of wind power generation is proposed in [12] with suggesting a novel flexibility index, but the uncertainties are not captured with a risk-based method. Moreover, a very short-term stochastic scheduling of power system using the flexible ramp reserve is proposed in [13], while the role of DR is not studied. A new approach for increasing the flexibility of power system with the aim of DUs and consumers is investigated in [14]; however, the risk analysis of uncertainties is not performed.

C) Contributions and organization: Investigating the aforementioned works, it can be realized that limited attempts have been dedicated to propose a flexibility-oriented scheduling framework for MGs considering the risks imposed by uncertainties in the presence of DR resources and high penetration of renewables.

In this paper, a risk-constrained stochastic model is presented to minimize the operation cost and reduce the power fluctuations in distribution system. The high penetration of WTs in MGs causes sharp fluctuations in exchanged power in some hours although the fast response resources such as ESS, DU and DR are utilized. Hence, such power exchanges are controlled by an applicable flexibility constraint. Furthermore, the uncertain behavior of WTs, loads and prices is captured by an efficient risk-based method. Also, the operator has the chance to participate in both real-time and day-ahead electricity markets to provide power for its consumers.

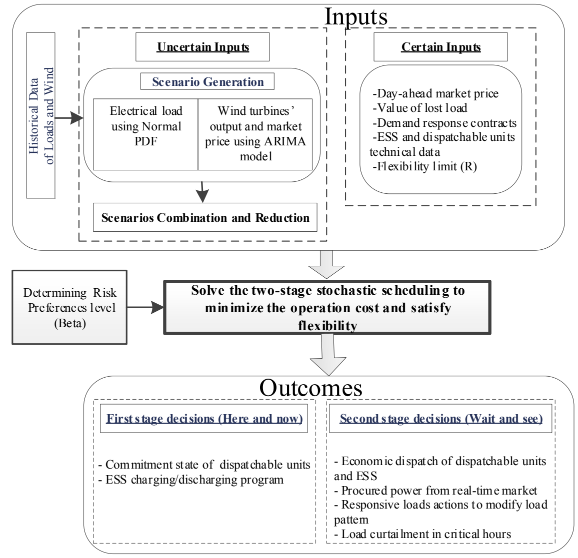

Fig. 1. Presented framework for MG day-ahead scheduling.

The rest of the paper is organized as follows. Section II reviews the methodology and formulations. Section III presents the numerical studies and analysis, and Section IV concludes the study.

II. Methodology and Formulations

A) Methodology: MG operator should consider economic operation and find the least-cost decisions in scheduling problem. Figure 1 shows the two-stage stochastic scheduling process of MG. The first stage decisions are associated with the commitments status of ESS charging/discharging and DU during the operation day. Decisions at the second stage are related to the economic dispatch of ESS and DU, DR actions and load curtailments. In the next sub-section, the mathematical interpretation of objective cost function and constraints is described.

B) Problem formulation: The objective function (OF) in (1)–(2) is to minimize the operation cost over scheduling horizon in the MG. In this objective function, the first term is associated with the cost of the provided energy from the day-ahead market. The second term implicates the scenario-related decisions which reflect the cost of the energy procured from the real-time market, DUs' operation, DR resources' action and load shedding.

$$OF = \min\left(\sum_{t=1}^{T}\left\{P_{DA}^{t} \times \pi_{DA}^{t} + \sum_{s=1}^{S}\mu_{s} \times C_{s}^{t}\right\}\right) \tag{1}$$

$$C_{s}^{t} = P_{RT,s}^{t} \times \pi_{RT,s}^{t} + \sum_{m=1}^{M} F\left(P_{DU,m,s}^{t}\right) + \sum_{e=1}^{E} IC_{e,s}^{t} + VoLL \times LC_{s}^{t} \tag{2}$$

Equation (3) guarantees the electrical power balances in the MG which links to the upstream grid.

$$\begin{aligned} &P_{DA}^{t}+P_{RT,s}^{t}+\sum_{m=1}^{M}P_{DU,m,s}^{t}+P_{WT,s}^{t} \\ &+\sum_{b=1}^{B}\left(P_{b}^{t,dis}-P_{b}^{t,ch}\right)+\sum_{e=1}^{E}IP_{e,s}^{t}+LC_{s}^{t}=P_{l,s}^{t} \end{aligned} \tag{3}$$

Constraints (4)-(7) shows the interruptible/curtailable (IC) program, so it defines the assigned reduction ranges by consumers when they participate in the *DR* program. $L_{e,c}$ and $L_{e,min}$ are associated with the maximum and minimum reductions of consumption in steps c and one, respectively. Furthermore, the aggregation of the reduced consumption should not be greater than $L_{e,c}$ at each hour [11].

$$L_{e,min} \le l_{e,1} \le L_{e,1} \tag{4}$$

$$0 \le l_{e,c} \le (L_{e,c+1} - L_{e,c}); \forall c=2,3... \tag{5}$$

$$IP_{e,s}^{t} = \sum_{c=1}^{C} l_{e,c} \tag{6}$$

$$IC_{e,s}^{t} = \sum_{c=1}^{C} o_{e,c} l_{e,c} \tag{7}$$

Constraint (8), known as flexibility constraint, limits the power transferred between MG and upstream grid in two consecutive hours, so it will reduce variation with respect to the amount of ramping capability (R) during the operation.

$$-R \le (P_{DA}^{t}+P_{RT,s}^{t}-P_{DA}^{t-1}-P_{RT,s}^{t-1}) \le R \tag{8}$$

ESS constraints are shown as (9)-(15). The state of charge (SOC) in ESS as well as its maximum and minimum limitation are presented as (9)–(10). Charging and discharging of ESS at time slots are limited by (11)–(12), in which the maximum and minimum level of charging and discharging is considered [15]. The charging and discharging procedures cannot happen simultaneously as restricted by (13). The minimum period of time for charging and discharging is ensured through (14) and (15), respectively [16]. Technical constraints of DUs are borrowed from [5], which are not presented here.

$$SOC_{b}^{t} = SOC_{b}^{t-1} + \eta_{b}^{ch} \times P_{b}^{t,ch} - \eta_{b}^{dis} \times P_{b}^{t,dis} \tag{9}$$

$$SOC_{b}^{min} \le SOC_{b}^{t} \le SOC_{b}^{max} \tag{10}$$

$$P_{b,min}^{ch} \times u_{b}^{t,ch} \le P_{b}^{t,ch} \le P_{b,max}^{ch} \times u_{b}^{t,ch} \tag{11}$$

$$P_{b,min}^{dis} \times u_{b}^{t,dis} \le P_{b}^{t,dis} \le P_{b,max}^{dis} \times u_{b}^{t,dis} \tag{12}$$

$$u_{b}^{t,ch} + u_{b}^{t,dis} \le 1 \tag{13}$$

$$MC_{b}\left[u_{b}^{t,ch} - u_{b}^{t-1,ch}\right] \le T_{b}^{t,ch} \tag{14}$$

$$MD_{b}\left[u_{b}^{t,dis} - u_{b}^{t-1,dis}\right] \le T_{b}^{t,dis} \tag{15}$$

In this study, constraints (16)-(19) are employed to manage the uncertainties. CVaR is defined as (16), showing the expected cost of worst scenarios [17]. Constraints (17)-(19) impose the risk preferences level within a determined β which defines the compromise between the expected value of objective function and risk aversion [17]. In fact, the amount of this parameter is subject to the operator's preference about risk-constrained controlling strategy. A risk-taker decision maker prefers a value larger than one, but a risk-averse person prefers a value close to one [11]. ζ_t , known as value at risk (VaR), is a cost that (1-α)×100% of the worst scenarios' cost is more than or even equal to it. $\eta_{t,s}$ is a continuous positive auxiliary parameter, determining the difference between ζ_t and scenarios' cost [11].

$$CVaR = \frac{1}{(1-\alpha)}\sum_{t=1}^{T}\sum_{s=1}^{S}\mu_{s}^{t} \times \eta_{t,s} - \zeta_{t} \tag{16}$$

$$CVaR \le \beta \times OF \tag{17}$$

$$\sum_{t=1}^{T}\left(\begin{aligned} &P_{DA}^{t}\times\pi_{DA}^{t}+P_{RT,s}^{t}\times\pi_{RT,s}^{t}+\sum_{m=1}^{M}F\left(P_{DU,m,s}^{t}\right)+ \\ &\sum_{e=1}^{E}IC_{e,s}^{t}+VoLL\times LC_{s}^{t}+\zeta_{t}-\eta_{t,s} \end{aligned}\right) \le 0 \tag{18}$$

$$0 \le \sum_{t=1}^{T}\eta_{t,s} \tag{19}$$

III. Numerical Analysis and Case Studies

A. System under study and data

The presented risk-constrained stochastic problem is tested on a renewable-based MG, which has the installed resources such as DU, ESS and WTs with the characteristics shown in Table I. Also, the DR's feature is represented in Table II. The VoLL of the loads is considered 1800 €/MWh [5]. As discussed about the scenario generation techniques using autoregressive moving average (ARMA) model for wind and prices as well as probability distribution function (PDF) for loads [5], [11], 1000 scenarios, each consisting of a vector of prices, wind turbines output and load profiles are obtained. These scenarios are reduced to 8 number through fast forward method in scenario reduction (SCENRED) of General Algebraic Modeling System (GAMS) software [17]. This reduction is performed to provide a tradeoff between the accuracy and complexity of the model. This reduction is performed to provide a tradeoff between model accuracy and complexity.

TABLE I. CHARACTERISTICS OF GENERATION UNITS

Generation Units	*Operation cost (€/MWh)*	*Min/Max Generation Power (MW)*	*Min Up/ Down hours*	*Ramp Up/Down Limit (MW/h)*
DU	56	0.4-3	1	2
WT	-	0-6	-	-
ESS	-	0.4-2	5	-

TABLE II. DR RESOURCE'S FEATURES

DR steps	*1*	*2*	*3*
Reduced power in each step (MW)	0.6	0.7	0.5
Incentives (€)	90	130	210

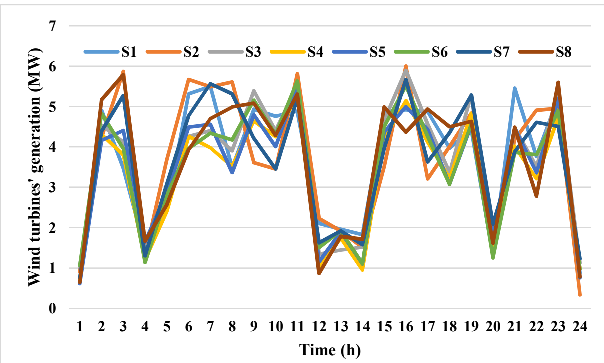

Fig. 2. Generated power of wind turbines for eight scenarios.

Figure 2 shows the aggregated *WTs*' output [18] obtained from the scenario generation tool, *ARMA*. The loads and market prices data are taken from [11].

In what follows, the MG scheduling model is solved by *IBM CPLEX*® Software [19] on a personal computer with 2.2 *GHz* processor and *8GB RAM* considering min gap of 0%, and the numerical results are discussed thoroughly.

B. *Numerical analysis and discussion*

The flexibility-oriented scheduling is performed with R =1.5 MW/h in two case as follows:

Case 1. *Flexibility-oriented scheduling neglecting risk constraints:* In this case, constraints (6)-(9) are not considered in scheduling process, so the operator deploys a risk-taker (risk-neutral) strategy for scheduling the resources.

Case 2. *Flexibility-oriented scheduling considering risk constraints:* In this scheduling, risk constraints represented in (6)-(9) are added to the mathematical framework, so the operator tries to mitigate the risk of costly or worst scenarios with the aim of risk-averse policy. The risk preferences level (β) and confidence level (α) are considered 1.15 and 0.7, respectively.

The operation costs of scenarios are shown in Table III from worst to best (high-cost to low-cost) scenarios, and the expected operation costs are also calculated based on the scenarios for case 1 and 2. As shown, implementing risk constraints for case 2 decreases the costs of worst or high-cost scenarios such as scenarios 6, 4, 8 and 3, but it increases the cost of low-cost scenarios such as scenarios 1, 2, 7 and 5. To be more specific, column 5 shows the changes in operation cost for case 2 in comparison with case 1. Although the expected cost in case 2 is increased € 65.2 due to the risk-averse strategy, the risk of worst scenarios is diminished once these scenarios happen in the operation day. Figures 3 and 4 depict the energy provided by various resources and consumption pattern in worst scenario (scenario 6) for case 1 and 2, respectively. As demonstrated, the day-ahead market provides more electrical energy in case 2 in comparison with case 1. In fact, in case 2, the operator uses the risk-averse strategy, so he prefers to provide power from the certain day-ahead market instead of uncertain real-time market. The *DU* operates significantly from hours 17 to 24 in high price hours of market and peak hours for both cases. The *ESS* is charged from 2 to 11, low market price hours, and then is discharged from 12 to 20 and hour 24 to compensate the power shortages. Moreover, the modified load is the result of *DR* actions in hour 20 for both cases.

TABLE III. DETAILS OF COSTS FOR ALL SCENARIOS

Scenario no.	Costs in Case 1 (€)	Costs in Case 2 (€)	Probability	Difference of costs (€)
6	6543.885	5914.706	0.08	- 629.179
4	6249.314	5819.291	0.12	- 430.023
8	5226.630	5049.514	0.06	- 177.116
3	5081.216	5010.569	0.14	- 70.647
1	4590.439	4716.007	0.14	125.568
2	4470.756	4681.495	0.17	210.739
7	3839.536	4242.941	0.14	403.405
5	3571.549	4191.27	0.15	619.721
Expected Cost (€)	4789.5	4854.7		65.2

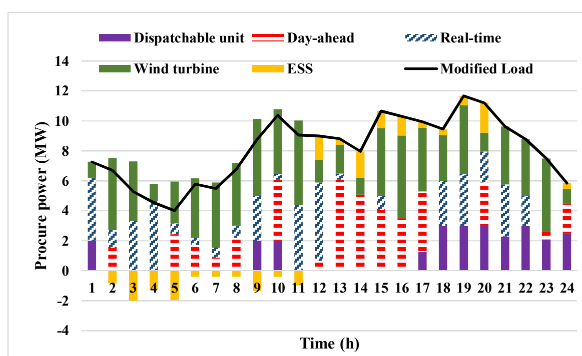

Fig. 3. Energy scheduling for consumers in case 1 (risk-neutral policy)

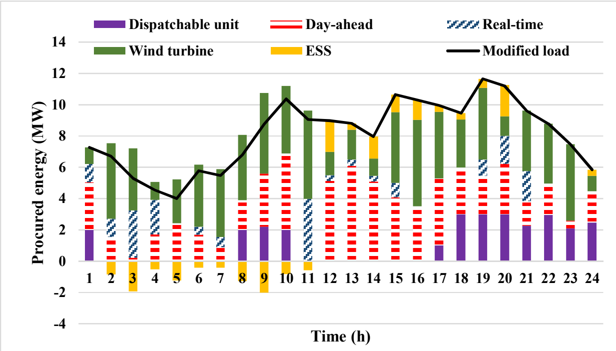

Fig. 4. Energy scheduling for consumers in case 2 (risk-averse policy)

C. Sensitivity analysis

Risk parameter (β): Changing β determines the risk preference level of the operator. A risk-averse decision-maker chooses a value near to one, but a risk-taker person prefers larger value. The effect of this parameter on expected cost versus *CVaR* is shown in Figure 5. Setting β on smaller values causes higher operation cost and lower *CVaR* value. However, choosing a larger value reduces the operation cost and increases the amount of *CVaR*. Considering the value of β more than 1.25, it can be realized that the operation cost is constant and equal to € 4789.5. It means that for these ranges of β, the risk constraints are being ineffective and the scheduling process changes to risk-neutral form. So, this point (i.e. $\beta=1.25$) is a saturation point, which we can take the advantages of risk constraints to handle the costly scenarios after that. Figure 6 represents the effect of adjusting β on power procurement from electricity markets. It is shown that by increasing this parameter the operator tends to buy electrical energy from the real-time market rather than the day-ahead market. This is because a risk-taker operator hopes to face low prices in real-time market. After saturation point (i.e. $\beta=1.25$), the changes of energy provided is insignificant from both markets as the scheduling policy will stay almost constant.

Ramping capability (R): This flexibility parameter can manage the fluctuation of transferred power between *MG* and distribution system.

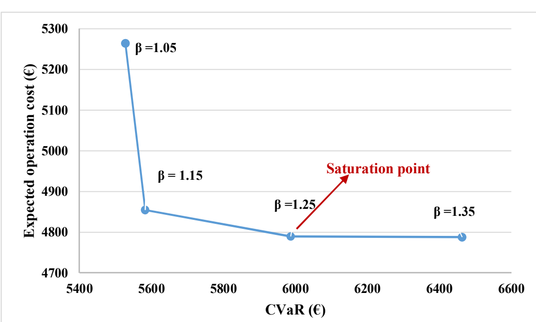

Fig. 5. Trend of expected operation cost versus CVaR for different value of β

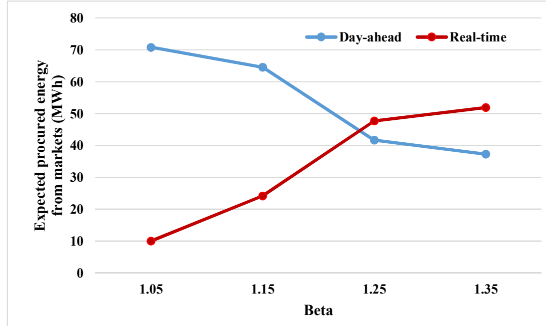

Fig. 6. Energy provided from markets for different value of β

Whenever the operator chooses smaller amount for R (i.e. R=0.5), the range of the fluctuation will decrease significantly, and provides operational flexibility for distribution system in the presence of renewable resources. However, neglecting this limitation causes sharp fluctuations and operational challenges for grid operators. Figure 9 shows the effect of considering R for controlling variation of net load, the power transferred that can be seen from grid operator's perspective. Therefore, it is necessary to set an optimum R for scheduling to satisfy both economic and flexible operations. Table IV presents the operation costs for different level of flexibility. Neglecting this constraint will reduce the operation cost while the flexibility of system would be reduced as shown in Figure 7. However, we should find an appropriate amount for R (i.e. R=1.5) to meet the operation concerns. Moreover, *DR* resources play beneficial role while the purchased power is limited by using the flexibility constraint. When R is set to 1.5, the *DR* action's cost is € 105.04, which prevents load shedding.

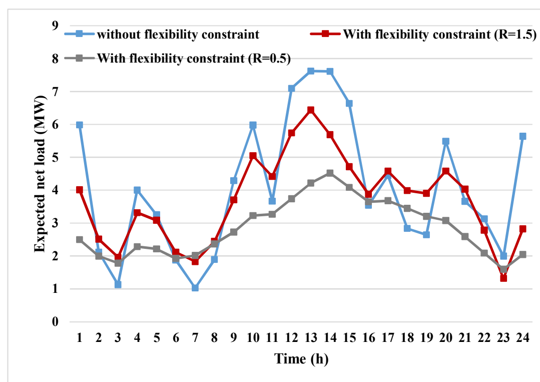

Fig. 7. Expected net load seen from upstream's perspective

TABLE IV. OPERATION COSTS WITH DIFFERENT LEVEL OF FLEXIBILITY

Flexibility consideration	Operation cost (€)	*DR* cost (€)	*VOLL* (€)	*DU*'s operation cost (€)
Neglected	4622.08	0	0	467.69
R=1.5	4854.73	105.04	0	907.14
R=0.5	5977.96	618.04	493.89	1828.9

TABLE V. COMMITMENT STATUS OF *DU* WITH AND WITHOUT FLEXIBILITY

	1	2	3	4	5	6	7	8	9	10	11	12
Neglecting *R*	0	0	0	0	0	0	0	1	1	0	0	0
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
	0	0	0	0	1	1	1	1	1	1	0	0
Considering *R=1.5*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
	1	0	0	0	0	0	0	1	1	1	0	0
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
	0	0	0	0	1	1	1	1	1	1	1	1

DU also is committed in more hours when the limited ramping capability is considered as shown with shaded blocks in Table V. The commitment status of *DU* is compared with and without considering flexibility constraint. This is because the power limitation of markets which is imposed by *R* would be compensated by this fast response unit.

IV. CONCLUSION

In this study, a flexibility-oriented stochastic scheduling was proposed, which considered the technical and economical constraints of risk, DR resources, ESS, DU and WTs in the mathematical model. The suggested model was developed to give a thorough perspective on minimizing the daily operation cost and reducing power fluctuations transferred between renewable-based MG and upstream distribution grid. The uncertainties associated with the loads, wind power and market prices were captured through the risk constraints that determined the risk-averse or risk-taker policy for scheduling. The numerical analysis has shown that an efficient risk-averse strategy reduced the operation cost of worst scenarios. Using this strategy enables the operator to participate in day-ahead market that had no uncertainty, but a risk-taker policy provided more electrical energy from the uncertain real-time market rather than the day-ahead market. The DR and DU resources had viable role in reducing the unintentional load shedding in a flexible operation. Consequently, the flexibility-oriented stochastic scheduling reduces the need for deploying new expensive generation resources in the grid for satisfying flexibility as it can be satisfied using the flexible constraint in scheduling. In our future work, intra-hour ramping constraint will be investigated, considering also solar-based generation.

ACKNOWLEDGMENT

J.P.S. Catalão and M.S. Javadi acknowledge the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under POCI-01-0145-FEDER-029803 (02/SAICT/2017).

REFERENCES

[1] A. Khodaei, “Provisional Microgrids,” *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1107–1115, May 2015.

[2] B. Mohandes, M. S. El Moursi, N. Hatziargyriou, and S. El Khatib, “A Review of Power System Flexibility with High Penetration of Renewables,” *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 3140–3155, Jul. 2019.

[3] A. Majzoobi and A. Khodaei, “Application of Microgrids in Supporting Distribution Grid Flexibility,” *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3660–3669, Sep. 2017.

[4] M. Shafie-Khah, M. Vahid-Ghavidel, M. Di Somma, G. Graditi, P. Siano, and J. P. S. Catalão, “Management of renewable-based multi-energy microgrids in the presence of electric vehicles,” *IET Renew. Power Gener.*, vol. 14, no. 3, pp. 417–426, Feb. 2020.

[5] H. Geramifar, M. Shahabi, and T. Barforoshi, “Coordination of energy storage systems and DR resources for optimal scheduling of microgrids under uncertainties,” *IET Renew. Power Gener.*, vol. 11, no. 2, pp. 378–388, 2017.

[6] M. S. Javadi, M. Lotfi, M. Gough, and J. P. S. Catalão, “Optimal Sizing and Siting of Electrical Energy Storage Devices for Smart Grids Considering Time-of-Use Programs,” in *IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society*, 2019, pp. 4017–4022.

[7] M. Lotfi, P. S. Joao Catalao, M. S. Javadi, A. E. Nezhad, and M. Shafie-khah, “Demand Response Program Implementation for Day-Ahead Power System Operation,” *2019 IEEE Milan PowerTech*, pp. 1–6, Jun. 2019.

[8] M. H. Shams, M. Shahabi, and M. E. Khodayar, “Stochastic day-ahead scheduling of multiple energy Carrier microgrids with demand response,” *Energy*, vol. 155, pp. 326–338, Jul. 2018.

[9] S. Talari, M. Yazdaninejad, and M. R. Haghifam, “Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads,” *IET Gener. Transm. Distrib.*, vol. 9, no. 12, pp. 1498–1509, Sep. 2015.

[10] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, “Stochastic Energy Management of Microgrids during Unscheduled Islanding Period,” *IEEE Trans. Ind. Informatics*, vol. 13, no. 3, pp. 1079–1087, Jun. 2017.

[11] M. Mansour-lakouraj and M. Shahabi, “Comprehensive analysis of risk-based energy management for dependent micro-grid under normal and emergency operations,” *Energy*, vol. 171, pp. 928–943, Mar. 2019.

[12] A. Nikoobakht, J. Aghaei, M. Shafie-Khah, and J. P. S. Catalão, “Assessing Increased Flexibility of Energy Storage and Demand Response to Accommodate a High Penetration of Renewable Energy Sources,” *IEEE Trans. Sustain. Energy*, vol. 10, no. 2, pp. 659–669, Apr. 2019.

[13] E. Nadermahmoudi, T. Amraee, and S. S. Oskouee, “Stochastic very short□term economic dispatch for wind power operation using flexible ramp reserve,” *Int. Trans. Electr. Energy Syst.*, Jun. 2020.

[14] M. Khoshjahan, P. Dehghanian, M. Moeini-Aghtaie, and M. Fotuhi-Firuzabad, “Harnessing Ramp Capability of Spinning Reserve Services for Enhanced Power Grid Flexibility,” *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 7103–7112, Nov. 2019.

[15] S. A. Mansouri, A. Ahmarinejad, M. Ansarian, M. S. Javadi, and J. P. S. Catalao, “Stochastic planning and operation of energy hubs considering demand response programs using Benders decomposition approach,” *Int. J. Electr. Power Energy Syst.*, vol. 120, p. 106030, Sep. 2020.

[16] S. A. Mansouri, A. Ahmarinejad, M. Ansarian, M. S. Javadi, and J. P. S. Catalao, “Stochastic planning and operation of energy hubs considering demand response programs using Benders decomposition approach,” *Int. J. Electr. Power Energy Syst.*, vol. 120, p. 106030, Sep. 2020.

[17] M. MansourLakouraj, M. Shahabi, M. Shafie-khah, N. Ghoreishi, and J.P.S. Catalão, “Optimal power management of dependent microgrid considering distribution market and unused power capacity,” *Energy*, vol. 200, p. 117551, Jun. 2020.

[18] "NREL: Western Wind Resources Dataset, " [Online]: http://wind.nrel.gov/web_nrel

[19] "User’s manual for CPLEX," [Online]: ftp://public.dhe.ibm.com/software/websphereoptimization/cplex/ps_usrmancplex.pdf