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Performance Prediction Model Based on Multi-Task Learning and Co-Evolutionary Strategy for Ground Source Heat Pump System

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ABSTRACT In order to effectively predict the performance of ground source heat pump system, a performance prediction method is proposed in this paper. Based on the basic model of forward neural network, the algorithm predicts the performance data of ground source heat pump system by inputting the time series of system performance and 12 variables including 7 drilling parameters, 2 u-pipe parameters, 2 ground parameters and 1 circulating liquid parameter. The training of the model is divided into three subtasks by the strategy of multi-task learning and co-evolution, where CMA-ES is used as the evolutionary algorithm of the subtask. The experimental results show that the RMSE of the predicted results obtained by the proposed algorithm is less than 0.2, which verifies the effectiveness of the method. At the same time, this algorithm fully considers various influencing factors and has good versatility, which can be used as a reference for the design of ground source heat pump system.

INDEX TERMS Ground source heat pump system, data mining, covariance matrix adaptation evolution strategy, multi-task learning, prediction model.

I. INTRODUCTION

The ground source heat pump system is an energy-efficient and environmentally-friendly air-conditioning system that utilizes geothermal resources in shallow underground to provide both heating and cooling. It can transfer energy from a low-temperature heat source to a high-temperature heat source by inputting a small amount of high-grade energy (electric energy). In winter, the heat in the soil is ''taken out'' and then used to raise the temperature by the heat pump technology to supply indoor heating. In summer, the heat indoor is ''taken out'' and then released into the soil, which can balance the underground temperature throughout the year [1]. The ground source heat pump system is driven by only a small amount of electric energy, which is energy-saving, environmentally friendly, and is in line to the sustainable development strategy. What's more, compared with conventional air-source heat pump systems, it has higher performance coefficient and economic efficiency [2]. At present, with the increasingly serious energy and environmental problems, the ground source heat pump system has been getting more and more attention [3]. Due to the large investment cost, some applications that are poorly designed will not only waste funds, but would also cause public doubts about the ground source heat pump system and hinder its development and promotion [4]. Therefore, establishing an accurate system performance prediction model is one of the key technologies to promote the development and application process of ground source heat pump systems.

At present, most of the research on the performance prediction of ground source heat pump system is mainly carried out through physical analysis and modeling methods. Due to many complex variables involved in the physical analysis, establishment of the prediction model is very difficult and the prediction error is large. In addition, specific physical models are generally only applicable to specific systems, not commonly used [5]. Therefore, it is imperative to replace the physical analysis of the system by data analysis.

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In the performance prediction of ground source heat pump systems, the traditional physical analysis methods pay more attention to the actual physical system combination and energy flow process. For example, physical analysis methods usually perform energy analysis or enthalpy analysis on geothermal heat exchangers to obtain data of the energy exchange process between geothermal heat exchangers and shallow soils [6]. However, the heat transfer process occurs between the fluid in the tube and the surrounding surface, involving large spatial scales, long time spans, and complex influencing factors. Therefore, many methods often simplify or even neglect some factors, which makes it impossible for the model to accurately simulate the condition of the system. In recent years, with the development of machine learning and big data technology, data mining technology has begun to be applied to the performance prediction of ground source heat pump systems. Esen et al. used adaptive neuro-fuzzy inference system and artificial neural network to predict the performance of ground source heat pump system, which proved that adaptive neuro-fuzzy system has good applicability in quantitative modeling of ground source heat pump system [7]. Ceci et al. used machine learning algorithms and big data technology to predict the output power of renewable energy production systems, and realized one-day forecast for photovoltaic energy systems [8]. Zhuang et al. adopted a data-mining based method to accurately predict the heat transfer performance of ground heat exchangers in ground-source heat pump coupling systems with support vector machine and M5 model tree technology [9]. Yan et al. used DM technology to process real-time monitoring data and established a data-driven model using BP neural network algorithm, which was then used to predict the performance of a ground source heat pump system in Shaoxing, China [10]. Xia et al. predicted the performance of the ground source heat pump system through an artificial neural network model, in which the genetic evolution algorithm was adopted as the optimization technology, both data generation and ANN model training were carried out through the simulation system made by TRNSYS [11]. Data mining method relies more on data than physical analysis, so it can make up for the shortcomings of traditional methods [9]. At present, the research on performance prediction of ground source heat pump system based on data mining is relatively rare and imperfect. How to use data mining technology to obtain better prediction for the ground source heat pump system performance is an urgent problem to solve. In this paper, based on the existing time series prediction model, the multi-task learning method is used to establish the forward neural network as the prediction model, which is trained by CMA-ES algorithm. It takes into account the parameters of different systems and can effectively predict performance data without complex physical modeling and analysis. The multi-task learning strategy makes the method very versatile and scalable. Experiments show that this method has higher prediction accuracy than the time series prediction model.

The rest of the paper is organized as follows. Firstly, the performance data of the ground source heat pump system concerned in this paper are shown in section II. The proposed prediction method for ground source heat pump system is illustrated in section III, and the experimental results are presented and discussed in section IV. Finally, conclusions are drawn in section V.

TABLE 1. Parameters of ground source heat pump system.

Variable	Description	Type	Min.	Max.
X_1	Borehole arrangement	Catalog	1	5
X_2	Borehole radius	Real	0.055	0.075
X_3	Borehole depth	Real	100	120
X_4	Borehole number	Real	46	56
X_5	Borehole vertical spacing	Real	4	5
X_6	Borehole column spacing	Real	4	5
X_7	Thermal conductivity coefficient	Real	1.3	2.8
X_8	U-tube nominal external diameter	Catalog	1	2
X_9	U-tube spacing	Catalog	1	4
X_{10}	Ground property	Catalog	1	8
X_{11}	Remote ground temperature	Real	10	20
X_{12}	Circulating liquid parameter	Catalog	1	11

II. DATA

The performance data of the ground source heat pump system concerned in this paper includes the power consumption and energy efficiency ratio of the heat pump unit and the system. A total of 5000 sets of data are used, each of which includes the unit power consumption (Y_1), system power consumption (Y_2), unit energy efficiency ratio (Y_3), and system energy efficiency ratio (Y_4) of the corresponding system of each month in 30 years. Parameters associated with system performance are also considered, including drilling, U-shaped tube, and the surface of the circulating fluid parameters, as is shown in table 1.

A. BOREHOLE PARAMETERS

$X_1 - X_7$ are borehole parameters, denoting geometry, radius, depth, quantity, row spacing, column spacing, and thermal conductivity of the filled material respectively. X_4 represents the number of boreholes, and can be expressed as $D = A \times B$, where D is the total number of drilled holes, and A and B are the number of rows and columns of the drilled hole distribution. X_7 is the thermal conductivity of the filler material, which is tested in the field based on the used material. There is a large difference in thermal conductivity between different filler material combinations, which in turn has a large impact on the performance of the system.

B. U-TUBE PARAMETERS

$X_8 - X_9$ are U-tube parameters, representing the nominal external diameter and spacing of U-tube. The material of U-tube is high-density polyethylene (PE3408), of which the thermal conductivity is 0.42 W/mK. The four types of U-shaped tube spacing represented by X_9 correspond to minimum spacing, small spacing, large spacing and maximum spacing. At minimum spacing, the center distance between two pipes is equal to the pipe diameter ($2r_p$). At small spacing, the center distance between two pipes is equal to the sum of

TABLE 2. Ground thermal conductivity.

Nominal value	Ground	Thermal conductivity $(W/(m \times K))$
1	Gabbros	2.1
2	Dolomites	1.6
3	Compact moist soils	1.3
4	Compact water-free soils	0.8
5	Light water-free soils	0.34
6	Granites	3.4
7	Marbles	2.6
8	Rocks	2.3

TABLE 3. Circulating liquid parameter.

Nominal value	Circulating liquid	Concentration $(W/(m \times K))$
1	Water	-
2	Glycol	8.4%
3	Glycol	16%
4	Glycol	19.8%
5	Sodium chloride	7%
6	Sodium chloride	11%
7	Sodium chloride	13.6%
8	Calcium chloride	9.4%
9	Calcium chloride	14.7%
10	Calcium chloride	18.9%
11	Glycol	12.2%

the pipe diameter and 0.3 times the drilling clearance $(2r_p + 0.3(2r_b - 4r_p))$. At large spacing, the center distance between two pipes is equal to the drilling radius (r_b). At maximum spacing, the center distance between two pipes is equal to the difference between the diameter of the borehole and the diameter of the pipe $(2r_b - 2r_p)$.

C. GROUND PARAMETERS

$X_{10} - X_{11}$ are ground parameters, representing the ground thermal conductivity and distal ground temperature respectively. X_{11} refers to the ground temperature without jamming GHEs, being equivalent to the local annual average outdoor temperature. Table 2 provides the detailed thermal conductivity X_{10} of different grounds in this study.

D. CIRCULATING LIQUID PARAMETERS

Eleven kinds of circulating liquid parameter X_{12} are given in Table 3. The total flow of all types of the circulating liquid is set to 46 m^3/h, the initial temperature is set to 15 °C at the beginning of the simulation, and then varies with time.

III. METHODOLOGIES

A. MODELING AND SUBTASKING

In this paper, the basic structure of the prediction model is a forward neural network. The input is the performance data of the ground source heat pump system at the first 25 years and 12 system parameters $(X_1 - X_{12})$. The output layer is the performance data predicted for the last five years. The working state of the ground source heat pump system fluctuates largely in different months of each year. So, the prediction model is established for a fixed month considering the training time. Therefore, the forward neural network is designed to input 100 system performance data and 12 system parameters, then output 20 performance data. The key task of this method is to determine the weight coefficients between the layers. In this paper, the methods of multi-task learning and dynamic programming are combined to train the network.

Multi-task learning enhances the generalization performance of the model by sharing presentation information between related tasks. It has been applied in many optimization problems and has shown good results [12]–[14]. In this method, the training task is divided into three subtasks, which are respectively recorded as $Task_1$, $Task_2$, and $Task_3$. Each subtask has been assigned the number of input layer neurons and hidden layer neurons, that is, each subtask corresponds to a neural network structure. The goal of $Task_1$ is to obtain the relationship between future system performance and the system performance of the last 15 years. Therefore, in addition to the bias term, the input layer should include the performance data $Y_1 - Y_4$ in 15 years. $Task_2$ is used to search the relationship between the performance data in the previous 10 years and the performance data in the last 5 years. Therefore, based on $Task_1$, the input layer of the neural network corresponding to $Task_2$ adds 40 performance data of the first 10 years, that is, there are 101 input neurons in total. $Task_3$ is used to research the influence of 12 system parameters on the system performance data. It adds $X_1 - X_{12}$ to the input on the basis of the corresponding network in $Task_2$, that is, 133 input layer neurons in total. The number of hidden layer neurons in the neural network corresponding to the three tasks is set to 62, 102, and 114 respectively. The output layer contains $Y_1 - Y_4$ of the future 5 years, which has 20 neurons in total. For convenience, in the i-th subtask, note the number of input layer neurons as $In(i)$, the number of hidden layer neurons as $Hid(i)$ and the number of output layer neurons as Out, note the number of weights to be trained as $Num(i)$, the solution obtained by the training as $Sol(i)$, and the solution of the weight coefficient of the neural network corresponding to the i-th task as $Net(i)$, then:

$$Net(i) = \begin{cases} Net(i-1) + Sol(i), & i = 2, 3 \\ Sol(1), & i = 1 \end{cases} \tag{1}$$

In this process, knowledge transfer has been reflected. $Task_1$ is used as an initial task to solve problems shared in each subtask, and the results of the training are transferred and applied to subsequent tasks. For subsequent tasks, they can obtain the results of the previous task through training and apply them directly to the training process as known information, and then transfer their own training results to the next subtask, until the last subtask's training process is complete. The weight coefficient solution Net of the final prediction model is:

$$Net = Net(N) = \sum_{i=1}^{n} Sol(i) \tag{2}$$

One of the advantages of this method is that when the number of input variables associated with the performance prediction of the system increases, the coefficients that have been trained can be transferred to the new task by adding or changing subtasks without redesigning and training the whole network. Once the numbers of input layer neurons and hidden layer neurons for each subtask are determined, the number of weight coefficients that need to be trained can be determined by the following formula:

$$Num(i) = \begin{cases} In(1) \times Hid(1) + Hid(1) \times Out, & i = 1 \\ [Hid(i) - Hid(i-1)] \times [In(i-1) + Out] & \\ +[In(i) - In(i-1)] \times Hid(i), & i > 1 \end{cases} \tag{3}$$

When the weight coefficient is updated using the collaborative evolution algorithm, the individual number of each population can be determined according to (3) and the individuals can be sorted in a certain way.

B. SUBTASK EVOLUTIONARY ALGORITHM

The CMA-ES (Covariance Matrix Adaptation Evolution Strategy) algorithm is applied to each subtask to update the weight coefficients. The CMA-ES, first proposed by Hansen, has good global search optimization capabilities and has been applied and improved in many researches [15]–[20]. As an evolutionary algorithm, it draws on the strategy of biological genetic evolution. Each point in the search space can be regarded as an individual, and multiple individuals make up a population. The superior individuals in the previous generation of populations produce the offspring through certain steps. Every individual has a corresponding fitness level, which is used to measure the degree of the individual's fitness to meet the task requirements, and then a selection process like the "survival of the fittest" rule in nature is carried out. Specifically, the CMA-ES algorithm adopts a random black box optimization strategy, that is, sampling is performed according to the distribution parameters to obtain the children, then the children are evaluated, and the distribution parameters are updated, and then the process is continued until the termination condition is satisfied. It mainly consists of three steps: sampling, evaluating, and updating the distribution parameters. The search space of the population should be set before applying the CMA-ES algorithm to each task. In this method, the dimension of the search space is the number of weight coefficients that the task needs to train, which can be obtained by (3) as described in the previous section. The setting of the search space range is not unique. For convenience, the search range of each weight coefficient can be uniformly set after the data is normalized.

The CMA-ES algorithm uses multi-dimensional normal distribution $N(M, \sigma^2 C)$ for random sampling. Its isodensity surface is a super-ellipsoid, and the probability density is the largest at the distribution center M. Individuals obtained by sampling will be evaluated for fitness level and then they will be sorted. Fitness level is used to measure whether an individual can meet the requirements. The higher an individual's fitness level, the more it meets the requirements. In this paper, the fitness level is defined as the amount of error between the prediction result obtained by the network and the actual data after the weight coefficient is placed in the corresponding forward neural network. The smaller the error, the better the set of weight coefficients. Therefore, the root mean square error can be used to measure the fitness level:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{4}$$

where $\hat{y}$ is the predicted data and y is the actual data. Whenever the CMA-ES algorithm produces a new generation of individuals, these individuals representing a set of weight coefficients will be applied to the forward neural network of the corresponding task, and then the data is input into the network to obtain the predicted values. By calculating the predicted value and the actual value by (4), the error size of the individual can be obtained, thereby quantifying the degree of the individual. This also requires a certain order to be followed when transforming the weight coefficients between the topology of the forward neural network and the individuals in the CMA-ES algorithm. Each individual in CMAES corresponds to a weight coefficient on the neural network. As is shown in Fig. 1, the individuals of $Task_1$ are derived from the weight coefficients of the neural network corresponding to $Task_1$. The individuals of $Task_2$ are the weight coefficients that $Task_2$ contains and that $Task_1$ does not contain. The coefficient of the neural network is updated as an individual in the CMA-ES algorithm, which makes the neural network updated, and the prediction error of this neural network can be applied to the individual evaluation in the CMA-ES algorithm.

The distribution parameters are then updated. The distribution parameters of CMA-ES include distribution center M, population covariance matrix C and step size σ. M determines the center of the distribution, which is updated according to the individuals with higher fitness in the offspring. The update formula is:

$$M = \sum_{i=1}^{\mu} w_i X_{i:\lambda} \tag{5}$$

where w_i is the weight, satisfying $w_n > w_{n+1}$ and $\sum_{i=1}^{\mu} w_i = 1$. The λ individuals obtained by sampling are ranked according to the fitness level from high to low, and $X_{i:\lambda}$ is the position of the i-th individual. The updated M will be closer to the individuals with high fitness level in the offspring, representing that the next generation of the populations will shift in the direction of the best individuals in this generation.

The covariance matrix of the population determines the shape of the isodensity surface. Its update combines two strategies: the Rank-μ-update strategy which updates by the deviation of the new generation from the distribution center M and the Rank-1-update strategy which updates by the evolutionary path. The update formula is:

$$C^{(g+1)} = (1 - c_{\text{cov}})C^{(g)} + \frac{c_{\text{cov}}}{\mu_{\text{cov}}} {P_c}^{(g+1)} {P_c}^{(g+1)^T} + c_{\text{cov}}\left(1 - \frac{1}{\mu_{\text{cov}}}\right) \times \sum_{i=1}^{\mu} w_i {y_{i:\lambda}}^{(g+1)} {y_{i:\lambda}}^{(g+1)^T} \tag{6}$$

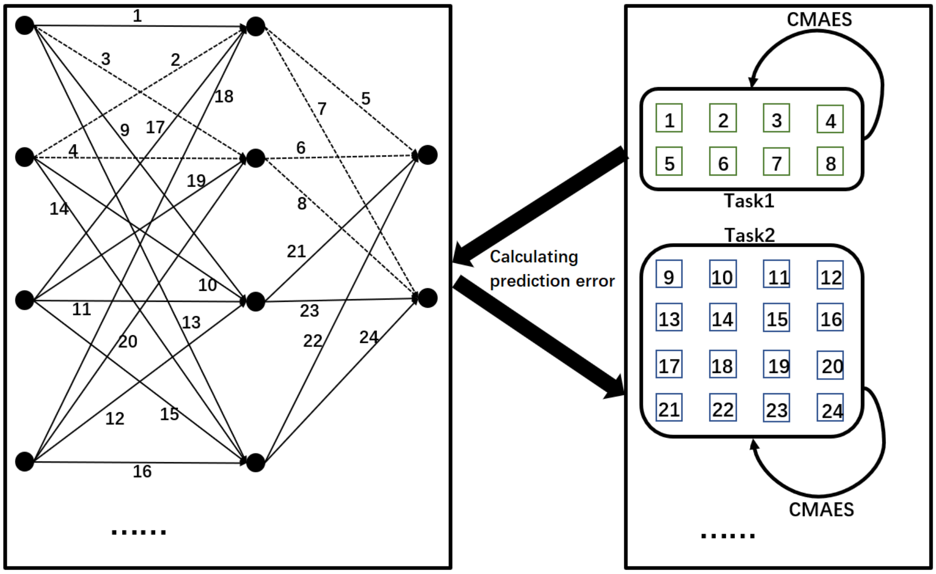

FIGURE 1. Transformation of weight coefficient between network structure and individuals in CMA-ES algorithm.

where P_c is the evolution path of the population covariance matrix. It shows the evolution direction of each generation since the beginning of the evolutionary process. In the calculation process, exponential smoothing is adopted to gradually dilute the influence of the direction information of a certain evolution on the future evolution process. The specific formula is:

$$P_c{}^{(g+1)} = (1 - c_c)P_c{}^{(g)} + \sqrt{c_c(2 - c_c)\mu_{eff}}\frac{M^{(g+1)} - M^{(g)}}{\sigma^{(g)}} \tag{7}$$

By updating the population covariance matrix C, the sampling process has a higher probability to obtain individuals with higher fitness, which guides the evolution direction of the whole population and greatly reduces the evolutionary stagnation caused by randomness. Moreover, by combining the two update strategies, only a small number of individuals need to be generated during the sampling process. However, the update of the covariance matrix C does not effectively control the evolution step size. Therefore, the CMA-ES algorithm also includes a control strategy for the step size, which is:

$$\sigma = \sigma \times \exp \frac{c_\sigma}{d_\sigma}(\frac{\|P_\sigma\|}{E\,\|N(0, I)\|}) - 1 \tag{8}$$

where P_σ is defined as the evolution path of the step size with an initial value of zero. The update method is as follows:

$$P_\sigma^{(g+1)} = (1 - c_\sigma)P_\sigma^{(g)} + \sqrt{c_\sigma(2 - c_\sigma)\mu_{eff}}C^{-\frac{1}{2}}\sum_{i=1}^{\mu} w_i y_{i:\lambda} \tag{9}$$

Equations (8) and (9) complete the step size update by comparing it with the ideal step size. Ideally, there will be no positive or negative correlations in successive evolutionary directions due to too short or too long steps. In other words, the ideal step size should make the evolutionary directions irrelevant. The randomness of small number samples can prevent the evolution process from ending prematurely at the local optimum.

In each round of the training process, the CMA-ES algorithm is sequentially adopted in $Task_1 - Task_3$. All subtasks, except for $Task_1$, are not only required to convert the individual into a weight coefficient applied to the network topology, but are also required to gain weight coefficient from the previous task. In other words, all subtasks except the last one should select an individual for the evolution in the subsequent tasks of this round. Different strategies can be used in this process [21]. For example, the previous task can provide the best individual in the latest generation, that is, the best group of weight coefficient combinations generated in the current round of evolution. It can also provide the best individual of all the progeny, that is, the optimal weight coefficient combination found since the CMA-ES algorithm started searching. Or randomly select from the individuals. This method adopts the second scheme, that is, all tasks except the last task provide the best individuals to the subsequent tasks.

Above is the main flow of the sub-task evolution. Although the formula of CMA-ES algorithm contains many parameters, most of the parameters are self-contained [15]. When the parameter setting and initialization are completed, the CMA-ES algorithm can cycle through the process of sampling, evaluating, and updating the distributed parameters to perform a global optimal solution search until the termination condition is met.

C. OVERALL PROCESS

The main process of this method is shown in Algorithm 1. In the evolutionary phase, each round of evolutionary process

Algorithm 1 Training Performance Prediction Model

Input: The performance data of ground source heat pumb system in 30 years Y. Parameters associated with system performance $X_1 - X_{12}$.
Output: The weight coefficient solution of the prediction model Net.
for *each subtask* **do**
  -Set the structure of the neural network corresponding to each subtask, the number of weight coefficients each subtask needs to search, and the conversion rules of the weight coefficients between the network structure and the individual.
  -Set the initial parameters, including the search range, the number of generations in the evolution of each round, and the number of reservations of each generation.
  -Generate initial individuals for subtasks.
end
while *the termination condition is not met* **do**
  for *each round* **do**
    for *each subtask* $Task_i$ **do**
      -Obtain offspring individuals by random sampling in multi-dimensional normal distribution $N(M, \sigma^2 C)$.
      if *current subtask is not* $Task_1$ **then**
        -Convert the best individuals provided by the previous task in this round into weight coefficients of the neural network $Net(i)$.
      end
      for *each offspring individuals* **do**
        -Obtain the prediction data using the forward neural network $Net(i)$.
        -Calculate the root mean square error is calculated according to (4).
      end
      -Sort the progeny according to the size of the root mean square error, only the first few individuals are retained.
      -Update the distribution center M, the population adaptive covariance matrix C, and the evolution step size σ.
      if *the best individuals obtained from this evolution has lower RMSE then the best individuals before* **then**
        -The best individuals obtained from this evolution become the new best individuals.
      end
    end
  end
end

is repeated until the termination condition is met. One of the termination conditions is that the error of the entire prediction model is lower than the threshold, which means that the prediction model satisfies our requirements has been obtained, so the search can be stopped. In addition, an upper limit should be set on the number of calculations of individual fitness level. Once the number of fitness calculations in the evolutionary stage exceeds the upper limit, the evolution process can be terminated to avoid an unlimited evolution process due to the low expected error setting. However, it should be noted that if the upper limit is set too low, it may lead to premature termination of the evolution process, resulting in a large error in the resulting prediction model.

IV. EXPERIMENTS

A. EXPERIMENTS SETTINGS

This experiments use MATLAB software to obtain the performance prediction model of the ground source heat pump system using the method described above. The model can predict the performance data of the future 5 years based on the system parameters and the performance data of the past 25 years. The experiment used 5000 sets of ground source heat pump system data. The first 4000 sets of data were used to train the neural network model, and the last 1000 sets of data were used for the prediction error test of the final model. The number of generations in the continuous evolution of each subtask is set to 10 in each round, and each dimension range of the search space is set to [−5,5].

When predicting the performance of a ground source heat pump system, each variable has a different range of variation, which has a detrimental effect on the following data mining process. For example, when applying the population evolution algorithm, directly using these raw data will make it difficult to determine the evolutionary region of the population. Therefore, these variables are normalized to dimensionless data, the specific method is:

$$\tilde{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{10}$$

where x_{min} and x_{max} are the maximum and minimum value of the variable x in the statistics respectively, and $\tilde{x}_i$ is the normalized result of the original data x_i. After processing, the statistics of all variables will change in the range of [0,1].

B. EXPERIMENTS RESULT

In the experiment, the search was terminated after 300,000 sub-generational evaluations. In several experiments, the

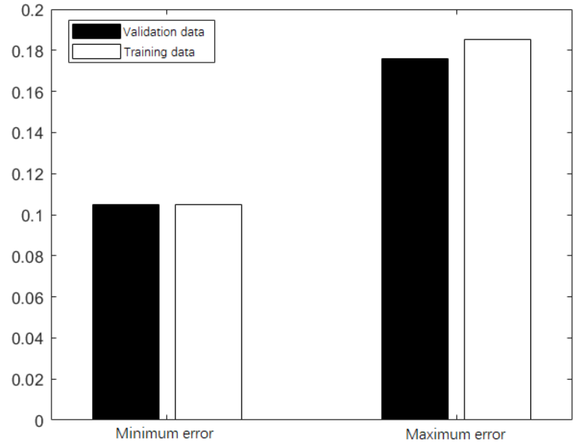

FIGURE 2. RMSE after 300000 individuals evaluation.

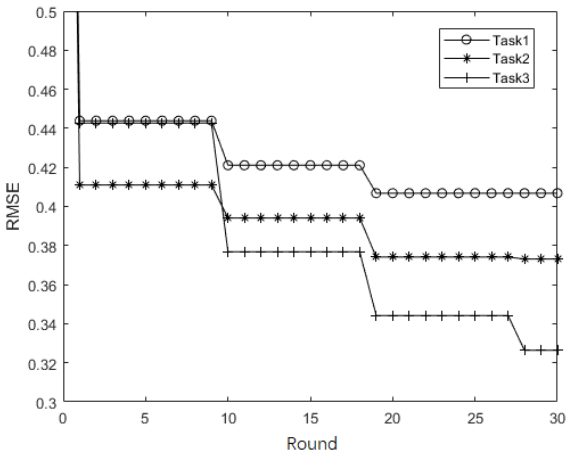

FIGURE 3. Evolution process in 30 rounds of training.

prediction model obtained by the method after 300,000 evaluations has an error of 0.1047-0.1851 and has the potential for further optimization, as shown in Fig. 2, which verifies the effectiveness of the method.

In several experiments, the prediction model obtained by the method after 300,000 evaluations has an error of 0.1047-0.1851 and has the potential for further optimization.

In order to observe the impact of system parameters on the prediction process, two time series prediction models are used for training comparison. The $Task_1$ model uses time series of the 10-25 years for prediction. The $Task_2$ model extends the time series used for prediction to 1-25 years based on $Task_1$. $Task_3$ adds 12 system parameters based on the time series. The three models are used as the three subtasks of the same training task, and 30 rounds of training are performed. The training process is shown in Fig. 3. After 30 rounds of training, the model with both system parameters and performance data as inputs has higher prediction accuracy than the model without considering system parameters, which shows that it is effective to take system parameters into account. The error between this model and the time series prediction model after 30 rounds of training is shown in Fig. 4.

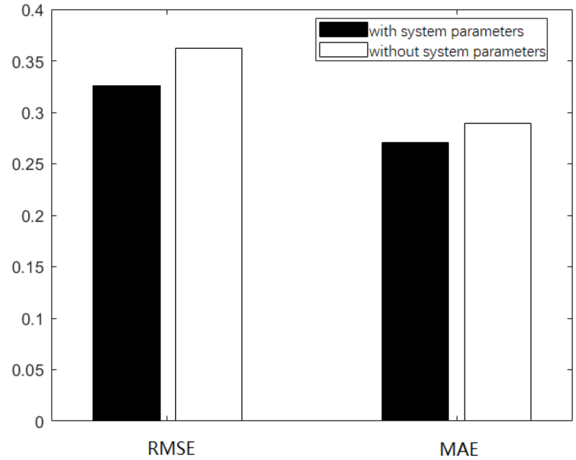

FIGURE 4. Errors of two models after 30 rounds of training.

TABLE 4. Comparative experimental results.

Variable	ES	AR	ARMA	ARIMA	This work
RMST	4.6730	11.2387	6.2574	5.9016	0.1047-0.1851

The comparison shows that the prediction model, which takes time series prediction and system performance data into account, has less error than the model that only uses time series to predict the system parameters after a short time's search. It shows that this model has a faster convergence speed than that of the time series prediction model.

In order to further highlight the effectiveness of the proposed method, in addition to the above experiments, the comparison experiments between the proposed method and other four classical time series analysis methods were carried out. The comparison experimental results are shown in Table 4.

According to Table 4, compared with exponential smoothing (ES), autoregressive model (AR), auto-regressive moving average model (ARMA) and auto-regressive comprehensive moving average model (ARIMA) methods, the root mean square error of this method is significantly smaller. And the model can be further optimized by adjusting the training parameters.

In practical engineering applications, the four energy conversion efficiencies representing the heat transfer performance of the system do exhibit different performance under different operating parameters. Therefore, ignoring the prediction of these parameters, the results are all general. The proposed method uses the neural network as the basic model, and the training of the forward neural network is carried out by integrating the ideas of multi-task learning and dynamic programming. The model established by this method considers not only the seasonal characteristics of the system performance data, but also the impact of the historical performance data and the system operating parameters on the future performance of the system, which is lacking in traditional time series analysis methods. The experimental results show that the proposed prediction method can effectively improve the accuracy of ground source heat pump system performance prediction.

V. CONCLUSION

1) This method can be used to predict long-term continuous performance of ground source heat pump systems. Compared with traditional methods, this data mining-based method does not require complex physical system modeling and energy analysis. In addition, it considers more factors affecting the performance of ground source heat pump systems. Experiments show that this data mining-based method can be successfully used for performance prediction of ground source heat pump systems and has great potential for improvement.
2) The multi-task learning strategy is conducive to knowledge transfer and network structure adjustment, which can improve the versatility and scalability of the ground source heat pump system prediction model.
3) When predicting the performance of the ground source heat pump system, the model considering the system parameters has lower error than the time series prediction model.

In the future research, the sub-task division method needs to be optimized. The sub-task division method affects the efficiency of the training process and the prediction error of the resulting model. In addition, the used CMA-ES algorithm should be adjusted and improved according to the characteristics of the ground source heat pump system performance prediction task. At present, the CMA-ES algorithm still has problems such as low evolution speed in the training process. If these problems can be solved, it is believed that the efficiency and prediction accuracy of this method will be greatly improved. Moreover, we may refer to metric learning [22]–[24] and multi-task graph classification [25]–[27] to predict the performance of ground source heat pump system.

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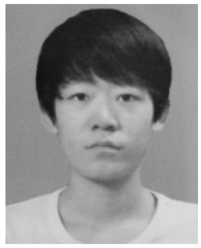

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