Energy Planning of Beijing Towards Low-carbon, Clean and Efficient Development in 2035

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***Abstract*—Energy transition towards clean, efficient energy supply has been a common sense of the government and public in China. However, lacking reasonable planning will lead to undisciplined development, resource waste, and excessive investment. In this context, this paper investigates potential pathways of Beijing energy transition towards a high-level low-carbon, clean and efficient energy system in 2035 with an extended energysocpe model. Firstly, based on available data, future energy demands are predicted by a newly proposed hybrid forecasting method, which combines the traditional regression model, grey model, and support vector machine model with an entropy-based weighted factor. Secondly, the superstructure-based optimization model is employed to investigate the system configuration and operation strategy of the future Beijing energy system. Finally, the uncertainty impact of electricity price, natural gas price, hydrogen price, and the capital expenditures of electrolyzer and steam methane reforming for hydrogen applications are studied. The forecasting results show that all walks of life will witness a continuously increasing energy demand in multiple sectors of Beijing towards 2035. The planning results suggest that the imported electricity and natural gas will dominate the energy supply of Beijing in 2035 with a contribution of 86% of the energy resources consumption of 384 TWh. Moreover, the energy system presents a high end-use electrification level of 65% and high penetration of efficient technologies, which supply 119 TWh via combined heat and power, 26 TWh via heat pump and 95 TWh via district heating network. The energy use of various sectors of energy resources, technologies and end-use are closely related. Hydrogen will have an increased penetration in the private mobility sector, but the locally generated hydrogen is mainly from steam methane reforming technology.**

***Index Terms*—Energy transition, energy planning, carbon-neutral, demand forecasting, energyscope.**

Manuscript received May 11, 2021; revised August 17, 2021; accepted October 31, 2021. Date of online publication April 13, 2022; date of current version January 5, 2023. This work was supported in part by the National Natural Science Foundation of China (No. 51821004), the Major Program of the National Natural Science Foundation of China (No. 52090062), the Interdisciplinary Innovation Program of North China Electric Power University, and the China Scholarship Council (CSC).

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DOI: 10.17775/CSEEJPES.2021.03620

I. INTRODUCTION

GLOBAL climate change, environmental pollution, and energy security have become major challenges for long-term sustainable human society development and ecosystem [1]–[3]. China, as the largest and fastest-growing developing country, suffers heavily from high coal consumption, which calls for the energy system transition towards fossil-free energy systems [4]. From 1978 to 2018, the energy consumption in China increased rapidly from 571 million tons of standard coal to 4640 million tons of standard coal, while the proportion of coal decreased from 71% to 59% due to the energy structure adjustment with increased penetration of renewable power reaching over 14%. China has taken responsibility and made a positive commitment in 2009 to control greenhouse gas (GHG) emissions that reducing the carbon emissions per unit gross domestic product (GDP) by 40–45% below 2005 levels by 2020 [5]. Considering the commitment of the carbon emissions peak no later than 2030 in the "Paris Agreement" [6] and the carbon neutrality target by 2060, a series of energy plans have been released [7], which sets the energy transition targets to increase the proportion of non-fossil fuels in primary energy consumption to 20% and 50% in 2030 and 2050, respectively [8].

The urban energy transition is crucial for shaping the energy transition [9], [10] since urban areas account for about 66.7% of primary energy demand and 70% of the energy consumption-related CO_2 emissions worldwide [11]. As one of the most developed megalopolises as well as the 'frontier' of Chinese Reform and Opening-up, Beijing is a pioneer in energy transition through energetically promoting decarbonization, diversification, and electrification of energy supply. Its energy transition went through four periods [10], [12]: (1) simultaneous growth between the economy and coal-dominated energy consumption (1978–1996), (2) decreasing growth rate of energy consumption with more imported electricity (1996–2000); (3) transferring into a relatively balanced and diversified energy structure during 2000 to 2007, and (4) a span-new stage with remarkable achievements of the de-coal process since the Olympic Games 2008. Moreover, Beijing was selected as a pilot city to carry out a cap-and-trade mechanism to mitigate carbon emission in 2011 [13]. To further promote the national GHG emissions mitigation, a goal in the 13 th Five-Year Plan was set to reach local GHG emissions peak by 2020 [14]. A new challenge for energy managers and policymakers left is how to carry out the next stage of energy transformation, namely, identifying the pathways to reduce the cap of GHG emissions.

The energy transition can be best handled by energy planning [15], [16]. The transition towards a non-fossil sustainable energy system is correlated with a high penetration of variable renewable energy sources for profound structural changes among multiple sectors [17]. There are various energy models available to capture the increasing complexity and to assist the planning of future energy systems. Connolly *et al.* [18] reviewed 37 computer tools for the integration of renewable energy and concluded that no tool can address all issues related to integrating renewable energy, but instead the ideal energy tool depends highly on the objectives considered. Limpens [17] further performed an extensive retrospect of 53 existing energy models in terms of multi-sector planning, optimization scope, solution precision, and computational effort, and proposed *Energyscope TD*, a novel superstructure-based model for long-term multi-sector planning considering an hourly solution. The boundary of the *energyscope* model is resources and end-use demands. Thus, it cannot employed to the area without reliable energy demands data directly.

For the energy planning of Beijing, recent studies are compared in terms of (1) multi-sector interaction, (2) investment cost optimization with hourly operation strategy, and (3) uncertainty analysis, and (4) planning period. Some studies focus on a specified sector without considering cross-sectoral interactions. For instance, Zhu and Shan [19] investigated the effects of industrial renovation on energy conservation and emission reduction in Beijing. Huang *et al.* [20] explored the way to decarbonize Beijing's electricity systems through renewable cooperation with Zhangjiakou by constructing an hourly Zhangjiakou-Beijing Renewable Electricity Cooperation system via the EnergyPLAN model. Zhang *et al.* [21] investigated the ways of developing a low-carbon heating sector for large metropolitan cities towards 2030 considering different scenarios of deploying natural gas (NG) boilers and heat pumps in the EnergyPLAN model. With the Long-range Energy Alternatives Planning (LEAP) model, Fan *et al.* [22] investigated the energy demand and main GHG emissions of Beijing's public transport under different scenarios during 2016–2030. However, these studies focused only on a specific sector of the energy system but ignored its interaction with other sectors.

Considering multi-sector energy system planning, Zhang *et al.* [14] analyzed the situations of social-economic development and energy consumption in Beijing and established the LEAP-Beijing model for the medium-to-long-term prediction of GHG emissions. With the EnergyPLAN model, Zhao *et al.* [23] presented 100% renewable energy scenarios of the Beijing energy system related to electricity and heat. Yu *et al.* [24] developed an interval-stochastic basic-possibilistic programming method of planning a sustainable energy system for the Beijing application. These studies, to some extent, consider cross-sectoral interaction and provide comprehensive medium-to-long-term energy planning schemes.

Both optimization- or simulation-based energy models should consider the operation of the energy system to identify the tempo-spatial synergy effects among various available energy resources, especially the integration of renewables. In literature (Table I), Zhang *et al.* [14] optimized the investment costs via the LEAP model, while Zhao *et al.* [23] optimized operation strategy via the EnergyPLAN model. Yu *et al.* [24] performed a robust optimization on a yearly basis. There is no available study to optimize both the system configuration and operation strategy simultaneously for the energy planning of Beijing. Moreover, the energy demands data across multiple sectors in the future of Beijing lack.

TABLE I
COMPARISON OF RECENT ENERGY PLANNING STUDIES OF BEIJING BASED ON FOUR GIVEN CRITERIA. LEGEND: ✓CRITERION SATISFIED; √ CRITERION PARTIALLY SATISFIED; × CRITERION NOT SATISFIED

Studies	Multi-sector	Optimiz-ation	Uncertainty analysis	Planning period
Zhu and Shan [19]	×	√	×	2020
Huang *et al.* [20]	×	✓	✓	2030
Zhang *et al.* [21]	×	✓	×	2030
Fan *et al.* [22]	×	√	×	2030
Zhang *et al.* [14]	✓	√[a]	✓	2050
Zhao *et al.* [23]	✓	√[b]	✓	2030
Yu *et al.* [24]	✓	√[c]	✓	2020

[a]Only investment considered.
[b]Only operation considered.
[c]The model focuses on robust optimization and is solved on a yearly basis.

Correspondingly, in this paper, the cross-sector energy system of Beijing 2035 is optimized by an extended *energyscope* model. The main contributions are (1) extending the boundary of *energyscope* model to the historical energy consumption data and macro statistic data by integrating a hybrid energy forecasting method, providing a general energy planning methodology for regions without reliable energy demands data; (2) proposing an entropy-based weighted method combining statistical models and machine learning methods; (3) exploring a reliable pathway towards a low-carbon, clean and efficient energy transition for Beijing 2035.

The remaining paper is organized as follows. Section II outlines the proposed hybrid energy demand forecasting method and *Energyscope TD* method. Section III introduces the assumptions and specifications. Section IV presents the basic results and discussion of the case study. Finally, Section V concludes the paper.

II. METHODOLOGY

A. Overall Method

The overall method of extended *energyscope* includes three steps (Fig. 1):

Step 1: Energy demand prediction by the newly proposed entropy-based weighted hybrid method. The method combines the traditional regression model, grey forecasting model and support vector machine model, and realizes the prediction by employing key macro-economic parameters, historical energy consumption data as well as long-term city plans of Beijing [25].

Step 2: Typical day (TD) selection based on the energy demands predicted, hourly distribution of resource availability and weather conditions (solar irradiance, wind speed, and reservoir's runoff). These input data are formatted and fed to a mixed-integer linear programming (MILP) problem [26] to obtain the typical day sequence.

Step 3: Energy planning with superstructure-based optimization model employing the typical-day sequence and model-related data to identify optimal configurations of the energy systems and operation strategy of the selected typical days. To reduce the computational effort, energy planning is formulated as a linear programming (LP) problem with input data including economic and technical parameters of various energy conversion and storage technologies, and the parameters of different development scenarios, e.g., local renewable energy share and CO_2 reduction targets.

Steps 1 and 2 can be performed only once for a specific region to obtain the energy demand profiles and typical day repetition, while step 3 may be performed multiple times for uncertainty analysis.

B. Energy Demand Forecasting Method

1) Literature Review

There are many studies (Table II) on long-term energy-demand forecasting with different methods: (1) statistical methods, (2) machine-learning methods [27], and (3) bottom-up methods. These methods have been reviewed in detail with a summary given below.

Statistical methods infer the development trend of future energy demand via historical data implying the past regularity. These methods mainly comprise traditional regression models, time series models (including ARIMA models) and econometric models. Regression models, with accurate data compilation and careful scenario creation, can perform better than those with complex programming or esoteric mathematics [28]; however, it is difficult to capture the characteristics of highly complex nonlinear data. Time series models perform well in terms of mean absolute percentage errors and prediction accuracy, however, the forecasting results present a large deviation compared with actual values under the impact of significant events, e.g. the unexpected coronavirus pandemic 2019. The econometric models can reveal the numerical relationships on economic phenomena better but have certain fatal flaws, e.g., the ignorance of the theoretical basis of empirical analysis, as well as region-dependent feature.

Artificial intelligence methods, e.g., artificial neural networks (ANNs), genetic algorithms, support vector machine (SVM) and particle swarm optimization (PSO) models, are also suitable for energy demands prediction. For example, ANNs are characterized as self-learning, self-adaptive, fault tolerance, flexible and real-time response, with the possibility of correlating the energy demand with a variety of parameters.

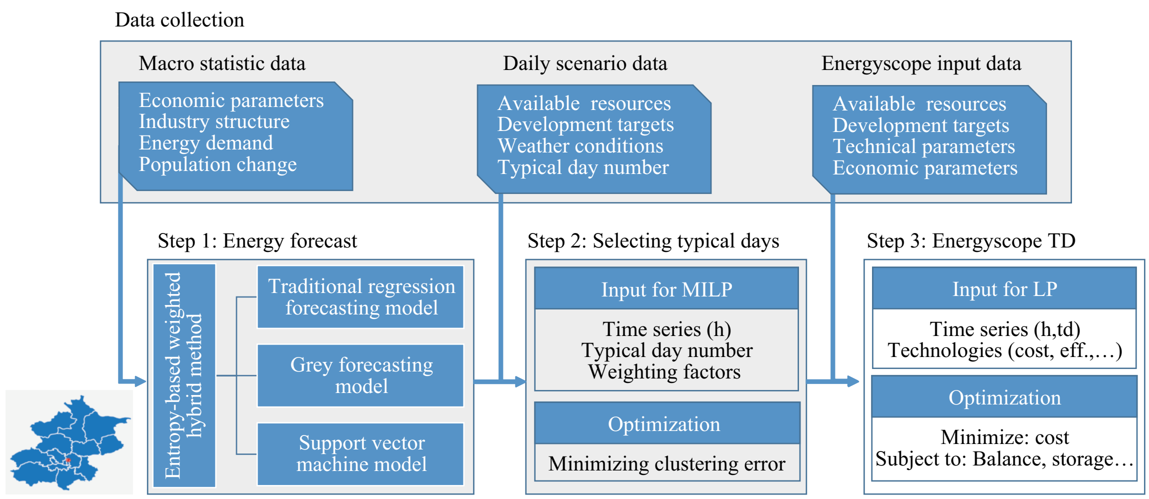

Fig. 1. Overall framework of energy planning for Beijing 2035.

TABLE II
CLASSIFICATION OF ENERGY DEMAND FORECASTING MODELS

Method	Category	Example	Sector
Statistical methods	Regression model	Al-Hamadi and Soliman (2005)	Electric sector
		Lee and Chang (2007)	Overall energy system
	Time series models	Hunt *et al.* (2000)	All demand sectors
		Kumar *et al.* (2010)	All demand sectors
	Econometric models	Iniyan *et al.* (2006)	All demand sectors
		Suganthi and Williams (2000)	All demand sectors
Machine learning methods	ANNs models	Aydinalp *et al.* (2002)	Residential sector
		Soezen *et al.* (2005)	All demand sectors
	Genetic algorithms	Canyurt and Ozturk (2008)	All demand sectors
		Haldenbilen and Ceylan (2005)	Transport sector
	SVM models	Fan *et al.* (2008)	Electric sector
		Hong (2009)	Electric sector
	PSO models	Alrashidi and El-Naggar (2010)	Electric sector
		ünler (2008)	All demand sectors
Bottom-up methods	MARKEL	Kannan and Strachan (2009)	Residential sector
		Strachan *et al.* (2008)	All demand sectors

They can deeply investigate the inherent nonlinear correlation between the energy demand and exogenous variables, e.g., population, industrial structure, and urbanization. However, these methods are limited by overfitting and underfitting.

Bottom-up models are represented by MARKEL, which are employed for modeling energy systems [29], [30] or evaluating policy impact [31], [32]. These models consider technologies and correlated energy consumption, as well as the supply-demand interactions; thus, they are unfit for forecasting only the energy demand in this study.

2) Entropy-based weighted hybrid energy-demand forecasting method

The hybrid method combines conventional regression, grey forecasting and support vector machine models referring to Refs [33]–[35], which can identify the development trend of energy demand via exploring the internal regularity of historical data and the inherent nonlinear correlation between it with macro exogenous variables. The results predicted separately by each of the models are weighted to obtain the robustly predicted values, for which the weighting factors are determined with the entropy concept. Entropy originally measures the degree of disorder in information theory. Thus, a larger variability of forecasting error sequence corresponds to a smaller weight factor in the hybrid forecasting method. The mathematical model is presented in detail in the supplementary materials. Moreover, the forecasting procedure is illustrated in Fig. 2.

1) Predicting energy demands separately through the three methods with historical data sets: energy demands and associated key impact factors, which are divided into training sample sets and test sample sets. The former sets are used to build the prediction models, while the prediction results can be further validated via the latter set.

2) Calculating relative prediction errors of a single forecasting approach by comparing the energy-demand prediction results with the actual values in the test sample sets. The relative error sequence is normalized to reflect the crucial index variability with entropy.

3) Defining entropy values for relative error sequences of each forecasting model in the form of the natural logarithm.

4) Defining the variability coefficient of the error sequences of each forecasting model considering the converse trends of entropy value and variability of a certain system index.

5) Identifying the weighted factors for each forecasting model.

6) Calculating the robust forecasting results by weighting the prediction results derived from each forecasting approach with the weighting factors.

3) Scope of Energy-demand Prediction

When using the entropy-based weighted hybrid forecasting method for energy-demand prediction, the categories of energy demands considered should be consistent with the requirement of the *Energyscope TD* modeling framework. Therefore, the end-use demands (EUD) involve three sectors: electricity, heating and mobility, as shown in Fig. 3. Heat demand considers high-temperature heat (Heat High T) for industry demand, low-temperature heat (Heat Low T) for hot water and space heating. Mobility demands include passenger mobility and freight transportation.

The recondite energy demand can hardly be estimated directly but could be observed by the energy consumption, thus, related historical data of multiple end-use sectors are collected (presented in supplementary material). The electricity sector covers three main industries and households, while the high-temperature heat is only considered for the secondary industry. The low-temperature heat need for space heating can be estimated by different industries' heat consumption data, municipal centralized heating data and overall heating area issued in the statistic bureau. The low-temperature heat used for hot water production $\mathrm{EUD}_{\mathrm{h,\,hw}}$ can be calculated as follows:

$$\mathrm{EUD}_{h,hw} = c_{hw} \cdot m_{\mathrm{per}} \cdot \Delta t \cdot \mathrm{Pop} \tag{1}$$

where c_{hw} is the specific heat capacity of hot water (J/(kg·°C)), is daily hot water consumption per capita (set as

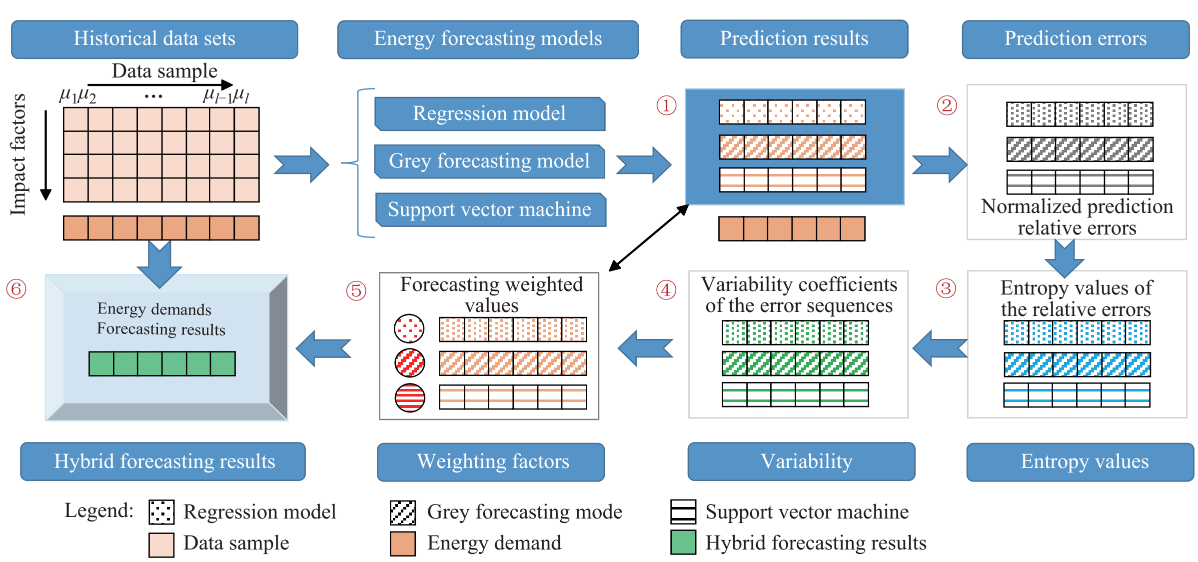

Fig. 2. The flowchart of the entropy-based weighted hybrid forecasting method with the mathematical formulations given in detail in the SI.

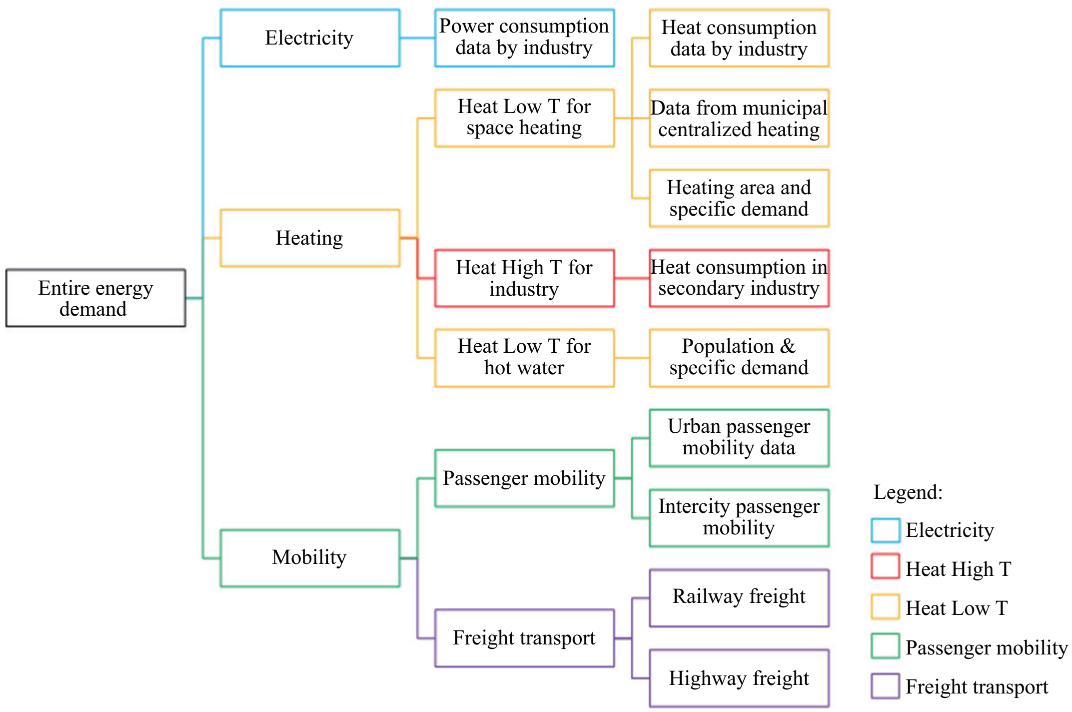

Fig. 3. The categories of energy demand considered following the requirement of the *Energyscope TD* framework.

50 L/day/person), Δt is the average temperature increment for hot water production (set as 40 °C), Pop is the permanent district population (million).

Energy demands in the transport sector are represented by traffic volumes and are affected by passenger and cargo turnovers. Passenger mobility covers urban (public transport, taxi and private cars) and intercity passenger transport (train and coach bus), while freight mobility considers railway and highway freight.

Considering the selection of key parameters, as listed in detail in the supplementary materials, multiple factors influence energy demands, including economic growth, population size, industrial structure, urbanization rate. The former two factors, represented by the GDP and district permanent population (including registered residents and migrant people), contribute the most to the energy demand growth. Moreover, energy demands are interlinked with the levels of urbanization and industrialization, represented by the urbanization rate and the proportion of different industries.

C. Typical Day Selection

To reduce the computational efforts, a series of typical days can be selected to represent 8760 h of the whole year. The information loss and unexpected error depend on the number of typical days employed. Considering the trade-off between accuracy and computational time, the number of typical days is set as 12 by comparing the relative clustering errors and computational costs of 4, 8, 12, 24, 48 and 96 TDs (presented in supplementary materials). The typical days are determined by clustering days with a given criterion. The modified k-medoids algorithm proposed by [26] is employed due to accuracy and computation efficiency. Since the models based on TDs are unable to settle intra days or seasonal storage due to the discontinuity between the selected days, the "coupling typical days" method referred to [36] is implemented to handle energy storage technologies, in which each day is associated with a specified TD through a sequence.

The typical days can be identified by two steps (Fig. 4): the calculation of the dissimilarity matrix and the application of a clustering algorithm. *Energyscope TD* model categorizes each real day with five key parameters (a 365-by-24 matrix for each variable), including end-use electricity demand, space heating demand, solar irradiance, wind speed, and water flow in run-of-river hydropower plants. These parameters present spatio-temporal characteristics of the energy system for the planning area. They are enable quantified and are used in the *energyscope* model. The categorical data is represented as a 365-by-120 matrix and each row represents a single day. The dissimilarity between two days can be calculated by their Minkowski distance according to the two-row data, and the dissimilarity matrix (an upper triangular matrix) can be further established. The elements in the matrix are close to zero when two days are near each other and become large when they differ significantly from each other. Thereafter, the clustering

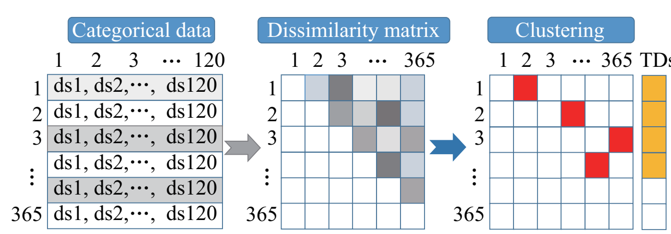

Fig. 4. The method for typical day selection. The red box represents the relationship between each day with its typical day. The orange box represents the typical day allocation.

algorithm proposed by [37] based on the analogy between the medoids selection problem and the optimal plant location problem is employed to identify the dependency matrix and TD vector. Each day of the year, i.e., each column in the dependency matrix, is allocated to one single typical day. Different rows in the dependency matrix represent the typical days and are limited by the TDs, which is further restricted by the number of the TDs. Finally, typical days are determined by minimizing the distance from all days to their corresponding typical days.

D. Superstructure-based Energyscope TD Model

The *Energyscope TD* model represents an energy system considering all energy flows in the application scenarios. The energy system comprises three parts: energy resources, energy technologies, and end-use demands. Each type of energy flow is defined as a *layer*. Different *layers* are interlinked by energy technologies, including end-user, storage, and infrastructure technologies. Each *layer* needs to be strictly balanced at each time by synergistic configuration and coordination operation. For instance, the *electricity layer* is balanced by (1) optimized schedule by different power generation technologies, (2) electricity consumption by electricity-consuming technologies and end-use electricity demand as well as transmission losses, and (3) electricity storage technologies.

A reference energy system (RES), illustrated in Fig. 5, is defined for Beijing, which includes 24 *layers*, 8 end-use demand types and 69 technologies (with emerging technologies). Compared to that applied to Switzerland in Ref. [17], coal-based cogeneration, combined heating and power (CHP) technologies are also considered to supply high-temperature heat and centralized low-temperature heat considering the actual situation in China. The energy conversion technologies are mainly divided into ten blocks: (1) Electricity production consists of conventional fossil-based and renewable resources-based power generation technologies to supply power for other technologies and end-use electricity demand. The technologies for (2) centralized heat and (3) decentralized heat provide low-temperature heat demand for the society, while (4) those for industrial heat aim at satisfying high-temperature heat demand. The technologies for both (5) public mobility and (6) private mobility are used to meet urban and intercity passenger mobility demand. (7) The freight transport demand can be executed through trains and trucks. Three types of energy storage technologies are considered to cope with the penetration of RES: (8) electricity storage, (9) thermal storage

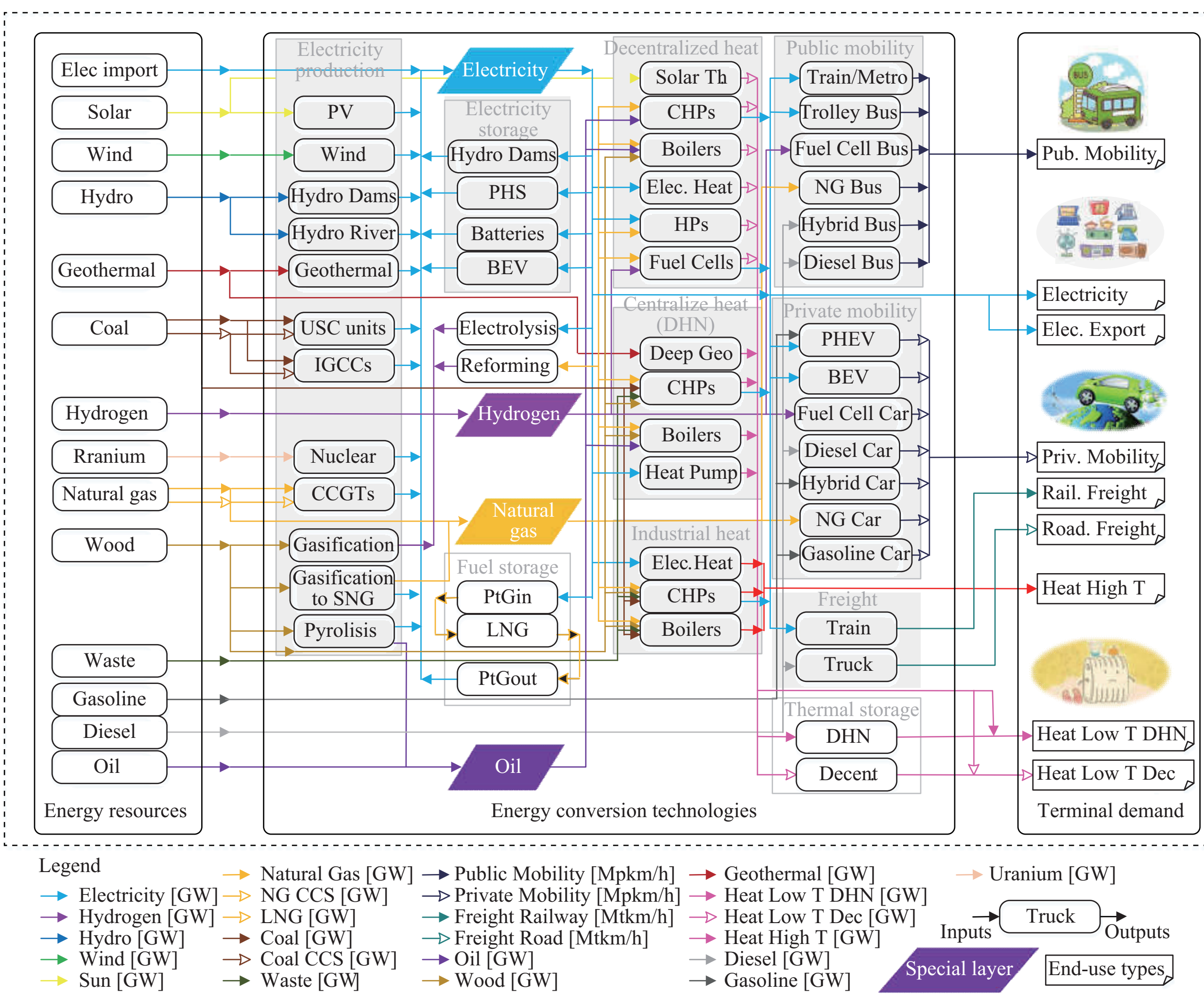

Fig. 5. The reference energy system of the *Energyscope TD* modeling framework for Beijing 2035.

and (10) fuel storage by liquid natural gas (LNG). Moreover, four multi-function mass layers including electricity, hydrogen, natural gas, and oil are emphasized: They can either be treated as available energy resources or be produced/converted by other technologies.

The *Energyscope TD* optimizes the energy system planning, including the optimal system configuration, i.e., the combination and sizes of various energy conversion and storage technologies, as well as the operational strategy of each technology, i.e., hourly energy flows allocation among different energy resources, energy conversion technologies, and energy storage devices, by minimizing the overall annual costs that consist of the overall investment costs, and operating and maintenance costs of the technologies employed, and the operating costs of resources fed into the energy system. Additional indicators for evaluating the derived energy systems include the GHG emissions represented by the global warming potential (GWP) (ktCO_2-eq./year) calculated via the life cycle assessment (LCA) method. The whole energy system planning is formulated as linear programming (LP) problem considering the balance of all energy layers, as well as additional physical limits related to the system design and operation:

1) The installed capacity of each technology is limited to a range expected considering its deployment potential in the future.

2) The operation strategy of each technology is constrained by the capacity factors related to resource availability, and its downtime and maintenance.

3) Each energy layer must be balanced for each time.

4) For the energy storage technologies, the energy storage level at a time (t) is derived by the last-time $(t-1)$ storage level (considering energy storage losses) as well as incoming and outgoing flows (considering input/output efficiencies) at the time (t).

Detailed information including mathematical formulations on energy planning models and specifications can be found in the supplementary material.

III. Assumptions and Specifications

A. Energy Supply for Beijing

The availability of energy resources has a significant impact on the pathway of the energy transition. Beijing has high energy consumption but limited resources [23]. The majority of energy consumed in Beijing, including NG, coal, oil and electricity, are imported from other resource-rich provinces such as Hebei, Shanxi, and Inner Mongolia. In this context, Beijing has advanced its four-stage energy transition to establish a stable energy supply.

For the current energy supply system, the consumption of crude oil, natural gas and imported power is comparable, which dominates the entire energy system. There has been a dramatic decrease in coal consumption in Beijing (Fig. 6), which attributes mainly to large-scale city clean energy actions such as the project of switching from coal into gas and electricity for district heating. Crude oil plays a crucial role in energy consumption and the proportion keeps at a stable level of one-third. The oil product supply of Beijing depends on the Sinopec Yanshan Petrochemical company with an annual crude oil process capacity of ten million tons, as well as the "one plant, one line, multiple warehouses and one thousand stations" refined oil supply system. It can be seen that the NG consumption witnessed an ever-increasing trend in the energy structure since the development of the NG-based local power generation and space heating, which is supported by a multi-sources, multi-directional NG supply system with "three gas sources, eight channels and a 10 MPa loop" (main NG pipelines illustrated in Fig. 7). As for the imported electricity, imported electricity increased with the enhancement of receiving external electric channels, 14 lines with a capacity of 35 GW during the 13 th Five-year Planning. Considering local renewable energy sources, Beijing is rich in solar energy in the category of class II according to solar energy radiant quantity, and rich in geothermal energy with ten main interconnected geothermal fields (see Fig. 7). However, the development of wind and hydrogen energy is limited by the scarcity of energy resources.

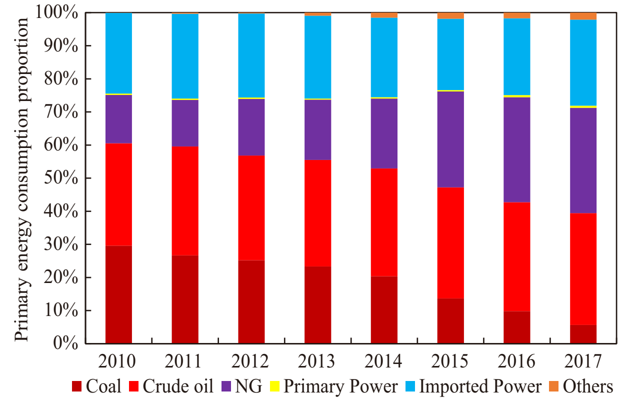

Fig. 6. The energy supply structure of Beijing from 2010 to 2017.

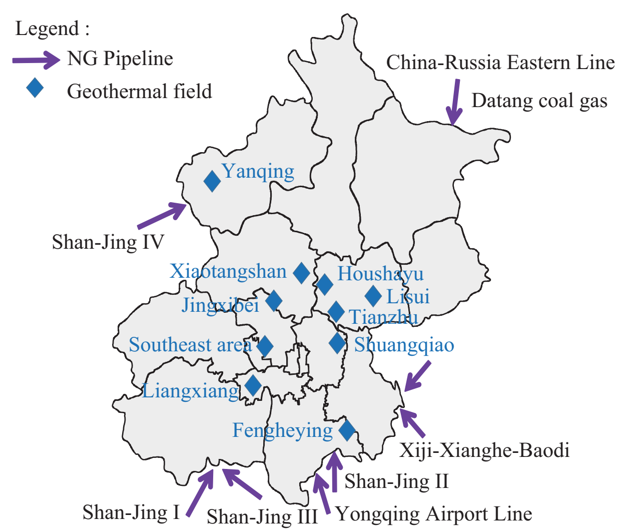

Fig. 7. The natural gas transmission pipelines and main geothermal field distribution of Beijing.

B. Key Assumptions of Energy Demand Forecasting

To guarantee the reasonability and feasibility of the energy demands forecasting results, essential analysis of the development and energy resources of Beijing is introduced. In the context of the "Beijing 13th Five-year Planning Outline" and "Beijing Urban Mater Plan (2016–2035)", Beijing's economic growth would slow down gradually. Referring to the report of "The Challenges, Policy Tool and Institutional Framework of a Typical City (Beijing)", the economic growth rate in different stages is assumed to be 6.5% during 2016–2020 and decreases by 0.5% every five years until 2035. Concerning the population increment, in the light of the "Beijing Urban Mater Plan (2016–2035)" and the process of non-capital function interpretation, the growth rate of Beijing's population will slightly drop. Beijing's permanent resident population will reach around 23 million in 2020 and keep at this level for a long time. Furthermore, we employed a time series forecasting method to predict the permanent resident population change trend (Fig. 8), concluding 21.45 million for 2035. The urbanization rate of Beijing is assumed as a constant value of 86.5% and the proportion of the tertiary industry is set as 85% with a stable economic structure with a feature of high-grade, high-precision, advanced technology. Thus, the essential national economic and social development scenarios are concluded in Table III.

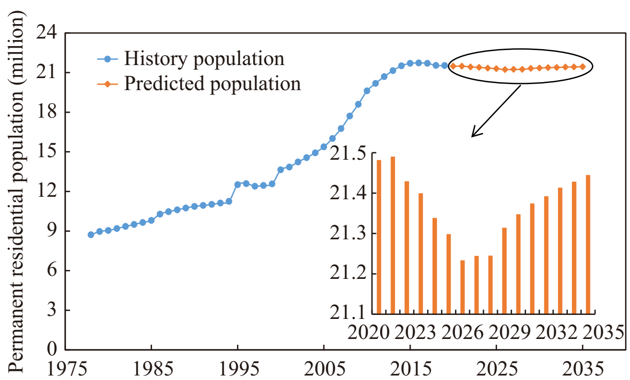

Fig. 8. The permanent residential population change trend of Beijing towards 2035.

TABLE III
ASSUMPTIONS OF THE ESSENTIAL ECONOMIC AND SOCIAL DEVELOPMENT IN DIFFERENT STAGES

Symbol	2016–2020	2021–2025	2026–2030	2031–2035
Economy growth rate (%)	6.5	6.0	5.5	5.0
Permanent population (million)	21.48	21.30	21.35	21.45
Urbanization rate (%)	86.5	86.5	86.5	86.5
Tertiary industry proportion (%)	80	85	85	85

C. Energy Demand Forecasting Results

This section presents the prediction results of various energy demands within the energy demand structure of Beijing for an eighteen-year horizon from 2018–2035. The historical energy consumption data and crucial exogenous variables in the general data sets from 2005 to 2017 are reported in the supplementary material. The entropy-based weighted hybrid energy forecasting method is adopted through two steps: i) determining the weighting factor for each single forecasting model and ii) forecasting energy demands for the target year with a hybrid method. Firstly, historical data sets are divided into two parts: data from 2005 to 2014 are used as training data to build forecasting models and the rest of the data are used for results validation, which is used for calculating the relative error sequence. The weighting factors of various forecasting models for various energy demands are obtained and presented in Fig. 9.

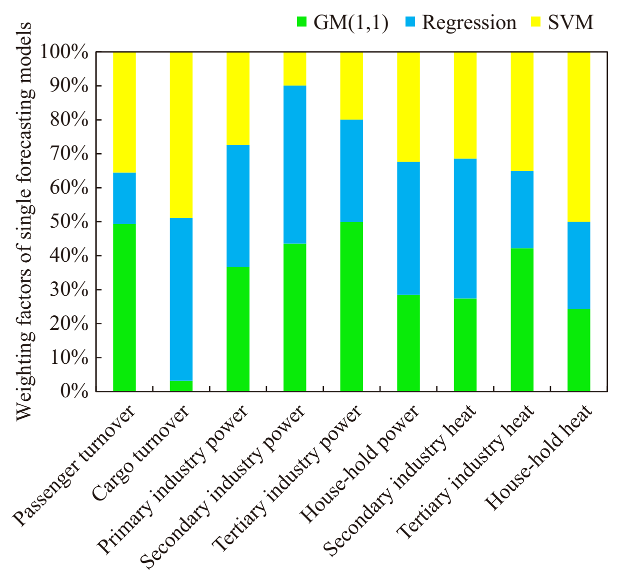

Fig. 9. Weighting factors of various single forecasting models for different.

Weighting factors of single forecasting models represent prediction accuracy on specific domains. Single forecasting models presents different accuracy on various prediction categories. For example, GM(1, 1) presents great performance on the tertiary industry power demand (weighting factor is 0.499) but behaves poorly on the cargo turnover prediction (weighting factor is 0.032). Moreover, concerning the nine categories investigated, the performance of the three forecasting models varies a lot in different categories. To be specific, the passenger turnover can be estimated correctly by GM(1, 1) and SVM with the weighting factors of 0.494 and 0.355, but the cargo turnover within the mobility sector can be estimated by regression and SVM models with the weighting factors of 0.479 and 0.489, while the secondary industrial power demand can be forecasted precisely by the GM(1, 1) and regression means with a corresponding weighting factor of 0.436 and 0.465. For the other six categories, the three approaches present a similar level of prediction precision. Based on the obtained weighting factors, the energy forecasting results of Beijing towards 2035 are illustrated in Fig. 10.

The hybrid forecasting method performs robust results when compared to the single forecasting approach, the forecasting results located between the energy demands ranges determined by individual forecasting results. The results demonstrated that it can avoid the errors caused by the weakness of single methods. The distribution of forecasting results for various approaches can reflect prediction precision, which is represented by the weighting factor. Taking the passenger

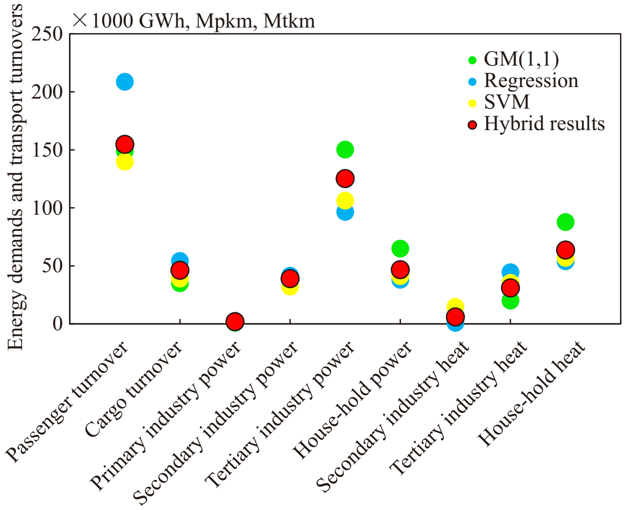

Fig. 10. Energy forecasting results of various categories of Beijing towards 2035.

turnover as an example, the forecasting results are 149002 (GM(1, 1)), 208680 (regression), and 139746 (SVM) Mpkm, respectively, in which the regression result is far from the other two approaches and corresponds to a relatively smaller weighting factor of 0.151.

For the prediction results of Beijing energy demands in 2035, based on the social and economic development assumptions, the passenger and cargo turnover will be 154758 MPkm and 46187 Mtkm, respectively. For electricity consumption, power demand among the multiple sectors is going to witness a different increase. A dramatic increase from 50630 GWh in 2017 to 125231 GWh in 2035 is foreseen in the tertiary industry due to the economic growth and industrial structure adjustment. Concerning the heating demand, the high-temperature heat demand of the secondary industry will decrease to 5956 GWh, while the low-temperature heat demand of the tertiary industry and household sector will increase to 31003 and 56899 GWh, respectively.

D. Typical Days Selection for Beijing Energy Planning

Based on the given five time-series data, 12 TDs are selected for Beijing energy planning towards 2035. The repetition of these typical days over the year is illustrated in Fig. 11.

The red points represent 12 typical days, which can be classified into four categories:

- 7 winter days (TDs 1–4 and TDs 10–12) with space heating demand. There are nuances between them: TDs 1–4 are sunny windy days, with a higher heating demand for TD-1, a stronger wind for TD-2 and stronger sunshine for TD-4. TD-10 and TD-13 are cloudy days, but TD-13 presents lower electricity demand and smaller water flow, and TD-12 is a sunny day.
- 3 cold intra-season days (TDs 5–7). TD-5 has a stronger wind than the other two days and a smaller water flow, TD-6 is a sunny day with stronger sunshine compare to the other two days.
- 1 hot summer day (TD-8), which is an unwind sunny day.

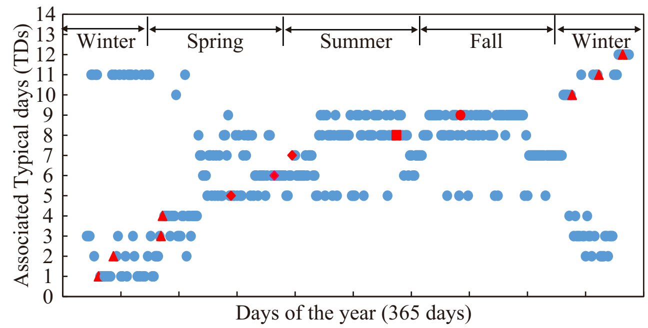

Fig. 11. Associations of days of the year (x-axis) to one of the twelve typical days (y-axis). Red points represent the selected typical days for each cluster and the blue points represent the real day of the year.

- 1 hot intra-season day (TD-9), with the lowest hydro river production due to the lowest water flow.

Figure 11 illustrates that some intra season days are connected with selected typical winter or summer days. For example, the 6th of July (day 187) is a cold summer day associated with TD-5, a cold intra-season day.

IV. Results and Discussion

A. Model Validation

Long-term energy planning is inherently unverifiable since they model an unknown future [38]. Limpens *et al.* [17] proposed that such models can be validated in representing the past or present state of the system. Thus, we assess whether the model can reconstruct the Beijing energy system in 2015 with good data availability and strong timeliness. Some key parameters, such as the end energy demands, shares of train freight, public mobility, and centralized heat supply for the comparison, are fixed to reproduce energy system configuration with the 12 TDs selected before. The results are compared to the public data for 2015 in terms of main energy consumption, global or per type of fuels, and global GHG emissions.

The *energysocpe* model provides a good approximation of the public energy consumption data for Beijing in 2015 (Table IV). The lower values of energy consumption calculated result from the higher efficiencies of various technologies employed for 2035. The difference is mostly related to the NG, gasoline and diesel. Other differences like the imported electricity result from the ignorance of some minor contributions in LP model. The total GHG emission from the main fuel combustion in 2015 is 52 $MtCO_2$-eq with a margin of error of 7%. The *energyscope* model can effectively provide good

TABLE IV
Model Results vs. Public Data for Beijing Energy Systems in 2015

Category	2015	ESTD	Δ	Δ_{rel}	units
NG	102.85	91.92	10.93	10.63%	TWh
Coal	33.59	37.39	−3.80	11.31%	TWh
Gasoline	55.43	51.21	4.22	7.62%	TWh
Diesel	21.45	15.01	6.44	30.02%	TWh
Elec. Imp.	56.84	64.01	−7.17	12.61%	TWh
GHG (Fuels)	51.76	48.08	3.69	7.12%	$MtCO_2$-eq

reproduction of the energy system of Beijing for a reference year.

B. Energy Planning Based on the 12 TDs Selected

The energy planning of Beijing towards 2035 with a 10% share of renewable energy and GHG emissions limitation referring to 2015 are studied, including (1) energy system structure optimization, and (2) operation strategy considering the penetration of renewable energies.

The Sankey diagram (Fig. 12) illustrates the energy conversion process from the energy resources to the end-use energy consumption. The overall energy consumption reaches 384 TWh with 10% coming from local renewable energies (imported electricity is not converted to fuels). The energy planning achieves the renewable energy development target in two steps without violating the GHG emission regulation. Firstly, compared to the scenario without renewable energy constraints, the energy resources consumption is decreased by 14% via employing emerging high efficient technologies, such as heat pumps (HPs), electrical vehicles (EVs), and district heating networks (DHN). Secondly, the development of renewable energy technologies, mainly solar energy and geothermal energy due to the regional resources endowment, is promoted.

Considering the relationship between energy supply and the end energy consumption of Beijing, the imported energies will continue to play a crucial role in the energy transition. To be specific, the imported electricity (163 TWh) and NG (163 TWh) contribute up to 86% of the energy resources. The overall annual cost of the energy system is 251 billion CNY, with the annualized capital expenditure (CAPEX) and system maintenance accounting for 28%. The remaining is contributed by imported electricity and other resources, corresponding to 97% of the overall GWP.

The energy transition pathway presents partial electrification of mobility and heat sectors, increased penetration of efficient technologies and local renewable energy sources (Fig. 13). Electricity demand accounts for 65% of the end energy demand, while the electrification level of the mobility sector reaches 44%. Particularly, the electrification of public transport reaches as high as 67%. Considering advanced technologies, (1) more than 80% NG is used by the CHP units to supply electricity and heat; (2) HPs supply 26 TWh low-temperature heat, only 6 TWh less than that supplied by the boilers; (3) DHN dominates the low-temperature heat supply (80% and

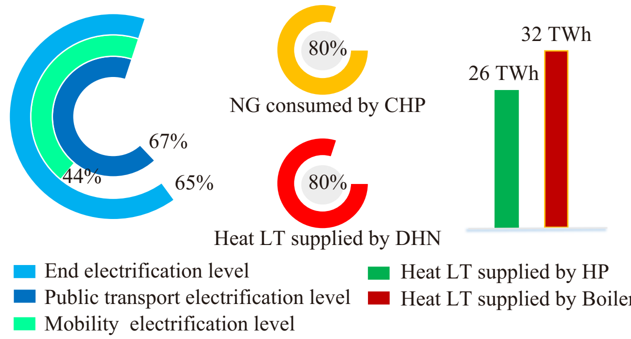

Fig. 13. The electrification level of end-use energy demand, mobility sector and public transport, as well as advanced technologies application under the scenario with a 10% renewable energy share in 2035.

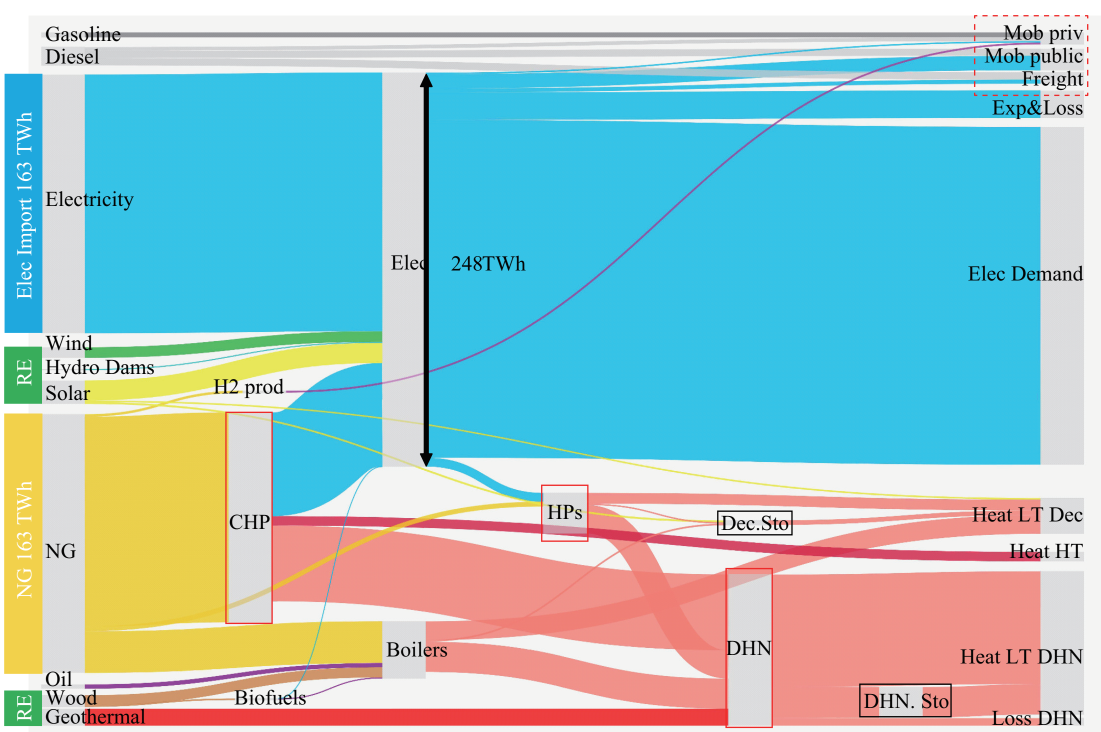

Fig. 12. Energy flows of a scenario representing a 10% renewable energy share of Beijing towards 2035, in which the energy resources is 10% renewable energy (green on left). Highly-efficient and energy storage technologies are framed in red and black, respectively, while the dotted line means that part of the technologies employed in this sector is efficient, for example, trolley (efficient) and diesel-fueled (not efficient) in the public mobility sector.

95 TWh); (4) thermal storage is used as a buffer for the electrical grid, as well as the supplement of electricity storage. Moreover, the large imported electricity proportion reduces the local energy storage need by rational electricity dispatching.

Figures 14 and 15 show the hourly energy flows of electricity and low-temperature heat for each day, respectively. The electricity supply is dominated by imported electricity and NG-based CHP technologies (92%), while electricity demand is partially satisfied by local renewable energy resources. The power generated from NG presents a remarkable seasonality due to the thermoelectric coupling of NG-based CHP technologies. The power generated from NG increases in the winter heating period and decreases in the summer. To satisfy the end electricity demand, imported electricity presents a reverse trend. Daily electricity supply is mainly from renewables, thus varies significantly in a tempo manner, for example, the PV peaks in midday and decreases at night. Considering the electricity demand, the process of electrification contributes to a remarkable increase to 248 TWh of Beijing in 2035. The electricity demand varying in an hourly time scale for each TD partially results from the electrification of the mobility sector (Fig. 14).

For low-temperature heat supply, fossil fuel plays a major role (67%) by employing three types of technologies: CHP, Boilers, and novel NG-based HP. The promising HP has great potential both for DHN and decentralized low-temperature heat supply. Renewable-driven heat supply is mainly based on geothermal and solar energy. The overall capacity of geothermal can reach 11 TWh in 2035 and remains constant during various TDs. Solar energy is used directly for heating during the daytime, e.g., during TD-6, hours 7 to 19. Seasonal heat demand is high in the winter heating period but keeps at a lower level in summer, accordingly, electricity generated from NG-based CHP units in winter is significantly larger than that in summer on account of the thermoelectric coupling effect. Daily heat demand presents a tendency contrary to the electricity demand: the demand peaks at midnight and down to the bottom at noon due to the change of ambient temperature. Moreover, considering thermal storage, the system stores thermal energy during the daytime and releases the stored energy at night (such as TD-4).

To further illustrate the effectiveness of the proposed plan-

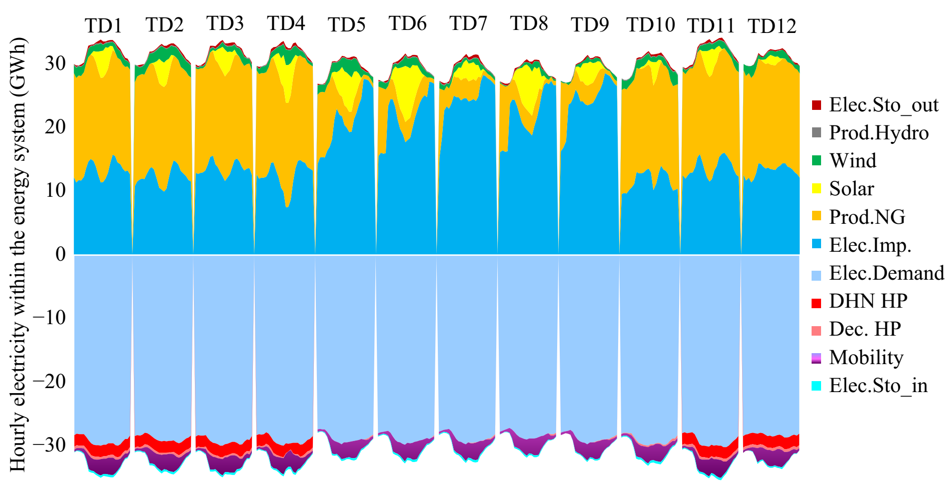

Fig. 14. Electricity balance of the 12 TDs. The electricity supply (positive) has to compensate for the power demand.

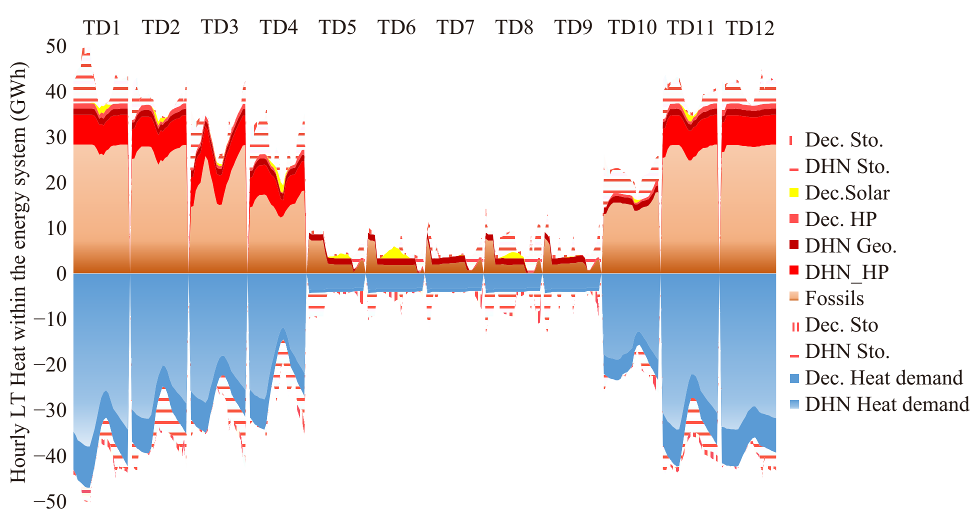

Fig. 15. Daily balance of the low-temperature heat of 12 selected TDs. The low-temperature heat supply has to compensate for demand and storage.

ning method, the results are compared with the study in Ref. [14]. In Ref. [14], the energy consumption in 2035 will reach 107.62, 92.13, 86.11, and 80.88 million tons of coal equivalent in business-as-usual, low-carbon, enhanced low-carbon, and peak-reaching scenarios, respectively. The energy consumption in this study is 73.7 million tons of coal equivalent with a conversion efficiency of 43% for imported electricity production. The results close to the scenario of peak-reaching and the difference may be resulted by three factors: (1) different energy efficiencies in the model; (2) advanced technologies employed in our model; (3) ignoring some small contributions.

C. Sensitivity Analysis

For real-world energy system planning, there are many uncertainties [39], e.g., resource availability and price. The impact of imported hydrogen price, imported electricity price, NG price, and the CAPEX of the electrolyzer and steam methane reforming (SMR) for the hydrogen application are studied via sensitivity analysis.

The overall cost of the energy system and yearly balance of energy resources with different NG prices is presented in Fig. 16. The overall system cost increases linearly with the NG price. With the reference price of 0.23 MCNY/GWh, the total system costs reach 232 billion CNY when the NG price falls by half, and increases to 269 billion CNY if the NG price rose by half. To study the effects of NG price change on the energy system planning, the yearly balance of energy resources is analyzed. The imported electricity presents a significant influence caused by the NG price change apart from the NG consumption change. There is a substantial decline of annual NG consumption from 163 TWh to 149 TWh after the NG price rises to more than 130% of the reference, which attributes mainly to the NG price being higher than the imported electricity. Thus, part of the NG is replaced by electricity, thus the annual imported electricity increases from 163 to 169 TWh. For other energy resources, the NG price change has a slight influence on the energy consumption structure. When varying within 50% and 150% of the reference NG price, the increase in the NG price may promote the consumption of other fossil fuels. Without the imported electricity and NG, the proportion of fossil fuels increased from 30.6% to 31.6%, in which the proportions of gasoline and diesel decrease slightly but that of the LFO increases from 3.5% to 4.9%. This change attributes to the fuel replacement of NG by LFO within the distributed integrated energy system for the sake of operating cost reduction.

Electricity price changes present a similarly linear impact on the overall cost of the energy system with NG price, increasing from 176 billion with 50% of reference electricity price (0.81 MCNY/GWh) to 317 billion CNY with 150% of the reference electricity price (Fig. 17). Moreover, the electricity price decrease will induce significantly the increment of the imported electricity but the increase in the electricity price has nuances on the energy system structure in the change range. When the electricity price drops by half, the amount of imported electricity reaches 241 TWh, accounting for 74% of the total energy resources consumption. Meanwhile, NG consumption decreases to 36 TWh with a share of 11%. It should be noted that the total energy resources consumption drops with the electricity price change. There is a 56 TWh

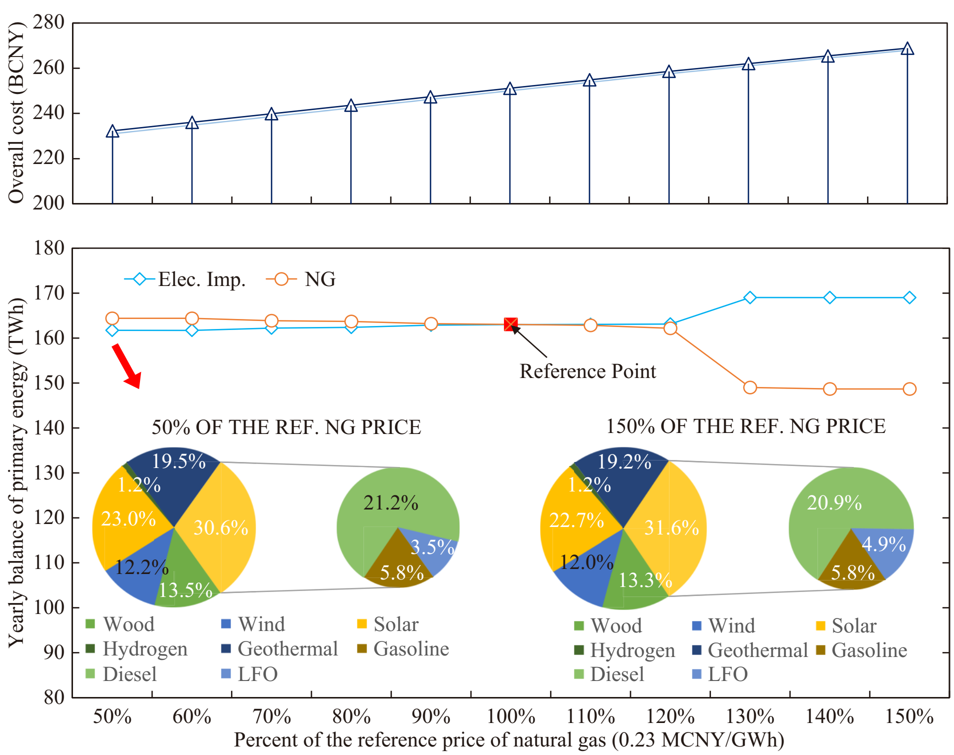

Fig. 16. The overall cost of the energy system and yearly balance of energy resources considering various NG prices in the range of 50%–150% of the reference price.

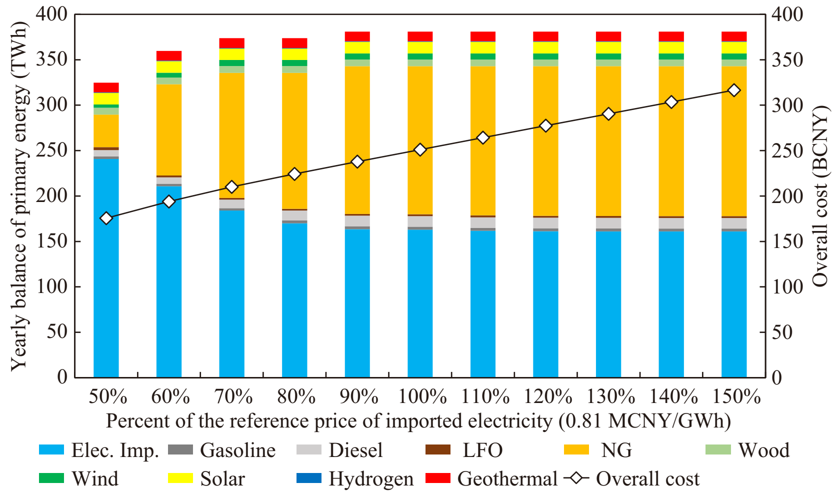

Fig. 17. The overall cost of the energy system and yearly balance of energy resources considering various imported electricity prices in the range of 50%–150% of the reference price.

decrease of the total energy resources consumption with a 50% referencing electricity price, which is caused by a larger scale imported electricity utilization and the imported electricity corresponds to another upstream energy conversion process.

Considering the electricity demand, the effects on the overall energy system with 50–150% of the reference electricity price have been discussed in detail in the supplementary material.

Hydrogen plays an important role in the transport sector, reaching the upper bounds (20%) of private mobility demands, and is mainly derived from SMR technology. With the decrease in the imported hydrogen price, hydrogen application presents a promising potential in terms of public mobility and decentralized combined heat and power generation (Fig. 18). When the imported hydrogen price is below 40 CNY/kg, end-use hydrogen is still mainly consumed by the private mobility sector and part of the hydrogen is supplied by the imported hydrogen. The imported hydrogen dominates the hydrogen supply when its price decreased to 18 CNY/kg. If the imported hydrogen price is further reduced to 14 CNY/kg, hydrogen might present considerable penetration in the public transport sector and the hydrogen-based technologies will undertake 20% of the total public transport task. Moreover, when the imported hydrogen price further reduces to 4 CNY/kg, the hydrogen starts to participate in decentralized CHP with a contribution of 1% to the decentralized low-temperature heat demand.

The influences of CAPEX of the electrolyzers and SMR technology on the hydrogen supply and consumption are also investigated. The variation of SMR CAPEX within 30–100% of the reference value (5299 MCNY/GW) does not affect the hydrogen supply and consumption (see supplementary information). For the CAPEX of the electrolyzer (Fig. 19), when it decreases to 65% of the reference value (2392 MCNY/GW), there will be 8 GWh hydrogen generated locally from the electrolyzer technologies and the value remains unchanged as the electrolyzer CAPEX further decreases, because the hydrogen cost is dominated by the OPEX, mainly the electricity cost.

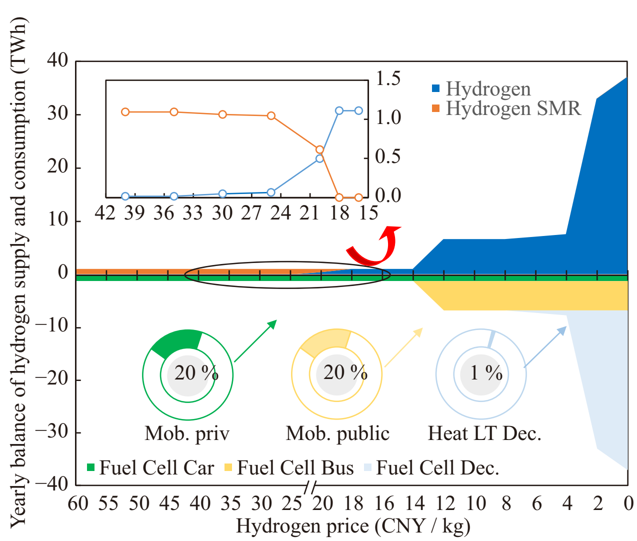

Fig. 18. Hydrogen supply and consumption considering various imported hydrogen prices in the range of 0–60 CNY/kg.

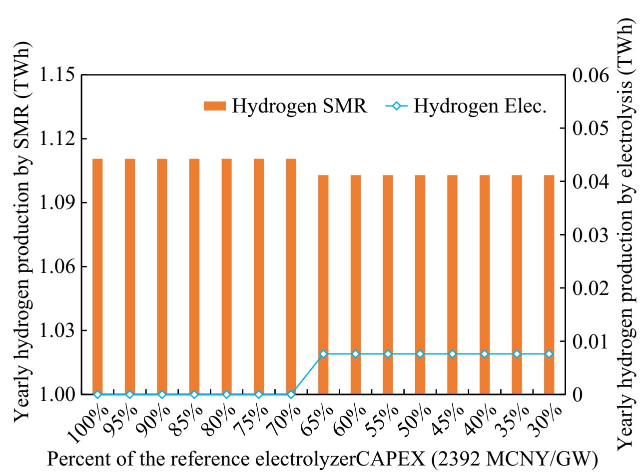

Fig. 19. Hydrogen production considering the impact of electrolyzer CAPEX in the range of 30%–100%.

V. Conclusions and Policy Implications

Beijing will build a clean, efficient, low-carbon energy system under the guideline of the "Beijing Urban Mater Plan (2016-2035)". A potential pathway for deeply energy transition of Beijing is studied with an extended *energyscope* model by integrating entropy-based weighted hybrid energy demands forecasting method. Moreover, the uncertainties of the energy transition and the penetration of hydrogen technologies are investigated by sensitivity analysis. The results show that imported energy and NG will dominate the energy supply in 2035 with a share of 86%. The optimized energy system presents higher electrification of mobility and heat sectors, as well as high penetration of efficient technologies such as CHP and HP. There is a coherent relationship between various energy resources and end-use sectors. The case study provides the following messages to support policy-making and energy planning:

1) Strengthen the electrification level of the end-use sectors. Making electricity accounts for 65% of the end energy consumption. Improving the electrification of the mobility sector will contribute to the mitigation of GHG emissions from fossil fuels. Facilitating electrification in heating sectors can enrich the heating supply means and increase renewable energy consumption.

2) Promote the application of high-efficient technologies. The application of promising technologies is an effective way for the gross control of energy consumption. In the context of the energy development target year of 2035, energy supplied by some innovative means can increase up to 119 TWh (CHP), 26 TWh (HP), and 95 TWh (DHN).

3) Prioritize the development of local superior renewable energy resources. Solar energy can be used in the form of both electricity through the PV (13 TWh) and low-temperature heat (2 TWh). Geothermal can be developed as an important part of DHN and the utilization scope will reach 11 TWh in the framework of the renewable share constraint and GHG limitation.

4) Guarantee the capacity of imported electricity and NG supply. The imported electricity and NG are inevitable for Beijing and affect each other largely. The NG price fluctuates within 50–150% accompanied by the same trend change of imported electricity quantity from 161.7 TWh to 169 TWh. In turn, the increase in the proportion of electricity will decrease NG consumption under the same energy demand.

5) Accelerate hydrogen-related technology development and application. Hydrogen plays a significant role in the transport sector, reaching the upper bounds (20%) of private mobility demands. With cost reduction, hydrogen will be promising for distributed CHP. Moreover, the decrease of electrolysis CAPEX will promote that part of hydrogen generated from SMR is replaced by electrolysis technology.

References

[1] J. Bollen, S. Hers, and B. van der Zwaan, "An integrated assessment of climate change, air pollution, and energy security policy," *Energy Policy*, vol. 38, no. 8, pp. 4021–4030, Aug. 2010.

[2] S. A. R. Khan, K. Zaman, and Y. Zhang, "The relationship between energy-resource depletion, climate change, health resources and the environmental Kuznets curve: Evidence from the panel of selected developed countries," *Renewable and Sustainable Energy Reviews*, vol. 62, pp. 468–477, Sep. 2016.

[3] N. Watts et al., "The 2018 report of the Lancet Countdown on health and climate change: shaping the health of nations for centuries to come," *The Lancet*, vol. 392, no. 10163, pp. 2479–2514, Dec. 2018.

[4] L. Li and A. Taeihagh, "An in-depth analysis of the evolution of the policy mix for the sustainable energy transition in China from 1981 to 2020," *Applied Energy*, vol. 263, p. 114611, Apr. 2020.

[5] L. Li, Y. Lei, S. Wu, C. He, J. Chen, and D. Yan, "Impacts of city size change and industrial structure change on CO_2 emissions in Chinese cities," *Journal of Cleaner Production*, vol. 195, pp. 831–838, Sep. 2018.

[6] UNFCC, "Paris Agreement," Paris, France, 2017, Available: Online: unfccc.int/process-and-meetings/the-parisagreement/the-paris-agreement (accessed 9 September 2018).

[7] National Energy Administration of China, National Development and Reform Commission of China, "Energy Strategy of Energy Production and Consumption Revolution (2016–2030)," Beijing, 2016, Available: http://www.ndrc.gov.cn/zcfb/zcfbtz/201704/.

[8] Y. Wen, B. Cai, X. Yang, and Y. Xue, "Quantitative analysis of China's Low-Carbon energy transition," *International Journal of Electrical Power & Energy Systems*, vol. 119, p. 105854, Jul. 2020.

[9] Y. Yu, N. Zhang, and J. D. Kim, "Impact of urbanization on energy demand: An empirical study of the Yangtze River Economic Belt in China," *Energy Policy*, vol. 139, p. 111354, Apr. 2020.

[10] P. Zhang, L. Zhang, X. Tian, Y. Hao, and C. Wang, "Urban energy transition in China: Insights from trends, socioeconomic drivers, and environmental impacts of Beijing," *Energy Policy*, vol. 117, pp. 173–183, Jun. 2018.

[11] IEA, "Energy Technology Perspectives 2016: Towards Sustainable Urban Energy Systems," Paris, France, Jun. 2016, Available: https://www.iea.org/reports/energy-technology-perspectives-2016, Accessed on: 10 January 2018.

[12] J. Liu, S. Chen, H. Wang, P. E. Campana, and J. Yan, "Evolution of China's Urban Energy Consumption Structure—A Case Study in Beijing," *Energy Procedia*, vol. 88, pp. 88–93, Jun. 2016.

[13] L. Li, " "Green" effects of hybrid actors through carbon trading: Cases in Beijing," *Global Transitions Proceedings*, vol. 1, no. 1, pp. 13–22, Jun. 2020.

[14] D. Zhang, G. Liu, C. Chen, Y. Zhang, Y. Hao, and M. Casazza, "Medium-to-long-term coupled strategies for energy efficiency and greenhouse gas emissions reduction in Beijing (China)," *Energy Policy*, vol. 127, pp. 350–360, Apr. 2019.

[15] V. Codina Gironès, S. Moret, F. Maréchal, and D. Favrat, "Strategic energy planning for large-scale energy systems: A modelling framework to aid decision-making," *Energy*, vol. 90, pp. 173–186, Oct. 2015.

[16] M. Viviana and O. L. Castillo, "Colombian energy planning - Neither for energy, nor for Colombia," *Energy Policy*, vol. 129, pp. 1132–1142, Jun. 2019.

[17] G. Limpens, S. Moret, H. Jeanmart, and F. Maréchal, "EnergyScope TD: A novel open-source model for regional energy systems," *Applied Energy*, vol. 255, p. 113729, Dec. 2019.

[18] D. Connolly, H. Lund, B. V. Mathiesen, and M. Leahy, "A review of computer tools for analysing the integration of renewable energy into various energy systems," *Applied Energy*, vol. 87, no. 4, pp. 1059–1082, Apr. 2010.

[19] B. Zhu and H. Shan, "Impacts of industrial structures reconstructing on carbon emission and energy consumption: A case of Beijing," *Journal of Cleaner Production*, vol. 245, p. 118916, Feb. 2020.

[20] X. Huang, H. Zhang, and X. Zhang, "Decarbonising electricity systems in major cities through renewable cooperation – A case study of Beijing and Zhangjiakou," *Energy*, vol. 190, p. 116444, Jan. 2020.

[21] H. Zhang, L. Zhou, X. Huang, and X. Zhang, "Decarbonizing a large City's heating system using heat pumps: A case study of Beijing," *Energy*, vol. 186, p. 115820, Nov. 2019.

[22] J. L. Fan, J. X. Wang, F. Li, H. Yu, and X. Zhang, "Energy demand and greenhouse gas emissions of urban passenger transport in the Internet era: A case study of Beijing," *Journal of Cleaner Production*, vol. 165, pp. 177–189, Nov. 2017.

[23] G. Zhao, J. M. Guerrero, K. Jiang, and S. Chen, "Energy modelling towards low carbon development of Beijing in 2030," *Energy*, vol. 121, pp. 107–113, Feb. 2017.

[24] L. Yu, Y. P. Li, B. G. Shan, G. H. Huang, and L. P. Xu, "A scenario-based interval-stochastic basic-possibilistic programming method for planning sustainable energy system under uncertainty: A case study of Beijing,

China," *Journal of Cleaner Production*, vol. 197, pp. 1454–1471, Oct. 2018.

[25] Beijing Municipal Commission of CPC, Beijing Municipal Government, "Overall Urban Planning of Beijing 2016–2035," Beijing, 2017, Available: https://www.beijing.gov.cn/gongkai/guihua/wngh/cqgh/201907/t20190701_100008.html.

[26] F. Domínguez-Muñoz, J. M. Cejudo-López, A. Carrillo-Andrés, and M. Gallardo-Salazar, "Selection of typical demand days for CHP optimization," *Energy and Buildings*, vol. 43, no. 11, pp. 3036–3043, Nov. 2011.

[27] L. Fan, J. Li, and X. P. Zhang, "Load prediction methods using machine learning for home energy management systems based on human behavior patterns recognition," *CSEE Journal of Power and Energy Systems*, vol. 6, no. 3, pp. 563–571, Sep. 2020.

[28] L. Suganthi and A. A. Samuel, "Energy models for demand forecasting—A review," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 2, pp. 1223–1240, Feb. 2012.

[29] A. Kanudia and R. Loulou, "Advanced bottom-up modelling for national and regional energy planning in response to climate change," *International Journal of Environment and Pollution*, vol. 12, no. 2/3, p. 191–216, Jan. 1999.

[30] A. Kanudia, M. Labriet, R. Loulou, K. Vaillancourt, and J. P. Waaub, "The World-Markal Model and Its Application to Cost-Effectiveness, Permit Sharing, and Cost-Benefit Analyses," in *Energy and Environment*, Boston, MA: Springer US, 2005: pp. 111–148.

[31] N. Strachan, R. Kannan, and S. Pye, "Scenarios and Sensitivities on Long-term UK Carbon Reductions using the UK MARKAL and MARKAL-Macro Energy System Models," UKERC, London, Feb. 2008.

[32] R. Kannan and N. Strachan, "Modelling the UK residential energy sector under long-term decarbonisation scenarios: comparison between energy systems and sectoral modelling approaches," *Applied Energy*, vol. 86, no. 4, pp. 416–428, Apr. 2009.

[33] S. D. Leo, P. Caramuta, P. Curci, and C. Cosmi, "Regression analysis for energy demand projection: An application to TIMES-Basilicata and TIMES-Italy energy models," *Energy*, vol. 196, p. 117058, Apr. 2020.

[34] M. R. Kazemzadeh, A. Amjadian, and T. Amraee, "A hybrid data mining driven algorithm for long term electric peak load and energy demand forecasting," *Energy*, vol. 204, p. 117948, Aug. 2020.

[35] Y. S. Lee and L. I. Tong, "Forecasting energy consumption using a grey model improved by incorporating genetic programming," *Energy Conversion and Management*, vol. 52, no. 1, pp. 147–152, Jan. 2011.

[36] P. Gabrielli, M. Gazzani, E. Martelli, and M. Mazzotti "Optimal design of multi-energy systems with seasonal storage," vol. 219, pp. 408–424, Jun. 2018.

[37] H. D. Vinod, "Integer programming and the theory of grouping," *Journal of the American Statistical Association*, vol. 64, no. 326, pp. 506–519, Jun. 1969.

[38] P. P. Craig, A. Gadgil, and J. G. Koomey, "What can history teach us? A retrospective examination of long-term energy forecasts for the United States," *Annual Review of Energy and the Environment*, vol. 27, no. 1, pp. 83–118, Nov. 2002.

[39] J. Qiao, T. Pu, and X. Wang, "Renewable scenario generation using controllable generative adversarial networks with transparent latent space," *CSEE Journal of Power and Energy Systems*, vol. 7, no. 1, pp. 66–77, Jan. 2021.

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