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Economic-Emission Dispatch Problem in Power Systems with Carbon Capture Power Plants

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***Abstract*— Despite the increasing level of renewable power generation in power grids, fossil fuel power plants still have a significant role in producing carbon emissions. The integration of carbon capturing and storing systems to the conventional power plants can significantly reduce the spread of carbon emissions. In this paper, the economic-emission dispatch of combined renewable and coal power plants equipped with carbon capture systems is addressed in a multi-objective optimization framework. The power system's flexibility is enhanced by hydropower plants, pumped hydro storage, and demand response program. The wind generation and load consumption uncertainties are modeled using stochastic programming. The DC power flow model is implemented on a modified IEEE 24-bus test system. Solving the problem resulted in an optimal Pareto frontier, while the fuzzy decision-making method found the best solution. The sensitivity of the objective functions concerning the generation-side is also investigated.**

***Index Terms*— Carbon capture, demand-side flexibility, economic-emission dispatch, multi-objective optimization, renewable generation.**

I. INTRODUCTION

The power generation sector has a considerable role in greenhouse gas production and global climate change. This negative role is continuously increasing considering the industrial developments [1]. To this end, there has been a trend toward emission reduction in the power generation sector by the utilization of renewable energy resources, particularly, wind power generation in large-sale. However, the intermittency of renewable energy systems poses some technical and economic challenges to the existing power systems infrastructure. This is the main reason for the coordination of generation-side and demand-side involving various techniques, e.g., demand response program (DRP), to create an eco-friendly energy system including renewable generation, hydropower plants with natural water inflows and pumped hydroelectricity storage (PHS), cooperated responsive consumers, and conventional power plants furnished by carbon capture systems (CCS). The CCS technology elucidates a practical solution for emission reduction in the power generation fragment as fossil-fueled power plants are the most common type of generation technology over the world [2]. The CCS by consuming a portion of the plant's energy captures the CO2 emission and stores it in a special tank. The procedure is described in [3] in detail; however, the description of the CCS mechanism is beyond the scope of this paper. Review article [4] showed the importance of CCS in academic research projects, as the environmental, economic, and social aspects of CCS have been focused from 1997 to 2017 in high-impact journals. Furthermore, the technical modeling of CCS technology, as well as optimization frameworks, are assessed in the mentioned reference. According to [5], by 2035 the coal-fired plants will be still the major source of electric power generation and CCS will result in 8 GTon of CO2 emission reduction by 2050.

Although 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 [6]. Moreover, the cost of power plants increases due to the performance of components of CCS [7]. This point magnifies the importance of cost-benefit evaluations in the presence of renewable energy penetration such as wind turbines incorporated with energy storage (ES) systems for compensating the intermittent nature of them.

By growing the demand for power systems, the studies on low-carbon generation dispatch are addressed using renewable generation, consumption-side penalization, and carbon capturing alternatives. Thanks to CCS, the thermal plants can reduce a large portion of produced CO2 pollution. The study done by [8] concluded that CCS retrofit from 2020 will extremely mitigate the carbon pollution and help the climate protection up to 80%. In recent years, several studies have verified the effectiveness of CCS retrofitting for decarbonization of power systems in real-world cases. For example, a techno-economic study by [9] evaluated the feasibility of a CCS retrofitting project on a coal-fired generation site in Croatia considering the EU emission trading scheme (ETS). The authors found that despite significant emission reduction by CCS retrofit, it is not financially viable without implementing stable regulatory policies. A similar attempt for a special generation unit in India is done by [10], which concluded that CCS retrofitting reduces CO2 emission of current combined cycles of power plants. Moreover, the output of combined cycle power plants could be converted into input fuel of gas generators thanks to CCS and the methanation process. However, they believe the CCS retrofitting project will reduce emission costs while adversely increasing power plant costs.

A comprehensive study by [11] regarding the Chinese carbon trading scheme showed that the carbon market motivates large developments of CCS technology. In this regard, carbon cost plays an important role as an incentive for expanding CCS devices. It is mentioned that the CO2 costs below $10/Ton are rarely viable for CCS retrofitting projects, however, carbon costs of $35-40/Ton could be encouraging, and costs higher than $100/Ton result in the huge expansion of CCS technology. The mentioned works are some examples of recent publications on the CCS retrofitting projects. The valuation framework is formed using optimization problem, and the analysis are performed based on economic metrics, such as net present value. To this end, a mathematical modeling for CCPPs is an inevitable subject. A comparison between energy flow scheme with a conventional thermal plant and carbon capture power plant (CCPP) is shown in Fig. 1. As shown, a portion of generated power by the CCPP is used to treat the polluting gases including CO2.

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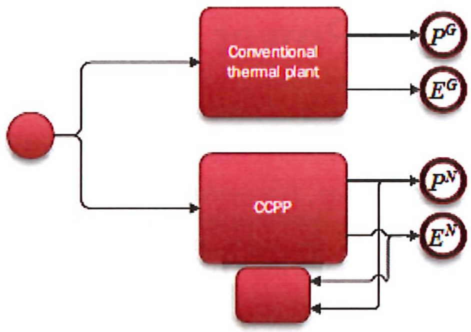

Fig. 1. Comparison between energy flow in conventional thermal and carbon capture power plants.

As one of the earliest works, including CCPPs in power systems is studied by the authors of [12] where a mixed-integer model for coal-fired plants with CCS is provided. The flexible dispatch problem of CCPPs in joint energy and emission markets is addressed by [13]. This reference helps to find the bidding strategy for the CCPP considering the volatility of power and carbon price in a day-ahead market. Under a low-carbon economy, a single objective (SO) optimization is presented by [14] considering the modeling of CCPPs. The objective function minimizes the costs of generation and carbon diffusion. However, the positive impacts of low-emission energy resources such as renewable wind energy and hydro plants are not elaborated. The authors of [15] have used a metaheuristic algorithm for low-carbon generation dispatch problem employing the CCS. The problem is tested on a 30-bus power system. However, the effects of renewable energy resources are not considered. A unit commitment problem considering post-combustion CCS is presented by [16]. In [17], the economic dispatch problem in the presence of CCPPs is investigated by proposing CCS and carbon emission transmission constraints. A simple power flow calculation verified the presented optimization model on the IEEE 118-bus test system. Reference [18] exploits the benefits of demand-side and generation management in a full-electric shipboard power system to reduce carbon emission with the help of CCS technology. The potential benefits of renewable generation have not been considered by these works.

Nevertheless, the integration of renewable generation, e.g., wind turbines, can significantly reduce CO2 emissions. In this regard, optimal economic dispatch of thermal plants in the presence of CCS and wind generation is addressed by [19], where the operational characteristics of CCPPs are expressed mathematically. However, the network model is not considered in their proposed model. In [20], the cost minimization targets a low-carbon energy system integrating CCPP, wind, and power-to-gas (P2G) facilities. However, the uncertainty of wind generation is ignored. For an integrated energy system, a low-carbon economic dispatch problem is presented as an SO problem by [21]. In their proposed scheme, the captured CO2 emission is used for the P2G process. Similarly, the authors of [22] proposed the cooperation of CCPPs and P2G technology to efficiently utilize the captured CO2 considering accurate modeling for CCS, electrolyzation procedure, and P2G systems. The optimization framework is developed based on the minimization of costs related to the electric sector and the penalty of carbon emission. These two last works included wind power generation in their analysis, however, the uncertainty of power output is not modeled. The idea of integrating CCPPs and P2G is extended in [23] by considering coupled electric and gas networks. The authors have addressed a low-carbon generation dispatch problem by modeling the wind generation uncertainty through stochastic programming (SP). Also, wind generation is managed to supply the power required by CCS. The presented framework is modeled as an SO problem with the goal of minimization of electric power generation cost and CO2 emission cost. In [24], the problem of generation dispatch in the presence of CCPPs and DRP is presented. The uncertainty of carbon penalty cost is considered using the conditional value at risk method. The stochastic low-carbon unit commitment problem is presented by [25], which investigates the cooperation of CCPPs and wind generation. The objective function is to minimize the costs of fuel consumption and CO2 penalty. However, the benefits of ES and DRP are not seen in this paper.

Also, developing a multi-objective (MO) optimization framework in this field is a key subject that is addressed commonly as a bi-objective optimization to minimize the generation cost and amount of produced emission. With this respect, using the bacterial colony chemotaxis algorithm, an economic-emission dispatch (EED) problem in the presence of CCPPs is structured in a MO framework by [26]. However, renewable energy resources such as wind or solar generation are not considered. Concerning the remarkable potential of wind generation and CCPPs in reducing carbon emission, a robust bi-objective problem is presented by [27], in which the Nash bargaining criterion determines the compromise between generation cost and produced emission. The uncertainty of wind generation is addressed but the benefits of ES and DRP as energy management schemes are not included. In [28], an MO optimization is presented for the EED problem considering the CCPPs and the uncertainty of wind power generation. Similarly, in [29], the problem of low-carbon generation dispatch in the presence of wind generation and DRP is studied in an MO framework. Indeed, the uncertainty of wind power generation is not modeled. In another attempt, the authors of [30] proposed an MO optimization problem for low-carbon generation dispatch in the presence of DRP and stochastic behavior of the wind generation. However, the CCPPs as the important parts of sustainable decarbonized power systems are missed. Furthermore, ES units are not involved to guarantee the constant power output of wind turbines.

An economic dispatch model considering the effects of wind generation and ES is presented by [31]. The tested power system is a 3-bus network including two thermal units, in which one of them is equipped with CCS. In [32], an SO optimization framework is proposed to optimally dispatch a power system considering CCS and responsive demands. The uncertainty of wind generation is modeled by SP. In [33], a novel decentralized economic dispatch problem is addressed under the low-carbon economy. The objective is to minimize the costs of power generation and carbon trades. In this manner, CCPPs are used to reduce the amount of diffused CO2 pollution. Besides, wind generation is included without modeling uncertain power output. Finally, the generation cost minimization problem considering the CCS and wind power generation besides the battery storage (BS) is elaborated by [34], in which the uncertainty of wind generation is modeled by an adjustable robust optimization approach (ROA).

The evaluation framework is constructed using an optimal power flow (OPF) algorithm, which integrates state and control variables in a power system scheduling problem. OPF is an optimization problem that addresses an objective function (single-objective or multi-objective), and several equality and inequality constraints to assure feasible operation of the power system [35]. In general, the single-level OPF tries to minimize the operation cost of the system. However, a multi-objective OPF provides a wider decision-making framework considering the system operator's preferences. Simultaneously, minimization of cost and emission in a power system is prevalent. However, the incompatibility of different objectives in a multi-objective OPF should be assessed carefully. The feasibility constraints of the power system include resource limits, ramping capability, limits of lines, and the flow of electric power within the power network [35]. The problem can be formulated as either alternating current (AC) power-flow or direct current (DC) power-flow models. In this paper, DC power flow is utilized, since it is more computationally efficient and leads to appropriate solutions at the transmission level.

A. Paper Contributions

To highlight the contributions of the paper, Table I is provided to compare this paper against the related works existing in the literature. It should be noted that this paper is an extended version of [36]. Among the references in Table I, only [26-30] propose an MO framework and are directly comparable to this paper. In [26], [27], [30], the MO problem is solved using a metaheuristic algorithm resulting in the optimal Pareto frontier. Then, the best solution is determined based on the technique for order preference similar to an ideal solution (TOPSIS), which is based on defining the distance of any solution from the positive or negative ideal solutions.

TABLE I. COMPARISON OF RELATED WORKS

Ref.	Network Model	Gen. type	Uncertain parameter	Uncertainty modeling	Type	DRP	ES
[12]	No	Thermal	No	No	SO	No	No
[13]	No	Thermal	No	No	SO	No	No
[14]	No	Thermal	No	No	SO	No	No
[15]	Yes	Thermal	No	No	SO	No	No
[16]	No	Thermal	No	No	SO	No	No
[17]	Yes	Thermal	No	No	SO	No	No
[18]	No	Thermal	No	No	SO	Yes	BS
[19]	Yes	Thermal/ wind	No	No	SO	No	No
[20]	Yes	Thermal/ wind	No	No	SO	No	P2G
[21]	Yes	Thermal/ wind	No	No	SO	No	No
[22]	No	Thermal/ wind	No	No	SO	No	No
[23]	Yes	Thermal/ wind	Wind gen.	SP	SO	No	No
[24]	No	Thermal/ wind	Carbon price	CVaR	SO	Yes	No
[25]	Yes	Thermal/ wind	Wind gen.	SP	SO	No	No
[26]	Yes	Thermal	No	No	MO	No	No
[27]	Yes	Thermal/ wind	Wind power	ROA	MO	No	No
[28]	Yes	Thermal/ wind	Wind gen.	Robust model	MO	No	No
[29]	Yes	Thermal/ wind	No	No	MO	Yes	No
[30]	No	Thermal/ wind	Wind gen.	SP	MO	Yes	No
[31]	Yes	Thermal/ wind	No	No	SO	No	BS
[32]	Yes	Thermal/ wind	Wind gen.	SP	SO	Yes	No
[33]	Yes	Thermal/ wind	No	No	SO	No	No
[34]	Yes	Thermal/ wind	Wind gen.	ROA	SO	No	BS
This work	Yes	Thermal/ wind/ hydro	Wind gen./ load demand	SP	MO	Yes	PHS

The best solution must have the shortest distance to the positive ideal solution and the farthest distance to the negative ideal solution. In [28], the Pareto frontier is calculated using the epsilon constraint, and the Nash bargain criterion is adopted to find the best solution strategy. This method is based on solving a game-theory optimization problem, where the objective functions act as virtual players who try to be as far as possible from the worst-case outcome. In [29], an algorithm based on the weighted sum method is implemented to reformulate the MO problem as a SO problem by defining proper weights. To this end, the analytic hierarchy process (AHP) approach is employed to find the weighting factors of objectives. However, this algorithm is rather complex and computationally inefficient. Compared to [26], [27], and [30], this paper proposes a mathematical formulation for finding optimal Pareto frontier which is more accurate than the heuristic algorithms. In comparison with [28-29], the decision-making process in this paper is less complex and faster by utilizing a fuzzy satisfaction algorithm. In summary, this paper makes the following contributions which to the best of the authors' knowledge have not been exploited in the literature yet:

- A stochastic MO framework for the low-carbon EED problem is provided.
- Epsilon-constraint and fuzzy decision-making techniques are utilized for finding the best solution.
- A comprehensive power system model including various generation and demand-side resources with drastic SP is created which assures finding the optimal and risk-averse strategy for the EED problem.
- The sensitivity of objective functions versus the generation-side parameters is evaluated.

B. Paper organization

The rest of the paper is organized as follows. The EED problem in the presence of CCPPs is described in Section II. The numerical simulations and discussions on results are provided in Section III. Finally, a conclusion of the paper is provided in Section IV.

II. PROBLEM FORMULATION

The proposed optimization framework tends to schedule the generation resources in order to minimize the generation cost, as well as, produced emission. These two objectives are conflicting and there is not a universal solution that optimizes both of them at the same time. Solving the MO results in optimal Pareto frontier including the feasible solutions, where the decision-maker is responsible for selecting the best solution according to the priorities.

A. Objective function

The objective functions are defined in (1) and (2). The first objective function, EC, calculates the expected generation costs of thermal units and the operating cost of the CCSs based on generated powers of conventional thermal plants, $P^{G}_{i,t,s}$, CCPPs, $P^{CCS}_{i,t,s}$, and captured emission, $E^{S}_{i,t,s}$, for each bus *i*, at time *t*, and for scenario *s*. λ^{G}_{g} and λ^{CCS}_{g} represent the generation costs of thermal and CCPP units, respectively. λ_{CO2} shows the cost of CO2 emission reduction by CCS. The second objective function, EE, calculates the produced CO2 emission by thermal power plants, $E^G_{i,t,s}$, and CCPPs, $E^N_{i,t,s}$. π_s denotes the probability of scenarios, ϕ_g and ϕ_c, respectively, show the set of buses including thermal plants, and CCPPs.

$$EC=\sum_{s=1}^{N_s}\sum_{t=1}^{T}\pi_s\cdot\{(\sum_{i\in\phi_g}P^G_{i,t,s}\times\lambda^G_g)+(\sum_{i\in\phi_c}P^{CCS}_{i,t,s}\times\lambda^{CCS}_g) +(\sum_{i\in\phi_c}E^S_{i,t,s}\times\lambda_{CO2})\} \quad (1)$$

$$EE=\sum_{s=1}^{N_s}\sum_{t=1}^{T}\pi_s\cdot\{(\sum_{i\in\phi_g}E^G_{i,t,s})+(\sum_{i\in\phi_c}E^N_{i,t,s})\} \quad (2)$$

B. Constraints of conventional thermal power plants

In (3)-(6), the feasible operation region of conventional thermal power plants is determined. Constraint (3) defines limitations on the power output of conventional generators. Constraints (4) and (5) model the ramping capability of thermal power plants. From (6), the produced CO2 emission, $E^G_{i,t,s}$, from the conventional thermal power plant is proportional to its power generation level, $P^G_{i,t,s}$, and emission intensity, η_g.

$$0\le P^G_{i,t,s}\le\overline{P}_i,\forall i\in\phi_g,t,s \quad (3)$$

$$P^G_{i,t-1,s}-P^G_{i,t,s}\le RU_g,\forall i\in\phi_g,t,s \quad (4)$$

$$P^G_{i,t+1,s}-P^G_{i,t,s}\le RD_g,\forall i\in\phi_g,t,s \quad (5)$$

$$E^G_{i,t,s}=P^G_{i,t,s}\times\eta_g,\quad \forall i\in\phi_g,t,s \quad (6)$$

C. Constraints of carbon capture power plants

Retrofitting a thermal power plant (for instance, a coal-fired one) with CCS reduces CO2 dispersal into the atmosphere. The integration of CCS changes the feasible region of the power plants operation. Regardless of CCS integration, generation capacity limitations must be included in the EED problem as a constraint for each CCS-based power plant, as shown by (7). Moreover, the generators' up/down ramping capability remains unchanged in the presence of CCS. Hence, the ramping capability is defined in (8) and (9) for each CCPP. Once the CCS is integrated with conventional power plants, due to power consumption of the CCS, the net delivered power, $P^N_{i,t,s}$, is not necessarily equal to the generated power of CCPP, $P^{CCS}_{i,t,s}$. Instead, a part of generated power supplies the base power and operational power of the CCS (as shown in Fig. 1). The base power of the CCS has assumed a constant value. For example, 0.5% of generation capacity is considered as a base consumption of CCS, which is ignored in this paper due to its lower value in comparison with the operational power, $P^{OP}_{i,t,s}$. The relation is formed by (10). The treated emission, $E^P_{i,t,s}$, is a decision variable that is determined by solving the MO problem. However, the amount of treated emission is directly associated with the power consumption of CCS, known as operational power. The relation between treated emission and consumed power during the CO2-abatement process is formed by (11) using a constant energy penalty coefficient, η^{CCPP}. According to the performance quality of CCS and the mechanism of CCS operation, the actual captured CO2 is not equal to the treated emission. The capture ratio, α^{CCPP}, indicates the efficiency of the CCS and its ability to capture the treated emission, as shown by (12). In this way, $E^S_{i,t,s}$, is defined as total captured emission. Similar to conventional power plans, the gross CO2 production is associated with total power generation and emission intensity, η_g. Considering this fact, the net CO2 diffusion into the atmosphere is found by (13). The captured CO2 will be transferred into carbon storage to be stored. It is assumed that there is enough capacity for storing daily captured carbon, hence, the storage capacity is not binding, and its modeling is overlooked in this paper.

$$0\le P^{CCS}_{i,t,s}\le\overline{P}_i,\forall i\in\phi_c,t,s \quad (7)$$

$$P^{CCS}_{i,t-1,s}-P^{CCS}_{i,t,s}\le RU_g,\forall i\in\phi_c,t,s \quad (8)$$

$$P^{CCS}_{i,t+1,s}-P^{CCS}_{i,t,s}\le RD_g,\forall i\in\phi_c,t,s \quad (9)$$

$$P^N_{i,t,s}=P^{CCS}_{i,t,s}-P^{OP}_{i,t,s},\forall i\in\phi_c,t,s \quad (10)$$

$$P^{OP}_{i,t,s}=\eta^{CCPP}E^P_{i,t,s},\forall i\in\phi_c,t,s \quad (11)$$

$$E^S_{i,t,s}=\alpha^{CCPP}E^P_{i,t,s},\forall i\in\phi_c,t,s \quad (12)$$

$$E^N_{i,t,s}=(P^{CCS}_{i,t,s}\times\eta_g)-E^S_{i,t,s},\forall i\in\phi_c,t,s \quad (13)$$

It should be noted that consumed power, $P^{OP}_{i,t,s}$, and capture ratio, α^{CCPP}, are indirectly related. The relation between consumed power and treated emission is based on the operating energy penalty rate, η^{CCPP}. On the other hand, the capture ratio determines how much treated emission is captured by CCS to prohibit the CO2 diffusion into the air. In fact, the capture ratio connects the treated emission and captured emission together, while treated emission is related to the consumed power employing energy penalty rate. Mathematically, the relation between consumed power and capture ratio can be written as $P^{OP}_{i,t,s}=\eta^{CCPP}\dfrac{E^S_{i,t,s}}{\alpha^{CCPP}}$.

D. Constraints of hydropower units

In (14)-(19), the operational constraints of the hydropower units are introduced according to [37]. Equation (14) defines the allowable margin for the generated power by hydro units, $P^H_{i,t,s}$. Equation (15) models the generated power of the hydro unit as a function of upward reservoir volume, $V^H_{i,t,s}$, water discharge rate, $Q^H_{i,t,s}$, and hydropower generation coefficients Ci. In (16) and (17), the dynamic of the reservoir is presented based on previous water volume, natural water inflow, discharged water and spilled water, which shows the volume of water in the reservoir. Equations (18) and (19) limit the water volume and water discharge rate. Hydro plants are fast response generators so the binary constraints on them are not introduced and they can be committed when they are required. ϕ_h indicates the buses that include hydropower units.

$$0\le P^H_{i,t,s}\le\overline{P^H_i},\forall i\in\phi_h,t,s \quad (14)$$

$$P^H_{i,t,s}=C1\times(V^H_{i,t,s})^2+C2\times(Q^H_{i,t,s})^2+C3\times V^H_{i,t,s}\times Q^H_{i,t,s}+ C4\times V^H_{i,t,s}+C5\times Q^H_{i,t,s}+C6,\forall i\in\phi_h,t,s \quad (15)$$

$$V^{H}_{i,t,s} = V^{0} + Inflow^{H}_{i,t} - Q^{H}_{i,t,s} - S^{H}_{i,t,s}, \forall i \in \phi_h, t = 1, s \quad (16)$$

$$V^{H}_{i,t,s} = V^{H}_{i,t-1,s} + Inflow^{H}_{i,t} - Q^{H}_{i,t,s} - S^{H}_{i,t,s}, \forall i \in \phi_h, t > 1, s \quad (17)$$

$$\underline{V}^{H}_{i,t,s} \le V^{H}_{i,t,s} \le \overline{V}^{H}_{i,t,s}, \forall i \in \phi_h, t, s \quad (18)$$

$$\underline{Q}^{H}_{i,t,s} \le Q^{H}_{i,t,s} \le \overline{Q}^{H}_{i,t,s}, \forall i \in \phi_h, t, s \quad (19)$$

E. Constraints of pumped hydro storage

PHS' modeling is adopted from [38]. The water reservoir's volume is modeled with $C_{i,t,s}$. $P^{ch}_{i,t,s}$ and $P^{dis}_{i,t,s}$ show the charged (pumping) and discharged (generated) electrical powers. Respectively, the power is used for pumping the water to an upward reservoir and generated power by the downward movement of water. Binary variables ($u^{ch}_{i,t,s}$, $u^{dis}_{i,t,s}$) are introduced to show the charging/discharging state. The limitations on charged/discharged powers could be determined based on binary variables as done in (20) and (21). Constraint (22) prohibits simultaneous charging and discharging. Furthermore, the immediate status change from pumping to generation is not available, which is molded by (23) and (24). Finally, the stored energy (equivalent to stored water) is calculated based on (25) and (26). Equation (27) limits the stored energy. ϕ_s shows the buses including PHS.

$$0 \le P^{ch}_{i,t,s} \le \overline{P^{ch}_i} \times u^{ch}_{i,t,s}, \forall i \in \phi_s, t, s \quad (20)$$

$$0 \le P^{dis}_{i,t,s} \le \overline{P^{dis}_i} \times u^{dis}_{i,t,s}, \forall i \in \phi_s, t, s \quad (21)$$

$$u^{ch}_{i,t,s} + u^{dis}_{i,t,s} \le 1, \forall i \in \phi_s, t, s \quad (22)$$

$$u^{dis}_{i,t-1,s} + u^{ch}_{i,t,s} \le 1, \forall i \in \phi_s, t, s \quad (23)$$

$$u^{dis}_{i,t,s} + u^{ch}_{i,t-1,s} \le 1, \forall i \in \phi_s, t, s \quad (24)$$

$$C_{i,t,s} = C^{0}_{i,t,s} + \eta^{HS} \times P^{ch}_{i,t,s} - P^{dis}_{i,t,s}, \forall i \in \phi_s, t = 1, s \quad (25)$$

$$C_{i,t,s} = C_{i,t-1,s} + \eta^{HS} \times P^{ch}_{i,t,s} - P^{dis}_{i,t,s}, \forall i \in \phi_s, t > 1, s \quad (26)$$

$$\underline{C}_i \le C_{i,t,s} \le \overline{C}_i, \forall i \in \phi_s, t, s \quad (27)$$

F. Constraints of the demand response program

The time-of-use DRP is employed in this paper. 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 (28), in which the total consumed load in a day would be constant according to (29). $P^{L}_{i,t,s}$ is the actual load, $P^{D}_{i,t,s}$ shows met load after implementing DRP and $P^{sh}_{i,t,s}$ is shifted load, which is limited by (30) according to the maximum percentage of shiftable load κ (here, $\kappa = 20\%$) [39]. ϕ_l indicates the buses including load demand.

$$P^{D}_{i,t,s} = P^{L}_{i,t,s} - P^{sh}_{i,t,s}, \forall i \in \phi_l, t, s \quad (28)$$

$$\sum_{t=1}^{T} P^{L}_{i,t,s} = \sum_{t=1}^{T} P^{D}_{i,t,s}, \forall i \in \phi_l, s \quad (29)$$

$$-\kappa P^{L}_{i,t,s} \le P^{sh}_{i,t,s} \le \kappa P^{L}_{i,t,s}, \forall i \in \phi_l, t, s \quad (30)$$

G. Constraints of the electrical network

The following equations model the network constraints using DC power flow calculation. The generation-consumption balance is satisfied using (31). $P^{W}_{i,t,s}$ indicates the wind power generation as a parameter of the generation-side. The exchanged power between connected buses, $P^{f}_{i,j,t,s}$, is modeled based on voltage angles of buses, $\delta_{i,t,s}$ and lines' reactance, x_{ij} according to (32). Constraint (33) limits the exchanged power between connected buses in the network. The voltage angle of the reference bus should be zero as shown by(34).

$$P^{W}_{i,t,s} + P^{N}_{i,t,s} + P^{G}_{i,t,s} + P^{H}_{i,t,s} + P^{dis}_{i,t,s} - P^{ch}_{i,t,s} + P^{sh}_{i,t,s} - P^{D}_{i,t,s} = \sum_{j \subset l, j \ne i}^{N_{bus}} P^{f}_{i,j,t,s}, \forall i, t, s \quad (31)$$

$$P^{f}_{i,j,t,s} = \frac{\delta_{i,t,s} - \delta_{j,t,s}}{x_{ij}}, \forall i, j, t, s \quad (32)$$

$$-\overline{P^{f}_{ij}} \le P^{f}_{i,j,t,s} \le \overline{P^{f}_{ij}}, \forall i, j, t, s \quad (33)$$

$$\delta_{i,t,s} = 0, \forall i = slack, t, s \quad (34)$$

H. Fuzzy decision-making method

The solutions of optimal Pareto frontier are found based on the epsilon constraint approach [40]. In this method, first, the maximum values of the objective functions are calculated and stored. Then, one objective function that its value is not greater than an epsilon is selected to be added as a constraint during the procedure of solving the MO problem. For example, if the considered objective function is (2), the additional constraint, $EE \le \varepsilon$, is added to the problem. Where the epsilon varies from the maximum value of EE to its minimum value; meanwhile the other objective function is optimized at each step. Using the prescribed algorithm, the Pareto optimal front for the EED problem will be found.

After obtaining the Pareto front, the best solution is selected based on a fuzzy decision-making tool [41]. The fuzzy sets are utilized to model the ambiguity of decision-makers' behavior concerning each objective function output. The fuzzy sets are defined based on membership functions. The degree of membership in a fuzzy set is determined by a value within the interval [0,1]. The degree of membership (or compatibility) is indicated by $\mu^{Z_k(x_{it})}$ in this paper, where $Z_k(\mathrm{x}_{it})$ is the amount of objective function k at the iteration step it. The term $\mu^{Z_k(x_{it})} = 0$ represents the inconsistency within the set; on the other hand, the term $\mu^{Z_k(x_{it})} = 1$ represents the full consistency. The membership function $\mu^{Z_k(x_{it})}$ shows the importance of a Pareto frontier with respect to satisfying the corresponding objective function. In other words, the value of membership describes the domination of the solution in satisfying the objective functions. A monotonously linear relation for membership function can be written as

$$\mu^{Z_k(x_{it})} = \begin{cases} 1 & , Z_k(\mathrm{x}_{it}) \le Z_k^{\min} \\ \dfrac{Z_k^{\max} - Z_k(\mathrm{x}_{it})}{Z_k^{\max} - Z_k^{\min}} & , Z_k^{\min} \le Z_k(\mathrm{x}_{it}) \le Z_k^{\max} \\ 0 & , Z_k(\mathrm{x}_{it}) \ge Z_k^{\max} \end{cases} \quad (35)$$

Herein, maximization of the minimum satisfaction is a measure to find the best risk-averse decision considering the obtained optimal Pareto frontier, mathematically stated as

$$X^{*} = \max_{it} \min_{k} (\mu^{Z_k(x_{it})}) \quad (36)$$

III. Numerical Evaluation

A. Case Study

The proposed optimization is tested on a modified IEEE 24-bus test system. The system includes ten conventional fossil fuel power plants, two hydropower plants, three wind turbines, and three PHSs to provide electrical power with a high level of reliability. The PHSs' nominal capacity and rated power are 150 MWh and 50 MW, respectively. Furthermore, the hydropower plants at buses 1 and 3 have fast ramping capability and pollution-free generation. The schematic of the studied network is shown in Fig. 2. The system's physical characteristics and average demand data can be found in [40]. In order to reduce the carbon emission produced by the conventional plants, the CCSs are considered at buses 7 and 8, i.e., the fossil fuel power plants 9 and 10 are equipped with CCS. The characteristics of the power plants are represented in Table II. Two last columns are defined for CCPPs. 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 output of wind turbines installed at buses 8, 19, and 23, and hydro plants' information are provided in [35].

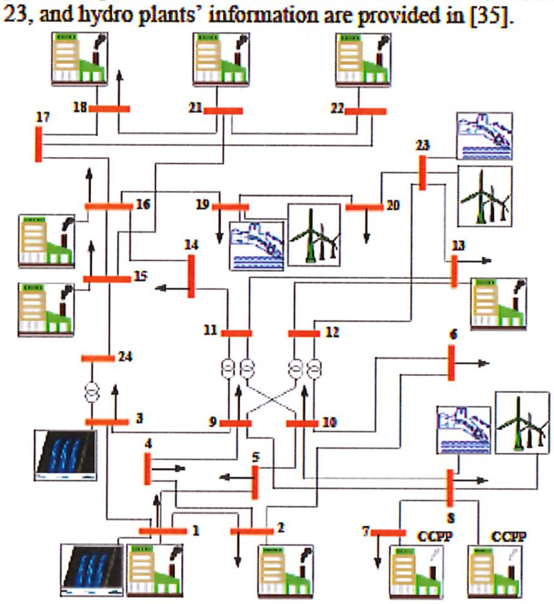

Fig. 2. IEEE 24-bus system.

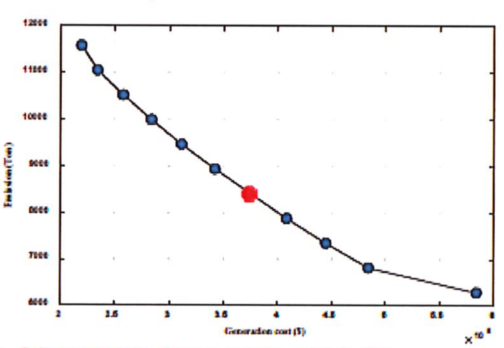

Fig. 3. Pareto front for the cost-emission minimization.

TABLE II. Information on the Fossil Fuel power plants

Power Plant	Bus	Pmax (MW)	λ_s^{m} ($/MW)	RU_s	RD_s	η_s (T/MW)	η^{CCPP}	α^{CCPP}
1	1	152	13.32	10	20	0.65	-	-
2	2	152	13.32	10	20	0.7	-	-
3	15	215	21	20	30	0.75	-	-
4	16	80	10.52	30	10	0.75	-	-
5	18	100	5.47	10	20	0.5	-	-
6	13	591	25	20	50	0.6	-	-
7	21	100	5.47	30	30	0.65	-	-
8	22	300	30	20	40	0.65	-	-
9	7	400	28.52	30	30	0.7	0.27	0.9
10	8	360	28.52	40	40	0.7	0.27	0.9

TABLE III. Optimal Pareto Front

it	μ^{cost}	$\mu^{emission}$	*EC* ($)	*EE* (Ton)	min $(\mu^{cost}, \mu^{emission})$
1	1.000	0.000	219848.404	11573.324	0.000
2	0.959	0.100	234631.785	11044.165	0.100
3	0.896	0.200	257873.737	10515.006	0.200
4	0.824	0.300	284002.389	9985.847	0.300
5	0.748	0.400	311688.958	9456.688	0.400
6	0.665	0.500	342170.209	8927.529	0.500
7	0.577	0.600	374138.554	8398.370	0.577
8	0.483	0.700	408497.053	7869.211	0.483
9	0.383	0.800	444817.653	7340.052	0.383
10	0.274	0.900	484494.993	6810.894	0.274
11	0.000	1.000	584494.024	6281.735	0.000

B. Results and Discussion

The multi-objective stochastic programming presented in Section II is mixed-integer non-linear programming which is modeled in General Algebraic Modelling System (GAMS) and solved using the DICOPT solver.

1) Pareto frontier

Each MO problem results in several optimal solutions with respect to the considered objective functions. The collection of these optimal points results in a Pareto optimal frontier, which is shown in Fig. 3 and summarized in Table III in detail. The best solution among the points identified by the optimal Pareto front is chosen using the fuzzy satisfying method. According to (37), the best Pareto frontier is associated with the iteration that maximizes the minimum of membership functions. In other words, the last column of Table III illustrates the minimum amount of $\{\mu^{cost}, \mu^{emission}\}$ as a set of membership degrees. The best solution for the MO corresponds to the maximum membership of the set (i.e. *it*=7).

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. Accordingly, with the best Pareto frontier, the expected cost of the system in a 24-hour operation horizon is $374138.554 and the total emission produced by thermal plants is 8398.370 Tons. Since, the amount of CO2 production and generation cost are conflicting objectives, in the best Pareto front, a compromise is done to determine the best generation dispatch among all of the conventional power plants and CCPPs. It should be noted that the CO2 abatement cost λ_{CO2} is assumed to be $25/Ton [32].

2) Thermal generation scheme

As mentioned before, four scenarios are considered to model the uncertainties of load and wind generation. Figure 3 illustrates the generation dispatch scheme under the considered scenarios for the best Pareto front. From Fig. 4, different scheduling for conventional power plants has been recorded according to generation cost and amount of emission intensity. Moreover, for different wind generation and load demand scenarios, various generation scheduling is deduced. In general, it can be expressed that the power plants with lower generation costs (e.g. power plant 1) are always on the priority list of dispatching, and fossil fuel power plants 3, 6, and 8 are rarely dispatched due to their higher generation cost.

3) CCPP generation scheme

The net delivered power to the network is not equal to the generated power when the power plant is equipped with CCS. Accordingly, the net delivered power by fossil fuel power plants 9 and 10 is shown by Fig. 5 under scenario 2, for example. As seen the ramping up/down constraints are seen as they were modeled as operational constraints of CCPPs. Moreover, as it was mentioned, a part of the power generated by CCPPs is consumed by the CCS; hence, the net delivered power by these plants is always lower than their nominal generating capacity that is obvious by comparing Figs. 3 and 4. Despite having higher generation costs and lower delivered power, fossil fuel power plants 9 and 10 are committed with a considerable capacity in all scenarios. The reason can be found by looking at Table III where the best-compromised solution is selected considering the importance of emission reduction.

4) Emission production of thermal power plants

For verifying the applicability of CCPPs for CO2 abatement, the total daily emission production and net emission diffusion by the existing thermal generators under scenario 2 are presented in Fig. 6. The black-colored bars represent the produced emission by the plants during power generation, and copper-colored bars represent the diffused emission by the thermal plants. As can be seen, the CCS of power plants 9 and 10 (placed at buses 7 and 8, respectively) has reduced the amount of CO2 emission diffusion by about 90%.

5) Hydropower generation scheme

Figure 6 shows the hydro plants' scheduling patterns for scenario 2. It was assumed that the operation cost of hydro plants is negligible. Hence, it is expected that these plants should be committed at their full capacity in the majority of the time. Also, insignificant emission production makes them a delightful power resource. For the best optimal Pareto solution, the amount of emission production is taken into account as important as cost. Instead, operational constraints such as considering the upward reservoir volume, water inflow rates, and water discharge rate are vital factors that should be addressed.

6) Pumped hydro storage operation

The charging and discharging patterns of PHSs' are represented by Fig. 8. The positive and negative amounts indicate, respectively, the charged and discharged powers by the PHSs located at buses 8, 19, and 23 under scenario 2. The important point regarding 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. 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.

7) Impacts of the demand response program

Fig. 9 shows the impact of DRP on the load demand of bus 4 during the operation under scenario 2. As mentioned, the uncertainty of load demand is also considered by the proposed SP. However, the illustration of them under different scenarios is not informative, hence, the result is depicted only for scenario 2. As mentioned, only 20% of the hourly load can be shifted from the hours with high load demand to hours with low demand to reduce the required generation capacity. Therefore, the DRP leads to reducing the generation cost and produced emission simultaneously. In fact, it can be claimed that the DRP is an economic solution for decarbonizing the power systems without redundant charges and investments. However, the key factor of a successful DRP is to estimate the elasticity of load demands and providing practical strategies.

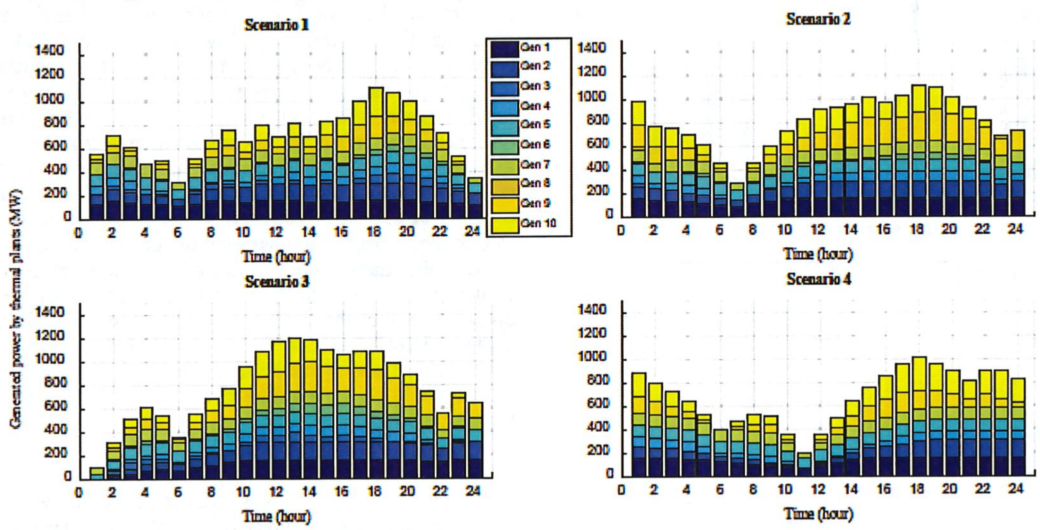

Fig. 4. Generation scheduling under different scenarios.

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8) Impacts of generation-side availability

The CCS retrofitting should be evaluated by considering the eco-friendly impacts and economic viability. Intuitively, this means that the impacts of renewable generation resources such as hydropower, wind farms, and energy storage systems, besides the flexibility of demand consumption should be considered in a multi-objective optimization problem. Since the renewable generation resources' availability is associated with some uncertainties, the sensitivity of the objective functions with respect to generation-side availability has been assessed in this part. Table IV summarizes the sensitivity of the objective function with respect to the availability of generation resources. The analysis is performed for three different case studies. In Case 1, 2, and 3, CCPPs, wind power generation, and hydro plants are excluded, respectively. In each case study, the best solution from the optimal Pareto frontier is selected to be reported. The last two columns show the deviations of expected cost (EC) and expected emission (EE) from the best solution obtained in Section III-B.

TABLE IV. OBJECTIVE FUNCTIONS SENSITIVITY

Case	EC (\$)	EE (Ton)	ΔEC (%)	ΔEE (%)
1	267568.808	10670.196	-28	+27
2	636352.204	12526.004	+160	+49
3	544175.023	11502.732	+45	+37

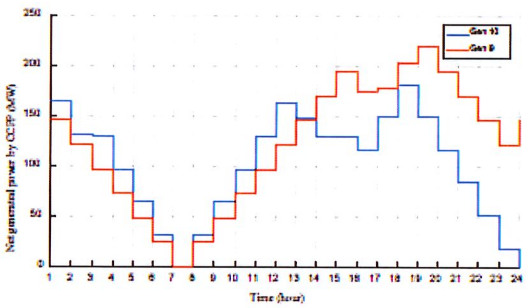

Fig. 5. Net delivered power by the CCPPs.

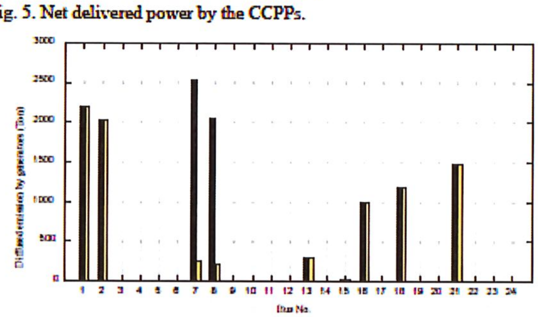

Fig. 6. Produced and diffused emission by generators.

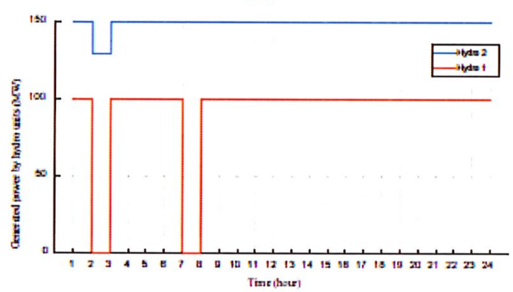

Fig. 7. The scheduling of hydro plants.

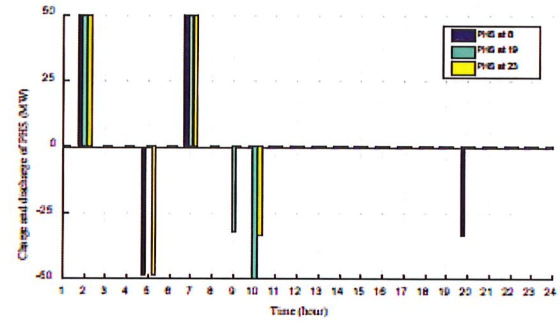

Fig. 8. Charged and discharged power of pumped hydro storage systems.

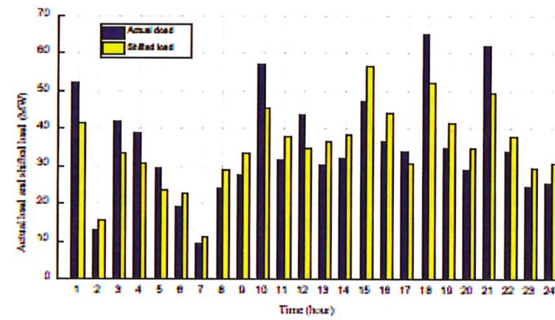

Fig. 9. The effect of DRP on load management.

As seen in Table IV, the expected cost of the power system is reduced by 28% in Case 1, while the CO2 emission has increased by 27%. The cost reduction is because of CO2 abatement cost removal in the absence of the CCPPs. In this case, the costly power plants 9 and 10 are rarely dispatched resulting in more cost reduction. Consequently, the load is fed by other power plants with higher emission intensity leading to more CO2 production. In Case 2, the exclusion of pollution-free wind turbines results in generation capacity deficiency; hence, the optimization algorithm dispatches more thermal power plants, leading to more expected generation cost and emission. Similarly, the exclusion of pollution-free hydropower plants with a total capacity of 250 MW, in Case 3, increased the expected generation cost and emission, by 45% and 37%, respectively. Comparing Case 2 and 3, the superiority of hydropower plants in emission reduction is inferred. In other words, assuming the same capacity for the wind farm and hydro plant, the hydro plant has a larger impact on the emission reduction. The elimination of wind farms with a maximum capacity of 650 MW results in an emission growth of 49% while excluding hydropower with a maximum capacity of 250 MW results in 37% emission increase. The role of hydro plants in emission reduction is because of their dispatchable nature. On the other hand, from an economic view of point, the wind farm has a higher impact on the total operation cost of the system. The wind farm not only incurs additional costs but also due to distributed arrangement of wind turbines and by modeling the network constraints using DC power flow, the wind turbines contribute to feeding the loads economically.

IV. CONCLUSION

In this paper, MO SP was proposed to solve the problem of low-carbon generation dispatch problem 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's generation dispatch is done under the low-carbon policy. To obtain the optimal Pareto front, the epsilon constraint method was used and the well-known fuzzy decision-making approach was employed to find the best solution from the optimal Pareto front. For the selected solution, the scheduling results were reported and discussed for a sample scenario 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 is directly related to the consumed power generated by the corresponding power plant. Moreover, the integration of PHS increased the flexibility to reach an optimal EED. DRP as load management has the potential benefit of reducing both emission and generation cost of the system in one direction without charging high investment costs and economic losses. Finally, the effects of the availability of CCS, wind generation, and hydropower on the objective functions are examined. It was concluded without having restrictions on carbon emission, retrofitting projects are not economical solutions.

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