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Development of PSO-based SVM model for Fault Detection in Power Distribution Systems

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In this paper, a new mutant particle swarm optimization (mPSO) algorithm for optimizing support vector machine (SVM) parameters is propose to detect short circuit faults in power distribution systems. Further, time domain reflectometry (TDR) with pseudo-random binary sequence (PRBS) excitation has been considered to generate fault simulation datasets. The proposed technique has been tested on a typical two-lateral radial distribution network to identify ten different types of short circuit faults. To demonstrate superiority of the proposed mPSO, comparative studies of fault diagnosis have been performed using SVM whose parameters are selected using cross-validation and classical PSO. The obtained high classification accuracy and the comparative results demonstrate the superiority of the proposed mPSO in classifying short circuit faults.

Keywords: power distribution system, fault diagnosis, particle swarm optimization, support vector machine.

1. Introduction

Power distribution systems deliver electrical power to the consumers. These systems often suffer from electrical short-circuit faults. Most of the faults of power systems occur in distribution systems alone. These short-circuit faults affect many consumers in various ways. So, it is essential to clear any such faults as soon as possible. For this, it is necessary to locate the fault and its type in order to clear it. Any delay in restoring the supply, severely degrade power quality and overall reliability of the system [1].

Time-domain reflectometry (TDR) is one of the most popular methods for finding faults in transmission lines [2-3], but not wide applied for distribution networks because of their complex characteristics, such as multi-branch topology, unbalance operation principles and a wide varying range of load [4-5]. Therefore, it requires an intelligent algorithm to support for detecting the fault on a multi-branch network from the reflectometry trace. With the ability of high generalization and global optimization, support vector machine (SVM) has emerged as a powerful tool to estimate nonlinear system accurately [6-8].

The optimum parameter selection of SVM plays the most important role in classifying dataset. Vapnik showed that the penalty parameter C and kernel function parameter such as gamma γ for the radial basis function (RBF) significantly affect the performance of SVM [9]. For obtaining optimum SVM parameters for fault classification various optimization techniques have been used [10]. Among these methods, grid search method [11], genetic algorith [12-13] and particle swarm optimization [14] are very effective. Although these methods have been very effective but suffer from getting trapped into local optima and also very large time require. To overcome these issues, an improved algorithm is introduced.

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In this paper, an mPSO algorithm has been proposed by removing the worst particle by a mutant particle generated randomly using personal best components of classical PSO. The mutant particle tries to escape the other particle from local optima. The proposed mPSO is applied to optimize SVM parameters in order to diagnose the short circuit fault types in radial distribution network. The effectiveness and robustness of the proposed algorithm has been demonstrated on datasets obtained from TDR analysis for a two-branched distribution system.

Rest of the paper is organized as follows. In Section 2, the detail of the time-domain reflectometry approach is described. In Section 3, the basic concepts of support vector machine are reviewed. In Section 4, the proposed mutant particle swarm optimization is discussed. The mPSO based SVM parameters for fault classification approach is developed in Section 5. Test results and discussion are given in Section 6. Finally, Section 7 presents the conclusion.

2. Time-Domain Reflectrometry

One of the most common instruments used for fault classification and location is time-domain reflectometry (TDR) method. It uses a single pulse injection into a line or cable and records echo responses which are caused by any impedance mismatches, including an electrical fault, tee joint or line terminal. These recorded echo responses are used for identifying the nature of any electrical fault [15].

An enclosed coaxial distribution line can be modeled by an equivalent circuit as shown in Figure 1. In this figure, L and C are the line inductance and shunt capacitance per unit length of the line respectively.

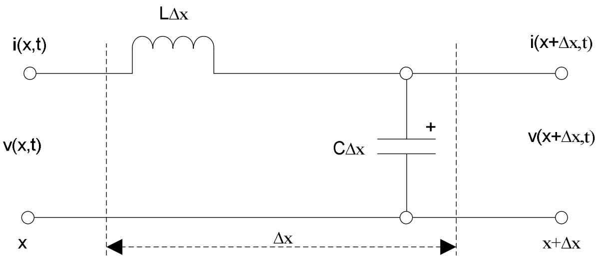

Figure 1. Approximate equivalent modelling of power distribution line.

For a small change in length, according to Kirchhoff's law the voltage and current equations for this circuit can be expressed as:

$$v(x+\Delta x,t)-v(x,t)=-L\Delta x\frac{\partial i(x,t)}{\partial t} \quad (1)$$

$$i(x+\Delta x,t)-i(x,t)=-C\Delta x\frac{\partial v(x,t)}{\partial t} \quad (2)$$

where $v(x,t)$ and $i(x,t)$ are the forward travelling voltage and current waves respectively. Using the Laplace transform and differential equation, we can obtain;

$$v(x,t)=v^{+}(t-\frac{x}{\upsilon})+v^{-}(t+\frac{x}{\upsilon}) \quad (3)$$

$$i(x,t) = i^{+}(t - \frac{x}{v}) + i^{-}(t + \frac{x}{v}) \quad (4)$$

where $v^{+}(t - x/v)$ and $i^{+}(t - x/v)$ are the forward travelling voltage and current waves respectively, $v^{+}(t + x/v)$ and $i^{+}(t + x/v)$ are the backward travelling voltage and current waves respectively and $v = 1/\sqrt{LC}$. Equations (3) and (4) give echo responses of voltage and current waves respectively. These echo responses are cross-correlated (CCR) with the incident impulse by the following formula:

$$C_{xy}(k) = \frac{1}{N}\sum_{i=1}^{N} x_i y_{i+k} \quad (5)$$

where C_{xy} is cross-correlation (CCR) function between reflected wave yi and incident wave xi. In this paper, the reflected signal obtained from TDR instrument along with CCR are used for SVM training phase.

It is to be noted that three echo responses of voltage and three echo responses of current obtained in a three-phase distribution system. Further, corresponding to each of these responses another three CCR responses for voltages and currents are obtained. Thus, the total number of deciding quantities for the nature of an electrical fault is twelve.

However, the main drawback of traditional TDR method using single pulse excitation is the amplitude attenuation along the line and the phase change distortion because of change in the frequency. In addition, the pulse width is one of the factors that effect to the accuracy of TDR method. To overcome these disadvantages, in this paper, an improved TDR method, using incident pseudo-random binary sequence (PRBS) is used. Further, a multi-layer SVM classifier is proposed as a supporting technique for TDR method to fault diagnosis in multi-branch distribution networks. The proposed approach is used to classify single phase to ground fault (AG, BG, CG), line to line fault (AB, AC, BC), double line to ground fault (ABG, ACG, BCG) and three phase fault (ABC).

3. Support Vector Machine

Support vector machine (SVM) is one of the most widely used techniques for classification of data. SVM maps the input data (x) into a high-dimensional feature space and builds an optimum hyperplane to separate samples from two classes [9]. A very basic concept of SVM is discussed below.

Let us assume that we have a set of training data, (x_i, y_i) , $i = 1, 2 \ldots m$ where $x_i \in R_n$ are feature vectors and $y_i \in (-1,+1)$ are label vectors. A binary classification problem can be posed as an optimization problem in the following way;

$$\text{Minimize } \frac{1}{2}\| \mathrm{w} \|_2^2 + C\sum_{i=1}^{m}\xi_i \quad (6)$$

Subjected to

$$y_i\left(\mathrm{w}.x_i\right) + b \geq 1 - \xi_i \text{ , } \xi_i \geq 0, i = 1,\ldots,m \quad (7)$$

where C is regularization parameter or penalty parameter; ξ_i is the penalizing relaxation variables. Equation (7) can be elaborated as follows;

$$\mathrm{w}.\phi(x_i) + b \geq +1 \text{ if } y_i = +1 \quad (8)$$

$$\mathrm{w}.\phi(x_i)+b \geq -1 \text{ if } y_i=-1 \tag{9}$$

The nonlinear classifier can be denoted in the input space as;

$$f(x)=sign(\sum_{i=1}^{m}\alpha_i^*.y_i.K(x_i,y_i)+b^*) \tag{10}$$

where $f(x)$ is the decision function, b^* is the bias calculated by the Karush-Kuhn-Tucker (KKT) conditions and $K(x_i, y_i)$ is the kernel function that produces the inner product for this feature space.

In this paper, the following radial basis function (RBF) is used as kernel function;

$$K(x,y)=\exp\left(-\gamma\|x-y\|^2\right) \tag{11}$$

where γ is kernel function parameter.

From equations (6) and (11), it is observed that the performance of SVM is dependent on regularization parameter C and kernel function parameter γ. Thus, to achieve the best classification, these two SVM parameters must be selected optimally. In this work, proposed mPSO is applied to optimize these two parameters to classify electrical faults.

4. Proposed Mutant-Particle Swarm Optimization

Particle swarm optimization (PSO) is inspired by social and cooperative behavior displayed by various species to fill their needs in the search space. The algorithm is guided by personal experience (P_{best}), overall experience (G_{best}) and the present movement of the particles to decide their next positions in the search space [16 - 18].

The initial population (swarm) of size N and dimension D is denoted as $X = [X_1, X_2,.., X_N]^T$, where 'T' denotes the transpose operator. Each individual (particle) X_p (p = 1, 2,..., N) is given as $X_p = [X_{p,1}, X_{p,2},...,X_{p,D}]$. Also, the initial velocity of the population is denoted as $V= [V_1,V_2,...,V_N]^T$. Thus, the velocity of each particle X_p (p = 1, 2, ..., N) is given as $V_p=[V_{p,1},V_{p,2}, ..., V_{p,D}]$. The index p varies from 1 to N whereas the index q varies from 1 to D.

4.1. Classical PSO (cPSO)

Mathematically, in cPSO, the updated positions of each particle in the search space can be expressed using the two equation discussed below.

$$V_{p,q}^{i+1}=w\times V_{p,q}^{i}+c_1r_1(P_{best\,p,q}^{\;i}-X_{p,q}^{i})+c_2r_2(G_{best\,q}^{\;i}-X_{p,q}^{i}) \tag{12}$$

$$X_{p,q}^{i+1}=X_{p,q}^{i}+V_{p,q}^{i+1} \tag{13}$$

In equation (12), c_1 and c_2 are two acceleration factors, r_1 and r_2 are two uniformly generated random numbers between [0, 1], w is inertia weight of the current movement of the population, $P_{bestp,q}^i$ represents personal best q^{th} component of p^{th} individual, whereas G_{bestq}^i represents q^{th} component of the best individual of population upto iteration i. Inertia weight decreases from its maximum value towards the minimum value as iteration proceeds. Mathematically, it is expressed as;

$$w=w_{\max}-(w_{\max}-w_{\min})\times ite/\max ite \tag{14}$$

where w_{min} and w_{max} are lower and upper limits on itertia weight *w*, *ite* is the current iteration and maxite is the maximum value of iteration set in the program [18].

The initial P_{best} of each particle is their initial position whereas the initial G_{best} is the initial best particle position among randomly initialized population [18]. The P_{best} and G_{best} of each particle are updated as follows;
At iteration k

$$if \quad F_p^{i+1} < F_p^i \quad then \quad P_{bestp}^{i+1} = X_p^{i+1}, \forall p \quad else \quad P_{bestp}^{i+1} = P_{bestp}^i, \forall p \tag{15}$$

$$if \quad F_{b1}^{i+1} < F_b^i \quad then\ G_{best}^{i+1} = P_{bestb1}^{i+1}, \quad and \quad b = b_1\ else \quad G_{best}^{i+1} < G_{best}^i \tag{16}$$

where f(·) is the objective function subject to minimization.

Repeat updating procedure until a stop condition is reached, such as a pre-specified number of iteration is met. Once terminated, the G_{best}^i and $f(G_{best}^i)$ are reported as the solution of PSO technique. The classical PSO suffers from getting trapped into local optima while solving a complex engineering problem. As a result, the obtained solution using classical PSO is only a sub-optimum solution. To escape classical PSO from getting trapped into local optima, in the paper a new modified mPSO is proposed. The proposed mPSO is having enough ability to escape from local optima because of introducing a mutant particle. The concept of mPSO is discussed below.

4.2. mPSO

The mPSO is a modified PSO in which the worst particle is replaced by the mutant-particle generated randomly by selecting one or more P_{best} components of some or all particles of the cPSO. The mutant-particle is a vector of the same size as each particle. It is denoted as M_{best}. For a population of NxD, where N is size of swarm and D is the dimension of each particle, M_{best} can be generated using the following;
for q=1:D

$$M_{bestq} = P_{best}(randi(N,1), q)$$

where randi(N,1) is a function uniformly generating an integer between 0 and N. Thus, in the above for-loop, a total of D integers are generated and the corresponding component from each column is selected from matrix P_{best} to form vector M_{best}. The process for forming M_{best} can easily be understood through an example. Let of suppose that the size of population is 6 and the dimension of each particle is 5. Now, in the for-loop, randomly generated indices are {3,5,1,5,4}. Thus, the components of vector M_{best} will the components of matrix P_{best} whose entries are non-italic.

	$P_{best1,1}$	$P_{best1,2}$	$P_{best1,3}$	$P_{best1,4}$	$P_{best1,5}$
	P_{best21}	$P_{best2,2}$	$P_{best2,3}$	$P_{best2,4}$	$P_{best2,5}$
	P_{best31}	$P_{best3,2}$	$P_{best3,3}$	$P_{best3,4}$	$P_{best3,5}$
P_{best} =	P_{best41}	$P_{best4,2}$	$P_{best4,3}$	$P_{best4,4}$	$P_{best4,5}$
	P_{best51}	$P_{best5,2}$	$P_{best5,3}$	$P_{best5,4}$	$P_{best5,5}$
	P_{best61}	$P_{best6,3}$	$P_{best6,3}$	$P_{best6,4}$	$P_{best6,5}$

M_{best} = [$P_{best3,1}$ $P_{best5,2}$ $P_{best1,3}$ $P_{best5,4}$ $P_{best4,5}$]

Once M_{best} is generated, the corresponding objective function is also evaluated. Also, the objective function corresponding to the worst particle is evaluated. If the mutant particle is having better value of objective function, then the worst particle is replaced by M_{best}. It can be expressed as follow;

At iteration k

$$If\ f\ (M_{best}{}^{i+1})\ <\ f\ \left(P_{best\ worst}{}^{i}\right)\ then\qquad P_{best\,worst}{}^{i+1} = M_{best}{}^{i+1} \tag{17}$$

The overall search mechanism in multidimensional search space of MPSO is similar to the classical PSO which is shown in Figure 2.

The MPSO algorithm can be expressed using the following steps:

- Set w_{min}, w_{max}, c_1, and c_2 parameters
- Initialize positions X and velocities V of each particle of population
- Evaluate fitness of each particle $F_p{}^i = f(X_p{}^i)$, $\forall p$ and find the best particle index b
- Select $P_{bestp}{}^i = X_p{}^i$, $\forall p$ and $G_{best}{}^i = X_b{}^i$
- Set iteration count $i = 1$
- $w = w_{\max} - (w_{\max} - w_{\min}) \times ite / \max ite$
- Update velocity and position of each particle using eqns. (12) and (13)
- Evaluate updated fitness of each particle $F_p{}^{i+1} = f(X_p{}^{i+1})$, ∀p and find the best particle index b_1
- Update P_{best} of each particle ∀p

If $F_p{}^{i+1} < F_p{}^i$ then $P_{bestp}{}^{i+1} = X_p{}^{i+1}$, else $P_{bestp}{}^{i+1} = P_{bestp}{}^i$,

- Update M_{best} of population and the corresponding particle of P_{best}

If $F_{worst}{}^{k+1} < F_{Mutant}{}^i$ then $P_{best worst}{}^{i+1} = M_{best}{}^{i+1}$

where $F_{Mutant}{}^i = f(M_{best}{}^i)$

- Update Gbest of population

If $F_{b1}{}^{i+1} < F_b{}^i$ then $G_{best}{}^{i+1} < P_{bestb1}{}^{i+1}$ and set $b = b_1$ else $G_{best}{}^{i+1} < G_{best}{}^i$

If $k < Maxite$ then $i = i+1$ and goto step 6 else goto step 13

- Optimum solution obtained print the results of optimum generation as $G_{best}{}^i$

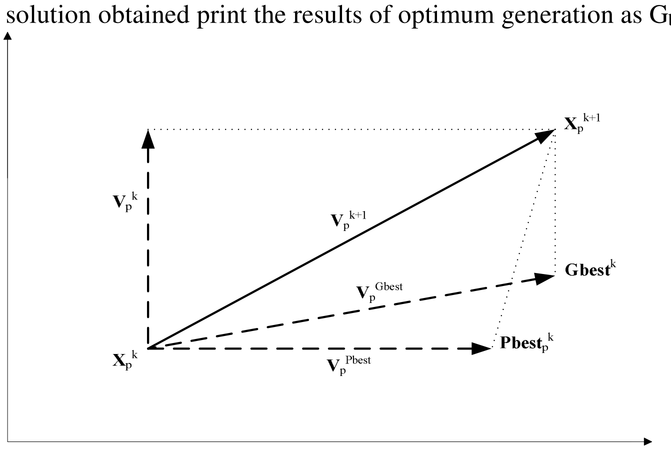

Figure 2. The PSO search mechanism of pth particle at kth iteration.

A detailed flowchart of mPSO considering the above steps is shown in Figure 3.

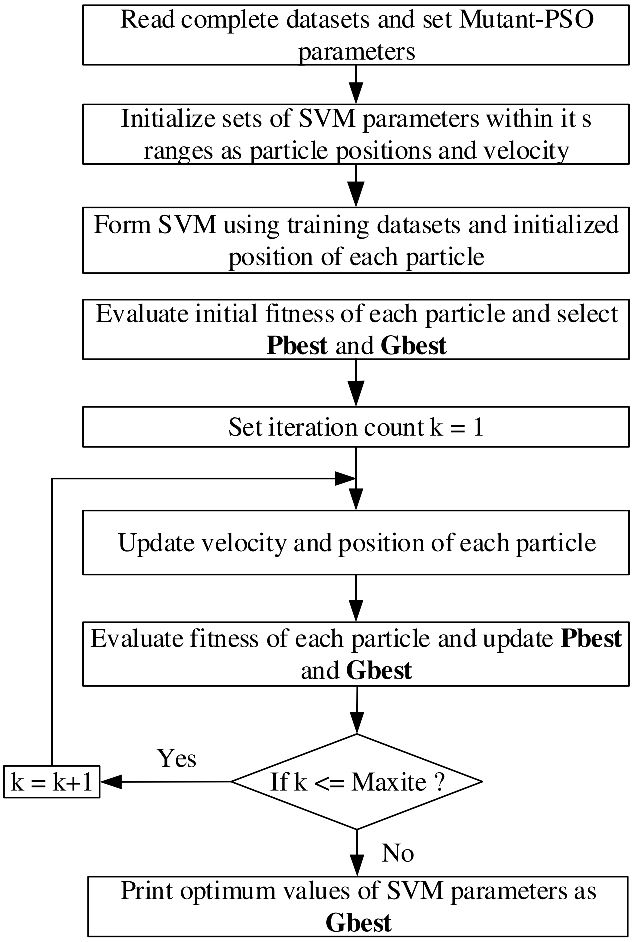

Figure 3. Flowchart of the proposed mPSO for optimizing parameters of SVM.

5. The mPSO based SVM for Fault Detection

Using TDR method with PRBS excitation faulted systems dataset is collected. The collected dataset is divided into two groups which are known as training and testing dataset. The proposed MPSO is used to optimize SVM parameters using training dataset. Once, SVM is trained, i.e., the optimum values of regularization parameter C and kernel function parameter γ are obtained, then SVM with these parameters are used to classify various faults on testing dataset. Overall approach is shown in Figure 4.

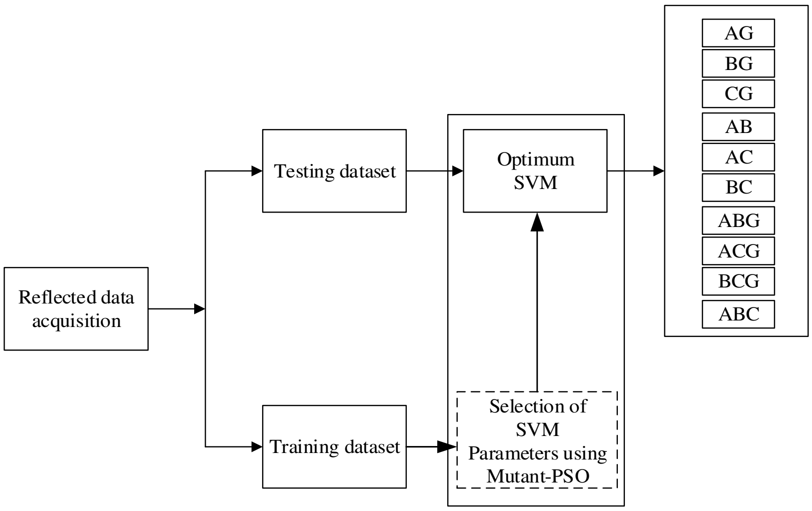

Figure 4. Proposed SVM using MPSO for fault classification.

6. Test Results and Discussion

Using TDR analysis with PRBS on a typical two-branch network shown in Figure 5, all the ten types of faults have been simulated and 12 features have been obtained at the substation end corresponding to each fault as discussed in Section 3.

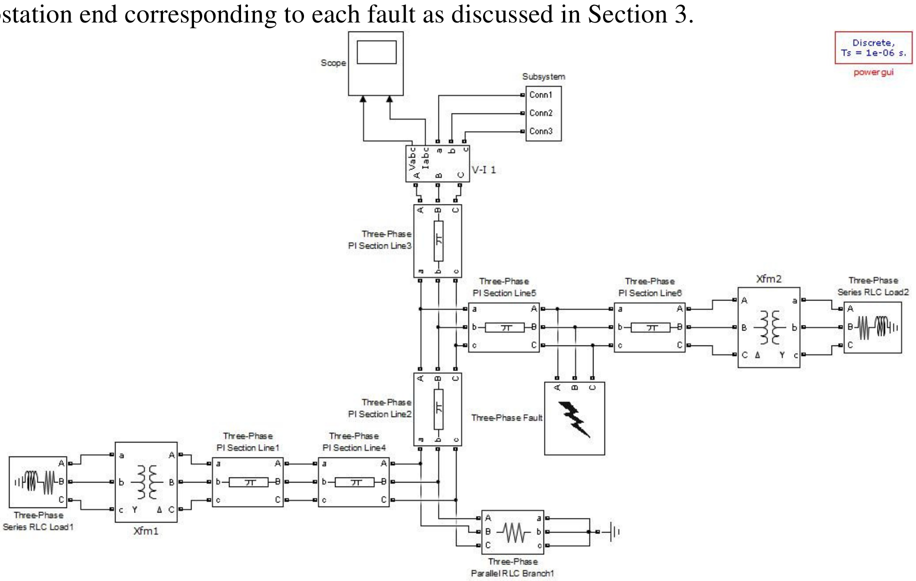

Figure 5. Simulating model of a two-branched distribution system.

By simulating equal numbers of each type of fault on various locations, a total of 5700 datasets have been recorded. This dataset has been divided randomly among training dataset and testing dataset. In training dataset, there are 4500 set of responses whereas in testing dataset, there are 1200 set of responses. It is to be noted that each set of response has 12 features.

The following parameters for classical PSO and mPSO have been considered. It is to be noted that these parameters have been selected after doing repeated run by varying them.

a) Swarm size has been taken as 10

b) Lower and upper limits of inertia weight have been taken as 0.4 and 0.9

c) Acceleration factors c_1 and c_2 have been taken as 1.5 and 2.5 respectively

d) Maximum iteration has been set to 1000.

Table 1 gives the results of the fault classification for the dataset discussed above using SVM classifier whose parameters are optimized by cross-validation, classical PSO, and the proposed mPSO techniques. The convergence characteristic of the proposed mPSO is shown in Figure 6.

Table 1. Results of MPSO SVM classification using various optimization techniques

classifier	C	γ	Classification accuracy (%)	Training time (sec)
Cross-validation SVM	181.0193	1.1212	93.00	63.54
cPSO-SVM	959.3098	6.2093	94.25	240.35
mPSO-SVM	16.7634	5.7330	96.00	198.67

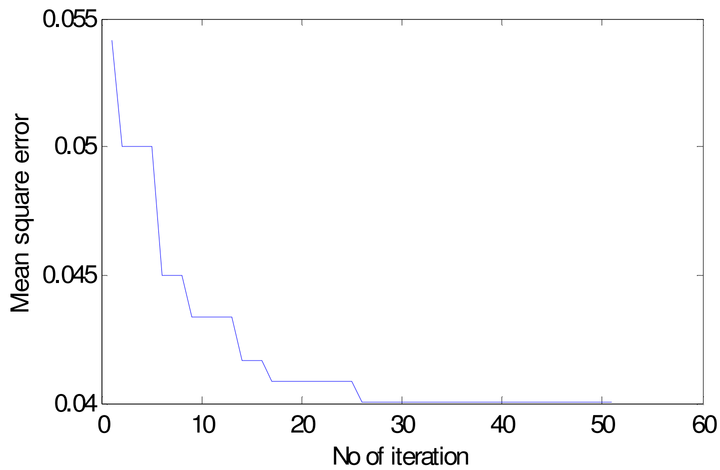

Figure 6. Convergence characteristic of the proposed MPSO.

From Table 1, it is observed that the optimum values of C and γ of SVM classifier are 16.7634 and 6.2093 with testing data accuracy of 96.00% in 198.67 seconds by the proposed mPSO. Furthermore, it can be observed that mPSO is resulting into the highest accuracy than any other SVM parameters optimizers. Also, training time taken by the proposed mPSO is less than that of PSO. However, cross-validation SVM has taken the least time but their resulting accuracy is the lowest (93.00%). As achieving higher accuracy is the most desirable feature for the fault diagnosis so the SVM parameters obtained using mPSO is the best among the all three methods discussed. From Figure 6, it is observed that MSE beyond 28 iterations are non-decreasing and thus the optimized parameters of SVM can be obtained much before the total training time taken (198.67 sec).

7. Conclusion

In this paper, a new modified PSO algorithm named mutant particle swarm optimization (mPSO) has been proposed for optimizing support vector machine (SVM) parameters to classify short circuit fault in radial power distribution network. Further, time domain reflectometry (TDR) with pseudo-random binary sequence (PRBS) stimulus has been utilized for generating fault current dataset. The proposed approach has been successfully applied to identify the all ten types of short circuit fault in a typical two-lateral radial distribution system. Further, the results obtained by the proposed mPSO has been compared by that obtained by cross-validation and cPSO. The obtained high classification accuracy (96%) and the comparative results demonstrate the superiority of the proposed mPSO in classifying short circuit faults.

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