A NEW MULTI-SWARM MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION BASED POWER AND SUPPLY VOLTAGE UNBALANCE OPTIMIZATION OF THREE-PHASE SUBMERGED ARC FURNACE

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Abstract. To improve the production ability of a three-phase submerged arc furnace (SAF), it is necessary to maximize the power input; minimize the supply voltage unbalances to reduce the side effect of the power grids. In this paper, maximizing the power input and minimum the supply voltage unbalances based on a proposed multi-swarm multi-objective particle swarm optimization algorithm are focused on. It is necessary to have objective functions when an optimization algorithm is applied. However, it is difficult to get the mathematic model of a three-phase submerged arc furnace according to its mechanisms because the system is complex and there are many disturbances. The neural networks (NN) have been applied since its ability can be used as an arbitrary function approximation mechanism based on the observed data. Based on the Pareto front, a multi-swarm multi-objective particle swarm optimization is proposed, which can be used to optimize the NN model of the three-phase SAF. The optimization results showed the efficiency of the proposed method.
Keywords: Multi-objective Optimization, Particle Swarm Optimization, Submerged Arc Furnace, Power optimization, Supply voltage unbalances

1 INTRODUCTION

In the past decades there has been a drastic increment in the number and size of Submerged Arc Furnaces (SAF) constructed for the production of Ferro-chromium and Ferro-manganese alloys. The economic benefit caused the use of larger furnaces which are relatively large, e.g. 48 MVA for ferro-chromium, and up to 81 MVA for ferro-manganese, with currents ranging from about 50 to 130KA [1]. With the increment of the furnaces' power, it is important to consider the side effects on the power grim such as supply voltage unbalances for three-phase submerged arc furnaces. Hence we have to consider the constraints or other objectives when furnaces are op-

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timally controlled. There are many parameters or variables about three-phase submerged arc furnace and the most important variables are voltages, equivalent resistance and temperature, for determining power of SAFs. However, it is difficult to construct a mathematical model SAF according to the mechanisms of the actual furnace plant system due to its complexity and many disturbances; and the neural network is a good option to model SAF as it is easy to use in modeling nonlinear functions based on the observed data. Neural networks have been widely used for modeling complicated systems and achieve good results [2],[3]. Hence, the optimization algorithm can be applied based on the neural network model of for three-phase submerged arc furnaces to get the control signals. Here, a proposed multi-swarm multi-objective particle swarm optimization algorithm was used to optimize the power and supply voltage unbalances.

The rest parts of the paper are organized as follows. Section II the multi-objective particle swarm optimization was reviewed and a multi-swarm multi-objective particle swarm optimization (MSMOPSO) method was proposed. Section III investigated the three-phase SAF. Three-phase SAF was modeled by BP neural network in Section IV. Section V presents MSMOPSO based power and voltage unbalances optimization. The concluding remarks were given in the last section.

2 MULTI-SWARM MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION

In general the single objective optimization algorithms will terminate when an optimal solution is obtained. But for most MOO problems, there can be a number of optimal solutions. A multi-objective optimization (MOO) problem can be described by

$$\text{Min } F(x) = (f_1(x), \cdots, f_m(x)) \qquad (1)$$
$$\text{Subject to } x \in \Omega .$$

Here Ω is the variable space, R^m is the objective space, and $F : \Omega \to R^m$ consists of m real-valued objective functions.

If there is no information regarding the preference of objectives, a ranking scheme based upon the Pareto optimality is regarded as an appropriate for MOO [4]. The solution to the MOO problem is described by a Pareto front set. For the more details related to Pareto front set, please refer to reference [5].

A good MOO algorithm should guarantee a high probability of finding the Pareto optimal set. Among the MOO algorithms, the multi-objective particle swarm optimization algorithm has been proven to be a promising algorithm [6]. To achieve good optimization performance, the particles can be divided to several swarms. If a multiple-swarm PSO employs an over large number of swarms, it will have a better chance of obtaining possible good solutions that lead to the optimal Pareto set, but it can also suffer from an undesirable computational cost. There are some multiple-swarm PSO algorithms, such as reference [6], [7], which used the adaptive swarm size methods. However, the existing MSMOPSOs do not use the information of the found Pareto front set to allocate the swarms. For most of the continuous optimization problems, the good results may be discovered if the particles search around the Pareto front. Based on this finding, we propose a MSMO optimization method. Several swarms are used to search regions around certain points of the Pareto front set. These swarms are called Pareto front swarms. There is still another swarm, which is called spare swarm and searches other spaces far away from the Pareto front to ensure all the particles are spread around the whole objective space. The main contributions of the proposed algorithm are:

1) Pareto front swarms are used to search different regions around some points of Pareto front, and the velocity update equation is

$$V_i(t+1) = \omega V_i(t) + c_1 R_1 (P_i - X_i(t)) + c_2 R_2 (P_g - X_i(t)) + c_3 R_3 (Core(m) - X_i(t)) \quad (2)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (3)$$

Here, $Core(m)$ is central point of the m^{th} swarm and is chosen dynamically, the relationship between m and i is $m = \text{floor}(\frac{i}{num_g}) + 1$, num_g is the particle number of the m^{th} swarm and $\text{floor}(A)$ rounds the elements of A to the nearest integers less than or equal to A. The number of the cores equals the number of the Pareto front swarms. The cores are from the Pareto front set and using the same way as choosing the Pareto front set.

2) The particles of the spare swarm are updated using

$$V_i(t+1) = \omega V_i(t) + c_1 R_1 (P_i - X_i(t)) + c_2 R_2 (P_g - X_i(t)) - c_4 R_4 (Core(m) - X_i(t)) \quad (4)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (5)$$

Here, c_4 is determined by the sharing function [8] according to the distance between particle i and core particles,

$$R_4 = \frac{1}{m_g} rand(\cdot) \quad (6)$$

and m_g is the number of Pareto front swarms.

3) To avoid the premature of PSO, small disturbance is added, that is,

$$V_i(t+1, irand) = V_i(t+1, irand) + \frac{R_v}{m_g} \quad (7)$$

Here, R_v is a random number within an interval of $[-1,1]$.

The method of choosing P_i and P_g is described in ref. [9].

The following procedure can be used for the proposed particle swarm algorithm:

1) Initialize the parameters of particles.

2) Evaluate the fitness functions for each particle.

3) Find the non-dominated Pareto front particles and store them in the repository set.

4) Determine the cores of Pareto front swarms and dynamically set up the relationship among the swarms and the cores.

5) Using (2) and (3); or (4), (7) and (5) to update particles.

6) Repeat steps (2)-(6) until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value).

3 THREE-PHASE SUBMERGED ARC FURNACES

A typical three-phase SAF consists of a fixed circular bath and three electrodes submerged in a charge of raw materials projected into it. The operation of the SAF involves trying to maintain the maximum real power input to the furnace within the constraints or limits of the associated equipment of the furnace [10]. To control the input power, the input voltage can be changed by the transformers. The transformers for the furnaces are different from the standard power system transformers in that the secondary winding has to supply very high currents at low voltages as shown in Fig. 1. Furnace transformers are used to step down from voltages between 11KV and 33 kV to levels of several hundred volts and control the input voltage of the furnace.

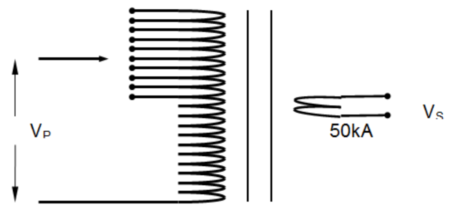

Figure 1 A single phase furnace transformer [12]

There are also constraints and limits for the operation of the three-phase SAF, for example, the voltage unbalance must be considered. The voltage unbalance occurs in SAFs, when current consumption is not balanced during the 3 cycle of processing (operation) or during a faulty condition before tripping. They impact negatively on three phase asynchronous motors by causing overheating and a tripping of protective devices. A voltage unbalance is a ratio of the negative sequence component to the positive sequence component and it can be determined by the following formulas [11] and the unbalance voltage, u_u, is given as:

$$u_u = \max_i \left(\frac{U_i - U_{avg}}{U_{avg}}\right) 100\%, \left(i = 1, 2, 3\right) \tag{8}$$

where U_i is the phase voltage, and $U_{avg} = \frac{1}{3}\sum_{i=1}^{3} U_i$.

Hence to achieve good control performance of the three-phase SAF, *there are at least two objectives: 1) maximum the power input; 2) minimum the voltage unbalances*. Of course, there are other constraints or limits such as harmonics, which should be considered when the SAF system is optimized/controlled. In this study, we only focus on these two objectives.

4 NEURAL NETWORK BASED MODELLING OF THREE-PHASE SAF

One of the most commonly used supervised neural networks is the back-propagation network which uses the back-propagation learning algorithm [13], [14], [15]. It was first proposed by Paul Werbos in 1974, but it wasn't until 1986, through the work of David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams [16], that it gained recognition, which led to a "renaissance" in the field of artificial neural network research. The back propagation neural network is essentially a network of simple processing elements working together to produce a complex output. The combination of weights which minimises the error function is considered to be a solution of the learning problem.

Here, the Neural Network Model is of two-layer feed-forward network with the default tan-sigmoid transfer function in the hidden layer with 45 neurons and the linear transfer function in the output layer. The units in each layer receive their inputs units of a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer and the inputs are fed into the layer of the hidden units. The input units are merely "fan out", meaning that no processing taking place in them. The activation of the hidden layer is a function of the weighted inputs plus a bias. The design SAF model is trained using the Levenberg-Marquardt back-propagation method. To test the performance of the proposed SAF neural network model, a set of electro-thermal variables from the 45 MW SAF Wonderkop Chrome Processing Plant (WCP) was used [12]. The input vectors (equivalent resistances, voltages and temperature) and the target vector (power) comprise of 120 samples each. It should be noted that only the first 90 samples are used to train neural network and the last 30 samples are used to validate and test the trained neural network.

The Neural Network Fitting Tool GUI is utilized to construct and train the neural network based on the software MATLAB 2009a. The linear regression performance between the obtained NN model outputs and the corresponding targets (power) shows that the model's output tracks the targets very well for training and validation as shown in Fig. 2, which means that the trained neural network model is acceptable.

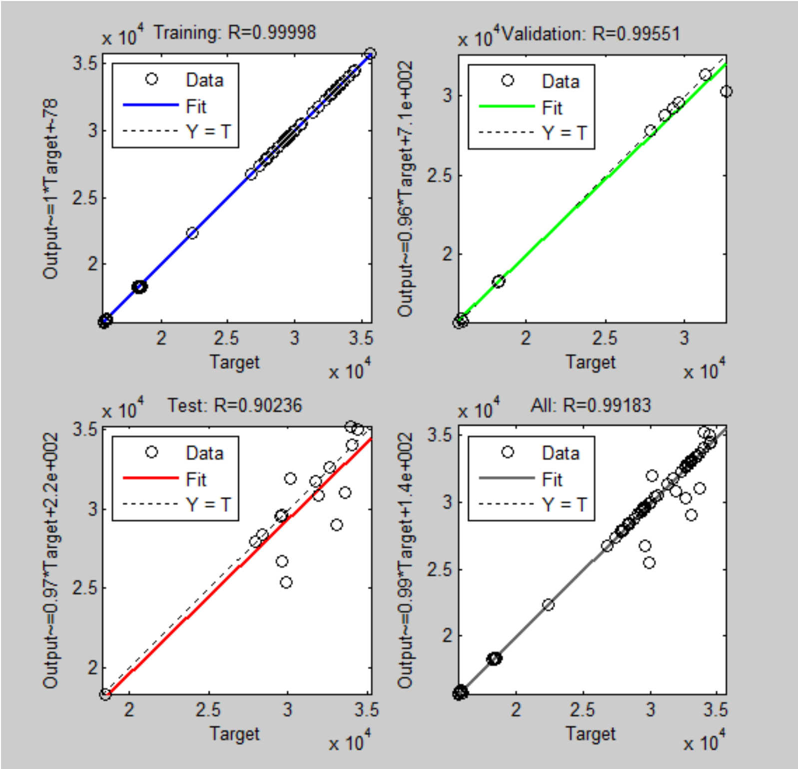

Figure 2: Simulated Regression Characteristics

The output of the SAF NN model and the real power data reveal some similarities explicitly. The real furnace power samples and the trained neural network model output are shown in in Fig. 3. As can be seen from Fig. 3, the obtained neural network model showed similar characteristics of the real samples although the last 30 samples were not used to train the BP neural network. Hence this NN model can be used as the representative of the real SAF system.

5 MULTI-SWARM MULTI-OBJECTIVE PSO BASED POWER AND VOLTAGE UNBALANCES OPTIZATION OF THREE-PHASE SAF

As the data is from the 45 MW SAF Wonderkop Chrome Processing Plant (WCP), the theoretic input power can be 45 MW. However, as can be seen from Fig. 3, the real sample input power is much lower than the theoretic value (the highest input sample power is about 35 MW). Hence, there should be space to improve the input power based on the optimization algorithm although the voltage unbalances to be considered. As mentioned in Section 3, to optimize the performance of this three-phase SAF, the optimization problem can be described by

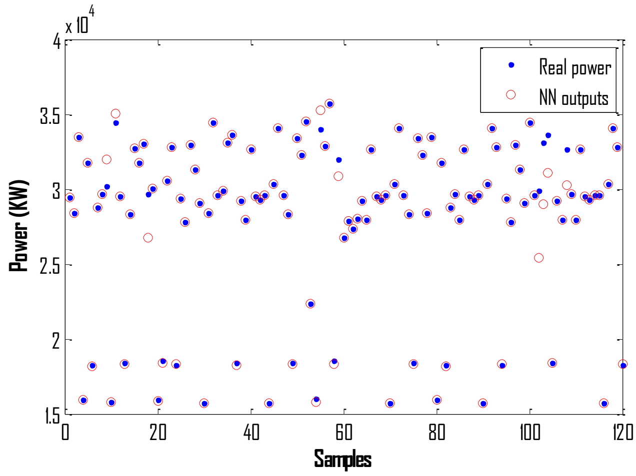

Figure 3 SAF neural network output versus real output data (power).

$$\text{Min } F(x) = (f_1(x),\ f_2(x)) \tag{9}$$

$$\text{Subject to } x \in \Omega \tag{10}$$

where, $f_1(x)$ and $f_2(x)$ are the input power and the voltage unbalance, respectively, and $x = [R_1, R_2, R_3, U_1, U_2, U_3, T]$, R_1, R_2, R_3 are three phase equivalent resistances, U_1, U_2, U_3 are three input phase voltages, and T is the furnace temperature. Since we cannot get the mathematical model of the input power, the neural network model obtained in Section 4 can be used as $-f_1(x)$. It should be noted that there is **a minus sign before** $f_1(x)$ since the first objective is to maximum the input power. The second objective is

$$f_2(x) = \min\left(\max_i \left(\frac{U_i - U_{avg}}{U_{avg}}\right) \cdot 100\% \right). \tag{11}$$

Altough there are 7 variables in the NN SAF model, only U_1, U_2, U_3 are looked as control variable and R_1, R_2, R_3, T can be looked as time-variant parameters since this system is a slow response system can R_1, R_2, R_3, T can be measured or calculated in real time. For the condition (10), we can choose $276 < U_1 < 300; 100 < U_2 < 290; 100 < U_3 < 263$ based on the samples. Table 1 gives the first 5 sets of samples and the simulation will be implement to verify the proposed method base on these 5 sets of samples.

Table 1 5 sets of samples [12]

	RESISTANCE			VOLTAGE (V)			Temp. (°C)	POWER (KW)
	R1	R2	R3	U1	U2	U3	T	P
S1	2.1	2.1	2.77	289	158	188	2349	29417.31
S2	2.73	2.27	4.21	286	187	200	2200	28363.93
S3	2.14	2.12	1.29	299	197	263	2670	33450.08
S4	4.27	4.18	2.09	300	100	100	2717	15914.31
S5	2.14	1.75	1.28	284	290	163	2706	31734.41

In the simulation, the total number of fitness function evaluations was set to 10 000. The particle number is 200. The number of Pareto front swarms is 20 and each swarm has 8 particles. A random initial population was created for each of the 20 runs on each test problem. The maximum number of external repository particles is 100. Parameters are set as $c_1 = c_2 = 2$ and $\omega = 0.5 + rand(\square)$.

Using the proposed method, the Pareto fronts were obtained and they are shown in Fig. 4, 5, 6, 7 and 8 for S1, S2, S3, S4 and S5, respectively. Here S1, S2, S3, S4 and S5 are referring to the underlined parameters in Table 1. As can be seen from Fig. 4, 5, 6, 7 and 8, the Pareto front is smooth and uniform which means the proposed multi-swarm multi-objective PSO works well.

Only considering the Figures 4, 5, 6, 7 and 8, higher input power may be obtained. However there are two limitations, which limit the increment of input power: 1) the voltage unbalance is acceptable if it is not more than 0.02 for long time; for short time, the voltage unbalance 0.04 is acceptable; 2) the input power cannot be more than 45 MW since this is a 45 MW SAF. For the first limitation and considering the real situation, the voltage unbalance 0.025 can be chosen to determine the power inputs based on the achieved Pareto front, and we can obtain the input voltages and the corresponding input power which are listed in Table 2. Consider the limitation 2), the maximum input power for S3 and S5 is 45 MW. In the real system, the input power more than 45 MW cannot be achieved due to the other limitations or constraints of the physical system. Comparing Table 1 and Table 2, the input power is similar with each other for S2, but the voltage unbalance was reduced. Hence the proposed method can improve the performance of three-phase SAF.

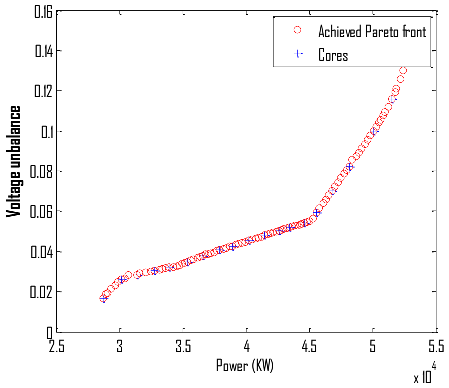

Figure 4 Pareto front for S1

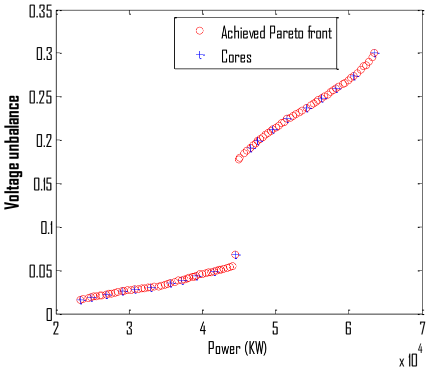

Figure 5 Pareto front for S2

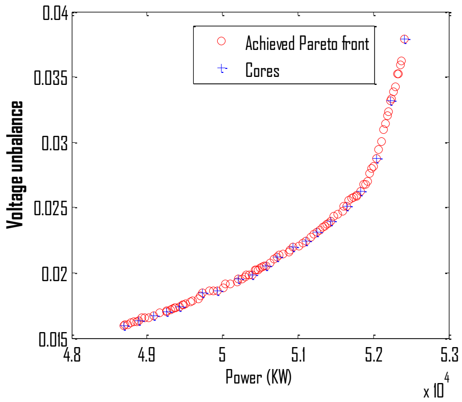

Figure 6 Pareto front for S3

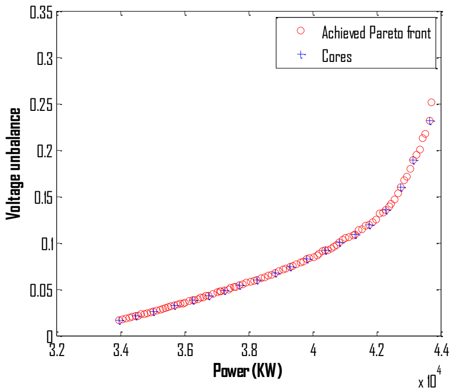

Figure 7 Pareto front for S4

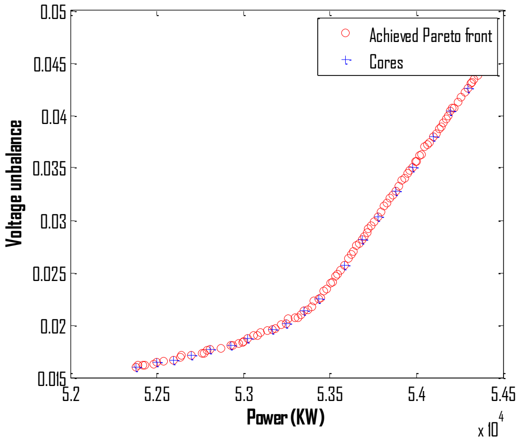

Figure 8 Pareto front for S5

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Table 2 Optimization result based on the five sets of samples

RESISTANCE			VOLTAGE (V)			Temp. (°C)	POWER (KW)
R1	**R2**	**R3**	**U1**	**U2**	**U3**	**T**	**P**
2.1	2.1	2.77	**276**	**276.5**	**257.1**	2349	**29906**
2.73	2.27	4.21	**283.3**	**283.1**	**263**	2200	**28275**
2.14	2.12	1.29	**276**	**276**	**263**	2670	**45000**
4.27	4.18	2.09	**276**	**276**	**256**	2717	**34936**
2.14	1.75	1.28	**276**	**276**	**263**	2706	**45000**

6 Conclusion

The power and voltage unbalance of three-phase SAF were optimized based on a proposed multi-swarm multi-objective particle swarm optimization (MSMOPSO). A back-propagation neural network was used to model the three-phase SAF, and then MSMOPSO was implemented on the obtained neural network model. The achieved Pareto fronts are smooth and uniform which means the proposed multi-swarm multi-objective PSO works well. Moreover, the simulation result showed the efficiency of the proposed method to improve the performance of three-phase SAF. In our future research, the more constraints such as harmonics, power factor, and so on, will be considered to make the optimization be used in the real SAF plants.

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