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Planning for Low-carbon Energy-transportation System at Metropolitan Scale: A Case Study of Beijing, China

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ABSTRACT

The urbanization and expansion of megalopolises have led to concerns on traffic, energy crisis and deteriorated green-house gas emissions, and thus the electric vehicles (EVs) are expected to be an essential role in alleviating these problems. In this study, a flexible-possibilist chanced constraints programming (FCCP) model is developed to plan low-carbon energy-transportation systems at the metropolitan scale (METS), which can incorporate multiple uncertainties in both the soft constraints and objective function. By integrating the possibilist programming with fuzzy sets and chanced constraint, the FCCP could tackle multiple complexities such as the combination of vague possibilities, flexibilities and probabilities, hence is superior to conventional approaches. The FCCP model is then applied for the planning METS in Beijing, and solutions are obtained under different satisfactory degrees and confidence levels. The results reveal that: 1) the power demand will be increasingly dependent on the imported power and renewable energy in Beijing; 2) the mass roll-out of EVs will reduce 6.7 million tonnes of CH, 44.7 million tonnes of CO and 1.08 $\times 10^5$ million tonnes of CO_2 respectively, while the need of battery supply facilities will cost approximately 4×10^9 dollars; 3) the carbon emissions will decrease with the growing number of EVs, the upgraded power supply pattern and the stringent policies. These findings could support decision-makers to plan the METS system when faced with multiple uncertainties.

1. Introduction

Highly urbanized areas and expansion of megalopolises lead to increased concerns on traffic system, energy crisis and environmental pollution, especially the climate change due to carbon emissions which has become a global concern [1]. The Chinese government announced the commitment to achieve the carbon peak by 2030 and the carbon neutralization by 2060. As the capital of China, Beijing has a central transportation system. By 2020, the number of vehicles in Beijing has reached 6 million, which consumes a massive amount of gasoline and diesel fuels, leading to a large amount of carbon emissions each year, such as carbon monoxide (CO), hydrocarbon (CH) and carbon dioxide (CO_2). According to the Beijing Municipal Environmental Protection Bureau, about 80% of CO and 70% of CH were produced from the transportation system in 2020 [5]. Therefore, the government has committed to respond actively by stimulating renewable energies by introducing new laws and taking measures to reduce carbon emissions. Among various alternatives to fossil fuel powered combustion engine vehicles, electric vehicles (EVs) that are environment-friendly with higher efficiency and better dynamic performance are expected to play a significant role [29], and the decision support tools are necessary for assisting the planning for integration of renewable energies and EVs at a metropolitan scale to achieve sustainable development.

Taking the metropolitan energy-traffic system (METS) as a unity, several factors should be considered in its planning. First, uncertainties exist in both the objective function (e.g. fluctuating energy purchase cost, uncertain electricity generation and capacity expansion cost) and constraints (e.g. uncertain electricity demands, varying capacities and resources) [44]. Besides, the integration of EVs such as EV types, electric vehicle supply equipment (EVSE) (e.g. indefinite battery charging and swapping capacity) and other elements (e.g. travel distance and energy consumption factor) would considerably affect the operating planning of the METS [17]. Third, the introduction of renewable energies brings uncertainties and complexities(e.g. imprecise renewable power utilization and installation capacity) [23]. Moreover, the environmental issues related to carbon mitigation (e.g. variable emission and control cost) also introduce complexities in the system management [25]. These uncertainties can be brought not only from the measurements and evaluations, but also from all the aspects of energy generation, conversion, transition and utilization. Besides, various uncertainties not only exist in the soft constraints with stochastic parameters expressed as a probability distribution (such as power demand and renewable energy supply), but also exist in the capacity expansion constraints presented as flexible possibilist (such as capacity expanded for EVSE system). These uncertainties and complexities make it laborious to obtain effective strategies for the METS planning problems using conventional optimization methods. Hence, efficient system analysis techniques are desired in response to variable uncertainties and complexities.

The main objective of this manuscript is to propose a flexible-possibilist chanced constraints programming (FCCP) method for the integrated energy-traffic system planning at a metropolitan scale. Take Beijing as a case study, and the

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planning would be formulated as a system cost minimization problem in association with a series of constraints, such as electricity supply-demand balance, EVs battery charging and swapping capacity expansion and environmental requirement. In this system, the tasks can be described as follows: 1) the end users' (e.g. primary industry, industry, construction, residential and tertiary industry) power consumption over the planning horizon would be estimated based on the Monte Carlo simulation; 2) plan the optimal system with flexible, possibilist and random uncertainties being introduced into the proposed model; 3) analyze the optimization results in terms of the system cost, integration of renewable energies and EVs, and carbon mitigation; 4) evaluate the strategy obtained from simulation and compare with the real system to assess the effectiveness of the proposed model.

2. Literature review

2.1. influence of EVs

As one of the three largest markets, China accounts for 4.9% market share of EVs, much larger than that of U.S. and Japan [21]. Numerous researches have been conducted to explore the EVs impacts on electricity and environment [18].

It is noteworthy that the mass roll-out of EVs can support the societal transition to deliver a low carbon and sustainable environment in the future. For example, the CO_x emission would be greatly dropped because of the incorporation of EVs into the power grid [26]. In the past ten years, EVs have become a key measure to achieve greenhouse gases (GHG) emission reduction [2]. The International Energy Agency reports that EVs have contributed to overall 29.4 million tonnes of CO_2 emission reduction worldwide based on the average carbon emission factor in 2015 [4]. Battery EVs account for a significant portion in the EV market, given its zero-tailpipe emissions and high efficiency [39]. In the U.S., transportation is a major source of greenhouse gas (GHG) emissions, accounting for 28.2% of 2018 total U.S. GHG emissions, and vehicle electrification is expected to achieve great environment benefits [40]. The impacts of EVs on the electricity side also have been researched intensively in the literature. The electricity demand pressure due to aggressive deployments of EVs should be concerned in a land and resource constrained and densely populated urban place, such as Singapore [42]. Vehicle-to-grid could be the 'tipping point' [9]. The huge volume of EVs imposes huge demand on electricity consumption in a local area and consequently can cause voltage fluctuations and shortage of the electricity supply [3]. The battery EVs would cause more overload pressure on power grid compared with plug-in hybrid EVs [19]. The optimal operations of distributed energy resources in a residential district are discussed with the consideration of private and public transportation systems [7]. It was shown that the application of one million EVs would increase the normal electric demand by about 1% in Germany [22]. Generally, these researches mainly focus on deterministic analysis with linear or dynamic programming, and they can not reflect the complex couplings between renewable energies, EVs types, battery supply facilities and emissions.

2.2. programming methods

Over the past decades, many programming methods have developed for the system management planning problems.

The linear programming is well known by its simple model, but at the application stage, the corresponding expert knowledge or problem specific details have to be introduced in the model. In many circumstances, the parameters or the measurements are of a vague nature, and this lack of precision can be avoided by simplifying the problem to be exact [34]. The other conventional optimization approaches typically aim to find the economical solutions with minimal cost, where the impacts of uncertainties can be roughly quantified in the objective function or rigidly reflected in the constraints [16]. However, it cannot handle various uncertainties expressed as soft constraints and fuzzy possibility distributions [32, 27]. For many real-world problems, the optimization results could be highly unreliable if the modelling inputs cannot be expressed precisely, however this uncertainties are inevitable, for example the renewable energy introduces more variability and uncertainty due to its intermittent nature [33]. Various inexact optimization approaches have been developed for planning the system operation strategy under uncertainty, such as fuzzy, interval and stochastic programming etc.[24, 12]. The fuzzy linear programming is proposed for solving the problem which has a vague (fuzzy) nature and not exact [31]. The fuzzy programming method can be applied for the situations which can not be clearly defined and thus have uncertainties, but it has difficulties to handle uncertainties with soft constraints and flexibility [41, 13]. The chance-constrained programming method provides a means of considering constraints in terms of the possibility [8, 46]. However, the flexibility on the target value can not be solved by different fuzzy sets [28]. The interval-parameter chance-constrained program can tackle uncertainties expressed as probability distributions and intervals while can not solve problems with initial fixed cost of facilities but having variable cost expressed as soft constraints [20]. Although these methods are effective for tackling uncertainties associated to random variables with interval parameters, known probability distributions and fuzzy sets, they are incapable of dealing with multiple soft uncertainties related to the integration of possibility distributions, stochastic and flexibility [45]. Furthermore, few studies have investigated the optimal planning strategies for the integrated energy-transportation system at a metropolitan level, considering multiple end-users, various renewable energies, diverse electric vehicles and different emissions over a planning period.

3. Mathematical formulation of FRCP-METS

3.1. flexible-possibilist chanced constraints programming (FCCP) model

Possibilist programming (PP) can handle the situation which lacks the knowledge of the exact parameters in the model (i.e. epistemic uncertainty in the form of imprecise/ambiguous parameters). The algorithm is modelled using possibility distributions, where the objective data and subjective knowledge/experience are available but most often insufficient to the decision-maker [37]. A PP model can be formulated as:

$$\begin{aligned}
&\text{Min } z = fg + cx \\
&\quad s.t.\ Ax \geq d, \\
&\qquad Sx \leq Ny, \\
&\qquad y \in \{0,1\},\ x \geq 0
\end{aligned} \tag{1}$$

where the vectors f, c and d denote the fixed costs, variable costs and end-users$'$ demands respectively; the matrices A, S and N are coefficient matrices of constraints; vectors y and x represent the binary and continuous parameters respectively.

In practical planning problems, the vectors f, c and d and the coefficient matrix N that represent the facility capacities are usually approximate values. Flexible programming can be applied to cope with flexible targets and constraints (i.e. fuzziness in the form of vague/unsharp boundaries and imprecise parameters) which is modelled by subjective or preference-based fuzzy set [6]. By integrating the flexible programming with PP, a flexible-possibilist programming (FPP) model can be developed as follows:

$$\begin{aligned}
&\text{Min } z = \tilde{f}y + \tilde{c}x \\
&\quad s.t.\ Ax \geq d - \tilde{t}(1-\alpha), \\
&\qquad Sx \leq Ny + [\tilde{r}(1-\beta)]y, \\
&\qquad y \in \{0,1\},\ x \geq 0
\end{aligned} \tag{2}$$

where a convex fuzzy set substitutes the constraints; α and β are set to obtain the minimum value of an objective function with different satisfaction levels; the fuzzy numbers $\tilde{t}$ and $\tilde{r}$ are brought in to reflect the violations of the constraints in model. In this study, the triangular possibility distributions are adopted for modelling imprecise parameters that can be defined by their three prominent points [36]. Thus, the triangular fuzzy sets $\tilde{t}$ and $\tilde{r}$ can be represented as $\tilde{t} = (t^p, t^m, t^o)$ and $\tilde{r} = (r^p, r^m, r^o)$. $\tilde{t}$ and $\tilde{r}$ can be defuzzied by:

$$\begin{cases} \tilde{t} = (t^m + \frac{\upsilon_t - \upsilon_t'}{3}) \\ \tilde{r} = (r^m + \frac{h_r - h_r'}{3}) \end{cases} \tag{3}$$

where υ_t and υ_t' (h_r and h_r') are the lateral margins of the triangular fuzzy sets and could be defined as $\upsilon_t = t^o - t^m$ and $\upsilon_t' = t^m - t^p$

Accordingly, the FPP model can be rewritten as:

$$\begin{aligned}
&\text{Min } z = \frac{f^p + f^m + f^o}{3}y + \frac{c^p + c^m + c^o}{3}x \\
&\quad s.t.\ Ax \geq d - (t^m + \frac{\upsilon_t - \upsilon_t'}{3})(1-\alpha), \\
&\qquad Sx \leq Ny + [(r^m + \frac{h_r - h_r'}{3})(1-\beta)]y, \\
&\qquad y \in \{0,1\},\ x \geq 0
\end{aligned} \tag{4}$$

It is evident that the FPP model can effectively handle the uncertainties in the objective function and soft constraints, while uncertainties often exist as random variables with known probability distributions [43]. Chance constraints programming (CCP) can tackle the problems whose constraints are not known crisply but can be described as probabilistic distributions [35]. Integrating CCP with FPP, a flexible-possibilist constraint programming (FCCP) model can be stated as follows:

$$\begin{aligned}
&\text{Min } z = \frac{f^p + f^m + f^o}{3}y + \frac{c^p + c^m + c^o}{3}x \\
&\quad s.t.\ \Pr\left\{ Ax \geq d - (t^m + \frac{\upsilon_t - \upsilon_t'}{3})(1-\alpha) \right\} \geq \delta, \\
&\qquad \Pr\left\{ Sx \leq Ny + [(r^m + \frac{h_r - h_r'}{3})(1-\beta)]y \right\} \geq \rho, \\
&\qquad y \in \{0,1\},\ x \geq 0
\end{aligned} \tag{5}$$

where "Pr" means "probability"; ρ and δ represent the confidence level of embracing uncertain constraints in the system. In the above formulation, the chance constraints should be satisfied with the confidence levels greater than 0.5.

3.2. FCCP-METS model formulation

Considering the real METS in Beijing, some complicated processes should be considered, such as different types of power generation (e.g. fossil-fired, wind, hydro, biomass, waste, photovoltaic and pumped storage), seven imported power grids (e.g. Hebei, Inner Mongolia, Jingjintang, Langfang, Qinhuangdao, Shanxi and Zhangjiakou), five end-users (e.g. primary industry, industry, construction, residential and others), six types of transportation (e.g. bus, truck, taxi, private car, metro and special purpose vehicle) and three types of EV power supply facilities (e.g. DC fast charging, level-I AC charging and level-II AC charging). For instance, power demand varies with some factors such as economic development, technology innovation and general randomness of individual usages. These imprecise processes would bring considerable complexities and uncertainties which can affect the optimization decision schemes. Based on the proposed FCCP method, an FCCP-METS model can be developed for planning the METS of Beijing. The model objective is to obtain the power generation pattern and transportation types with a minimized system cost associated with the carbon emission requirement. The total system cost contains energy resources purchase, electricity importation, generation and transmission, fixed and variable costs of power facilities and EVs charging infrastructures, transportation cost and carbon mitigation costs. The complex objective function is defined as follows:

$$\text{Min } E = (1) + (2) + (3) + (4) + (5) + (6) + (7) + (8) \tag{6}$$

(1) Purchase cost for energy resources: In practical applications, energy resource (i.e. coal, gas and oil) purchase

cost in METS consists of purchase cost of local and imported energy.

$$\sum_{i=1}^{3}\sum_{t=1}^{3} P\tilde{CE}_{i,t} \times N\tilde{SE}_{i,t} \tag{7}$$

(2) Cost for electricity importation: In Beijing, the amount of local electricity generation is insufficient to meet the demand, thus importing electricity from neighboring regions is necessary. The cost for electricity importation from other regions is determined by the quantity and the unit-price.

$$\sum_{t=1}^{3} P\tilde{CP}_{t} \times N\tilde{IP}_{t} \tag{8}$$

(3) Fixed and variable costs for power generating stations: The power generation station entails fixed and variable costs, which is remarkably complex. The fixed cost is essentially capital and land cost while the variable cost includes fuel, labour and maintenance costs.

$$\begin{aligned}&\sum_{k=1}^{7}\sum_{t=1}^{3} FP\tilde{G}_{k,t} \times (R\tilde{C}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t})\\ &+\sum_{k=1}^{7}\sum_{t=1}^{3} VP\tilde{G}_{k,t} \times (PG\tilde{A}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t} \times S\tilde{T}_{k,t})\end{aligned} \tag{9}$$

(4) Fixed and variable costs for capacity expansion: The power capacity expansion cost include the costs for labor, maintenance and operation, as well as financial investment.

$$\sum_{k=1}^{7}\sum_{t=1}^{3} (FP\tilde{E}_{k,t} + VP\tilde{E}_{k,t}) \times E\tilde{C}_{k,t} \times YC_{k,t} \tag{10}$$

(5) Cost for power transmission loss: The generating facilities are often located in remote places, far from the point of consumption. Thus, the distance of power transmission always reaches thousands of kilometres, leading to large power loss.

$$\sum_{k=1}^{7}\sum_{t=1}^{3} (PG\tilde{A}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t} \times S\tilde{T}_{k,t}) \times C\tilde{U}_{k,t} \tag{11}$$

(6) Cost for transportation system: For the transportation system, the cost mainly depends on the types of vehicles, their energy consumption factor and service distance

$$\sum_{j=1}^{6}\sum_{t=1}^{3} TC\tilde{A}_{j,t} \times T\tilde{OV}_{j,t} \times TS\tilde{D}_{j,t} \tag{12}$$

(7) Fixed and variable costs for electric vehicle power supply equipment (EVSE): The electric vehicle power supply equipment (EVSE) provides power to vehicles, including the electric conductors, related equipment and communications protocols. The EVSE is mainly classified as battery charging facilities which indicate DC Fast Charger (480 volts DC and higher), Level-I AC charger(120 volts) and Level-II AC charger (240 volts) and battery swapping facilities.

$$\begin{aligned}&\sum_{m=1}^{5}\sum_{t=1}^{3} (FB\tilde{C}_{m,t} + VB\tilde{C}_{m,t}) \times BC\tilde{E}_{m,t} \times YBC_{m,t}\\ &+\sum_{m=1}^{5}\sum_{t=1}^{3} (FB\tilde{S}_{m,t} + VB\tilde{S}_{m,t}) \times BS\tilde{E}_{m,t} \times YBS_{m,t}\end{aligned} \tag{13}$$

(8) Cost for carbon mitigation: The carbon mitigation of METS is related to various power generation and transportation processes. Thus the associated cost is calculated based on the emission rates, the unit cost of control and relevant financial subsidies.

$$\begin{aligned}&\sum_{k=1}^{7}\sum_{t=1}^{3}\sum_{q=1}^{3} (PG\tilde{A}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t} \times S\tilde{T}_{k,t})\\ &\times (CP_{t,q} + CE_{t,q}/S\tilde{T}_{k,t} - SU_{k,t})\end{aligned} \tag{14}$$

Constraints consider the energy resource, power demand-supply balance, capacity expansion (e.g. power generation, EVSE facilities) and carbon abatement. They can be formulated as follows.

a) Energy resource availability: It is required that energy resource utilisation must be no more than the available quantity of energy supply.

$$\begin{aligned}&N\tilde{SE}_{i,t} \leq A\tilde{R}_{i,t}\\ &PG\tilde{A}_{k=1,t} \times C\tilde{R}_{k=1,t} \leq \sum_{i=1}^{2} N\tilde{SE}_{i,t}\end{aligned} \tag{15}$$

b) Capacity limitation of power generation facilities: There are several power generating techniques in the system and this constraint can guarantee that the capacity is greater than the total amount of output.

$$\begin{aligned}&\Pr\Bigg\{ PG\tilde{A}_{k,t} \leq (R\tilde{C}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t}) \times S\tilde{T}_{k,t}\\ &+\left[(r^m + \frac{h_r - h'_r}{3}) \times (1-\beta)\right] \times YC_{k,t} \times S\tilde{T}_{k,t} \Bigg\} \geq \rho\end{aligned} \tag{16}$$

c) Capacity limitation of EVSE facilities: The capacity of battery charging and swapping facilities should satisfy the demand of the whole EV population.

$$\begin{aligned}&\Pr\Bigg\{ T\tilde{OV}_{m,t} \times SO\tilde{C}_{m,t} \leq RB\tilde{C}_{m,t} + RB\tilde{S}_{m,t} + BC\tilde{E}_{m,t}\\ &\times YBC_{m,t} + YBS_{m,t} \times BS\tilde{E}_{m,t} + \left[(r^m + \frac{h_r - h'_r}{3}) \times (1-\beta)\right]\\ &\times \left(YBC_{m,t} + YBS_{m,t}\right) \Bigg\} \geq \rho\end{aligned}$$

(17)

d) Constraint of electricity power demands: It is established to ensure that the total power generated from the existing and expanded facilities and purchased from other areas should not be less than the power demands.

$$\Pr\left\{ \sum_{k=1}^{7} P\tilde{GA}_{k,t} + N\tilde{IP}_t + \sum_{k=1}^{7} YC_{k,t} \times S\tilde{T}_{k,t} \times E\tilde{C}_{k,t} \geq \sum_{d=1}^{5} De\tilde{d}_{t,d} - \left[t^m + \frac{\upsilon_t - \upsilon'_t}{3} \right] \times (1-\alpha) \right\} \leq \delta \tag{18}$$

e) Constraint of carbon emission: The constraint is to confirm that the amount of carbon emission should satisfy the policy permits.

$$\Pr\left\{ \sum_{k=1}^{7} (E\tilde{C}_{k,t} \times YC_{k,t} \times S\tilde{T}_{k,t} + P\tilde{GA}_{k,t}) \times AM\tilde{R}_{k,t,q} + \sum_{j=1}^{6} T\tilde{CA}_{j,t} \times T\tilde{OV}_{j,t} \times T\tilde{SD}_{j,t} \times TE\tilde{F}_{j,t,q} \leq A\tilde{AP}_{t,q} \right\} \geq \rho, \forall t, q \tag{19}$$

f) Constraints for capacity expansion: These constraints are formulated to ensure that the capacity of facilities should satisfy the power demand in the long-term planning. And the integer variables can indicate if a facility expansion can be undertaken.

$$\Pr\left\{ R\tilde{C}_{k,t} + E\tilde{C}_{k,t} \times YC_{k,t} \leq CapU_{k,t} \right\} \geq \rho \tag{20}$$

g) Nonnegative constraints: It is assured to eliminate infeasibilities while computing the solutions.

$$P\tilde{GA}_{k,t}, N\tilde{SE}_{i,t} \geq 0 \quad \forall i, k, t \tag{21}$$

$$YBC_{m,t}, YBS_{m,t}, YC_{k,t} \begin{cases} = 1 & undertaken \\ = 0 & otherwise \end{cases} \tag{22}$$

The specific definition of parameters and variables are provided in the Appendix. All variables in the FCCP-METS model are considered either as continuous variables or binary (0-1) variables. The proposed model is solved using the simplex algorithm [38, 14]. The optimal solution under different confidence degree and satisfaction level with violations can be obtained by taking various α, β, δ and ρ values. The detailed process for calculating the FCCP-METS model can be summarized as follows.

Step 1: formulate the FCCP-METS model.

Step 2: solve the FCCP-METS model to obtain a global solution under a α and β level.

Step 3: solve the FCCP-METS model (under the same α level) to achieve a global solution under a δ and ρ.

Step 4: repeat step 2 and step 3 for every α and δ in order to get all solution results.

Step 5: analyze the results and provide them to decision-makers.

4. applications

4.1. overview of the study system

Beijing is the capital of China. It is one of the most famous capital cities globally, with over 21 million residents in an administrative area of 16,808 km^2. As one of the world‘s leading economic and culture centers, the adverse impacts of energy crises, transportation, and environmental issues should be considered (as shown in fig 1). The current power generation in Beijing primarily depends on fossil fuels and renewable energy occupies about 10% of the total power generation [30].

On the other hand, the extensive transportation network of buses, taxis, trucks and passenger cars not only bring convenience to people but also significant pollutant emissions at the same time. In the transportation system, the EVs are treated as new energy vehicles and reached 225,000 in 2018, and the annual growth rate reaches to 35.6% from 2017 to 2018 [10]. These growth has led to massive carbon emission reduction, but this is not yet sufficient. Based on the Municipal Environmental Protection Bureau in Beijing, the daily average concentration of CO is 1.3 mg/m^3 in 2020 which only meets the second level of National Ambient Air Quality Standard. Thus, the electric power generation, transportation system and carbon emissions should be considered holistically as they are all significant factors to consider in the METS planning in Beijing, and high emphasis should be focused on the integration of renewable energy, transportation system, EVSE and battery swapping facilities and carbon emission reductions. For example, based on the electric vehicles infrastructure strategy of Beijing, there are approximate 0.4 million charging facilities required by the end of 2021; the capacity of renewable energy would reach to 2GW, which will account for about 15% of total capacity.

4.2. data collection and scenario design

This context focuses on the energy-transportation system of Beijing and its carbon emissions. The relevant cost parameters are based on the China statistical yearbook, Beijing traffic development annual report and Beijing statistical yearbook; technical data are obtained from government official reports, published papers and survey [11, 15]. The power energy demand is simulated based on the Monte Carlo under one thousand runs with probability level being 0.05. The simulated power demands are used as the FCCP-METS model input values in the planning. The emission factors of carbon pollutants from different vehicles are specified by triangle fuzzy numbers and are listed in table 1. For instance, the emission factor of CH of buses in period 1 would be

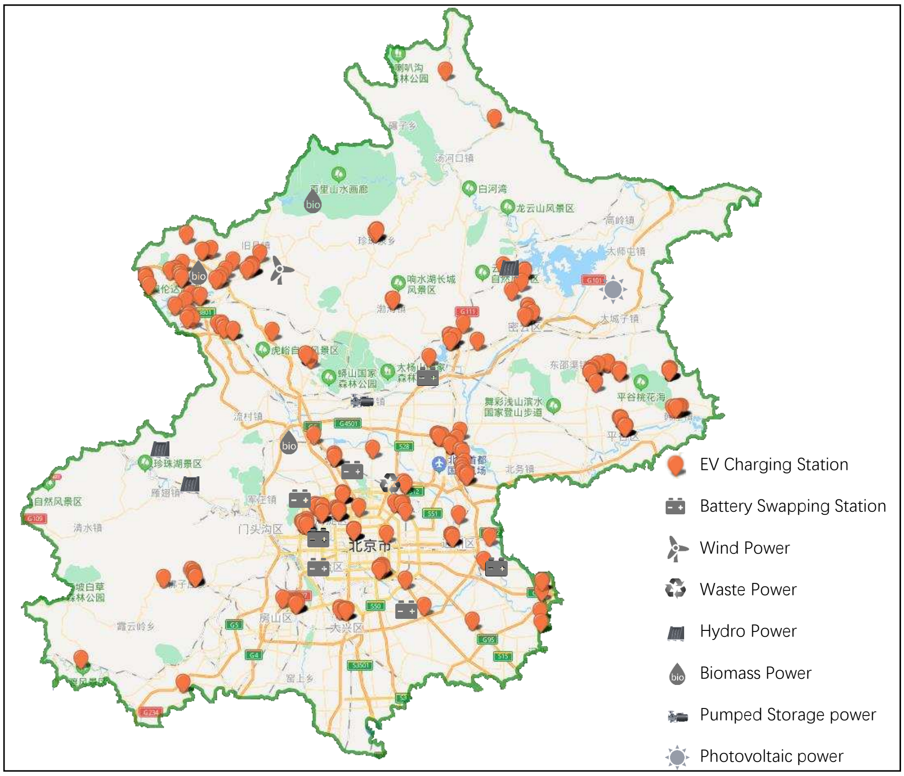

Figure 1: The study system of Beijing

Table 1
emission factors of pollutants from different vehicles ($g \cdot km^{-1}$)

time	emissions	bus	truck	taxi	pravite car	special purpose vehicle
	CH	(0.187,0.190,0.212)	(1.616,2.210,2.977)	(0.086,0.092,0.103)	(0.085,0.098,0.104)	(0.009,0.011,0.014)
period 1	CO	(0.775,0.800,0.814)	(2.001,3.300,3.541)	(0.521,0.623,0.724)	(0.521,0.625,0.728)	(0.012,0.014,0.017)
	CO_2	(1115,1173,1197)	(6720,7432,7987)	(118,130,154)	(142,189,225)	(83,106,142)
	CH	(0.155,0.170,0.176)	(1.269,2.500,2.726)	0.085,0.090,0.103)	(0.083,0.092,0.102)	(0.009,0.010,0.013)
period 2	CO	(0.765,0.798,0.835)	(2.626,3.104,3.588)	(0.519,0.620,0.722)	(0.522,0.623,0.726)	(0.008,0.009,0.012)
	CO_2	(877,951,1043)	(5147,5929,6897)	(102,112,132)	(142,152,163)	(61,81,91)
	CH	(0.112,0.130,0.148)	(1.045,1.403,1.448)	(0.082,0.099,0.101)	(0.082,0.091,0.099,	(0.007,0.009,0.011)
period 3	CO	(0.754,0.770,0.794)	(2.655,2.920,3.042)	(0.517,0.619,0.720)	(0.518,0.620,0.721)	(0.005,0.007,0.008)
	CO_2	(767,845,936)	(4254,5558,6263)	(88,98,127)	(107,117,137)	(39,59,88)

[0.187, 0.190, 0.212] $g \cdot km^{-1}$, which means the possible value is 0.19 $g \cdot km^{-1}$ and there is no possibility that the value is lower than 0.187 $g \cdot km^{-1}$ or more than 0.212 $g \cdot km^{-1}$. Moreover, the planning horizon includes three periods, each covering three years.

Several scenarios are designed with different confidence and satisfactory levels. The optimal solutions related to various confidence and satisfactory levels could be obtained by taking different α, β, δ and ρ values. In the experiment, ten satisfaction degrees (e.g. $\alpha = \beta = 0.1$ to 1) are adopted for the soft constraints on violating the power energy demands from end users and capacity expansion activities, and six confidence levels (e.g. $\delta = \rho = 0.5$, 0.6, 0.7, 0.8, 0.9 and 1) are used for embracing uncertainties with the imprecision of parameters and they are used to represent the uncertainties in both the soft constraints and the objective function.

5. results analysis

5.1. system cost

The system cost is the sum of all costs generated from every sector in the considered planning period. It is shown in fig 2 that the system cost changes with different satisfaction degrees (α and β) and confidence levels (ρ and δ) which is corresponding to the preference of decision-makers. The satisfaction degree is related to the system violation risk, namely the demand backlog. The demand backlog indicates the robustness of the tradeoff between demand and supply (e.g. energy resource and EVs battery charging and swapping capacity). Higher α and β values mean lower violation risk, and then the decision-makers prefer to achieve planning with a lower backlog in the system, thus leading to a higher total cost. On the other hand, the confidence level presents a valuation element associated with the probability of meeting soft constraints of the system, which is also somehow re-

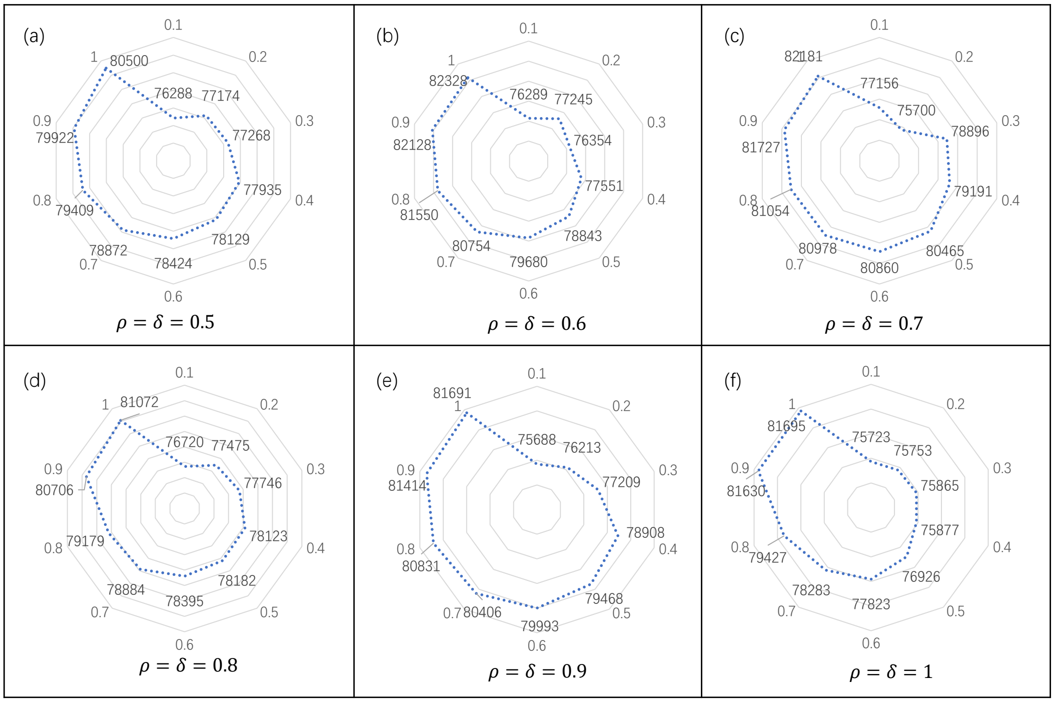

Figure 2: The system costs with satisfaction degree α and β changing from 0.1 to 1 ($\times 10^{12}$\$)

lated to the outputs. Since higher ρ and δ values mean easier to implement the uncertain constraints for decision-makers, the system cost would increase with the confidence level.In summary, the higher satisfaction degree ($\alpha = \beta = 1$) and confidence level ($\rho = \delta = 1$) will lead to a higher system cost (\$ 76288×10^{12}), while lower cost (\$ 81695×10^{12}) is achieved by lower satisfactory degree and lower confidence level.

5.2. renewable energy power

As illustrated in Fig 3, uncertainties could affect the optimization processes and thus the electricity power supply patterns. For instance, as the satisfaction degree and confidence level vary, the fossil power could even account for more than 80% of the total energy generation while the renewable energy power only accounts for a small percentage, [11.24, 17.39]% throughout. The proportion of renewable power is far smaller than the developed countries, even though relevant policies are introduced to improve the power supply structure in the local regions. When $\alpha = \beta = 1$ and $\delta = \rho = 1$, the ratio of renewable energy power changes from 11.24% to 15.73 along with the time. In detail, the hydro, photovoltaic and waste power generation are among the top three and account for about 3.31%, 2.80% and 4.38% at the end of the planning period. The status of these types of non-fossil fuel based power generation would become increasingly more important over time. At the end of the planning period, the proportions of power from renewable energies are in the range of [3.31, 4.85]%, [1.88, 2.45]%, [2.80, 3.02]%, [0.81, 1.39]%, [4.38, 5.16]% and [1.48, 1.95]% for hydro, wind, photovoltaic, biomass, waste and pumped-storage power respectively as the satisfactory and confidence levels change. The capacity expansion of renewable energy power is necessary to meet the rapid change of the generation mix. Besides, the percentage of imported power could vary along with time, mainly caused by increased power demands, available energy resources and incentives for adopting renewable energies. In summary, the power demands are expected to increase continuously; the proportion of renewable energy power would increase accordingly with time over the planning horizon.

5.3. carbon emission

For the carbon emission requirement, the satisfactory degree and the confidence level are both employed in the constraints. The higher satisfactory and confidence values would refer to a tighter environment requirement, thus leading to a lower emission. Fig 4 shows the multiple carbon emissions –CH, CO and CO_2 of the METS system (e.g. electricity power plants, trucks, buses and private cars) when satisfactory and confidence levels are both equal to 1. It is obvious that the fossil-fired (e.g. gas-fired) power generation process has a bigger influence on the air quality than the renewable energy (e.g. hydro and waste) plant. Furthermore, the carbon emissions of all the power generation processes are much less than the transportation sector. Two reasons can explain this scenario: 1) about 60% power demand in Beijing is met by the imported power from other regions; 2) Beijing has ended coal-fired power plants in 2017, and the fossil-fired plants are all gas-fired which produce less emissions. Moreover, for the end-users sector, the amount of industry would decrease due to the pollutant mitigation.

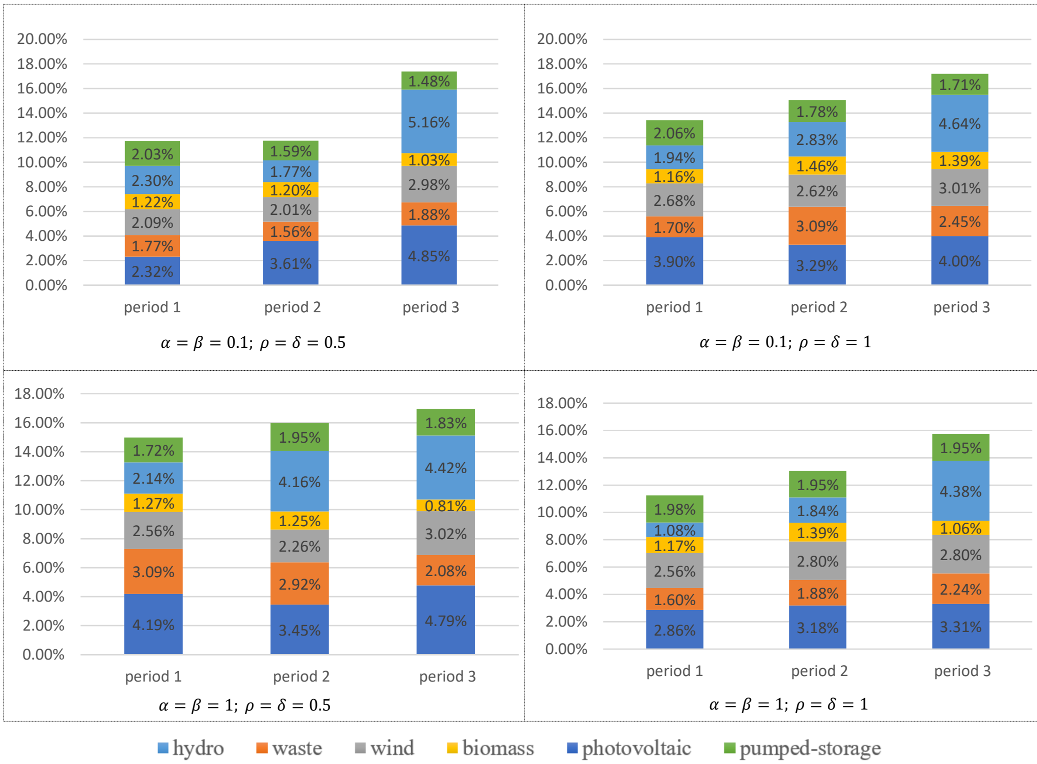

Figure 3: The power supply patterns with various renewable energies

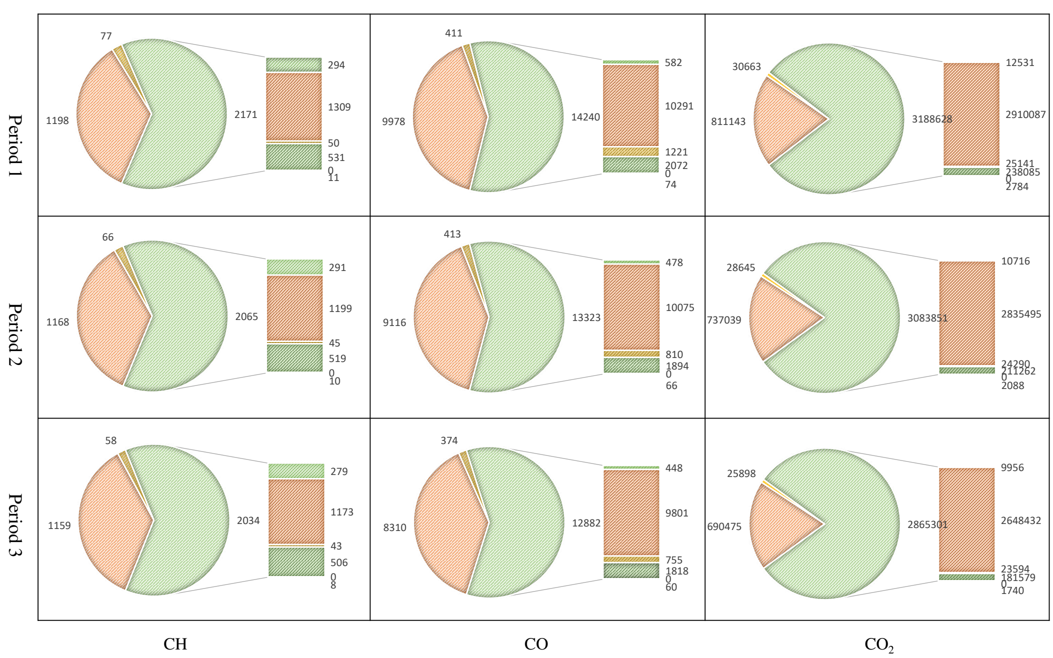

Figure 4: The sectoral carbon emissions ($\times 10^4$ ton)

For the transportation sector, the trucks are the major contributor to the pollution accounting for nearly 54.39%, 73.37% and 80.59% of the transport carbon emissions (CH, CO and CO_2 respectively), and the emissions from trucks are about ten times of the ordinary cars and this implies that the logistic has developed swiftly and aggressively over these periods. The next important emission source is from the private cars. In comparison, the proportion of this part decreases along with time in the planning period because of the vehicles' upgrade (such as lightweight) and roll-out of

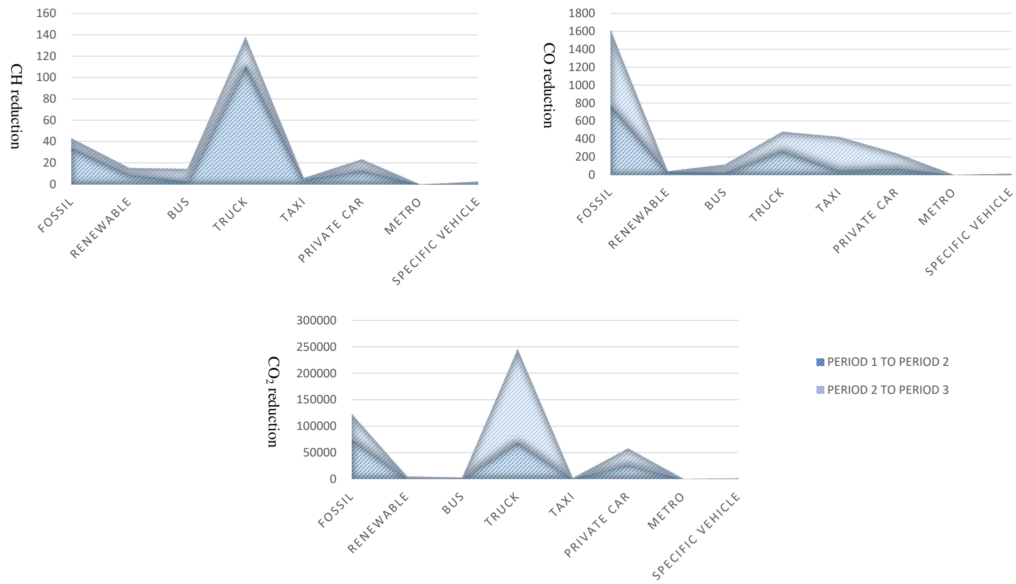

Figure 5: Carbon emission reduction in the planning horizon ($\times 10^4$ ton)

EVs. For public transport, the total emissions from buses and metros are even less than that of private cars while they serve more people. It is therefore highly recommended to encourage people to take public transportation by considering the economic and environment impacts. In summary, the carbon emission would be reduced over time in response to various carbon emission control policies in the planning horizon, such as incentives for renewable energies and mass adoption of EVs in the METS system.

Fig. 5 illustrates the reductions of carbon emission in the planning horizon. It is clear that the carbon emissions have gradually reduced, while the abatement potentials of various sectors are different. From the first period to the last period, the carbon reduction of transportation sector accounts for the largest proportion, among which the trucks play a major role. The fossil-fired power generation is the second contributor to the carbon emission reduction. In conclusion, the power conversion sector and the transportation sector are the first two dominant sector for carbon emission reduction, accounting for the reduction of 10% and 15% respectively by 2030. Therefore, the power generation and transportation sectors are promising to play a key role to reduce carbon emissions in the future. Furthermore, it is necessary to develop more renewable energy resources to achieve the goal of carbon peak by 2030.

5.4. influence of EVs

In the METS system, the deployment of EVs would impact the system cost and carbon emission significantly. Fig 6 illustrates the quantities of carbon emissions and their proportions in the transportation sector at the end of the planning period. The emissions will decrease when considering the EVs and the amount of reductions are 6.7 million tonnes for CH, 44.7 million tonnes for CO and 1.08 $\times 10^5$ million tonnes for CO_2 respectively. Among the transportation vehicles, the adoption of electric trucks contributes hugely to the reduction of carbon emissions. This is related to a policy issued by the government that the light logistic vehicles (less than 4.5 tons) in the city should be mainly changed to electric trucks. The following categories are buses and taxis as the proportion of electric buses would be more than 70% and the ownership of electric cabs would be more than 20 thousand in Beijing. The increase in the number of private electric cars reduces the carbon emissions further. In addition, the special-purpose vehicles (e.g. sanitation trucks) in Beijing are almost electrical, which also improves the air quality. The metro system is all electrified and no carbon emissions are discharged.

On the other hand, the EVs indicate the additional system cost due to the capacity expansion of battery supply facilities. Over the planning horizon, the number of public charging piles in Beijing would increase from 9 thousand to 50 thousand, approximate 5.6 times. Specifically, 22 thousand DC fast chargers (480 volts DC and higher), 18 thousand Level-I chargers (120 volts), 10 thousand Level-II chargers (240 volts) and 150 thousand private charging piles are required to be built at the end of the planning period. Meanwhile, the number of batteries swapping stations would be around 160 in Beijing. In summary, approximate 4×10^9 dollars would be spent on building and operating the electric vehicle power supply equipment (EVSE) corresponding to the increased adoption of EVs.

6. Implementation and discussion

The proposed model is adopted for the planning of the METS system in Beijing to obtain the optimal trade-offs between system cost, electric power and transportation sectors. To further illustrate the accuracy of FCCT-METS model, the comparison between the model prediction (under satisfac-

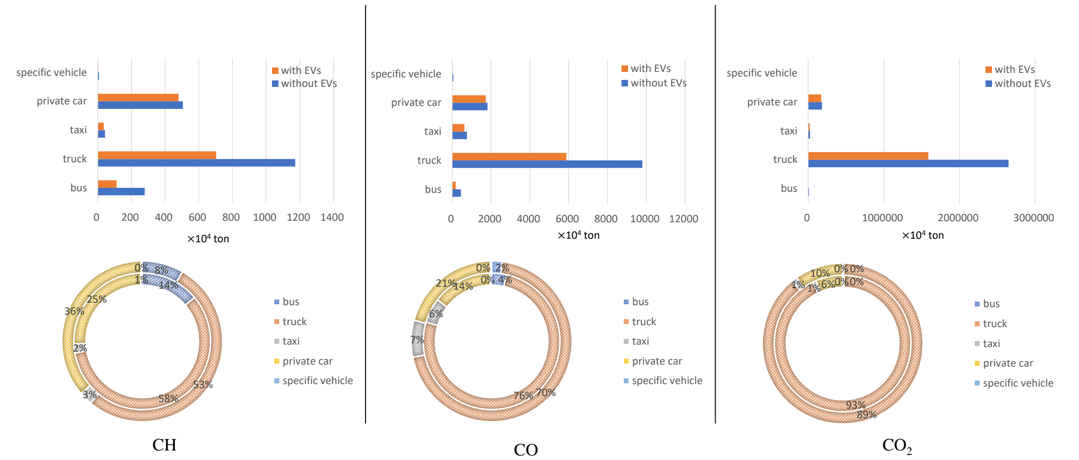

Figure 6: The impacts of EVs for carbon emission

tion degree and confidence level being 1) and the fact situation at the end of the planning horizon is studied as follows.

For the electric power side, in fact, the proportion of the imported power from other regions reaches 70% of the total power demand; the fossil-fired power and the renewable energy power account for 92% and 8% of the total power generation respectively; while under the FCCT-METS model analysis, the ratios are 65.5%, 88.4% and 11.6% separately. This result indicates that the electric power supply pattern of the prediction model is close to the reality. The increased proportions of the imported power and the renewable energy power would be consistent with the government policy. According to the 14th five-year plan, the share of non-fossil in the mixed energy would reach 20% by 2025. Among the renewable energies, the solar and wind power generation would be the main contributors to the incremental power capacity for the next decade.

For the transportation sector in FCCT-METS model, the EVs ownership would reach 450,000 with 350,000 cars and 100,000 buses in the last planning period. According to the electric vehicle charging infrastructure plan in Beijing, the ratio of vehicle and electric charger should be less than 7 and there would be 50 thousand chargers built which can satisfy the battery power supply requirement of 600,000 electric vehicles by 2025. In the future, there would be more EVs for different applications (e.g. logistics and sanitation) due to carbon control and prevention. This predictive result is consistent with the actual situation of Beijing. In fact, the local government has been taking various steps to improve the air quality in the last ten years, especially in order to meet the traget of reaching the carbon peak by 2030. These measures are effective for environment and clearly benefit Beijing citizens, as there is hardly haze weather nowadays in Beijing in recent years. In summary, based on the validation with the actual METS system in Beijing, the proposed FCCP-METS model can be applied to the METS system planning in Beijing and other cities, and the desired METS planning strategies for the Beijing can be designed effectively.

7. Conclusion

In this study, a flexible-possibilist chanced constraints programming (FCCP) model has been proposed for handling multiple complexities such as the combination of fuzzy possibilities, flexibilities and probabilities. Superior to conventional optimization approaches, the FCCP model could handle uncertain information and enhance the robustness of the solutions. It can also quantitatively analyze the effects of the uncertain parameters on system cost from individual and coupling aspects. The proposed FCCP model has been applied to the METS planning for Beijing. Several conclusions can be drawn: 1) the system cost would increase as the satisfactory degree and confidence level increase. 2) the power demand will gradually be met by the imported power from other regions and also more from the renewable energy as time goes on, and the proportion of the renewable energy power would increase to approximate 11% at the last planning period. 3) the carbon emission would be reduced with the growing number of EVs, the upgraded power supply pattern and the stringent air quality control policy. 4) the EVs would be adopted in most transportation fields, such as cars, buses, metros, logistics and sanitation. The mass roll-out of EVs would have significant impact on the environment by reducing 6.7 million tonnes of CH, 44.7 million tonnes of CO and 1.08 $\times 10^5$ million tonnes of CO_2 respectively.

The FCCP-METS model has been verified with the real-world METS system in Beijing and the results indicate that the proposed approach could deal with the metropolitan-scale complex problems with uncertain parameters. However, several assumptions for the model formulation would bring limitations and should be addressed in the future study. Firstly, the capacity expansions of renewable energy plant, battery charging facility and battery swapping facility are limited to their service life and the financial investment. Secondly, the binary variables are used to indicate whether a capacity expansion should be undertaken or not, which is a quite simplified approach. Thirdly, the EVs could be used as energy storage in the distributed energy source, which would benefit more to the METS system, but this has not yet been considered in this study.

A. Appendix

Nomenclatures for parameters and variables

i – resource type (where $i = 1$ for coal, $i = 2$ for oil and $i = 3$ for natural gas)
k – power generating technology (where $k = 1$ for fossil-fired power, $k = 2$ for hydro power, $k = 3$ for wind power, $k = 4$ for photovoltaic power, $k = 5$ for biomass power, $k = 6$ for waste power and $k = 7$ for pumped-storage power)
t – time period ($t = 1 - 3$)
j – traffic types (where $j = 1$ for bus, $j = 2$ for truck, $j = 3$ for taxi, $j = 4$ for private car, $j = 5$ for metro and $j = 6$ for special purpose vehicle
m – EVs types (where $m = 1$ for electric bus, $m = 2$ for electric truck, $m = 3$ for electric taxi, $m = 4$ for electric private car and $m = 5$ for pure electric special vehicle)
$A\tilde{A}P_{t,q}$ – the allowed amounts of pollutant q in period t ($10\hat{3}$ tonne)
$AM\tilde{R}_{k,t,q}$ – pollutant emission coefficients (tonne/GWh)
$A\tilde{R}_{i,t}$ – the amount of available resource type i in period t (TJ)
$BC\tilde{E}_{m,t}$ – the expanded capacities of battery charging for EV type m in period t (unit)
$BS\tilde{C}_{m,t}$ – the expanded capacities of battery swapping for EV type m in period t (unit)
$CE_{t,q}$ – the pollutant discharge fee for type q in period t ($/GW)
$CP_{t,q}$ – the pollutant control fee for type q in period t ($/GW)
$C\tilde{U}_{k,t}$ – the power transmission fee for technology k in period t ($/GWh)
$De\tilde{d}_{t,d}$ – the power demand for end-user d in period t (GWh)
$E\tilde{C}_{k,t}$ – the expanded capacity for electricity-conversion technology k in period t (GW)
$FB\tilde{C}_{m,t}$ – the fixed cost of battery charging for EV type m in period t ($/unit)
$FB\tilde{S}_{m,t}$ – the fixed cost of battery swapping for EV type m in period t ($/unit)
$FP\tilde{E}_{k,t}$ – the fixed cost for power expanding capacity by power k in period t ($/GW)
$FP\tilde{G}_{k,t}$ – fixed cost for power generation by power technology k in period t ($/GW)
$N\tilde{I}P_t$ – the importing power amount in period t (GWh)
$N\tilde{S}E_{i,t}$ – the supply amount of energy resource i for power in period t (TJ)
$PC\tilde{E}_{i,t}$ – the purchasing cost of energy resource i for power in period t ($/TJ)
$P\tilde{C}P_t$ – the importing power fee in period t ($/GWh)
$P\tilde{G}A_{k,t}$ – the power generation amount by power technology k in period t (GWh)
$RB\tilde{C}_{m,t}$ – residual capacity of battery charging for m type EV in period t (unit)
$RB\tilde{S}_{m,t}$ – residual capacity of battery swapping for m type EV in period t (unit)
$R\tilde{C}_{k,t}$ – residual capacity for power-conversion technology k in period t (GW)
$SO\tilde{C}_{m,t}$ – service capacity of EV type m in period t (unit)
$S\tilde{T}_{k,t}$ – service time of power-conversion technology k in period t (h)
$SU_{k,t}$ – the financial subsidies for power technology k in period t ($/GWh)
$T\tilde{C}A_{j,t}$ – the fuel consumption amounts for traffic type j in period t ($/km)
$T\tilde{O}V_{j,t}$ – the operating vehicles for traffic type j in period t (unit)
$TE\tilde{F}_{j,t,q}$ – the pollutant emission factor of pollutant q for traffic type j in period t
$TS\tilde{D}_{j,t}$ – the service distance of vehicles for traffic type j in period t (km)
$VB\tilde{C}_{m,t}$ – the variable cost of battery charging for m type EV in period t ($/unit)
$VB\tilde{S}_{m,t}$ – the variable cost of battery swapping for m type EV in period t ($/unit)
$VP\tilde{E}_{k,t}$ – variable cost for power expanding capacity by power technology k in period t ($/GW)
$VP\tilde{G}_{k,t}$ – variable cost for power generation by power technology k in period t ($/GW)
YBC – 0-1 variables for battery charging
YBS – 0-1 variables for battery swapping
$YC_{k,t}$ – 0-1 variables for power expansion by power technology k in period t

References

[1] Agency, I.E., . Improving the sustainability of passenger and freight transport. https://www.iea.org/topics/transport.

[2] Bamisile, O., Obiora, S., Huang, Q., Okonkwo, E.C., Olagoke, O., Shokanbi, A., Kumar, R., 2020. Towards a sustainable and cleaner environment in china: Dynamic analysis of vehicle-to-grid, batteries and hydro storage for optimal re integration. Sustainable Energy Technologies and Assessments 42, 100872.

[3] Bibak, B., Tekiner-Moğulkoç, H., 2021. A comprehensive analysis of vehicle to grid (v2g) systems and scholarly literature on the application of such systems. Renewable Energy Focus 36, 1–20.

[4] Bunsen, T., Cazzola, P., Gorner, M., Paoli, L., Scheffer, S., Schuitmaker, R., Tattini, J., Teter, J., 2018. Global EV Outlook 2018: Towards cross-modal electrification. International Energy Agency.

[5] Bureau, B.M.E.P., . Beijing statistical yearbook, 2020. http://sthjj.beijing.gov.cn/.

[6] Cadenas, J.M., Verdegay, J.L., 1997. Using fuzzy numbers in linear programming. IEEE Transactions on Systems Man & Cybernetics Part B 27, 1016–22.

[7] Calvillo, C.F., Sanchez-Miralles, A., Villar, J., 2017. Synergies of electric urban transport systems and distributed energy resources in smart cities. IEEE Transactions on Intelligent Transportation Systems , 1–9.

[8] Charnes, A., Cooper, W.W., 1959. Chance-constrained programming. Manag Sci 6, 73–79.

[9] Chen, C.f., de Rubens, G.Z., Noel, L., Kester, J., Sovacool, B.K., 2020. Assessing the socio-demographic, technical, economic and behavioral factors of nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. Renewable and Sustainable Energy Reviews 121, 109692.

[10] Cheng, S., Lu, F., Peng, P., 2020. Short-term traffic forecasting by mining the non-stationarity of spatiotemporal patterns. IEEE Transactions on Intelligent Transportation Systems PP, 1–19.

[11] of Statistics of China, N.B., . National data. https://data.stats.gov.cn/easyquery.htm?cn=A01.
[12] Dalman, H., Bayram, M., 2017. Interactive fuzzy goal programming based on taylor series to solve multiobjective nonlinear programming problems with interval type 2 fuzzy numbers. IEEE Transactions on Fuzzy Systems , 1–1.
[13] Dalman, H., Bayram, M., 2018. Interactive fuzzy goal programming based on taylor series to solve multiobjective nonlinear programming problems with interval type 2 fuzzy numbers. IEEE Transactions on Fuzzy Systems 26, 2434–2449.
[14] Dantzig, G.B., 1982. Reminiscences about the origins of linear programming. Operations Research Letters 1, 43–48.
[15] of Development, B.B.M.C., Reform), . Beijing electric vehicles charging infrastructure special plan of 2016-2020. http://www.evpartner.com/news/12/detail-19416.html.
[16] Didier, Dubois, , , Henri, Prade, 1991. Fuzzy sets in approximate reasoning, part 1: Inference with possibility distributions. Fuzzy Sets & Systems .
[17] Dong, X., Mu, Y., Jia, H., Wu, J., Yu, X., 2016. Planning of fast ev charging stations on a round freeway. IEEE Transactions on Sustainable Energy 7, 1–1.
[18] Ferro, G., Minciardi, R., Robba, M., 2020. A user equilibrium model for electric vehicles: Joint traffic and energy demand assignment. Energy 198, 117299.
[19] Gray, M.K., Morsi, W.G., 2015. Power quality assessment in distribution systems embedded with plug-in hybrid and battery electric vehicles. IEEE Transactions on Power Systems 30, 663–671.
[20] Guo, P., Huang, G.H., He, L., Sun, B.W., 2008. Itssip: Interval-parameter two-stage stochastic semi-infinite programming for environmental management under uncertainty. Environmental Modelling & Software 23, 1422–1437.
[21] Gur, T., et al., 2020. Global ev outlook 2020 entering the decade of electric drive. International Energy Agency, France .
[22] Hartmann, N., Ozdemir, E.D., 2011. Impact of different utilization scenarios of electric vehicles on the german grid in 2030. Journal of Power Sources 196, 2311–2318.
[23] He, H., Wang, Y., Han, R., Han, M., Bai, Y., Liu, Q., 2021. An improved mpc-based energy management strategy for hybrid vehicles using v2v and v2i communications. Energy .
[24] Kall, P., 1982. Stochastic programming. European Journal of Operational Research 10.
[25] Kropiwnicki, J., 2019. A unified approach to the analysis of electric energy and fuel consumption of cars in city traffic. Energy 182, 1045–1057.
[26] Lasisi, A., Ashley, G., Attoh-Okine, N., Ali, F., 2020. Transportation emissions and evs in smart cities: A study of multi-dimensional us emission data. IEEE Transactions on Smart Grid .
[27] Li, P., Zhang, Y., Zhang, Y., Zhang, K., Jiang, M., 2021. The effects of dynamic traffic conditions, route characteristics and environmental conditions on trip-based electricity consumption prediction of electric bus. Energy 218.
[28] Liu, B., 2001a. Fuzzy random chance-constrained programming. IEEE Transactions on Fuzzy Systems 9, 713–720.
[29] Liu, H.C., Yang, M., Zhou, M., Tian, G., 2019. An integrated multi-criteria decision making approach to location planning of electric vehicle charging stations. IEEE Transactions on Intelligent Transportation Systems .
[30] Liu, N., He, L., Yu, X., Ma, L., 2018. Multiparty energy management for grid-connected microgrids with heat- and electricity-coupled demand response. IEEE Transactions on Industrial Informatics 14, 1887–1897.
[31] Liu, X., 2001b. Measuring the satisfaction of constraints in fuzzy linear programming. Fuzzy Sets and Systems 122, 263–275.
[32] Manousakis, N., Korres, G., 2016. Optimal allocation of pmus in the presence of conventional measurements considering contingencies. IEEE Transactions on Power Delivery , 1–1.
[33] Martín, I., Berrueta, A., Sanchis, P., Ursúa, A., 2018. Methodology for sizing stand-alone hybrid systems: A case study of a traffic control system. Energy 153, 870–881.
[34] Mhanna, S., Mancarella, P., 2021. An exact sequential linear programming algorithm for the optimal power flow problem. IEEE Transactions on Power Systems .
[35] Miller, B.L., Wagner, H.M., 1965. Chance Constrained Programming with Joint Constraints. INFORMS.
[36] Peidro, D., Mula, J., Poler, R., Verdegay, J.L., 2009. Fuzzy optimization for supply chain planning under supply, demand and process uncertainties. Fuzzy Sets & Systems 160, 2640–2657.
[37] Pishvaee, M.S., Razmi, J., Torabi, S.A., 2012. Robust possibilistic programming for socially responsible supply chain network design: A new approach. Fuzzy Sets and Systems 206, 1–20.
[38] Sengupta, J.K., 1981. Linear Programming under Uncertainty. Springer Berlin Heidelberg.
[39] Sheng, M.S., Sreenivasan, A.V., Sharp, B., Du, B., 2021. Well-to-wheel analysis of greenhouse gas emissions and energy consumption for electric vehicles: A comparative study in oceania. Energy Policy 158, 112552.
[40] Sperling, D., 2018. Three revolutions: Steering automated, shared, and electric vehicles to a better future. Island Press.
[41] Tanaka, H., Asai, K., 1984. Fuzzy solution in fuzzy linear programming problems. IEEE Transaction on System Man & Cybernetics 14, 325–328.
[42] Wang, L., Nian, V., Li, H., Yuan, J., 2021. Impacts of electric vehicle deployment on the electricity sector in a highly urbanised environment. Journal of Cleaner Production 295, 126386.
[43] Wang, Y., Zhao, S., Zhou, Z., Botterud, A., Xu, Y., Chen, R., 2017. Risk adjustable day-ahead unit commitment with wind power based on chance constrained goal programming. IEEE Transactions on Sustainable Energy .
[44] Yang, H., Hao, P., Luo, F., Jing, Q., Deng, Y., Lai, M., Zhao, Y.D., 2017. Operational planning of electric vehicles for balancing wind power and load fluctuations in a microgrid. IEEE Transactions on Sustainable Energy PP, 1–1.
[45] Yu, L., Li, Y.P., 2018. A flexible - possibilistic stochastic programming method for planning municipal - scale energy system through introducing renewable energies and electric vehicles. Journal of Cleaner Production 207, 772–787.
[46] Zhou, B., Chen, G., Song, Q., Dong, Z.Y., 2020. Robust chance-constrained programming approach for the planning of fast-charging stations in electrified transportation networks. Applied Energy 262, 114480–.