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# An interval-fuzzy possibilistic programming model to optimize China energy management system with $CO_2$ emission constraint

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A B S T R A C T

Energy system contains multiple uncertainties, and it is hard to express all its uncertainties by only one method. In order to solve this problem, an interval-fuzzy possibilistic programming (IFPP) method was developed based on the interval parameter programming (IPP), the fuzzy possibilistic programming (FPP) and fuzzy expected value equation within a general optimization framework. In this model, uncertainties presented in terms of crisp intervals and fuzzy-boundary intervals in both the objective function and constraints can be effectively addressed, and decision maker can choose the credibility degree of constraints based on his preference. The method was applied to optimize China energy management system with CO2 emission constraint, in which a CO2 emission coefficient model was employed to estimate the CO2 emission of each province. The study set two CO2 emission scenarios to analyze China energy system planning. The optimization results showed the approach could be used for generating a series of optimization schemes under multiple credibility levels, ensuring the energy system could meet the society demand, considering a proper balance between expected energy system costs and risks of violating the constraints of CO2 emission. Strengthening the CO2 emission constraint suggests the increasing of non-fossil energy generation and a higher system costs.



## 1. Introduction

Today, climate changing is a hot topic in the society, and carbon dioxide emissions have significant effect on climate change [1]. In the Copenhagen UN Climate Change Conference, China made carbon reduction commitments that the carbon dioxide emissions of per unit gross domestic product (GDP) will decrease 40%–45% by 2020 than 2005 [2]. With the rapid growth of national economy, China energy production and consumption are increasing rapidly, and based on the [3]; China has become the largest energy consumption country and also the largest carbon dioxide emission country in the world. For achieving the carbon reduction commitments, it is important for China to plan China energy system under the constraint of carbon dioxide emissions. In this case, identification of the solution of energy system planning is desired to achieve multiple targets, such as the minimization of system costs and carbon dioxide emissions. However, it is hard to find the solution, because many factors such energy transmission, energy price, and energy availability make the system complex and uncertain. So it is necessary to develop a systems approach to solve these problems and calculate the solution of China energy planning.

In recent years, a number of optimization techniques have been developed to manage energy system [4–15]. For example, Zhu et al. [16] applied an inexact mixed-integer fractional energy system planning (IMIF-EP) model in supporting sustainable energy system management under uncertainty. Samadi et al. [17] proposed a real-time pricing algorithm for demand response based on stochastic approximation to minimize the peak-to-average ratio (PAR) in aggregate load demand. Hejazi and Mohsenian-Rad [18] put forward a non-parametric chance-constrained optimization approach to operate and plan energy storage units in power distribution girds. Yi et al. [19] developed a multi-region power sector optimization model based on the perspective of bottom-up modeling to planning inter-regional power considering renewable energy development and regional pollutant control. Some researchers began to consider $CO_2$ emission in energy system [20–22]. For example, Li et al. [23] used an integrated optimization modeling approach for planning $CO_2$ emission mitigation through emission

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trading scheme and clean development mechanism in an electric-power system (EPS). Liu et al. [23] developed an inexact mixed-integer fuzzy robust linear programming model for coupled management of coal and power with consideration of $CO_2$ emissions mitigation system planning (IMIFLP-CCPM). Lamadrid et al. [24] presented a hybrid stochastic-robust optimization and used it to calculate a look-ahead, security-constrained optimal power flow considering renewable energy sources, which could reduce $CO_2$ emissions. In practical energy systems, uncertainties may exist in many aspects, such as energy costs, carbon dioxide emission coefficient, energy demand and energy availability [9,16,17]. These uncertainties may be further multiplied by the site-specific features of many system components, factors, and parameters, which bring significant difficulties to the formulation of management models and the generation of effective solutions [25]. Due to these multiform uncertainties, researchers paid more attention to the reliability and sustainability of energy management system. Generally, uncertain parameters could be expressed as intervals, fuzzy sets and probability density functions [26], and in energy system they could also be showed energy consumption scheduling [17] and other data sets, which could be considered as a kind of probability density functions. To overcome the risk problem, chance-constrained method [18] was applied most frequently. And many other methods were also employed to calculate results and increase the reliability of results, such as Online Learning Algorithm [4,5]; and stochastic-robust method [24]. So many methods can be used to solve uncertainty problems, but researches should choose method based on the system characteristics.

In the system, many data often can not meet the requirement of creating distribution or membership functions, uncertainty usually can be represented as an interval number, which has only a lower and an upper bound. An interval parameter programming (IPP) model was proposed for addressing optimization problems in the system with interval numbers in objective function coefficients and constraint parameters [27]. Fuzzy possibilistic programming (FPP) can be used to address optimization problems with fuzzy goals and constraints, which can be expressed as fuzzy membership functions [28]. Previously, FPP method was created with a fuzzy chance-constrained programming method using possibility to measure the occurrence chance of a fuzzy event [29]. Then, based on the credibility measure averaging of the possibility and necessity measures, a credibility chance-constrained programming method was developed [30]. In the energy management system, due to the inherent economic fluctuations, lower and upper bounds of energy cost parameters may be provided as subjective judgments from a number of stakeholders and decision makers. At the same time, with regard to unavailable stochastic distribution information and various influence factors, $CO_2$ emission coefficient on the left-hand side of constraints is acquired by limited data and presented by fuzzy membership functions. So IPP and FPP models may be unavailable and may lose information when two bounds of intervals in the objective function and constraints are presented by possibility distributions (i.e., fuzzy boundary intervals). It is necessary to develop an interval-fuzzy possibilistic programming (IFPP) method for better accounting for uncertainties by integrating the IPP and FPP models.

Therefore, in order to solve such complexities and uncertainties, the first objective of this study is to develop an interval fuzzy possibilistic programming (IFPP) method. In this model, uncertainties presented in terms of crisp intervals and fuzzy-boundary intervals in both the objective function and constraints can be effectively addressed, and decision maker can choose the credibility degree of constraints based on his preference. Then, the method will be applied in a new modeling framework of China energy management system to solve China energy planning under multiple uncertainty environments, and the study area is shown in Fig. 1. The study will set two $CO_2$ emission scenarios to analysis the China energy system planning, and costs and violation risks of fuzzy credibility constraints under different confidence levels will be investigated and analyzed.

## 2. Modeling development

In the optimization model, parameter uncertainty (i.e., cost coefficients) could be presented as ambiguous coefficients with possibility distributions. The related system characterizes epistemic uncertainty because of incomplete, unavailable and subjective information of the decision makers and stakeholders. Such an imprecise problem can be solved by fuzzy possibilistic programming (FPP) [31,32]. A FPP model can be formulated as follows:

$$\text{Min } \sum_{j=1}^{n} \underset{\sim}{C}_j x_j \tag{1a}$$

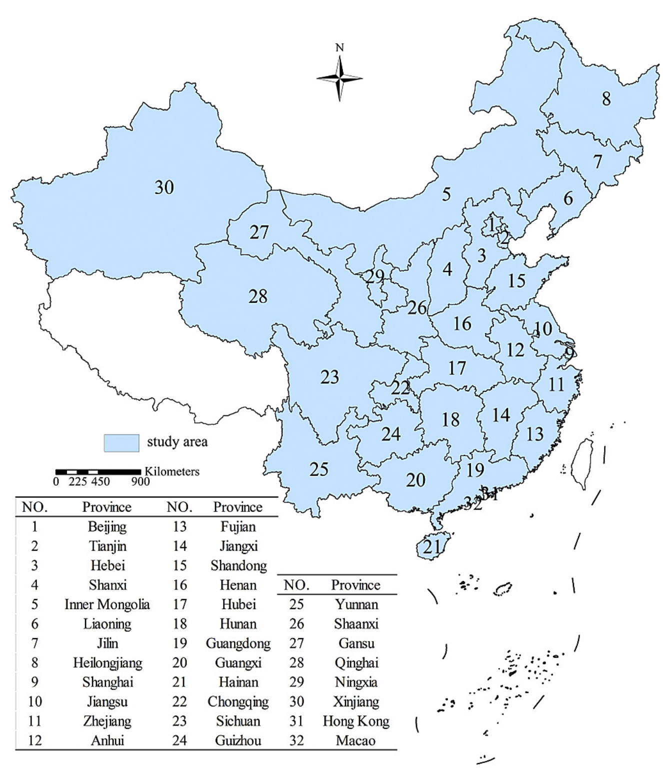
Subject to:

$$\sum_{j=1}^{n} \underset{\sim}{a}_{ij} x_j \geq b_i, \; i = 1, 2, \ldots, m \tag{1b}$$

$$\sum_{j=1}^{n} \underset{\sim}{a}_{ij} x_j \leq d_i, \; i = 1, 2, \ldots, m \tag{1c}$$

$$x_j \geq 0, \; j = 1, \; 2, \ldots, \; n \tag{1d}$$

where $\mathbf{x} = (x_1, \; x_2, \ldots, \; x_n)$ is the vector of non-fuzzy decision variables; $b_i$ and $d_i$ are the right-hand side coefficients; $\underset{\sim}{C}_j$ and $\underset{\sim}{a}_{ij}$ are




| NO. | Province | NO. | Province | NO. | Province |
|---|---|---|---|---|---|
| 1 | Beijing | 13 | Fujian | | |
| 2 | Tianjin | 14 | Jiangxi | | |
| 3 | Hebei | 15 | Shandong | | |
| 4 | Shanxi | 16 | Henan | | |
| 5 | Inner Mongolia | 17 | Hubei | 25 | Yunnan |
| 6 | Liaoning | 18 | Hunan | 26 | Shaanxi |
| 7 | Jilin | 19 | Guangdong | 27 | Gansu |
| 8 | Heilongjiang | 20 | Guangxi | 28 | Qinghai |
| 9 | Shanghai | 21 | Hainan | 29 | Ningxia |
| 10 | Jiangsu | 22 | Chongqing | 30 | Xinjiang |
| 11 | Zhejiang | 23 | Sichuan | 31 | Hong Kong |
| 12 | Anhui | 24 | Guizhou | 32 | Macao |

**Fig. 1.** Study area distribution in China.