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Research Article

Modeling and Optimization of Beam Pumping System Based on Intelligent Computing for Energy Saving

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Beam pumping system which is widely used in petroleum enterprises of China is one of the most energy-consuming equipment. It is difficult to be modeled and optimized due to its complication and nonlinearity. To address this issue, a novel intelligent computing based method is proposed in this paper. It firstly employs the general regression neural network (GRNN) algorithm to obtain the best model of the beam pumping system, and secondly searches the optimal operation parameters with improved strength Pareto evolutionary algorithm (SPEA2). The inputs of GRNN include the number of punching, the maximum load, the minimum load, the effective stroke, and the computational pump efficiency, while the outputs are the electric power consumption and the oil yield. Experimental results show that there is good overlap between model estimations and unseen data. Then sixty-one sets of optimum parameters are found based on the obtained model. Also, the results show that, under the optimum parameters, more than 5.34% oil yield is obtained and more than 3.75% of electric power consumption is saved.

1. Introduction

Beam pumping system is one of the most important oil recovery equipment in China, the occupancy of which reaches to 70% [1]. However, its system efficiency is very low, due to the negative torque, long gear train, poor working conditions, and other reasons. Researching the energy saving of beam pumping system is very important and necessary [2].

Improving the structure of the beam pumping unit is a kind of effective methods for energy saving [3, 4]. Through optimizing of the four-bar linkage design and improving the balance system, the fluctuation of the net torque curve becomes flat and the loading coefficient of beam pumping unit is reduced, which leads to the increasing of motor's efficiency. Nonsynchronous crank balance beam pumping unit and secondary balanced beam pumping unit are the typical cases. It is reported that the nonsynchronous crank balance beam pumping unit can save 3~4% energy in some conditions and the secondary balanced beam pumping unit can save 14% energy. However, they are not always energy-saving and their energy-saving levels are related to the working conditions. For instance, if the balance parameters are not adjusted properly, the efficiency of the secondary balanced beam pumping unit should not be increasing.

Changing the working characteristic of the motor is another solution of this issue [5–8]. This way is represented by high-slip motor and ultrahigh-slip motor. Under the same working condition of the well, the average of the power-current curve of ultrahigh-slip motor is much less than that of conventional-slip motor. The curve is flatter, and consequently the cyclic loading coefficient is greatly reduced and the efficiency of the beam pumping unit is increased. However, since the efficiency of the high-slip motor is lower than that of the conventional-slip motor, there is a small amount of space to cut down the energy consumption and the energy-saving effect is remarkable only in the light-load conditions.

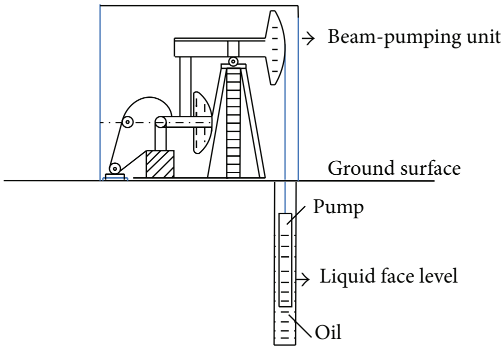

Figure 1: The schematic diagram of beam pumping system.

The aforementioned two ways, which try to improve the mechanical or electrical structures of the beam pumping system, need large investment and long time. It will be more economical to reduce the energy consumption based on the existing system by optimizing the operation parameters.

Only if we can build accurate and reliable process optimization model, the optimization of operation parameter is meaningful. Artificial neural network (ANN) modeling, because of its strong nonlinear approximation ability, is suitable for large-scale, parallel processing, and complex or unknown mechanism problems [9]. Since the beam pumping system is very complicated in nature, mainly due to unknown dynamic behaviors, nonlinear relations and numerous involved variables. In this paper, we proposed to build beam pumping system model by general regression neural network (GRNN). Then to identify the optimum operating parameters, multi-object optimization problem of minimizing the electric power consumption and maximizing the oil yield is solved by strength Pareto evolutionary algorithm (SPEA2).

The rest of this paper is organized as follows. Section 2 briefly introduces the beam pumping system. Section 3 presents the proposed modeling and optimization method for beam pumping system's energy saving. Experimental results and discussions are given in Section 4. The conclusions are finally drawn in Section 5.

2. A Sketch of Beam Pumping System

Beam pumping unit is the widely used traditional pumping equipment. A simple beam pumping system is sketched in Figure 1. The unit and motor at the surface supply the oscillating motion to the sucker and so to the pump. And the downhole oil is carried to the ground by the pump. In a rush time, the motor works in electrical state or generates electricity state, respectively, when the sucker is up or down.

The reservoirs are extremely complex, including rich oil, lean oil, thin oil, and thickened oil. The unit is impossible to work in constant speed. Additionally, there are many facts influencing the capacity and energy consumption of the oil pump, such as the leakage between the worn piston and the bush, and the polytropic stratum elements. It is hard or even impossible to develop an accurate mathematical model. This paper tries to find the potential law of the beam pumping system by the history production data and then utilize the law to improve the yield and save the energy consumption.

Table 1: Parameters used for modeling.

Inputs		Outputs parameters
Decision parameter	NP (time/min)	EPC (kw/h)
	MAXL (kN)	
Environment parameters	MINL (kN)	
	ES (m)	OY (t/d)
	CPE (%)	

3. Modeling and Optimization of Beam Pumping System

Different from the mechanical structure or electrical structure, modification method needs to replace the original equipment; the solution in this paper is to make the system work under the optimal operation parameters which are obtained by intelligent computing method based on the history production data of the original equipment.

As the analysis in Section 2, the beam pumping system is complicated and nonlinear. Its energy consumption is influenced by many factors. We first select the decision parameter and environment parameters, and then a GRNN model is built up to simulate the beam pumping system, and finally the optimization problem according to saving energy is constructed and solved by SPEA2 algorithm.

3.1. Parameters Selection. The monitored parameters of beam pumping system usually contain three-phase voltage, three-phase current, maximum load, the minimum load, theoretical pumpage, computational pump efficiency, effective stroke, number of punching, power factor, average power factor, average active power, average reactive power, electric power consumption, and oil yield, for the example of DaGang oilfield of China. Obviously, the first eight parameters are related to the system status, while the rest are related to the system efficiency.

In these parameters, the number of punching (NP) is adjustable and directly related to the status of the beam pumping unit. It is quite important to the energy consumption and the oil yield. Consequently, we selected it as the decision parameter. Moreover, it is not hard to find that some of these parameters show close relationship. In other word, there is redundancy in the parameters. Using all the parameters to model will increase the complexity of algorithm as well as reduce the reliability of the model. By analysis of their interrelation, we finally choose the maximum load (MAXL), the minimum load (MINL), the effective stroke (ES), and the computational pump efficiency (CPE) as the environment parameters and the electric power consumption (EPC) and the oil yield (OY) as the evaluation criterions. All the parameters used in modeling are shown in Table 1.

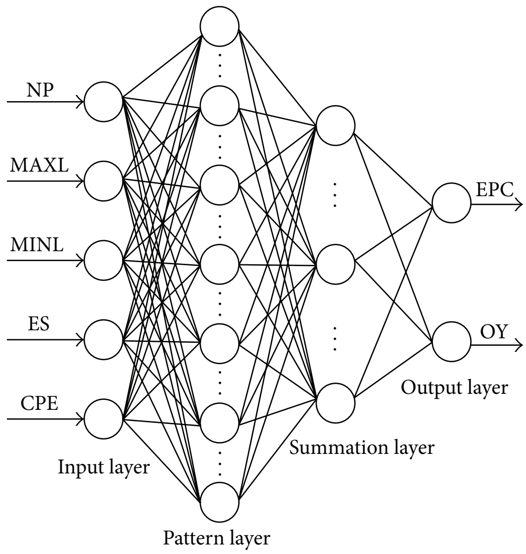

Figure 2: GRNN model of the beam pumping system.

3.2. Modeling of Beam Pumping System. GRNN [10], which evolved from probabilistic neural network (PNN) [11], belongs to the forward neural networks. It has many advantages: (1) strong nonlinear mapping ability and high error-tolerance, (2) strong approaching ability and high learning speed, (3) good performance for the small sample size problem, and (4) strong ability to deal with unstable data. So GRNN is quite suitable to model the complex nonlinear beam pumping system.

As Figure 2 shows, the GRNN model of beam pumping system comprises of four layers, namely, input layer, pattern layer, summation layer, and output layer. The input neurons in the first layer are distribution neurons which assigned all the measured values of $\mathbf{X}$, where $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$, $\mathbf{x}_i = (x_i^1, x_i^2, \ldots, x_i^p)^T$, n is the number of samples, and p is the dimension of samples.

Most processing is done in the pattern layer and the summation layer. The number of neurons of pattern layer is equal to the number of training samples, n, and the transform function is shown as the following formula:

$$t_i = \exp\left[-\frac{(\mathbf{X}-\phi_i^x)^T(\mathbf{X}-\phi_i^x)}{2\sigma^2}\right], \quad i = 1, 2, \ldots, n, \tag{1}$$

where $\mathbf{X}$ is the input vector of training sample, ϕ_i^x is the input portion of the ith training vector represented by the ith neuron in the pattern layer, and σ is the smoothing parameter, which can be adjusted to provide different levels of function smoothing. Larger values for σ cause smoother estimated function.

In summation layer, arithmetic summations and weighted summations are performed in the neurons. The arithmetic summation of the output value of all pattern layer units is

$$s_D = \sum_{i=1}^{n} t_i. \tag{2}$$

And the weighted summation of the output value of all pattern layer units is

$$s_{Nj} = \sum_{i=1}^{n} y_{ij} t_i, \quad j = 1, 2, \ldots, p, \tag{3}$$

where y_{ij} is the weight between the ith neuron of pattern layer and the jth neuron of summation layer; it is equal to the jth component of the output vector $\mathbf{y}_i$ of the ith training sample.

The number of output layer neuron s equals the dimension of output vector of training sample, and every neuron divides the output values of summation layer; namely,

$$\hat{y}_j = \frac{s_{Nj}}{s_D}, \quad j = 1, 2, \ldots, p, \tag{4}$$

where $\hat{y}_j$ is the estimation value of jth component of output vector of forecasting sample.

3.3. SPEA2 Optimization of Parameters. Once the GRNN model of the beam pumping unit production system model is developed, it can be used to obtain the optimal values of the input variables. SPEA2 [12] is an improved version of the strength Pareto evolutionary algorithm (SPEA) also proposed by Zitzler and Thiele [13] in 1999. It is a multiobjective evolutionary algorithm characterized by the concepts of strength and density. Compared to SPEA, SPEA2 has an improved fitness assignment strategy and hence can search the global optimum of all objective functions. Consequently, SPEA2 becomes one of the most popular optimization techniques in nonlinear multiobjective combinatorial optimization problems. In this paper, the optimization problem for energy saving is solved using SPEA2 algorithm.

The objective functions are

$$\begin{aligned} y_{\mathrm{EPC}} &= \min J_{\mathrm{EPC}} = f(x_{\mathrm{NP}}, x_{\mathrm{MAXL}}, x_{\mathrm{MINL}}, x_{\mathrm{ES}}, x_{\mathrm{CPE}}), \\ y_{\mathrm{OY}} &= \max J_{\mathrm{OY}} = f(x_{\mathrm{NP}}, x_{\mathrm{MAXL}}, x_{\mathrm{MINL}}, x_{\mathrm{ES}}, x_{\mathrm{CPE}}). \end{aligned} \tag{5}$$

Considering that SPEA2 always searches the minimum fitness, the maximum objective is converted to minimum one by taking its negative. Finally, the multiobjective problem of the beam pumping system energy saving is described as follows:

$$\hat{y} = \min J(\hat{x}) = \min(J_1(\hat{x}), -J_2(\hat{x})). \tag{6}$$

In the above expression, it has

$$\begin{gathered} \hat{x} = (x_{\mathrm{NP}}, x_{\mathrm{MAXL}}, x_{\mathrm{MINL}}, x_{\mathrm{ES}}, x_{\mathrm{CPE}}) \in X \\ \hat{y} = (y_{\mathrm{EPC}}, -y_{\mathrm{OY}}) \in Y \\ X = \{(x_1, x_2, \ldots, x_n) \mid l_i \le x_i \le u_i, i = 1, 2, \ldots, 5\} \\ L = (l_1, l_2, \ldots, l_5) \\ U = (u_1, u_2, \ldots, u_5), \end{gathered} \tag{7}$$

where L and U are the lower and the upper boundaries of optimal parameters, respectively.

Table 2: Instances of experiment data from a certain oilfield.

Number	NP	MAXL	MINL	ES	CPE	EPC	OY
1	3.01	97.2	44.7	3.0746	69.2602	11.97	31.05
2	2.99	97.3	44.9	3.2502	73.1920	12.00	32.87
3	2.97	103.2	42.6	3.0683	70.7739	13.37	30.65
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

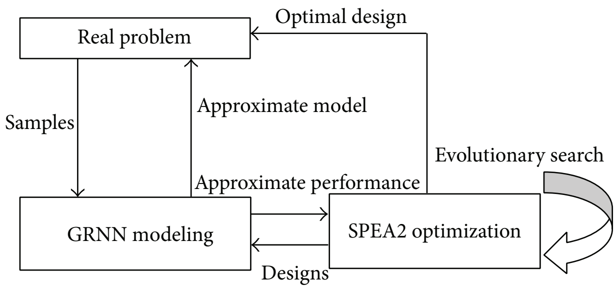

Figure 3: Framework of GRNN-SPEA2 strategy.

The main loop of the SPEA2 algorithm is as follows.

Step 1. $i = 0$: initialize population P_0 and set archive population $P'_0 = \emptyset$.

Step 2. Function evaluation: calculate fitness values of all individuals in $P_i \cup P'_i$.

Step 3. Environmental selection: copy all nondominated individuals in P_i and P'_i to P'_{i+1}. If size of P'_{i+1} exceeds N (archive size), then reduce P'_{i+1} by means of the truncation operator; otherwise if size of P'_{i+1} is less than N, then fill P'_{i+1} with dominated individuals in P_i and P'_{i+1}.

Step 4. Termination: if stopping criterion (maximum generations) is satisfied, set $P_{\text{final}} = P_{i+1}$ and terminate.

Step 5. Perform tournament selection with replacement on P'_{i+1} to fill the mating pool. Apply recombination and mutation operators to the mating pool and set P'_{i+1} to the resulting population.

Step 6. $i = i + 1$: go to Step 2.

3.4. GRNN-SPEA2 Strategy. To obtain the optimal parameters, the modeling and the optimization procedure should be combined. The framework of GRNN-SPEA2 strategy is briefly illustrated in Figure 3.

The procedure can be briefly described as follows: as approximating the model of the real problem, GRNN is developed with certain calculated algorithm based on experiment data. The SPEA2 is applied to explore good solutions among solution spaces. Once the SPEA2 generates a new solution, the GRNN will be used to determine its fitness value for the SPEA2 to continue its searching process. Until the SPEA2 satisfies certain termination criterion, the strategy will export the best solution and its performance determined by detail evaluation based on real problem.

Table 3: MSE and RE of GRNN model.

Performance index	EPC	OY
E_{MS}	0.0336	0.0951
E_R	0.0148	0.0071

4. Experimental Results and Analysis

4.1. Experimental Data. The proposed method is evaluated by real production data from a certain oilfield. Experiments employ 3234 samples which recorded the production status of 8 beam pumping wells from 6/1/2011 to 10/18/2011. Several instances of the dataset are listed in Table 2.

To void the influence caused by the difference between the absolute values of different parameters, the data were normalized to the range of $[-1, 1]$ before used to model.

4.2. GRNN Modeling. In the GRNN modeling process, the data is divided randomly into two subsets, one is used to train the model called training set and the other one is used evaluate the model called test set. The training set and test set contain 3150 samples and 84 samples, respectively. Figure 4 shows the comparison of the predicted objectives and the real objectives.

It can be seen from Figure 4 that the predicted values and the real ones are very close. To show the diversity more clearly, the percentage errors of EPC and OY by GRNN model are shown in Figure 5. From Figure 5, we find that the absolute percentage error of EPC is less than 0.05%, while that of OY is less than 0.04%, which indicates that the obtained GRNN model gets nice description of the real model.

Also, the commonly used mean square error (MSE) and relative error (RE), whose formula is given in (8), are used to

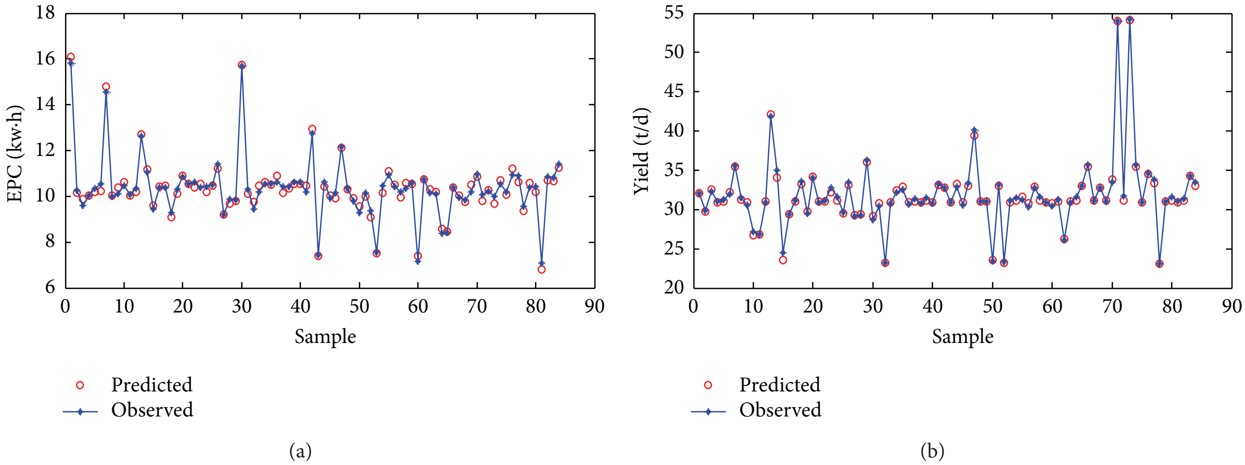

FIGURE 4: Comparison of the predicted and real objectives of GRNN model. (a) EPC and (b) OY.

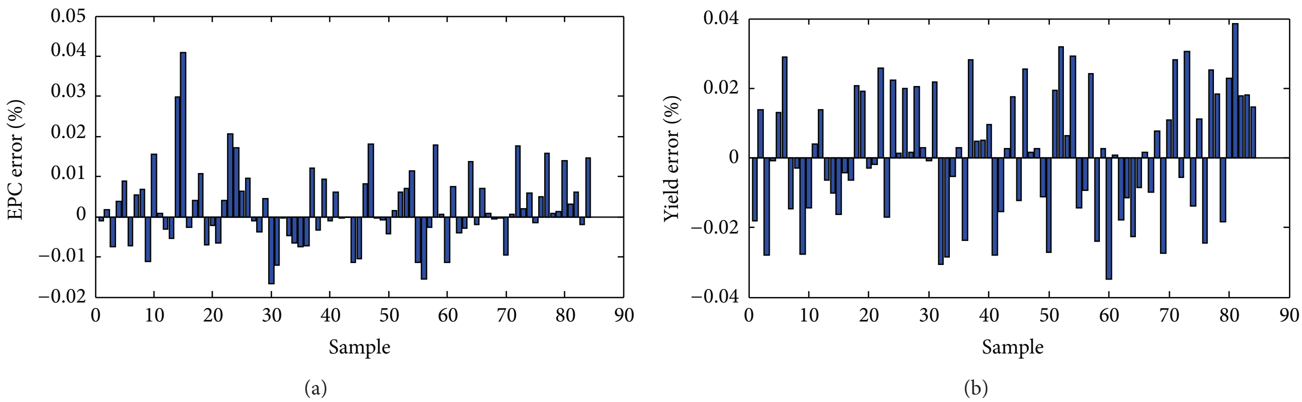

FIGURE 5: The percentage error of GRNN model.

further verify the performance of the model. The result is as shown in Table 3. Consider

$$E_{MS} = \sqrt{\frac{\sum (y - x)^2}{n - 1}}$$
$$E_R = \sum \left(\frac{|\mathbf{y} - \mathbf{x}|}{\mathbf{x}} \right), \quad (8)$$

where $\mathbf{x}$ is the observed value and $\mathbf{y}$ is the prediction value; n is the dimensionality of $\mathbf{x}$ and $\mathbf{y}$.

From the simulation results, it can be found that the simulated values match well with the measured values. This proves that the GRNN model of beam pumping system is stable and reliable and could be regarded as a knowledge source for follow-up parameters optimization.

4.3. Optimal Parameters Searching by SPEA2. As discussed in Section 3.3, the searching boundaries should be set at first. It is not difficult to understand that the parameters should not fluctuate too drastically, and then using the statistical range of each parameter as the boundary will be reasonable. The boundaries of the five inputs are shown in Table 4.

In experiments, the initial population is set to 50. Then the maximum generations are set to 20, 50, 100, and 200, respectively, to find the optimum generation. Figure 6 illustrates the result of Pareto frontiers when the maximum generation is 20, 50, 100 and 200, respectively. From Figure 6, it can be seen that when the maximum generation is 100, the Pareto front is basically stable. And hence, we set the generation to 100. In this case, there are 61 sets of optimum solutions. Some instances of the optimum solutions are shown in Table 5.

From Table 5, we find that the optimal number of punching is bigger than the original setting, which confirms with the fact that big number of punching will achieve high system efficiency. Comparing the optimized results and the original data, there are above 3.75% decreasing of the electric power consumption and above 5.34% increasing of the oil yield. It verifies the correctness of obtaining optimum decision parameters.

5. Conclusions

This paper presents a novel way to saving the energy consumption of beam pumping system by general regression neural network modeling and improved strength Pareto

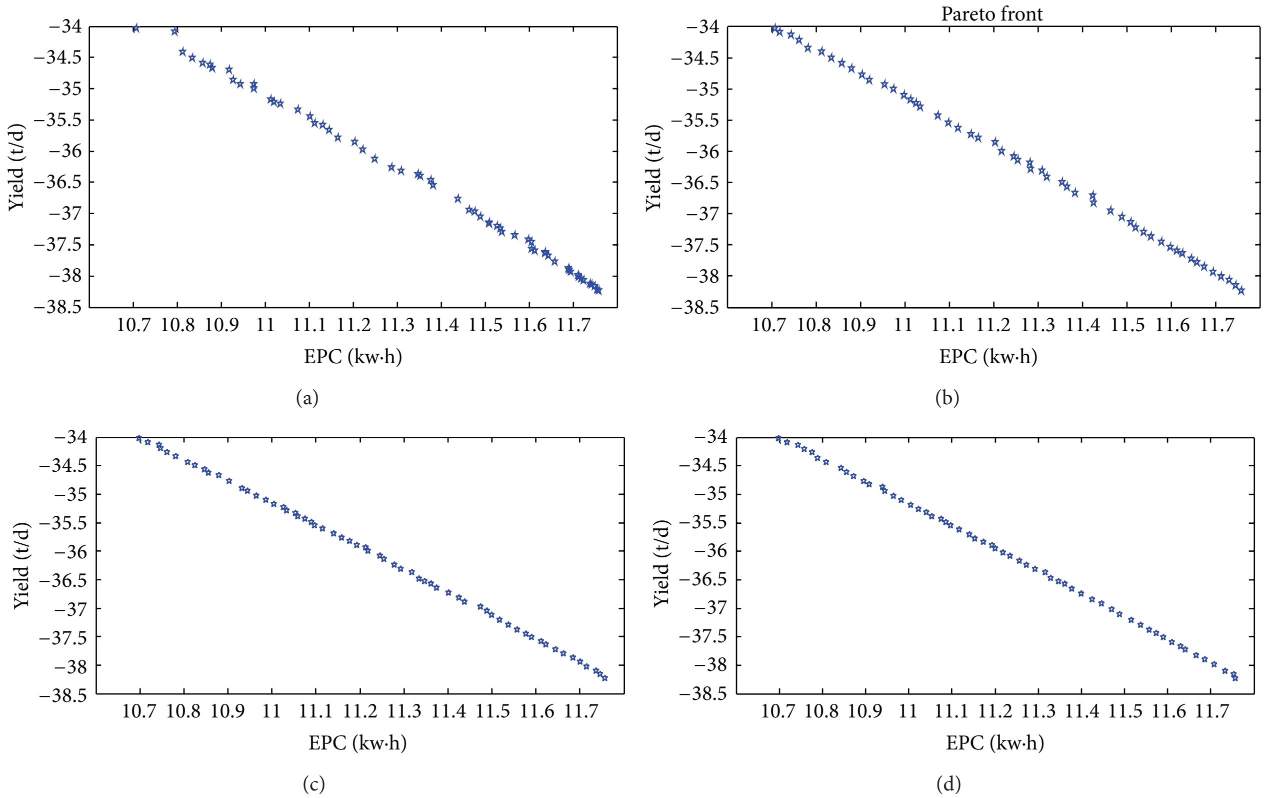

Figure 6: SPEA2 Pareto frontier when the maximum generations are 20, 50, 100, and 200. (a) Maximum generation is 20, (b) maximum generation is 50, (c) maximum generation is 100, and (d) maximum generation is 200.

Table 4: Searching boundaries of the parameters.

Boundary	NP	MAXL	MINL	ES	EPC
Upper	2.5	93.3	42.3	3.1	71
Lower	3.5	93.5	42.5	3.2	72

Table 5: Instances of solutions of Pareto optimal set.

Number	NP (time/min)	MAXL (kN)	MINL (kN)	ES (m)	CPE (%)	EPC (kw)	OY (t/d)
1	3.29	93.3	42.3	3.1034	71.2198	11.1938	35.89
2	3.29	93.4	42.3	3.1029	71.0810	11.5908	37.51
3	3.29	93.5	42.3	3.1030	71.3858	11.3190	36.37
4	3.31	93.5	42.5	3.1999	71.9633	11.3349	36.48
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
61	3.28	93.3	42.3	3.1000	71.3138	11.0982	35.54

evolutionary optimization. This method need not modify the original equipment but just tries to make the equipment work in energy-saving status. Experimental results on 3234 real samples from a certain oilfield show that the performance of the beam pumping system is significantly improved after using the optimum parameters. Specifically, the electric power consumption decreases more than 3.75% and the oil yield increases more than 5.34%. It verified that the proposed method is an alternative effective solution for energy saving of oilfield.

This paper puts forward a feasible solution for the intensive production of oilfiled; however, the achieved result is not a determinate solution but a set of Parato fronts. How to find the robust optimal solution to guide the production will be our future research direction.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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