Article

Energy–Water–CO$_2$ Synergetic Optimization Based on a Mixed-Integer Linear Resource Planning Model Concerning the Demand Side Management in Beijing's Power Structure Transformation

Yuan Liu [1] , **Qinliang Tan** [1,2,3,*], **Jian Han** [1] **and Mingxin Guo** [1]

1   School of Economics and Management, North China Electric Power University, Beijing 102206, China; clarencely517@163.com (Y.L.); hj19940929@163.com (J.H.); 18360825506@163.com (M.G.)
2   Beijing Key Laboratory of Renewable Electric Power and Low Carbon Development, North China Electric Power University, Beijing 102206, China
3   Research Center for Beijing Energy Development, North China Electric Power University, Beijing 102206, China
*   Correspondence: tan.qinliang1@gmail.com or tql@ncepu.edu.cn

Abstract: Studies on the energy–water–CO$_2$ synergetic relationship is an effective way to help achieve the peak CO$_2$ emission target and carbon neutral goal in global countries. One of the most valid way is to adjust through the electric power structure transformation. In this study, a mixed-integer linear resource planning model is proposed to investigate the energy–water–CO$_2$ synergetic optimization relationship, concerning the uncertainties in the fuel price and power demand prediction process. Coupled with multiple CO$_2$ emissions and water policy scenarios, Beijing, the capital city of China, is chosen as a case study. Results indicate that the demand-side management (DSM) level and the stricter environmental constraints can effectively push Beijing's power supply system in a much cleaner direction. The energy–water–CO$_2$ relationship will reach a better balance under stricter environmental constraints and higher DSM level. However, the achievement of the energy–water– CO$_2$ synergetic optimization will be at an expense of high system cost. Decision makers should adjust their strategies flexibly based on the practical planning situations.

Keywords: energy–water–carbon synergetic optimization; mixed-integer linear programming; uncertainty; DSM; power structure transformation

1. Introduction

In recent decades, the potential adverse impact of atmospheric CO$_2$ emissions has drawn more and more attention. The global warming issue is mainly driven by a strong increase in the carbon dioxide released in the atmosphere by human activities [1]. Potential threats caused by global warming may include the increase in land surface temperature, the global climate changes, ocean level rising, and even the food production disruption [2]. Generally, CO$_2$ emissions is closely related to human activities such as the exploitation of energy resources, energy utilization, energy transportation, and deforestation, as well as other industrial, residential, and commercial activities. It mainly comes from the combustion of fossil fuels such as coal, natural gas, and oil [3]. Due to their contributions to the CO$_2$ emissions, most of them come from the energy intensive sectors, such as the electric power (especially the thermal power), the steel industry, and the construction industry in each country. In recent years, China has become the largest CO$_2$ emitter in the world and has tried its best to make a contribution to the global CO$_2$ emissions reduction. Among all the CO$_2$ emitters, electric power industry accounts for 40% of the total CO$_2$ emissions in China, and it is still the largest CO$_2$ emitter [4]. The Chinese government has laid out the detailed CO$_2$ reduction schedule: that is, to reach the CO$_2$ emissions peak before 2030

and realize the carbon neutral target before 2060 [5]. However, with the development of the society and the economy, the electric power demand increases as time goes on. The question of whether China can decarbonize its electric power sector will have important implications on its contributions to reducing the global warming and achieving the total CO_2 emissions reduction target [6]. However, there will be sharp conflicts between the increasing power demand and the CO_2 reduction target. Finding the balance between these two problems will become a significant and practical issue.

Simultaneously, the increasing demand for the electric power also aggravates water consumption, which may bring potential ecological and environmental risks, especially in the arid and semiarid regions, for the majority of the thermal power plants which are the main water consumers concentrate in these regions [7]. In China, water consumption of electricity generation accounted for 39% of total industrial water consumption; therefore, it is of great significance to improve the utilization efficiency of water resources, especially in water-deficient areas [8]. Meanwhile, how to ease the conflicts between the increasing power supply and the water consumption reduction is another important issue besides conflicts between the power supply and CO_2 emissions reduction target; therefore, investigating the synergetic optimization relationship among the electric power supply, the CO_2 emissions reduction target, and the water-saving target in regional electric power system (EPS) is fairly important.

In recent years, the energy–water–emissions nexus study has become a research hotspot. Some studies try to investigate energy–carbon or energy–water nexus optimization through the technique perspective, for example, Bahador et al. [9] investigated a more environment-friendly process for CO_2 capture concerning the ionic liquids. Saeed et al. [10] proposed a hybrid combined system to conduct the energy, exergy, economic, and exergo-environmental analyses on the performance, viability, and environmental impact when operating in Tehran. Hu et al. [11] investigated the key factors that affected the carbon dioxide adsorption and oil recovery factor in tight reservoirs, which could help better understand the carbon dioxide injectivity performances. Sikdar et al. [12] presented and highlighted the most important issues of decarbonization from technological viewpoints in detail, which provided effective guidelines for choosing carbon reduction technologies with high efficiency. These studies mainly evaluated the impacts of high proportion of renewable energy techniques on the energy system. Some studies mainly focused on the potential effectiveness of hydropower on the energy–water or energy–carbon nexus, for example, Kuriqi et al. [13] investigated the water–energy–ecosystem nexus and provided strategic recommendations on energy–ecosystem regulation for sustainable hydropower operation. Kuriqi's study also found that the diversion weir and the pondage hydropower schemes were less ecofriendly, while the dam-toe hydropower scheme had the opposite characteristic [14].

The other studies investigate the energy–water–carbon nexus in the same research framework from the optimization perspective.

Lee et al. [15] focused on the energy–water–CO_2 nexus of the fossil-fuel-based power generation and mainly provided the policy implications on the optimization path of fossil fuel power structure adjustment. Wang et al. [16] applied a plant-level nexus approach to assess the relationship between energy and water consumption, and CO_2 emission in a typical Chinese steel company. Damiana [17] presented a low-temperature waste-heat recovery in the European electric steelmaking industry and evaluated the impact of feasible interventions on primary energy and water consumption, as well as on CO_2 equivalent emissions. These studies supplied effective ways to investigate the energy–water–carbon nexus in the energy system. However, as the energy system includes various branches, most of the existing studies focused on the steel industry, construction industry, and the agriculture, while the literature on the energy–water–CO_2 synergetic relationship in the EPS, especially focusing on the urban energy system, is still limited. Ayman [18] proposed a dynamic material flow-stock model to analyze the resources nexus and CO_2 emissions in China's power generation system. The results indicated that PV and wind may result

in the highest water, energy, and CO_2 under some situations. Tan et al. [19] figured out that the application of clean development mechanism could still have positive effects on the energy–water–CO_2 nexus optimization in the energy system in Hebei Province, China. However, these studies just paid attention to the power supply side without concerning the disruptions from the demand side, which may bring power supply uncertainty and system risks during the electric power supply process in the urban energy system. Meanwhile, it may also have great impacts on the CO_2 emissions reduction goals and the water consumption saving, which may further affect the decision process of the decision makers.

Some studies conduct the energy–water–CO_2 nexus through the input–output analysis [20]; although the input–output analysis has the advantages in dealing with macroregional material flows, it has difficulties in tackling the relatively microregional problems. The optimization model is a common and effective tool to investigate the energy–water–CO_2 nexus. In recent nexus studies, researchers tried to apply the multiobjective/multilevel models [21] or the game theoretical models [22] in the nexus studies. For example, Ye et al. [23] propose a combined multiobjective optimization method to examine five different scenarios of renewable energy systems. Zohrabian et al. [24] used a case study to highlight the trade-offs and tensions that can occur in balancing priorities related to reliable water supply, energy demand for water, and greenhouse gas emissions. Besides the comprehensive analysis ability, these models also face some problems, such as the complexity of that model will have a significant increase if there are too many parameters and variables in the model, and sometimes the overall optimization results cannot even be achieved. Mixed-integer linear programming is an effective tool in dealing with capacity expansion problems [25]. It is valid for lowering the system complexity, achieving stable solution, and improving the convergence speed [26]. Meanwhile, it is an effective way to help achieve the global optimum with minimum error [27].

Therefore, to effectively evaluate the impact of disruption from the demand side on the urban electric power supply, which may further affect the energy–water–CO_2 synergic relationship in the urban energy system, a mixed-integer linear resource planning (MILRP) model is proposed to investigate the potentially steady power supply path and assess the system cost under different demand side management (DSM) levels. Meanwhile, the globally optimized electric power supply path, concerning the uncertainty from demand side disruption and the fuel price, which could help to reach the best balance among the power supply, the water saving, and CO_2 emissions mitigation targets, is presented. As Beijing, the capital city of China, has extensively used the DSM to improve the power supply efficiency, it is chosen as the case study to demonstrate the validity of the proposed MILRP model. The main novelty of this study is to evaluate the effects of the demand side disruption on the energy–water–CO_2 nexus collaborative optimization in the urban energy system. It also helps provide effective policy implications on the electric power supply path concerning the energy–water–CO_2 nexus.

2. Methodology

In this study, the MILRP model is built to explore the optimized energy–water–CO_2 emissions nexus in Beijing's power supply system. The MILRP model is applied to help obtain the optimized electric power supply schemes to guarantee not only the energy supply security but also to achieve the carbon emissions mitigation and water-saving targets under multiple scenarios; the scheme includes the capacity expansion level of each power technologies, the DSM level, and the imported power from other regions. To ensure the optimization process close to the reality, the uncertainty during the simulation process the fuel price and power demand are considered and effectively controlled. The decision variables and parameters of the MILRP model are presented in Table 1.

Table 1. The decision variables and parameters of the MILRP model.

A. The abbreviations and acronyms		j	The DSM program
MILRP model	Mixed-integer linear resource planning model	CI_{it}	The cost to consumers who interrupt power supplies
DSM	Demand side management	CT_t	The cost for the power transmission
f_t	Total system cost in period t (RMB/¥)	CW_t	The cost of water consumption (m^3)
B. Decision variables		LS_{pt}	
V_{it}	The amount of energy supply (PJ)	RM	The capacity reserve margin
x_{it}	The generation capacity of technology i in period t	Vol_t	The maximized visible supply volume of natural gas
γ_{jt}	The binary (0 or 1) determining whether the capacity expansion process happens	CM_{it}	The CO$_2$ emissions mitigation efficiency
QP_t	The quantity of power transferred	WWI_{it}	The water withdrawals intensity
QC_{it}	The quantity of CO$_2$ emissions	CF_{it}	The fixed cost of power technology i constructed in year t
QW_{it}	The quantity of water withdrawals	CV_{it}	The variable cost including the operating and maintenance fees
G_{it}	The amount of power generation (MW)	CD_{jt}	The cost of implementing the DSM program j
μ_{it}	The binary variable (0 or 1) determining whether the capacity expansion process happens	t	The planning period
		δ_{jt}	The occurrence probability of different program j
C. Parameters		u_t	The amount of demand (MW) that goes unserved
$\tilde{C}_t$	The cost for purchasing the nature gas	CCT_t	The carbon emission tax (RMB¥/m^3)
CF_{it}	The fixed cost of generation capacity	E_{it}	The capacity expansion ability
L_{it}	The Length of period t for technology i	LS_{pt}	The fraction of power lost during the electricity transmission process (%)
i	Different power technologies	$\hat{DEM}_t$	The power demand
CL_t	The CO$_2$ emissions limitation (ton)	RC_{it}	CO$_2$ emissions rate
TWR_t	The total water resource supply (ton)	DDe_{jt}	The decrease in power demand

2.1. The Mixed-Integer Linear Resource Planning Model (MILRP)

$$
\begin{aligned}
Min\ f_t \quad &= \sum_i \tilde{C}_t V_{it} + \sum_i CF_{it} x_{it} + \sum_i CV_{it} L_{it} x_{it} + \sum_j CD_{jt} \gamma_{jt} \delta_{jt} \\
&+ \sum_i CI_{it} L_{it} u_t + CT_t QP_t + \sum_i CCT_t QC_{it} + \sum_i CW_t QW_{it}
\end{aligned} \tag{1}
$$

f_t is the total system cost in period t (RMB/¥). $\tilde{C}_t$ is the cost for purchasing the natural gas concerning the price uncertainty in period t (10^6 RMB ¥/PJ). V_{it} denotes the amount of energy supply from technology i in period t (PJ). CF_{it} is the fixed cost of power technology i constructed in year t (10^6 RMB ¥/MW), with $i = 1$ for the cogeneration power technology, $i = 2$ for the solar power technology, $i = 3$ for the wind power technology, and $i = 4$ for the geothermal power generation technology. x_{it} is the generation capacity of technology i in year t [MW]. CV_{it} is the variable cost including the operating and maintenance fees (10^6 RMB ¥/MWh). L_{it} is the length of period t for technology i; it equals 8760 for the gas thermoelectric power, the number of hours in a year. CD_{jt} is the cost of implementing the DSM program j starting in year t (10^6 RMB), γ_{jt} is the binary (0 or 1) determining whether the DSM program j has been implemented. δ_{jt} is the occurrence probability of different program j. CI_{it} is the cost to consumers who interrupt power supplies during period t (10^6 RMB ¥/MWh). u_t is the amount of demand (MW) that goes unserved in period t. CT_t is the cost for the power transmission in period t (10^6 RMB ¥/MWh). QP_t is the quantity of power transferred (MWh). CCT_t the carbon emission tax, RMB¥/m^3. QC_{it} is the quantity of CO$_2$ emissions from technology i in period t (m^3). CW_t is the cost of water consumption (10^3 yuan/tonne). QW_{it} is the quantity of water withdrawals from technology i in period t (tonne).

Constraints:

(1) Energy supply and demand balance:

$$\sum_i G_{it} + \sum_j DDe_{jt}\gamma_{jt} + u_t + \sum_p QP_{pt}(1 - LS_{pt}) = D\hat{E}M_t \tag{2}$$

$$G_{it} = x_{it} + E_{it}\mu_{it} \tag{3}$$

$$x_{it+1} = \begin{cases} x_{it}, & \text{if } \eta_{it} = 0 \\ x_{it} + E_{it} & \text{if } \eta_{it} = 1 \end{cases} \tag{4}$$

G_{it} is the power generation during the period from technology i (MW). DDe_{jt} is the decrease in demand because of the implementing of DSM program j (MW). LS_{pt} is the fraction of power lost during the electricity transmission process (%). E_{it} is the capacity expansion ability of technology i in period t (MW). μ_{it} is the binary variable (0 or 1) determining whether the capacity expansion process happens.

(2) Reserve margin constraint:

$$\sum_i G_{it} + (1 + RM)\sum_j DDe_{jt}\gamma_{jt}\delta_{jt} \geq (1 + RM)D\hat{E}M_t \tag{5}$$

RM is the capacity reserve margin which means the excess capacity over peak demand required to meet the reliability need. $D\hat{E}M_t$ is the power demand in period t forecasted by the IOWA-AHP method.

(3) Capacity and energy constraints:

$$\sum_i V_{it} \leq Vol_t \tag{6}$$

$$\sum_{i=1}^{I} L_{it} G_{it} \leq D\hat{E}M_t \tag{7}$$

Vol_t is the maximized visible supply volume of natural gas in Beijing.

(4) DSM constraints:

$$RM \cdot DDe_{jt} < DDe_{jt}\delta_{jt} \leq \sum_{i=1}^{I} G_{it} \tag{8}$$

(5) CO_2 emissions constraints:

$$\sum_i G_{it} \cdot RC_{it} \cdot (1 - CM_{it}) \leq CL_t \tag{9}$$

RC_{it} is the CO_2 emissions rate by utility i in period t (ton/GWh). CM_{it} is the CO_2 emissions mitigation efficiency in period t, $CM_{it} \in [0,1]$. CL_t is the CO_2 emissions limitation in period t (ton).

(6) Water withdrawals constraints:

$$QW_t = \sum_i WWI_{it} \times G_{it} \times L_{it} \tag{10}$$

$$0 < QW_t \leq TWR_t \tag{11}$$

WWI_{it} is the water withdrawals intensity for utility i in period t (ton/GWh). TWR_t denotes the total water resource supply during the electricity production process in period t (ton).

2.2. Measuring the Fuel Price

The fuel price here is the natural gas. We assume that both of their price p_F follow the geometric Brownian motion [28]:

$$dp_F = \alpha_F p_F dt + \chi_F p_F dz \tag{12}$$

where p_F denotes the fuel prices; α_F is the drift parameters; χ_F is the variance parameter; and dz denotes the independent increments of the Wiener process.

$$dz = \gamma_t \sqrt{dt} \tag{13}$$

The discrete approximation to Equation (1) is as follows:

$$p_F(t + \Delta t) = p_F(t) \exp(\alpha_F \Delta t + \chi_F (\Delta t)^{1/2} \gamma_t) \tag{14}$$

where γ_t is a random variable, and $\gamma_t \sim N(0,1)$, $E(\gamma_i, \gamma_j) = 0$, $\forall i, j$, $i \neq j$

In this study, parameters α_F and χ_F are firstly set based on the publish references [29,30], and on the basis of this value, the relative future values are calculated. If the value set is too high or too low, the simulated future values will be outside a reasonable scope. Thus, the parameter value should be adjusted until it reaches a reasonable scope. The reasonable scope of the natural gas price is between 1×10^4 yuan/PJ~10×10^4 yuan/PJ.

The real option (RO) theory is introduced during the prediction process of the natural gas price because it is highly efficient to help control the uncertainty factors [31]. The uncertainty factors in this study include the electric power price and the natural gas price. In the RO theory, there is some probability that the investor abandons the investment and the investor compares the net present value between adjacent time t and $t + 1$. If the former is larger than the latter, the investor does not execute the abandon option. However, if the latter is larger than the former, then the investor does implement the abandon option. In this study, we use the Bayesian Monte Carlo simulation (BMC) to calculate the expected value of an abandon option.

The detailed procedures are as follows:

(1) Generate 15 paths of changes for each uncertain factor by simulating calculation.
(2) Compute the net present value of a project $P(t)$ at the final observation date of a given period (period t).

$$P(t) = \begin{cases} 0, & if \ PV(t) \leq I(t) \\ PV(t) - I(t), & if \ PV(t) > I(t) \end{cases} \tag{15}$$

where $PV(t)$ is the present value, and $I(t)$ is the investment cost of the CHP power plants.

(3) Calculate the value of the project $P(t-1)$ at the stage of period $t-1$,

$$P(t-1) = \begin{cases} 0, & if \ PV(t-1) \leq I(t) \\ PV(t) - I(t), & if \ PV(t-1) > I(t) \end{cases} \tag{16}$$

(4) The discount rate of $P(t)$ at stage of $t-1$ is $P(t) \times (1+r)^{-1}$, which is set as the dependent variable, while $P(t-1)$ is set as the independent variable. Then, compute the estimated value of $P(t)$ through the stepwise regression method, and compare the estimated value with $P(t-1)$, if the estimated value greater than $P(t-1)$, then train the abandon optimization in stage $t-1$, or it has to wait at stage t.
(5) Repeat the above comparison until the satisfied decision could be achieved.

2.3. The Electricity Demand Forecasting

This study introduces the IOWA-AHP method to predict the electricity demand in the planning periods. Firstly, three models, including the fuzzy linear regression model,

stepwise regression model, and grey system model, predict the electricity demand independently and get three groups of predicted results; secondly, these results are integrated with the IOWA-AHP method to predict the fourth group of electricity consumption results. In this way, the uncertainty factor could be effectively controlled. The detailed algorithm of the prediction process is from the Reference [21].

3. Case Study and Scenario Setting

In recent years, the government of Beijing tries the best to implement the energy supply structure adjustment based on the reality of local power sources. The spatial distribution of Beijing's energy resource in different regions is shown in Figure 1. Beijing's energy supply structure adjustment strategy depends on three aspects: the first aspect is self-adjustment based on the local power sources. On the one hand, the construction of four gas thermoelectric centers was completed in recent years to displace the traditional thermal power facilities for the urgent need of atmospheric environment in Beijing; on the other hand, more renewable energy resource gradually becomes the effective supplement of energy supply to further replace the traditional ways mainly depends on the coal-fired power. The second aspect is that more electric power depends on importing from other regions to guarantee the abundant energy demand in Beijing [32]. The final aspect is that, as the intelligent development of the electric power system, the government of Beijing advocates the application of demand-side management (DSM) to take advantage of the existing facilities to improve the energy efficiency, such as the load controls, off-peak uses of electricity, and so on. As Beijing, the capital city of China, is the typical city facing the energy transition to achieve the carbon peak target by 2030, it was chosen as a case study. The key economic and technique data are shown in Table 2.
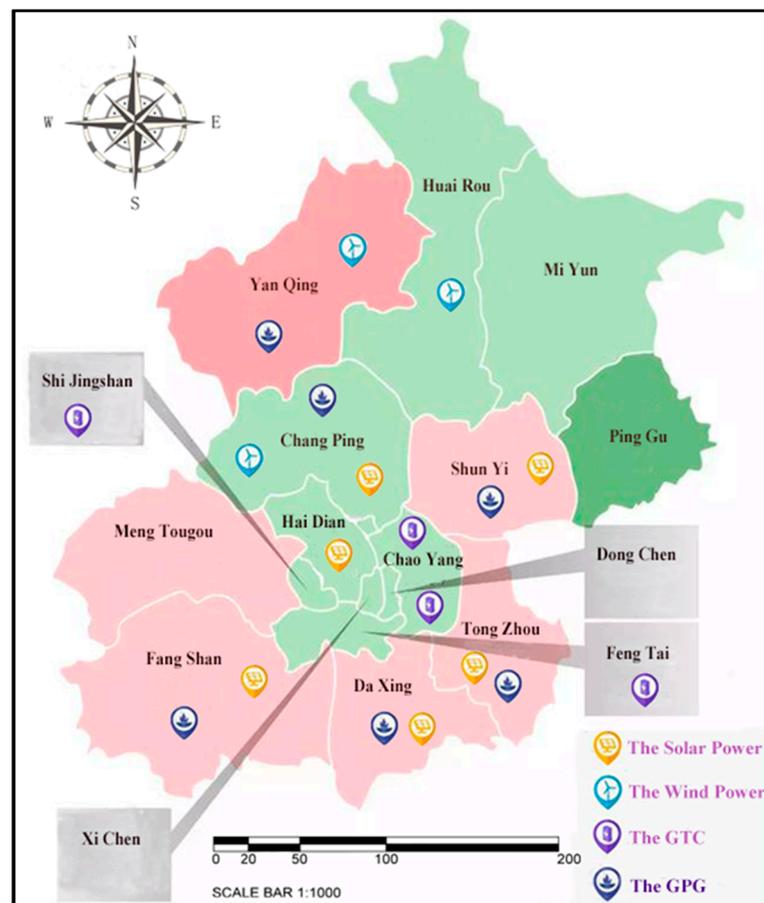

Figure 1. The distribution of the Beijing's electric power resource (the GTC is the gas thermoelectric power center; the GPG is the geothermal power generation).

Table 2. The key economic and technique data.

Parameters	Periods			
	t = 1	t = 2	t = 3	t = 4
The fixed cost of generation capacity (10^6 RMB ¥/GW) [33]				
Cogeneration power	24.53	25.29	27.42	29.54
Solar power	47.36	45.52	42.74	38.53
Wind power	38.34	34.65	32.82	31.76
Geothermal power	32.46	31.71	29.43	25.36
The cost of power transmission (10^6 RMB ¥/GWh) [22]				
	0.85	0.94	1.12	1.25
The carbon emission tax (RMB¥/ton) [29]				
	16.2	20.4	28.6	35.4
The purchasing fee for the water resource (RMB/ton) [32]				
	17.7	19.7	24.5	28.4

This study mainly takes three key planning periods into consideration, including 2021, 2025, and 2030, under the policy background of the carbon peak target in 2030. Different technologies coupled with the DSM are taken into account to meet both the electric power supply target but also the environmental goals in Beijing, including the CO_2 emissions mitigation target and water conservation goals. In this study, the gradient CO_2 emissions mitigation strategies are set based on the official statement in the planning periods, which can effectively help to achieve the CO_2 emissions peak target and is shown in Table 3. The key parameters of the gas price used in the prediction process is shown in Table 4.

Table 3. The CO_2 emissions level in different planning periods [33].

Year	The Baseline	Carbon Emission Level
2021	2005′s level in Beijing	Decrease by 45%
2025	2005′s level in Beijing	Decrease by 55%
2030	2005′s level in Beijing	Decrease by 65%

Table 4. Parameters and the descriptions during the gas price simulation.

Parameter	Symbol	Value	Data Source
Natural gas drift rate	α_F	0.05	Zhu et al. [30]
Natural gas deviation rate	χ_F	11.5%/year	Zhao et al. [29]

Meanwhile, three different DSM scenarios are designed to cover different electricity supply likelihoods. The DSM levels and corresponding cost to those who interrupt the power supplies are shown in Table 3, which is set based on the References [25,34]. Given that the occurrence probability of different DSM levels is different, according Reference [33], the occurrence probability of three DSM levels δ_{jt} is defined in Table 5.

λ denotes the amount of power participated the DSM scheme; while $\bar{\lambda}$ is the nonparticipated power. TEC denotes the total electricity consumption.

Seeing as Beijing is located in the typical semiarid region with drought-stressed water resources, two possible water conservation policy scenarios are taken into account. As the air cooling system is the water cooling technology with the least water consumption, it has great potential to be widely applied in Beijing's cogeneration power plants; therefore, it was chosen as the main technique measures to save water consumption. The detailed water consumption factor under each water policy scenario is based on the national water intake standard: Water Quota Part I: Thermal Power (GB/T18916) [35], which is shown in Table 6. The utilization hours information of the wind and solar power is shown in Table 7.

Table 5. The DSM scenarios and corresponding cost.

Scenario (j)	DSM Level	DSM Amount	The Cost to Those Interrupting Power Supplies	Probability (δ_{jt})
S1	Low	5% of the total electricity consumption is interrupted when peak load appears	10% higher than the price of the industrial and commercial electricity.	$0 \leq \frac{\bar{\lambda}-\lambda}{TEC} \leq 5\%$
S2	Medium	10% of the total electricity consumption is interrupted when peak load appears	15% higher than the price of the industrial and commercial electricity.	$5\% < \frac{\bar{\lambda}-\lambda}{TEC} \leq 15\%$
S3	High	20% of the total electricity consumption is interrupted when peak load appears	20% higher than the price of the industrial and commercial electricity.	$15\% < \frac{\bar{\lambda}-\lambda}{TEC} \leq 30\%$

Table 6. The water consumption factor under three water policy scenarios.

Scenario	The Proportion	The Cooling form of Different Technologies	Unit Capacity $\leq$ 300 MW	Unit Capacity > 300 MW
The baseline	100% 0%	The cycling cooling system The air cooling system	1.7 0.39	1.49 0.31
The flexible water policy	50% 50%	The cycling cooling system The air cooling system	1.7 0.39	1.49 0.31
The strict water policy	0% 100%	The cycling cooling system The air cooling system	1.7 0.39	1.49 0.31

Table 7. The utilization hours for the wind and solar power in Beijing (hours) [36].

	t = 1	t = 2	t = 3	t = 4
Wind power	1847	2079	2940	3675
Solar power	1059.25	1213.95	1536.27	2023.44

The mix of these scenarios will help to investigate the energy–water–carbon nexus during the achievement of the 2030 carbon emissions peak path in Beijing.

4. Result and Discussion

4.1. The Uncertainty Simulation in Different Periods

(1) The fuel price simulation

Figure 2 shows the price variation of the natural gas from 2015~2030 in Beijing under 15 simulation scenarios. Through the BMC model, 15 possible paths of uncertainty factor are simulated. As the life span of the GTC plants is more than 25 years, in this study, we simulated the investment decision period from 2015 to 2030. It indicates that the natural gas price shows an increasing trend, although the prediction price fluctuates dramatically under many scenarios, especially after the year 2024, which means that uncertainty during the prediction process makes it difficult to avoid the forecasting errors. To make the price prediction P of natural gas available for the proposed model, the price values in each period is multiplied by their occurrence probability P_i, $\sum_{i=1}^{15} p_i = 1$. $\sum_{i=1}^{15} P \cdot P_i$. under 15 scenarios is the input gas price of the MILRP model.

(2) The power demand prediction

Figure 3 shows the prediction results of the electric power demand through the IOWA-AHP method. It indicates that the electric power demand increases as time goes on. The power demand of 2025 in Beijing is 276,254 GWh, which will increase by 57.92% on the base of 2021, while the power demand of 2030 is 494,547 GWh, which will increase by

182.71% on the base of 2021. The power demand prediction will be the input data of the proposed MILRP model.
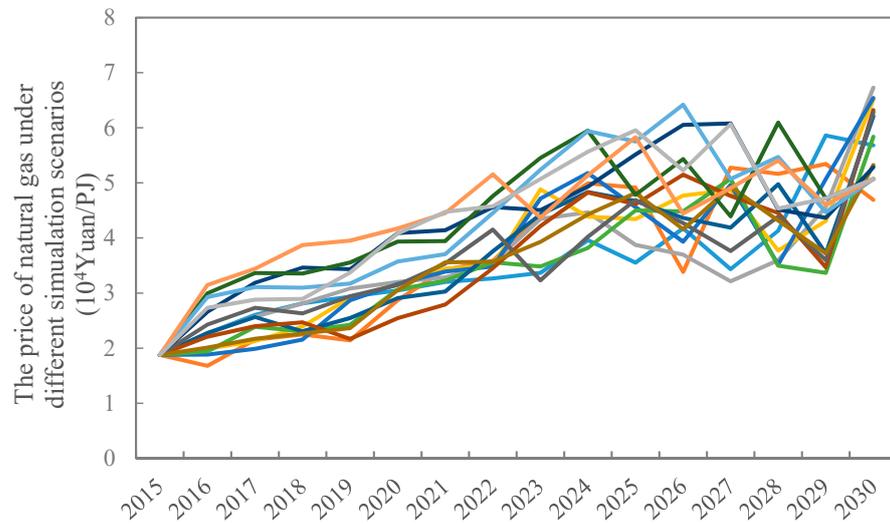

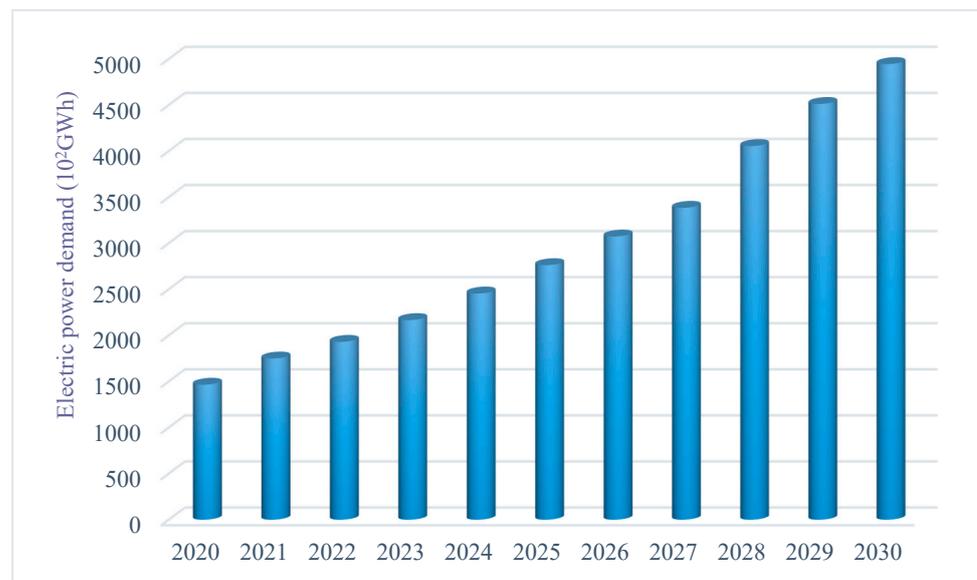**Figure 2.** The simulation result of the price of the natural gas.

Figure 3. The prediction of the electric power demand from 2020 to 2030.

4.2. The Capacity Expansion and Imported Power

Figure 4 shows the optimized capacity expansion in Beijing in different periods under different scenarios. It indicates that the capacity expansion for each technology increases as time goes on, which may result from the increase in the electric power demand in Beijing. However, the capacity expansion performances for different technologies under different scenarios are different. It shows that the capacity expansion of the wind and solar power increases when the water policy is included compared with the scenario only concerning the CO_2 limit; the strict water policy calls for more capacity expansion than that under the flexible scenario. Meanwhile, as time goes on, the capacity expansion under the same scenario increases, which may result from the increase in the electric power demand. For example, in 2025, the capacity expansion of solar power is 17 MW under the CO_2 limit scenario, while it increases by 11.5% (2 MW) under the CO_2 and flexible water policy and

by 32.4% (8 MW) under the strict water scenario. Although the capacity expansion of cogeneration power also increases as time goes on, the capacity expansion need under the CO_2 limit scenario is larger than that under the scenarios concerning the water policy, which means that when the water consumption constraints are taken into consideration, the capacity expansion will be replaced by the other three power technologies in Beijing. The capacity expansion of DSM also shows the increasing trend when the time goes on. Meanwhile, the performance of the DSM is just the same as that of the wind and solar power: that is, the capacity expansion under the CO_2 limit is the least while it is the most under the CO_2 and strict water policy scenario. The reason could be attributed to the fact that when the water constraints are taken into consideration, more cooling facilities, which may activate the DSM scheme such as the air-cooling units, are put into utilization, meaning more interruption loads appear. Meanwhile, more imported power is needed in Beijing to make up for the power shortage because of the involvement of the water policy; for example, 58.24% (74.25%) more power is required to import under the CO_2 and strict water scenario than that under the only CO_2 limit scenario in 2025 (2030).
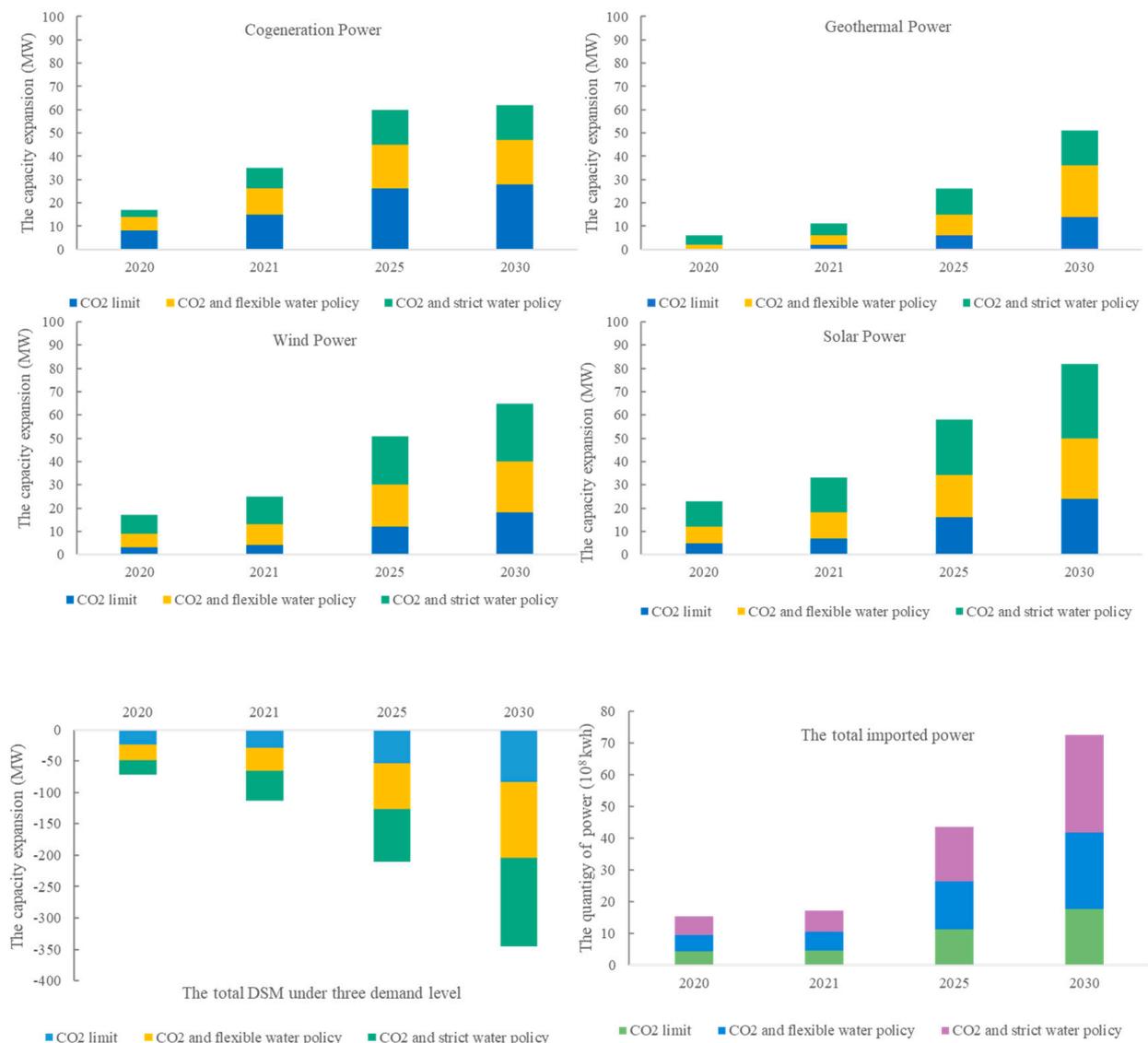

Figure 4. The capacity expansion level of different power resource, DSM, and the imported power.

4.3. The Optimized Energy–Water–CO$_2$ Relationship

The optimized electricity supply from each electric power technology in each period under three DSM levels is presented in Figure 5. The power supply level under different CO$_2$ emissions and water policy scenario is also compared in Figure 5. It indicates that the imported power shows an increasing trend as the DSM level increases, while the co-generation power shows the opposite trend in the same condition. Meanwhile, the involvement of the water policy constraints further promotes the proportion of the imported power and reduces the proportion of the cogeneration power in the power supply system in Beijing. The wind power, solar power, and geothermal power remain in a relatively steady level compared with the cogeneration power and the imported power, although the quantity of the power from these three technologies has increased when the DSM level and the environmental constraints become more stringent. However, as the proportion of these technologies in the power structure of Beijing is still quite limited, the variation of the proportion of these technologies is not apparent. For example, in t = 2, the proportion of the cogeneration is 50.62% (243.03 $\times$ 10^2 GWh) in the low DSM level under the CO$_2$ limit scenario, while the imported power is 28.75% (141.24 $\times$ 10^2 GWh). However, the proportion of the cogeneration decreases to 39.63% (286.29 $\times$ 10^2 GWh) in the medium DSM level under the CO$_2$ limit scenario, while the imported power increases to 41.44% (297.51 $\times$ 10^2 GWh). When the strict water policy scenario is taken into consideration, the proportion of the cogeneration power further decreases to 36.20% (27.18%) in the low (medium) DSM level in t = 2, while the proportion of the imported power increases to 36.55%. The solar power increases from 45.89 $\times$ 10^2 GWh in the low DSM level to 66.82 $\times$ 10^2 GWh in the high DSM level in period t = 2 under the CO$_2$ limit scenario. The wind and geothermal power is the same increasing trend.
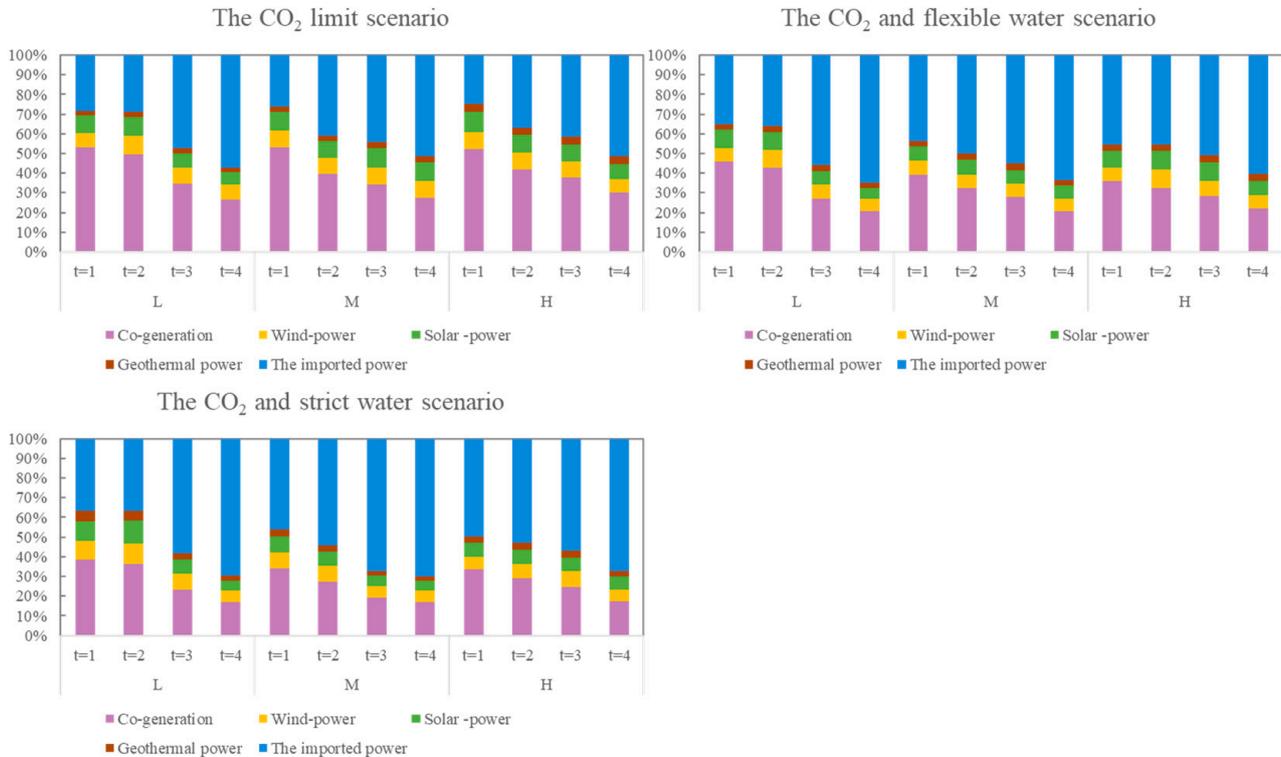

Figure 5. The electric power generation under three DSM scenarios.

The energy–water–CO$_2$ nexus is presented in Figure 6. The total energy supply, the water consumption, and the CO$_2$ emissions under the medium DSM level are presented as column, scatter line, and the pie charts, respectively. The optimized results indicate that

the total energy demand in Beijing shows an increasing trend not only as the DSM level increase but also as the environmental constraints become tougher. The reason should be attributed to that: on the one hand, the power demand increases to meet the social and the economic development in Beijing, and high DSM level means more disruptions on the normal power supply; therefore, more power is essential to maintain the steady operation of the power system; on the other hand, the gradually stricter environmental constraints may result in more clean electric power schemes, such as the coal-to-electricity scheme. which is proposed to provide the heat supply in the winter of Beijing instead of the traditional heat supply by the combustion of the bulk coal in the rural areas. Meanwhile, both the air and water constraints require less electricity generation in the domestic areas in Beijing, but more imported power from other regions. As the proportion of the imported power increase in the power structure in Beijing's electric power system as time goes on, the stricter environmental constraints lead to more power demand in Beijing.

The CO_2 emissions show the downward trend as the DSM levels increase and the environmental constraints become stricter. For example, the quantity of CO_2 emissions in t = 4 is 19.46×10^6 (14.08×10^6) tons in the low (high) DSM level under the CO_2 limit scenario, while it is 10.78×10^6 (9.05×10^6) tons in the low (high) DSM level under the CO_2 and strict water policy scenario. The CO_2 emissions reduction effect is mainly from the decrease in the cogeneration power, and the increase in the renewable and the imported power in the power structure, as the increasing in the DSM levels just further improve the power supply level, which is higher DSM, may result in higher power demand levels. However, it does not change the power structure variation trend; therefore, higher DSM levels also have the effects of helping decrease the CO_2 emissions. As stricter environmental constraints further help to promote the proportion of the renewable power technologies, the CO_2 emissions shows the decreasing trend when the water policy is considered.

The proportion of the water consumption under different DSM levels is relatively close to each other in each time period, although the gradually stricter environmental constraints lead to the decrease in the total water consumption when the water constraints become stricter.
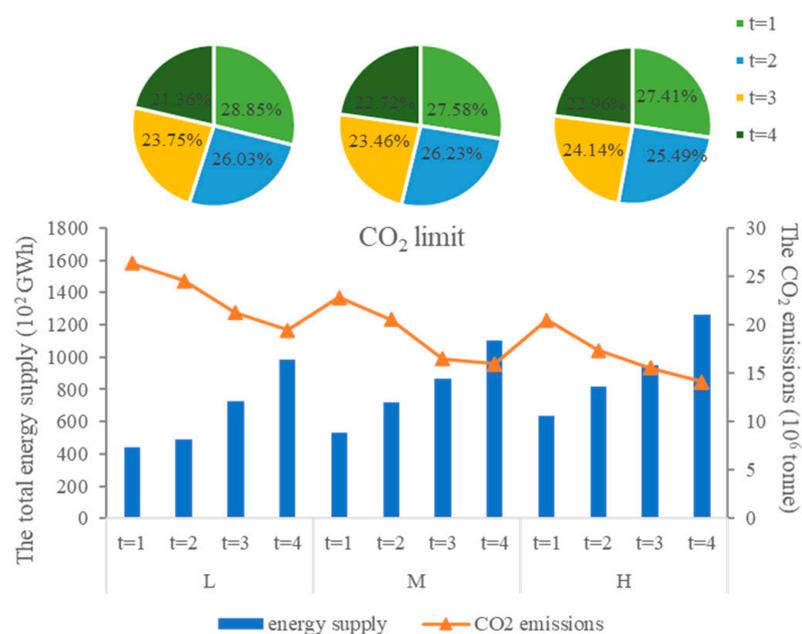

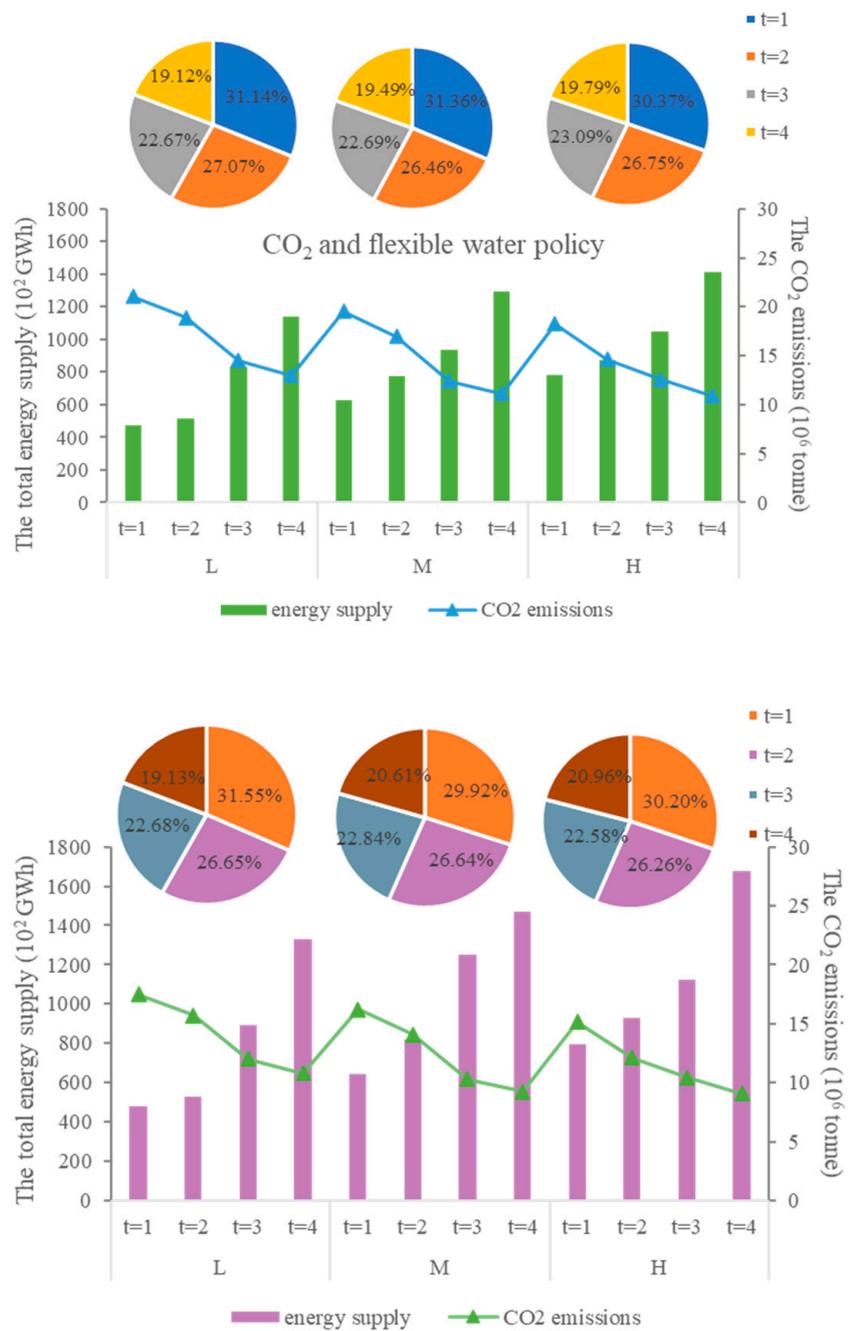**Figure 6.** The energy–water–CO_2 synergetic relationship under different scenarios.

Figure 6. *Cont.*

4.4. The System Cost

The system cost under each period in three scenarios is shown in Table 8. It indicates that the system cost shows an increasing trend as the time goes on, which means that higher CO_2 emissions reduction level results in higher system cost as time goes on. Meanwhile, when it is under the same period, the gradually stricter water policy also leads to the increase in the system cost. The reason can be attributed to the fact that stricter environmental constrains, regardless of the CO_2 reduction level or the stricter water policy, all require the construction and capacity expansion of more renewable and the imported power, which may need more cost than the traditional cogeneration technology. Meanwhile, the application of the air cooling technology and DSM units may also be the main factor to increase the system. The results indicate that the achievement of the energy–water–CO_2

synergetic optimization (electric power adjustment, the CO_2 emissions reduction target, and the water saving goal) will be at the expense of high system cost.

Table 8. The system cost under different environmental scenarios.

Time Periods	Scenarios (10^{13} RMB/10^{12} $)		
	The CO_2 Limit (The Baseline in the Water Policy)	The Flexible Water Policy	The Strict Water Policy
t = 1	2.84/4.43	3.97/6.20	4.15/6.48
t = 2	4.92/7.69	5.27/8.23	5.84/9.12
t = 3	7.15/11.17	7.66/11.97	8.24/12.88
t = 4	8.13/12.70	8.25/12.89	9.46/14.78

4.5. Discussion

The MILRP model is proposed to determine the electric power supply path in Beijing, concerning the energy–water–CO_2 nexus collaborative optimization. The disruption from the demand side and the fuel price is mainly considered as the uncertainty factors, which may affect the final decision making in Beijing's energy system. Although the MILRP model can provide the optimized solution to the problem and help achieve the minimized system cost under each scenario, the model also has some limitations which should be ignored. Firstly, compared with the multiobjective or multilevel models, although the MILRP model has the advantages such as its high efficiency in achieving the optimized solution and effectively decreasing the calculation complexity, its optimized result may be one-sided because it is only constrained by the single objective instead of multiple objectives, and it may have difficulties in assessing the impact from other targets. Secondly, the model depends heavily on the input data accuracy as its algorithm does not have the capacity to verify or train the input data just as some intelligence methods. Therefore, the input data may seriously affect the output results, which may further bring new uncertainty in the decision making process. In this way, selecting the reasonable model according to the practical planning needs is fairly important and should also be the significant step during the optimization process.

5. Conclusions

In this study, a mixed-integer linear resource planning (MILRP) model is proposed for the optimization of Beijing's power supply, concerning the synergic promotion of energy–environmental relationship (the energy–water–CO_2 nexus) and multiple uncertainties during the fuel price and the power demand prediction process. In the MILRP model, three periods from 2021(t = 2) to 2030(t = 4) are taken into consideration. The situation in 2020(t = 1) is set as the baseline. The mixed-linear programming model can effectively help to obtain the capacity expansion scheme of each power technology under multiple energy–environmental scenarios, it is applied into the Beijing city to help optimize the electric power supply and investigate the feasible energy–water–CO_2 synergic relationship.

The results indicate that the power demand shows an apparent increasing trend as the time goes on. The increasing of the DSM level and the stricter environmental constraints further lead to the change of the power structure in Beijing's power supply system: that is, the proportion of the cogeneration technology decreases, and it is replaced by the three renewable power technologies and the imported power from other regions. The average reduction rate of the cogeneration technology is 28.93%, 26.35%, and 19.14% in each period under the low, medium, and high DSM level when it is under the CO_2 limit scenario, when the water policy constraints are involved. Although the average reduction rate of the cogeneration technology almost remains the same, the installed capacity and the expansion has the similar decreasing trend. Compared with three renewable technology, the proportion of the imported power has a relatively sharp increase to make up the power shortage from the decreasing the cogeneration in each period, which means that to achieve

the coordinated development of the energy–water–emissions relationship, imported power is an advocated and valid power source.

The optimized energy–water–CO_2 relationship under multiple scenarios shows that the CO_2 and water policy constraints further help lead the power structure in Beijing to a cleaner direction, for it increases the proportion of the renewable power and the imported power but decreases the cogeneration power. However, the strict environmental constraints also lead to a high system cost. Given that Beijing is the capital city with specifically important political and economic status, guaranteeing abundant power supply should be the primary target. In this way, some suggestions based on the optimized results are listed: (1) expanding the proportion of the imported power in the future is essential for Beijing because it is the cleanest way to safeguard Beijing's power supply. (2) Renewable power, especially the solar power should have expanding utilization because of its flexibility and the gradually decreasing fixed cost, coupled with the wind power and DSM facilities, they are effective ways to help achieve the carbon emissions peak target of Beijing in 2030. (3) The price of the imported power is suggested to be higher than that produced from the power units of Beijing so that it could be an effective economic compensation to regions that export power to Beijing but contaminate their local environment during the process of producing the exporting power.

References

1. Adedoyin, F.; Ozturk, I.; Abubakar, I.; Kumeka, T.; Folarin, O.; Bekun, F.V. Structural breaks in CO_2 emissions: Are they caused by climate change protests or other factors? *J. Environ. Manag.* **2020**, *266*, 110628. [CrossRef] [PubMed]
2. Nwaka, I.D.; Nwogu, M.U.; Uma, K.E.; Ike, G.N. Agricultural production and CO2 emissions from two sources in the ECOWAS region: New insights from quantile regression and decomposition analysis. *Sci. Total Environ.* **2020**, *748*, 141329. [CrossRef]
3. Yi, C.; Chuan, T.; Ying, C.; Qiang, L.; Zheng, X. Research on peaking carbon emission of power sector in China and the emissions migitation analysis. *Clim. Chang. Res.* **2020**, *16*, 632–640.
4. Ju, L.; Tan, Q.; Lin, H.; Mei, S.; Li, N.; Lu, Y.; Wang, Y. A two-stage optimal coordinated scheduling strategy for micro energy grid integrating intermittent renewable energy sources considering multi-energy flexible conversion. *Energy* **2020**, *196*, 117078. [CrossRef]
5. He, L.; Chen, Y.; Li, J. A three-level framework for balancing the tradeoffs among the energy, water, and air-emission implications within the life-cycle shale gas supply chains. *Resour. Conserv. Recycl.* **2018**, *133*, 206–228. [CrossRef]
6. Tan, Q.; Liu, Y.; Zhang, X. Stochastic optimization framework of the energy-water-emissions nexus for regional power system planning considering multiple uncertainty. *J. Clean. Prod.* **2021**, *281*, 124470. [CrossRef]
7. Liu, Y.; Tan, Q.L.; Han, J.; Guo, M.X. Energy-Water-Carbon Nexus Optimization for the Path of Achieving Carbon Emission Peak in China considering Multiple Uncertainties: A Case Study in Inner Mongolia. *Energies* **2021**, *14*, 1067. [CrossRef]
8. Sambito, M.; Freni, G. LCA Methodology for the Quantification of the Carbon Footprint of the Integrated Urban Water System. *Water* **2017**, *9*, 395. [CrossRef]
9. Daryayehsalameh, B.; Nabavi, M.; Vaferi, B. Modeling of CO_2 capture ability of Bmim BF4 ionic liquid using connectionist smart paradigms. *Environ. Technol. Innov.* **2021**, *22*, 101484. [CrossRef]
10. Esfandi, S.; Baloochzadeh, S.; Asayesh, M.; Ehyaei, M.A.; Ahmadi, A.; Rabanian, A.A.; Das, B.; Costa, V.A.F.; Davarpanah, A. Energy, Exergy, Economic, and Exergoenvironmental Analyses of a Novel Hybrid System to Produce Electricity, Cooling, and Syngas. *Energies* **2020**, *13*, 6453. [CrossRef]
11. Hu, X.; Xie, J.; Cai, W.; Wang, R.; Davarpanah, A. Thermodynamic effects of cycling carbon dioxide injectivity in shale reservoirs. *J. Pet. Sci. Eng.* **2020**, *195*, 107717. [CrossRef]

12. Subhas, K.; Sikdar, F.P. Advances in Carbon Management Technologies. *Biomass Util. Manuf. Electr. Manag.* **2021**, *2*, 242–251.

13. Kuriqi, A.; Pinheiro, A.N.; Sordo-Ward, A.; Garrote, L. Water-energy-ecosystem nexus: Balancing competing interests at a run-of-river hydropower plant coupling a hydrologic–ecohydraulic approach. *Energy Convers. Manag.* **2020**, *223*, 113267. [CrossRef]

14. Kuriqi, A.; Pinheiro, A.N.; Sordo-Ward, A.; Bejarano, M.D.; Garrote, L. Ecological impacts of run-of-river hydropower plants—Current status and future prospects on the brink of energy transition. *Renew. Sustain. Energy Rev.* **2021**, *142*, 110833. [CrossRef]

15. Lee, K.; Bakshi, B. *Energy-Water-CO$_2$ Nexus of Fossil Fuel Based Power Generation*; CRC Press: Boca Raton, FL, USA, 2020; pp. 184–202.

16. Wang, X.; Zhang, Q.; Xu, L.; Tong, Y.; Jia, X.; Tian, H. Water-energy-carbon nexus assessment of China's iron and steel industry: Case study from plant level. *J. Clean. Prod.* **2020**, *253*, 119910. [CrossRef]

17. Chinese, D.; Santin, M.; Saro, O. Water-energy and GHG nexus assessment of alternative heat recovery options in industry: A case study on electric steelmaking in Europe. *Energy* **2017**, *141*, 2670–2687. [CrossRef]

18. Elshkaki, A. Material-energy-water-carbon nexus in China's electricity generation system up to 2050. *Energy* **2019**, *189*, 116355. [CrossRef]

19. Tan, Q.; Liu, Y.; Ye, Q. The impact of clean development mechanism on energy-water-carbon nexus optimization in Hebei, China: A hierarchical model based discussion. *J. Environ. Manag.* **2020**, *264*, 110441. [CrossRef]

20. Chai, L.; Liao, X.; Yang, L.; Yan, X. Assessing life cycle water use and pollution of coal-fired power generation in China using input-output analysis. *Appl. Energy* **2018**, *231*, 951–958. [CrossRef]

21. Liu, Y.; He, L.; Shen, J. Optimization-based provincial hybrid renewable and non-renewable energy planning—A case study of Shanxi, China. *Energy* **2017**, *128*, 839–856. [CrossRef]

22. He, L.; Chen, Y.; Zhao, H.; Tian, P.; Xue, Y.; Chen, L. Game-based analysis of energy-water nexus for identifying environmental impacts during Shale gas operations under stochastic input. *Sci. Total Environ.* **2018**, *627*, 1585–1601. [CrossRef] [PubMed]

23. Ye, B.; Zhou, M.; Yan, D.; Li, Y. Multi-Objective Decision-Making for Hybrid Renewable Energy Systems for Cities: A Case Study of Xiongan New District in China. *Energies* **2020**, *13*, 25. [CrossRef]

24. Zohrabian, A.; Sanders, K.T. The Energy Trade-Offs of Transitioning to a Locally Sourced Water Supply Portfolio in the City of Los Angeles. *Energies* **2020**, *13*, 5589. [CrossRef]

25. Hobbs, B.F. Optimization methods for electric utility resource planning. *Eur. J. Oper. Res.* **1995**, *83*, 1–20. [CrossRef]

26. Dahlbeck, M. A mixed-integer linear programming approach for the T-row and the multi-bay facility layout problem. *Eur. J. Oper. Res.* **2021**. [CrossRef]

27. Moazeni, F.; Khazaei, J. Optimal operation of water-energy microgrids; a mixed integer linear programming formulation. *J. Clean. Prod.* **2020**, *275*, 122776. [CrossRef]

28. Roy, R.; Jadhav, H.T. Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 562–578. [CrossRef]

29. Zhao, X.; Yao, J.; Sun, C.; Pan, W. Impacts of carbon tax and tradable permits on wind power investment in China. *Renew. Energy* **2019**, *135*, 1386–1399. [CrossRef]

30. Lei, Z.; Fan, Y. Optimization of China's generating portfolio and policy implications based on portfolio theory. *Energy* **2010**, *35*, 1391–1402.

31. Myers, S.C.; Turnbull, S.M. Capital Budgeting and the Capital Asset Pricing Model: Good News and Bad News. *J. Financ.* **1977**, *32*, 321–333. [CrossRef]

32. The People's Government of Beijing Municipality. *Energy Development Plan of Beijing during the 13th Five-Year Plan Period*; The People's Government of Beijing Municipality: Beijing, China, 2017. Available online: http://www.beijing.gov.cn/zhengce/gfxwj/201905/t20190522_60416.html (accessed on 23 June 2017).

33. Leonard, J.M.; Decker, C.S. Determinants of voluntary electricity demand management program participation. *Util. Policy* **2012**, *20*, 17–21. [CrossRef]

34. The People's Government of Beijing Municipality. *Review the 13th Five-Year Plan and look forward to the 14th Five-Year Plan*; The People's Government of Beijing Municipality: Beijing, China, 2021. Available online: http://www.beijing.gov.cn/ywdt/zwzt/hgssw/index.html (accessed on 28 April 2021).

35. Standardization Administration of China. *The State Standard of the People's Republic of China: Norm of Water Intake: Part I The Thermal Power*; Standards Press of China: Beijing, China, 2012. Available online: https://max.book118.com/html/2019/0413/8107133125002016.shtm (accessed on 1 January 2013).

36. Jiang, B.F. China Wind Power Industry Analysis Report; Atomic Consultin.g 2020; pp. 1–33. Available online: https://news.bjx.com.cn/html/20200429/1068002.shtml (accessed on 29 April 2020).