Modeling of Solar Field in Direct Steam Generation Parabolic Trough Based on Heat Transfer Mechanism and Artificial Neural Network

SU GUO, HUANJIN PEI, FENG WU, (Member, IEEE), YI HE, AND DEYOU LIU
College of Energy and Electrical Engineering, Hohai University, Nanjing 210098, China
Corresponding author: Su Guo (guosu81@126.com)

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ABSTRACT Accurate calculation of water/steam temperature and pressure in the solar field of direct steam generation (DSG) parabolic trough is essential to power dispatch and control. However, it is very difficult to achieve satisfied accuracy in limited time because of the existence of two-phase flow that has complex dynamic characteristics. In this work, a new hybrid model is proposed, which is based on the heat transfer mechanism enhanced by artificial neural network. This hybrid model has two characteristics as follows. (1) A heat-transfer and hydrodynamic coupling steady-state mechanism model as a prior model, which is used to quickly obtain the prior values including mechanism factors that are then used as input to an artificial neural network (ANN) model. (2) An ANN model consisting of two four-hidden-layer back propagation (BP) networks. The inlet pressure and outlet temperature of solar field are modelled in the first four-layer neural network, and then the outlet temperature of solar field is analyzed in the second four-layer neural network to improve the simulation accuracy. This model is verified by the data from DISS plant on 26 June 2001, and can be used for control studies and dispatching optimization. The calculation results show that the mean absolute percentage error (MAPE) of predicted inlet pressure and outlet temperature are 0.48% and 1.14%, respectively, which are better than the results of BP model, general regression neural network (GRNN) model, hybrid model with one BP network mentioned in this paper, and the dynamic simulation model mentioned in the literature.

INDEX TERMS Direct steam generation, parabolic trough, heat transfer mechanism, deep neural network, combining prediction model, working fluid parameters.

I. INTRODUCTION

As one of the novel types of concentrated solar power systems, Direct Steam Generation (DSG) parabolic trough uses parabolic trough concentrators to focus the direct solar irradiation onto an absorber tube, in which water is directly heated to steam. Then, the superheated steam drives the turbine generators set to generate electricity [1]–[3]. The DSG parabolic trough collector consists of the concentrator and the absorber tube, and many groups of DSG trough collector are arranged together in a certain way to form the solar field of DSG parabolic trough system [4]. Compared to traditional oil-based parabolic trough, the DSG parabolic trough uses water as working fluid instead of oil, so heat exchanger is no longer needed. DSG parabolic trough system has the following advantages: no risk of environmental pollution because the oil is replaced by water; oil/steam heat exchanger and its accessories are waived, therefore the system structure is simplified resulting in a sharp drop in plant investment; reducing the operation cost of the power plant; steam temperature and power generation efficiency is improved [1]–[3], [5]–[7]. Therefore, DSG parabolic trough is one of the most potential parabolic trough systems in the future. In DSG parabolic trough, accurate and fast calculation of water/steam temperature and pressure in solar field is essential to power dispatch and control.
At present, there are two main types of models: mechanism models or statistical models. Mechanism models are generally divided into steady-state models and dynamic models, which are composed of mathematical models of energy conversion devices and control systems in power generation. The calculation validity depends on the degree of understanding of the object structure, physics rules, and the accuracy of the model parameters. Because the DSG parabolic trough is still in the stage of demonstration and development, its operation data is hard to obtain, so the mechanism model is often used to calculate the working fluid parameters of the solar field in the literature. However, mechanism models frequently employ differential equations or partial differential equations, which are complicated and difficult to solve [26].

Heinzl et al. [8] established an optical model for parabolic trough and simulated the LS2 collector with oil using the optical model and a basic heat loss model. The simulation results well match the experimental data from Sandia National Laboratory [5]. In several studies from 1996 to 2003, Odeh [9]–[12] summarized the thermodynamic properties of collector in SEGS trough power station, established the heat loss model, the efficiency model, the hydrodynamic steady state model and the unified model of trough collector in DSG trough system with the tube wall temperature as independent variable. Design optimization of the once-through DSG trough collector and steady-state operation strategy of the DSG collector are analyzed and discussed in these works. Serrano-Aguilera et al. [13] provided the thermal hydraulic RELAP5 model for a DSG parabolic trough system. Eck [14], [15] established the non-linear dynamic model of DSG trough collector in recirculation mode based on the Modelica language and an explicit differential equation set was established. In this work, simulations were performed considering only the boiler section, and the superheating section was replaced by an adequate pressure loss element. Guo [16]–[19] has established the nonlinear distribution parameter models for once-through and recirculation DSG parabolic trough. Lobón et al. [20] used CFD package STAR-CCM+ to implement an efficient multiphase model. Biencinto et al. [21] developed a quasi-dynamic simulation model for DSG parabolic trough in TRNSYS. The main characteristics of the quasi-dynamic approach include fast computation considering the thermal inertia, and the flexibility to use different types of collector or collector field configurations. The models from Lobón and Biencinto are both developed for DSG parabolic trough solar collectors instead of the collector field. Bonilla [22], [23] developed a distributed parameter model using the finite volume method for the once-through mode DSG parabolic trough system, which sets the heat transfer coefficients and friction factors as constants. Feldhoff et al. [24] proposed a discretized finite element model and a moving boundary model to analyze once-through DSG parabolic trough. This moving boundary model is a lumped parameter model combined with distributed information, which can be used for control studies and model based predictive controllers. This discretized finite element model is used for a detailed system analysis, based on a distributed parameter model, which assumes the heat transfer coefficient in two-phase flow to be constant.

Compared with the mechanism models, the statistical learning method has higher accuracy in power calculation [27]. It includes artificial neural network (ANN), autoregressive moving average model, support vector machine, multivariate linear regression model and Kalman filter model et al. [28]. Among them, ANN is widely used because it can approximate any complex nonlinear function, and has strong adaptability and good prediction ability [29], [33]. Ronay et al. [30] proposed a multi-layer perception artificial neural network (MLPNN) to forecast prediction intervals (PIs) of the wind power and load. Chitsaz et al. [31] proposed a structure of Wavelet Neural Network (WNN) with the activation functions of the hidden neurons using multi-dimensional Morlet wavelets. Zhong et al. [32] proposed a prediction method for the generated power of photovoltaic (PV) power station using the GRNN and BP neural network prediction method. Tzuc et al. [33] established ANN model of the Parabolic Trough Collectors (PTC) based on the work fluid of single-phase water in solar heat industrial process adopting the experimental data, which made computing simpler and faster. Tzuc et al. [34] introduced an ANN model of thermal performance of PTC to determine techno-economic performances of parabolic trough. Boukalia et al. [35] proposed an ANN model trained by the data calculated from the software SAM to optimize and predict the oil-based parabolic trough with thermal energy storage. Heng et al. [36] proposed a fast and accurate transient thermal prediction method to predict outlet temperature of solar field in DSG parabolic trough with ANN and the principle of superposition. However, there’s no discussion of the pressure prediction.

In the above analysis, the presented methods to calculate main parameters of parabolic trough system are mainly employs mechanism models. However, dynamic mechanism models require massive amount of computational time while steady mechanism models do not achieve satisfied accuracy. In order to describe accurately dynamic process and calculate precisely parameters of DSG parabolic trough within limited time, a new hybrid model is proposed in this paper, which has the following characteristics: (1) A heat-transfer and hydrodynamic coupling steady-state mechanism model as a prior model, which rapidly obtains the prior values including the mechanism factors as the input of the ANN model. (2) A neural network consisting of two four-hidden-layer BP networks. The inlet pressure and outlet temperature of the solar field are modelled in the first four-layer neural network, and then the outlet temperature of the solar field is analyzed in the second four-layer neural network to improve the simulation accuracy. This model can be used for control studies and dispatching optimization.

In this paper, the heat transfer and hydrodynamic coupling steady-state mechanism model is established in Section II. The hybrid model of BP neural network coupled with
the above steady-state mechanism model is proposed in Section III. Reference models which use to compare the simulation results are introduced in Section IV. A calculation case is proposed and its results are analyzed in Section V. The conclusions are presented in Section VI.

II. HEAT TRANSFER AND HYDRODYNAMIC COUPLING STEADY-STATE MECHANISM MODEL

A. MECHANISM MODEL

As shown in the Fig. 1(a), a concentrator reflects the solar irradiation onto the focal line (the absorber tube). The concentrated beams first penetrate through the surrounding glass tube wall, evacuated space (for insulation purpose), and finally reaches the absorber tube to exchange heat. The key parameters of the above heat exchange process are shown in Fig 1(b). The heat transfer and hydrodynamic coupling steady state mechanism (HHC) model is built based on the references [16]–[19]. The HHC Model are presented as follows, while the equations of working fluid property parameter, heat transfer coefficient, thermodynamic loss and friction pressure drop are same as that of the dynamic mechanism model mentioned in the authors’ previous research papers [16]–[19].

According to the energy balance, the solar flow rate transmitted by the per unit length of the absorber tube is

$$Q_{ab,o} = I_{direct}B\eta_{opt}K_{\tau a} - q_l \cdot \pi D_{ab,o}, \quad (1)$$

where $I_{direct}$ is the direct normal irradiation, W/m²; $B$ is the width of the aperture of the concentrator, m; $\eta_{opt}$ is the DSG collector’s optical efficiency of [18]; $K_{\tau a}$ is the incident angle correction coefficient [16]; $q_l$ is the heat loss of DSG collector, W/m² [9] and $D_{ab,o}$ is the collector’s outer diameter, m.

The large ratio between length and diameter allows a one-dimensional discretization of the absorber tube and the connecting pipes [17]. Considering a control volume with $dy$ length in the absorber tube, mass conservation equation is

$$\frac{d\dot{m}}{dy} = 0, \quad (2)$$

where $\dot{m}$ is the fluid mass flow rate in the absorber, kg/s, and $y$ is the length of the pipe, m.

Towards this control volume, energy conservation equation in the absorber tube can be simply described as

$$Q_{ab,o} = \frac{d}{dy} [\dot{m}(h + \frac{\omega^2}{2} + gL)], \quad (3)$$

where $h$ is the specific enthalpy of the working fluid in the absorber tube, J/kg, $\omega$ is the fluid velocity, m/s, $g$ is the gravitational acceleration, m/s², and $L$ is the height of fluid, m.

Ignoring the local pressure drop of DSG collector, the pressure drop of working fluid in DSG collector is mainly composed of three parts: acceleration pressure drop, gravity pressure drop, and friction pressure drop. For DSG collectors, the acceleration pressure drop is negligible compared to the friction pressure drop [25].

$$\frac{dP}{dy} + \rho g \frac{dL}{dy} + P_{d} = 0, \quad (4)$$

where $P$ is the fluid pressure, Pa, $\rho$ is the fluid density, kg/m³ and $P_{d}$ is the friction pressure drop per unit pipe length, Pa/m [19].

The heat transfer equation in absorber tube can be expressed as

$$Q_{ab,o} = \alpha \cdot \pi D_{ab,i} (T_{wall} - T), \quad (5)$$

where $\alpha$ is the heat transfer coefficient, W/m²K [17]; $D_{ab,i}$ is the inner diameter of the absorber tube, m; $T_{wall}$ is the wall temperature of the absorber tube, K; $T$ is the working fluid temperature, K.

For single-phase working fluid, the density, temperature, dynamic viscosity, specific heat capacity, thermal conductivity, Prandt number and other parameters can be calculated by specific enthalpy and pressure.

For two-phase working fluid, steam quality $x$ can be expressed as

$$x = \frac{h - h'}{r}, \quad (6)$$

FIGURE 1. The Model of DSG Parabolic Trough Collector [16].
B. MODEL SOLUTION

The detailed solution process of the above proposed HHC model is as follows. The DSG trough collector is divided into \( n \) segments, and the total average parameters of each segment are replaced by the outlet parameters of each segment, as shown in Fig. 2. Starting from the inlet of DSG trough collector, the HHC steady-state model is applied to calculate each pipe section one by one; and at the end of each calculation, the flow state of the working fluid in the pipe section is judged by the calculated outlet working fluid pressure \( P \) and specific enthalpy \( h \). The detailed solution flow is shown in Fig. 3.

\[
\frac{1}{\rho} = \left( \frac{1}{\rho'} + \frac{1}{\rho''} \right) x \left( \frac{1}{\rho'} - \frac{1}{\rho''} \right),
\]

where, \( \rho' \) and \( \rho'' \) are the densities of saturated water and saturated steam under the current pressure, kg/m\(^3\), respectively.

C. VERIFICATION AND ANALYSIS

In this work, the experimental data in Ref. [10] have the complete data of temperature, pressure and the fluid state along the pipeline of DSG parabolic trough on one calculation point. Therefore, this data is suitable for verifying the correctness of the above HHC model. The test parameters of solar field in DSG parabolic trough in Ref. [10] are shown in Table 1. The DSG trough collector is divided into 60 segments on average. Because of the lack of experimental data, exception of outlet fluid temperature and outlet fluid pressure, the lengths of hot water region, two-phase region and dry steam region are compared with experimental data to verify the model. The calculated results in this paper are compared with the experimental results in Ref. [10] as shown in Table 2. The maximum error is only 3.20%, occurred in the length of hot water. The errors of two main parameters of outlet temperature and pressure are only 1.91% and 0.20% respectively. Therefore, the HHC Model presented in this paper is accurate.

III. HYBRID MODEL BASED ON HEAT TRANSFER MECHANISM AND BP NEURAL NETWORK

The hybrid model with one four-layer BP neural network (called Pre-Value-DNN model) is proposed, which based on mechanism model and BP Neural Network as shown Fig.5.

The inputs include: direct normal irradiation and differences, \( I_{\text{direct}} \) and \( \Delta I_{\text{direct}} \); the inlet working fluid mass flow rate and differences, \( \dot{m} \) and \( \Delta \dot{m} \); the design value of inlet fluid pressure in DSG trough collector, \( P_{\text{in}} \); and the design value of inlet fluid temperature of DSG trough collector, \( T_{\text{in}} \).

The difference values of direct normal irradiation and inlet working fluid mass flow rate are calculated as follows.

\[
\Delta I_{\text{direct}} = I_{\text{direct}} - I_{\text{direct}-1},
\]

\[
\Delta \dot{m} = \dot{m}_{t} - \dot{m}_{t-1}.
\]
where \( t \) is the time, \( I_{\text{direct}} \) and \( m \) represent the current direct normal irradiation, W/m\(^2\), and inlet working fluid mass flow rate, kg/s, respectively, \( I_{\text{direct}} - 1 \) and \( m_{\text{in}} - 1 \) represent the direct normal irradiation and inlet working fluid mass flow rate at the previous time of \( t \), respectively.

The estimated values of pressure and temperature, \( P_{\text{pre}} \) and \( T_{\text{pre}} \), are obtained from HHC Model with the inputs of \( I_{\text{direct}} \), \( m \), \( P_{\text{in}} \) and \( T_{\text{in}} \). \( P_{\text{pre}} \) and \( T_{\text{pre}} \), the corresponding differences \( \Delta T_{\text{pre}} \) and \( \Delta P_{\text{pre}} \), as well as \( I_{\text{direct}}, m, \Delta I_{\text{direct}} \) and \( \Delta m \) are taken as inputs of the four-layer BP neural network which
is named a cell. In this cell, it includes of 128 weights and 16 thresholds on the input layer; 160+80+48 weights and 40 thresholds on the four hidden layers; and 12 weights and 2 thresholds on the last output layer. The inlet fluid pressure $P_{\text{final}}$ and the outlet fluid temperature $T_{\text{final}}$ are the outputs of the Pre-Value-DNN model.

After testing, the Pre-Value-DNN model only improves the accurate inlet fluid pressure, but not improves the accurate outlet fluid temperature. Therefore, a revised hybrid model with two cells named Cell 1 and Cell 2 is described in Fig. 6, called Revised-HHC-DNN hybrid model. The learning objects of Cell 1 are inlet fluid pressure and outlet fluid temperature of solar field, while the learning object of Cell 2 are outlet fluid temperature of solar field. $P_{\text{pre}}$, $T_{\text{pre}}$, $\Delta P_{\text{pre}}$, $\Delta P_{\text{pre}}$, $I_{\text{direct}}$, $\dot{m}$, $\Delta l_{\text{direct}}$ and $\Delta \dot{m}$ are taken as inputs of Cell 1. $P_{\text{final}}$ and $T_{\text{mid}}$ are obtained from Cell 1, where $P_{\text{final}}$ represents the final result of inlet fluid pressure and $T_{\text{mid}}$ represents the intermediate value of outlet fluid temperature. After Cell 1, Cell 2 is added to improve the performance of outlet fluid temperature. The inputs of Cell 2 are $P_{\text{final}}, T_{\text{mid}}, I_{\text{direct}}, \dot{m}, \Delta l_{\text{direct}}$ and $\Delta \dot{m}$, while the output of
Cell 2 is the final result of outlet fluid temperature $T_{\text{final}}$. The transfer function in different cells and neural networks can be changed according to the actual situation and data outputs. The flow chart of hybrid model is shown in Fig. 7.

The accumulative BP algorithm is adopted to minimize the total accumulated error of network. To minimize the problem of over-fitting [37], the regularization method is adopted in the loss function [37]. The basic idea is to add a part of the loss function to describe the network complexity. Therefore, the loss function is:

$$E = \lambda \frac{1}{m} \sum_{k=1}^{m} E_k + (1 - \lambda) \sum_i w_i^2,$$  \hspace{1cm} (10)

where, $m$ represents the number of training sets, $w_i$ represents the $i$th connection weight. $\lambda \in (0, 1)$ is a parameter used to make a compromise between empirical error and network complexity. In this work, the value of $\lambda$ is calculated by the procedure to obtain the best network performance.

IV. REFERENCE MODELS
Two reference models as follows are used to compare the simulation results in this work. BP neural network model is shown in Fig. 8. There are 32 weights and 8 thresholds on the input layer, $56 + 35 + 20$ weights and 24 thresholds on the four hidden layers, and 8 weights and 2 thresholds on the last output layer. GRNN model is shown in Fig 9.

V. RESULT ANALYSIS
In this part, the data of Spain’s DISS concentrated solar power demonstration plant are used because the data have the inlet and outlet parameters of DSG parabolic trough pipeline during a period, which is suitable for comparing the accuracy of data-driven models mentioned in this paper. Moreover, the irradiation and steam flow data are measured by sensors in DISS plant on 26 June 2001, shown in Fig. 10 and Fig. 11 [14]. 37.5% of the data is clear sky data,
while there are many sharp changes, even zero, in direct normal irradiation at other times, which is representative.

It is suitable to verify the performance of the Revised-HHC-DNN hybrid model. The design values of pressure and temperature in DSG trough collector are 40 bar and 125°, respectively. Taking the direct solar irradiation and its difference, the working fluid mass flow rate and its difference, the designed value of inlet fluid temperature and pressure as inputs of hybrid model, prior time series of outlet working fluid temperature and inlet working fluid pressure of the solar field are obtained by HHC model and normalized as part of the inputs of neural network structure designed in Fig. 6.

To avoid over-fitting problem, 10-fold cross validation is used. The data is randomly divided into 10 parts, 9 of them used for training and the other one is used for testing. The process is repeated 10 times, each time using different test data. After training the networks, the main parameter algorithm of DSG parabolic trough based on heat transfer mechanism and ANN is obtained, which is named Revised-HHC-DNN hybrid model. In order to better verify the accuracy of hybrid model, we established some models based on some commonly used and effective neural network structures for comparison, such as BP model, general regression neural network (GRNN) model and Pre-Value-DNN model. The hybrid model is also compared with the results of experimental and dynamic mechanism model in reference [14]. The mean square error (MSE) and mean absolute percentage error (MAPE) of results using five mentioned models are presented in Table 3.

The formula for MSE and MAPE are expressed as:

\[
\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} (\text{obs}_t - \text{pre}_t)^2, \tag{11}
\]

\[
\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\text{obs}_t - \text{pre}_t}{\text{obs}_t} \right| \times 100\%, \tag{12}
\]

where \( \text{obs}_t \) is an experimental value at \( t \) time and \( \text{pre}_t \) is the simulation value at \( t \) time.

MATLAB software is used to obtain the results in Fig. 12 and Fig. 13. From Fig. 12 and Fig. 13, it can be seen that the pressure of BP neural network model is much better than that of dynamic mechanism model from Ref. [14], however the extreme values of temperature (such as the two temperature peaks in the figure) can’t be accurately identified. After the application of GRNN model, the accuracy is
TABLE 3. Comparison of calculation results from dynamic mechanism model in Ref. [14], BP model, GRNN model, Pre-Value-DNN model and Revised-HHC-DNN model proposed in this work.

| ITEM                        | Inlet pressure (MSE) | Outlet temperature (MAPE) |
|-----------------------------|----------------------|--------------------------|
| Dynamic mechanism model in Ref.[14] | 2.76 bar² | 3.94% | 32.23 °C² | 1.16% |
| BP model                    | 1.19 bar²           | 1.97% | 78.78 °C² | 1.79% |
| GRNN model                  | 0.70 bar²           | 1.29% | 79.04 °C² | 1.75% |
| Pre-Value-DNN model         | 0.11 bar²           | 0.48% | 98.16 °C² | 2.17% |
| Revised-HHC-DNN model       | 0.11 bar²           | 0.48% | 23.89 °C² | 1.14% |

TABLE 4. External verification results of the Revised-HHC-DNN hybrid model.

| Mathematical equation | Condition | Inlet working fluid pressure | Outlet working fluid temperature |
|-----------------------|-----------|------------------------------|---------------------------------|
| \( R = \frac{\sum_{i=1}^{n} (y_i - \bar{y}_{ss}) (y_p - \bar{y}_{ss})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y}_{ss})^2 \sum_{i=1}^{n} (y_p - \bar{y}_{ss})^2}} \) | \( R \geq 0.8 \) | 0.9923 | 0.9652 |
| \( K = \frac{\sum_{i=1}^{n} y_i y_p}{\sum_{i=1}^{n} y_i^2} \) | \( 0.85 < K < 1.15 \) | 1.0024 | 1.0001 |
| \( R_m = R^2 - R_{0}^2 \) | \( R_m \geq 0.5 \) | 0.8734 | 0.6882 |
| \( R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \bar{y}_{ss})^2}{\sum_{i=1}^{n} (y_i - \bar{y}_{ss})^2} \) | | 0.9987 | 1.0000 |
| \( R_{0}^2 = 1 - \frac{\sum_{i=1}^{n} (\bar{y}_{ss} - \bar{y}_{ss})^2}{\sum_{i=1}^{n} (y_i - \bar{y}_{ss})^2} \) | \( |m| < 0.1 \) | -0.0129 | -0.0733 |
| \( m = \frac{R^2 - R_{0}^2}{R^2} \) | \( |n| < 0.1 \) | -0.0127 | -0.0733 |

FIGURE 13. Comparison of measured data and simulation data of outlet working fluid temperature of solar field in DISS plant.

obviously improved, MSE and MAPE are together improved at the same time, but there are still some mismatches for large fluctuations in GRNN. Although the values of pressure in Pre-Value-DNN model is greatly improved, the prediction of temperature is unsatisfactory because it is still difficult to fit in the large fluctuating places. The simulation results of temperature and pressure using Revised-HHC-DNN model proposed in this work have the best accuracy, which are illustrated by MSEs and MAPEs shown in Table 3.

In order to ensure the prediction ability of the model, the external verification of the model is also carried out in this paper. \( y_i \) and \( y_p \) are the experimental measurement data and the calculated value respectively, while \( \bar{y}_{ss} \) and \( \bar{y}_{ss} \) represent the average experimental measurement value and the average calculated value respectively. The validation results are shown in Table 4, and all parameters meet the validation requirements, therefore, the model is acceptable \[38\]–\[40\].

The hybrid model is compared with the experimental results of DISS plant \[14\], the simulation results of dynamic mechanism model from Reference \[14\], BP neural network model, GRNN model, and Pre-Value-DNN model. The results show that the hybrid model owns the best performance. Moreover, the external verification values of the hybrid model in the paper are within a reasonable range. Therefore, the hybrid model has high accuracy and is suitable for the prediction of large fluctuation of irradiation data.

VI. CONCLUSION

In this work, based on both a steady-state physical model and an artificial neural network model, a hybrid model
of water/steam parameters of DSG parabolic trough is developed and validated using experimental data. First, the water/steam pressure and temperature are estimated by using the steady-state mechanism model. Then the theoretical calculation results are taken as part of the inputs for neural network model to obtain the final results, and the neural network structure with two four-hidden-layer BP networks is proposed to improve prediction accuracy. With data from the DISS experimental power plant in Spain as a validation set, the calculation results of water/steam parameters were compared against the simulation results of dynamic model in literature, BP, GRNN, and the hybrid model with one BP network. The Revised-HHC-DNN hybrid model proposed in this paper has achieved the best calculation accuracy with MAPEs of the inlet pressure and the outlet temperature of 0.4784% and 1.1408%, respectively, and the external verification values of the hybrid model are within a reasonable range. Therefore, this model has high correctness and accuracy. Moreover, the sensitivity analysis of independent variables in revised hybrid model, dynamic characteristics of water/steam parameters and control strategies in DSG parabolic trough will be continued to study in the next work.

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**SU GUO** was born in Liaoning, China, in 1981. She received the Ph.D. degree in power engineering and engineering thermophysics from Southeast University, China, in 2014. She is currently an Associate Professor with the College of Energy and Electrical Engineering, Hohai University, Nanjing, China. Her research interests are coupling prediction and operation optimization of solar irradiation resources, and concentrated solar power plant.

**HUANJIN PEI** is currently pursuing the master’s degree with the College of Energy and Electrical Engineering, Hohai University, Nanjing, China. His research interests include model analysis, and operation and control for hybrid renewable energy systems.

**DEYOU LIU** was born in Zhejiang, China, in 1962. He received the Ph.D. degree in water conservancy and hydropower engineering from Hohai University, China, in 2004. He is currently a Senior Professor with Hohai University and the Director of the International Center on Small Hydro Power. His research interest is modeling, optimization, and control in the area of hydropower, pumped storage technology, CSP, and wind energy.

**FENG WU** (Member, IEEE) was born in Zhejiang, China, in 1977. He received the Ph.D. degree in water conservancy and hydropower engineering from the University of Birmingham. He is currently a Professor and the Dean of the College of Energy and Electrical Engineering, Hohai University, Nanjing, China. His research interest is the modeling and control of power system and renewable energy generation system.

**YI HE** is currently pursuing the master’s degree with the College of Energy and Electrical Engineering, Hohai University, Nanjing, China. His research interest includes model analysis, and operation and control for hybrid renewable energy systems.