

Article

Multi-Constraint Multi-Objective Collaborative Optimization Control of Geothermal Water Extraction Systems

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Abstract

To overcome the rapid expansion of the drawdown cone, severe inter-well interference, and high operating costs caused by independent geothermal well operation, this study investigated the coordinated optimal scheduling of geothermal water extraction. Fifteen geothermal production wells in the main urban area of Kaifeng City were selected as the study case. The intake intervals of these wells are located at depths of 1020 to 1330 m. Based on the exploitable yield of the geothermal reservoir, user water demand, and well layout, a management model for coordinated scheduling was developed. Design drawdown, water demand, and heating capacity were used as constraints. The objectives were to minimize operating cost, nodal drawdown, and drawdown interference between wells. The results from several optimization algorithms show that the improved Cheetah Optimization Algorithm converged faster and produced more consistent solutions. Compared with the preoptimization scheme, the optimized scheme reduced total operating cost by 31.64%, total drawdown in the study area by 69.5%, and the sum of inter-well drawdown interference by 34.7%. This study provides useful support for selecting efficient optimization algorithms and offers a basis for the scientific development, utilization, and protection of geothermal water resources.

Keywords: geothermal water; water level drawdown; inter-well drawdown interference; extraction and supply; optimized scheduling; cheetah optimization algorithm



Academic Editor: Zheming Shi

Received: 30 March 2026

Revised: 28 April 2026

Accepted: 6 May 2026

Published: 12 May 2026

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1. Introduction

Under the background of the “dual-carbon” goals, China urgently needs to establish a low-carbon, clean, and diversified modern energy system, including renewable energy sources such as wind, solar, and geothermal energy [1]. Among these resources, geothermal energy has attracted increasing attention due to its high energy utilization efficiency and stable energy supply characteristics [2]. China ranks among the leading countries worldwide in the scale of direct geothermal utilization [3]. By 2020, the total

proven geothermal resources accounted for approximately 8% of the global total, which is equivalent to more than 400 billion tons of standard coal [4]. However, in recent years, the lack of scientific planning in geothermal resource exploitation in some regions has led to a series of problems. In particular, during the joint operation of multiple geothermal wells, the extraction rates have not been properly regulated, resulting in superposition effects in the subsurface geothermal reservoir pressure field and consequently affecting the stability of the groundwater flow field. Such pressure field variations can disturb the local flow regime and lead to a decline in the discharge capacity of individual wells, thereby reducing the extraction efficiency of geothermal water. Therefore, research on the optimal scheduling of deep geothermal water extraction well systems is valuable for improving the benefits of geothermal water extraction systems. It also helps reduce negative hydrological geological effects on the environment and achieve efficient development and long-term utilization of geothermal resources [5].

With the rapid development of computer science, numerical simulation methods have shown significant advantages in groundwater simulation, analysis, and prediction. At present, the most commonly used regional groundwater numerical simulation software mainly includes GMS and MODFLOW based on the finite difference method, as well as FELOW based on the finite element method. Omar et al. [6] selected the Ganges region in Varanasi, India, as the study area and constructed a three-dimensional groundwater flow numerical model using GMS to evaluate groundwater resources and flow conditions, thereby providing a scientific basis for regional groundwater resource management. Mohammed et al. [7] used existing statistical data to simulate groundwater level fluctuations in the Songor Plain using the GMS model and evaluated model accuracy through calibration and validation stages. Their work significantly assisted researchers in using high-precision artificial intelligence to predict groundwater-level variations in both dry and wet years. Zhao et al. [8] based on the groundwater occurrence patterns of the Wulan Basin and combined with exploration results and planned water source exploitation layouts, established a groundwater numerical model using the Visual MODFLOW (version 2015.1) platform to further analyze the hydrogeological conditions and groundwater resource potential of the basin. Qi et al. [9] employed the Visual MODFLOW numerical simulation software to evaluate groundwater resources and allowable exploitation in the Qaidam Basin, thereby maintaining the healthy ecological development of lakes and wetlands within the basin and supporting regional socioeconomic development. Peng et al. [10] used Groundwater Vistas (version 6.0) software to predict groundwater drawdown and variations in water resources under different runoff conditions at a proposed water source site, providing predictions that support the ecological and geological stability of the Qinghai Lake basin.

Multi-objective optimization of groundwater extraction scheduling has become a major research focus in the field of water resources. Through the rational application of various extraction engineering measures and regulation strategies, groundwater withdrawal can be scientifically regulated, controlled, and allocated in both time and space. This process plays an important role in guiding the sustainable development and utilization of water resources and is crucial for achieving multiple objectives such as water supply security, ecological protection, and economic benefits. Tabari et al. [11] established a simulation optimization model for the Bandargaz-Nokandeh coastal groundwater system in northern Iran, taking the minimization of total groundwater level decline and the maximization of pumping rates as objective functions. The model combined the GMS numerical model with the Non-dominated Sorting Genetic Algorithm II for multi-objective evolutionary optimization. The results showed that, after optimization, the area of the aquifer affected by groundwater level drawdown was reduced by 29.54%, providing useful guidance for groundwater extraction from other aquifers. Song et al. [12] constructed a multi-objective

water allocation optimization model with the average water shortage rate, total pumping capacity of pumping stations, and the standard deviation of water shortage rate in receiving areas as objective functions. The model was solved using the Non-dominated Sorting Genetic Algorithm II and optimized using the entropy weight method, providing decision support for the operation and management of the Hanjiang to Huaihe Water Diversion Project in Henan Province. Li et al. [13] established a multi-objective water resource allocation model with the objectives of minimizing total water shortage, reducing chemical oxygen demand emissions, and maximizing net water supply benefits. An improved particle swarm optimization algorithm was applied to study water resource allocation in Yangquan City, Shanxi Province, providing a scientific reference for water allocation planning in other regions experiencing severe water shortages. Wang et al. [14] developed a multi-objective water allocation optimization model for the receiving areas of the northern extension emergency water diversion project, using water shortage and water transfer cost as objective functions and solving the model based on the Non-dominated Sorting Genetic Algorithm II. Among the seven optimized allocation schemes, the water supply guarantee rate exceeded the planned value of 38%, significantly improving water supply reliability while ensuring economic efficiency in water transfer costs.

Existing studies on the evaluation of groundwater exploitable resources and their optimal allocation have contributed significantly to improving water resource utilization. However, relatively few studies have simultaneously addressed the three integrated objectives of minimizing operating cost, minimizing water level drawdown at each node, and minimizing drawdown interference among wells while meeting water demand requirements. In this study, geothermal wells with intake depths ranging from 1020 m to 1330 m in the main urban area of Kaifeng City were selected as the research objects. Based on the relationship between geothermal well extraction rates and water level drawdown established by the hydrodynamic field model, an optimization control model for the joint operation of multiple geothermal wells was developed. The gray wolf optimization algorithm, genetic algorithm, Cheetah Optimization Algorithm, and an improved Cheetah Optimization Algorithm were applied for comparative analysis. The results demonstrate the accuracy and reliability of the proposed algorithm and provide guidance for the coordinated optimization scheduling of deep geothermal water production wells.

2. Overview of the Study Area

Influenced by factors such as lithology, geological structure, hydrogeological conditions, and the regional geothermal field [15], geothermal water with temperatures exceeding 25 °C occurs within rock strata deeper than 300 m in Kaifeng City, China (Figure 1) [16]. The average geothermal gradient in the study area is approximately 3.46 °C per 100 m. Economically exploitable geothermal water is mainly stored in the fine sand, medium sand, and silty fine sandstone formations of the Minghuazhen Formation and the Guantao Formation of the Neogene (Figure 2).

Existing research results indicate that the geothermal water recharge sources in Kaifeng City are located in the exposed Minghuazhen Formation and Guantao Formation strata in the western valley of the main urban area of Zhengzhou, more than 70 km away [17]. Due to weak recharge and slow runoff, long-term exploitation will lead to a rapid decline in geothermal water levels and induce problems such as ground subsidence. Therefore, Kaifeng City has currently suspended geothermal water extraction at depths of less than 1000 m.

The main urban area of Kaifeng City covers 112 km². Currently, there are 15 geothermal wells with production intervals buried at depths of 1020 to 1330 m (Table 1 and Figure 3). This stratigraphic interval corresponds to the Neogene Minghuazhen Formation and Guantao Formation. It has become a key target for resource utilization and management due to its stable reservoir thickness and effective confining capacity, especially following the comprehensive prohibition of shallow geothermal water extraction at depths of less than 1000 m. However, most of these 15 wells currently operate independently under an on-demand water supply model. This operational approach has resulted in several issues, including a rapid decline in geothermal water levels, a swift expansion of the drawdown cone area, and significant inter-well interference. To fully leverage the benefits of this valuable geothermal water resource while mitigating its environmental impacts, optimizing the regulation of the geothermal water extraction system is urgently needed [18].

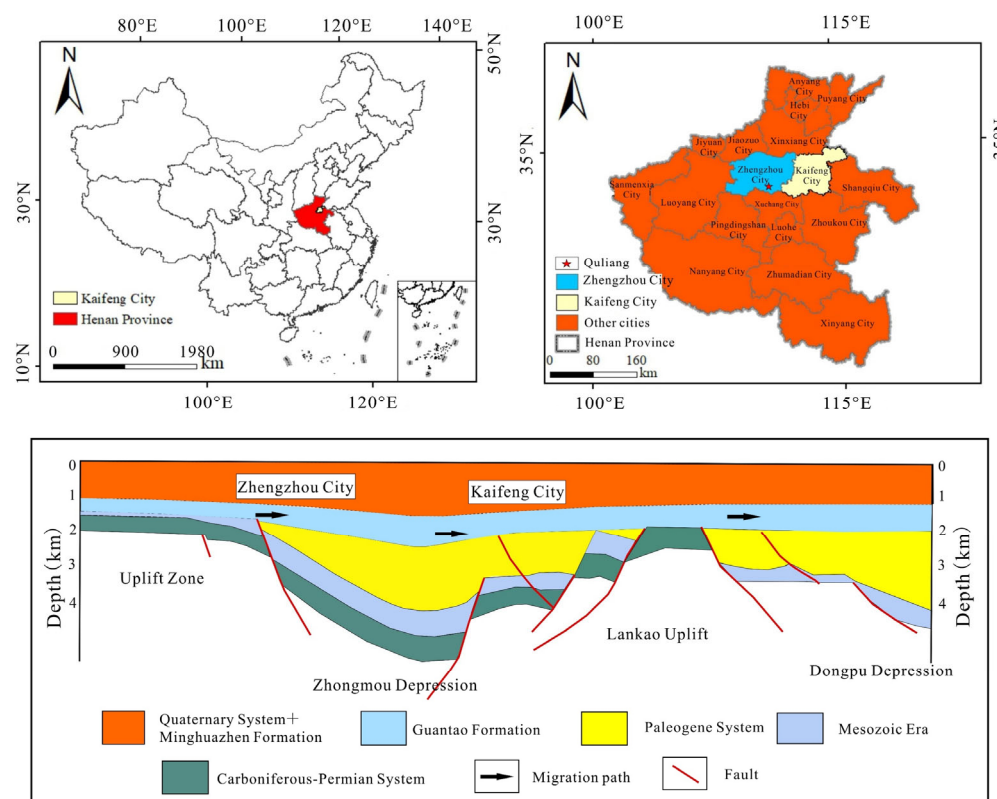


Figure 1. Location map of Kaifeng City.

Table 1. Geothermal well parameters.

Number	Geothermal Well	Well Depth (m)	Wellhead Temperature (°C)	Non-Heating Season Water Demand (m ³ /d)	Heating Season Water Demand (m ³ /d)	Permitted Extraction Rate Q _{max} (m ³ /d)	Geothermal Flux Value (MW/m ²)
G1	Yuegong Imperial Garden	1200	53.00	64	533	1200	56.08
G2	Gaotun Village	1354	66.00	112	456	1200	73.05
G3	Tiansheng Qinghua Garden	1363	63.00	63	285	1920	66.26
G4	Forest Peninsula	1350	65.00	109	603	1200	63.22
G5	Longxi Hot Spring	1200	60.00	58	179	1200	63.76
G6	Lijing Garden	1350	56.00	327	268	1200	56.97
G7	Urban Classic Garden	1300	61.60	131	520	1200	57.87
G8	Tianhe Bathing Center	1370	62.00	528	1230	768	64.83
G9	Kaifeng Water Conservancy Bureau	1254	53.50	126	368	768	61.8

Table 1. Cont.

Number	Geothermal Well	Well Depth (m)	Wellhead Temperature (°C)	Non-Heating Season Water Demand (m ³ /d)	Heating Season Water Demand (m ³ /d)	Permitted Extraction Rate Q _{max} (m ³ /d)	Geothermal Flux Value (MW/m ²)
G10	Hongda Garden	1250	47.00	194	256	1512	45.19
G11	Xiangtiwan	1220	60.00	55	185	1200	65.72
G12	New campus of Henan University	1250	53.00	169	721	1200	60.01
G13	Jiuding Yayuan	1260	49.00	258	849	1200	61.44
G14	Jiuding Songyuan	1380	55.00	139	468	1200	61.97
G15	Yellow River Conservancy Technical University	1350	50.00	63	220	1200	53.94

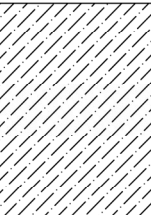
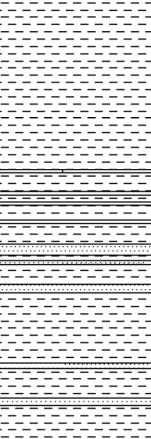
System	Formation	Burial depth (m)	Lithologic column	Lithologic characteristics
Quaternary System		250–400		Composed of thick layers of brown-red, gray-green clay, silty clay, and yellow-brown fine sandy silt and medium-fine sand.
Neogene System	Minghuazhen Formation (Nm)	400–1250		Brown-red clay, silty fine sand interbedded with gray-white fine sandy layers; alternating layers of yellow-brown fine sand, gray-green silty fine sand, and brown-red silty clay, with semi-consolidated lithification state. The strata have a high content of mud and a low hardness.
	Guantao Formation (Ng)	1250–1800		The upper part consists of light green fine sandstone, interbedded with purple mudstone and siltstone. The middle part is composed of gray-green fine sandstone, loose sand layers, and gravelly sandstone. The lower part consists of brown-gray limestone, mudstone, and calcareous sandstone, with poor lithification and high mud content in the strata.
	Dongying Formation (Ed)	>1800		Dark red sandstone and mudstone.

Figure 2. Schematic columnar diagram of Kaifeng City's rock formations.

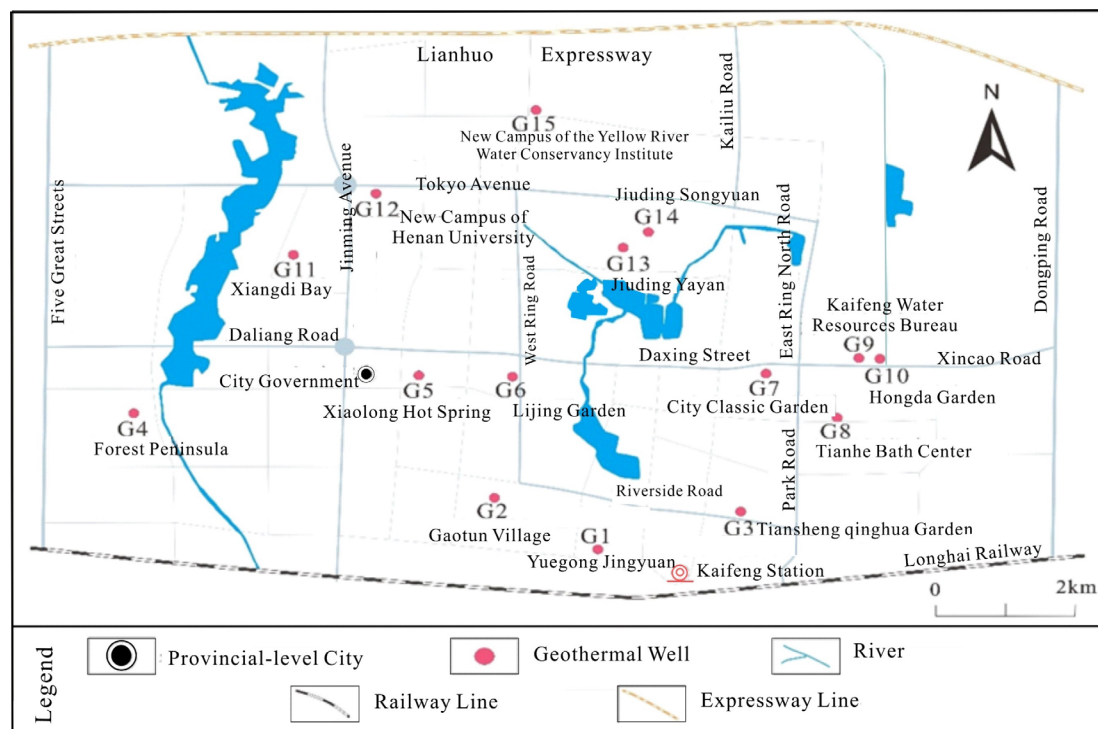


Figure 3. Schematic diagram of geothermal well locations.

3. Optimization Control Model

3.1. Objective Function

Reducing the joint operation costs of geothermal wells is essential. It is important to minimize mutual interference between wells. Achieving the lowest possible drawdown of the geothermal water table in the study area is also crucial. These measures will maximize the benefits of geothermal water development while avoiding environmental hydrogeological issues. Therefore, the objective function for optimizing the regulation of Kaifeng City's urban geothermal water extraction system is as follows:

(1) Minimum operating costs

To reduce operating costs for multiple geothermal wells within the same thermal reservoir, the operating costs should be kept as low as possible:

$$\min F_1 = \min \sum_{k=1}^{MK} \sum_{i=1}^{NQ} \frac{1}{(1+r)^{kt}} [C_1(i, kt)Q_1(i, kt) + C_2(i, kt)Q_2(i, kt)] \quad (1)$$

where F_1 is the operating cost of geothermal wells during the management years (yuan); r is the discount rate (discount rate); $C_1(i, kt)$, $C_2(i, kt)$ are the operating costs of extracting the unit of geothermal water during the non-heating and heating periods in the kt -th year (yuan/m³); $Q_1(i, kt)$, $Q_2(i, kt)$ are the amounts of geothermal water extracted from the i -th well during the non-heating and heating periods in the kt year (m³); MK is the number of years for optimizing the management period; NQ is the number of geothermal wells;

The operating cost C required to extract a unit volume of geothermal water is

$$C = \frac{0.00272fH}{\eta} \quad (2)$$

where f denotes the electricity price, yuan/kWh; H denotes the geothermal water burial depth (m); η is the pump efficiency.

(2) Minimizing the sum of the water level drop at nodes

Under the condition of meeting the geothermal water demand, the minimum depth drop of the geothermal water level in the whole region is realized:

$$\min F_2 = \min \sum_{kt=1}^{MK} \sum_{j=1}^{NM} [D_1(j, kt) + D_2(j, kt)] \quad (3)$$

where F_2 denotes the sum of water level drop depths at each node at the end of the management period (m); NM denotes the total number of dissected nodes in the management area; $D_1(j, kt)$, $D_2(j, kt)$ denote the values of water level drop depths (m) at the j -th node at the end of the heating period and at the end of the non-heating period of the kt -th year, respectively.

The drawdown value at the node under geothermal water extraction conditions can be calculated based on a mathematical model of the hydrodynamic field.

(3) Minimizing interference value of water level drop between wells

To fully utilize the engineering benefits of the 15 geothermal wells, inter-well interference should be minimized:

$$\min_i F_3 = \min_i \sum_{kt=1}^{MK} \sum_{j=1}^{NM} [D_1'(i, j, kt) + D_2'(i, j, kt)] \quad (4)$$

where F_3 is the sum of water level drop depth impact values between geothermal wells at the end of the management year (m); $D_1'(i, j, kt)$, $D_2'(i, j, kt)$ denote the water level drop depth impact values (m) from the extraction at well i on well j at the end of the heating and non-heating periods of the kt -th year, where $i \neq j$.

3.2. Constraint Conditions

(1) Water Balance

The total water supply from geothermal wells during the management period shall meet user demand, with the daily supply from a single well not exceeding its permitted extraction volume:

$$\sum_{i=1}^{NQ} Q_1(i, kt) = QP_1(kt); \quad (5)$$

$$\sum_{i=1}^{NQ} Q_2(i, kt) = QP_2(kt); \quad (6)$$

$$0 \leq Q_1(i, kt) \leq Q_{1,max}(i, kt); \quad (7)$$

$$0 \leq Q_2(i, kt) \leq Q_{2,max}(i, kt) \quad (8)$$

where $Q_1(i, kt)$, $Q_2(i, kt)$ are the extraction volumes of the i -th well during the heating and non-heating periods in the kt year, respectively (m^3); $QP_1(kt)$, $QP_2(kt)$ are the geothermal water demands during the heating and non-heating periods in the kt -th year (m^3), as shown in Table 1; NQ is the number of geothermal wells in the 1020–1330 m geothermal reservoir in the main urban area of Kaifeng City; $Q_{1,max}(i, kt)$ and $Q_{2,max}(i, kt)$ denote the maximum permitted extraction volumes of the i -th well during the heating season and non-heating season in year kt , respectively (m^3), as shown in Table 1.

(2) Heat Balance

During the management period, the heat extracted from geothermal wells should be less than the heat supply from the geothermal heat flow value:

$$Q_{\text{heat collection}} = Q_{\text{water collection}} * \rho_w * C_w * (T - T_0) \leq Q_{\text{heat supply}} = M * q \quad (9)$$

where $Q_{\text{heat collection}}$ denotes the heat extracted from a geothermal well (kcal/h); $Q_{\text{water collection}}$ is the amount of hot water extracted from a geothermal well (m^3/h); ρ_w is the density of geothermal water, taken as $1000 \text{ kg}/\text{m}^3$; C_w is the specific heat of geothermal water, taken as $1.0 \text{ kcal}/(\text{kg} \cdot ^\circ\text{C})$; T is the temperature of water at the wellhead ($^\circ\text{C}$); T_0 is the temperature of the constant thermostatic zone ($^\circ\text{C}$); $Q_{\text{heat supply}}$ denotes the amount of heat supplied within the influence range of a geothermal well (mw); M denotes the influence area of a geothermal well (m^2); q is the value of geothermal heat flow (mw/m^2), as shown in Table 1.

(3) Water level drop depth

The water level drawdown at each subdivided node at the end of the management period shall not exceed the geothermal water design allowable drawdown:

$$h(j) = \sum_{kt=1}^{MK} [D_1(j, kt) + D_2(j, kt)] \leq h_p(j), j = 1, 2, 3 \dots, NM \quad (10)$$

where $h(j)$, $h_p(j)$ are the management of the end of the year at the j -th point of the depth of the water level and the design of the allowable depth of drop (m); MK is the number of years for optimizing the management period.

4. Hydrodynamic Field Mathematical Simulation

4.1. Mathematical Model

Drilling data indicate that the thickness of the 1020–1330 m geothermal reservoir in the main urban area of Kaifeng is stable, the top and bottom aquitards have good impermeability, and the top and bottom plates are basically horizontal. The hydrogeological conceptual model can be simplified as a heterogeneous, anisotropic, three-dimensional unsteady flow model. Under natural conditions, geothermal water flows from the southwest to the northeast. The surrounding boundaries are generalized as second-type boundaries. The corresponding mathematical model is as follows:

$$\begin{cases} S_z \frac{\partial H}{\partial t} = \frac{\partial}{\partial x} \left(K_{xx} \frac{\partial H}{\partial x} \right) + \frac{\partial}{\partial y} \left(K_{yy} \frac{\partial H}{\partial y} \right) + \frac{\partial}{\partial z} \left(K_{zz} \frac{\partial H}{\partial z} \right) + \varepsilon, (x, y, z) \in \Omega, t \geq 0 \\ H(x, y, z, t)|_{t=0} = H_0(x, y, z), (x, y, z) \in \Omega, t \geq 0 \\ K \frac{\partial H}{\partial n} \Big|_{\Gamma_2} = q(x, y, z, t), (x, y, z) \in \Gamma_2, t \geq 0 \end{cases} \quad (11)$$

where H_0 denotes the initial hydraulic head of the groundwater (m); K_{xx} , K_{yy} , K_z denote the permeability coefficients in the x , y , and z principal axes directions, respectively (m/d); ε is the strength of the source-sink term (m/d); S_s denotes the specific storage of the confined aquifer ($1/\text{m}$); q is the flow rate per unit area across the second type of boundary, $\text{m}^3/(\text{d} \cdot \text{m}^2)$; Ω denotes the seepage region; Γ_2 is the flow boundary; n denotes the outward normal direction at the boundary Γ_2 .

Based on the characteristics of geothermal water flow, the CDEFGA segment in the study area represents a constant-flow recharge boundary, while the ABC segment constitutes a constant-flow discharge boundary (Figure 4). The study area was divided into three parameter zones. This division is due to variations in stratigraphic structure, lithology, and hydraulic properties across different regions. The zones were based on initial parameter

values and spatial lithological variations. The parameter ranges for each zone are detailed in Table 2.

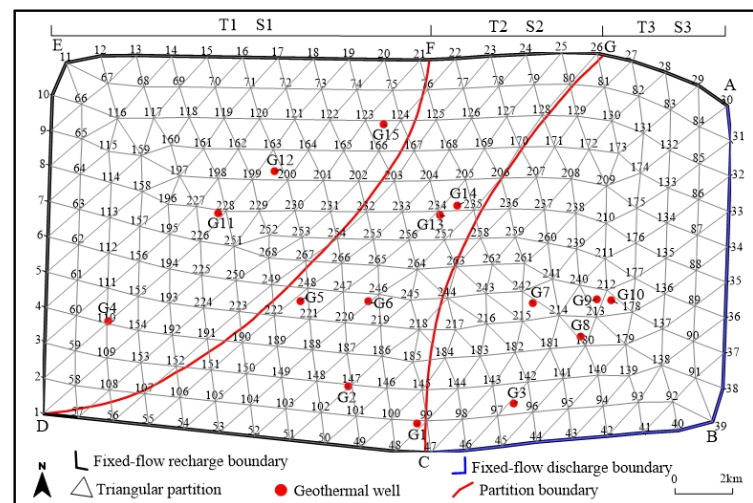


Figure 4. Division of the study area and distribution of nodes.

Table 2. Range of variation in geologic parameters of water level in different subzones.

Aquifer	Zoning	Hydraulic Conductivity ($\text{m} \cdot \text{d}^{-1}$)	Elastic Drainable Porosity (10^{-4})
Confined aquifer	Zone I	2.21~2.58	6.55~6.84
	Zone II	1.90~2.21	4.73~5.15
	Zone III	1.72~2.09	2.10~2.56

4.2. Temporal and Spatial Discretization

4.2.1. Spatial Discretization

In the process of numerical simulation solving using the GMS (version 10.8) software, based on the characteristics of the 1020~1330 m thermal reservoir in the main urban area of Kaifeng City and the layout of geothermal wells [19,20], the study area of 112 km² was divided into 477 triangular elements, with a total of 268 nodes, including 211 internal nodes and 57 type II boundary nodes (Figure 4).

4.2.2. Time Discretization

According to the extraction characteristics and utilization patterns of geothermal water, the simulation period was discretized on an annual basis into a heating period and a non-heating period. The heating period extends from November 15 to March 15 of the following year, with a total duration of 120 days, while the non-heating period lasts from 16 March to 14 November, totaling 245 days.

The simulation period of the geothermal groundwater flow field spans from April 2018 to April 2023. Within this period, the calibration period covers April 2018 to April 2021, and the validation period extends from April 2021 to April 2023.

4.3. Model Identification and Validation

4.3.1. Model Identification

Based on the pumping test data of geothermal wells and existing research results, the mathematical model was repeatedly adjusted within the given ranges of hydrogeological parameters to achieve good agreement between the simulated and observed groundwater levels [15]. The measured groundwater level field and the simulated groundwater flow field for the entire study area are shown in Figures 5 and 6, respectively, while the simulated hydrogeological parameters are summarized in Table 3.

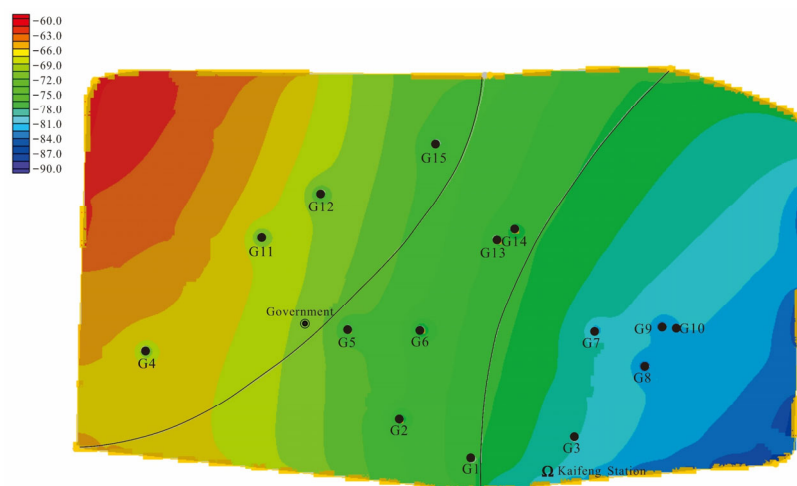


Figure 5. Measured water level flow field on 15 April 2022.

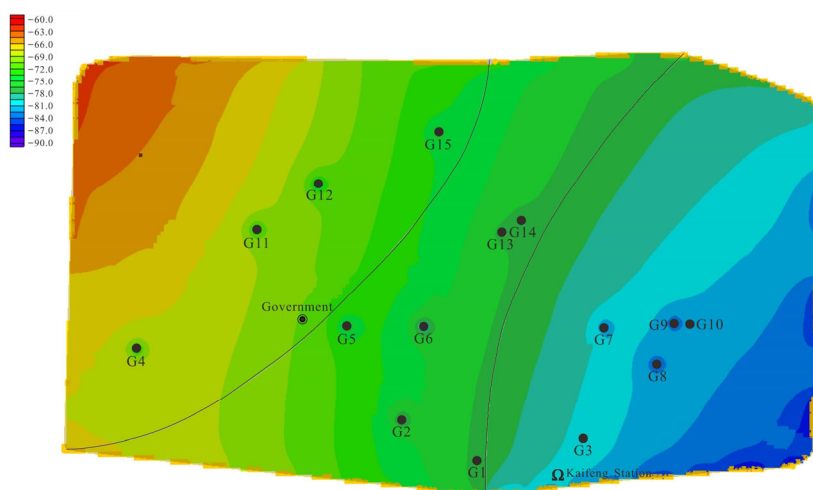


Figure 6. Simulated water level flow field for 15 April 2022.

Table 3. Geological parameter values of water levels in different zones.

Aquifer	Zoning	Hydraulic Conductivity ($\text{m} \cdot \text{d}^{-1}$)	Elastic Drainable Porosity (10^{-4})
Confined aquifer	Zone I	2.39	6.64
	Zone II	2.16	4.95
	Zone III	1.78	2.39

4.3.2. Model Validation

Parameter validation was conducted using water level observation data from 15 geothermal wells. The coefficient of determination R^2 [21] and the Nash efficiency coefficient E_{ns} [22] were selected for quantitative assessment, with the calculation formulas as follows:

$$R^2 = \frac{\left(\sum_{i=1}^n (H_m - H_{avgm})(H_s - H_{avg_s}) \right)^2}{\sum_{i=1}^n (H_m - H_{avgm})^2 \sum_{i=1}^n (H_s - H_{avg_s})^2} \quad (12)$$

$$Ens = 1 - \frac{\sum_{i=1}^n (H_m - H_s)^2}{\sum_{i=1}^n (H_m - H_{avgm})^2} \quad (13)$$

where H_s denotes the simulated water level (m); H_m is the measured water level (m); H_{avgm} is the average of the measured data (m); H_{avg_s} is the average of the simulated data (m); n denotes the number of observations, in count.

The evaluation of groundwater fitting (Table 4) shows that both metrics exceed 0.7. The minimum R^2 value is 0.8967, while the maximum is 0.9998. For the Nash–Sutcliffe efficiency (Ens), the minimum value is 0.7846, and the maximum is 0.9490. These results indicate that the groundwater model demonstrates a high degree of fit. Based on the optimized hydrogeological parameters, the study randomly selected two geothermal wells, G2 and G10, to construct the model fitting curves (Figures 7 and 8), and the simulated values were compared with the measured data to verify the reliability and accuracy of the model.

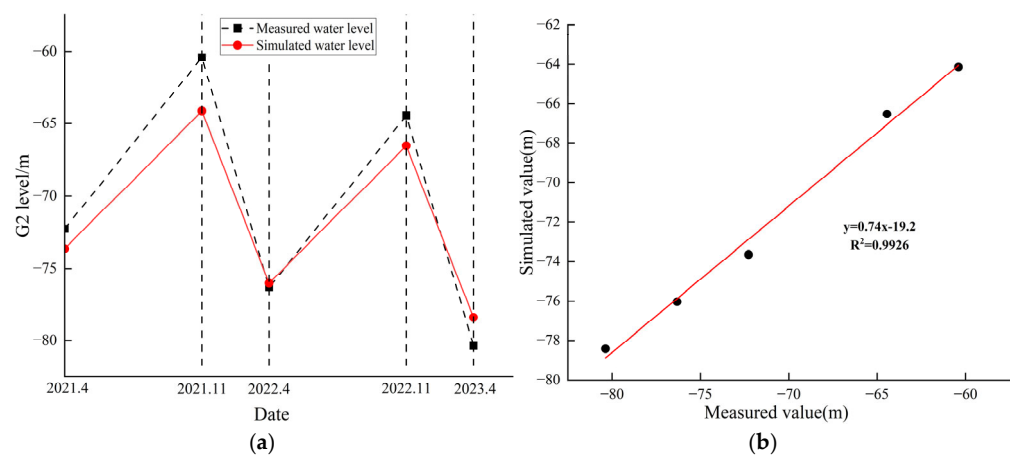


Figure 7. Comparison and correlation of simulated values of G2 water level.

Table 4. Groundwater fitting evaluation of 1020–1330 m thermal reservoirs.

Evaluation Indicators	R^2	Ens
G1	0.9942	0.9293
G2	0.9926	0.9117
G3	0.9956	0.9307
G4	0.9844	0.7846
G5	0.9863	0.8772
G6	0.9950	0.8382
G7	0.9971	0.9109
G8	0.9998	0.9490
G9	0.9944	0.9277
G10	0.9966	0.9322
G11	0.9815	0.9017
G12	0.9433	0.9106
G13	0.9918	0.8098
G14	0.9938	0.9300
G15	0.8967	0.8454

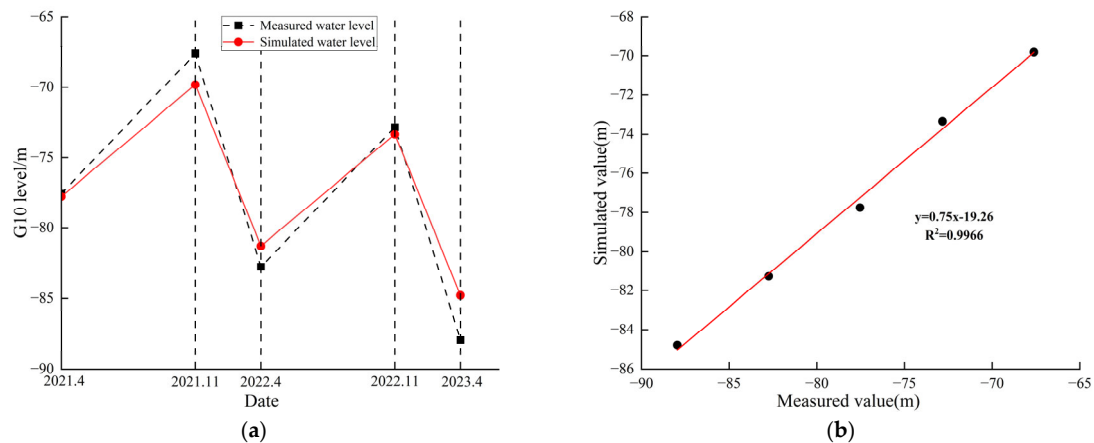


Figure 8. Comparison and correlation of simulated values of G10 water levels.

5. Optimization and Control of Geothermal Water Extraction

5.1. Cheetah Algorithm and Improvement

5.1.1. Traditional Cheetah Algorithm

The Cheetah Optimizer (CO) is a novel swarm intelligence optimization algorithm inspired by the hunting behavior of cheetahs in nature [23]. The algorithm draws its inspiration from the predatory strategies of cheetah populations. By simulating the hunting process of cheetahs, the optimization procedure is divided into three distinct stages: searching for prey, sitting and waiting for prey, and attacking the prey [24]. In the optimization framework, the problem to be optimized is regarded as the prey, while the search strategy and physiological characteristics of cheetahs are incorporated to solve practical optimization problems in an efficient, accurate, and rapid manner [25].

(1) Search strategy

Cheetahs search for prey in two ways: either by full range scanning over an area or by active search. During the hunt, depending on the condition of the prey, the coverage of the area and the cheetah's own condition, the cheetah may choose a chain of these two search modes. The expression for its position update is

$$X_{i,j}^{t+1} = X_{i,j}^t + r_{i,j}^{-1} \cdot \alpha_{i,j}^t \quad t = 1, 2, \dots, T \quad (14)$$

where $X_{i,j}^{t+1}$ and $X_{i,j}^t$ are the next and current positions of the i -th ($i = 1, 2, \dots, n$) cheetah in the j -th ($j = 1, 2, \dots, d$) dimension, respectively; t is the current search time; T is the maximum number of iterations; $r_{i,j}^{-1}$ denotes the randomization parameter of the i -th cheetah in the j -th dimension; $\alpha_{i,j}^t$ denotes the update step size of the i -th cheetah in the j -th dimension, which can be set as $0.001 \times t/T$ [26].

(2) Sit and wait strategy

During the search process, cheetahs not only actively move in the search space to look for prey, but may also adopt a strategy of temporarily remaining still to wait for a more favorable hunting opportunity. The expression of this strategy is

$$X_{i,j}^{t+1} = X_{i,j}^t \quad (15)$$

The meanings of the parameters are the same as described above.

(3) Attack strategy

When the prey moves, the cheetah not only relies on high-speed pursuit, but also flexibly adjusts its position according to the direction of the prey's escape in order to occupy the best hunting position. The expression of this strategy is

$$X_{i,j}^{t+1} = X_{B,j}^t + \beta_{i,j}^t \theta_{i,j} \quad (16)$$

where B denotes the prey; $X_{B,j}^t$ denotes the current position of the prey in the j -th row; $\theta_{i,j}$ and $\beta_{i,j}^t$ are the turning factor and the interaction factor, respectively, associated with the cheetah i in the j -th row, where $\theta_{i,j}$ is a random number, equal to $|b_{i,j}|^{\exp(b_{i,j}/2)} \sin(2\pi b_{i,j})$; and $b_{i,j}$ is a standard normal distribution random number.

5.1.2. Improved Cheetah Algorithm

(1) Search strategy improvement

In the scanning search strategy of the Cheetah Optimization Algorithm, each cheetah updates its position based on its own position at the previous moment. On this basis, the original position update strategy (Equation (14)) is optimized and adjusted to construct a new position update strategy:

$$X_{i,j}^{t+1} = X_{L,j}^t + \alpha_{i,j}^t \cdot r^t \quad (17)$$

where $X_{L,j}^t$ is the position of the leader in the population at the t -th time interval, and its r^t is modified as

$$r^t = \frac{r^1}{r^2} \quad (18)$$

where r^1 and r^2 are random values drawn from a normal distribution.

The improved search strategy in this paper is to update the location of each cheetah in the leader's neighborhood, increasing the diversity of understanding and improving the global search capability.

(2) Attack strategy improvement

During the optimization process, the interaction factor $\beta_{i,j}^t$ is used to characterize the positional relationship between neighboring cheetahs, but in reality, cheetahs generally attack prey according to the prey's position. Therefore, the improved attack strategy can adjust its position in real time according to the movement trajectory of the prey by dynamically updating the position of the cheetah, and its improved interaction factor can be expressed as follows:

$$\beta_{i,j}^t = X_{B,j}^t - X_{i,j}^t \quad (19)$$

The improved attack strategy helps to speed up the convergence of the algorithm so that it can approach the optimal solution faster, and also improves the optimization performance so that the algorithm has higher stability and accuracy in solving complex optimization problems.

(3) Random parameter improvement

The randomization parameters of the attack strategy are adjusted by introducing an exponentially decreasing coefficient $r_{i,j}$ based on the cosine function for dynamic optimization. During the iterative operation, as the number of iterations increases, both the cosine function and the exponential function exhibit a gradual decrease. This decrease causes the randomization parameter $r_{i,j}$ to decline correspondingly with each iteration. As a result, the outcomes move progressively closer to the optimal solution throughout the operational process. This not only minimizes the likelihood of overlooking the optimal solution but

also enhances the optimization search capability, allowing for more effective convergence toward the best possible results.

$$r_{i,j} = \lambda e^{\cos(\frac{1}{T+1}\pi t)} \quad (20)$$

where λ is a constant, taken as 0.05.

(4) Algorithm Process

The optimization steps for improving the Cheetah Algorithm are as follows:

Step 1: Set parameters such as population size, number of generations, and search time to determine the search range and execution duration of the algorithm. Generate the initial velocity and initial position of each individual to ensure that the population individuals are reasonably distributed within the specified d-dimensional search space.

Step 2: Simulate the cheetah's hunting process, calculate the potential position for the next step based on the current speed and position, evaluate the fitness of the individual, and adjust its movement state.

Step 3: Combine search results to dynamically optimize the speed and position of candidate solutions to adapt to environmental changes and improve the efficiency of the algorithm.

Step 4: Individuals optimize the quality of the solution by exchanging information with each other and adjusting their positions in combination with the prey movement state, and optimize the quality of the solution in continuous iteration, while the fitness calculation is carried out for the new generation of individuals to bring them closer to the optimal solution.

Step 5: Determine if the condition is met. If not, return to continue optimizing; otherwise, output the result.

5.2. Multi-Algorithm Accuracy Comparison

In this study, a multi-objective Cheetah Optimization Algorithm was implemented in the MATLAB (version R2023a) programming environment. To present the final optimal solution more clearly, and with reference to previous studies [27,28], the weights of the objective functions F_1 , F_2 , and F_3 were set to 0.3, 0.4, and 0.3, respectively. To verify the effectiveness of the improved Cheetah Optimization Algorithm, it was compared with the gray wolf optimization algorithm, the genetic algorithm, and the original Cheetah Optimization Algorithm.

Figure 9 shows the convergence curves of different optimization algorithms when solving the joint optimization scheduling problem for multiple geothermal extraction wells. The maximum number of iterations was set to 500, and each algorithm was run ten times. The results are summarized in Table 5. The optimization process indicates that the convergence fitness values of all algorithms gradually decreased with the increase in iteration number. However, compared with the other optimization algorithms, the improved Cheetah Optimization Algorithm exhibited a significantly faster convergence rate during the early iterations, enabling it to approach the optimal solution within a shorter time. In addition, the improved Cheetah Optimization Algorithm produced the smallest mean square deviation among the algorithms tested, indicating stronger solution consistency. Overall, the improved Cheetah Optimization Algorithm outperformed the other algorithms.

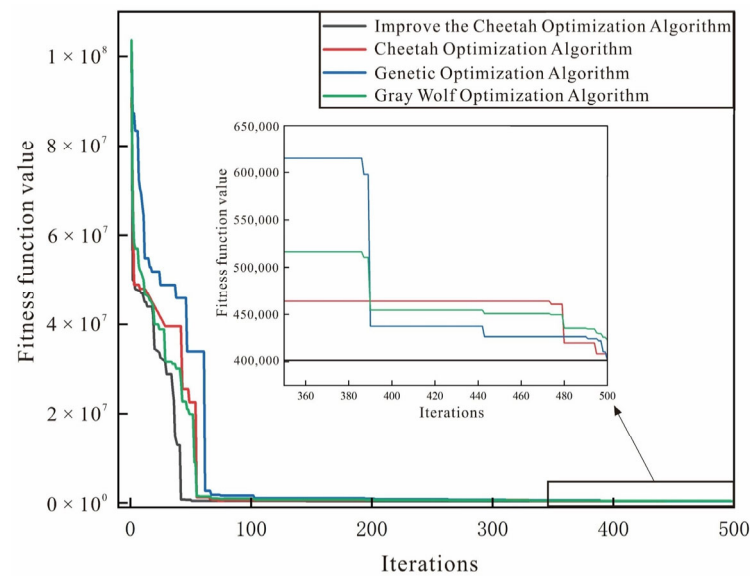


Figure 9. Convergence curves of different algorithms.

Table 5. Calculation of the algorithm's fitness function.

Algorithms	Iterations	Population Size	Maximum	Minimum	Average	Mean Squared Error
Genetic Optimization Algorithm	500	30	401,872.62	401,483.48	401,662.56	114.24
Gray Wolf Optimization Algorithm	500	30	410,254.87	406,263.28	408,151.92	1145.54
Cheetah Optimization Algorithm	500	30	423,468.19	421,368.28	422,618.27	554.47
Improved Cheetah Optimization Algorithm	500	30	401,415.32	401,158.62	401,321.36	86.35

6. Discussion and Conclusions

6.1. Discussion

The comparison of geothermal water extraction volume before and after optimization management is shown in Table 6, and the comparison of objective function values is shown in Table 7. The operating cost of 15 geothermal wells in the study area decreased from 214,820.85 yuan to 146,853.27 yuan, a reduction of 31.64%, indicating a significant reduction in costs.

Table 6. Comparison of geothermal well production preoptimization and postoptimization.

Management Period	Comparison	G1	G2	G3	G4	G5	G6	G7	G8
Non-heating period (m ³ /d)	Preoptimization	64	112	63	109	58	327	131	528
	Postoptimization	41	130	46	87	21	302	180	583
Heating period (m ³ /d)	Preoptimization	533	456	285	603	179	268	520	1230
	Postoptimization	507	445	249	631	221	239	678	1027
Management period	Comparison	G9	G10	G11	G12	G13	G14	G15	Total
Non-heating period (m ³ /d)	Preoptimization	126	194	55	169	258	139	63	2396
	Postoptimization	88	183	62	223	247	160	47	2400
Heating period (m ³ /d)	Preoptimization	368	256	185	721	849	468	220	7141
	Postoptimization	345	291	200	862	805	423	277	7200

Table 7. Comparison of objective function values preoptimization and postoptimization.

Objective Function	F_1 (yuan)	F_2 (m)	F_3 (m)
Preoptimization	214,820.85	538.70	1368.90
Postoptimization	146,853.27	164.20	893.70
Change rate/%	−31.64	−69.50	−34.70

As shown in Table 7, compared with the conditions before optimization management, the total water level drawdown at the 268 nodes decreased from 538.7 m to 164.2 m, corresponding to a change rate of -69.5 percent. Meanwhile, the total drawdown interference among geothermal wells decreased from 1368.9 m to 893.7 m, with a change rate of -34.7% . These results indicate that the trend of groundwater level decline was significantly slowed, demonstrating that the optimization management produced a positive effect in suppressing water level decline.

The mean and variance of water level drawdown at the nodes in the three zones of the study area were calculated, and the corresponding violin plots are shown in Figure 10. These plots provide a clearer comparison of the changes in water level drawdown in each zone before and after optimization. After optimization, water level drawdown generally decreased in all zones compared with the preoptimization condition. This reduction was especially pronounced in Zone III, where water level drawdown decreased from 11.14 m before optimization to 5.59 m after optimization, corresponding to a change rate of 49.82% . This marked improvement indicates that optimized regulation of the geothermal water extraction system can extend the service life of geothermal wells under the same design drawdown and prolong the geothermal water supply period. Therefore, optimization and regulation of the geothermal water extraction system are of great importance for the efficient utilization and scientific protection of geothermal resources.

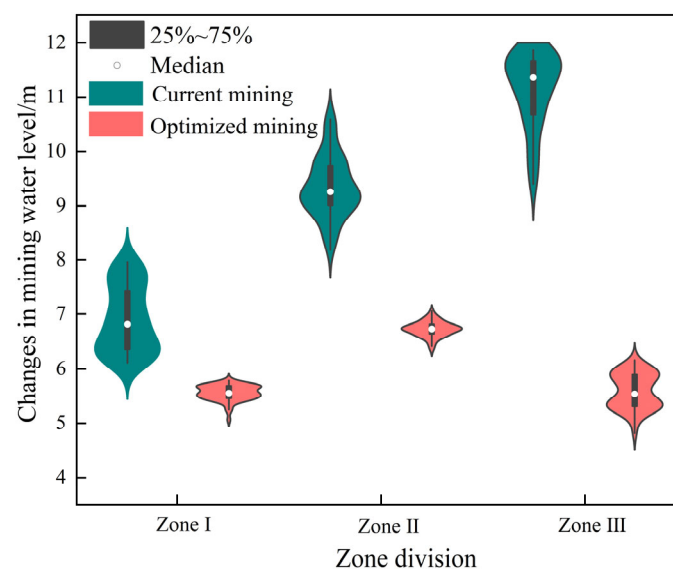


Figure 10. Violin plot of water level changes in each subdivision.

6.2. Conclusions

- (1) Taking the minimum operating cost of geothermal wells, the minimum sum of water level drawdown at each node, and the minimum drawdown interference among wells as objective functions, and considering the design water level drawdown and the satisfaction of water and heat demand as constraints, a coordinated optimization scheduling management model for geothermal water extraction wells was established. This model provides support for the rational development, utilization, and scientific protection of geothermal water resources.
- (2) A hydrogeological conceptual model and mathematical model of the geothermal reservoir at depths of 1020–1330 m in the main urban area of Kaifeng City were constructed. Based on GMS numerical simulation technology and combined with long term dynamic monitoring data of geothermal water levels, model calibration and

validation were completed. The model provides a scientific basis for further analysis of the migration and flow behavior of deeply buried geothermal water.

- (3) Focusing on the search strategy, attack strategy, and random parameters, the traditional Cheetah Optimization Algorithm was improved to enable it to solve multi-objective constrained optimization problems. Through effectiveness tests using multiple algorithms, the improved Cheetah Optimization Algorithm demonstrated superior performance in both convergence speed and solution accuracy. Based on this improvement, a multi-objective optimal allocation method for geothermal water exploitation was developed, providing a new approach for the scientific management and efficient development of geothermal resources.
- (4) The optimization results show a total water level drawdown of 69.5% at the partitioned nodes. The total water level drawdown among geothermal wells decreased by 34.7%. The rate of water level drawdown in Zones I, II, and III decreased by 19.53%, 28.04%, and 49.82%, respectively. In addition, the total operating cost of geothermal wells decreased by 31.64 percent. These results are of significant importance for ensuring the sustainable development and utilization of deep geothermal water resources.

Author Contributions: Z.Y.: Methodology, Writing—Original Draft; Y.P.: Methodology, Writing—Review and Editing; W.J.: Writing—Review and Editing; Q.W.: Data Curation, Supervision; J.H.: Data Curation; Y.Q.: Supervision, Project Administration; X.D.: Visualization; X.W.: Validation, Writing—Review and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Key Research and Development Project of Henan Province (no. 25111322300), the National Natural Science Foundation of China (no. 41972254), and the Innovative Scientific and the Scientific Research Project of Henan Yudi Science and Technology Group Co., Ltd. (no. 2026-32).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: Authors Zhijia Yu, Qi Wang and Jianggen He were employed by The Second Institute of Resources and Environment Investigation of Henan Province Co., Ltd. All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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