Stochastic Multi-objective Low-Carbon Generation Dispatch Considering Carbon Capture Plants

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***Abstract*—This paper presents a multi-objective (MO) optimization for economic/emission dispatch (EED) problem incorporating hydrothermal plants, wind power generation, energy storage systems (ESSs) and responsive loads. The uncertain behavior of wind turbines and electric loads is modeled by scenarios. Stochastic programming is proposed to achieve the expected cost and emission production. Moreover, the carbon capture systems are considered to lower the level of carbon emission produced by conventional thermal units. The proposed optimization problem is tested on the IEEE 24-bus case study using DC power flow calculation. The optimal Pareto frontier is obtained, and a fuzzy decision-making tool determined the best solution among obtained Pareto points. The problem is modeled as mixed-integer non-linear programming in the General Algebraic Modelling System (GAMS) and solved using DICOPT solver.**

***Index Terms*—Carbon capture power plants, fuzzy decision-making tool, low carbon generation dispatch, multi-objective optimization, stochastic programming.**

I. INTRODUCTION

The power generation sector has a considerable quota in greenhouse gas production and plays a key role in global climate change. This share is continuously deemed to be intensified considering the industrial developments [1]. The trends toward emission reduction in the power generation sector and the utilization of green energy resources are considered as primary targets for power system researchers. This goal is realized somehow by introducing renewable energies, particularly, wind power generation in a large-sale. However, the intermittency of these power generation systems, as well as the traditional standards of the existing power systems, pose huge economic expenses to renewal the electrical power infrastructures. This is the main reason for coordination of generation-side and demand-side involving various techniques (such as demand response program (DRP)) to create an eco-friendly energy system including renewable generation, hydro plants with natural water inflows and PHS, cooperated responsive consumers, and conventional power plants furnished by carbon capture system (CCS). The CCS technology elucidates a practical solution for emission reduction in the power generation section as the fossil-fuel power plants are the most common type of generation resource around the world [2]. The mechanism of the CCS is to consume a portion of the plant's power to capture CO2 emission and store it in a special tank. The procedure is described in [3] with details, however, the description of the CCS mechanism is beyond the scope of this paper. According to [4], till 2035 the coal-fired plants will be still the major source of electric power generation and the contribution of CCS would be 8 GTon in CO2 emission reduction by 2050.

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However, the CCS systems might be a valuable technology for CO2 reduction, the energy requirements of these systems increase the fuel consumption of the plants which can affect their performance and may lead to increasing other multi-media emissions [5]. Moreover, the cost of power plants increases due to the performance of components of CCS [6]. This magnifies the importance of cost-benefit evaluations and renewable energy penetration increments such as wind turbines incorporated with ESS to compensate for the uncertain and intermittent nature of them.

Thanks to CCS, the thermal plants can reduce a large portion of produced CO2 pollution. Hence, the optimal dispatch of thermal plants considering the effects of CCS has taken enormous attention in recent years. As one of the earliest works in this area, authors of [7] provided a mixed-integer model for coal-fired plants with CCS. The optimal economic dispatch of thermal plants in the presence of CCS and wind generation is addressed by [8], where the operational characteristics of carbon capture power plants (CCPPs) are expressed mathematically. However, the network model is not considered. In [9], the problem of generation dispatch in the presence of CCPPs and responsive loads is presented. The uncertainty of carbon emission penalty cost is considered using conditional value at risk method. In [10], a multi-objective optimization is presented for the EED problem considering the CCPPs and the uncertainty of wind power generation. In [11], the cost minimization targeted in a low-carbon energy system integrating CCPP, wind and power-to-gas (PtG) facilities. However, in this paper, the uncertainty of wind generation is ignored. Also, a unit commitment problem considering post-combustion CCS is presented by [12]. Recently, an economic dispatching model considering the effects of wind generation and energy storage systems is presented by [13]. The tested system in this paper is a three bus test system including two thermal units in which one of them is equipped with CCS. In [14] a single objective (SO) optimization framework is presented to optimally dispatching a power system considering CCS and responsive demands. The uncertainty of wind generation is modeled by stochastic programming (SP). Finally, the power system generation cost minimization problem considering the CCS and wind power generation besides the battery storage system (BSS) is elaborated by [15], in which the uncertainty of wind generation is modeled by an adjustable robust optimization approach (ROA).

Table I compares the presented work with the previously mentioned works to highlight the gaps and the contributions of the presented work. According to Table I, this paper gives out the below contributions:

1. Providing a multi-objective framework for finding optimal Pareto frontier for CCS based EED problem and proposing fuzzy decision-making tool for selecting the best solution.

2. The provided case study includes a variety of components including, thermal plants (with/without CCS), hydro plants, pumped hydro storage (PHS), wind power generation and responsive demands.

3. The uncertainty of the wind generation and load consumption is modeled by scenarios using SP.

Table I. COMPARISON OF RELATED WORKS

Ref.	Network	Generator	Uncertain parameter	Uncertainty modeling	Type	DRP	ESS
[7]	No	Coal	No	No	SO	No	No
[8]	Yes	Thermal/ wind	No	No	SO	No	No
[9]	No	Thermal/ wind	Carbon price	CVaR	SO	Yes	No
[10]	Yes	Thermal/ wind	Wind generation	Robust model	MO	No	No
[11]	Yes	Thermal/ wind	No	No	SO	No	PtG
[12]	No	Thermal	No	No	SO	No	No
[13]	Yes	Thermal/ wind	No	No	SO	No	BSS
[14]	Yes	Thermal/ wind	Wind generation	SP	SO	Yes	No
[15]	Yes	Thermal/ wind	Wind generation	ROA	SO	No	BSS
This work	**Yes**	**Thermal/ wind/ hydro**	**Wind generation/ load demand**	**SP**	**MO**	**Yes**	**PHS**

II. PROBLEM FORMULATION

The proposed optimization framework tends to find the generation scheduling in order to minimize the generation cost as well as produced emission. These two objectives are conflicting and there is not a general solution that optimizes both of them at the same time. The Pareto frontier includes these feasible solutions and the decision-maker is responsible for the selection of the best solution according to the priorities. In the following (1) and (2), the objective functions are defined. The first one EC calculates expected generation costs of thermal and hydro plants and the operating cost of the CCSs based on generated powers by thermal plants $P_{i,t,s}^{Th}$, CCPPs $P_{i,t,s}^{CCS}$, and hydro plants $P_{i,t,s}^{H}$ and captured emission $E_{i,t,s}^{S}$ for each bus *i*, time *t*, and scenario *s*. λ_g^{Th}, λ_g^{CCS} and λ_g^{H} represent the generation costs offered by thermal, CCPP and hydro units, respectively; and λ_{CO2} shows the cost of CO2 emission reduction for CCS operating. The second objective function EE calculates the produced CO2 emission by thermal plants. From (3) and (4), the produced CO2 emission from conventional generators $E_{i,t,s}^{G}$ is assumed to be related to their power generation level. However, for CCPPs the relation is indirect and the net produced emission $E_{i,t,s}^{N}$ is not equal to the initially generated emission. η_g shows the emission intensity of power plants. π_s indicates the probability of scenarios and ϕ_g, ϕ_c, ϕ_h, respectively show the set of buses including thermal plants, CCPPs, and hydro units.

$$EC = \sum_{s=1}^{N_s}\sum_{t=1}^{T}\pi_s \cdot \{(\sum_{i\in\phi_g} P_{i,t,s}^{Th}\times\lambda_g^{Th}) + (\sum_{i\in\phi_c} P_{i,t,s}^{CCS}\times\lambda_g^{CCS}) + (\sum_{i\in\phi_h} P_{i,t,s}^{H}\times\lambda_g^{H}) + (\sum_{i\in\phi_c} E_{i,t,s}^{S}\times\lambda_{CO2})\} \tag{1}$$

$$EE = \sum_{s=1}^{N_s}\sum_{t=1}^{T}\pi_s \cdot \{(\sum_{i\in\phi_g} E_{i,t,s}^{G}) + (\sum_{i\in\phi_c} E_{i,t,s}^{N})\} \tag{2}$$

$$E_{i,t,s}^{G} = P_{i,t,s}^{Th}\times\eta_g, \quad \forall i\in\phi_g \tag{3}$$

$$E_{i,t,s}^{N} = (P_{i,t,s}^{CCS}\times\eta_g) - E_{i,t,s}^{S}, \forall i\in\phi_c \tag{4}$$

In the following constraints (5)-(7), the feasible operational region of conventional generators is determined. Constraint (5) defines limitations on the power output of the conventional generators. Constraints (6) and (7) model the ramping capability of thermal power plants. Constraints (5)-(7) are true for thermal generators with/without CCS. The operational constraints of CCS are also represented by (8)-(10). Equation (8) shows that the net delivered power $P_{i,t,s}^{N}$ to the grid is not equal to generated power $P_{i,t,s}^{CCS}$ and it is affected by the operational power of CCS $P_{i,t,s}^{OP}$, which is related to the efficiency of CCPP η^{CCPP} and treated emission $E_{i,t,s}^{P}$. The captured emission is proportional to treated emission by (10) and the capture rate of CCPP denoted by α^{CCPP}.

$$0 \le P_{i,t,s} \le \overline{P_i}, \forall i\in\{\phi_g,\phi_c\} \tag{5}$$

$$P_{i,t-1,s} - P_{i,t,s} \le RU_g, \forall i\in\{\phi_g,\phi_c\} \tag{6}$$

$$P_{i,t+1,s} - P_{i,t,s} \le RD_g, \forall i\in\{\phi_g,\phi_c\} \tag{7}$$

$$P_{i,t,s}^{N} = P_{i,t,s}^{CCS} - P_{i,t,s}^{OP}, \forall i\in\phi_c \tag{8}$$

$$P_{i,t,s}^{OP} = \eta^{CCPP} E_{i,t,s}^{P}, \forall i\in\phi_c \tag{9}$$

$$E_{i,t,s}^{S} = \alpha^{CCPP} E_{i,t,s}^{P}, \forall i\in\phi_c \tag{10}$$

In constraints (11)-(16), the operational constraints of the hydro units are introduced according to [15]. Equation (11) defines the allowable region for power generation. Equation (12) models the generated power of the hydro unit as a function of upward reservoir volume $V_{i,t,s}^{H}$ and water discharge rate $Q_{i,t,s}^{H}$. In (13) and (14), the dynamics of the reservoir (or volume of water in the reservoir) are calculated based on previous water volume, natural water inflow, discharged water and spilled water. Equations (15) and (16) limit the water volume and water discharge rate. Hydro plants are fast response generator so the binary constraints on them are not introduced and they can be committed when they are needed.

$$0 \le P_{i,t,s}^{H} \le \overline{P_{i,t,s}^{H}} \tag{11}$$

$$P_{i,t,s}^{H} = C1\times(V_{i,t,s}^{H})^2 + C2\times(Q_{i,t,s}^{H})^2 + C3\times V_{i,t,s}^{H}\times Q_{i,t,s}^{H} + C4\times V_{i,t,s}^{H} + C5\times Q_{i,t,s}^{H} + C6 \tag{12}$$

$$V_{i,t,s}^{H} = V^0 + Inflow_{i,t}^{H} - Q_{i,t,s}^{H} - S_{i,t,s}^{H}, \forall t=1 \tag{13}$$

$$V_{i,t,s}^{H} = V_{i,t-1,s}^{H} + Inflow_{i,t}^{H} - Q_{i,t,s}^{H} - S_{i,t,s}^{H}, \forall t>1 \tag{14}$$

$$\underline{V}_{i,t,s}^{H} \le V_{i,t,s}^{H} \le \overline{V}_{i,t,s}^{H} \tag{15}$$

$$\underline{Q}_{i,t,s}^{H} \le Q_{i,t,s}^{H} \le \overline{Q}_{i,t,s}^{H} \tag{16}$$

PHS' modeling is adopted from [17]. The water reservoir's volume is modeled with $C_{i,t,s}$. $P_{i,t,s}^{ch}$ and $P_{i,t,s}^{dis}$ show the charged (pumping) and discharged (generated) electrical powers used for water pumping to the upward reservoir and generated from the downward movement of water. However, binary variables ($u_{i,t,s}^{ch}, u_{i,t,s}^{dis}$) are used to prohibit the simultaneous charging and discharging as shown in (17)-(21) that show the charged and discharged powers' limitations. Furthermore, the immediate statue change from pumping to discharging is not available according to the reference, which is molded by (22) and (23). Finally, the stored energy (equivalent to stored water) is calculated based on (24) and (23). Equation (24) limits the stored energy.

$$\underline{P_i^{ch}} \times u_{i,t,s}^{ch} \le P_{i,t,s}^{ch} \le \overline{P_i^{ch}} \times u_{i,t,s}^{ch} \tag{17}$$

$$\underline{P_i^{dis}} \times u_{i,t,s}^{dis} \le P_{i,t,s}^{dis} \le \overline{P_i^{dis}} \times u_{i,t,s}^{dis} \tag{18}$$

$$u_{i,t,s}^{ch} + u_{i,t,s}^{dis} \le 1 \tag{19}$$

$$u_{i,t-1,s}^{dis} + u_{i,t,s}^{ch} \le 1 \tag{20}$$

$$u_{i,t,s}^{dis} + u_{i,t-1,s}^{ch} \le 1 \tag{21}$$

$$C_{i,t,s} = C_{i,t,s}^{0} + \eta^{HS} \times P_{i,t,s}^{ch} - P_{i,t,s}^{dis}, \qquad \forall t = 1 \tag{22}$$

$$C_{i,t,s} = C_{i,t-1,s} + \eta^{HS} \times P_{i,t,s}^{ch} - P_{i,t,s}^{dis}, \qquad \forall t > 1 \tag{23}$$

$$\underline{C_i} \le C_{i,t,s} \le \overline{C_i} \tag{24}$$

The time-of-use DRP is employed here. In this program, a particular portion of hourly load consumption at each bus can be shifted from peak times to off-peak times (according to (25)), in which total consumed load in a day would be constant according to (26). $P_{i,,t,s}^{L}$ is the actual load, $P_{i,,t,s}^{D}$ shows met load after implementing DRP and $P_{i,t,s}^{sh}$ is shifted load, which is limited by (27) according to the maximum percentage of shiftable load κ (here, $\kappa = 20\%$) [18].

$$P_{i,t,s}^{D} = P_{i,t,s}^{L} - P_{i,t,s}^{sh} \tag{25}$$

$$\sum_{t=1}^{T} P_{i,t,s}^{L} = \sum_{t=1}^{T} P_{i,t,s}^{D} \tag{26}$$

$$-\kappa P_{i,t,s}^{L} \le P_{i,t,s}^{sh} \le \kappa P_{i,t,s}^{L} \tag{27}$$

The following equations model the network constraints using DC power flow calculation. The generation-consumption balance is satisfied using (28). The exchanged power between connected buses is modeled based on voltage angles of buses according to (29). Constraint (30) limits the exchanged power between connected buses in the network. The voltage angle of the reference bus should be zero as (31).

$$P_{i,t,s}^{W} + P_{i,t,s}^{N} + P_{i,t,s}^{Th} + P_{i,t,s}^{H} + P_{i,t,s}^{dis} - P_{i,t,s}^{ch} + P_{i,t,s}^{sh} - P_{i,t,s}^{D} = P_{i,j,t,s}^{f} \tag{28}$$

$$P_{i,j,t,s}^{f} = \frac{\delta_{i,t,s} - \delta_{j,t,s}}{x_{ij}} \tag{29}$$

$$-\overline{P^f} \le P_{i,j,t,s}^{f} \le \overline{P^f} \tag{30}$$

$$\delta_{i,t,s} = 0, \; \text{for slack bus} \tag{31}$$

The solutions of optimal Pareto frontier are found based on the epsilon constraint method prescribed by [19]. After obtaining the Pareto front, the best solution is selected based on a fuzzy decision-making tool [20]. Using this method, for each optimal solution shown by the Pareto front, a membership function $\mu^{Z_k(x_{it})}$ is defined, which varies from zero to one and shows the importance of the corresponding Pareto front while minimizing the objective functions. A linear method is used here to select the optimal solution and defined as (32). A risk-averse decision-maker tries to maximize the minimum satisfaction based on (33).

$$\mu^{Z_k(x_{it})} = \left\{ \begin{array}{ll} 0 & otherwise \\ \dfrac{Z_k^{\max} - Z_k(\mathrm{x}_{it})}{Z_k^{\max} - Z_k^{\min}} & \end{array} \right\} \tag{32}$$

$$X^* = \max_{it} \min_{k} (\mu^{Z_k(\mathrm{x}_{it})}) \tag{33}$$

k and it represent the number of objective functions and Pareto points, respectively.

III. Numerical Evolutions

A. Case Study

As mentioned before, the proposed optimization is tested on a modified IEEE 24-bus test system. The system includes ten conventional fossil-fuel generators, three wind turbines, and PHSs to provide electrical power with a higher level of reliability. The PHSs' nominal capacity and rated power are 150 MWh and 50 MW. Furthermore, hydro plants at buses 1 and 3 provide fast ramping capability and pollution-free power generation. The schematic of the studied network is presented in Fig. 1. The system's physical characteristics including demand information can be found in [19]. In order to reduce the carbon emission produced by the conventional generation plants, the carbon capture systems are considered at bus 7 and 8, i.e., the generation plants #9 and #10 are equipped with CCS. For these generators, the net delivered power is not necessarily equal to their generated power as a portion of generated power by power plants #9 and #10 is consumed for supplying CCSs and consequently the production cost of these units considered to be more than the others'. In order to consider the uncertainties with electric demand and wind generation, four scenarios are considered with the same amount of possibilities (i.e. 0.25). The forecasted power generation by the wind turbines at buses 8, 19 and 23 is depicted in Fig. 2. The characteristics of the conventional power plants are represented by Table II. The information regarding hydro plants is presented in Tables III, IV, and V including plants' characteristics and water inflow rate.

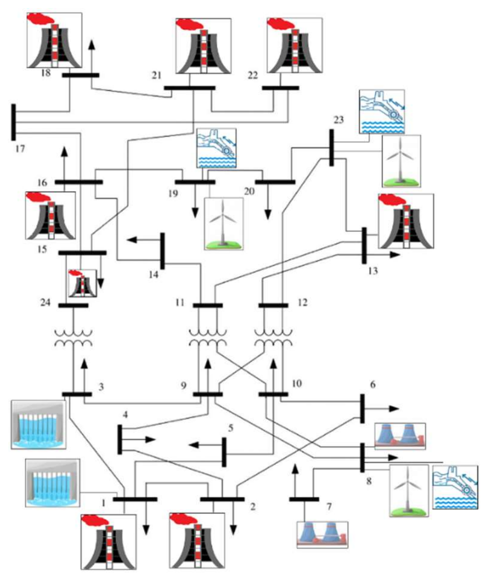

Fig. 1. Studied power system.

Table II. Information On The Conventional Power Generation System

Gen. No.	Bus	Pmin (MW)	Pmax (MW)	λ_g^{Th} ($/MW)	RU_g	RD_g	η_g (T/MW)	η^{CCPP}	α^{CCPP}
#1	1	0	152	13.32	10	20	0.65	-	-
#2	2	0	152	13.32	10	20	0.7	-	-
#3	15	0	215	21	20	30	0.75	-	-
#4	16	0	80	10.52	30	10	0.75	-	-
#5	18	0	100	5.47	10	20	0.5	-	-
#6	13	0	591	25	20	50	0.6	-	-
#7	21	0	100	5.47	30	30	0.65	-	-
#8	22	0	300	30	20	40	0.65	-	-
#9	7	0	400	28.52	30	30	0.7	0.27	0.9
#10	8	0	360	28.52	40	40	0.7	0.27	0.9

Table III. TECHNICAL INFORMATION ON HYDRO UNITS

HG	Bus	Pmin (MW)	Pmax (MW)	$\underline{V}^{H}_{i,t,s}$	$\overline{V}^{H}_{i,t,s}$	$\underline{Q}^{H}_{i,t,s}$	$\overline{Q}^{H}_{i,t,s}$	V^{0}	V^{fin}
#1	1	0	100	80	150	0	15	100	120
#2	3	0	150	60	120	0	15	80	70

Table IV. HYDRO GENERATION COEFFICIENTS

HG	c1	c2	c3	c4	c5	c6
#1	-0.0042	-0.42	0.03	0.9	10	-50
#2	-0.004	-0.3	0.015	1.14	9.5	-70

Table V. NATURAL WATER INFLOW TO THE RESERVOIRS

Time	HG1	HG2	Time	HG1	HG2	Time	HG1	HG2
1	10	8	9	10	8	17	9	7
2	9	8	10	11	9	18	8	6
3	8	9	11	12	9	19	7	7
4	7	9	12	10	8	20	6	8
5	6	8	13	11	8	21	7	9
6	7	7	14	12	9	22	8	9
7	8	6	15	11	9	23	9	8
8	9	7	16	10	8	24	10	8

B. Results and Discussion

The multi-objective stochastic programming presented in Section II has resulted in the following Pareto optimal frontier which is shown in Fig. 3 and is reported in Table VI in detail. The best solution between the shown points in the optimal Pareto front is chosen using the fuzzy satisfying method. The best Pareto front is tinted with a red diamond in Fig. 3. This point would be selected by a risk-averse decision-maker who tries to minimize the maximum dissatisfaction among all objectives. In the following, the results are obtained and discussed for the best optimal Pareto front. As mentioned before, four scenarios are considered to model the uncertainties of load and wind generation, hence, the results are presented for four scenarios to make them visually comparable.

From Fig. 4, different scheduling for conventional power plants has been recorded. This is occurred due to different wind power generation and load consumption under various scenarios. However, it can be expressed that power plants with lower generation costs are in the priority list and power plants #3, #6 and #8 are rarely dispatched due to their higher cost. The net delivered power to the network is not equal to the generated power when the plant is equipped with CCS.

Accordingly, the net delivered electric power by generators #9 and #10 is shown by Fig. 5. Despite having higher generation cost and lower delivered power, power plants #9 and #10 are committed under all scenarios. The reason can be found by looking at Table VI where the best-compromised solution is selected considering the importance of emission reduction. And the net produced emission by these plants is remarkably lower than the others'. For verifying the applicability of CCPPs for pollution abatement, the total daily emission production and net emission diffusion by the conventional generators under scenario 1 are presented by Table VII.

Figure 6 shows the hydro plants' scheduling curves for various scenarios. As can be seen, regardless of the cost, these plants are committed at their full capacity in the majority of times. The reason is their emission-free power generation. For the best optimal Pareto solution, the amount of emission production is taken into account as important as cost. The generation cost of the hydro plants assumed to be $\lambda_g^H = 2\lambda_g^{Th}$, and the CO2 abatement cost λ_{CO2} is assumed to be 25 \$/Ton [13].

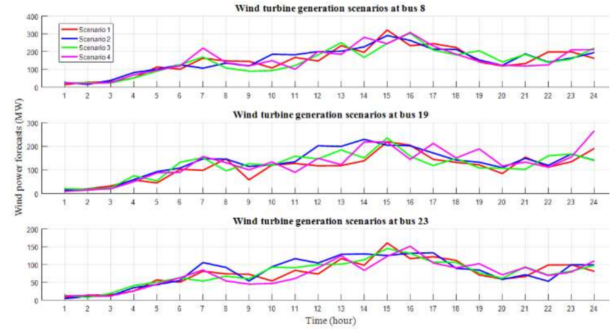

Fig. 2. Wind power generation scenarios.

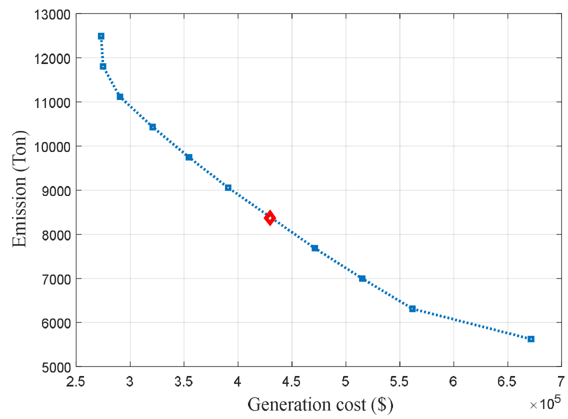

Fig. 3. Pareto front for the cost-emission minimization.

Table VI. OPTIMAL PARETO FRONT

it	μ^{cost}	$\mu^{emission}$	EC (\$)	EE (Ton)	min ($\mu^{cost}, \mu^{emission}$)
1	1.000	0.000	273019.612	12489.254	0.000
2	0.995	0.100	274855.820	11802.755	0.100
3	0.957	0.200	290473.198	11116.257	0.200
4	0.882	0.300	320882.208	10429.758	0.300
5	0.800	0.400	354511.902	9743.259	0.400
6	0.710	0.500	390832.757	9056.761	0.500
7	**0.615**	**0.600**	**429616.479**	**8370.262**	**0.600**
8	0.513	0.700	471161.274	7683.763	0.513
9	0.405	0.800	515168.772	6997.264	0.405
10	0.290	0.900	561764.328	6310.766	0.290
11	0.020	1.000	671702.351	5624.267	0.02

Table VII. PRODUCED AND DIFFUSED EMISSION

Gen. No	Produced CO2 (Ton)	Diffused CO2 (Ton)
1	2195.70	2195.70
2	2147.60	2147.60
3	450.00	450.00
4	1042.50	1042.50
5	1175.49	1175.49
6	246.00	246.00
7	1475.50	1475.50
8	3.76	3.76
9	**1141.13**	**0.00**
10	**1399.31**	**0.00**

The charging and discharging patterns of PHSs' are represented by Fig. 7. The positive and negative amounts indicate respectively the charged and discharged powers by the PHSs located at buses 8, 19 and 23. The important point regarding these storage systems is that the efficiency of the PHSs in the charging mode (i.e. water pumping process) is about 67% and the power generation efficiency is considered to be 100%. Because of this assumption, the charged powers are always greater than the discharged powers to fulfill the effect of power losses. Hence, the PHSs are only dispatched when the requested electric demand is higher than the generation capacity. For example, in scenario #4 the insignificant power shortage in hours 7 and 9 are procured by the initial energy of the PHSs at buses 19 and 23. However, these systems are emission-free but considering power losses, the scheduling of conventional generation for PHS charging is not an economic solution and the charged powers are mainly from wind generation surpass.

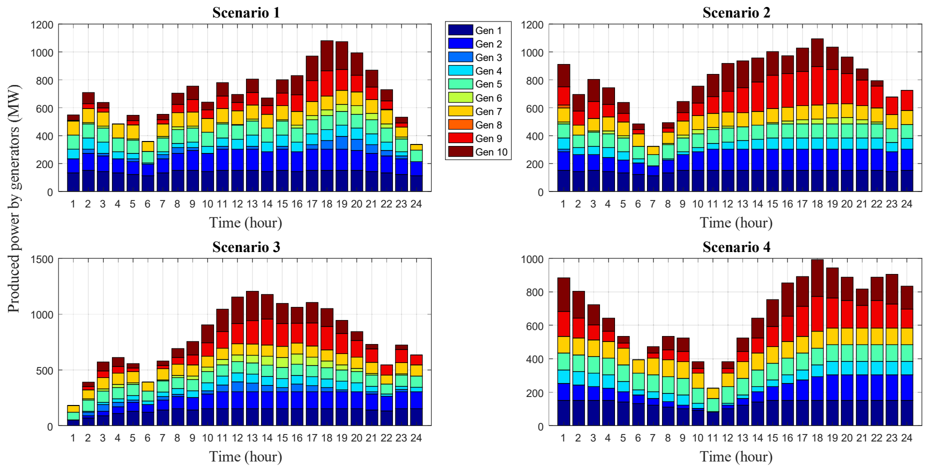

Fig. 4. Generation scheduling under different scenarios.

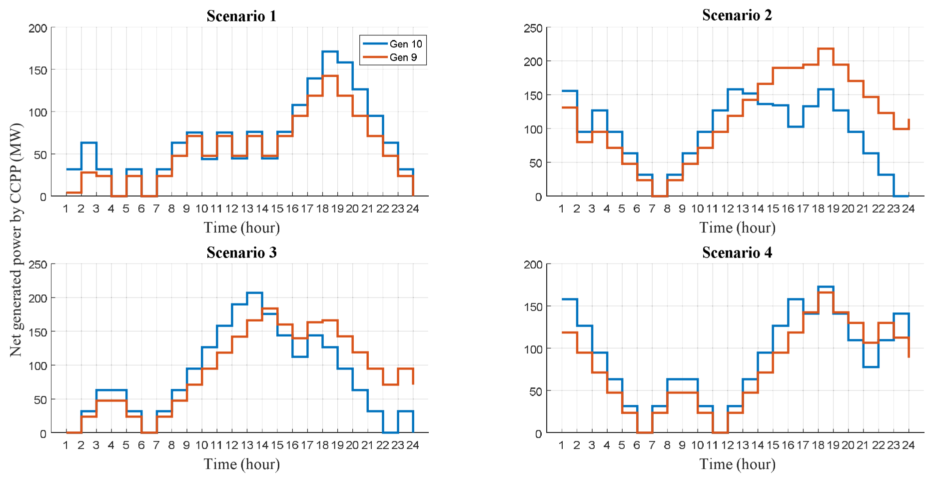

Fig. 5. Net delivered power by the CCPPs.

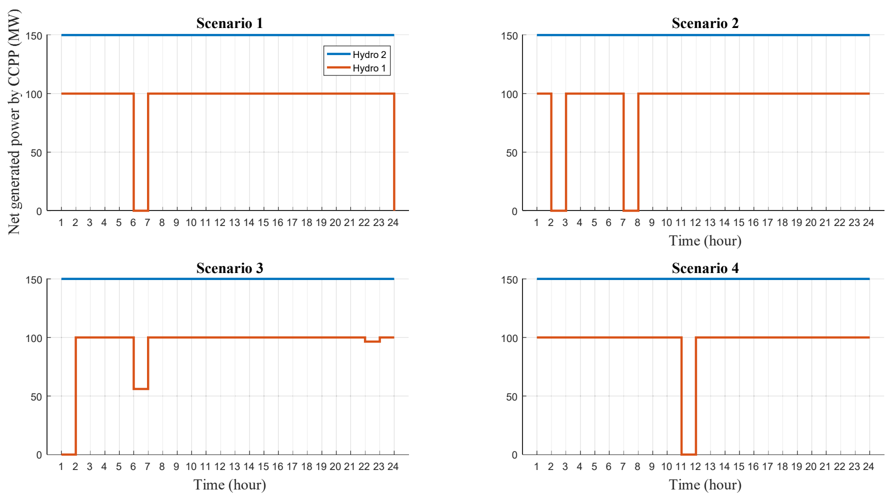

Fig. 6. The scheduling of hydro plants.

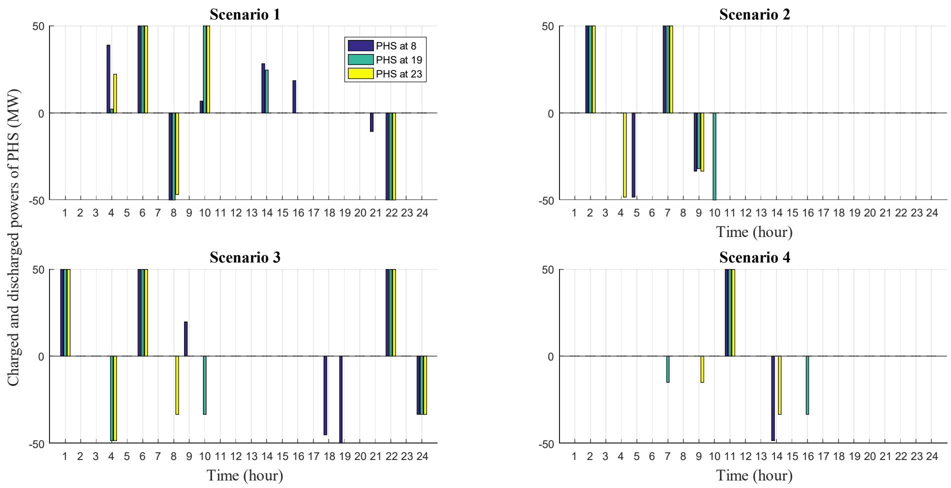

Fig. 7. Charged and discharged power of pumped hydro storage systems.

V. Conclusion

In this paper, multi-objective stochastic programming was proposed to solve the problem of generation dispatch in the presence of wind generation, responsive demands, and PHSs. In order to model the stochastic behavior of wind power generation and load demands, four scenarios with the same probability were considered. A trade-off between cost and emission seems important to be considered when the system faces uncertainties. In order to obtain the optimal Pareto front, the epsilon constraint method was used and the well-known fuzzy decision-making system was employed to find the best solution from the optimal Pareto front. For the selected solution, the scheduling results were reported and the comparison between four scenarios was accomplished to justify the validation of the proposed optimization framework. The results indicated that the integration of CCS beside the conventional generation leads to a great reduction in the amount of CO2 diffusion. However, the performance of the CCS in the emission abatement task is directly related to the consumed power generated by the corresponding power plant, and consequently to the generation cost.

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