Energy Management Optimization of Open-Pit Mine Solar Photothermal-Photoelectric Membrane Distillation Using a Support Vector Machine and a Non-Dominated Genetic Algorithm

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ABSTRACT As a distributed energy source, open-pit mine solar photothermal-photoelectric membrane distillation can convert solar energy into heat and electrical energy to provide power for a membrane distillation water purification system. In mine sewage treatment, the solar membrane distillation system has the advantages of high desalination rate, good water quality and low cost. However, this system has not been widely promoted and applied because of its high energy consumption and low membrane flux. Different operating parameters have a greater impact on the operating efficiency of the solar membrane distillation system. In this study, a natural cooling film distillation system was built, the response surface method was used to analyze it, and a multi-objective optimization algorithm was used to optimize the operating conditions and improve the energy efficiency of the system. In our experiment, the hot end feed temperature, hot end feed flow rate, cold end cooling water flow rate, and membrane area were used as variables, and the membrane flux, thermal efficiency, and energy consumption values were investigated as target values. We used a support vector machine (SVM) with improved fitting, and substituted the fitting prediction model into the response surface method for the relationship between the variable and the target value. Collaborative analysis was followed by substituting the model into a non-dominated sorting genetic algorithm-II (NSGA-II). After the optimization operation, the optimal working conditions were obtained to improve the operating efficiency of the solar membrane distillation system, which will enable open-pit mine prosumers to realize intelligent management of solar energy generation, storage and consumption simultaneously.

INDEX TERMS Distributed energy resources, energy management optimization, solar photothermal-photoelectric membrane distillation, sewage treatment, NSGA-II, open-pit mine.

I. INTRODUCTION

Distributed energy resources (DERs), such as photovoltaics, energy storage and heat pump devices, play a central role...
in the energy transition from fossil fuels to renewables. Combining membrane distillation technology with solar photovoltaic-photothermal technology, the system does not require external heat sources and electricity, and can operate independently in remote areas (such as open-pit mines). However, there are still many problems to be solved in the membrane distillation system, such as small membrane flux and low thermal efficiency, which hinder the further promotion of membrane distillation technology [1]. The problem of pollution and emissions has always been a key issue in the process of industrial development. It is related to the comfort and health of the environment on which people depend. If a large amount of mine water is discharged directly without treatment, it not only wastes precious water resources, but also pollutes the soil, surface water and shallow groundwater around the mine, and destroys the ecological environment of the mine. Mine water mainly contains suspended matter mainly composed of coal rock powder, soluble inorganic salts, and few organic pollutants. Its treatment includes pretreatment and desalination. Pretreatment mainly removes suspended solids (SS) in mine water. Desalination is the difficult area. By comparing the three technologies of distillation, electrodialysis and reverse osmosis membrane (RO) technology to treat high-mineralization mine water, it has been found that the effluent water quality of the distillation method is good, and it can be obtained in the specific environment of low-cost heat sources near the coal mine; RO has comprehensive advantages in effluent quality, power consumption, desalination efficiency, floor space, and degree of automation [2]. Membrane distillation (MD) is a separation process combining membrane technology and distillation, and has unique advantages in the field of high-salt wastewater treatment [3]. For concentrated water after the RO treatment, the MD process is used, and the performance of the new hydrophobic composite membrane is optimized by the coating method. The results show that the optimization method of the coating can improve the poly partial concentration in the vacuum MD process and efficiency of vinyl fluoride membrane modules [4]. It should be noted that only when combined with a cheap heat source, MD has significant economic advantages [5]. The main problem with the current industrial application of membrane distillation technology is that it consumes a large amount of energy, about 90% [6]. The consumption comes from the heating of the raw water, the thermal efficiency is low, and the traditional electric heating and other methods causes the energy consumption and operating cost of the membrane distillation system to be too high. There are abundant low-cost heat sources such as solar energy, geothermal heat and industrial waste heat in mining areas in western China. Combining solar heat collection with membrane distillation technology and using solar heat collection to replace traditional heating methods to provide the heat energy required by the membrane distillation process has become a cutting area in membrane distillation [7], [8].

As shown in Figure 1, the water circulation of a solar membrane distillation system is mainly divided into two types of water supply circuits: cold circulation and thermal circulation [9]. In the thermal cycle, the working fluid is heated by the solar collector and the hot material liquid in the hot water storage tank is heated. The hot material liquid in the insulated water tank enters the thermal chamber of the membrane distillation module driven by the circulation pump [10]. In the cold cycle, the circulating water in the cold chamber enters the spray head driven by the circulating pump. After multiple heat streams exchange heat with the surrounding environment, they enter the cold water bath below under the action of gravity, and then continue to enter the cold chamber [11]. In the circuit, the electric energy generated by the solar photovoltaic panel is stored in the storage battery through the charge controller to provide electric energy for the power-consuming equipment such as the circulating pump 1 and the circulating pump 2.

Figure 1 shows a constructed photovoltaic solar thermal membrane distillation system with a membrane area of 10 m², a collector area of 2 m², a maximum water production of 15.2 L/h, and a daily water production of 86 L [12]. The system water production is affected by solar radiation relative to the ambient temperature; the entire system investment cost 3800 Euros. TRNSYS 17.2 software has been used to simulate the solar-driven membrane distillation system [13]. The system set the effective area of the collector to 22.6 m², the membrane surface area to 7.2 m², and the initial water volume of the feed tank to 3m³. Hourly weather data was used as meteorological input data, and the running time was 5 days. The research simulated and analyzed the membrane flux and thermal efficiency of the system under different operating conditions. The research showed that the temperature of the feed liquid had the greatest impact on membrane flux. When the temperature of the feed liquid rose from 30°C to 80°C, the thermal efficiency significantly improved. A solar-assisted direct contact membrane distillation seawater treatment system that could run continuously for 24 hours has been proposed [14]. It is mainly composed of a solar heat collection system, a temperature adjustment unit, a heat recovery unit, and a shell and tube direct contact membrane distillation (DCMD) modules, including seawater. The storage tank was 160 m³, vacuum tube collector area 3360 m², with 50 DCMD modules. The heat collection system collected solar energy and exchanges heat with the seawater in the storage tank to provide hot seawater for the DCMD module. When the solar radiation is high and the temperature of the seawater in the storage tank is higher than the inlet temperature of the membrane distillation, the valve was used to control the mixed water volume of the storage tank and the recharged seawater to maintain the temperature of the intake water and store heat. In addition, the heat recovery unit recovered heat from membrane distillation permeate water and concentrated water to heat the incoming water. The system produced 31 m³/d of water (the total membrane area is 180 m²), 53% of collector efficiency, and about 436 kWh/m³ of energy consumption, which is a 43% reduction compared to no kerosene heat recovery. The heat energy consumption of
the system could be reduced by about 55% by recovering the latent heat of condensation in the solar membrane distillation system [15]. The system combined a flat air gap membrane distillation membrane module with a solar heat collector. The experimental device is located in Spain’s Plataforma Solar de Almería (PSA). The solar heat collector system consists of 252 fixed CPC collectors with a total area of about 500 m$^2$; the membrane distillation system is composed of three membrane distillation modules, each of which has a membrane specific surface area of 2.8 m$^2$; the NaCl solution with a mass concentration of 1.35 g/L is used as the feed liquid, and the hot feed liquid temperature is 85°C. The seawater desalination treatment capacity of the system is 3 m$^3$/h, and the maximum membrane flux is 7 L/(m$^2$·h). The latent heat of condensate can be recovered to preheat the feed liquid, and optimize the energy efficiency of the solar membrane distillation system [16]. The unit energy consumption and GOR were improved by about 35% and 26% on the summer solstice, and about 22% on the winter solstice.

Many single-objective optimization methods including genetic algorithms, particle swarm optimization, ant colony algorithms, and response surface methods can be used to optimize the operating efficiency of solar membrane distillation systems [17]. Empirical genetic programming models have been used to predict the performance of air and water gap membrane distillation processes [18]. For the two (AGMD and WGMD) methods, the influence of operating factors on the permeation flux was studied under the condition that the gap width remained unchanged. In order to evaluate the accuracy of the fitted model, it was compared with experimental data, and the optimal operating conditions of the system obtained used genetic algorithms. A two-dimensional numerical model involving energy saving, momentum transfer and continuity equations can be used to obtain the temperature, velocity and pressure curves in the hollow fiber membrane distillation module [19]. By optimizing the four operating variables including feed temperature, hollow fiber length, feed volume flow rate and vacuum pressure, a genetic algorithm (GA) can be used to optimize the minimum water production cost (WPC). Case studies show that WPC can be reduced by 38.1% [20]. An air gap membrane distillation module with energy recovery can be used for desalination experiments and the system can be optimized using response surface methodology [21]. The parameters of cold feed inlet temperature ($T_1$), hot feed inlet temperature ($T_3$) and feed flow rate ($F$) are considered, and the membrane flux ($J$) and thermal efficiency (GOR) are the targets [22]. Based on the regression model, it was found that $T_3$ had the greatest impact on both $J$ and GOR. When $T_1$ and $F$ changed, there was a trade-off between $J$ and GOR. Using a non-dominant sorting genetic algorithm for $J$ and GOR optimization, under optimal conditions the maximum GOR and $J$ reached 8.78 and 5.07 L/m$^2$·h, respectively [23]. The permeate gap membrane distillation (PGMD) components can be modeled using response surface methodology (RSM) and artificial neural networks. Taking the condenser inlet temperature, evaporator inlet temperature, feed flow rate and feed salt concentration as the input variables of the model, and select permeation flux and specific heat energy consumption (STEC) as the response, using analysis of variance (ANOVA) and root mean square error (RMSE) analysis, the predictive capabilities of RSM and ANN models were compared. The results showed that the ANN model more accurately used experimental data to make predictions within the variable range and obtain the best operating conditions [24]. A hybrid system consisting of PEMFC (Proton Exchange Membrane Fuel Cell) and DCMD (Direct Contact Membrane Distillation) has been proposed, and used the waste heat recovered from PEMFC for salt water desalination [25]. In order to analyze the best performance of the system, the maximum energy utilization degree was used as the objective function, and the genetic algorithm used to obtain the optimal PEMFC current density and DCMD solution inlet mass flow rate. It was found that the energy utilization degree could be improved by 201%-266% after optimization. Heuristic algorithms can also be used to optimize air gap membrane distillation systems [26]. Based on
the analysis of heat and mass transfer within the module, a mathematical model for predicting the membrane flux of the AGMD system was developed. Substituting the mathematical model into ant colony optimization (ACO) and particle swarm optimization (PSO), taking the hot end feed liquid temperature, cooling water temperature, air gap width, hot end feed flow rate and cooling water flow rate as variables, membrane flux was the target value for optimization. The study found that the difference between the optimal flux values of the two technologies were less than 3% [27]. However, this optimization only used membrane flux as a single target for optimization, and could not optimize the system from a more comprehensive perspective [26]. In order to study the relationship between the input and output parameters and variables in the air gap membrane distillation system, a mathematical method was developed using the Volterra function series theory [28]. In addition, a control neural network based on particle swarm optimization was carried out to explore the effects of input operating parameters on the GOR, membrane flux, and cold-end circulating water outlet temperature in each model, and to find out the best operating conditions [29]. The application of optimization algorithms in membrane distillation systems and other fields has gradually emerged and achieved good optimization results [30]. However, most researchers use a single-objective optimization algorithm, that is, only one target (such as membrane flux) [31]. For example, although a better membrane flux value may obtained, it results in higher energy consumption and lower thermal efficiency [32]. Our multi-objective optimization algorithm considers the relationship between energy consumption, thermal efficiency, membrane flux and other multi-objectives to obtain the optimal operating conditions of the solar membrane distillation system and so improve the overall operating efficiency of the mine wastewater treatment system.

The remainder of the paper is organized as follows. In Section II, we introduce theoretical methods for simulating and optimizing membrane distillation systems. Section III introduces the experimental design scheme. In Section IV, we analyze the experimental results and optimize the experimental conditions of the photoelectric-photothermal film distillation. Finally, we conclude our work and discuss further work in Section V.

II. FITTING AND OPTIMIZATION ALGORITHM

A. SUPPORT VECTOR MACHINE

In order to obtain the relationship between the experimental variables and the experimental target values, the data were fitted using a correlation fitting method. Compared with the conventional polynomial fitting method, the support vector machine can obtain a fitting model with higher fitting accuracy when the amount of experimental data is small. SVM was proposed by V. Vapnik for linearly separable binary classification problems [33]. Our study uses nonlinear support vector machines [34]. This fitting uses the Libsvm toolbox.

We set the hot-end feed temperature, hot-end feed flow rate, cold-end cooling water flow rate, and membrane area as input variable sets. In order to unify the data from different sources under the same reference system, in order to facilitate data processing, we ensured the convergence speed, and improved the classification accuracy, by normalizing the relevant index data. For the solar membrane distillation system data set, the normalization interval was set to [−1,1], and the normalization formula was:

\[
y = \frac{x - \min(V)}{\max(V) - \min(V)}
\]

where \(x\) is the index data value to be normalized, \(\max(V)\) and \(\min(V)\) are the maximum and minimum values in the index data, and \(y\) is the converted result. The SVM classifier uses a non-linear mapping \(\theta\) on the normalized sample set to map the data into a high-dimensional feature space and perform linear regression processing [35]. The regression function was:

\[
f(x) = \left[\omega^T \cdot \theta(x)\right] + b
\]

where \(\omega\) is the weight vector, \(\theta(x)\) is the nonlinear mapping from the original space to the high-dimensional feature space, and \(b\) is the offset vector. According to the principle of structural risk minimization, after introducing the relaxation variable \(\xi_i\), the optimal hyperplane problem is transformed into a convex quadratic optimization problem:

\[
\begin{align*}
\text{Minimize} & \quad \frac{1}{2} \| \omega \|^2 + C \cdot \sum_{i=1}^{n} \xi_i^2 \\
\text{s.t.} & \quad y_i = \omega^T \cdot \theta(x_i) + b - \xi_i \quad \xi_i \geq 0; C > 0; \theta(x_i) = \cdot, \quad K(x_i, x_j)
\end{align*}
\]

\(K(x_i, x_j)\) is a positive definite kernel function satisfying Mercer’s condition. The key to modeling with SVM is to choose the kernel function. Radial basis function (RBF) is the most widely used kernel function [36]. RBF kernel functions are applicable regardless of the number of samples or the dimensions. The function formula is as follows:

\[
K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}, \quad \gamma > 0
\]

When the RBF function is used to construct the SVM model, its classification performance is affected by the kernel function parameter \(\gamma\) and the penalty factor \(c\). The genetic algorithm can comprehensively optimize the parameters \(\gamma\) and \(c\), and obtain the parameter combination that makes the cross-validation accuracy the highest. The algorithm has low
complexity, high parallelism, and accurate parameter acquisition results. The algorithm was introduced to optimize the parameters $\gamma$ and $c$.

![B. Multi-Objective Genetic Algorithm](image)

**FIGURE 2.** Example of multi-objective optimization problem.

**B. MULTI-OBJECTIVE GENETIC ALGORITHM**

Generally speaking, most optimizations in scientific research and engineering practice can be attributed to multi-objective optimization problems [37]. In single-objective optimization, each objective (such as membrane flux, energy consumption value, etc.) mutually restricts each other. When the membrane flux objective is optimized, the system energy consumption is often increased at the cost, and the unit of each objective is often inconsistent [38]. It is difficult to objectively evaluate the pros and cons of solutions to multi-objective problems. The essential difference between a multi-objective optimization algorithm and a single-objective optimization algorithm is that the solution of a multi-objective optimization algorithm is not unique, but there is a set of optimal solutions. The elements in the set are called Pareto optimal solution sets [39]. In an optimization problem, $f_1$ and $f_2$ are two objective functions. As shown in Figure 2, the objective functions $f_1$ and $f_2$ are contradictory. Because the variable $A_1 < B_1$ and $A_2 > B_2$, the improvement of one objective function has to be costed by the reduction of another objective function. Such solutions $A$ and $B$ are called non-inferior solutions, or Pareto optimal solutions. The purpose of the multi-objective algorithm is to find these Pareto optimal solutions.

A general mathematical model for constrained high-dimensional multi-objective optimization problems [40]:

$$\begin{align*}
\min F(x) &= (f_1(x), \ldots, f_M(x))^T \\
\text{s.t. } g_j(x) &\geq 0 \quad j = 1, \ldots, P \\
h_k(x) &= 0 \quad k = 1, \ldots, Q \\
x &\in \Omega \\
\Omega &= \prod_{i=1}^{P} [a_i, b_i] \subseteq \mathbb{R}^n \\
x &= (x_1, \ldots, x_P)^T \in \Omega 
\end{align*}$$

where $M$ is the number of objective functions and $M$ is greater than 3, $P$ is the number of inequality constraints, $Q$ is the number of equality constraints, $\Omega$ is the decision variable space [41], and $x$ is a candidate solution (variables to be optimized, such as hot-end feed temperature, feed flow at the hot end, cooling water flow at the cold end, and membrane area), $F$ is $M$ conflicting objective function vectors (replaced by support vector machines in this paper), and $R^M$ is the objective function space. $h_k(x) = 0$ is a linear equality constraint for the variable $x$; $g_j(x) \geq 0$ is a linear inequality constraint for $x$. A solution that satisfies all constraints is a feasible solution. When there is a constraint that is not satisfied, the solution is a non-feasible solution. The solution of the high-dimensional multi-objective optimization problem is not unique, but a set of balanced solutions, called the optimal non-inferior solution set or Pareto optimal solution set, and there is no difference in this set of solutions. A multi-objective genetic algorithm (NSGA-II) has a faster convergence speed and a shorter running time, and has become the benchmark for other multi-objective algorithms. The basic flow chart of the multi-eye genetic algorithm is shown in Figure 3.

![NSGA-II](image)

**FIGURE 3.** Multi-objective genetic algorithm operation process.

NSGA-II is a multi-objective genetic algorithm proposed by Srinivas and Deb in 2000. This algorithm has a better fitness distribution method, and has a high advantage in population diversity and avoiding the loss of excellent solutions. NSGA-II mainly has three components: fast undominated sorting method, density estimation and comparison operator [42].

1) FAST UNDOMINATED SORTING METHOD

The main idea of fast non-dominated sorting is: in population $P$, each individual $p$ has two parameters $s_p$ and $n_p$ corresponding to it, where $s_p$ is the set of individuals dominated by individual $p$, and $n_p$ is the number of individuals dominating individual $p$. First put all individuals whose $n_p$ is 0 into the set $F_1$, and assign their corresponding non-dominated serial number $i_{rank}$; then for each individual $p$ in the set $F_1$, examine its $s_p$ set, and put each individual $q$ in the set corresponding $n_q$ minus 1 (because the individual $p$ that dominates the individual $q$ has been put into $F_1$), if $n_q - 1 = 0$, it means that the individual $q$ is a non-dominated solution in $s_p$, and it is put into another set $Q$, and to classify $Q$ and assign it a non-dominated serial number; repeat the above operation until all individuals are hierarchized [43].

2) CROWDEDNESS DISTANCE ESTIMATION

In order to get the crowdedness distance of individuals, it is necessary to calculate the distance between each individual in the population relative to two adjacent individuals. The formula for calculating the congestion distance is as
follows:

\[ d_i = \sum_{j=1}^{m} \left| \frac{f_j(i+1) - f_j(i-1)}{f_j^{\text{max}} - f_j^{\text{min}}} \right| \]  

(7)

Among formula 7, \( f_j \) is the optimization objective value, which is sorted according to the size of the objective value; \( d_i \) is the crowdedness distance, \( f_j(i+1) \) and \( f_j(i-1) \) are the objective function value of the neighboring individuals of individual \( i \), and \( f_j^{\text{max}} \) and \( f_j^{\text{min}} \) are the extreme value of the objective function. The strategy used in selection is to select individuals with a large crowding distance to participate in evolution under the same conditions to maintain the diversity of the population [44].

3) COMPARISON OPERATORS

The main function of comparison operators in the NSGA-II algorithm is to promote the distribution of pareto frontiers more evenly. Each individual in the population will calculate two comparison values, one is the frontier value \( i_{\text{rank}} \) and the other is the crowdedness distance \( i_{\text{distance}} \). The comparison operators defined based on these two values are as follows:

\[
\begin{align*}
  i &\geq n, \\
  \text{if} &\ (i_{\text{rank}} < j_{\text{rank}}) \text{or}(i_{\text{rank}} = j_{\text{rank}} \text{ and } (i_{\text{distance}} > j_{\text{distance}}))
\end{align*}
\]  

(8)

According to the comparison operator, for individuals with different frontier values, individuals with lower frontier values are better, and for individuals with the same frontier value, individuals with higher crowding distance are better.

Algorithm 1 NSGA-II Algorithm

1. Input parameters to generate the initial population \( P_0 \).
2. Sort, select, cross, and mutate the population \( P_0 \) to produce the offspring population \( Q_0 \), set the parameter \( t = 0 \), and mix the current offspring and parents to produce a new population, namely \( R_t = P_t \cup Q_t \).
3. Perform fast non-dominant sorting and crowding distance calculation on \( R_t \), and then take out the first \( N \) excellent individuals as the next parent \( P_{t+1} \);
4. Select, cross, and mutate \( P_{t+1} \) to produce a new generation of \( Q_{t+1} \). Use binary competition selection method when selecting, and use single point crossover to generate new chromosomes when crossover;
5. When \( t + 1 \) is greater than the maximum number of iterations, the operation is ended; otherwise, return to step 2.
6. Output the Pareto optimal solution set.

III. LABORATORY TEST

Considering the economy, environmental protection and energy saving of this experiment, and the stability of the system, the feed temperature of the hot end was adjusted by using a constant temperature hot water bath to heat the hot end liquid, and the cold end was naturally cooled. The cold-end natural cooling film distillation system used in the experiment is shown in Figure 4. The frequency conversion pump used indoor AC power. The experiment recorded the energy consumption of the constant temperature hot water bath and the energy consumption system of the frequency conversion pump. The frequency conversion pump was powered by the indoor AC power. The energy consumption of the constant temperature hot water bath and the frequency conversion pump were recorded. In the thermal cycle, the feed liquid heated by the constant temperature hot water bath was driven by inverter pump 2 into the thermal chamber of the membrane distillation module for circulation. In the cold cycle, the cooling water in the cold-water bath was driven by frequency conversion pump 1 into the cold chamber of the membrane module. After taking away the heat of the wall surface of the cold chamber and circulating to the nozzle, it was divided into several streams to fully exchange heat with the surrounding environment under the action of gravity. The condensed droplets in the air gap of the membrane module entered the sump under the action of gravity. This experiment used a flat-plate membrane distillation module as shown in Figure 5(a), and a natural cooling stage as shown in Figure 5(b).

In this experiment, the hydrophobic membrane produced by the American MILLIPORE company was used. The hydrophobic membrane is composed of a polytetrafluoroethylene (PTFE) film supported by high-density polyethylene, which has a wide range of chemical compatibility. The hydrophobic membrane parameters are shown in Table 1.

The main component of high-salinity mine water is soluble inorganic salt, and the content of organic matter is very low. Better water quality conditions have a positive effect on controlling the pollution and wetting of the hydrophobic membrane, which is beneficial to the stable operation of the membrane distillation system. Table 2 lists the organic matter (calculated by petroleum), total hardness (calculated by CaCO₃) and total dissolved solids (TDS) in the mine water in this experiment.
The price of evacuated tube solar collectors is relatively economical, and the heat collection efficiency is still relatively high at lower temperatures. The collector used in this experiment is the all-glass evacuated tube collector produced by Shandong Linuorit Company. The collector model is BJF-2-100/1.82/0.6. There are 16 evacuated collector tubes in total. The length is 1.94 m, and the distance between the two collector tubes is 0.08 m. The lighting area is 1.82 m² and the capacity is 2.5 L. The photovoltaic power used in the experiment is 235 W (under 1000 W/m² irradiation), the open circuit voltage is 36.8 V, and the short circuit current is 8.35 A. Since the electrical energy generated by photovoltaic panels is greatly affected by radiation, the output power is unstable, which will damage the battery, so install a solar charge controller in the photovoltaic experimental system to adjust the current and voltage output by the photovoltaic panel to prevent the battery from overcharging and over-discharge phenomenon, so as to achieve the purpose of protecting the battery.

In the air-gap membrane distillation module, due to the pressure of the hot fuel liquid in the hot cavity, the hydrophobic film of the hot cavity will swell out due to elasticity, and some of it will be attached to the cold wall. In order to test the effect of the membrane drum on the membrane distillation process, a comparative experiment was carried out. As shown in Figure 5(c), we investigated the water stains produced by the cold wall bonding in the previous experiment, in a circle with a diameter of 70 mm. In order to avoid damage to the membrane surface by the support, rubber particles were used as the membrane support. The rubber particles had a diameter of 3 mm and a height of about 2 mm, pasted on the copper wall of the cold cavity in a ring-shaped arrangement, as shown in Figure 5(d).

In this experiment, the operating variables of the hot end feed temperature, hot end feed flow rate, cold end cooling water flow rate and membrane area of the membrane distillation module were used as the operating variables. The experimental design was carried out with the membrane flux, thermal efficiency and energy consumption values as target values. In the experimental design, the Box-Behnken Design (BBD) test program was the main method, and additional arrays of different test combinations with the same level of BBD design were added to further increase the number of tests and reduce the experimental error. In the natural cooling film distillation system, the cooling water temperature varies greatly between different working conditions, and it was impossible to predict and design a constant cooling water temperature working condition. Therefore, the initial temperature of the cooling water was designed to be 18°C; the air gap of the membrane module was 5 mm. The variable design level is shown in Table 3.

### TABLE 1. Hydrophobic film related parameters.

| Project name                | Property parameter      |
|-----------------------------|-------------------------|
| Filter membrane trademark   | Fluoropore              |
| Material                    | Hydrophobic PTFE        |
| Membrane water flux         | 122 (ml/min•cm²)        |
| Bubble point at 23 °C       | ≥0.7 bar                |
| Attributes                  | Surface filter          |
| Maximum temperature         | 130 °C                  |
| Aperture                    | 3.0 μm                  |
| Wettability                 | Hydrophobic             |
| Thickness                   | 150 μm                  |
| Membrane porosity           | 85 %                    |
| Air velocity                | 6 (L/min•cm²)           |

### TABLE 2. Organic matter, TDS and total hardness in mine waters.

| Index parameter       | Value       |
|-----------------------|-------------|
| Organic matter        | 0.55 (mg/L) |
| Total hardness        | 590 (mg/L)  |
| TDS                   | 3270 (mg/L) |
| Organic matter/TDS    | 1.07 (×10⁴) |
| Total hardness/TDS    | 0.18        |

### TABLE 3. BBD design impact factor coding level.

| Factor                          | Real values of coded levels |
|---------------------------------|-----------------------------|
| -1                              | 0                           | 1                           |
| $x_1$ : Hot end feed temperature, °C | -1                          | 0                            | 1                           |
| $x_2$ : Hot end feed flow, L/h   | 40                          | 55                           | 70                          |
| $x_3$ : Cold-end cooling water flow, L/h | 50    | 175                          | 300                         |
| $x_4$ : Membrane area, m²       | 50                          | 175                          | 300                         |

FIGURE 5. Experimental apparatus. (a) Flat membrane distillation module. (b) Natural cooling gantry physical map. (c) Cold cavity component film surface fit water stain. (d) Membrane support rubber particle layout.
In this experiment, the membrane flux, thermal efficiency and energy consumption values were taken as the target values of the cold-end natural cooling membrane distillation system. The expression of membrane flux \( J \) is as follows:

\[
J = \frac{W}{S \cdot t}
\]  

(9)

where: \( W \)—weight of water produced by membrane distillation module, kg;  
\( S \)—the membrane area of a membrane module, \( m^2 \);  
\( t \)—the time required for the experimental test, h.

The expression of the system thermal efficiency \( \eta \) is as follows:

\[
\eta = \frac{J \cdot S \cdot \Delta H}{Q_{in}} = \frac{J \cdot S \cdot \Delta H}{Q \cdot C_p \cdot (T_1 - T_2)}
\]  

(10)

In formula 10: \( \Delta H \)—enthalpy of evaporation, J/K;  
\( Q_{in} \)—hot end feed flow rate, L/h;  
\( C_p \)—specific heat capacity of the hot end feed, \( J/(kg \cdot K) \);  
\( T_1 \)—Temperature inlet temperature, \( ^\circ C \);  
\( T_2 \)—The outlet temperature of the hot cavity, \( ^\circ C \)

The system energy consumption is composed of the constant temperature hot water bath electrical energy consumption and the system pump energy consumption.

\[
P_e = P_{e1} + P_{e2}
\]  

(11)

In formula 11: \( P_{e1} \)—Consumption of constant temperature hot water bath, W;  
\( P_{e2} \)—Energy consumption of circulating pump in the system, W.

The processing of experimental results was divided into SVM fitting prediction analysis and a multi-objective optimization process. Firstly, the variables (hot end feed temperature, hot end feed flow rate, cooling water flow rate, and membrane area) were fitted to the target value of membrane flux, thermal efficiency, and energy consumption in order. Secondly, the fitting models between the four variables and the membrane flux, thermal efficiency, and energy consumption values were obtained. In order to detect the fitting effect of the fitting model, the working condition variables under some experiments were extracted and substituted into the fitting model, and the difference between the experimental value and the fitting value was observed within a reasonable range to verify whether the fitting effect of the model was good. The fitting model was then substituted into the response surface drawing program, and the obtained response surface was analyzed. Finally, the fitting model was substituted into the multi-objective optimization algorithm to analyze the Pareto solution set and obtain a set of optimal solution set conditions.

IV. PERFORMANCE ANALYSIS

A. MEMBRANE FLUX ANALYSIS

In the SVM modeling process, the fitting accuracy of the fitted model is a critical issue. It is necessary to verify the effectiveness of the fitted model and ensure that the fitted value obtained by the model is close to the known experimental value before proceeding. Figure 6(a) is the fitness curve of the genetic algorithm. During the optimization process, the average fitness was close to the optimal fitness, indicating that the appropriate \( c \) and \( g \) values can be found under the goal of membrane flux. The temperature of the hot end inlet, the hot end inlet flow rate, the cold end cooling water flow rate, and the membrane area of the membrane distillation system were used as variables. The membrane flux was used as the target value for fitting. After support vector machine (SVM) fitting, the order of randomly extracted working condition variables was defined as the test sequence. SVM optimal fitting parameters are shown in Table 4. Comparing the fitted values obtained from the prediction model with the experimental values, as shown in Figure 6(b), good results were obtained, showing the fitted model could be used to predict membrane flux.

In the case of cooling water flow rate of 175 L/h, air gap of 5 mm, and membrane area of 0.06 \( m^2 \), the influence of the membrane module hot end feed temperature and hot end feed flow on the membrane flux is shown in Figure 7(a). From the figure, at the lower hot end feed temperature and hot end
feed flow, the synergistic change of the two has no significant effect on the membrane flux; while at the higher hot end feed flow and hot end feed temperature, the synergistic change of the two is very significant to the membrane flux. This is because at low temperature and flow rate, the content of water vapor molecules in the thermal cavity of the membrane module is low, its saturated vapor pressure drops, and the number of vapor molecules passing through the hydrophobic membrane is small; under the influence of low flow rate, the liquid material in the thermal cavity causes the material liquid to stay in the hot cavity for a longer time, which further reduces the temperature of the material liquid in the hot cavity. Based on the above two reasons, it caused a decrease in membrane flux. When the feed flow at the hot end was 175 L/h, the air gap 5 mm, and the membrane area 0.06 m², the effects of the circulating water flow at the cold end and the feed temperature at the hot end on the membrane flux are shown in Figure 7(b). It can be seen from the figure that in the area where the feed temperature of the hot end is lower, the change of the circulating water flow at the cold end has no significant effect on the membrane flux; in the area of the feed temperature of the higher hot end, the change of the circulating cooling water flow on membrane flux is more significant. This is due to the small heat transfer volume of the cold and hot cavity and the small temperature difference of the fluid at the lower feed temperature of the hot end, which leads to a decrease in the mass transfer driving force of the membrane module, resulting in insignificant changes in membrane flux. Therefore, at a higher temperature difference between the cold and hot chambers, increasing the circulating water flow in the cold chamber can increase the membrane flux. The effect of the cold end flow rate and membrane area on the membrane flux when the hot end feed temperature was 55°C, the air gap 5 mm, and the hot end flow rate 175 L/h is shown in Figure 7(c). When the membrane area is large, the change of the cooling water flow at the cold end has no significant effect on the membrane flux, while when the membrane area is small, the influence of the cooling water flow at the cold end has a significant effect on the membrane flux; the membrane flux as a whole increases with the membrane area. The larger the film area (the more the number of heat chambers), the following factors will exist: (1) The large heat loss causes a decrease in the temperature in the heat chamber; (2) The temperature of the cooling water at the cold end increases as a whole, and the heat dissipation capacity of the cold end of the system decreases, which leads to a decrease in the temperature difference between the cold and hot chambers and a reduction in the mass transfer driving force. Eventually, the membrane

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TABLE 4. SVM fitting related parameters.

| SVM fitting related parameters | Fitting of membrane flux | Fitting of thermal efficiency | Fitting of energy consumption |
|-------------------------------|-------------------------|-----------------------------|-----------------------------|
| Best cvmse                    | 7.7952e-04              | 0.0370                      | 0.0104                      |
| Best c                        | 53.5406                 | 41.3145                     | 48.9291                     |
| Best γ                        | 0.0308                  | 0.8310                      | 0.5023                      |
| Mean squared error            | 0.000284581             | 0.00129529                  | 0.00797513                  |
| Squared correlation coefficient| 0.994976                | 0.998663                    | 0.986469                    |
| Mean squared error            | 0.000132098             | 0.000102262                 | 0.000941564                 |
| Squared correlation coefficient| 0.995615               | 0.999019                    | 0.999532                    |
flux decreases. When the membrane area is smaller (the number of hot chambers is less), the cold chamber can provide sufficient cooling load (lower cooling water temperature). When the flow rate changes, the larger the cooling water temperature changes, the larger is the entire membrane flux. In the case of membrane area (the number of hot chambers is small), the cold chamber can provide sufficient cooling load (the temperature of the cooling water is low), and the variation range of the temperature difference of the cooling water when the flow rate changes is large, resulting in a high overall membrane flux. When the circulating water flow rate of the cold chamber was 175 L/h and the hot end feed temperature 55°C, the influence of the hot end feed flow rate and membrane area on the membrane flux is shown in Figure 7(d). It can be seen that the membrane flux as a whole increases with the hot end feed flow rate and the membrane area, and the membrane flux increases with the increase of the hot end feed flow rate under different membrane areas. From the analysis, it can be seen that when the membrane area and the hot end feed flow rate increase at the same time, the membrane flux will increase accordingly. When the hot end feed flow rate was 175 L/h, the air gap 5mm, and the cold end cooling water flow rate 175 L/h, the synergy between the hot end feed temperature and membrane area is shown in Figure 7(e). It can be seen that as the feed temperature of the hot end increases and the membrane area decreases, the membrane flux increases accordingly. When the feed temperature at the hot end was 55°C and the membrane area was 0.06 m², the effects of the feed flow rate at the hot end and the cooling water flow rate at the cold end on the flux are shown in Figure 7(f). It can be seen that in the smaller hot end feed flow area, the hot end feed flow rate and the membrane area have little synergy; while in the larger hot end feed flow area, the change of the cold end cooling water flow rate becomes more significant. This is because in the lower hot end feed temperature region, the lower surface temperature of the film causes the cold wall temperature of the cold chamber to be lower. The smaller cold end cooling water flow is enough to remove the heat of the cold wall, so the cold end cooling water flow the change is not obvious to the membrane flux; under the conditions of larger hot end feed flow, the heat transfer of the hot cavity is enhanced, and the lower cold end cooling water flow is not enough to remove the heat of the cold wall, so the cold end cooling water has a significant effect on the membrane flux.

B. THERMAL EFFICIENCY ANALYSIS

After substituting the optimal fitting parameters c and g into the fitting model (as shown in Table 4, in order to verify the fitting accuracy of the fitting model, randomly selected working conditions of known variables (hot end feed temperature, the hot end feed flow rate, cold end cooling water flow rate, and membrane area) were substituted into the fitting model, and the target value obtained by the model compared with the known experimental result target value. The comparison of the fitting prediction results is shown in Figure 8. It can be seen that the model has a good fitting prediction effect and can be substituted into the response surface for the next analysis. The effects of hot-end feed temperature and hot-end feed flow on the thermal efficiency under the conditions of 175 L/h circulating water flow at the cold end and membrane area of 0.06 m² are shown in Figure 9(a). The overall thermal efficiency varies with the hot-end feed temperature and the hot end feed flow increases synergistically, the thermal efficiency is greater under the conditions of lower hot end feed flow and higher hot end feed temperature, while at the higher hot end feed flow and lower hot end feed temperature the lower thermal efficiency is smaller. This is because under the conditions of higher hot end feed temperature and lower hot end feed flow rate, due to the slower flow rate, a large number of water vapor molecules in the hot fuel liquid in the hot cavity can fully penetrate the hydrophobic membrane and pass through the cold wall. It is condensed into small water droplets, the membrane flux is large, the heat utilization is also sufficient, and the thermal efficiency is high. The effect of the feed temperature of the hot end and the membrane area on the thermal efficiency at the hot end feed flow rate of 175 L/h and the cold end cooling water flow rate of 175 L/h is shown in Figure 9(b). It can be seen that the overall thermal efficiency increases first and then decreases with the increase of the film area. The maximum thermal efficiency is within
the range of 0.04-0.06 m$^2$. The trend of thermal efficiency changes with the temperature of the hot end feed temperature. This is because under the condition of lower hot end feed temperature, the required cold load of the hot end is smaller when the film area is smaller, but the cold end provides excessive cold load, resulting in lower thermal efficiency; in the case of the area, the amount of cold load required at the hot end is relatively large, and the cold load provided by the cold end is not sufficient to supply. There is an unbalanced heat matching between the hot and cold ends, so the thermal efficiency is small. In the area where the feed temperature of the hot end is high, the amount of cold load provided by the required cold chamber increases with the increase of the membrane area due to the high temperature of the feed liquid in the hot chamber; under a certain amount of cold load, only under the condition of small membrane area it can achieve a good balance of heat supply and demand at the hot and cold ends, so the thermal efficiency is higher. At the hot end feed temperature of 55°C and the cold end cooling water flow rate of 175 L/h, the analysis of the influence of the hot end feed flow rate and cold end cooling water flow rate on the thermal efficiency is shown in Figure 9(c). The overall thermal efficiency varies with the film area and hot end; the feed flow rate increases synergistically. Under the same membrane area, its thermal efficiency increases with the increase of the feed temperature of the hot end. Under the condition of a larger membrane area, the increase in the number of hot chambers leads to an increase in the required cooling load, and the cold chamber provides a limited amount of cold, so the thermal efficiency is low; under the condition of a small membrane area, the hot chamber requires cold. The load is small, the cold end can provide a good cooling load supply, so the thermal efficiency is high. When the feed temperature of the hot end is 55°C and the feed temperature of the hot end is 175 L/h, the analysis of the influence of the cooling water flow rate and film area on the thermal efficiency of the cold end is shown in Figure 9(d). When the membrane area is large, the hot end feed flow has little effect on the thermal efficiency; when the membrane area is small, the thermal efficiency decreases with the increase of the cold end cooling water flow. The number of hot chambers is small, and the required cooling load is small, and a small cold end cooling water flow can provide a good cooling load supply.

### C. ENERGY CONSUMPTION ANALYSIS

In order to make the system more energy efficient, the energy consumption value target was used to evaluate the system. Taking the hot-end inlet temperature, hot-end inlet flow rate, cold-end inlet flow rate, and membrane area as variables, and analyzing the energy consumption value as the target value, the optimal fitting parameters of support vector machines are shown in Table 4, while the comparison of fitting prediction results is shown in Figure 10.

At the hot end feed flow rate of 175 L/h, air gap of 5 mm, and membrane area of 0.06 m$^2$, the influence of the hot end feed temperature and cold end cooling water flow rate on
energy consumption is shown in Figure 11(a). It can be seen that the energy consumption value shows a trend of increasing synergistically with the cold-end cooling water flow rate and the hot-end feed temperature. This is because the greater the cold-end cooling water flow rate, the greater the energy consumption required by the pump. Larger, and the higher the hot end feed temperature, the more electric energy required to maintain the temperature of the constant temperature hot water bath; secondly, the greater the hot end feed flow, the more heat it takes off the membrane surface. The greater the power consumption that needs to be maintained at constant temperature, the higher the energy consumption. At the cold end cooling water flow rate of 175 L/h, air gap of 5 mm, and membrane area of 0.06 m², the influence of the hot end feed flow rate and hot end feed temperature on energy consumption is shown in Figure 11(b). It can be seen that the energy consumption value increases with the increase of the hot-end feed flow and the hot-end feed temperature. This is
due to the increase in the speed of the inverter pump motor when the hot-end feed flow increases, resulting in an increase in electrical energy consumption. When the feed flow at the hot end is 175 L/h, the air gap is 5 mm, and the feed temperature at the cold end is 175 L/h, the effect of the feed temperature at the hot end and the membrane area on energy consumption is shown in Figure 11(c). It can be seen that the energy consumption value increases with the increase of the membrane area and the feed temperature of the hot end. This is because when the membrane area increases, the number of heat chambers increases and the flow of the hot material liquid increases. The heat exchange area with the cold cavity is increased, and the heat loss of the hot material liquid is increased, so the electric energy required to maintain the constant temperature of the constant temperature hot water bath has increased. At the hot end feed temperature of 55°C, air gap of 5 mm, and cold end cooling water flow of 175 L/h, the effect of membrane area and hot end feed flow on energy consumption is shown in Figure 11(d). It can be seen that the overall system energy consumption value is higher when the membrane area is larger, and both increase with the increase of the hot end feed flow.

**D. PARETO SOLUTION SET ANALYSIS**

As shown in Figure 12(a), the three-dimensional Pareto solution set obtained by multi-objective genetic algorithm (NSGA-II) optimization is used, and the multi-objective particle swarm algorithm (MOPSO) is used for comparative verification. The Pareto solution set obtained by the two multi-objective algorithms has a high degree of coincidence, indicating that the multi-objective optimization results are more accurate and can be used for analysis.

In order to test the optimization performance of NSGA-II proposed in this paper for the membrane distillation system, the ZDT1, ZDT2, ZDT3, ZDT4, ZDT5, and ZDT6 test functions are used to analyze the convergence index $\gamma$ and diversity index $\Delta$ proposed in the literature [45]. The smaller the value of $\gamma$ and $\Delta$, the better the convergence performance and distribution performance of the algorithm. The parameters

![Figure 12. Pareto solution analysis. (a) 3D Pareto solution analysis. (b) Pareto solution analysis of membrane flux and energy consumption. (c) Pareto solution analysis of energy consumption and thermal efficiency. (d) Pareto solution analysis of membrane flux and thermal efficiency.](image-url)
of the algorithm are set as follows: NSGA-II algorithm uses polynomial mutation, and the rest are all coded with real numbers. The population size is 100, the number of iterations is 300, the crossover probability is 0.9, and the mutation probability is 0.01. The algorithm is run 20 times to obtain the average value of $\gamma$ and $\Delta$. Comparing the data in Table 5, we can find that for several test functions such as ZDT1, the convergence and diversity of NSGA-II are better than traditional MOPSO, indicating that the algorithm proposed in this paper has certain advantages and is more suitable for multi-objective optimization.

We used the solution set in Figure 11(a) to project the XY, YZ, and XZ planes to obtain the three-dimensional Pareto solution set projection. The projection of the three-dimensional Pareto solution set in the direction of energy consumption-membrane flux is shown in Figure 12(b). The energy consumption value increases as the membrane flux increases. It can be seen from the previous analysis that when the membrane flux increases, the corresponding hot-end feed temperature, hot-end feed flow rate, and circulating cooling water flow value are high, so the energy consumption value of the variable frequency pump and the constant temperature hot water bath energy consumption will also increase accordingly, so the overall energy consumption of the system increases with the increase of membrane flux. In the higher membrane flux part (25 kg/m$^2$h and later), the energy consumption value increases more steeply with the membrane flux increase. This is due to the feed temperature of the hot end of the membrane flux corresponding to the working conditions. The values of the hot end feed flow rate and the cold end circulating water flow rate are correspondingly large, and the system heat loss is large. Therefore, the membrane flux conditions in this part have a significant impact on the energy consumption value. Choosing conditions near the inflection point of the growth trend cannot only obtain a larger membrane flux, but also reduce unnecessary system energy consumption. The projection of the three-dimensional Pareto solution set in the direction of energy consumption-thermal efficiency is shown in Figure 12(c). The thermal efficiency increases first and then decreases with the energy consumption value. The higher the consumption, the greater the thermal efficiency. In the part with lower energy consumption value, since the feed temperature at the hot end is lower, close to the ambient temperature and the cooling water temperature, and the external heat loss is lower, the thermal efficiency is higher under some lower energy consumption conditions. In the part with higher energy consumption value, although the membrane flux is higher under these corresponding working conditions, the temperature of the hot end hot material liquid is also higher, causing a large amount of heat loss, and higher energy consumption. The projection of the three-dimensional Pareto solution in the direction of membrane flux-thermal efficiency is shown in Figure 12(d). The thermal efficiency generally increases first and then decreases as the membrane flux increases. From the definition of thermal efficiency, it can be seen that the increase in membrane flux will cause the thermal efficiency to increase to a certain extent; but at a higher membrane flux, because the feed temperature of the hot end is higher under most operating conditions, the ambient temperature is higher than that of the phase. The temperature difference is relatively low, which makes the system heat loss increase. Although the membrane flux is large, its thermal efficiency is low. From the analysis in this figure, it can be seen that there is a maximum thermal efficiency point in the relationship between membrane flux and thermal efficiency. Therefore, when selecting the optimal operating conditions, the operating conditions should be selected as close to the inflection point of the approximate fitting curve as possible.

Based on the multi-objective optimization of SVM and NSGA-II, a set of optimal operating conditions are shown in Table 6. A set of optimal energy consumption value obtained by MOPSO algorithm is 852.53 W, thermal efficiency is 0.81, membrane flux is 19.17 kg/m$^2$h, which differs from NSGA-II algorithm optimal working condition results by 7.05%, 6.17% and 5.37%. Comparing the three
experimental working conditions, it is found that the optimal working condition obtained by the NSGA-II algorithm is optimized to obtain higher thermal efficiency and membrane flux under the condition of lower energy consumption, which significantly optimizes the operation of the solar membrane distillation system effectiveness.

V. CONCLUSION AND FUTURE WORK

This research proposes a method for optimizing distributed energy resources production management, which improves the operating efficiency of photovoltaic-photothermal solar energy resources production management, which improves. The main research conclusions are as follows:

1) At lower hot end feed flow and hot end feed temperature, the synergistic change of the two has no significant effect on membrane flux; while at higher hot end feed flow and hot end feed temperature, the synergistic change of the two is very significant to the membrane flux. Therefore, the solar membrane distillation system is best operated under conditions of higher hot end feed flow and hot end feed temperature. In the area with a lower feed temperature at the hot end, the change in the circulating water flow at the cold end has no significant effect on the membrane flux; while in the area with a higher feed temperature at the hot end, the change in the circulating cooling water flow has a more significant effect on the membrane flux. Therefore, at higher feed temperatures, the cooling water flow at the cold end should be properly adjusted to increase the membrane flux.

2) The overall thermal efficiency increases with hot-end feed temperature and hot-end feed flow. The thermal efficiency is greater under the conditions of lower hot-end feed flow and higher hot-end feed temperature, while feeding at the higher hot end the thermal efficiency is smaller under the conditions of flow rate and lower hot end feed temperature. To maintain a higher system thermal efficiency, it should be operated under conditions of lower hot end feed flow and higher hot end feed temperature.

3) The energy consumption value generally shows a trend of increasing with the cold end cooling water flow and the hot end feed temperature. The energy consumption value increases with the increase of the hot end feed flow and the hot end feed temperature. As the area of the membrane and the feed temperature of the hot end increases, it should be reduced as much as possible when considering reducing the system energy consumption.

4) In the Pareto disaggregation analysis, the energy consumption value increases with the increase of membrane flux, the thermal efficiency increases first and then decreases with the energy consumption value, and there is a maximum thermal efficiency operating point. As a whole, the thermal efficiency increases first and then decreases as the membrane flux increases. After optimization by SVM fitting and an NSGA-II multi-objective optimization algorithm, a set of optimal working conditions of the solar membrane distillation system was obtained: the hot end feed temperature is 65.76°C, the hot end feed flow is 171.56 L/h, and the cold end cooling water flow is 194.14 L/h, and the membrane area is 0.03 m².

The combination of solar energy and membrane distillation technology can greatly reduce the energy consumption of the system and reduce the operating cost. It has attracted more and more attention from people and has become a new field of membrane distillation technology research. With the continuous progress of membrane distillation and solar technology, this technology has very bright application prospects. Future research should involve the following: (1) Consider adding other variables such as environmental wind speed, environmental temperature, and environmental humidity as parameters, and perform multi-objective optimization of the solar membrane distillation system from a comprehensive perspective. In practical applications, to achieve low energy consumption and maximum flux operation of the entire system, membrane fouling under optimal conditions should also be considered, including cleaning frequency, how to clean, membrane loss, etc.. (2) Study other multi-objective optimization algorithms to improve the accuracy of the optimization algorithm. (3) The photo-thermal-photovoltaic matching analysis of the natural cooling film distillation system and the thermoelectric cooling film distillation system will be carried out. After analysis, the optimal solar collector area and photovoltaic panel area will be obtained to achieve the optimal matching effect. (4) At present, the cooling of the cold end adopts the natural cooling method, we will consider the thermoelectric cooling method and compare the results of the two methods.

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Z. Sai et al.: Energy Management Optimization of Open-Pit Mine Solar Photothermal-Photoelectric MD
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