Research Article

Heat Transfer Simulation and Temperature Rapid Prediction for Trench Laying Cable

Chen-Zhao Fu,¹ Wen-Rong Si ,¹ Ke-Ke Fang,² and Jian Yang ²

¹State Grid Shanghai Electrical Power Research Institute, Shanghai 200437, China

²MOE Key Laboratory of Thermo-Fluid Science and Engineering, Xi'an Jiaotong University, Xi'an 710049, China

Correspondence should be addressed to Jian Yang; yangjian81@mail.xjtu.edu.cn

Received 29 July 2021; Accepted 11 October 2021; Published 29 October 2021

Academic Editor: Sardar Muhammad Bilal

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Heat transfer process for trench laying cable is complex. To guarantee safe operation of the cable, it is necessary to predict the temperature and maximum current capacity of trench laying cable rapidly and accurately. Therefore, in this study, an adaptive optimized particle swarm optimization algorithm (LFVPSO) is proposed based on Levy flight algorithm, and it is used to modify the back propagation neural network algorithm (LFVPSO-BPNN). Then, combined with numerical simulations, a network algorithm for temperature prediction of trench laying cable is developed using LFVPSO-BPNN. Finally, the maximum current capacity of four-loop three-phase trench laying cable is calculated using LFVPSO-BPNN together with genetic algorithm (GA&LFVPSO-BPNN). At first, it is found that the LFVPSO-BPNN algorithm proposed in this study is reliable and accurate to predict the cable maximum temperature for different loops ($T_{\max,i}$) in the trench. Furthermore, as compared with other similar algorithms, when LFVPSO-BPNN algorithm is used to predict the temperature of trench laying cable, its computation time would be reduced and the prediction accuracy would be improved as well. Second, it is revealed that the effect of ground air temperature (T_{sur}) on the maximum current capacity of trench laying cable ($I_{t,\max}$) is remarkable. As T_{sur} increases, the $I_{t,\max}$ for both flat-type and trefoil-type trench laying cable would significantly decrease. In addition, with the same T_{sur} , the $I_{t,\max}$ for the flat-type trench laying cable are obviously higher.

1. Introduction

Due to the urban development and aesthetic demand, the underground cable distributions are prevailing for urban power distribution [1]. Among these distributions, trench laying cables are often used in power plants or transformer substations. As compared with other underground cable laying methods, trench laying is more convenient for cable construction and maintenance, and it can accommodate multiloop cables [2]. The insulation performance of trench laying cable is closely related to its cable core temperature. When the cable core temperature is higher than 363.15 K, the cable insulation aging will be accelerated and cable service life will be greatly shortened [3]. Therefore, to prevent cable overheating and guarantee cable safe operation, it is necessary to predict the temperature rise of trench laying cable rapidly and accurately.

Currently, the temperature prediction and ampacity calculation for underground cable mainly include equivalent thermal circuit method and numerical simulation method. For the equivalent thermal circuit method, it is mainly based on the IEC-60287 standard [4], where the heat transfer process between the cable and environment is equivalent to a thermal circuit for the calculations. This method can predict temperature rise for direct buried cable rapidly and accurately [5]. However, for the trench laying cable, the heat transfer process is much more complex. When the equivalent thermal circuit method is adopted for the calculation, the prediction model would be oversimplified, and it may lead to large prediction errors [6]. For the numerical simulation method, the heat transfer process between the cable and environment is numerically simulated, and the temperature distributions and cable ampacity are obtained based on the finite-element method (FEM) or finite-difference

method (FDM). For example, Al-Saud et al. [7] numerically studied the temperature variations of direct buried cables using perturbed FEM. They found that the effect of thermal conductivities of soil and backfill material on the cable temperature was remarkable. The effect of cable layout on the temperature distributions and current capacity of trench laying cable was numerically studied by Xiong et al. [8] with FEM. It was found that as compared with regular arrangement, when cables were irregularly arranged in the trench, the cable temperature was higher and its current capacity was lower. While in this work, the radiation heat transfer in the trench was not considered. Liu et al. [9] numerically studied the heat transfer of three flat-type laying cables in a rectangular trench with different Rayleigh numbers. They found that the effect of cable distance on cable heat transfer performance is remarkable. Furthermore, the cable core temperature of shallow trench laying cable was calculated by Anders et al. [10] using thermal circuit method and FEM, respectively. It was found that compared with the thermal circuit method, the computational results obtained using FEM were more accurate, but the computational time of FEM was much longer. The temperature distribution of direct buried cable was numerically studied by Vollaro et al. [11] with FDM, and a calculation correlation of thermal resistance between cable and ground was obtained. It was showed that the prediction results obtained by the FDM were more accurate than those of IEC-60287 standard. Some other thermal modelling studies were also performed by Foteinopoulos et al. [12], Salonitis et al. [13], and Marano et al. [14]. A two-dimensional finite-difference model of the thermal history of parts manufactured in powder bed fusion additive manufacturing processes was presented by Foteinopoulos et al. [12]. In their study, an algorithm for node birth and distance adaptation over time was used, minimizing computational time and memory. Salonitis et al. [13] performed the thermal modelling of the material removal rate and surface roughness for die-sinking electrical discharge machining. In their study, a simple, thermal based model had been developed for the determination of the material removal rate and the average surface roughness achieved as a function of the process parameters, and the model's predictions could agree well with experimental results. The thermal behavior of trench-isolated bipolar transistors was thoroughly investigated by Marano et al. [14]. In their study, a novel strategy to analytically evaluate the temperature field was proposed, which accounted for the heat propagation through the trench and the nonuniform heat flux distribution over the interface between the silicon box surrounded by trench and the underlying substrate. This novel strategy could be employed for an accurate, yet fast evaluation of the thermal resistance of a trench-isolated device as well as of the temperature gradients within the silicon box. Most of these researches showed that as compared with the thermal circuit method, when the heat transfer of trench laying cable was studied with numerical simulations, the accuracy of prediction results would be greatly improved, but its computational time would also be much longer. To solve this problem, artificial intelligence algorithms combined with numerical simulations are

recommended for rapid and accurate prediction of cable temperature rise. Recently, for underground cable, artificial intelligence algorithms are mainly focused on the fields of cable laying cost optimization, cable maximum current capacity calculation, and cable temperature prediction. For example, a modified JAYA algorithm was proposed by Ocloń et al. [15] to optimize the laying cost of 400 kV direct buried cables. It was found that as compared with the traditional particle swarm optimization algorithm (PSO), lower cable laying cost could be obtained with this modified JAYA algorithm. A formula for laying cost calculation of direct buried cable was proposed by Cichy et al. [16], where the costs of labor, material, and operation loss were considered. Combining this formula with genetic algorithm (GA), the optimum cable size and filling size of backfill material were obtained. The maximum current capacity of pipe laying cables, containing 12 cables and 15 pipes, was calculated by Moutassem and Anders [17] with vector immune system algorithm. They found that as compared with numerical simulation using FEM, the calculation time could be greatly reduced with vector immune system algorithm. Combining shuffled frog-leaping algorithm with PSO algorithm, the maximum current capacity of pipe laying cable was calculated by Zarchi et al. [18]. They found that current harmonics would have great influence on maximum cable current capacity. The temperature rise of pipe cable was predicted by Zarchi and Vahidi [19] with Monte Carlo method and Hong point estimate method (HPEM), respectively, and the maximum current capacity of pipe cable was also calculated. It was found that as compared with Monte Carlo method, the HPEM requires fewer input parameters and its calculation cost was lower. Furthermore, a temperature prediction network for parabolic-type buried cable filled with fluidized thermal backfill material was proposed by Fu et al. [20] with radial basis neural network algorithm. Combining this temperature prediction network with genetic algorithm (GA), the optimum cable laying cost was obtained. These studies showed that for recent years, artificial intelligence algorithms used for underground cable were mainly focused on the researches about laying cost optimization for direct buried cable or maximum current capacity calculation for pipe laying cable, while the related researches for temperature prediction of underground cable were few, almost no studies were performed on rapid prediction of temperature rise for trench laying cable.

Therefore, in this study, to predict the temperature rise of trench laying cable rapidly and accurately, an adaptive optimized particle swarm optimization algorithm (LFVPSO) is proposed based on Levy flight algorithm, and it is used to modify the back propagation neural network algorithm (LFVPSO-BPNN). Then combined with numerical simulations, a network algorithm for temperature prediction of trench laying cable is developed using LFVPSO-BPNN. Finally, the maximum current capacity of four-loop three-phase trench laying cable is calculated using LFVPSO-BPNN together with genetic algorithm (GA&LFVPSO-BPNN). According to the authors' knowledge, almost no such studies were performed yet, and it would be meaningful for temperature rapid prediction and maximum current capacity calculation of trench laying cable.

2. Physical Model and Computational Method

2.1. Physical Model and Geometric Parameters. The physical model and geometric structure for trench laying cable are presented in Figure 1. In this study, since the trench length is much larger than its cross-sectional dimension, the trench laying cable is simplified as a two-dimensional model for the computations. Four-loop three-phase cables are laid in the trench, including flat-type laying model (Figure 1(a)) and trefoil-type laying model (Figure 1(b)). The dimension of the trench is 2 m (width) $\times$ 2.2 m (height). The trench wall is made of concrete, and its thickness is 0.2 m. The inside and outside areas of the trench are filled with air and soil, respectively. It is assumed that the soil temperature far away (20 m) from the trench bottom is fixed at consistent ($T_{\text{soil}} = 283.15$ K), and the soil far away (20 m) from trench lateral walls are adiabatic. The top surface of trench is exposed to the environment with temperature of T_{sur} and the equivalent surface heat transfer coefficient is h_f (11 W/(m²·K)). The radiation heat transfer is existed between cable surface and inner surface of trench, where the radiant emissivity on the cable surface is 0.9, and it is 0.6 on the inner surface of the trench. For flat-type trench laying cable models (Figure 1(a)), the distance between the cable core and trench side wall is 0.12 m. The cable core distance between the upper and lower layer cables is 0.4 m. The distance between the lower layer cable core and trench bottom is 0.15 m. And the cable core distance between two adjacent cables in the same loop is 0.15 m. For trefoil-type trench laying cable models (Figure 1(b)), the distance between the cable core and trench side wall is 0.21 m. The cable core distance between the upper and lower layer cables is 0.5 m. And the distance between the lower layer cable core and trench bottom is 0.15 m. The arrangement for a single-loop three-phase trefoil cables is presented in Figure 1(c), where the cables are in a regular triangle arrangement. To improve the quality of computational mesh near the contact points between cables, the cables are assumed to be stacked with small gaps between each other, where the gap width is 1% r_e [21]. The structure for a single cable (8.7/15 kV YJV 1 $\times$ 400) is presented in Figure 1(d). It shows that the cable is mainly composed of cable core, insulation layer, sheath layer, and external layer, and their radii are r_c , r_{ins} , r_s , and r_e , respectively. Typical geometrical and physical parameters for the trench laying cable are listed in Tables 1 and 2.

2.2. Governing Equations and Computational Method. In this study, the electromagnetic effect, heat transfer, and air flow are coupled with each other. The computational domain is divided into solid domain and fluid domain for the coupling

computations. For solid domain, the governing equations for the heat transfer are as follows:

$$\begin{cases} 0 = \nabla(\lambda \cdot \nabla T) + Q_e, & \text{Cable core and sheath layer,} \\ 0 = \nabla(\lambda \cdot \nabla T), & \text{The rest solid regions,} \end{cases} \quad (1)$$

where T is temperature and λ is the solid thermal conductivity. The thermal conductivity of soil (λ_{soil}) changes with temperature, which is defined as follows [23]:

$$\begin{cases} \lambda_{\text{soil}}(T) = \lambda_{\text{dry}} + (\lambda_{\text{wet}} - \lambda_{\text{dry}}) \cdot \exp\left[-a_1 \left[\frac{(T - T_{\text{ref}})}{(a_2 \cdot T_{\text{lim}})}\right]^2\right], \\ a_1 = \frac{T_{\text{lim}}}{T_{\text{ref}}}, \\ a_2 = 1 - \left(\frac{1}{a_1}\right), \end{cases} \quad (2)$$

where λ_{dry} and λ_{wet} are the thermal conductivities under dry and wet conditions for soil, which are 0.3 W/(m·K) and 1 W/(m·K), respectively; T_{lim} is the cable limit temperature, 363 K; T_{ref} is the reference temperature of surrounding soil, 293 K; and Q_e is the electromagnetic loss density, which is defined as follows [24]:

$$Q_e = Q_{\text{rh}} + Q_{\text{ml}} = \frac{1}{2} \text{Re} \cdot \left(\vec{J} \cdot \vec{E}^* \right) + \frac{1}{2} \text{Re} \cdot \left(j\omega \vec{B} \cdot \vec{H}^* \right),$$

$$\nabla \times \vec{A} = \vec{B},$$

$$\vec{E} = -j\omega \vec{A},$$

$$\vec{B} = \mu \vec{H},$$

$$\vec{J} = \sigma(T) \cdot \vec{E}.$$

(3)

where Q_{rh} and Q_{ml} are the electrical loss density and magnetic loss density, respectively; Re is the real part of imaginary number; $\vec{J}$ is current density; j is the imaginary unit; ω is the phase angle, $2\pi f$; f is frequency of electrical excitation, 50 Hz; $\vec{B}$ is the magnetic induction intensity; $\vec{A}$ is the magnetic vector potential; $\vec{E}$ is the electric field intensity; $\vec{H}$ is magnetic field intensity; $\vec{E}^*$ and $\vec{H}^*$ are the

FIGURE 1: Physical model and geometrical structure for trench laying cable [22]: (a) flat-type trench laying cable; (b) trefoil-type trench laying cable; (c) trefoil cable arrangement; (d) cable structure.

TABLE 1: Typical geometric parameters for trench laying cable [22].

r_c (mm)	r_{ins} (mm)	r_s (mm)	r_e (mm)
11.9	17.8	18.8	23.4

conjugate complex numbers of $\vec{E}$ and $\vec{H}$; and $\sigma(T)$ is the electrical conductivity, which is defined as follows:

$$\sigma(T) = \frac{1}{\rho_{ref}(1 + \alpha(T - T_{ref}))}, \quad (4)$$

where ρ_{ref} is the reference electrical resistivity and α is the temperature coefficient.

The air flow in trench is a two-dimensional natural convection turbulent heat transfer, and governing equations are formulated as follows:

$$\nabla \cdot \vec{v} = 0,$$

$$\rho(\vec{v} \cdot \nabla \vec{v}) = -\nabla p + \nabla \cdot [(\mu_f + \mu_t) \cdot (\nabla \vec{v} + (\nabla \vec{v})^T)] + \rho_0 g [1 - \beta(T - T_0)], \quad (5)$$

$$\rho(\vec{v} \cdot \nabla T) = \nabla \cdot \left[\left(\frac{\lambda_f}{c_p} + \frac{\mu_t}{\sigma_t} \right) \cdot (\nabla T) \right],$$

where $\vec{v}$ is the velocity vector; T_0 is the air reference temperature; ρ and ρ_0 are the air density at T and T_0 , respectively; p , g , and β are the pressure, gravitational acceleration,

and volumetric expansion coefficient, respectively; μ_f and μ_t are the air dynamic viscosity and turbulence viscosity, respectively. λ_f is the thermal conductivity of air; c_p is the

TABLE 2: Typical physical parameters for trench laying cable [22].

	Material	Thermal conductivity (W/(m·K))	Electronic conductivity (S/m)	Relative dielectric constant
Cable core	Copper	377	5.998×10^7	1.0
Insulation layer	XLPE	0.285	1×10^{-15}	2.5
Sheath layer	Aluminium	238	3.774×10^7	1.0
External layer	Polyethylene	0.132	1×10^{-15}	2.5
Concrete trench	Concrete	1.73	1×10^{-15}	1.0
Soil layer	Soil	1	1×10^{-15}	1.0

specific heat at the constant pressure of air; and σ_t is the turbulence Prandtl number in energy equation.

As for air turbulent flow, the standard k - ε model is adopted, which are defined as follows:

$$\begin{cases} \rho(\vec{v} \cdot \nabla k) = \nabla \left[\mu_f + \frac{\mu_t}{\sigma_k} \cdot \nabla k \right] + P_k - \rho \varepsilon, \\ \rho(\vec{v} \cdot \nabla \varepsilon) = \nabla \left[\left(\mu_f + \frac{\mu_t}{\sigma_\varepsilon} \right) \right] + C_{\varepsilon 1} \frac{\varepsilon}{k} P_k - C_{\varepsilon 2} \rho \frac{\varepsilon^2}{k}, \end{cases} \quad (6)$$

where k is the turbulent kinetic energy; ε is the turbulent dissipation rate; P_k is the shear production of turbulence; σ_k and σ_ε are the turbulence Prandtl numbers in k and ε equations; and $C_{\varepsilon 1}$ and $C_{\varepsilon 2}$ are the turbulent model parameters in k and ε equations.

The boundary conditions are set as follows:

$$\begin{cases} \text{bottom soil Boundary:} & T = T_{\text{soil}} = 283.15 \text{ K}, \\ \text{Left and right soil boundary:} & \frac{\partial T}{\partial n} = 0, \\ \text{Ground surface:} & \lambda \frac{\partial T}{\partial n} = h_f (T - T_{\text{sur}}), \\ \text{Air contact surface inside trench:} & \lambda_i \frac{\partial T}{\partial n} = h_i (T - T_f) + \frac{\sigma T^4 - J_i}{(1 - \varepsilon_i)/\varepsilon_i}; \quad u = v = 0, \end{cases} \quad (7)$$

where T_{soil} is the deep soil temperature; h_f is the equivalent heat transfer coefficient on the ground surface, which is set as $11 \text{ W}/(\text{m}^2 \cdot \text{K})$; T_{sur} is the air temperature on the ground; λ_i ($i=1, 2$) represents the thermal conductivity of cable external layer or concrete layer, respectively; h_i ($i=1, 2$) represents the convective heat transfer coefficient on the cable surface or trench inner surface; T_f is the air temperature in the trench; ε_i (ε_c and ε_T) represents the radiant emissivity on the cable surface or trench inner surface, respectively; J_i (J_c and J_T) represents the effective radiation on the cable surface or trench inner surface, respectively; and σ is the blackbody radiation constant.

In this study, the governing equations are solved with the Pardiso solver embedded in commercial code COMSOL Multiphysics 5.2. The current frequency is set as 50 Hz. The conservative interface flux conditions for mass, momentum, and heat transfer are adopted at the solid-solid and solid-fluid interfaces. For convergence criteria, all residuals of the calculations are less than 10^{-3} .

3. Grid Independence Test and Model Validations

3.1. Grid Independence Test. First, the grid independence tests were performed for both flat-type trench laying cable model (Figure 1(a)) and trefoil-type trench laying cable model (Figure 1(b)). For the test cases, the air temperature on the ground (T_{sur}) is set as 293.15 K, and the cable current for different loops are kept the same ($I=800 \text{ A}$, $f=50 \text{ Hz}$). The computational grids for different trench laying cable models are presented in Figure 2. The unstructured mesh is constructed for the computations, and the mesh is intensified near the surfaces of cable and trench wall. The cable maximum temperature (T_{max}) and electromagnetic loss (Φ_{loss}) with different computational grids are presented in Table 3. It shows that for the flat-type trench laying cable model, when the total element number changes from 27,610 (Grid 3) to 50,188 (Grid 4), the difference of cable maximum temperature (T_{max}) is 0.05%, and the difference of

FIGURE 2: Computational grids for different trench laying cable models: (a) flat-type trench laying cable and (b) trefoil-type trench laying cable.

TABLE 3: Cable maximum temperature and electromagnetic loss with different computational grids ($T_{\text{sur}} = 293.15 \text{ K}$, $I = 800 \text{ A}$, and $f = 50 \text{ Hz}$).

Cable model	Grid	Region	Maximum grid size (m)	Minimum grid size (m)	Total element number	T_{max} (K)	Φ_{loss} (W)
Flat-type trench laying cable	Grid 1	Zone 1	0.0097	0.0024	10,881	336.520	190.65
		Zone 2	0.2971	0.0049			
		Zone 3	0.3192	0.0199			
		Zone 4	3.1044	0.2489			
	Grid 2	Zone 1	0.0057	0.0017	18,070	333.742	183.38
		Zone 2	0.1137	0.0049			
		Zone 3	0.1815	0.0181			
		Zone 4	2.1844	0.1411			
	Grid 3	Zone 1	0.0043	0.0015	27,610	333.708	182.55
		Zone 2	0.0938	0.0042			
		Zone 3	0.1515	0.0117			
		Zone 4	1.8306	0.1117			
	Grid 4	Zone 1	0.0024	0.0013	50,188	333.541	182.25
		Zone 2	0.0682	0.0020			
		Zone 3	0.1256	0.0117			
		Zone 4	0.9978	0.0951			

TABLE 3: Continued.

Cable model	Grid	Region	Maximum grid size (m)	Minimum grid size (m)	Total element number	$T_{\max}$ (K)	Φ_{loss} (W)
Trefoil-type trench laying cable	Grid 1	Zone 1	0.0060	0.0015	14,408	342.287	190.67
		Zone 2	0.1140	0.0013			
		Zone 3	0.1815	0.0260			
		Zone 4	2.5112	0.1411			
	Grid 2	Zone 1	0.0059	0.0015	22,618	343.014	189.69
		Zone 2	0.0911	0.0012			
		Zone 3	0.1457	0.0227			
		Zone 4	1.7810	0.1088			
	Grid 3	Zone 1	0.0047	0.0011	27,798	341.779	188.69
		Zone 2	0.0885	0.0012			
		Zone 3	0.1173	0.0127			
		Zone 4	0.9868	0.1031			
	Grid 4	Zone 1	0.0033	0.0011	53,290	341.411	188.71
		Zone 2	0.0877	0.0011			
		Zone 3	0.1093	0.0103			
		Zone 4	0.4872	0.0748

FIGURE 3: Physical model for pipe laying cable and cable structure [3]: (a) physical model for pipe laying cable and (b) cable structure.

electromagnetic loss (Φ_{loss}) is 0.16%. Therefore, for the flat-type trench laying cable model, the Grid 3 with total element number of 27,610 should be good enough for the test. For this grid, the minimum size of the grid element in the cable zone (Zone 1), air zone (Zone 2), trench wall zone (Zone 3), and soil zone (Zone 4) are 1.5 mm, 4.2 mm, 11.7 mm, and 111.7 mm, respectively. As for the trefoil-type trench laying cable model, when the total element number changes from 27,798 (Grid 3) to 53,290 (Grid 4), the difference of cable maximum temperature ($T_{\max}$) is 0.11%, and the difference of electromagnetic loss (Φ_{loss}) is 0.01%. Therefore, for the trefoil-type trench laying cable model, the Grid 3 with total element number of 27,798 should be good enough for the test. For this grid, the minimum size of the grid element in the cable zone (Zone 1), air zone (Zone 2), trench wall zone (Zone 3), and soil zone (Zone 4) are 1.1 mm, 1.2 mm, 12.7 mm, and 103.1 mm, respectively. Based on the aforementioned analysis, similar mesh settings to the Grid 3 (27,610) for flat-type trench laying cable model and Grid 3

(27,798) for trefoil-type trench laying cable model were finally adopted for the following simulations.

3.2. Model Validations. Subsequently, the computational model and methods are validated. Since numerical study on multiphysics coupling simulation for the trench laying cable is few, the numerical simulations for three-phase pipe laying cable [3] are restudied. The physical model for pipe laying cable [3] is presented in Figure 3. Three-phase cables are laid in a polyvinyl chloride (PVC) pipe. Both natural convection and radiation heat transfer are considered on the cable surfaces and pipe inner surface. The cable diameter is 150 mm, the outer diameter of PVC pipe is 620 mm and its thickness is 10 mm. The radiant emissivity on the cable surface is 0.8, and it is 0.5 on the inner surface of PVC pipe. The equivalent heat transfer coefficient on the outer surface of PVC pipe (h_r) is $5 \text{ W}/(\text{m}^2 \cdot \text{K})$, and the environment temperature on the outside surface of PVC pipe (T_r) is 293.15 K. Typical geometrical and

TABLE 4: Typical geometrical and physical parameters for the pipe laying cable [3].

	Diameter (mm)	Thermal conductivity (W/(m•K))	Electronic conductivity (S/m)	Relative dielectric constant
Cable core	60.4	400	5.998×10^7	1.0
Insulation layer	120	0.286	1×10^{-15}	2.5
Sheath layer	140	238	3.774×10^7	1.0
External layer	150	0.280	1×10^{-15}	2.5
PVC pipe	620	0.167	1×10^{-16}	1.0

FIGURE 4: Computational results for pipe laying cable: (a) cable maximum temperature and (b) heat flux on cable surface.

physical parameters for the pipe laying cable [3] are listed in Table 4. The computational results for the cable maximum temperature ($T_{\max}$), radiation heat flux (Φ_{rad}), convection heat flux (Φ_{conv}), and total heat flux (Φ_{tot}) on the cable surface are presented in Figure 4. It shows that the present computational results are in good agreement with those as reported by Fu et al. [3], where the maximum deviations for $T_{\max}$, Φ_{rad} , Φ_{conv} , and Φ_{tot} are 0.056%, 4.70%, 4.41%, and 4.47%, respectively.

In addition, since the air flow inside PVC pipe is laminar flow in Fu et al.'s study [3], the turbulence natural convection heat transfer in a two-dimensional square cavity [25] is restudied. The physical model for the two-dimensional square cavity [25] is presented in Figure 5. It shows that the top and bottom walls of the cavity are adiabatic. Two vertical walls are high temperature and low temperature walls, where the wall temperature is kept constant and the temperature difference is 40 K. The computational results for the average Nusselt number (Nu_{ave}) are presented in Table 5. It shows that the average Nusselt numbers (Nu_{ave}) obtained from the present simulations can agree well with those in Kuznetsov and Sheremet's study [25], and the maximum deviation is 6.26%.

4. Prediction Algorithm

In this study, an adaptive optimized particle swarm optimization algorithm (LFVPSO) is proposed based on Levy flight algorithm, and it is used to modify the back propagation neural network algorithm (LFVPSO-BPNN). Then combined with numerical simulations, a network algorithm for temperature prediction of trench laying cable is developed using LFVPSO-BPNN. Finally, the maximum current capacity of four-loop three-phase trench laying cable is calculated using LFVPSO-BPNN together with genetic algorithm (GA&LFVPSO-BPNN).

4.1. LFVPSO-BPNN Algorithm. Back propagation neural network algorithm (BPNN) is a multilayer feed-forward network algorithm trained by back propagation of computational errors [26], and it is often used to predict and analyze nonlinear correlations. As presented in Figure 6, the BPNN topology structure is composed of input layer, hidden layers, and output layer [27].

Where x is the input variable of BPNN; W^h represents the transitive relation between input layer and hidden layer; θ^h is

FIGURE 5: Physical model for two-dimensional square cavity [25].

TABLE 5: Computational results for Nu_{ave} of present simulation and the study by Kuznetsov and Sheremet [25].

Ra	Nu_{ave} (present simulation)	Kuznetsov and Sheremet's study [25]	Deviation (%)
10^7	18.60	17.72	4.97
10^8	35.50	33.41	6.26

the threshold of the hidden layer neuron; W^o represents the transitive relation between hidden layer and output layer; θ^o is the threshold of output layer neuron; and y is the output variable of BPNN.

Before BPNN training, the weights and thresholds between neurons should be preset. Improper setting of weights and thresholds will lead to unreasonable prediction results. To improve the prediction accuracy of BPNN algorithm, the weights and thresholds of the network can be optimized in advance. Particle swarm optimization algorithm (PSO) has a good advantage in multiobjective optimizations. When large number of weights and thresholds of BPNN need to be optimized, the PSO algorithm can be used for the optimizations [28, 29]. However, it should be noted that the PSO algorithm may lead to local optimum results. Try to avoid this defect of PSO algorithm, the Levy flight algorithm is recommended to improve the performance of PSO [30, 31]. Levy flight trajectory is composed of frequent short-distance random walks and occasional long-distance random jumps. The Levy flight extremum can produce random jumps and extreme speed changes in direction, which is helpful to expand searching space. Therefore, combining PSO algorithm with Levy flight algorithm, the local optimum risk of PSO algorithm might be greatly reduced. Huseyin and Uğuz [30] combined PSO algorithm with Levy flight algorithm to update the position of particle swarm, and then selected the optimum particle position to calculate the optimum value of the objective function. This improved PSO algorithm (LFPSO) can effectively avoid the local optimum risk of PSO algorithm, but its computation time is relatively long because sometimes the position of particle swarm is needed to be calculated twice for a single iteration during the iterative process. Jensi and Jiji [31] proposed an enhanced PSO algorithm together with Levy flight algorithm by setting a random number ($\text{rand} \in [0, 1]$) to combine the PSO algorithm with Levy flight algorithm (PSOLF). When $\text{rand} \in [0.5, 1]$, the PSO algorithm and Levy flight algorithm were combined with linearly decreasing

weight method to update the position of particle swarm and calculate the optimum value of the objective function. When $\text{rand} \in [0, 0.5]$, only PSO algorithm was used to update the position of particle swarm and calculate the optimum value of the objective function. As compared with LFPSO algorithm [30], the computation time of this algorithm (PSOLF) can be greatly reduced. However, when the weight of the Levy flight algorithm becomes smaller, the local optimum risk of PSOLF algorithm would increase. Therefore, in this paper, based on the study of Jensi and Jiji [31], an adaptive optimized PSO algorithm (LFVPSO) is further proposed together with Levy flight algorithm, and it is used to find the optimum weights and thresholds of BPNN. For the LFVPSO algorithm, when $\text{rand} \in [0.5, 1]$, the PSO algorithm and Levy flight algorithm are directly combined, and the adaptive mutation idea of genetic algorithm (GA) is also adopted to update the position of particle swarm and calculate the optimum value of the objective function. As compared with PSOLF algorithm [31], the local optimum risk of present algorithm (LFVPSO) would be reduced, and its prediction accuracy would be improved. According to the authors' knowledge, almost no such studies were performed yet.

In LFVPSO algorithm, a random number ($\text{rand} \in [0, 1]$) is set first. When $\text{rand} \in [0, 0.5]$, the PSO algorithm is used to update the position of particle swarm. When $\text{rand} \in [0.5, 1]$, the PSO algorithm is combined with Levy flight algorithm to update the position of particle swarm. Then, find out the position of the particle with the worst fitness in the current particle swarm and update particle swarm position to far away from the worst particle position at a certain rate. The next particle swarm position is calculated as in equation (8). Meanwhile, the adaptive mutation idea of genetic algorithm (GA) is also adopted, and the adaptive mutation operation is introduced into the PSO algorithm. For this operation, a random number ($\text{rand}' \in [0, 1]$) is set, and the position of some particle in the swarm is randomly updated again with a certain probability as $\text{rand}' > 0.95$. The flowchart for BPNN

FIGURE 6: BPNN topology structure [27].

FIGURE 7: The flowchart for BPNN optimization with LFVPSO (LFVPSO-BPNN).

optimization with LFVPSO (LFVPSO-BPNN) is presented in Figure 7. In LFVPSO algorithm, the prediction error of BPNN is set as fitness function. The particle swarm position is randomly initialized using Levy flight algorithm and

updated with equation (8). The optimum weights and thresholds of BPNN are calculated with iteration method to minimize the fitness function. Based on these operations, the optimum BPNN prediction model is constructed, which is

FIGURE 8: The flowchart of prediction algorithm for temperature rise of trench laying cable.

the LFVPSO-BPNN model. The particle swarm position is updated and calculated as follows:

$$\begin{cases} X_i^{k+1} = X_i^k + a_1 V_i^{k+1} - a_2 r_1 (P_w^k - X_i^k), & \text{rand} \in [0, 0.5), \\ X_i^{k+1} = X_i^k + a_1 V_i^{k+1} + [\vartheta_0 \cdot (X_i^k - P_g^k)] \otimes \text{Levy}(\beta) - a_2 r_3 \cdot (P_w^k - X_i^k), & \text{rand} \in [0.5, 1], \end{cases} \quad (8)$$

where X_i^{k+1} is the position of particle i at iteration $k+1$; X_i^k is the position of particle i at iteration k ; V_i^{k+1} is the velocity of particle i at iteration $k+1$; P_w^k is the position of the particle with the worst fitness in the current particle swarm; P_g^k is the position of the particle with the best fitness in the previous particle swarm; a_1 is the scaling factor of velocity weight, 0.2; a_2 and ϑ_0 are the step scaling factors, 0.01; r_1 is a random number between 0 and 1; and β is the Levy distribution index.

4.2. Temperature Prediction Network of Trench Laying Cable.

When the trench structure and cable layout are determined, the cable maximum temperature of each loop in the trench ($T_{\max,i}$) is mainly affected by the air temperature on the ground (T_{sur}) and cable current of each loop (I_i), and the maximum current capacity of trench laying cable ($I_{t,\max}$) is mainly affected by T_{sur} . Therefore, in this study, T_{sur} and I_i are selected as the input variables, $T_{\max,i}$ is selected as the output variable, and a temperature prediction network of trench laying cable is developed with LFVPSO-BPNN. Then, $I_{t,\max}$ was calculated using LFVPSO-BPNN together with genetic algorithm (GA), where T_{sur} is set as the input variable, and the maximum value of $T_{\max,i}$ should not exceed the safe operating temperature of cable (363.15 K). The flowchart of prediction algorithm for temperature rise of trench laying cable is presented in Figure 8. First, for different trench laying cable models, including flat-type laying model (Figure 1(a)) and trefoil-type laying model (Figure 1(b)), the input variables of training samples (T_{sur} and

I_i) for temperature prediction network of trench laying cable (LFVPSO-BPNN) are selected using random sampling function. With this method, 80 training samples are selected for each cable model. The input variables of typical training samples for LFVPSO-BPNN are listed in Table 6, where T_{sur} changes from 283.15 K to 313.15 K, and I_i changes from 200 A to 1200 A. Based on the input variables of training samples in Table 6, the heat transfer processes for trench laying cables are numerically simulated with COMSOL Multiphysics, and the computational results of $T_{\max,i}$ are set as the output variables of LFVPSO-BPNN. Then, the temperature prediction network for trench laying cable (LFVPSO-BPNN) is trained and constructed, and the predicted results of $T_{\max,i}$ with LFVPSO-BPNN are further validated using COMSOL Multiphysics. Finally, the maximum current capacity of trench laying cable ($I_{t,\max}$) under different T_{sur} is calculated using LFVPSO-BPNN together with genetic algorithm (GA&LFVPSO-BPNN). During the iteration process, the T_{sur} should be set in advance, and the maximum value of $T_{\max,i}$ should not exceed the safe operating temperature of cable (363.15 K). After that, the predicted results with GA&LFVPSO-BPNN should also be validated using COMSOL Multiphysics.

In this study, there are 5 input variables and 4 output variables in the temperature prediction network for trench laying cable (LFVPSO-BPNN). The input variables are T_{sur} and I_i ($i = 1, 2, 3$, and 4), and the output variables are $T_{\max,i}$ ($i = 1, 2, 3$, and 4). One hidden layer is set in the present temperature prediction network, and the hidden layer is

TABLE 6: Input variables of typical training samples for LFVPSO-BPNN.

Samples	T_{sur} (K)	I_1 (A)	I_2 (A)	I_3 (A)	I_4 (A)
<i>Flat-type trench laying cable</i>					
1	308.11	554.02	514.73	861.26	741.50
2	295.38	207.81	625.83	423.51	956.98
3	302.36	788.37	633.43	444.17	628.96
...	...	...	...	...	...
78	311.10	1014.92	340.50	1079.87	295.38
79	312.90	356.64	993.89	841.81	539.38
80	287.40	637.42	946.18	667.91	1060.83
<i>Trefoil-type trench laying cable</i>					
1	310.92	1099.94	724.11	320.20	377.79
2	292.43	929.32	711.42	404.30	270.93
3	293.66	285.55	267.38	1088.39	433.17
...	...	...	...	...	...
78	311.67	764.76	716.10	641.85	374.49
79	288.16	869.65	976.86	877.1	604.80
80	303.72	848.03	633.37	339.76	951.93

FIGURE 9: The prediction and simulation results of cable maximum temperature for different loops in the trench (80 training samples for the flat-type trench laying cable model): (a) Loop 1; (b) Loop 2; (c) Loop 3; (d) Loop 4.

FIGURE 10: The prediction and simulation results of cable maximum temperature for different loops in the trench (80 training samples for the trefoil-type trench laying cable model): (a) Loop 1; (b) Loop 2; (c) Loop 3; (d) Loop 4.

TABLE 7: The prediction and simulation results of cable maximum temperature for different loops in the trench (5 random test samples for the flat-type trench laying cable models).

Input	Case	T_{sur} (K)	I_1 (A)	I_2 (A)	I_3 (A)	I_4 (A)			
	1	304.33	941.11	825.35	485.39	1055.20			
	2	284.10	231.00	594.87	543.40	888.97			
	3	291.46	915.68	368.19	640.79	601.03			
	4	310.67	337.14	943.24	684.51	1096.52			
	5	305.59	275.99	559.80	433.88	920.06			
Output	Case	LFVPSO-BPNN				COMSOL Multiphysics			
		$T_{\text{max},1}$ (K)	$T_{\text{max},2}$ (K)	$T_{\text{max},3}$ (K)	$T_{\text{max},4}$ (K)	$T_{\text{max},1}$ (K)	$T_{\text{max},2}$ (K)	$T_{\text{max},3}$ (K)	$T_{\text{max},4}$ (K)
	1	355.53	348.99	336.81	364.49	354.91	348.70	336.03	363.27
	2	297.51	307.24	304.27	322.88	298.35	307.83	305.95	322.32
	3	331.44	309.58	319.49	315.85	331.42	309.83	319.21	317.43
	4	337.21	360.46	346.99	371.73	336.68	360.09	347.39	371.04
5	318.92	326.98	322.51	344.59	319.33	326.85	322.64	343.92	

composed of 10 neuron nodes. Therefore, there are 104 weights and thresholds need to be optimized for the prediction network. The weight and threshold for the prediction

network are set to be ranged in $[-5, 5]$, and the number of particle swarm for LFVPSO is set to 60. The fitness function of present prediction network is defined as follows:

TABLE 8: The prediction and simulation results of cable maximum temperature for different loops in the trench (5 random test samples for the trefoil-type trench laying cable models).

	Case	T_{sur} (K)	I_1 (A)	I_2 (A)	I_3 (A)	I_4 (A)			
Input	1	293.54	596.05	765.13	394.86	828.06			
	2	305.35	866.33	643.07	633.3	375.24			
	3	306.64	552.56	793.42	785.18	867.68			
	4	305.80	885.1	521.95	454.42	686.91			
	5	309.71	456.11	1086.56	646.8	1015.99			
	Case	LFVPSO-BPNN				COMSOL Multiphysics			
		$T_{\text{max},1}$ (K)	$T_{\text{max},2}$ (K)	$T_{\text{max},3}$ (K)	$T_{\text{max},4}$ (K)	$T_{\text{max},1}$ (K)	$T_{\text{max},2}$ (K)	$T_{\text{max},3}$ (K)	$T_{\text{max},4}$ (K)
Output	1	323.46	331.00	314.61	336.96	322.27	331.47	313.84	337.53
	2	347.95	336.14	336.14	324.74	348.10	335.48	335.70	325.09
	3	337.69	350.01	349.72	357.11	338.18	350.24	350.07	357.03
	4	349.50	330.27	328.46	338.26	350.35	329.16	328.80	337.64
	5	342.75	378.23	350.32	375.5	343.07	377.40	350.45	376.17

FIGURE 11: The convergence curves of fitness function for the modified BPNN with LFPSO [30], PSOLF [31], or LFVPSO algorithm: (a) flat-type trench laying cable and (b) trefoil-type trench laying cable.

TABLE 9: The prediction and simulation results of maximum current capacity for different trench laying cables ($T_{sur} = 283.15$ K and 313.15 K).

Cases	$T_{sur}(K)$	GA&LFVPSO-BPNN						COMSOL
		$I1(A)$	$I2(A)$	$I3(A)$	$I4(A)$	$I_{t,max}$ (A)	$(T_{max,i})_{max}$ (K)	$(T_{max,i})_{max}$ (K)
<i>Flat-type trench laying cable</i>								
1	283.15	1111.22	1136.97	1093.90	1102.13	9427.61	363.15	—
2	283.15	1110.86	1138.37	1092.23	1102.13	9426.28	363.15	—
3	283.15	1111.16	1137.48	1093.26	1102.86	9428.76	363.15	—
Averaged	283.15	1111.08	1137.61	1093.13	1102.37	9427.55	363.15	363.73
1	313.15	892.48	905.78	877.03	875.87	7533.15	363.15	—
2	313.15	893.95	905.64	876.60	874.77	7532.72	363.15	—
3	313.15	894.37	903.90	876.00	875.95	7531.15	363.15	—
Averaged	313.15	893.60	905.10	876.54	875.53	7532.32	363.15	363.00
<i>Trefoil-type trench laying cable</i>								
1	283.15	1043.16	1080.67	997.77	1012.59	8769.94	363.15	—
2	283.15	1043.52	1080.57	998.08	1011.92	8769.73	363.15	—
3	283.15	1044.68	1080.74	997.25	1011.61	8770.13	363.15	—
Averaged	283.15	1043.78	1080.66	997.70	1012.04	8769.92	363.15	362.95
1	313.15	848.16	852.47	813.57	833.91	7102.41	363.15	—
2	313.15	847.29	852.94	812.61	833.79	7099.27	363.15	—
3	313.15	848.20	852.45	813.55	833.93	7102.46	363.15	—
Averaged	313.15	847.89	852.62	813.25	833.88	7101.42	363.15	363.32

$$\text{fitness} = \sum_i^M |\hat{y} - \hat{y}'|_i^2, \quad (9)$$

where $\hat{y}$ is the normalized simulation value of training samples; $\hat{y}'$ is the normalized prediction value of training samples; and M is the number of training samples, $M = 80$.

The maximum current capacity of trench laying cable ($I_{t,\max}$) is defined as follows:

$$I_{t,\max} = \text{Max} \left(\sum_1^4 3 \frac{I_i}{\sqrt{2}} \right), \quad (T_{\max,i})_{\max} \leq 363.15 \text{ K}, \quad (10)$$

where I_i is the single-cable current for loop i and the currents of three cables in the same loop are kept the same and $T_{\max,i}$ is the cable maximum temperature of loop i in the trench.

5. Results and Discussion

5.1. Temperature Prediction for Trench Laying Cable. The prediction and simulation results of cable maximum temperature for different loops in the trench (80 training samples for the flat-type trench laying cable model) are presented in Figure 9. It shows that the correlation coefficient (R^2) between the prediction and simulation results of cable maximum temperature for different loops in the trench (flat-type trench laying cable model) is higher than 0.9990. Similarly, the prediction and simulation results of cable maximum temperature for different loops in the trench (80 training samples for the trefoil-type trench laying cable model) is presented in Figure 10. It shows that the correlation coefficient (R^2) between the prediction and simulation results of cable maximum temperature for different loops in the trench (trefoil-type trench laying cable model) is higher than 0.9992. This means the temperature prediction network (LFVPSO-BPNN) for both flat-type and trefoil-type trench laying cable models trained in this study is reliable, which can successfully predict the cable maximum temperature of different loops in the trench. Meanwhile, five additional random test samples are also selected to verify the accuracy of the temperature prediction network (LFVPSO-BPNN). The prediction and simulation results of cable maximum temperature for different loops in the trench (5 random test samples for different trench laying cable models) are presented in Tables 7 and 8. They show that the predicted cable maximum temperatures for different loops ($T_{\max,i}$) in the trench can agree well with those obtained by COMSOL Multiphysics, and the maximum deviation is less than 2 K. This confirms that the LFVPSO-BPNN algorithm proposed in this study can accurately predict the cable maximum temperature for four-loop trench laying cables.

Based on the same training samples (Table 6) and same number of particle swarm (60), the convergence curves of fitness function for the modified BPNN with LFPSO [30], PSOLF [31] or LFVPSO algorithm are presented in Figure 11. It shows that, for the flat-type trench laying cable model, when the iteration reaches convergence, the computation times for the LFPSO-BPNN, PSOLF-BPNN, and LFVPSO-BPNN algorithm are 5651 s, 3801 s, and 3977 s, respectively, and their convergence values of fitness function

are 0.2307, 0.2223, and 0.1005, respectively. Similarly, for the trefoil-type trench laying cable model, when the iteration reaches convergence, the computation times for the LFPSO-BPNN, PSOLF-BPNN, and LFVPSO-BPNN algorithm are 5918 s, 3977 s, and 4195 s, respectively, and their convergence values of fitness function are 0.1672, 0.2070, and 0.1008, respectively. It is indicated that, under the same restrictions, as compared with LFPSO-BPNN algorithm, the computation time would be great reduced by using PSOLF-BPNN and LFVPSO-BPNN algorithm. Meanwhile, as compared with LFPSO-BPNN and PSOLF-BPNN algorithm, the prediction accuracy would be further improved using LFVPSO-BPNN algorithm. Therefore, as compared with LFPSO-BPNN and PSOLF-BPNN algorithm, when LFVPSO-BPNN algorithm is used to predict the temperature of four-loop three-phase trench laying cables, its computation time would be reduced and the prediction accuracy would be improved as well.

5.2. Prediction of Maximum Current Capacity for Trench Laying Cable. The prediction and simulation results of maximum current capacity for different trench laying cables under different T_{sur} are presented in Table 9. The air temperature on the ground (T_{sur}) is set as 283.15 K and 313.15 K, which represents moderate environment temperature and hot summer environment temperature, respectively. To reduce the prediction error of GA&LFVPSO-BPNN algorithm, the cable current of each loop (I_i) and the maximum current capacity of trench laying cable ($I_{t,\max}$) were calculated three times and averaged under different T_{sur} . Meanwhile, the T_{sur} and I_i predicted using GA&LFVPSO-BPNN algorithm are input into COMSOL Multiphysics, and the maximum value of the cable maximum temperature for different loops in the trench ($(T_{\max,i})_{\max}$) is computed and compared with the safe operating temperature of cable (363.15 K). As is shown in Table 9, for different cases, the maximum deviation between the simulation results of $(T_{\max,i})_{\max}$ and safe operating temperature of cable (363.15 K) is 0.58 K, which means the prediction results obtained using GA&LFVPSO-BPNN algorithm should be reliable.

In Table 9, it also shows that, under different T_{sur} , when the current capacity of trench laying cable (I_t) reaches its maximum value ($I_{t,\max}$), the cable current of Loop 2 (I_2) is the highest, and the cable currents of upper layer loops (I_1 , I_2) are higher than those of lower layer loops (I_3 , I_4). This may indicate that, for the case under $I_{t,\max}$, when both natural convection and radiation heat transfer are considered on the cable surfaces, the overall heat transfer on the cable surfaces of Loop 2 should be the best, and the heat transfer on the cable surfaces of upper layer loops should be better than that of lower layer loops. For the flat-type trench laying cable model, as T_{sur} increases from 283.15 K to 313.15 K, the maximum current capacity of trench laying cable ($I_{t,\max}$) decreases from 9427.55 A to 7532.32 A, which decreases by 1895.23 A (20%). Similarly, for the trefoil-type trench laying cable model, as T_{sur} increases from 283.15 K to 313.15 K, the maximum current capacity of trench laying

cable ($I_{t,max}$) decreases from 8769.92 A to 7101.42 A, which decreases by 1668.5 A (19%). This may indicate that when T_{sur} increases from 283.15 K to 313.15 K, the overall heat transfer of trench laying cable should be weakened, and its maximum current capacity ($I_{t,max}$) is decreased significantly. Furthermore, when air temperature on the ground (T_{sur}) is fixed at 283.15 K, as compared with the trefoil-type laying trench cable model, the $I_{t,max}$ for the flat-type trench laying cable model can increase by 657.63 A (7.5%). Similarly, when air temperature on the ground (T_{sur}) is fixed at 313.15 K, as compared with the trefoil-type laying trench cable model, the $I_{t,max}$ for the flat-type trench laying cable model can increase by 430.9 A (6.1%). This means, under the same T_{sur} , the overall heat transfer performance for the flat-type trench laying cable should be better than that for the trefoil-type laying trench cable, and the maximum current capacity ($I_{t,max}$) for the flat-type trench laying cable are obviously higher. Therefore, with the same working conditions, the flat-type laying method is recommended for the cable arrangement in the trench.

6. Conclusion

In this study, an adaptive optimized particle swarm optimization algorithm (LFVPSO) is proposed based on Levy flight algorithm, and it is used to modify the backpropagation neural network algorithm (LFVPSO-BPNN). Then combined with numerical simulations, a network algorithm for temperature prediction of trench laying cable is developed using LFVPSO-BPNN. Finally, the maximum current capacity of four-loop three-phase trench laying cable is calculated using LFVPSO-BPNN together with genetic algorithm (GA&LFVPSO-BPNN). The main findings are as follows:

- (1) The correlation coefficient between the prediction and simulation results of cable maximum temperature for different loops ($T_{max,i}$) in the trench is higher than 0.9990, and the maximum deviation of $T_{max,i}$ is less than 2 K. Therefore, the LFVPSO-BPNN algorithm proposed in this study can accurately predict $T_{max,i}$ for four-loop trench laying cables. Furthermore, under the same restrictions, as compared with LFVPSO-BPNN and PSOLF-BPNN algorithm, when LFVPSO-BPNN algorithm is used to predict the temperature of four-loop three-phase trench laying cable, its computation time would be reduced, and the prediction accuracy would be improved as well.
- (2) The effect of ground air temperature (T_{sur}) on the maximum current capacity of trench laying cable ($I_{t,max}$) is remarkable. When T_{sur} increases from 283.15 K to 313.15 K, the overall heat transfer of trench laying cable should be weakened, and its maximum current capacity ($I_{t,max}$) is decreased significantly. For the flat-type trench laying cable model, the $I_{t,max}$ decreases from 9427.55 A to 7532.32 A, which decreases by 20%. And for the trefoil-type trench laying cable model, the $I_{t,max}$

decreases from 8769.92 A to 7101.42 A, which decreases by 19%.

- (3) Under the same ground air temperature (T_{sur}), the overall heat transfer performance for the flat-type trench laying cable should be better than that for the trefoil-type laying trench cable, and the maximum current capacity ($I_{t,max}$) for the flat-type trench laying cable is obviously higher. When T_{sur} is fixed at 283.15 K, as compared with the trefoil-type laying trench cable model, the $I_{t,max}$ for the flat-type trench laying cable model can increase by 7.5%. Meanwhile, when T_{sur} is fixed at 313.15 K, as compared with the trefoil-type laying trench cable model, the $I_{t,max}$ for the flat-type trench laying cable model can increase by 6.1%.

These results would be meaningful for temperature rapid prediction and maximum current capacity calculation of trench laying cable. Furthermore, it should also be noticed that, the service life of a trench laying cable is closely related to the cable temperature. Therefore, as next step, the prediction work for the service life of a trench laying cable based on the predicted cable temperature should also be performed in the near future.

Nomenclature

a_1 :	Scaling factor of velocity weight
a_2 :	Step scaling factor
A :	Magnetic vector potential (Wb/m)
B :	Magnetic induction intensity (T)
c_p :	Specific heat at constant pressure (J/(kg·K))
$C_{\varepsilon 1}$,	Turbulence model parameters
$C_{\varepsilon 2}$:	
$\vec{E}$:	Electric field strength (N/C)
$\vec{E}^*$:	Conjugate complex number of electric field strength
f :	Electrical excitation frequency (Hz)
g :	Gravitational acceleration (m/s ²)
h_1 :	Convective heat transfer coefficient on the cable surface (W/(m ² ·K))
h_2 :	Convective heat transfer coefficient on the concrete surface (W/(m ² ·K))
h_f :	Equivalent heat transfer coefficient on the ground surface (W/(m ² ·K))
$\vec{H}$:	Magnetic field strength (A/m)
$\vec{H}^*$:	Conjugate complex number of magnetic field strength
I :	Cable current (A)
$I_{t,max}$:	Maximum current capacity (A)
J :	Current density (A/m ²)
J_1 :	Effective radiation on the cable surface (W/m ²)
J_2 :	Effective radiation on the concrete surface (W/m ²)
k :	Turbulent kinetic energy (m ² /s ²)
Nu_{ave} :	Average Nusselt number
p :	Pressure (Pa)
P_g^k :	Position of the particle with the best fitness in the previous particle swarm

P_k :	Shear production of turbulence ($\text{kg}/(\text{m}\cdot\text{s}^3)$)
P_w^k :	Position of the particle with the worst fitness in the current particle swarm
Q_e :	Total electromagnetic loss (W/m^3 or W/m^2)
Q_{ml} :	Magnetic loss (W/m^3 or W/m^2)
Q_{rh} :	Electrical loss (W/m^3 or W/m^2)
r_c :	Cable core radius (m)
r_e :	External layer radius (m)
r_{ins} :	Insulation layer radius (m)
r_s :	Sheath layer radius (m)
T :	Temperature (K)
T_f :	Air temperature in the trench (K)
T_{max} :	Cable maximum temperature (K)
T_{soil} :	Deep soil temperature (K)
T_{sur} :	Air temperature on the ground (K)
$\vec{v}$:	Velocity vector (m/s)
V_i^{k+1} :	Velocity of particle i at iteration $k+1$
W_h :	Transitive relationship between the input layer and the hidden layer
W_o :	Transitive relationship between the hidden layer and the output layer
x :	Input variable
X_i^k :	Position value of the particle i at iteration k
X_i^{k+1} :	Position value of the particle i at iteration $k+1$
y :	Output variable
X :	The normalized simulation value of training samples
$\hat{y}'$:	The normalized predicted value of training samples

Greek letters

β : Volumetric expansion coefficient of air (K^{-1})

Index of Levy distribution

ε :	Turbulent dissipation rate (m^2/s^3)
ε_c :	Cable surface emissivity
ε_T :	Surface emissivity of the inner wall of the trench
λ :	Solid thermal conductivity ($\text{W}/(\text{m}\cdot\text{K})$)
μ_f :	Dynamic viscosity of air ($\text{kg}/(\text{m}\cdot\text{s})$)
μ_t :	Turbulent viscosity of air ($\text{kg}/(\text{m}\cdot\text{s})$)
ρ :	Air density (kg/m^3)
σ :	Electrical conductivity (S/m)

Blackbody radiation constant

$\sigma_k, \sigma_t, \sigma_\varepsilon$:	Turbulent Prandtl numbers
Φ :	Heat flux (W)
ω :	Phase angle ($^\circ$)

Abbreviations

BPNN:	Backpropagation neural network
GA:	Genetic algorithm
LFPSO:	Modified particle swarm optimization algorithm combined with Levy flight algorithm
LFVPSO:	

	Adaptive optimized particle swarm optimization algorithm combined with Levy flight algorithm
PSOLF:	Enhanced particle swarm optimization algorithm combined with Levy flight algorithm
PVC:	Polyvinyl chloride
XLPE:	Cross-linked polyethylene.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

Acknowledgments

This work was supported by the Science and Technology Project (no. 52094019006Z) of State Grid Shanghai Electric Power Company.

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