Risk-aware multi-objective planning of a renewable hybrid microgrid incorporating energy storage systems and responsive loads

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The environmental pollution problem is intensified in recent years due to increasing fossil fuel consumption. In this regard, deployment of renewable resources can be a practical solution to decrease greenhouse gases and global warming. This paper proposes a risk-aware multi-objective programming consisting of operation cost and pollution objective functions to optimize the operation of a renewable hybrid microgrid composed of biomass-based conventional generators, wind turbines, photovoltaics and electrical and heat storage systems. According to the presence of uncertainties in such infrastructures, fluctuations of wind speed, solar radiation, loads and market price are modeled through a scenario generation and reduction procedure and then, the conditional value-at-risk index is used to measure the risk of decisions. Moreover, the epsilon constraint and fuzzy logic approaches are utilized to solve the problem and select the best solution in the Pareto set, respectively. A demand response program is also implemented for electrical and heat loads to analyze the influence of responsive loads. The results validate that the operation cost and pollution increase by about 10.03% and 11.31% in the risk-averse strategy, in return, robustness in the worst-case scenarios improves. As well, responsive loads decrease operation cost by about 9.8% under the uncertainties, however, the pollution increases by about 0.88%.

keywords: *Demand response program; Energy storage systems; Multi-objective programming; Renewable microgrid; Risk analysis.*

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NOMENCLATURE

Parameters

BA : Blade area (m^2)
BC : Cost of buying energy (\$/kWh)
BFC : Biomass fuel cost (\$/kWh)
EE : Emission factor (kg/kWh)
EL : Electrical load demand (kW)
GT : Solar radiation (kW/m^2)
HL : Heat load demand (kW)
MC : Maintenance cost (\$)
$NSandNP$: Series and parallel cells in PV module
OC : Operation cost (\$/kWh)
P_line : Tie-line limitation (kW)
$Prob$: Probability (%)
SC : Cost of selling energy (\$/kWh)
u : Binary variable
V : Wind speed (m/s)
α, β : Risk parameters
γ : Temperature coefficient (°C)
n : Efficiency factor
ρ : Air density (kg/m^3)
μ : DRP index

Index

S : Scenario
t : Time (h)

Variable

A : Equivalent energy to air (kWh)

C : Total cost (\$)
E : Energy (kWh)
EM : Total Emission (kg)
G : Produced gas by biomass unit (m^3)
H : Heat (kW)
P : Electrical power (kW)
RL : Responsive load (kW)
T : Temperature (°C)
Ψ : Risk variable

Subscript/Superscript

Ch : Charge
Dch : Discharge
Env : Environmental
Inj : Injected
$NOCT$: Normal operating cell temperature
Pu : Pumped
STC : Standard test condition

1. INTRODUCTION

A. Motivation

Penetration of renewable resources in electrical energy systems has increased in recent years due to their various advantages[1]. Since the generated power by such components depends on weather conditions, the uncertainty in renewable-based structures is a critical issue. As a practical solution, the energy storage units can solve the mentioned problem, however, a high investment cost is required[2]. The contribution of responsive loads in energy management is suggested as another method to mitigate the influence of uncertainties [3].

B. Literature review

The planning of microgrids under the uncertain environment has been investigated in recent researches. In this regard, a multi-objective stochastic energy management approach is proposed for a microgrid including conventional and renewable energy resources, storage systems and electrical and thermal loads[4]. In a similar study, energy management of a grid-connected microgrid is analyzed considering portable renewable resources to minimize operation cost and pollution [5]. A two-point stochastic technique is applied to overcome the uncertainties of an isolated microgrid composed of renewable resources and pumped storage, where operation cost and energy not supplied (ENS) are used as the objective functions and a demand response program (DRP) is implemented to improve the flexibility [6]. A stochastic day-ahead programming is suggested to optimize the operation cost and environmental pollution in distribution systems incorporating responsive loads, conventional and renewable resources [7]. In order to manage the load consumption and optimize power fluctuations, an energy management strategy based on hybrid storage systems is presented [8]. The results approve the optimal peak load shaving by energy storage units such as battery and heat tank. A novel economic planning is proposed to specify the operation of a biomass-based microgrid [9]. The simulations validate that the operation cost is decreased by about 6.06%, while the efficiency is increased by about 6.34%. Reference [10] introduces a new strategy to determine the operation of heat pump, photovoltaic (PV) system and energy storage for domestic applications. The energy management of a microgrid composed of wind turbine (WT), combined heat and power (CHP) equipped with biomass fuel, PV, boiler, thermal and gas storage systems is optimized in [11]. The Monte Carlo simulation (MCS) is also utilized to cope the uncertainties of renewable resources and energy price. According to the requirements of residential apartments, the design of cooling and heating resources, biomass plant, cooling and heating storage units is performed in different seasons, where the results show that the biomass combined cooling, heating and power (BCCHP) system has a significant impact on the operation cost and environmental pollution [12]. The optimal stochastic scheduling of a network consisting of WT, conventional power plant, and compressed air energy storage (CAES) is analyzed in the presence of responsive loads to reduce the operation cost and increase the profit of loads [13]. In order to achieve the energy equilibrium and optimize heat pump operation, a solar energy system integrated with battery storage unit and heat pump is designed [14]. A two-stage stochastic approach is suggested for a microgrid integrated with renewable energies, electric vehicles (EVs) and flexible loads to minimize the cost [15]. The comparative results between stochastic and deterministic methods illustrate the positive role of responsive loads in reducing the influence of uncertainties. Reference [16] investigates the capability of rolling horizon optimization, interval and scenario-based approaches to determine the best economic decisions in competitive electricity markets. A stochastic multi-objective model is presented for management of CHP-based microgrids considering economic, environmental and reliability aspects under the forecast errors of electrical load demand and wind power [17]. In this regard, the availability of units is taken into account to model the reliability and the exchange market algorithm, weighted sum method and fuzzy satisfying are utilized to solve the problem. In a similar research, a stochastic framework is introduced for CHP-based microgrids consisting of WT, fuel cell (FC), boiler, conventional power generators, energy storage units and responsive loads to specify the optimal set points of resources and maximize profit under the uncertainties of wind speed, market and load [18]. The stochastic day-ahead scheduling of microgrids considering load curtailment cost and spinning reserve requirements is optimized in the presence of load, electricity price, wind and solar uncertainties [19]. Reference [20]discusses the operation of a hybrid microgrid consisting of CHP, WT, energy storage and auxiliary boiler and it uses the stochastic-robust method to manage the uncertainty of energy price, wind power and load demand. A multi-stage power and energy management approach including distributed explicit model predictive control (DEMPC) and mixed-integer quadratic programming (MIQP) is presented for a microgrids with PV, battery storage system, FC and electrolyzer to solve the unit commitment problem [21]. Due to the uncertainties of load demand and renewable resources, a novel cumulative relative regret decision-making strategy is proposed for optimal energy management of a grid-connected multi-energy microgrid to enhance the robustness and reduce the operation conservatism [22]. An incentive optimization model is suggested to obtain the maximum profit in the reconfigured grid-connected microgrid, where the results express that the energy dependency on the main grid and conventional energy sources is decreased by about 9.62% and 29.06%, respectively [23]. A real-time dynamic framework based on deep reinforcement learning algorithm, Markov decision process and proximal policy optimization is designed to achieve the optimal schedule decisions in microgrid under the uncertainty of load and renewable resources [24].

C. Research contribution

According to the literature review, energy management of microgrids is investigated from different points of view, however, still several issues exist. In this regard, Table 1 shows the main differences of this research compared to the previously published papers. As observed, the operation of renewable-based microgrids and their problems such as high penetration of uncertainties and risk analysis of the worst-case conditions have not been well analyzed. As well, the role of responsive loads in such systems to mitigate the influence of uncertainties and improve the system flexibility is not evaluated. In this study, the day-ahead planning of a renewable-based microgrid is optimized, where the key points and contribution are summarized as follows:

- Developing a hybrid renewable microgrid composed of PV, WT, biomass-based CHP (BCHP), biomass-based micro turbine (BMT), heat pump (HP), electrical and heat storage systems and loads.
- Modeling a risk-aware multi-objective mixed-integer linear programming (MILP) to simultaneously minimize the operation cost and pollution functions.
- Proposing an algorithm consisting of the epsilon constraint method (ECM), fuzzy satisfying and conditional value-at-risk (CVaR) metric to solve the problem and analyze the risk of uncertainties including wind speed, solar radiation, electrical and heat loads and energy price.
- Implementing a time of use (ToU) DRP for electrical and heat loads to enhance the system flexibility and mitigate the influence of uncertain parameters.

D. Paper organization

The rest parts of paper are organized as follows: The problem formulation including components modeling, responsive loads, objective functions and constraints is described in Section 2, the risk-based multi-objective planning is explained in Section 3, the test system introduction and simulation results are proposed in Section 4 and eventually, Section 5 is assigned to the conclusion.

2. PROBLEM FORMULATION

A. Modeling of components

A.1. Wind turbine

The generated power by WTs is impressed by many factors such as wind speed, turbine position, blade area and wind direction [25]. The WT power should be restricted by minimum and maximum wind speeds due to economic and technical aspects (1).

$$P_{WT}(s,t) = 0.5 \times \rho \times BA \times \eta^{WT} \times V(s,t)^3 : V^{\min} \leq V(s,t) \leq V^{\max} \tag{1}$$

A.2. Photovoltaic

The PV power depends on cell temperature and solar radiation [25]. The solar cell temperature is formulated in (2) and then, the PV output can be obtained by (3).

$$T(s,t) = T_{Env} + \frac{GT(s,t)}{GT_{STC}} \times (T_{NOCT} - T^{Env}_{NOCT}) \tag{2}$$

$$P_{PV}(s,t) = \left(\begin{array}{l} \left[P_{STC} \times \frac{GT(s,t)}{GT_{STC}} \times (1 - \gamma \times (T(s,t) - T_{STC}))\right] \\ \times NS \times NP \end{array} \right) \tag{3}$$

A.3. Heat pump

The HP produces heat by consuming electrical energy [25]. The relationship between the generated heat by HP and consumed power is calculated by (4).

$$H_{HP}(s,t) = \eta^{HP} \times P_{HP}(s,t) \tag{4}$$

A.4. Biomass-based components

The co-production systems receive much more attention in recent years due to the high efficiency and low greenhouse gases emission [11]. In this regard, BCHP and BMT are utilized in this paper to provide local electrical and heat loads. The generated electrical power of BCHP and BMT is modeled by (5) and (6), respectively. As well, BCHP can produce heat power by a coefficient that is determined in (7). The constraints (8) and (9) are used to restrict the maximum electrical and heat powers.

$$P_{BCHP}(s,t) = \eta^{P}_{BCHP} \times G(s,t) \tag{5}$$

$$P_{BMT}(s,t) = \eta^{BMT} \times G(s,t) \tag{6}$$

$$H_{BCHP}(s,t) = \eta^{H}_{BCHP} \times P_{BCHP}(s,t) \tag{7}$$

$$P_{BCHP}(s,t) \leq P^{\max}_{BCHP} \tag{8}$$

$$P_{BMT}(s,t) \leq P^{\max}_{BMT} \tag{9}$$

A.5. Compressed air energy storage

In large-scale structures, compressed air storage is more applicable as the electrical storage system (ESS) due to its high capacity and low price [11, 26]. The injected and pumped air into/from the storage and their limitations are specified by (10)-(13), respectively. The storage should operate in charging or discharging mode in the same time, as determined in (14). The amount of stored air in each interval is formulated by (15) and the storage capacity is restricted by (16).

$$A^{Inj}(s,t) = \eta^{Inj}_{CAES} \times P^{Inj}_{CAES}(s,t) \tag{10}$$

$$A^{Pu}(s,t) = \eta^{Pu}_{CAES} \times P^{Out}_{CAES}(s,t) \tag{11}$$

$$[A^{\min}_{Inj} \times u^{Inj}_{CAES}(s,t) \leq A^{Inj}(s,t) \leq A^{\max}_{Inj} \times u^{Inj}_{CAES}(s,t) \tag{12}$$

$$A^{\min}_{Pu} \times u^{Pu}_{CAES}(s,t) \leq A^{Pu}(s,t) \leq A^{\max}_{Pu} \times u^{Pu}_{CAES}(s,t) \tag{13}$$

$$u^{Pu}_{CAES}(s,t) + u^{Inj}_{CAES}(s,t) \leq 1 \tag{14}$$

$$A(s,t+1) = A(s,t) + A^{Inj}(s,t) + A^{Pu}(s,t) \tag{15}$$

$$A^{\min} \leq A(s,t) \leq A^{\max} \tag{16}$$

A.6. Heat energy storage

The power of heat storage system (HSS) is calculated by (17), the energy limitation is modeled by (18) and the total power of storage is restricted by (19) [27]. In order to make the storage usable for future day, the energy in last interval should be equal to its initial state (20). As well, (21) limits the charging and discharging power in each time.

$$P_{HSS}(s,t) = E_{HSS}(s,t) - E_{HSS}(s,t-1) \tag{17}$$

$$E^{\min} \leq E_{HSS}(s,t) \leq E^{\max} \tag{18}$$

$$E^{\min} - E_{HSS}(t_1) \leq \sum_t P_{HSS}(s,t) \leq E^{\max} - E_{HSS}(t_1) \tag{19}$$

$$E_{HSS}(s,t_1) = E_{HSS}(s,t_{24}) \tag{20}$$

$$\begin{cases} P_{HSS}(s,t) \big/ \eta^{Dch}_{HSS} \leq P^{\max}_{Dch} \text{discharge}\,(P_{HSS}(s,t) > 0) \\ -\eta^{Ch}_{HSS} \times P_{HSS}(s,t) \leq P^{\max}_{Ch} \text{charge}\,(P_{HSS}(s,t) < 0) \end{cases} \tag{21}$$

Table 1. Comparison between presented research and previously published papers.

Ref	Uncertainty	Uncertainty modeling	Risk	Objective function	Responsive load	Renewable structure
[4]	Wind, solar and load	Scenario-based	×	Cost and pollution	×	×
[5, 7]	Wind, solar and load	Scenario-based	×	Cost and pollution	✓	×
[6]	Wind and solar	Two-point estimate method	×	Cost and energy not supplied	✓	×
[8, 21]	×	×	×	Cost	×	×
[9]	Solar and load	Monte Carlo	×	Cost	✓	×
[10]	×	×	×	Cost	✓	×
[11]	Wind, solar and price	Monte Carlo	×	Cost	×	×
[12]	×	×	×	Cost	×	✓
[13, 18]	Price, wind and load	Scenario-based	×	Cost	✓	×
[14]	Price and load	Scenario-based	×	Cost	×	×
[15]	load, EVs, wind, solar and price	Two-stage stochastic	×	Cost	✓	×
[16]	Price	Hybrid	✓	Cost	×	×
[17]	Load and wind	Scenario-based	×	Cost, pollution and reliability	×	×
[19]	load, wind, solar and price	Two-stage stochastic	✓	Cost	×	×
[20]	Price, wind and load	Stochastic-robust	✓	Cost	×	×
[22]	Wind, solar and load	Robust	✓	Cost	✓	×
[23]	Load	Point estimation	×	Profit	✓	×
[24]	Wind, solar and load	Heuristic	×	Cost	×	×
This paper	**Price, wind, solar and load**	**Scenario-based**	✓	**Cost and pollution**	✓	✓

B. Demand response program

In order to optimize the consumption of local loads and achieve the flexible energy management, a ToU DRP is implemented [28]. It is noteworthy that both electrical and heat loads can participate in the program. The new electrical and heat demands in the presence of responsive loads are determined by (22) and (23), respectively. The constraints (24) and (25) limit the flexible loads in each interval and eventually, constraints (26) and (25) specify that the summation of flexible loads over all time intervals should be zero to avoid any load curtailment.

$$EL_{DRP}(s,t) = RL_{EL}(s,t) + EL(s,t) \tag{22}$$

$$HL_{DRP}(s,t) = RL_{HL}(s,t) + HL(s,t) \tag{23}$$

$$|RL_{EL}(s,t)| \leq \mu_{EL}^{DRP} \times EL(s,t) \tag{24}$$

$$|RL_{HL}(s,t)| \leq \mu_{HL}^{DRP} \times HL(s,t) \tag{25}$$

$$\sum_{t} RL_{EL}(s,t) = 0 \tag{26}$$

$$\sum_{t} RL_{HL}(s,t) = 0 \tag{27}$$

C. Objective functions and constraints

C.1. Operation cost function

The total cost of microgrid includes the operation cost of components and market trading cost is determined by (28).

$$\begin{aligned} F_1(s) = {} & C_{BCHP}(s) + C_{WT}(s) + C_{PV}(s) + C_{HP}(s) + \\ & C_{HSS}(s) + C_{CAES}(s) + \\ & C_{BMT}(s) + C_{Buy}(s) - C_{Sell}(s) \end{aligned} \tag{28}$$

The operation costs of BCHP and BMT are calculated by (29) and (30), respectively. Since the produced gas by biomass unit depends on the demand of BCHP or BMT, its operation cost is considered in BCHP and BMT formulation. In this regard, their first term indicates fuel cost and the second and third terms show the operation and maintenance costs, respectively. The operation and maintenance costs of WT, PV, HP, HSS and CAES are also given by the first and second terms of (31)-(35), respectively.

Furthermore, the costs of buying and selling power from/to the main grid are modeled by (36) and (37), respectively.

$$C_{BCHP}(s) = \sum_t \left(\begin{array}{c} \frac{BFC(t)\times P_{BCHP}(s,t)}{\eta^{BCHP}} + \\ OC_{BCHP} \times P_{BCHP}(s,t) \end{array} \right) + MC_{BCHP} \quad (29)$$

$$C_{BMT}(s) = \sum_t \left(\begin{array}{c} \frac{BFC(t)\times P_{BMT}(s,t)}{\eta^{BMT}} + OC_{BMT}\times \\ P_{BMT}(s,t) \end{array} \right) + MC_{BMT} \quad (30)$$

$$C_{WT}(s) = \sum_t OC_{WT} \times P_{WT}(s,t) + MC_{WT} \quad (31)$$

$$C_{PV}(s) = \sum_t OC_{PV} \times P_{PV}(s,t) + MC_{PV} \quad (32)$$

$$C_{HP}(s) = \sum_t OC_{HP} \times H_{HP}(s,t) + MC_{HP} \quad (33)$$

$$C_{HSS}(s) = \sum_t OC_{HSS} \times P_{HSS}(s,t) + MC_{HSS} \quad (34)$$

$$C_{CAES}(s) = \sum_t OC_{CAES} \times P_{CAES}(s,t) + MC_{CAES} \quad (35)$$

$$C_{Buy}(s) = \sum_t BC(s,t) \times P_{Buy}(s,t) \quad (36)$$

$$C_{Sell}(s) = \sum_t SC(s,t) \times P_{Sell}(s,t) \quad (37)$$

C.2. Environmental pollution function

The total generated pollution of microgrid is specified by (38), where the released pollution by BCHP and BMT is calculated in (39) and (40), respectively. Moreover, the pollution caused by power purchase from the main grid is determined by (41).

$$F_2(s) = EM_{BCHP}(s) + EM_{BMT}(s) + EM_{MG}(s) \quad (38)$$

$$EM_{BCHP}(s) = \sum_t P_{BCHP}(s,t) \times EF_{BCHP} \quad (39)$$

$$EM_{BMT}(s) = \sum_t P_{BMT}(s,t) \times EF_{BMT} \quad (40)$$

$$EM_{MG}(s) = \sum_t P_{Buy}(s,t) \times EF_{MG} \quad (41)$$

C.3. Problem constraints

In order to achieve the optimal solution, the problem should be limited to additional technical and economical restrictions. Hence, the constraints (42) and (43) model the balance of electrical and heat powers, respectively. The maximum amount of selling and buying power is also specified by (44)-(46).

$$\begin{aligned} EL(s,t) = {} & P_{WT}(s,t) + P_{PV}(s,t) + P_{BMT}(s,t) + \\ & P_{BCHP}(s,t) + P_{Inj}(s,t) + P_{Buy}(s,t) - P_{Sell}(s,t) \\ & - P_{Pu}(s,t) - P_{HP}(s,t) \end{aligned} \quad (42)$$

$$HL(s,t) = H_{HP}(s,t) + H_{BCHP}(s,t) + H_{HSS}(s,t) \quad (43)$$

$$P_{Buy}(s,t) \le u^{Buy}(s,t) \times P_{Line}^{\max} \quad (44)$$

$$P_{Sell}(s,t) \le u^{Sell}(s,t) \times P_{Line}^{\max} \quad (45)$$

$$u^{Sell}(s,t) + u^{Buy}(s,t) \le 1 \quad (46)$$

3. RISK-BASED MULTI-OBJECTIVE PLANNING

The uncertain parameters affect the reliable operation of system due to their unpredictable behavior. In this section, the risk-based multi-objective planning is modeled, as depicted in Fig. 1 and explained below [25], [28]-[30]:

- First stage: The uncertain parameters should be determined, where the wind speed, solar radiation, electrical and heat loads and energy price are considered as uncertainties.
- Second stage: The probability distribution functions (PDFs) with a 20% standard deviation from the deterministic value are used to generate sufficient random scenarios.
- Third stage: Since implementing the simulations for a huge number of scenarios is time- consuming, the backward/forward algorithm is utilized to select four scenarios as the final sets.
- Fourth stage: The risk metric is inserted into both objective functions to analyze the risk of decisions under the uncertain environment. As a result, the cost and pollution functions are reformulated by (46).

$$F_{Risk} = (1-\beta) \times \sum_s F(s) \times Prob(s) + \beta \times CVaR \quad (47)$$

$$CVaR = VaR + \frac{1}{1-\alpha} \times \sum_s Prob(s) \times \psi(s) \quad (48)$$

$$F(s) - VaR \le \psi(s) \quad (49)$$

The CVaR and value-at-risk (VaR) indices are determined by (47) and (48), respectively. It is noteworthy that the β equal to 0 and 1 is related to the risk-neutral and risk-averse strategies, respectively.

- • Fifth stage: The ECM is implemented to solve the risk-based multi-objective planning and obtain the Pareto set and eventually, fuzzy satisfying method is used to select the best solution.

4. RESULTS AND DISCUSSIONS

A. Test system and primary data

As illustrated in Fig. 2, the under study microgrid is composed of WT, PV, BCHP, BMT, heat tank and CAES that is connected to the main grid for power transferring. The wind speed, solar radiation, electrical and thermal loads and energy price scenarios are depicted in Fig. 3, where their deterministic values are gathered from [**?** , r25] Moreover, the tie-line limitation is equal 200 kW and the flexible loads can only shift 10% of their demand in each time interval. The specifications of all other components are extracted from references [5, 7, 26, 27].

B. Simulation results

B.1. Risk-based planning of microgrid

In this section, the results are investigated for the risk-neutral and risk-averse strategies to evaluate the operation of renewable-based microgrid. It is noteworthy that the risk-neutral strategy refers to α=β=0 and the risk-averse strategy refers to α=0.3 and β0.4. In this regard, the Pareto set for the mentioned strategies is illustrated in Fig. 4. As revealed, the risk-averse curve has higher value in all iterations which means that such a strategy simultaneously increases both objective functions, however, the system robustness against the worst-case scenarios improves.

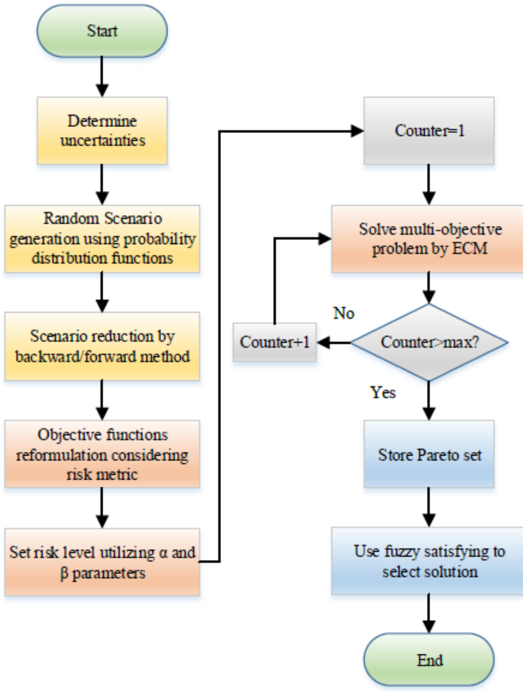

Fig. 1. Process of implementing risk-based multi-objective planning

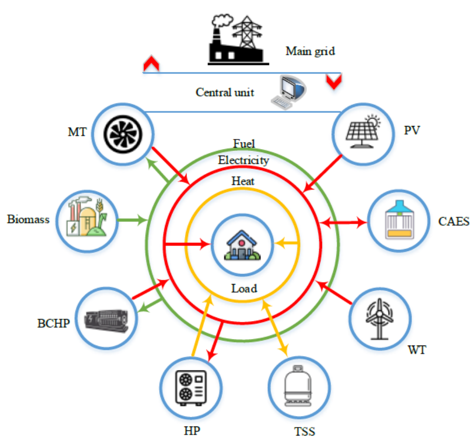

Fig. 2. Structure of under study renewable-based microgrid.

According to the fuzzy satisfying approach, the best solution in Pareto set for the risk-averse strategy is equal to 240.2 $ and 2803 kg, whereas it is equal to 218.3 $ and 2518 kg in the risk-neutral strategy. The influence of risk parameters on the objective functions is also exhibited in Fig. 5. As observed, ifα=0.3 and β changes from 0 to1, operation cost and pollution increase from 218.341 $ to 282.507 $ and from 2518.335 kg to 3175.542 kg, respectively. Moreover, if β =0.4 and α changes from 0 to 0.9, operation cost and pollution increase from 215.104 $ to 652.802 $ and from 2527.769 kg to 8054.544 kg, respectively. In order to have a better perspective, operation of components in the worst-case scenario for the risk-averse strategy with α=0.3 and β=0.4 is compared with the risk-neutral strategy. As shown in Fig. 6, the produced power by WT and PV is equal in both strategies due

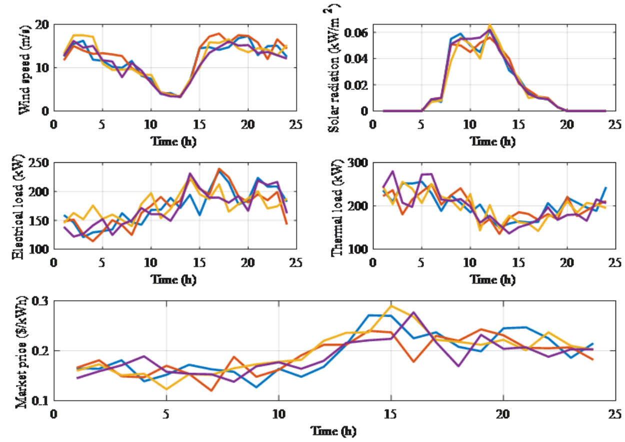

Fig. 3. Selected scenarios of wind speed, solar radiation, loads and energy price.

to the same decisions of risk-neutral and risk-averse operators about renewable resources. The results in Fig. 7 indicate that the total produced power by BMT and BCHP is increased from 776.458 kW to 921.837 kW and from 1852.853 kW to 1871.834 kW, respectively. According to Fig. 8, the total imported power is reduced from 436.389 kW to 318.876 kW, while the exported power is increased from 194.855 kW to 248.19 kW. These simulations approve that the dependency of the local microgrid on the main grid is decreased in the risk-averse strategy. Fig. 9 validates that the operation of heat components in the 1st, 2nd, 3rd and 15th intervals is updated to match the new conditions, however, their total variations are negligible. The operation of storage systems in Fig. 10 indicates that the HSS is out of service in the risk-averse strategy due to heat power balance in each interval and availability of heat resources. In return, the ESS is charged in the 12th and 18th intervals and discharged in the 15th, 21st and 24th intervals to reduce the power shortage in the mentioned times.

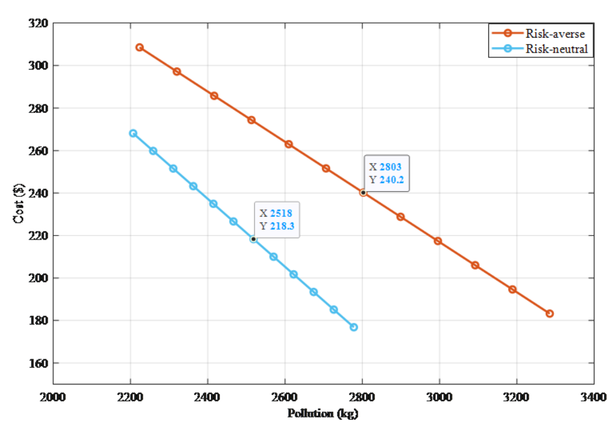

Fig. 4. Pareto set in the risk-averse and risk-neutral strategies

B.2. Impact of demand response program

In this section, a DRP is implemented for electrical and heat loads to show their influence on the energy management. Hence, the results for the calculated Pareto set in the risk-neutral and

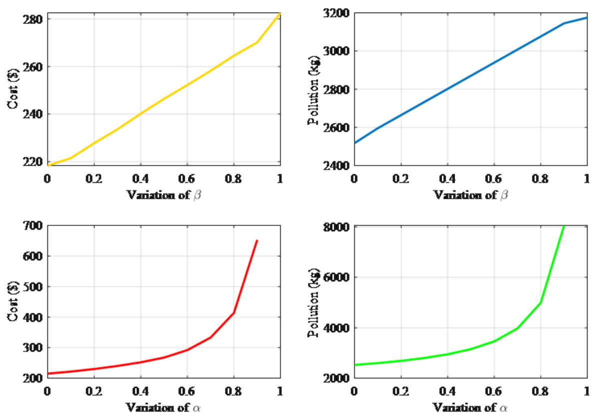

Fig. 5. Influence of risk parameters on the cost and pollution objective functions.

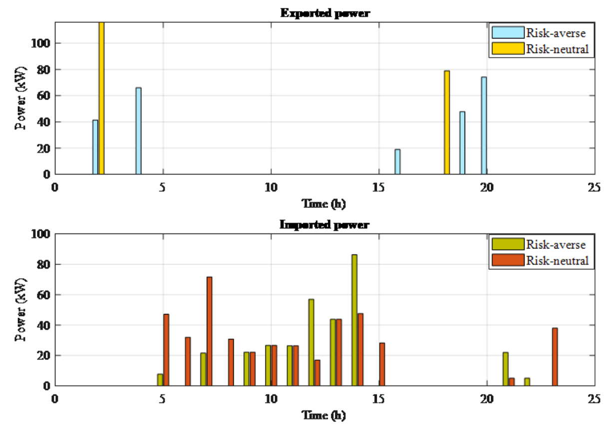

Fig. 8. Imported and exported power in different risk strategies.

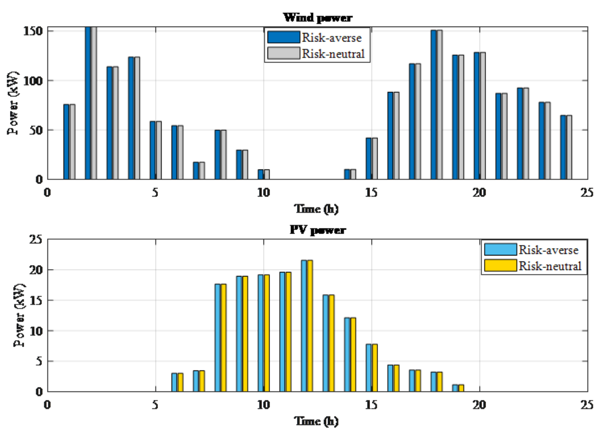

Fig. 6. Power of wind turbine and photovoltaic in different risk strategies.

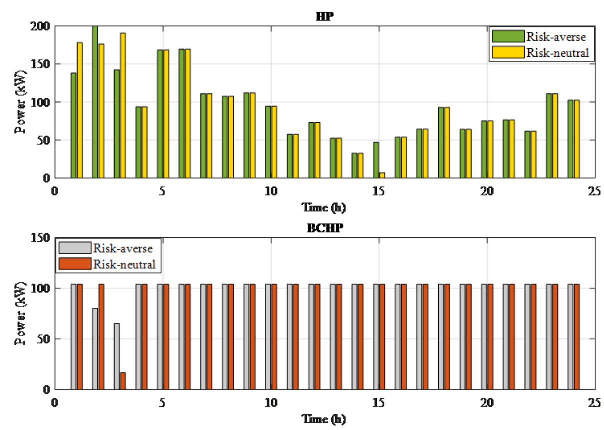

Fig. 9. Heat power of HP and BCHP in different risk strategies.

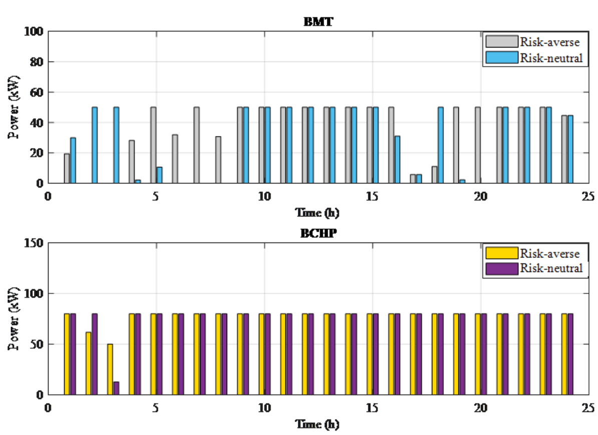

Fig. 7. Electrical power of BMT and BCHP in different risk strategies.

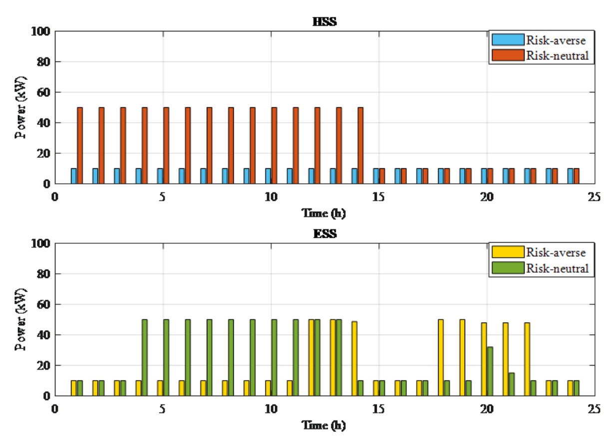

Fig. 10. Operation of heat and electrical storage systems in different risk strategies.

risk-averse strategies are depicted in Fig. 11. As observed, considering responsive loads in the mentioned strategies reduces the operation cost from 218.3 $ to 196.9 $ and from 240.2 $ to 218.7 $, respectively. However, environmental pollution has a slight increase in both strategies, where it changes from 2518 kg to 2539 kg and from 2803 kg to 2828 kg, respectively. In order to show the impact of responsive loads more precisely, variations of flexible electrical and heat loads are illustrated in Fig. 12.

As evident, a huge amount of electrical and heat loads equal to 184.923 kW and 231.516 kW are shifted from on-peak and high price times to the off-peak and low price times, respectively. In this regard, the results in Fig. 13 validate that the exported power to the main grid is increased in the most of high price times such as 16th, 17th, 19th and 20th intervals. Moreover, imported power from the main grid is decreased in the high price times such as 12th, 13th, 14th, 21st and 22nd intervals. In return, it increases in the first intervals to supply the transferred load. As a result, the total exported and imported powers are changed from 248.195 kW to 462.02 kW and from 318.876 kW to 374.248 kW, respectively.

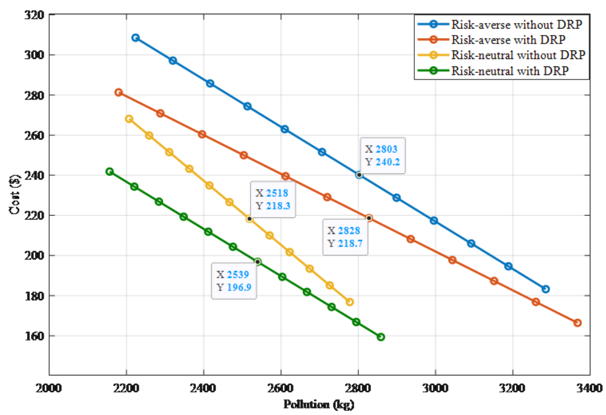

Fig. 11. Calculated Pareto set considering responsive loads in different risk strategies.

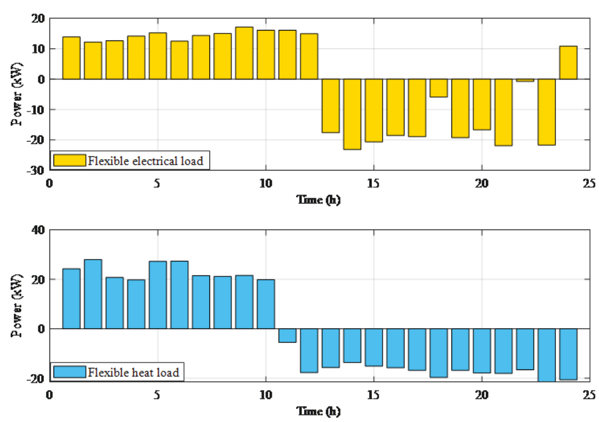

Fig. 12. Flexible electrical and heat loads in the risk-averse strategy.

5. CONCLUSION

This paper proposes a risk-aware multi-objective programming to optimize the planning of a renewable hybrid microgrid. In this regard, a network consisting of WT, PV, biomass-based conventional resources and energy storage systems is considered as the test system. In order to model the fluctuations of uncertain parameters and the risk of decisions, CVaR metric is also utilized. Moreover, ECM and fuzzy satisfying procedures are

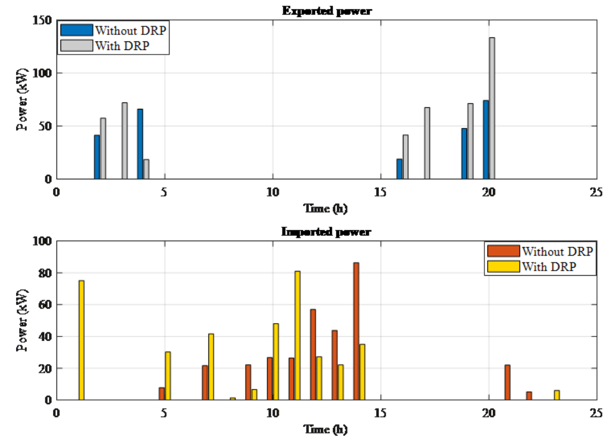

Fig. 13. Exported and imported powers considering responsive loads in the risk-averse strategy.

implemented to simultaneously minimize the cost and pollution. The simulations for the risk-based planning show that the amount of cost and pollution in the risk-averse strategy with α= 0.3 and β =0.4 are about 21.9 $ and 258 kg higher than the risk-neutral strategy, respectively. Furthermore, the analysis of the risk parameters approves that variation of α has a higher impact on the objective functions compared to the β. As well, the responsive loads improve the system flexibility, where the cost is decreased about 21.5 $, however, the pollution increases about 25 kg which is acceptable due to high cost reduction. As future studies, several suggestions are presented as follows: Modeling further uncertainties such as fuel cost, integrating renewable-based microgrids with other infrastructures, and implementing robust optimization algorithms to cope the uncertainties.

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