Carbon-Oriented Electricity Balancing Market for Generators and Flexible Loads

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***Abstract*—In the transition to a low-carbon economy, the market share for renewable energy is significantly increasing and gradually substituting traditional energy. The high renewables penetration results in increased balancing action volumes due to system stability requirements. The balancing market (BM) primarily turns down renewable generation and turns up traditional carbon-intensive generation in response to real-time energy imbalance. Existing dual-stage market mechanisms conflict with the carbon reduction trajectory by implementing balancing actions regardless of their carbon footprint. This paper proposes a novel balancing market model by evaluating the negative externality of carbon to coordinate the environmental targets in both markets. Firstly, mathematical models are formulated for key participants in the dual-stage market. The emissions of dispatchable generators and flexible loads are distinguished by their operation modes and flexibility types, respectively. Carbon signals are incorporated into their bid/offer pricing models through the carbon emission flow (CEF) model. By integrating these incentives for carbon reduction, the dual-stage market model is formulated to minimize economic and environmental costs. Simulation results demonstrate that the proposed model effectively reduces carbon emissions in the BM and strike a balance between cost-efficiency and environmental benefits. It enables system operators to incentivize decarbonized energy resources in both stages.**

***Index Terms*—Balancing market, carbon signal, decarbonized energy resources, low carbon.**

NOMENCLATURE

Indices and sets

g, Ω^G	Index and set of electricity generation units
t, Ω^T	Index and set of scheduling time
b,Ω^B	Index and set of buses
l, Ω^L	Index and set of transmission lines
Ω^{G^I},Ω^{G^F}	Set of inflexible and flexible generation units
Ω^{FL}	Set of flexible load aggregators

Variable

c_{tax}	Carbon tax
$c_{t,u}^{fl}$, $c_{t,d}^{fl}$	The upward and downward capacity of EV or BESS
C_f, C_{var}, C_{car}	Fuel cost, variable cost and carbon emission cost of generators
D	Electricity demand
e_t^{fl}	Energy stored in EV or BESS at time t
E_{end}^{fl}	Energy stored in EV or BESS at the end of its charging period
f^p, f^q	Active and reactive power flow through the transmission line
p_{bid}^{BM}, p_{offer}^{BM}	Bid and offer prices for BM
p_t^{fl}	The shifted power of flexible load at time t
p_{max}^{fl}, p_{min}^{fl}	Maximum and minimum charging power of EV or BESS
$\bar{P}$	Maximum power output of generation units
P^{fl}	Total shiftable volume of flexible load submitted in the BM
P_0, P_r	Electricity outputs of generation units in the day-ahead dispatch and real-time balancing process
M_{bid}, M_{off}	Bid and offer price multiplier
t_{fl}	The actual continuous working time of flexible load
$[t_0, t_{end}]$	The shiftable time interval of flexible load
T^{on},T^{off}	Startup and shutdown time for generators
$U_i(t), U_j(t)$	Head and tail bus voltage of line i, j at distribution system
U^{min},U^{max}	Bus voltage limit
v_τ^{fl}	A binary variable showing the startup state of the flexible load
x	AKDE independent variable
λ_{down}, λ_{up}	Downward and upward volumes for generators participating in the balancing market
r_g	Ramp rate
δ	Binary variable for upward or downward regulation
ρ_g	Carbon intensity of electricity generation (tCO_2/MWh)
η^{fl} ,DT	Charging efficiency and duration of EV or BESS

Parameter

A, G	Bus-electricity line and bus-generator incidence matrix
$T_{g,min}^{on}$, $T_{g,min}^{off}$	Minimum startup and shutdown time for generator g
UoS	Use of system charge
r_{b-j},x_{b-j}	Resistance and reactance of line b, j
μ	Generation efficiency

I. INTRODUCTION

THE worldwide zero-carbon targets inevitably necessitate decarbonizing the electricity system with increasing renewable energy resources. The European Union aims to eliminate net EU emissions by 2050, from 1990 levels [1]. To meet the target, the Commission has set an ambitious target to raise the share of renewable energy to 40% of final consumption by 2030, which means it grows by 20% from 2019. To achieve net-zero emissions by 2050, the UK's Committee of Climate Change concluded that there is scope for the penetration of clean energy to reach 30 - 45% of all energy consumption in the UK by 2030 [2]. The US Energy Information Administration also reveals that renewables grow around one percent annually to their share of the nation's electricity supply, which could be one-third of US electrical generation in 2030 [3]. Even though the increasing share of low-carbon electricity generation brings substantial environmental benefits, it poses significant challenges to network operation, planning and energy trading.

The remarkable growth of renewable energy resources (RER) and gradual phase-out of traditional carbon-intensive plants in the wholesale market seems to align with the decarbonization process. Nevertheless, high RER uncertainties increase the balancing action volumes due to system stability requirements. The system operator (SO) needs to turn up traditional flexible plants through balancing mechanism actions, which unwinds a significant proportion of the market. Considering the high carbon intensity of conventional flexible plants, total carbon emissions accordingly increase in the balancing market. During the early lockdown in the UK, electricity demand dropped by around 15% compared to the previous year. It has resulted in frequent periods of high renewable and low thermal generation, causing enormous carbon emissions from BM actions, which make up 15-25% of total power sector emissions.

The contradiction of high renewable penetration in the wholesale market and considerable carbon output of BM actions impedes the low-carbon economy. Even though facilitating RER penetration has been deeply investigated, the environmental trade-off between renewable shares in the wholesale day-ahead (DA) market and decarbonized balancing actions is generally ignored. Therefore, reasonable incentives and market designs are required to ensure both markets are consistent with the Net Zero carbon reduction trajectory.

Tremendous efforts have been devoted to addressing operation and planning problems with wide utilization of renewables, e.g., probabilistic power flow modeling [4] and flexible investment decision making [5]. Multiple models have been formulated to increase renewable generation and materialize ambitus carbon targets. Paper [6] develops a data-driven model to analyze the operation mode variety under high renewable shares of the energy mix. Results indicate that the dispersion and time variation of operation mode increase with the growth in RER penetration until saturation. To accommodate more RER in the power system, paper [6] concludes that sufficient flexible resources and corrective measures are required to ensure the growing frequency of operation mode switching in system operation. Paper [7] construct a unit commitment model to take advantage of demand-side flexibility (DSF) by analyzing the effects of carbon emission trading on the generation schedule. It integrates the carbon emission cost of generators and vehicle-to-grid (V2G) in the unit commitment model. Results verify that the participation of DSF in the power supply-demand balance decreases as expected.

Reference [8] capitalize on the virtual power plant (VPP) ,which aggregates distributed renewable energy and controllable loads to improve the utilization capacity of renewable energy. An optimal bidding strategy of VPP is proposed through carbon-electricity integration trading and user satisfaction. Reference [9] presents a demand-side management approach for carbon footprint control. It benefits both the demand and generation sides by supporting the carbon policy and engaging with the demand adjustment process. Paper [10] designs a conjectural-variations equilibrium model to reach the equilibria in electricity, natural gas, and carbon-emission markets. The equilibria reached in those three markets varies with carbon-emission trading and transmission constraints. However, limited efforts have been devoted to managing emissions in the DA and the balancing markets considering their conflicting goals.

Compared with extensive research of RER utilization in the DA market, the carbon emission issues in the balancing market are relatively under-researched [11]. There exists some research on BM bidding strategies and settlement pricing schemes with high RER penetration. Paper [11] analyses the fundamental drivers and the predictability of imbalance prices in the British balancing market. It quantitatively assesses how the key drivers, i.e., wind deviation, solar deviation, demand forecast errors, scarcity variables, and lagged imbalance volumes impact the imbalance prices. Paper [12] studies the bidding behavior in the balancing market with increasing wind and photovoltaic (PV) by econometric analysis. Results demonstrate the impact of updated forecasting errors of variable generation on the imbalance price changes. Paper [13] proposes a dual-pricing scheme by regarding controllable production units as “active” participants and renewable units as “passive” actors. The objective is to maximize the profits of VPPs by optimizing their active and passive participation in the day-ahead and balancing market, considering renewable and controllable units. Paper [14] designs a hierarchical market structure for local microgrids to provide ancillary services by participating in the balancing market. It optimizes the interactive performance of distribution system operators and microgrids by minimizing their operational costs. Paper [15] proposes a dynamic energy balancing cost model for the DA market to solve wind uncertainty. It models multiple types of costs due to wind and traditional generation uncertainty, providing an effective tool for acquiring techno-economic benefits. However, these models all ignore the carbon footprint of balancing actions and only investigate their economic aspects. A large share of renewable generation capacity leads to economic and environmental pressures for real-time balancing. Given that the environmental effects and balancing costs of BM actions are not always consistent, a comprehensive analysis is of great significance to facilitating low carbon transitions in the power sector.

Flexible resources are the main BM measures, categorized as generation flexibility and demand-side flexibility (DSF). They are indispensable tools to deliver cost-effective decarbonization in the power sector. However, they have distinct carbon-emitting characteristics, ignored in most papers. Existing literature emphasizes quantitatively analyzing economic values when optimizing BM actions. Paper [16] proposes a systematic method to evaluate the flexibility of a given day-ahead scheduling model, considering fast ramping units (FRU), hourly demand response (DR), and energy storage in power system operation. The flexible resources are assessed based on their ability to address the uncertainties linked with wind energy production (WEP). Numerical results demonstrate that the largest value of the proposed flexibility index is obtained by combing FRU, hourly DR, and energy storage.

Remarkably, among all investigated flexible resources, the hourly DR contributes significantly to the system flexibility. Reference [17] explores the capability of current and potential accessible future residential DSF (e.g., EVs. Stationary batteries and storage heaters) to reduce the energy supply costs of a flexibility aggregator with highly penetrated RERs. Results demonstrate that even a low saturation of flexible demand can reduce the generation costs in microgrids. Despite the fact that flexible resources play an important role in integrating RER and thus achieving the carbon reduction trajectory, their carbon intensities vary greatly. For instance, during the startup and shutdown conditions, excessive CO_2 is generated from flaring [18], which is considered a major greenhouse source of utilizing fully flexible generators.

Therefore, utilizing them indiscriminately is unlikely to align with the Net Zero target. To the best of the authors' knowledge, there is virtually nothing in the literature to make a comprehensive and systematic analysis of flexible resources in BM considering their carbon footprint. The major drawbacks and gaps of the existing literature are: 1) They propose multiple operational methods and technologies to accommodate high renewable penetration, e.g., BESS and DSR. Nevertheless, the economic and environmental challenges embodied in the sharp rise in BM actions are not analyzed and solved from the market point of view. 2) The absorption of RER in the day-ahead (DA) market greatly raises BM action volumes from carbon-insensitive flexible generators, which impedes decarbonization in the power sector. No quantitative models have explicitly striked a balance between them. 3) Most research focuses on ensuring cost-effective, flexible resource capacities by integrating multiple technologies, e.g., BESS, intermittent generation, and EVs. Nevertheless, no models evaluate carbon emissions in procuring flexible capacity to favor decarbonized BM actions.

To fill the research gaps, this paper proposes a novel balancing mechanism to simultaneously capture the carbon footprint of energy resources in the dual-stage market. Unlike existing research, this paper will tap the potential of BM actions in reducing carbon emissions from a market perspective. The main contributions of this paper are as follows:

- It for the first time quantitatively analyze both economic and environmental costs of BM actions due to high renewable penetration in the DA market. Existing literature emphasizes facilitating RER in power system operation, e.g., solving the unit commitment problems [8] and ensuring the high frequency of operation mode switching [6]. Even though some papers [11] [12] analyze the impact of renewables on the balancing mechanisms, they only investigate their economic values. Ignoring the environmental costs would run counter to the low carbon development since economical BM actions (e.g., flexible thermal generators) tend to have high carbon intensity. To coordinate the environmental targets in the dual-stage market, the proposed method classifies BM actions through their flexibility capacities and incorporates their carbon emissions in the balancing costs. It provides useful insights on evaluating the externality of carbon in the BM, incentivizing flexibility capacity compatible with Net Zero.
- It for the first time distinguishes the generator emissions over normal, startup and shutdown operation in the electricity market. Conventionally, the carbon emission intensities of generators are set as constant regardless of their operation modes [19]. With increasing renewable supply fluctuations, thermal plants are more frequently started up or shut down in the real-time balancing market. The proposed market strategy utilizes EEAF (emissions estimate adjustment factor) to estimate the carbon emissions during the startup and shutdown periods.
- It achieves the trade-off of RER penetration in the DA market and the BM action volumes in terms of both imbalance costs and carbon emissions. If the incentives for carbon reduction in both markets remain the same, emissions in balancing services are unlikely to conform to carbon neutrality. Existing literature [11] [20] [21] undertakes system balancing based on cost minimization with increasing intermittent renewable generation. They ignore the impact of high renewable penetration on the carbon-emitting growth in BM. The proposed model integrates carbon signals in BM to further unlock the emission reduction potential.
- It provides clear categorization and methodology for all flexibility services regarding carbon targets and cost efficiency by incorporating their carbon costs into their bids and offers. Most papers use DSF to address real-time uncertainties, bypassing their environmental contributions. Since flexible generators tend to have higher carbon intensities, existing models conflict with the carbon reduction trajectory by facilitating flexible generators and DSF indiscriminately in the electricity market. The proposed market design accommodates both their economic and environmental values when bidding in the balancing market, enabling system operators (SOs) to incentivize the decarbonized flexibility in the power sector.

The remainder of this paper is organized as follows. Section II formulates the mathematical models of the key input data of the designed market. Section III demonstrates the market structure and clearing mechanisms. Section IV illustrates the implementation of the developed market model. Section V validates the efficacy of the proposed model. Section VI summarizes the key findings and conclusions of this paper.

II. Mathematical Formulation

This section presents the detailed mathematical formulation of key input data in the dual-stage market, including the bid/offer pricing, flexible resource modeling, and uncertainty analysis of net imbalance volumes (NIV).

A. Bidding Price in the DA Market

This paper utilizes the extended short-run marginal costs (E-SRMC) for multiple generators to compete in the DA market. Generators submit their electricity generation prices based on their short-run marginal cost (SRMC) in the day-ahead process. SRMC represents the change in total generation cost from a small output change in units of £/MWh. Generally, SRMC is mainly given by the underlying fuel prices and the carbon emission cost [22]. E-SRMC is extended from this concept by incorporating more factors, e.g., the Use of System (UoS) charge. It is defined as the sum of the non-fuel variable cost (including the transport costs, the port costs, and the average startup costs), the carbon price, the UoS charge and the efficiency-adjusted fuel cost, as shown in equation (1) [23].

$$E-SRMC=\frac{C_f}{\mu}+C_{var}+UoS+C_{car}\cdot\gamma \tag{1}$$

$$C_{car}=\rho_g\cdot c_{tax} \tag{2}$$

where the first term in (1) represents the efficiency-adjusted fuel cost. The coal and oil prices are calculated as a three-monthly average. The second term denotes the non-fuel variable cost. The third term means the UoS charge, which is used to recover the cost of the day-to-day operation of the transmission system [24] [25]. The final term denotes the carbon emission cost, calculated by multiplying the carbon density ρ_g of generator g and the carbon tax c_{tax}.

B. Flexible Resource Modelling

Flexible generators and loads can participate in the BM. Nevertheless, their flexibility characteristics are vastly different. The main parameters to evaluate generation-side and demand-side flexibilities are demonstrated below.

1) Generation flexibility

Conventional generators' flexibility depends on their generation characteristics, e.g., ramp rate. For instance, nuclear plants are generally regarded as inflexible since they cannot readily and securely be ramped up and down to keep the system balanced. In comparison, some high carbon-intensive generators (e.g., fossil-fuelled generators) are much more flexible and can be dispatched economically and securely. This paper uses the following parameters to evaluate generators' flexibility as shown below:

- *Ramp rate:* It is the average speed at which generators can increase or reduce their output between the peak and valley levels per hour (MW/h) [26]. It can be mathematically expressed as:

$$|P_r^t(g)-P_r^{t-1}(g)|\le r_g,\forall g\in\Omega^{G^F}. \tag{3}$$

where $P_r^t(g)$ is the re-dispatched power output of generator g at time t during the balancing process.

- *Capacity:* The regulation capacity of generating units denotes generators' maximum upward and downward power output under secure operation conditions. It can be expressed as:

$$\begin{gathered}\overline{P_{down}}<P_0^t(g)-P_r^t(g),\\ if\ P_0^t(g)>P_r^t(g),\forall g\in\Omega^{G^F}\end{gathered} \tag{4}$$

$$\begin{gathered}\overline{P_{up}}>P_r^t(g)-P_0^t(g),\\ if\ P_r^t(g)>P_0^t(g),\forall g\in\Omega^{G^F}\end{gathered} \tag{5}$$

where $\overline{P_{down}}$ and $\overline{P_{up}}$ represent the downward and upward capacities, respectively. $P_r^t(g)$ defines the maximum redispatched power output of generator g at time t during the balancing process, while $P_0^t(g)$ is the original production of generator g that is agreed one day ahead to be delivered.

- *Startup and shutdown time:* Startup time refers to the time between mechanical completion and the point at which the plant reaches its operating capability. The shutdown time represents the desynchronization of the generator from the grid frequency [27]. They can be formulated as :

$$T_g^{on}\ge T_{g,min}^{on},T_g^{off}\ge T_{g,min}^{off},\forall g\in\Omega^{G^F}. \tag{6}$$

2) Load flexibility

In this paper, flexible loads refer to electric vehicles (EV) and battery energy storage systems (BESS). They are aggregated to participate in the balancing market. To capture the characteristics of load flexibility, this paper models their availability (i.e., time flexibility) and adjustable capacity (i.e., power flexibility) as follows:

- Time availability

Time availability/flexibility of aggregated load denotes that they are shiftable during a certain interval [28]. Their energy consumption behaviors are modeled in equations (7) and (8).

$$p_t^{fl}=\sum_{\tau=t-t_{fl}+1}^{t}\upsilon_\tau^{fl}\cdot P^{fl} \tag{7}$$

$$\sum_{\tau=t_0}^{t_{end}-t_{fl}}\upsilon_\tau^{fl}=1 \tag{8}$$

where p_t^{fl} is a continuous variable indicating the shifted power of flexible load at time slot t; υ_τ^{fl} is a binary variable showing the startup state of the flexible load; t_{fl} denotes the actual continuous working time of the flexible load; P^{fl} is the total shiftable volume that flexible load aggregators submit in the BM; $[t_0,\ t_{end}]$ is the shiftable time interval. Equation (7) demonstrates that the shifted power is equal to P^{fl} if the time slot t is within $[t_0+t_{fl}-1,t_{end}-t_{fl}]$. Equation (8) indicates that the load can be turned on only once during the available working time interval.

- Adjustable Capacity

Power flexibility means that the load volumes are adjustable within a range, which is modeled as follows:

$$c_{t,u}^{fl}=min\{p_{max}^{fl}-p_t^{fl},(E_{end}^{fl}-e_t^{fl})/DT\} \tag{9}$$

$$c_{t,d}^{fl}=p_t^{fl}-p_{min}^{fl} \tag{10}$$

$$e_t^{fl}=\sum_{\tau=1}^{t}p_\tau^{fl}\cdot\eta^{fl}\cdot DT \tag{11}$$

where e_t^{fl} is the total energy stored in EV or BESS; $c_{t,u}^{fl}$ and $c_{t,d}^{fl}$ are the adjustable capacity. Equation (9) indicates that the upward consumption capacity depends on the maximum charging power and the energy constraints of EV and BESS. Equation (10) demonstrates that the downward capacity depends only on the minimum charging power. Equation (11) indicates that the total stored energy is subject to the duration of the charging period, efficiency and power.

C. Carbon Emission Pricing for Flexible Resources

Apart from the physical characteristics of flexible resources in the BM, their economic efficiency and carbon footprint are also different. This part accommodates carbon emission pricing for dispatchable generators and flexible loads to incentivize decarbonized BM actions.

1) Flexible Generators

Unlike the DA market in which the carbon intensity is directly integrated into E-SRMC, the BM accepts both bids (i.e., decrease in generation/downward regulation) and offers (i.e., increase in generation/upward regulation) from flexible generators. The low carbon economy entails that the offers of low carbon-intensity generators are favored, while the bids of high carbon-intensity generators are preferred. Additionally, compared with normal operation, emissions have been found to spike, sometimes dramatically when the generators are started up and shut down [29] due to complicated reasons, e.g., 'memory effect'. The following equations are formulated for flexible generators to fairly capture their carbon emissions during normal, startup and shutdown operation.

$$E_{m_g}^t(\Delta P_g) = E_{m_g}^n(\Delta P_g) + E_{m_g}^{su}(\Delta P_g) + E_{m_g}^{sd}(\Delta P_g) \tag{12}$$

$$C_{car_g}^{BM}(\Delta P_g) = E_{m_g}^t(\Delta P_g) * c_{tax} \tag{13}$$

where $E_{m_g}^n$, $E_{m_g}^{su}$, $E_{m_g}^{sd}$ are the normal, startup and shutdown emissions of generator g due to output variation ΔP_g; $E_{m_g}^t$ is the total carbon emissions during the BM period; $C_{car_g}^{BM}$ is the carbon cost of upward or downward generation ΔP. Equation (12) indicates the total emission from the three operation modes. Equation (13) calculates the total carbon emission cost.

The generator emissions under different operation modes are formulated in (14)-(16).

$$E_{m_g}^{su,sd}(\Delta P_g) = \Delta P_g * EF_E \tag{14}$$

$$EF_E = (EF_{avg} \times EEAF)/(1 - PCDE) \tag{15}$$

$$E_{m_g}^n(\Delta P_g) = \rho_g * \Delta P_g \tag{16}$$

where $E_{m_g}^{su,sd}(\Delta P_g)$ (i.e., $E_{m_g}^{su}(\Delta P_g)$ or $E_{m_g}^{sd}(\Delta P_g)$) represents the actual carbon emissions of corresponding output increase or reduction during periods of startup or shutdown operation; EF_E is the adjusted emission factor; EF_{avg} is the average emission factor; $EEAF$ is the emission estimate adjustment factor; $PCDE$ is the pollution control device treatment efficiency.

Equation (14) represents that the actual emission change is the product of the adjusted emission factor EF_E and the corresponding production deviation ΔP_g. Equation (15) provides the emission calculation by modifying the normal emission factor for the abnormal periods by the efficiency of the control device. The carbon emission during startup and shutdown are calculated through the EEAF method in [30], as shown in equation (14) and (15). Equation (16) presents the carbon emission under normal operating conditions.

2) Flexible Load

As illustrated in Section B, the load flexibility can be categorized as shiftable load with flexible working time and adjustable load with flexible demand volumes. The total energy consumption for shiftable loads during the BM period remains unchanged regardless of the final operation schedule. Thus, their flexibility does not cause changes in the total greenhouse emissions, which can be mathematically expressed as below:

$$E_m^{sl} = 0 \tag{17}$$

$$C_{car_{sl}}^{BM} = 0 \tag{18}$$

where E_m^{sl} is the total carbon emission change of shiftable loads before and after BM; $C_{car_{al}}^{BM}$ is the corresponding carbon cost. In comparison, the adjustable load can induce a variation of demand consumption. Thus, the carbon emission will accordingly change after BM. The carbon emission flow (CEF) model [31] is used to denote the node carbon intensity by proportionally allocating the carbon emissions from the energy generation to the demand side, which can be expressed as shown in (19).

$$NCI_b = \frac{\sum_{g\in\Omega^G} P_0(g) * \rho_g + \sum_{j:(b,j)\in\Omega_b^{L+}} |f_{bj}|\, \rho_{bj}^{Line}}{\sum_{g\in\Omega^G} P_0(g) + \sum_{j:(b,j)\in\Omega_b^{L+}} |f_{bj}|} \tag{19}$$

where NCI_b is the carbon intensity of node b; Ω_b^{L+} is the set of transmission lines that inject active power into bus b; $P_0(g)$ is the power output of generator g in the DA market; ρ_g is the emission intensity of generator g; f_{bj} is the power flow from bus b to j; ρ_{bj}^{Line} is the branch carbon intensity, i.e., the emissions per MWh along the power flow of the line $b - j$. All transmission lines share the same assumption that the branch carbon intensity ρ_{bj}^{Line} outflowing from a bus is equal to the node carbon intensity (NCI) of that bus [31], as illustrated in (20).

$$\rho_{bj}^{Line} = \begin{cases} NCI_b, & if\ f_{bj} > 0 \\ NCI_j, & if\ f_{bj} < 0 \end{cases} \tag{20}$$

Thus, the changed carbon emissions of adjustable loads due to demand variation ΔD_b and the related costs can be calculated through equations (21) and (22), respectively.

$$E_{m,b}^{al}(\Delta D_b) = \Delta D_b * NCI_b \tag{21}$$

$$C_{car_{al}}^{BM}(\Delta D_b) = E_{m_{al}}^t(\Delta D_b) * c_{tax} \tag{22}$$

where $E_{m,b}^{al}(\Delta D_b)$ and $C_{car_{al}}^{BM}(\Delta D_b)$ are the emission and cost changes, respectively.

D. Bid/offer Prices in the Balancing Market

The real-time bid/offer prices show the desired prices to reduce/increase output for flexible generators or increase/reduce demand for flexible load aggregators in the BM. They are the sum of the operation and carbon costs or incentives. The operation cost is formulated based on the bid/offer multipliers that National Grid introduces in the BID3 that is an economic dispatch optimization tool presented in [32]. The carbon costs and incentives for flexible generators, shiftable loads and adjustable loads can be calculated through equations (13), (18) and (22), respectively. Considering their economic and environmental values, their final bid/offer prices are modeled in (23) and (24).

$$p_{bid}^{BM} = \left(\frac{C_f}{\mu} + C_{var} + UoS\right) * M_{bid} + C_{car}^{BM} \tag{23}$$

$$p_{offer}^{BM} = \left(\frac{C_f}{\mu} + C_{var} + UoS\right) * M_{off} + C_{car}^{BM} \tag{24}$$

where M_{bid} and M_{off} are the bid/offer multipliers. The first term indicates that the operation cost is the product of SRMC and the multiplier. The second term denotes the carbon costs or incentives. To parameterize multipliers for different flexible resources, this paper utilizes historical data of balancing actions by the system operator (SO). The selected five years of data include bid/offer volumes and costs from 2011/12 to 2015/16 [32]. The multipliers are calculated in different categories according to the flexibility types. By grouping every bid/offer action, they can be calculated as shown below:

$$M_{bid} = \frac{Yearly\ average\ bid\ cost}{Yearly\ average\ SRMC} \tag{25}$$

$$M_{off} = \frac{Yearly\ average\ offer\ cost}{Yearly\ average\ SRMC} \tag{26}$$

E. Uncertainty of Net Imbalance Volume

It is assumed that NIV is caused by the forecast error of variable generation, i.e., PV and wind. The resulting NIV can be positive or negative, referring to the power surplus or shortage, respectively. The cumulative expected method is used to capture the uncertain NIV to be balanced through BM, as shown below:

$$NIV_{p,b} = \int_0^{Ca_{d,b}} x \cdot f(x) \cdot T dx \tag{27}$$

$$NIV_{n,b} = \int_0^{Ca_{u,b}} x \cdot f(x) \cdot T dx \tag{28}$$

where $NIV_{p,b}$ and $NIV_{n,b}$ are the positive and negative cumulated expected NIV at bus b, respectively; $f(x)$ is the probability density function (PDF) of PV and wind forecast error; T is the duration of the scheduling time; $Ca_{d,b}$ and $Ca_{u,b}$ are downward and upward regulating capacity from flexible resources at bus b. The PDF of the generation forecast error is modeled as a normal distribution with zero means, i.e., $N\left(0, \sigma^2\right)$ [33].

III. Market Model Formulation

This section introduces the dual-stage framework composed of day-ahead and balancing markets. It is assumed that both markets operate at 30-minute intervals. In the first stage, generation capacity is dispatched in a least-cost fashion based on load forecasting. In the second stage, flexible generation and demand are re-dispatched to respect additional constraints, e.g., network constraints and NIV uncertainties.

A. DA Market

To align with the actual market models that are used by most European countries [34], this paper assumes that the transmission network constraints and constraints on generating units (i.e., startup, shutdown, and ramping constraints) are not taken into account in the DA market, but solved through BM actions. This clearing mechanism indicates that the energy balance is satisfied as long as the total generation meets the demand, regardless of their geographical location. Thus, the dispatch process is formulated as a least-cost unconstrained schedule (LCUS) problem, assuming that the power system can deliver electricity wherever it is needed. This process can also be considered as a merit order stack model that ranks and dispatches available generators in order of their submitted E-SRMC. Assuming that there are no transmission constraints, the objective of DA dispatch is to minimize the total electricity production cost considering power balance constraints, as shown below:

$$Min\ C_{DA}^t = \sum_g ESRMC(g) \cdot P_0^t(g), \forall g \in \Omega^G, \forall t \in \Omega^T \tag{29}$$

$$D^t = \sum_g P_0^t(g), \forall t \in \Omega^T \tag{30}$$

$$0 \le P_0^t(g) \le \bar{P}(g) \tag{31}$$

Equation (29) minimizes the total cost of all generators based on their E-SRMCs for each scheduling time interval. Constraint (30) ensures the power balance of the total generation output and the predicted demand. Constraint (31) enforces the power output limit of generators. According to the pay-as-clear rule, the DA price is determined through the most expensive generating set required to operate in each half-hour, i.e., the highest $E - SRMC(g)$ among those generators whose $P_0^t(g)$ are more than zero.

B. Balancing market

After DA schedules, the TSO (transmission system operator) operates a real-time redispatch process, e.g., a system balancing market [34]. System balancing refers to the process that a TSO ensures the energy balance in and close to real-time after the gate closure [35], considering both network constraints and forecast deviations in supply and demand. Deviations from the nomination of generators in the DA market, and load forecasting errors inevitably cause NIVs in the balancing market. Moreover, due to constraints on the transmission network, generation [32] should be restricted in some domains and increased in other areas to meet boundary constraints and maintain power balance. Therefore, the re-dispatch procedure not only supports the power balance, but also ensures a secure real-time operation of the power grid.

TSO aims to minimize the total balancing costs by transforming the day-ahead optimal schedules into real-time schedules to enable a secure grid operation. The binary variable δ is introduced to represent the regulation types (i.e., upward or downward) of flexible generators and DSF aggregators from a start position, i.e., the initial day-ahead schedule and load forecasting.

The objective function of BM is as shown in (32), i.e., minimizing the total cost to solve energy imbalance and system constraints.

$$Min\ C_{BM}^t = \sum_{g \in \Omega^{G^F} \cup \Omega^{FL}} p_{bid}^{BM} \cdot \left(P_r^t(g) - P_0^t(g)\right) \cdot (1-\delta) + p_{offer}^{BM} \cdot \left(P_r^t(g) - P_0^t(g)\right) \cdot \delta \tag{32}$$

The optimization model is subject to the operational constraints of flexible resources and system constraints. The former constraints have been demonstrated in equations (3)-(11) in Section II-B, while the system constraints are shown below:

$$\sum_{g \in \Omega^G} G_{bg} P_r^t(g) + \sum_{l \in \Omega^L} A_{bl} f_{l,t}^p = NIV_b + D_b^t, \forall b \in \Omega^B, \forall t \in \Omega^T \tag{33}$$

$$\sum_{g \in \Omega^G} G_{bg} Q_r^t(g) + \sum_{l \in \Omega^L} A_{bl} f_{l,t}^q = NIV_b + D_b^t, \forall b \in \Omega^B, \forall t \in \Omega^T \tag{34}$$

$$Re\{U_j(t)\} = |U_b(t)| - \frac{f_{b-j,t}^p \cdot r_{b-j} + f_{b-j,t}^q \cdot x_{b-j}}{|U_b(t)|}, \forall b, j \in \Omega^B, \forall t \in \Omega^T \tag{35}$$

$$Im\{U_j(t)\} = -\frac{f_{b-j,t}^p \cdot x_{b-j} - f_{b-j,t}^q \cdot r_{b-j}}{|U_b(t)|}, \forall b, j \in \Omega^B, \forall t \in \Omega^T \tag{36}$$

$$|U_j(t)| = \sqrt{Re\{U_j(t)\}^2 + Im\{U_j(t)\}^2}, \forall j \in \Omega^B \quad (37)$$

$$U^{min} \leq Re\{U_j(t)\} \leq U^{max} \quad (38)$$

$$-\overline{P_{flow}} \leq {P_{flow}}_l^t \leq \overline{P_{flow}}, \forall l \in \Omega^L \quad (39)$$

Constraints (33) and (34) ensure the nodal active and reactive power balance, respectively. Constraints (35)-(37) calculate the bus voltage magnitude of line $b-j$, while equation (38) demonstrates the boundary of voltage capacity, which is set to [0.95 pu, 1.05 pu]. Equation (39) illustrates the power capacity boundary for transmission lines.

Considering constraints (35)-(36) are nonconvex [14], they are simplified by assuming the voltage magnitude $U_b(t)$ as 1 p.u. and the bus voltage angle $Im\{U_b(t)\}$ as 0 rad. The constraints can be rewritten as shown in (40)-(41).

$$Re\{U_j(t)\} = Re\{U_b(t)\} - (f_{b-j,t}^p \cdot r_{b-j} + f_{b-j,t}^q \cdot x_{b-j}), \forall b, j \in \Omega^B, \forall t \in \Omega^T \quad (40)$$

$$Im\{U_j(t)\} = -(f_{b-j,t}^p \cdot x_{b-j} - f_{b-j,t}^q \cdot r_{b-j}), \forall b, j \in \Omega^B, \forall t \in \Omega^T \quad (41)$$

The dual-stage market model is implemented in Fig.1. The day-ahead dispatch market is cleared given the predicted demand, the bidding price and committed generating volumes of all generators. The optimal DA schedule is obtained through Merit Order. Flexible generators and load aggregators participate in the real-time balancing market through flexibility models and carbon-based bid/offer prices. Respecting system constraints and operational limits, the NIV is solved in real time to optimally redispatch flexible generators and DSF resources to minimize carbon emissions and balancing costs.

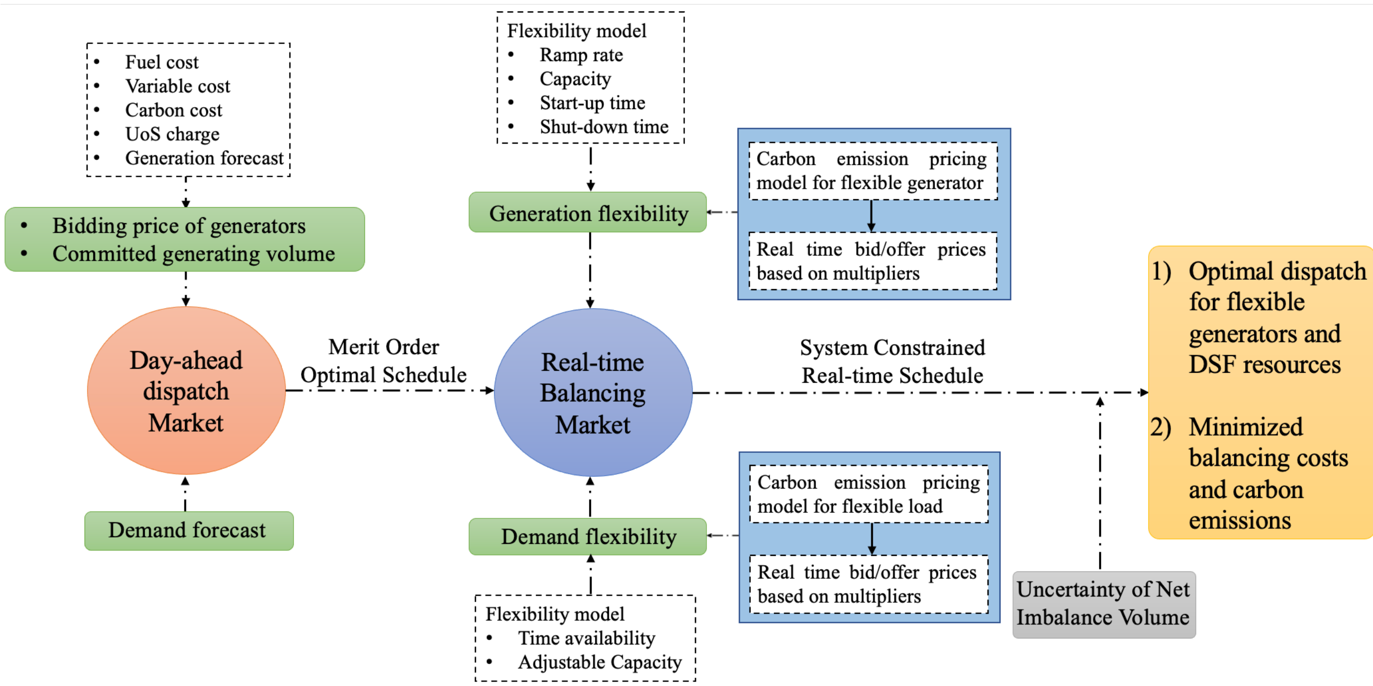

Fig. 1. Implementation of the proposed dual-stage market model

IV. Case Study

A. Test System Description and Modelling Parameters

The presented dual-stage market model is verified on a modified IEEE 39-bus system. The power system is supplied by coal-fired, OCGT (open cycle gas turbine), oil-fired, nuclear, PV, offshore and onshore wind, and biomass generating units. The total generation capacity is 8000 MW, while the average predicted demand is 6254.2 MW. The aggregated shiftable loads are located at buses 1-5, while the fully adjustable loads are at buses 6-10. Their parameters are listed in Table I-II. The predicted daily generation curves of PV, offshore and onshore wind turbines are shown in Fig. 2. The offshore and onshore wind generators dominate the overall renewable energy supply.

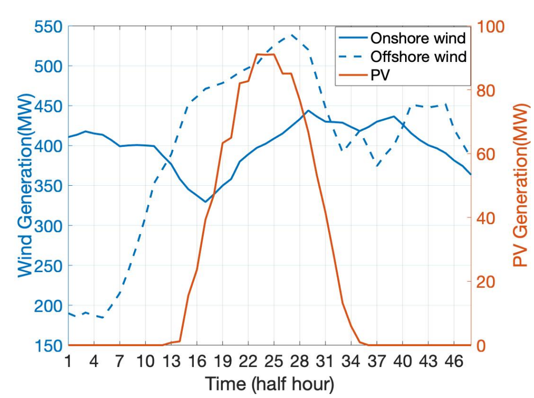

Fig. 2. Day-ahead forecast power of PV, offshore and onshore wind turbines

TABLE I
Parameters of Adjustable Load

Parameter	AL1	AL2	AL3	AL4	AL5
Upper adjustable limits (MW)	500	400	500	440	500

Lower adjustable limits (MW)	-200	-300	-500	-440	-500

TABLE II
PARAMETERS OF SHIFTABLE LOAD

Parameter	SL1	SL2	SL3	SL4	SL5
Power (MW)	200	350	500	440	450
Energy (MWh)	40	50	30	40	30
Available period (half hour-half hour)	8-20	12-40	10-36	8-44	12-40

B. *Bid-offer Pairs in the Dual Markets*

The E-SRMC for thermal and renewable generators are calculated according to equation (1) and demonstrated in Table III. The table shows that E-SRMC consists of efficiency-adjusted fuel cost, non-fuel variable cost, UoS and carbon price. The non-fuel variable cost for PV and wind are calculated by referring to the Renewables Obligation Annual Report [36]. In terms of other generators, their variable costs are defined from the renewable energy subsidies as illustrated in Electricity Generation Costs [37]. It is assumed that the UoS charge is the same for all generators. Since the fuel cost and the variable cost for PV and wind generating units are zero, they have very low bidding prices in the DA market. Developed from E-SRMC and empirical multipliers, the bid/offer prices in the BM are time-variant. They do not reflect any imbalance exposure but would reflect fuel, variable and carbon costs, etc. Since the downward regulation of fully flexible generators contributes to carbon reduction, the final bid price paid to SO is lower than that without considering carbon emissions over rescheduling. Comparably, the final offer price that these generators would be paid by SO to increase their output exceeds the offer price bypassing carbon costs in the BM. WTs do not participate in the BM as fully flexible resources. Instead, they only have the capability to reduce generation with a loss of Renewable Obligation Certificates (ROCs).

TABLE III
E-SRMC FOR DIFFERENT GENERATION TYPES IN THE DA MARKET

Generator	Efficiency-adjusted fuel cost (£/MWh)	Non-Fuel variable cost (£/MWh)	TNUoS (£/MWh)	Carbon price (£/MWh)	E-SRMC (£/MWh)
Coal G1	2.22	3.38	1.53	16	23.13
OCGT G2	2.88	0.08	1.53	8	12.49
Oil G3	15.38	1	1.53	15	32.9
Nuclear G4	0	2.5	1.53	0.02	4.05
Onshore wind G5	0	-42.45	1.53	0.02	-40.9
Offshore wind G6	0	-86.45	1.53	0.02	-84.9
PV G7	0	-86.37	1.53	0.1	-84.74
Biomass G8	0	1.4	1.53	1.8	4.74

C. *Dispatch and Redispatch Results*

Based on the PDF of predicted demand errors, the net imbalance volumes are simulated based on the PDF of generation forecast errors with variable regulating capacities. Fig. 3. demonstrates the cumulative expected NIV with varying regulating capacities and different forecast errors, i.e., sigma σ. As the standard deviations of the normally distributed forecast errors increase, the cumulative expected NIV also grows remarkably, especially when the downward regulating capacity varies between 3 MW to 30 MW.

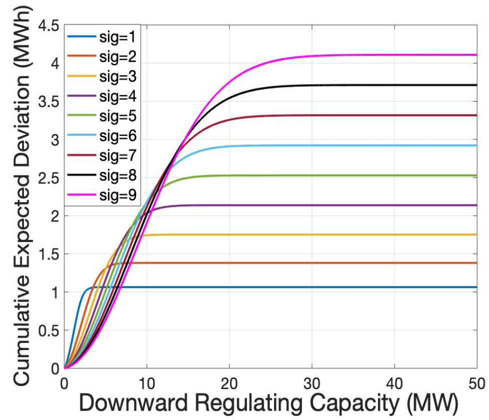

Fig. 3. Cumulative expected NIV with different forecast errors

Setting σ as 3 [28], Fig. 4. demonstrates the DA prices with variable renewable shares in the total energy mix. Higher renewable penetration remarkably reduces the DA price as expected, especially during the time slots of [1,7], [11,18], and [40,48]. Results explicitly indicate the contribution of different proportions of renewable penetration to the DA price reduction. For instance, with the penetration rate increasing from 90% to 100%, the average DA system price falls mainly due to that the price reduction over the time periods of [30,31], [41,42] and [45,47].

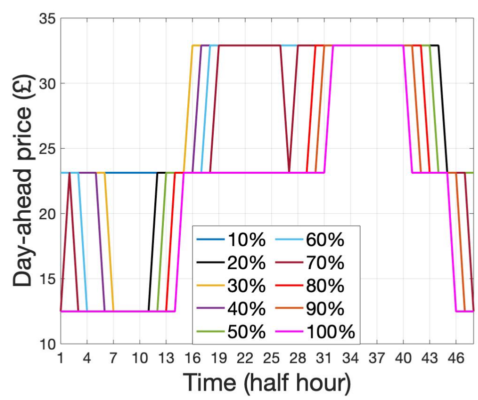

Fig. 4. DA price with variable renewable penetrations

The redispatch results in the BM reflect real-time supply and demand. If the power system is short of supply (i.e., positive NIV), the SO will accept more offers (including upward generation and flexible load reduction) than bids. More bids will be accepted at negative NIV when the system is long.

Without respect of the carbon footprint of balancing actions, the redispatch results of the traditional market model are as shown in Fig. 5, including generators G1-G8, shiftable loads SL1-SL5, and fully adjustable loads AL1-AL5. They are painted in different colors in the bar graph to show their contributions to real-time energy balance. NIV is demonstrated through the line chart. As shown in the figure, when NIV is positive, coal generator G1, OCGT G2, oil generator G3, fully adjustable loads AL3, AL4, AL5, and shiftable loads SL2 are the main resources to make up the shortfall. In comparison, OCGT G2, oil generator G3, biomass generator G8, and shiftable loads SL2, SL3, SL4 mainly contribute to balancing negative NIV. Due to the time distribution features of shiftable loads and their carbon-neutral footprint, they are frequently dispatched over the time slot [9,40].

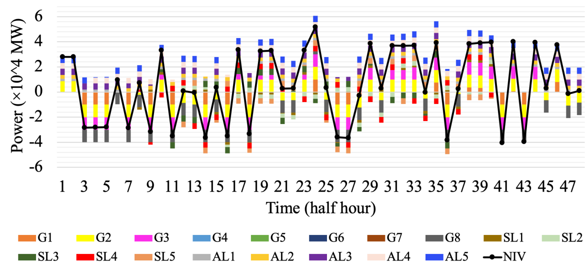

Fig. 5. Balancing actions with no carbon signals in the traditional market model

Considering the diversity of balancing actions in carbon emissions, the redispatch results in the BM are as shown in Fig. 6. It can be found in the figure that adjustable and shiftable loads are more frequently used to compensate for bi-directional NIV. The bids of carbon-intensive generators (i.e., coal-fueled generator G1 and oil-fueled generator G3) are more likely to be accepted at negative NIV. At the same time, their offers are disfavored at positive NIV. Compared to the traditional BM, the volumes of offers for the environmental-friendly nuclear generator G4 are increased, while bids are reduced. In terms of renewables, PV generator G7 is non-dispatchable in the BM. Wind generators G5 and G6 only possess the capacity for downregulation. The accepted bids are reduced due to their negative impacts on carbon reduction.

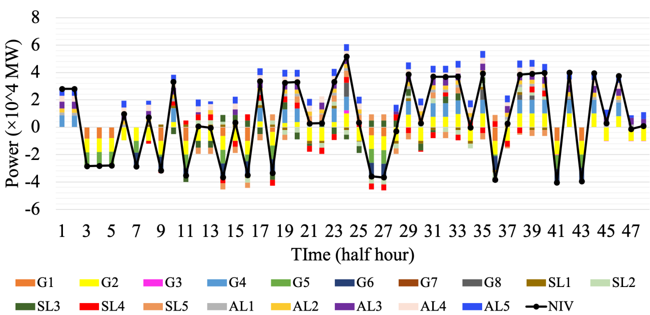

Fig. 6. Balancing actions considering carbon signals in the proposed market model

Fig. 7. demonstrates the volume changes of accepted bids/offers in the proposed market compared to the traditional market. It can be seen that in the proposed market, more offers are accepted for G4, G8, while more bids are accepted for G1, G2, AL1, AL2, AL3, AL4, AL5 over the whole scheduling period. It suggests that the proposed market model prefers upward regulation of nuclear and biomass generation and downward output regulation of coal and OCGT generation. Additionally, the proposed BM shows bi-directional preferences in G3, G7, SL1, SL2, SL3, SL4, SL5, depending on the scheduling time slots.

The carbon cost variance from the proposed market model is demonstrated in Fig. 8 to verify the performance of the proposed market model from a carbon point of view. As shown in Fig. 8, the carbon cost reduction varies over the scheduling period, with the highest values of nearly 20 m£ at time points 24 and 35. At time points 6, 14, 28, and 41, the emission costs show marginal declines, less than one m£. Over the scheduling time points 4, 5, 6, 8, 28, and 47, G1, G3, AL4, and AL5 increase the carbon cost slightly. OCGT G2, Oil generator G3, wind generator G4, biomass generator G8 provide the greatest contribution to carbon reduction in the BM.

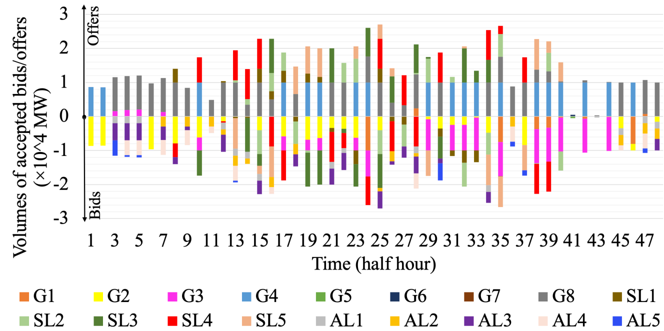

Fig. 7. Volume changes of accepted bids/offers in the proposed market compared to the traditional market

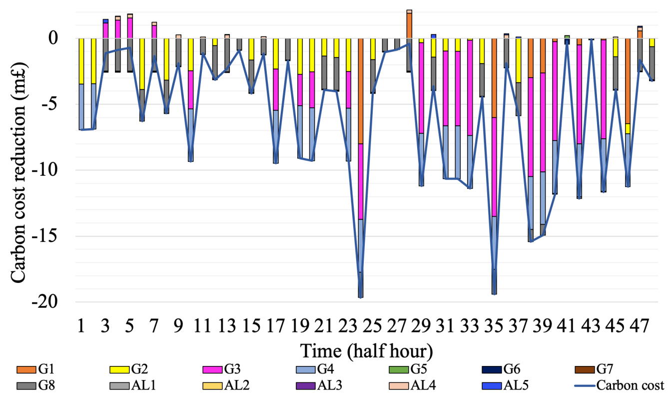

Fig. 8. Carbon cost reduction of the proposed market model

Table IV presents the total cost variance of the proposed BM mechanism and the traditional model. It verifies both the economical and environmental performances of the proposed market model. It can be found that the balancing cost of generators increases by 159.10 m£, while their carbon cost drops by 294.14 m£. The total cost of generators in BM decreases by 135.04 m£. Flexible loads' balancing and carbon costs do not change significantly, with -0.16 m£ and 2.04 m£, respectively. Their total cost increases by 1.88 m£. Overall, the total balancing cost of all participants increase by 158.94 m£, while the total carbon cost decreases by 134.84 m£. Results suggest that the proposed BM mechanism outperforms the traditional model by striking a balance between cost-efficiency and environmental benefits.

TABLE IV
TOTAL COST VARIANCE OF THE PROPOSED MARKET MODEL

Cost variance	Generators	Flexible loads	All Participants
Balancing cost (m£)	159.10	-0.16	158.94
Carbon cost (m£)	-294.14	2.04	-292.10
Total cost (m£)	-135.04	1.88	-134.84

V. CONCLUSION

High renewable penetration in the wholesale electricity market and resulting carbon-intensive balancing actions have conflicting environmental impacts. To coordinate the emissions reduction in both markets, this paper designs a novel market model that optimizes the economic and environmental costs of balancing actions in response to intermittent and uncertain generation. Unlike existing operation models, it leverages market measures to decarbonize the power sector by integrating real-time carbon signals into the bidding strategy. The performance of the proposed method is validated in a modified 39-bus power system. Results show that the total emissions from balancing services are transparently reduced by coordinating dispatchable generators, fully adjustable loads and shiftable loads. The proposed market model strikes the appropriate balance between climate ambition and the requirement to deliver cost-effective decarbonization of the power sector. It enables SOs to apply carbon factors in balancing services procurement and dispatch.

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