Carbon-Oriented Operational Planning in Coupled Electricity and Emission Trading Markets

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***Abstract*—Carbon financing policies such as emission trading have been used to assist in emission mitigation worldwide. As energy end-users/consumers are the underlying driver of emissions, it would be difficult to effectively mitigate carbon emissions by creating an emission trading market without active end-users' involvement. In electricity markets, demand side management (DSM) in the smart grid can manage demands in response to power supply conditions and influence end-users to contribute to improving both network efficiency and economic efficiency. However, it is a relatively new topic to study the environmental benefits of DSM. This paper proposes a two-stage scheduling model to comprehensively investigate the environmental benefits of consumers participating in both electricity and carbon emission trading markets through active DSM. A developed zero sum gains-data envelopment analysis (ZSG-DEA) model based multi-criteria allocation scheme for emission allocation is employed. Meanwhile, the carbon emission flow model (CEF) is applied to track the "virtual" carbon flow accompanying power flow. According to case studies on the IEEE 24-bus system and IEEE 118-bus system, the proposed model can effectively achieve carbon emission mitigation and provide consumers extra environmental benefits in some scenarios. This model can be an important guide for governments to establish emission trading schemes.**

***Index Terms*—Low-carbon economy, emission market, climate change policy, energy economics, demand side management.**

NOMENCLATURE

Indices and Sets

d	Index of time periods for the carbon trading market
k, Ω_G	Index and set of generators in the electricity network
m, Ω_D	Index and set of demand bus in the electricity network
t	Index of time periods for electricity market
n	Index of electricity network nodes
ℓ	Index of branches in the electricity network
$f^+,\ f^-$	Set of branches with inflow power and outflow power

Parameters

a, b	First, second order coefficients of utility function
a_k, b_k, c_k	First, second, third order cost coefficients of power generator k
C_R	Capital recover factor for PV
e_{Gn}	Carbon intensity for generator injected power to bus n
$E_{Dm}^{Cap}, E_{Gk}^{Cap}$	Carbon dioxide emission allowance for demand bus m and carbon dioxide emission allowance for generator k
O_{ZSG}	Minimum DEA efficiency of DMU i
T	Daily operational horizon, with index of time t
y_m	Quantified principles of equity, efficiency, feasibility, and sustainability for DMU m
$\hbar$	Time range that demand adjustment is subject to the impact of price
Δt	Time interval
α_0	Parameter of residual term in EGARCH model
α_1	Innovation parameter
α_i, α_j	Fixed influence coefficient of electricity price for consumers at time i and time j
β_0, β_1	Coefficients of the variance term in EGARCH model
β_2	Asymmetric parameter in EGARCH model
β_t	Influence coefficient of electricity price for consumers at time t
η_{pv}	Efficiency for solar energy conversion
θ	Coefficient of the autoregressive term
$\bar{\mu}_{r,k,t}, \underline{\mu}_{r,k,t}$	Lagrange multipliers associated with bounds of generator k at time t
$\bar{\mu}_{Qs,\ell,t}, \underline{\mu}_{Qs,\ell,t}$	Lagrange multipliers associated with bounds of branch ℓ at time t
τ_{pv}	Unit price for PV panel
ω_i	Electricity price deviation at time i
ϖ	Solar radiation for PV panel

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$Ramp_{Gk}^{Up}$	Ramp-up rate limit for generator k
$Ramp_{Gk}^{Down}$	Ramp-down rate limit for generator k
$\overline{(\bullet)}$, $\underline{(\bullet)}$	Upper and lower bounds

Variables

A_{ci}	Attraction of electricity price for consumers at time i
D_{ci}, D_i	Demand amount of commodity c at time i and total demand amount for similar commodity including c at i
e, e_n	Nodal carbon intensity, nodal carbon intensity for bus n
$e_{Dm,t}$	Carbon intensity for demand bus m at time t
e_{Gk}	Carbon intensity for generator k
$E_{Gk,t}$	Carbon emission amount emitted by generator k time at t
$E_{Dm,t}$	Virtual carbon emission amount at demand bus m time t
P_{Gn}	Inflow power from generator into bus n
P_n	Power flow in branch n
$P'_{Dm,t}$	Power demand amount of bus m before demand response at time t
$P_{Dm,t-1}$, $P_{Dm,t}$	Power demand amount of bus m after demand response at time $t-1$ and t
$P_{Gk,t}$	Power output from generator k at time t
$P_{Gs,t}$	Output power of marginal generator at time t
$P_{pv,t}$	Power output from PV at time t
$P_{\ell,t}$	Power flow in branch ℓ at time t
Q, ΔQ	Purchase amount of commodity associated with price λ and changing purchase amount
Q_i, Q_j	Purchase amount of electricity at time i and time j
r_d, r_{d-1}	Carbon emission revenue from carbon trading market at time d and $d-1$
R	Virtual carbon dioxide emission flow
S_{ci}	Sharing proportion of commodity c at time i
w_m	Weight for the decision marking unit (DMU) m
$\Delta P_{Dm,t}$	Demand response amount for bus m at time t
σ_d, σ_{d-1}	The conditional variance of EGARCH model at time d and time $d-1$
δ_k^{avg}, δ_m^{avg}	Average of predicted carbon price for generator k and demand bus m
ε_{ii}, ε_{ij}	Self-elasticity coefficient, and cross-elasticity coefficient subjected to dynamic price at related time i and j
κ	Efficiency of data envelopment analysis for i th decision marking unit (DMU)
λ, $\Delta\lambda$	Commodity price and changing price
λ_t, λ_i, λ_j	Electricity price at time t, time i and time j
$\lambda_{m,t}$	Electricity price of demand bus m at time t
$\mu_{c,t}$	Marginal price of generators at time t
ν_d	Sequence of random variables following normal white noise distribution
ρ_n, $\rho_{f_\ell^-}$	Branch carbon intensity for branch n and branch carbon intensity for outflow branch f_ℓ^-
φ_k^ℓ, φ_m^ℓ	Injection shift factor (ISF) for bus k and bus m in branch ℓ
ψ_{km}^ℓ	PTDF in branch ℓ from bus k to bus m
χ_m	Numbers of PV installed at bus m
$temp$	Local temperature

Matrices

$\boldsymbol{P}_{Inj}$	Vector for power injection or withdrawal
$\boldsymbol{A}$	Matrix for branch to node incidence with vector $\boldsymbol{a}_\ell^T$
$\boldsymbol{B'}$	Matrix for diagonal branch susceptance with vector $\boldsymbol{b}_\ell$
$\boldsymbol{S}$	Matrix for reduced nodal susceptance
$\boldsymbol{\varepsilon}$	Elasticity Matrix including self-elasticity coefficient and cross-elasticity coefficient
$\boldsymbol{\varphi}$	Matrix for injection shift factor

I. Introduction

Fossil fuel consumed by power generators is one of the main reasons contributing to carbon emissions in the majority of countries around the world [1]. According to the studies on greenhouse gases emission (mainly carbon dioxide), over 40% of carbon emission is produced by fossil fuel combustion during the process of power generation [2]. Hence, the power sector is one of the biggest pollutants and emitters, which requires effective methods to consider carbon policies when optimizing power scheduling.

Most of the current carbon financing policies (e.g., carbon tax, carbon trading market) aim to utilize financial incentives to motive emission reduction. However, many existing research works focus on the "observed" emission, i.e., the interaction between power systems and carbon policies is considered from the generation perspective. For instance, Ref. [3] proposes an agent-based approach via Q-learning algorithm to model interactions between the carbon trading market and the electricity market, and carbon emission is regulated from generation side. Carbon emission cost per unit of energy consumption is added as carbon price in [4]. In [5], financial cost and revenue from emission trading in the carbon trading market is considered in power system expansion planning. Under the cap-and-trade principle of carbon trading market, the carbon emission is formulated as an inequality constraint in [6]. The influence of different carbon prices on power systems has been investigated in [7], [8]. Refs. [9], [10] propose multi-objective functions, one of them is to minimize total carbon emission amount.

However, it has been criticized by many carbon pricing opponents that power generators would simply fully (or almost fully) pass-through carbon cost to energy end-users [11]. It should be noted that end-users are the underlying driver of emissions [12]. Therefore, carbon emission produced from generation side should be identified from the perspective of demand side. The concept of "virtual" carbon flow accompanying power

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flows has been introduced in [12]. Ref. [13] introduces a carbon emission flow (CEF) model in power electricity network in order to clarify the responsibility of end-users mathematically. Based on the concept and calculation of CEF model, a project in China has been demonstrated to evaluate benefits from the smart distribution grid under low-carbon orientation [14]. Further, a bi-level multi-energy system planning model with two market interaction is proposed in [15], CEF model is employed to calculate emission amount from demand side for regional emission constraints. Although the CEF model provides a more accurate perspective to calculate emission amount, all the studies mentioned above fail to involve active end-users/consumers.

By contrast, it is recognized that demand side management (DSM) in the smart grid can manage demands in response to power supply conditions and influence end-users to contribute to improving both network efficiency and economic efficiency. Existing DSM resources such as flexible loads, distributed generation and energy storage can provide various services to power systems by modifying load consumption patterns. In [16], a DSM model with fixed price elasticity is proposed under time-of-use (TOU) tariffs. However, this fixed price elasticity cannot fully present the consumption behaviors of consumers. A parametric utility model is proposed in [17], the price elasticity is formulated as a set of multi-dimensional demand-price functions. Ref. [18] introduces a price elasticity matrix with cross-elasticity, but the detailed calculation is not given.

To be the best of our knowledge, we are among the first to study the environmental benefits of DSM in coupled carbon trading market and electricity market. It should be noted that in this paper the timescale of emission trading is a day, which is different to the timescale of the studied power market (power dispatch timescale is an hour in this paper). Although the two markets have different timescales, carbon cost will be implicitly considered in power system scheduling; while power dispatch plans will also affect the cost or revenue related to carbon allowance. Moreover, the carbon emission allocation is an accumulative value for a power generator, (i.e., x ton per year). Our idea is to investigate the interactive impacts of accumulative profit or cost for power generators, looking at the two markets with different timescales, so as to achieve a long-term emission reduction target.

In reality, end-users are responsible for undertaking a certain fraction of the carbon cost, as the costs of power generation, transmission, distribution and carbon tax are already reflected in the retail electricity price that consumers pay. This fraction depends on the carbon cost pass-through rate. Please be noted that studying the carbon cost pass-through rate is out of the research scope of this paper. On the contrary, this paper aims to manage end-users' behavior to better mitigate carbon emission in a cost-reflective way, as they are the underlying driver of emissions, not the power generators.

Overall, this paper is of significance to study the refined carbon management and how to hand in emission allowances in a more cost-reflective way for the power sector. In other words, this paper can help power generators make cost-reflective dispatch plans in a carbon-constrained market environment.

Compared with the existing research, the novel contributions of this paper are threefold:

1) The feasibility of a double carbon taxation mechanism is investigated regarding its role as a supplement to the existing carbon trading principles. Further, the developed ZSG-DEA model based multi-criteria allocation is employed to reallocate emission allowance for end-users.

2) A developed demand response model with cross-elasticity consideration is proposed. Our model can better understand the underlying driver of carbon emissions in electricity markets. The detailed calculation based on energy economics theory is provided to reveal the relationship between demand change and dynamic electricity price at different correlated times.

3) A two-stage framework is proposed to comprehensively investigate the environmental benefits of end-users participating in both electricity and carbon trading markets through DSM. Also, Power Transfer Distribution Factor (PTDF) is utilized to calculate power dispatch subproblem. The carbon emission flow (CEF) model is employed to calculate detailed carbon flows and nodal emission intensities.

The remaining paper is organized as follows: in Section II, the double carbon taxation mechanism, CEF model and carbon price prediction model are discussed. Then the proposed framework of two-stage power scheduling is given in Section III. Section IV presents the carbon emission allocation problem solved by a developed ZSG-DEA model. Section V presents case study results. Finally, conclusions are given in the last section.

II. Double Carbon Taxation and Carbon Sub-Problems

A. Double Carbon Taxation Mechanism

Double carbon taxation refers to a taxation principle that carbon emission is taxed at both supply level and consumption level. Like the existing double taxation in economic theory, double carbon taxation definitely demonstrates the responsibility of emission. For example, there are many light industrial products (e.g., cloths) made in developing countries (e.g., China), but the majority of them are exported and consumed in developed countries (e.g., USA). It is always a big debate on which country should actually pay for the carbon cost. The "observed" emission occurs in developing countries, while demand of developed countries is the original cause of emission and the "virtual" emission should not be ignored. Overall, this philosophy holds the same for the power sector. Although emissions are physically produced by fossil fuel combustion at power generators, end-users are the underlying driver of emission. End-users should pay carbon cost for electricity consumption. However, it is unreasonable to simply pass-through the carbon cost to end-users, as this would make generators' responsibility in emission control vague. As an example, the double carbon taxation mechanism will be under trial in Shenzhen in China.

B. Carbon Emission Flow (CEF) Model

In order to trace carbon emissions from the generation side to the consumer side, a CEF model based on proportional sharing principle has been proposed in [12]. In this case, a "virtual"

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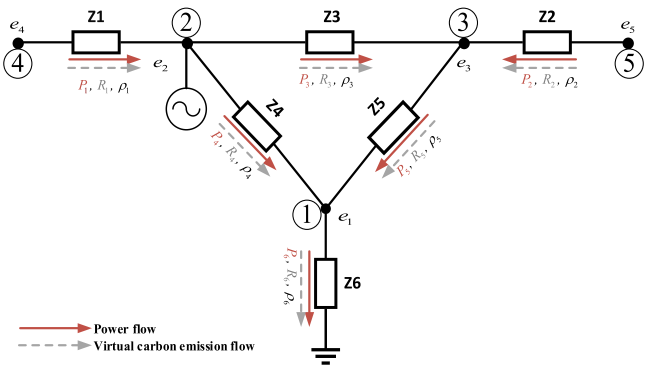

Fig. 1. CEF accompanying with power flow in power system.

emission flow accompanying power flow is introduced to clarify the footprint of carbon emission, as shown in Fig. 1.

According to [13], for a given node, its nodal carbon emission intensity e, only depends on the total inflow branch carbon emission flow and the ejected carbon emission flow from any generators at this node; all the outflow branches from this node share the same branch carbon emission flow intensity ρ, the value equals to nodal carbon intensity of node which they travel out. It should be noted that the proportional sharing principle (PSP) is the basic assumption for CEF model, which can linearize the relationship between power flow and the accompanying virtual emission flow. Moreover, in this paper, power loss over transmission line is not considered.

According to the PSP in [19] and [20], take the node 2 as an example, the nodal carbon intensity in a typical time can be calculated as:

$$\rho_3 = e_2 = \frac{P_1 \cdot \rho_1 + P_{G2} \cdot e_{G2}}{P_1 + P_{G2}} = \frac{R_1 + R_{G2}}{P_1 + P_{G2}} \tag{1}$$

where ρ_1, ρ_3 represent branch carbon emission flow intensity for branch 1 and branch 3, respectively; e_2 denotes nodal carbon emission flow intensity of node 2; e_{G2} denotes the carbon emission intensity of generation injected at node 2, which is generation 2; P_{G2} expresses the inflow power from generation 2; P_1 is the power flow in branch 1; R_1 is the virtual carbon flow accompanying P_1; R_{G2} describes the rate of carbon emission flow ejected from generation 2.

Extending node 2 to a general node n, and employ f^+, f^- representing the sets of branches with inflow power and outflow power, Gn refers to the generator at node n. The branch carbon emission flow intensity for an outflow branch f_ℓ^- can be expressed as:

$$\rho_{f_\ell^-} = \frac{\sum_{n \in f^+} P_n \cdot \rho_n + P_{Gn} \cdot e_{Gn}}{\sum_{n \in f^+} P_n + P_{Gn}} \tag{2}$$

Moreover, if power is consumed at node n, that power load can be represented as another outflowing branch. According to [12]–[14], for a large network with big renewable power generators, their carbon emission factors are set at zero. The big renewable generators centers are like hydro power plants which have zero emission intensity. On the contrary, for small and distributed renewable power generators like distributed PV generation, they are assumed to be non-dispatchable and modeled as a negative load.

Applying (2), as for a general node n at a N bus system, the nodal carbon emission intensity e_n can be calculated as:

$$e_n = \frac{\sum_{n \in f^+} P_n \cdot \rho_n + P_{Gn} \cdot e_{Gn}}{\sum_{n \in f^+} P_n + P_{Gn}} \tag{3}$$

where $\rho_{f_\ell^-}$ denotes carbon intensity for outflow branch f_ℓ^-; e_{Gn} represents the carbon intensity of generator injected power to bus n; ρ_n denotes the branch carbon intensity for branch n; P_n denotes the power flow in branch n; P_{Gn} denotes the inflow power from generator into bus n.

Further, we only consider the carbon emission at power supply and demand side. Therefore, based on the result of power flow, the carbon emission amount can be calculated based on equation (3) as:

$$E_{Dm,t} = P_{Dm,t} \cdot e_{Dm,t} \cdot \Delta t \tag{4}$$

$$E_{Gk,t} = P_{Gk,t} \cdot e_{Gk} \cdot \Delta t \tag{5}$$

where $E_{Dm,t}, P_{Dm,t}, e_{Dm,t}$ denote the emission amount, power consumpted, nodal emission intensity for demand m at time t, respectively; $E_{Gk,t}$, $P_{Gk,t}$, e_{Gk} is the emission amount, power output, nodal emission intensity for generator k at time t, respectively.

C. Carbon Price Prediction Model

This subsection employs the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) based on reference [21], [22] to build a dynamic carbon price prediction model considering features of carbon emission price in terms of fluctuation, asymmetry, leverage effect.

$$r_d = \ln \delta_d - \ln \delta_{d-1} \tag{6}$$

where r_d describes the carbon emission revenue at day d; δ_d, δ_{d-1} denote the carbon trading price at day d and $d-1$, respectively.

According to the EGARCH model, future carbon emission price can be predicted based on historical carbon price:

$$r_d = \beta_0 + \theta \cdot r_{d-1} + \gamma_d \tag{7}$$

$$\gamma_d = \sigma_d \cdot \nu_d \tag{8}$$

$$\ln \sigma_d^2 = \alpha_0 + \beta_1 \cdot \ln \sigma_{d-1}^2 + \alpha_1 \cdot \left(\left| \frac{\gamma_{d-1}}{\sigma_{d-1}} - \sqrt{\frac{2}{\pi}} \right| \right) + \beta_2 \cdot \frac{\gamma_{d-1}}{\sigma_{d-1}} \tag{9}$$

where α_1 denotes innovation parameter; β_0 and β_1 denote persistence parameters of sequence; β_2 is asymmetric parameter, θ is a constant less than 1; ν_d follows normal white noise distribution whose mean is 0 and variance is 1.

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III. Proposed Framework

A. DSM Model With Cross-Elasticity

Normally, consumers' demand would increase following the decrease in electricity price. In economic theory, elasticity coefficient, ε, is defined to describe the rate of this changing relationship, expressed as [23]:

$$\varepsilon = \frac{\frac{\Delta Q}{Q}}{\frac{\Delta \lambda}{\lambda}} = \frac{\lambda}{Q}\frac{\Delta Q}{\Delta \lambda} \tag{10}$$

where λ, $\Delta\ \lambda$ denote commodity price and changing price, respectively; Q, ΔQ denote purchase amount of commodity associated with price λ and changing purchase amount, respectively.

However, this relationship might be more complex in electricity markets. Taking TOU tariffs as an example, for the same consumer, demand change at time t is not only affected by the price at this time, also related to the price at the related time.

When considering the consumers' demand change caused by dynamic price during a time interval, an elasticity matrix including self-elasticity coefficient and cross-elasticity coefficient is necessary to describe the changing relationship [24].

$$\boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_{11} & \cdots & \varepsilon_{1j} & & \varepsilon_{1J} \\ \vdots & & \vdots & & \vdots \\ \varepsilon_{i1} & \cdots & \varepsilon_{ij} & \cdots & \varepsilon_{iJ} \\ \vdots & & \vdots & & \vdots \\ \varepsilon_{I1} & \cdots & \varepsilon_{Ij} & \cdots & \varepsilon_{IJ} \end{pmatrix}$$

where,

$$\varepsilon_{ii} = \frac{\partial \lambda_i}{\lambda_i}\frac{Q_i}{\partial Q_i} \tag{11}$$

$$\varepsilon_{ij} = \frac{\partial \lambda_i}{\lambda_i}\frac{Q_j}{\partial Q_j} \tag{12}$$

Market Share Model (MSD) and Discrete Attraction Model (DAM) are usually used to analyze the relationship between demand of consumers and attraction of commodities at different times mathematically. These two models can provide a methodology to investigate the calculation of elasticity matrix. MSD describes the sharing proportion for one commodity among similar commodities in a trading market:

$$S_{ci} = \frac{D_{ci}}{D_i} \tag{13}$$

$$D_i = \sum_{h=1}^{H} D_{hi} \tag{14}$$

where S_{ci} denotes the sharing proportion of commodity c at time i; D_{ci} denotes the demand amount of commodity c at time i; D_i denotes overall demand amount of similar commodities including c at time i; $h = 1, 2, \ldots, H$ denotes the amount of commodities.

Following MSD, DAM reveals that attraction of commodities to consumers is the key influence for its sharing proportion in the trading market. If one commodity has high attraction, it means this commodity would share more market proportion. In other words, demand amount of this commodity is massive. Therefore, according to the logic consistency principle, the problem of changing demand corresponding to various price can be carried out by switching the problems of attraction to price under combination models of MSD and DAM [25]. Note that price and attraction is also a negative correlation. Further, in electricity markets, low electricity price would lead to high attraction, and then the demand for electricity under this price would increase. This would share more market proportion for electricity under this price in the overall demand amount.

Equations (11) and (12) can be rewrite as:

$$\varepsilon_{ii} = \frac{\partial \lambda_i}{\lambda_i}\frac{Q_i}{\partial Q_i} = \frac{\partial D_{ci}}{D_{ci}}\frac{Q_i}{\partial Q_i} = \frac{\partial S_{ci}}{S_{ci}}\frac{Q_i}{\partial Q_i} \tag{15}$$

$$\varepsilon_{ij} = \frac{\partial \lambda_i}{\lambda_i}\frac{Q_j}{\partial Q_j} = \frac{\partial D_{ci}}{D_{ci}}\frac{Q_j}{\partial Q_j} = \frac{\partial S_{ci}}{S_{ci}}\frac{Q_j}{\partial Q_j} \tag{16}$$

$$\varepsilon_{ji} = \frac{\partial \lambda_j}{\lambda_j}\frac{Q_i}{\partial Q_i} = \frac{\partial D_{cj}}{D_{cj}}\frac{Q_i}{\partial Q_i} = \frac{\partial S_{cj}}{S_{cj}}\frac{Q_i}{\partial Q_i} \tag{17}$$

Multiplicative competitive interaction model (MCI) is utilized to build this problem.

Substitute attraction to the definition equation, market share proportion can be described as:

$$A_{ci} = e^{\alpha_i}\omega_i \prod_{t=1}^{T} \lambda_t^{\beta_t} \tag{18}$$

where $t = 1, 2, \cdots, T$; A_{ci} denotes the attraction of electricity price for consumers at time i; α_i is the fixed influence coefficient of electricity price for consumers at time i; λ_t is the electricity price at time t; ω_i is the electricity price deviation at time i; β_t is the influence coefficient of electricity price for consumers at time t.

Substitute equation (18) to (13),

$$S_{ci} = \frac{e^{\alpha_i}\omega_i \prod_{t=1}^{T} \lambda_t^{\beta_t}}{\sum_{j=1}^{T} e^{\alpha_j}\omega_j \prod_{t=1}^{T} \lambda_t^{\beta_t}} \tag{19}$$

where i, j are time point in the time interval T.

Substitute this back to equations (15)–(17), elasticity can be denoted as:

$$\varepsilon_{ii} = \beta_i (1 - S_{ci}) \tag{20}$$

$$\varepsilon_{ij} = -\beta_i S_{cj} \tag{21}$$

$$\varepsilon_{ji} = \beta_j S_{ci} \varepsilon_{ji} = \beta_j S_{ci} \tag{22}$$

The characteristics of natural logarithm can be utilized to simplify and linearize the above expression. Parameters α_t and β_t can be estimated by employing linear regression.

After obtaining the estimated elasticity coefficient, as a result of changing price, the amount of changing demand can be obtained. Normally, a quadratic function is used to describe this relationship [26], according to [24], a more accurate exponential function is illustrated as:

$$P_{Dm,t} = P_{Dm,t-1} \times e - \sum_{\hbar=-0.5T}^{0.5T} \varepsilon_{m,t+\hbar} \cdot \lambda_{t+\hbar} \tag{23}$$

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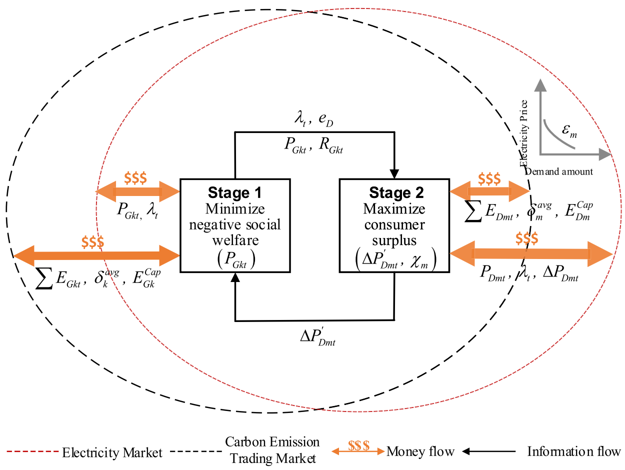

Fig. 2. The framework of proposed two-stage model.

where $P_{Dm,t}$, $P_{Dm,t-1}$ denote the demand amount at bus m at time $t, t-1$, respectively; T is the time interval; $\varepsilon_{m,t+\hbar}$ denotes the price elasticity coefficient of bus m at time $t+\hbar$; $\lambda_{t+\hbar}$ is the electricity price at time $t+\hbar$.

B. Proposed Two-Stage Scheduling Model

The following assumptions are considered in the proposed model:

1) Carbon emission is related to real power consumption and rarely effected by reactive power in power transmission. Both power flow and carbon flow analyses use DC power flows and ignore power and carbon losses in transmission lines.
2) We treat consumers as aggregated PQ loads which are managed by electricity retailers. These retailers will need to bid in the transmission-level power market to purchase electricity, and then sell electricity to end-consumers at retail prices.
3) PV installed at consumer side is considered as the primary renewable source in the proposed model.

The proposed framework is modeled as a two-stage scheduling problem, as shown in Fig. 2. At the first stage, there would be an optimization for social welfare in the electricity market. At the same time, the potential environmental revenue or cost for power generators is also considered. Compared to the initial stage, this step changes the local marginal price at buses of generators, which causes dynamic electricity price in the electricity market. Moreover, the emission intensity of each bus at demand side can be obtained by CEF model in Section II-B along with the optimal power flow at the first stage. At the second stage, as a result of dynamic electricity price, there would be a changing demand amount related to different characteristics of consumers. Afterwards, consumers can improve their satisfaction by optimizing cost including potential environmental benefits under the aforementioned double taxation mechanism in the carbon trading market. This optimization motivates consumers to cut demand with high emission intensity, a new demand amount of each consumer after DSM would be sent back to generation side to reschedule power output at the first stage. This procedure of two-stage iterates until the stop criterion is satisfied, e.g., convergence.

The first stage model is formulated as an objective function (24) that minimizes the negative social welfare in the electricity market and cost of generators in coupled electricity market and carbon trading market:

$$\min f_1$$
$$= \left\{ \begin{array}{l} \sum_{\text{Season}} \sum_{t=1}^{T} \underbrace{\sum_{k\in\Omega_G} C\left(P_{Gk,t}\right) - \sum_{m\in\Omega_D} U\left({P'}_{Dm,t}\right)}_{\text{Negative social welfare}} \\ \underbrace{+\sum_{k\in\Omega_G} \delta_k^{avg} \cdot \left(\sum_{\text{Season}} \sum_{t=1}^{T} E_{Gk,t} - E_{Gk}^{Cap} \right)}_{\text{Environmental revenue or cost}} \end{array} \right\} \tag{24}$$

s.t.

$$\underline{P}_{Gk} \leq P_{Gk,t} \leq \bar{P}_{Gk}, \quad \forall t \in 1:T, \ \forall k \in \Omega_G \tag{25}$$

$$\underline{P}_{\ell ine} \leq P_{\ell,t} \leq \bar{P}_{\ell ine}, \ \forall t \in 1:T, \ \forall \ell \in 1:L \tag{26}$$

$$\sum_{k\in\Omega_G} P_{Gk,t} = \sum_{m\in\Omega_D} {P'}_{Dm,t}, \quad \forall t \in 1:T \tag{27}$$

$$P'_{Dm,t} = P_{Dm,t} - \Delta P_{Dm,t} - P_{pv,t} \tag{28}$$

$$\begin{cases} P_{Gk,t} - P_{Gk,t-1} \leq Ramp_{Gk}^{Up}, & \text{if } P_{Gk,t} \geq P_{Gk,t-1} \\ P_{Gk,t-1} - P_{Gk,t} \leq Ramp_{Gk}^{Down}, & \text{if } P_{Gk,t-1} \geq P_{Gk,t} \end{cases} \tag{29}$$

$$C\left(P_{Gk,t}\right) = a_k \cdot p_{Gk,t}^2 + b_k \cdot P_{Gk,t} + c_k \tag{30}$$

Eqs. (5); (6)–(9)

where $C(P_{Gk,t})$ denotes the total operation cost of generators at time t, $U({P'}_{Dm,t})$ employs utility function to describe the satisfaction of consumers related to electricity amount purchase. In this paper, a piecewise function is used to model this purchase behavior of consumers. In the first step, consumers can be easily satisfied by increasing massive purchasing amount, so that a quadratic function is used to reveal the relationship between satisfaction of consumers and purchasing amount. In the second step, there is no more change of satisfaction by increasing the purchasing amount, therefore, it can be considered approximately as constant function with the value at vertex point of previous quadratic function. The overall utility function can be denoted as:

$$U\left(P'_{Dm,t}\right) = \begin{cases} b \cdot \left(P'_{Dm,t}\right) - a \cdot \left(P'_{Dm,t}\right)^2, & P'_{Dm,t} < \frac{b}{2a} \\ \frac{b^2}{2a}, & P'_{Dm,t} \geq \frac{b}{2a} \end{cases} \tag{31}$$

In the case of electricity trading, the difference between the cost of electricity purchase for consumers, $Z(P'_{Dm,t})$, and $C(P_{Gk,t})$ is the revenue for power generators. Moreover, benefits for consumers can be expressed via the difference between

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$U(P'_{Dm,t})$ and $Z(P'_{Dm,t})$. The social welfare S_w for both generation side and consumer side can be expressed as:

$$S_w = Z\left(P'_{Dm,t}\right) - C\left(P_{Gk,t}\right) + U\left(P'_{Dm,t}\right) - Z\left(P'_{Dm,t}\right) \tag{32}$$

The expression in first bracket in the objective function (24) describes the negative global social welfare in the electricity market.

Constraints (25)–(29) impose the power system related constraints; (25) and (29) denote the generators power output constraints and generation ramping constraints, respectively. Constraints (27), (28) ensure the power balance between supply and demand. Constraints (30) explains the operation cost for various generations at different time. Finally, equation (5) denotes the emission amount from CEF model. It should be noted that DC power flow constraints involving nodal power balance constraint and phase angle constraint must be satisfied. In this paper, power flow is carried out based on the *Power Transfer Distribution Factor (PTDF)*, details of *PTDF* will be introduced later.

Furthermore, the electricity price for each consumer can also be obtained by the result of optimal power flow at the first stage. The *Lagrange Multiplier method* is applied in this process. The Lagrange expression for the objective function under constraints can be illustrated as:

$$L(t) = \begin{Bmatrix} \sum_{\text{Season}} \sum_{t=1}^{T} \left[\sum_{k\in\Omega_G} C(P_{Gk,t}) - \sum_{m\in\Omega_D} U\left(P'_{Dm,t}\right)\right] \\ + \sum_{k\in\Omega_G} \delta_k^{avg} \cdot \left(\sum_{\text{Season}} \sum_{t=1}^{T} E_{Gk,t} - E_{Gk}^{Cap}\right) \\ + \sum_{k\in\Omega_G} \bar{\mu}_{r,k,t} \cdot \left(P_{Gk,t} - \bar{P}_{Gk,t}\right) \\ + \sum_{k\in\Omega_G} \underline{\mu}_{r,k,t} \cdot \left(\underline{P}_{Gk,t} - P_{Gk,t}\right) \\ + \sum_{\ell=1}^{L} \bar{\mu}_{Qs,\ell,t} \cdot \left(P_{\ell,t} - \bar{P}_{\ell ine}\right) \\ + \sum_{n=1}^{N} \underline{\mu}_{Qs,t} \cdot \left(\underline{P}_{\ell ine} - P_{\ell,t}\right) \\ + \mu_{c,t} \left(\sum_{k\in\Omega_G} P_{Gk,t} - \sum_{m\in\Omega_D} P'_{Dm,t}\right) \end{Bmatrix} \tag{33}$$

where $\bar{\mu}_{r,k,t}$, $\underline{\mu}_{r,k,t}$, $\bar{\mu}_{Qs,\ell,t}$, $\underline{\mu}_{Qs,\ell,t}$, $\mu_{c,t}$ represent Lagrange Multipliers associated with each of the constraints in (25), (26), (27) and (28), respectively. Here, $\mu_{c,t}$ can be considered as an incremental cost at generation side corresponding to the unit energy consumption at demand side, which means $\mu_{c,t}$ denotes the marginal price of generators. Moreover, based on this marginal price, nodal electricity price for each consumer can be obtained during the process of economic dispatch in a competitive circumstance.

According to equation (33), it is obvious to see that these two prices are related to the power output of generation and demand amount at different time. These two prices can be calculated by tracking the derivate of $L(t)$ concerning power output of the marginal generation and demand amount of each consumer.

Before that, define some functions to reduce the complexity of expression.

$$M\left(P_{Gk,t}\right) = \sum_{\text{Season}} \sum_{t=1}^{T} \sum_{k\in\Omega_G} C\left(P_{Gk,t}\right) \tag{34}$$

$$Y\left(P'_{Dm,t}\right) = \sum_{\text{Season}} \sum_{t=1}^{T} \sum_{m\in\Omega_D} U\left(P'_{Dm,t}\right) \tag{35}$$

$$B\left(E_{Gk,t}\right) = \sum_{k\in\Omega_G} \delta_k^{avg} \cdot \left(\sum_{\text{Season}} \sum_{t=1}^{T} E_{Gk,t} - E_{Gk}^{Cap}\right) \tag{36}$$

Therefore,

$$\frac{\partial L(t)}{\partial P_{Gs,t}} = \left[\frac{\partial M\left(P_{Gk,t}\right)}{\partial P_{Gs,t}} + \frac{\partial B\left(P_{Gk,t}\right)}{\partial P_{Gs,t}} + \bar{\mu}_{r,s,t} - \underline{\mu}_{r,s,t} + \sum_{\ell=1}^{L} \bar{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Gs,t}} - \sum_{\ell=1}^{L} \underline{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Gs,t}} - \mu_{c,t}\right] \tag{37}$$

$$\frac{\partial L(t)}{\partial P_{Dm,t}} = \left[-\frac{\partial Y\left(P'_{Dm,t}\right)}{\partial P_{Dm,t}} + \sum_{\ell=1}^{L} \bar{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Dm,t}} - \sum_{\ell=1}^{L} \underline{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Dm,t}} + \mu_{c,t}\right] \tag{38}$$

where $P_{Gs,t}$ denotes the output power of the marginal generation in network. The absolute value of first term on the right of equation (38) is nodal electricity price.

At last, simultaneous equations (37) and (38) at equilibrium point as value of zero, $\frac{\partial Y(P'_{Dm,t})}{\partial P_{Dm,t}}$ can be obtained:

$$\lambda_{m,t} = \frac{\partial Y\left(P'_{Dm,t}\right)}{\partial P_{Dm,t}} = \mu_{c,t} + x_{Qs,m,t} \tag{39}$$

where,

$$\mu_{c,t} = \left[\frac{\partial M\left(P_{Gk,t}\right)}{\partial P_{Gs,t}} + \frac{\partial B\left(P_{Gk,t}\right)}{\partial P_{Gs,t}} + \bar{\mu}_{r,s,t} - \underline{\mu}_{r,s,t} + \sum_{\ell=1}^{L} \bar{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Gs,t}} - \sum_{\ell=1}^{L} \underline{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Gs,t}}\right] \tag{40}$$

$$x_{Qs,m,t} = \sum_{\ell=1}^{L} \bar{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Dm,t}} - \sum_{\ell=1}^{L} \underline{\mu}_{Qs,\ell,t} \cdot \frac{\partial P_{\ell,t}}{\partial P_{Dm,t}} \tag{41}$$

For the calculation of DC power flow, *PTDF* is employed to reduce the complexity while remaining network topology but changing demand amount. Mathematically, *PTDF* can be calculated via Injection shift factor (ISF) at each node, which can be represented:

$$\psi_{km}^{\ell} = \varphi_k^{\ell} - \varphi_m^{\ell} \tag{42}$$

where φ_k^{ℓ} , φ_m^{ℓ} denote ISF in branch ℓ for generator bus k and demand bus m, respectively; $\boldsymbol{\varphi}$ denotes the ISF matrix with L row N column. This matrix can be obtained using (43), (44),

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(45) and (46).

$$\varphi = \boldsymbol{B}'\boldsymbol{A}\boldsymbol{S}^{-1} \tag{43}$$

where $\boldsymbol{B'}$ is a $L \times L$ diagonal branch susceptance matrix; $\boldsymbol{A}$ is a $L \times N$ branch to node incidence matrix and $\boldsymbol{S}$ is a $N \times N$ reduced nodal susceptance matrix. In matrix $\boldsymbol{A}$, In matrix $\boldsymbol{A}$, $\boldsymbol{a}_\ell^T$ is ℓth row where there exists a branch between node x and y, $\boldsymbol{a}_\ell^T = [0 \;\cdots\; 0 \;\overset{x}{1}\; 0 \;\cdots\; \overset{y}{-1} \;0 \;\cdots 0]$.

$$\boldsymbol{B}' = diag\left[\boldsymbol{b}_1, \boldsymbol{b}_2, \cdots, \boldsymbol{b}_L\right] \tag{44}$$

$$\boldsymbol{A} = \left[\boldsymbol{a}_1, \boldsymbol{a}_2, \cdots \boldsymbol{a}_L\right]^T \tag{45}$$

$$\boldsymbol{S} = \boldsymbol{A}^T\boldsymbol{B}'\boldsymbol{A} \tag{46}$$

Therefore, the power flow travels through branch ℓ can be obtained by the equation below:

$$P_{\ell,t} = \sum_{k\in\Omega_G}\sum_{m\in\Omega_D}\psi_{km}^{\ell}\cdot\boldsymbol{P}_{Inj}\left(P_{Gk,t},\; P_{Dm,t}\right) \tag{47}$$

where $\boldsymbol{P}_{Inj}(P_{Gk,t},\; P_{Dm,t})$ is the vector of power injection or withdrawal at nodes.

The second stage model is formulated as:

$$\max f_2 = \left\{\begin{array}{l} \sum_{\text{Season}}\sum_{t=1}^{T}\sum_{m\in\Omega_D} \\ \underbrace{\left[U\left(P_{Dm,t}-\Delta P_{Dm,t}\right)-\lambda_{m,t}\cdot\left(P_{Dm,t}-\Delta P_{Dm,t}\right)\right.}_{\text{Consumer surplus}} \\ +\underbrace{\lambda_{m,t}\cdot P_{pv,t}}_{\text{Revenue related to renewable source}} - \underbrace{C_R\cdot\chi_m\cdot\tau_{pv}}_{\text{Renewable source cost}} \\ -\underbrace{\sum_{m\in\Omega_D}\delta_m^{avg}\cdot\left(\sum_{\text{Season}}\sum_{t=1}^{T}E_{Dm,t}-E_{Dm}^{Cap}\right)}_{\text{Environmental revenue}} \end{array}\right\} \tag{48}$$

s.t.

$$\Delta P_{Dm,t} \leq \Delta\bar{P}_{Dm,t}, \quad \forall t\in 1:T,\ \forall m\in\Omega_D \tag{49}$$

$$0 \leq \chi_m \leq \bar{\chi}_m,\ \forall m\in\Omega_D \tag{50}$$

$$P_{pv,t} = \chi_m\cdot f\left(\text{temp, rad}\right) \tag{51}$$

$$f\left(\text{temp, rad}\right) = \eta_{pv}\cdot\varpi\cdot\left[1-0.005\cdot\left(\text{temp}\ -25\right)\right] \tag{52}$$

Eqs. (4); (6)–(9); (23); (39)–(41).

The objective function (48) maximizes the total revenue of consumers in coupled electricity market and carbon trading market. Constraints (49) imposes the demand changing constraint. Constraints (50)–(52) denote constraints related to renewable source, (51) and (52) introduce the power output of renewable at various time, (50) imposes the installation of renewable source constraint. Similar to stage one, (6)–(9) are used to obtain the carbon price. Equations (39)–(41) describe the dynamic electricity price. Equation (23) provides the changing demand amount. Finally, equation (4) denotes the "virtual" emission amount from CEF model.

TABLE I
MULTIPLE INDICATORS FOR ZSG-DEA MODEL

	Equity	Efficiency	Feasibility	Sustainability
Economy	Gross industrial output (GIO)	Energy intensity	Elasticity of energy consumption	
Society	Employment	Ratio of expenditure on R&D to GIO	Energy budget	Proportion of urban residence
Environment	Historical energy consumption			Renewable source installation

IV. CARBON EMISSION ALLOCATION

Carbon emission allocation has been under discussed since the establishment of carbon trading markets. As we use the cap-and-trade carbon policy. The carbon emission allowances for power generators are calculated based on the historical data. This method aligns with the existing carbon emission trading market mechanism in European Union. However, for the demand side, it is more reasonable to consider as many indicators as possible from an overall perspective. This is because that consumers may have different regional conditions from economic background to local social aspect. Compared to single-criterion, multi-criterion can accommodate a more systematic approach for how various indicators share the responsibilities to emission reduction in different aspects. Four principles involving equity, efficiency, feasibility and sustainability principles in [27] are applied in this section for emission allocation, as shown in Table I. Detailed indicators have been reconsidered from the energy sector perspective.

The zero sum gains-data envelopment analysis (ZSG-DEA) in [28] is applied in this paper. Detailed description can be found in [28], [29], [30]. The major advantage of this model is that it can bring all decision making units (DMUs) together into the DEA frontier without altering the overall carbon emission allocation. Basically, there would be a reduction for input of inefficient of a given DMU (e.g., carbon emission allocation for one consumer) by improving the DEA efficiency of this DMU, but other DMUs are supposed to take the redundant emission allocation to keep the overall allocation unchanged. Assume that the i th DMU, DMU_i, is an inefficient unit with its DEA efficiency of value κ, and its input inefficient carbon emission is E_i. To reach the DEA frontier, DMU_i has to reduce by $E_i\cdot(1-\kappa)$. Other DMUs would increase their carbon emission allocation to the weights, these weights can be denoted as $\frac{E_i\cdot(1-\kappa)}{\sum_{m=1,m\neq i}^{M}E_m}$. The inefficient DMUs would be reallocated until all reach the DEA frontier, the DEA efficiency of all DUMs will be equal to 1. Therefore, as the total emission amount is given to demand side in a power system, each consumer can be considered as a DMU. According to the individual indicators in four allocation principles. We have

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employed a developed ZSG-DEA model in reference [28] to allocate emission allowances E_{Dm}^{Cap} for different consumers.

The ZSG-DEA model is formulated as follows [28]:

$$O_{ZSG} = \min \kappa \tag{53}$$

s.t.

$$\sum_{m=1}^{M} w_m \cdot y_m^{equity} \geq y_i^{equity} \tag{54}$$

$$\sum_{m=1}^{M} w_m \cdot y_m^{efficiency} \geq y_i^{efficiency} \tag{55}$$

$$\sum_{m=1}^{M} w_m \cdot y_m^{feasibility} \geq y_i^{feasibility} \tag{56}$$

$$\sum_{m=1}^{M} w_m \cdot y_m^{sustainability} \geq y_i^{sustainability} \tag{57}$$

$$\sum_{m=1}^{M} w_m \cdot E_m \cdot \left[1 + \frac{E_i \cdot (1-\kappa)}{\sum_{m=1,m\neq i}^{M} E_m} \right] \leq \upsilon \cdot E_i \tag{58}$$

$$\sum_{m=1}^{M} w_m = 1 \tag{59}$$

$$w_m \geq 0, \quad \forall m \in \Omega_D \tag{60}$$

where κ denotes the DEA efficiency of DMUs, O_{ZSG} is the minimum DEA efficiency of DMU_i; w_m refers to the weight of DMU of m; E_m represents the initial carbon emission allocation as input; y_m^{equity}, $y_m^{efficiency}$, $y_m^{feasibility}$, $y_m^{sustainability}$ denote the quantified principles of equity, efficiency, feasibility and sustainability, respectively.

It should be noted that emission allocation is not the key focus of this paper, more information can be found in [28]–[30]. The key innovation of this paper is to investigate consumers' role in emission reduction through DSM, in order to better understand the underlying driver of carbon emissions in electricity markets.

V. Case Studies

The proposed model is verified on a modified IEEE 24-bus system and a modified IEEE 118-bus system. Electricity demand data are from the Australian Energy Market Operator website from 2015 to 2016 [31]. Moreover, the emission allocation and carbon price subproblem are based on [28] and the environmental strategy report provided by CSIRO [32].

The proposed two-stage model is verified using the following three cases:

Case 1: Traditional power scheduling with demand response based on price elasticity but without carbon pricing policy.

Case 2: Proposed two-stage scheduling model with DSM in coupled electricity and carbon trading markets.

Case 3: Proposed two-stage scheduling model with DSM in coupled two markets and with optimizing the PV installation on the consumer side.

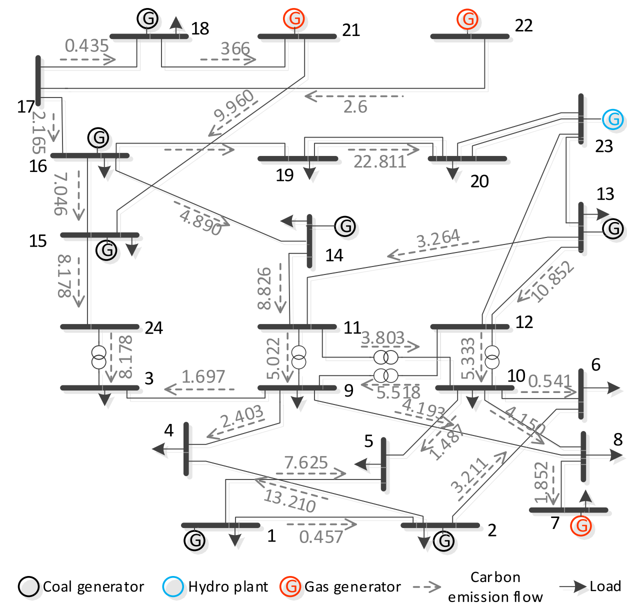

Fig. 3. Carbon emission flow for case 3 in the modified IEEE 24-bus system.

The sequential quadratic programming is applied to solve the two-stage optimization model on Matlab by a PC with an Intel Core (TM) i5-2400 CPU @ 3.10 GHZ with 4.00 GB RAM.

A. 24-bus System

The result of detailed carbon emission flow in a typical hour for case 3 is shown in Fig 3. The unit of carbon emission flow is ton. It is observed that there are renewable generators installed at demand buses after optimization. At this hour, the power output from renewable generators can not fulfill the load at demand buses. All branches have carbon emission flows excepted the three branches outflowing from the hydro plant. Therefore, no demand bus has zero carbon intensity in the electricity network, which means fossil generations are not totally replaced by clean energy.

Moreover, for bus 20, it is suspected to be zero emission intensity, since it is connected directly to a hydro plant, and its demand can be easily covered by the clean power. All the saving emission allocation can be sold in the carbon trading market. However, the result indicates that there is still a need for purchasing power from other coal generators under the economic objective of power dispatch. It is also proved the need to consider two coupled markets together.

The solution for two stages would converge after 14 times of iteration, Fig. 4 presents the details about base-ten logarithm of errors and convergence iterations for cases 2 and 3.

The dynamic electricity price in the electricity market for one typical day scheduling can be obtained as shown in Fig. 5. It is clear to see that the electricity price has a fluctuant trend in case 1. The highest value of price is almost four times higher than the lowest. However, for the cases with proposed two-stage low carbon-oriented DSM (case 2 and case 3), the waves of price become smoother, prices stay at around \$16/MWh, especially

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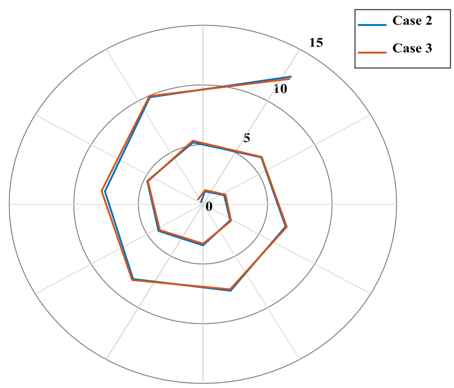

Fig. 4. Convergence analysis for iteration of two stages for 24-bus system.

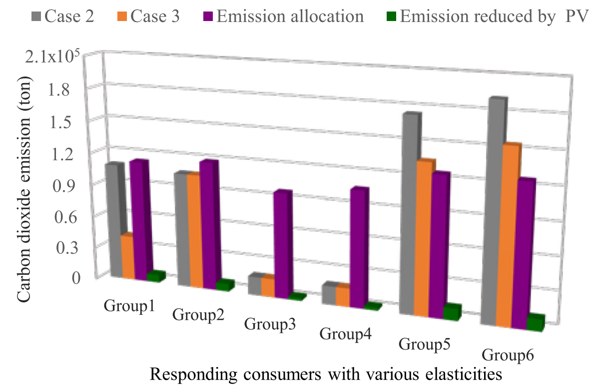

Fig. 6. Carbon dioxide emission of different groups in scenario 1.

Fig. 5. Dynamic electricity price in the electricity market.

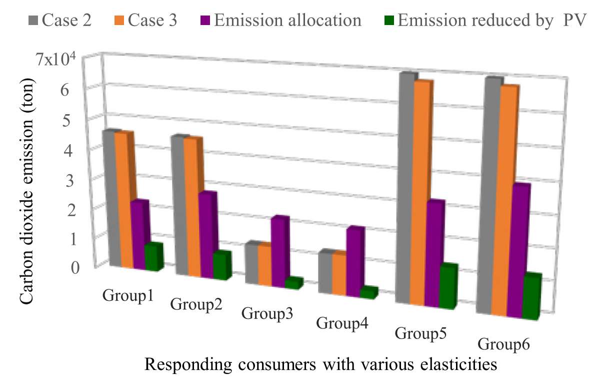

Fig. 7. Carbon dioxide emission of different groups in scenario 2.

for case 3 with PV installation in the system. Consumers with distributed PV do not absolutely depend on the main grid when sunshine is adequate, which would push further reduction of electricity price in the market.

In the modified IEEE-24 bus system, the overall demand buses are divided into six groups as group 1 to group 6 based on their price elasticity characteristics. Further, as the analogical characteristic of total electricity consumption, condition of winter and summer is considered as scenario 1, the condition of spring and autumn is considered as scenario 2. The emission allocation results for various groups in different scenarios and detailed emission conditions are shown in Fig. 6 and Fig. 7. The emission allowance for each group follows the developed ZSG-DEA model. Based on this emission allocation, the total emission amount of each scenario can be obtained. Details of total emission amount and financial conditions are shown in Table II. Compared to case 1, system transition with the proposed model has a decided advantage in carbon emission mitigation. By cutting demand and increasing installation of renewable generation, consumers can independently control their virtual emission to affect the total emission. However, it is obvious to see whether consumers can obtain extra environmental financial benefit is dependent on emission allocation. In scenario 1, both case 2 and case 3 can earn environmental benefits. Case 3 has the lowest total emission amount, and the highest environmental profit rewards. In scenario 2, case 3 has the lowest total emission

TABLE II
RESULTS FOR ALL CASES IN DIFFERENT SCENARIOS

Scenario		Case 1	Case 2	Case 3
1	Total emission (kton)	790.2	615.3	**472.4**
	Environmental profit (k$)	0	1678.3	**4965.6**
2	Total emission (kton)	658.5	257.2	**253.1**
	Environmental profit (k$)	**0**	-2073.4	-1980.4

amount, but consumers in case 2 and case 3 have to bear the increasing environmental cost. The reason for this result is that under the current criteria in the ZSG-DEA model, emission allocation for scenario 2 is so low for consumers that they have to purchase extra allowance in the carbon trading market.

Moreover, the influence of emission allocation on various groups is also different. Four groups produce less emission than the allowance in scenario 1. However, four groups produce more emission than the allowance in scenario 2 due to the tight emission allocation. Therefore, price elasticity in the electricity market can cause demand profile to change, and emission allowance plays a key role in the carbon-oriented demand response. Revenues of selling emission allowance would stimulate consumers to participate in DSM to reduce the total carbon emission. It should be noted that there is an increasing

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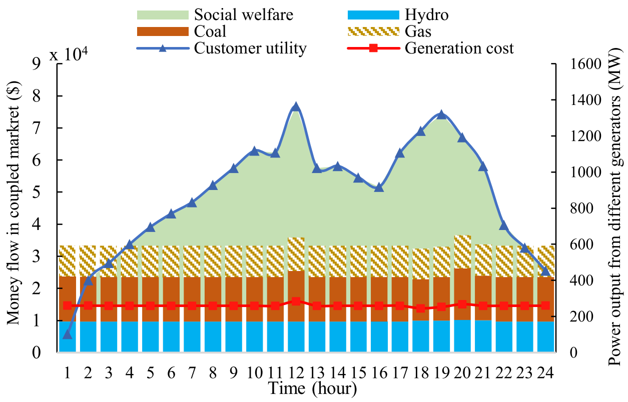

Fig. 8. One day mixes of power output for case 1 in the IEEE-24 bus system.

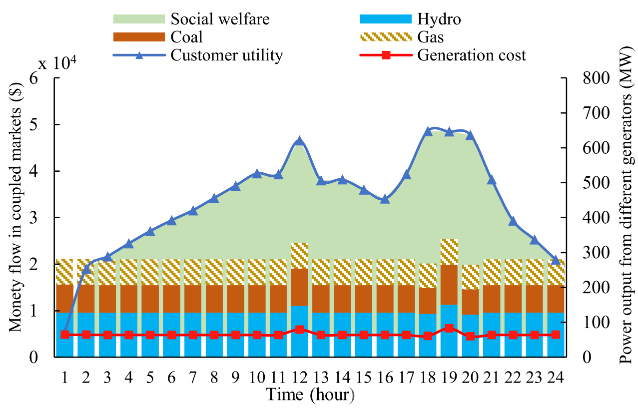

Fig. 9. One day mixes of power output for case 2 in the IEEE-24 bus system.

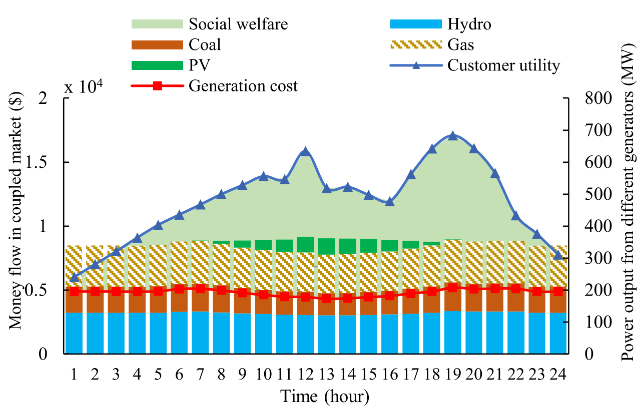

Fig. 10. One day mixes of power output for case 3 in the IEEE-24 bus system.

amount of PV installation in scenario 2, since consumers try to save more emission allowance and electricity cost by utilizing clean energy. In the same scenario, carbon emission with PV installation is lower than cases without PV installation. This amount of emission reduction is because of the transition of renewable energy generation.

The optimal results for generation mixes of all cases on a typical day are shown in Fig. 8, Fig. 9 and Fig. 10. It is evident that there is a reduction of total social welfare in case 2 and case 3,

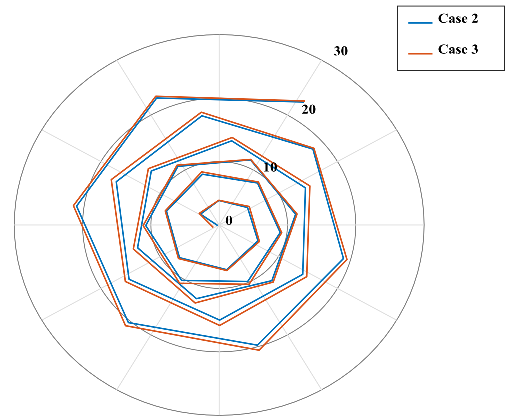

Fig. 11. Convergence analysis for iteration of two stages for 118-bus system.

because the proposed model decreases the consumers' utility by affecting the satisfaction of their electricity purchase and utilization. However, the social welfare of the system with PV installation is higher than case 2. This is because of the benefits in the carbon trading market by saving emission allowance. Furthermore, there is a significant total power output reduction from case 1 to case 3, especially the power produced from coal. The power produced from coal holds almost 40% of the total power generation on average in case 1, and this amount changes to about 28% in case 2 and less than 25% in case 3. On the contrary, the proportion from clean power like hydro has been increased in cases 2 and 3.

B. 118-bus System

The proposed model is also tested on a modified IEEE-118 bus system. There are 186 branches, 91 load sides and 54 power units involving 39 coal generators, 13 gas generators and 1 hydro plant in the modified system. Cases 2 and case 3 in Section V-A are chosen for comparison. The model convergence for cases 2 and 3 is demonstrated in Fig. 11. We still use the relationship between the base-ten logarithm of errors and convergence iterations for cases 2 and 3.

As seen in Fig. 11, the required iteration times increase to 34 for both case 2 and case 3. It is obvious to see that a larger network increases the iteration number. One of the main reasons is that the larger size of consumers increases the different characteristics in terms of electricity purchase utility, electricity utilization utility and price elasticities, which would lead to more iterations in the demand response process.

In order to study the detailed impact of carbon emission on each bus, carbon intensities at demand buses in two typical hours are illustrated in Fig. 12 and Fig. 13. Peak hour and bottom hour under scenario 1 in Section V-A are chosen. As seen, the average value of carbon intensity in peak hour is less than that in the bottom hour. That is mainly due to the utilization of PV at high solar irradiation and temperature, clean power from PV reduces the nodal carbon intensity at the overall level. Similarly, with the help of the clean energy from PV, it is no doubt that carbon intensity would decrease in case 3 for the

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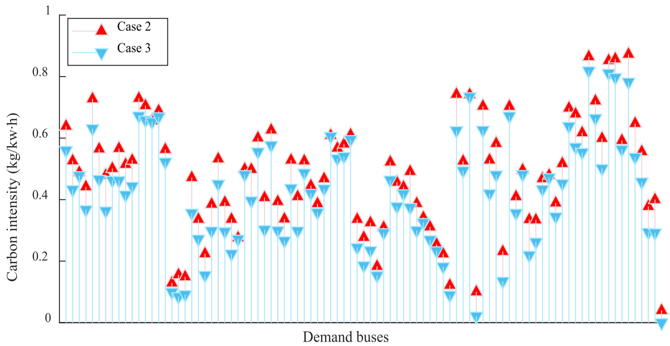

Fig. 12. Carbon intensity of demand bus in peak hour.

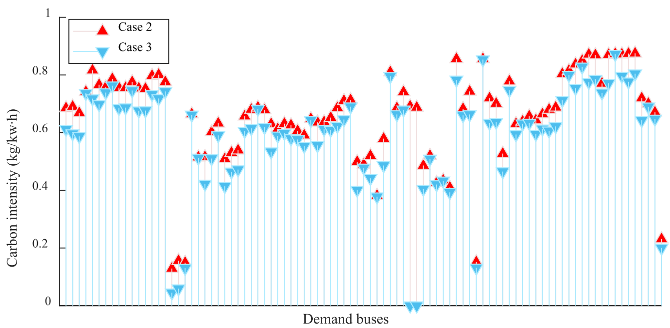

Fig. 13. Carbon intensity of demand bus in bottom hour.

TABLE III
RESULTS OF COMPARISON FOR TWO CASES

	Average carbon intensity (kg/kw·h)	Total emission (kton)	Environmental profit (k\$)
Case 2	0.635	1371.6	3740.5
Case 3	0.557	1203.1	7604.8

condition in the same hour. In the peak hour, fulfilling the high demand has a priority over economic consideration. Therefore, there are some buses that persist in using fossil generators, their nodal intensities do not change and remain in high value, like bus 82. Moreover, in the larger system, the hydro plant with a limited capacity might not be selected as the first choice in power dispatch. This is why only buses (bus 17, 18, 19, 34, 35 and 36) next to the hydro plant remain in low carbon intensities. In the bottom hour, the environmental condition restricts the power output of PV. As a result, there is no much difference in nodal carbon intensity for most buses. For bus 108 in Fig. 12, the nodal carbon intensity equals to the carbon intensity of the injected coal generators, which means demand in 108 can be satisfied by the coal generator at bus 108. For buses 67 and 70, the low demand amount can be fulfilled by the installed PV, so that their nodal carbon intensities are equal to zero.

Moreover, total emission and economic profit for case 2 and case 3 in the IEEE-118 system are given in Table III. It is clear to see that compared to case 2, there is a decrease in average carbon intensity in case 3 due to the installation of PV. Following the emission allocation principle in scenario 1 in Section V-A, although there is no evident difference between the two values,

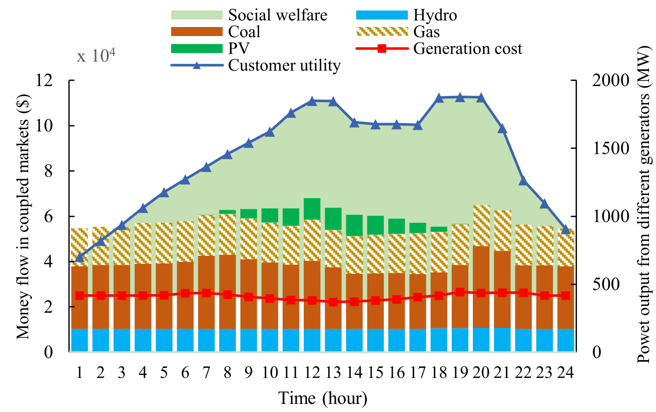

Fig. 14. One day mixes of power output for case 3 in IEEE-118 bus system.

case 3 has better performance in terms of emission mitigation and carbon trading profit.

The detailed power output for case 3 in one typical day is demonstrated in Fig. 14. Compared to the 24 bus system, the proportion of clean power from the hydro plant in total mixed power is significantly reduced. It has the lowest value of proportion in mixed power, except dynamic PV output, which is approximate to 15%. By contrast, power output from coal generators holds the largest proportion in the total mixed power, and the value is about 58%. This is because that the limited capacity of hydro cannot satisfy the massive demand amount. Further, this reason also leads to the no change of nodal carbon intensity at some buses between case 2 and case 3.

VI. CONCLUSION

This paper proposes a two-stage scheduling model to comprehensively investigate the environmental benefits of consumers participating in both electricity and carbon emission trading markets through active DSM. In the carbon trading market, a double carbon taxation mechanism is studied to clarify the financial responsibility of emissions. Further, a developed zero sum gains-data envelopment analysis (ZSG-DEA) model based multi-criteria allocation scheme for emission allocation is employed. In this model, four principles are still employed, but we rearrange multiple indicators to adapt to the characteristics of consumers, such as employment, Gross Industrial Output (GIO). In the electricity market, a developed demand response model with cross-elasticity consideration is introduced. The CEF model is applied to track the carbon flows accompanying power flows to calculate. By studying the two coupled markets simultaneously, the interactive impacts of accumulative profit or cost related to carbon-constrained power dispatch have been obtained, thus providing a more refined carbon management strategy for both power generators and consumers.

In our paper, we treat consumers as aggregated PQ loads which are managed by electricity retailers. These retailers will need to bid in the transmission-level power market to purchase electricity, and then sell electricity to end-consumers at retail prices. End-consumers' behaviour is responsive to retail prices, which are implicitly determined by transmission-level electricity

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prices from power dispatch. When aggregating lots of heterogeneous consumers, the demand characteristics will still remain at zone or substation levels.

Regardless of how the carbon tax is collected, end-consumers should pay the carbon tax, as they are the underlying driver of emissions, not the power generators. More importantly, if end-consumers can manage their demands in a more cost-reflective way, the economic and environmental efficiencies of power systems can be enhanced. This is the exact value and aim of this paper, i.e., carbon-oriented demand side management. Case studies show that the proposed model can achieve carbon emission mitigation significantly. Also, the amount of emission allocation can affect the result of carbon reduction. Optimal results of power scheduling can provide suggestions to planners for improving future carbon emission schemes. Compensation or other related incentive approaches regarding modeling distributed consumers might be our future work.

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