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A novel perturbed particle swarm optimization-based support vector machine for fault diagnosis in power distribution systems

Hoang THI THOM[1,*], Cho MING YUAN[1], Vu QUOC TUAN[2]
[1]Department of Electrical Engineering, National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan
[2]Department of Basic Engineering, Naval Academy, Vietnam

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Abstract: In this paper, a novel perturbed particle swarm optimization (PPSO) algorithm is investigated to improve the performance of a support vector machine (SVM) for short-circuit fault diagnosis in power distribution systems. In the proposed PPSO algorithm, the velocity of each particle is perturbed whenever the particles strike into a local optimum, in order to achieve a higher quality solution to optimization problems. Furthermore, the concept of proposed perturbation is applied to three variants of PSO, and improved corresponding algorithms are named perturbed C-PSO (PC-PSO), perturbed T-PSO (PT-PSO), and perturbed K-PSO (PK-PSO). For the purpose of fault diagnosis, the time-domain reflectometry (TDR) method with pseudorandom binary sequence (PRBS) excitation is considered to generate the necessary fault simulation data set. The proposed approaches are tested on a typical two-lateral radial distribution network.

Key words: Fault diagnosis, particle swarm optimization, power distribution networks support vector machine, time-domain reflectometry

1. Introduction

A distribution system is one of the most important parts of an electrical power system. As a large number of connections are present in any distribution system, systems are highly susceptible to various types of electrical short-circuit faults. These electrical faults not only interrupt the electrical power supply, but may also severely damage the system [1,2]. Therefore, it is necessary to locate the fault and classify its type in order to guarantee the reliability of the system [3].

Various approaches have been proposed to identify the types of short circuit fault in distribution systems. These approaches can be divided into three separate categories: impedance-based method [4,5], travelling wave-based method [6,7], and artificial intelligence-based method [8,9]. Among them, the most popular method for fault diagnosis in distribution systems is based on the travelling wave theory, in which time-domain reflectometry (TDR) is widely used [10–12]. However, TDR is an imperfect method due to the complex characteristics of distribution systems [13]. As such, it requires an intelligent algorithm to support fault diagnosis in multibranch networks from the reflectometry trace provided. Artificial neural networks (ANNs) [14,15] and support vector machines (SVMs) [16–18] have been widely applied to fault diagnosis in distribution systems, in which SVM gives better results compared to ANN.

*Correspondence: thomht@ntu.edu.vn

In classification problems, the parameter selection of SVM plays the most important role [19]. As a result, to obtain optimum SVM parameters, various optimization techniques have been used such as the grid search method (GSM) [20], genetic algorithm (GA) [21,22], and particle swarm optimization (PSO) [23,24]. Although these methods are quite effective, they suffer from becoming trapped into local optima and from excessive time requirements.

In this paper, a novel perturbed particle swarm optimization (PPSO) algorithm is investigated whenever the particles strike into a local optimum to improve the classification accuracy of the SVM classifiers for fault classification in distribution systems. Furthermore, the concept of proposed perturbation is applied to three variants of PSO, and the corresponding PPSO algorithms are validated on five benchmark optimization problems. For the purpose of fault classification, the TDR method with pseudo-random binary sequence (PRBS) excitation in MATLAB-Simulink environment has been considered to generate the necessary fault data set. Ten types of fault are classified, including single line-to-ground faults (AG, BG, CG), line-to-line faults (AB, AC, BC), double line-to-ground faults (ABG, ACG, BCG), and three-line faults (ABC).

2. Time-domain reflectometry approach

TDR uses a single pulse injection into a line or cable, and records echo responses that are caused by any impedance mismatches, including electrical faults, tee joints, or line terminals. Therefore, these obtained TDR curves are useful for identifying the nature of any electrical fault [25].

Assume a distribution line is modeled by a lumped-parameter equivalent circuit, as shown in Figure 1, with a distributed series inductance L, resistance R, capacitance C, and conductance G.

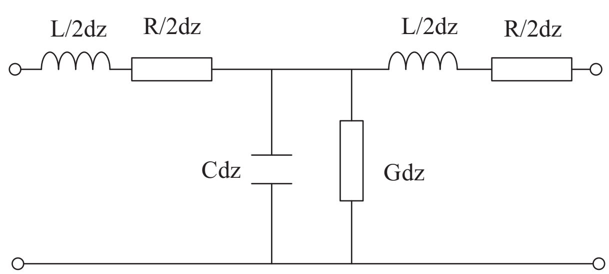

Figure 1. Approximate modeling of a typical distribution line.

The voltage and current traveling along the line can be expressed as

$$\frac{\partial v(x,t)}{\partial x} = -Ri(x,t) - L\frac{\partial i(x,t)}{\partial t} \tag{1}$$

$$\frac{\partial i(x,t)}{\partial x} = -Gv(x,t) - C\frac{\partial v(x,t)}{\partial t} \tag{2}$$

In Eqs. (1) and (2), $v(x,t)$ and $i(x,t)$ are the forward-travelling voltage and current waves, respectively. The solution to these equations, after taking the Laplace transform, can be expressed as

$$V(x,s) = V^{+}(s)e^{-\gamma(s)x} + V^{-}(s)e^{+\gamma(s)x} \tag{3}$$

$$I(x,s) = I^{+}s)e^{-\gamma(s)x} + I^{-}(s)e^{+\gamma(s)x}, \tag{4}$$

where $\gamma(s) = \sqrt{(R+sL)(G+sC)}$. The inverse transformer of these equations can be expressed as

$$v(x,t) = e^{-\alpha x} v^{+}(t - \frac{x}{v}) + e^{+\alpha x} v^{-}(t + \frac{x}{v}) \tag{5}$$

$$i(x,t) = e^{-\alpha x} i^{+}(t - \frac{x}{v}) + e^{+\alpha x} i^{-}(t + \frac{x}{v}) \tag{6}$$

In Eqs. (5) and (6), $v^{-}(t + x/v)$ and $i^{-}(t + x/v)$ are the backward-traveling voltage and current waves, respectively, $v^{+}(t - x/v)$ and $i^{+}(t - x/v)$ are the forward-traveling voltage and current waves, respectively, and $v = 1/\sqrt{LC}$ are the traveling velocity.

In this paper, since the fault diagnosis methods based on TDR traces are inherently imprecise, the reflected responses obtained from TDR analysis are cross-correlated (CCR) with the incident impulse, using Eq. (7). After that, the reflected signals and CCR are input into an enhanced SVM classifier for the purpose of fault classification.

$$C_{xy}(k) = \frac{1}{N} \sum_{i=1}^{N} x_i y_{i+k}, \tag{7}$$

where C_{xy} is the CCR function between the reflected wave y_i and the incident wave x_i.

3. Support vector machine

SVM is one of the most widely utilized techniques for classifying data. This technique maps the input data (x) into a high-dimensional feature space and builds an optimum hyperplane to separate samples from two given classes. Constructing this hyperplane is considered as solving an optimization problem as follows:

Minimize:

$$\frac{1}{2} ||w||_2^2 + C \sum_{i=1}^{m} \xi_i \tag{8}$$

Subjected to:

$$y_i \left(w \cdot x_i \right) + b \geq 1 - \xi_i, \xi_i \geq 0, i = 1, ..., m, \tag{9}$$

where $\mathrm{x}_i \in \mathrm{R}_n$ are feature vectors, $\mathrm{y}_i \in (-1,+1)$ are label vectors, C is the tradeoff regularization parameter, and ξ_i are the penalizing relaxation variables.

The nonlinear classifier can be denoted in the input space as

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

where f(x) is the decision function, α_i are the Lagrangian multipliers, b^* is the bias, and $\mathrm{K}(\mathrm{x}_i, \mathrm{y}_i)$ is the kernel function. In this paper, the following radial basis function (RBF) is used as a kernel function:

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

where γ is the kernel function parameter for RBF.

From Eqs. (8), (10), and (11), it is observed that the classification accuracy of SVM is dependent on the regularization parameter C and the kernel function parameter γ.

4. Proposed perturbed particle swarm optimization algorithm

4.1. Review of particle swarm optimization

PSO is a swarm intelligence-based optimization technique. It is inspired by the social and cooperative behavior displayed by various species to fulfil their needs. The algorithm is guided by the present movement, personal experience (Pbest), and overall experience (Gbest) of the particles to decide their next positions in the search space. Furthermore, the experiences are accelerated by factors c_1 and c_2, and random numbers r_1 and r_2, generated between [0, 1], whereas the present movement is multiplied by an inertia factor w. More details about the basic conceptualization of PSO can be found in [26,27]. Several popular variants of PSO are classical PSO [28], time-varying acceleration coefficients PSO (T-PSO) [29], and constriction PSO (K-PSO) [30].

PSO convergence is faster compared to many swarm intelligent algorithms due to the ability of the particles to converge towards the nearest optimum point, resulting from the value of the inertia weight, which is less than one (between 0.4 and 0.9). The presence of this factor reduces the velocity of each particle in the search space. Therefore, the velocity of each particle becomes very small after a certain number of iteration; each particle is unable to change its position considerably and, hence, becomes trapped into a local optimum. The dynamics of the particles with a larger length of arrows in IPs in the multidimensional search space in the PSO algorithm are given in Figure 2.

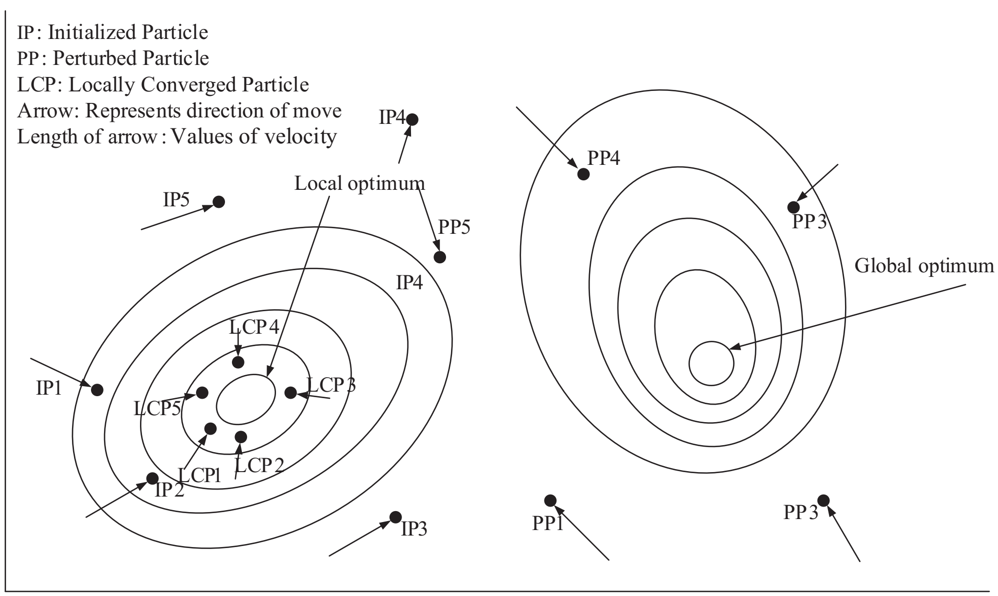

Figure 2. Particle dynamics in the multidimensional search space in the PSO algorithm.

To overcome this problem, a newly improved PPSO algorithm is introduced in this paper.

4.2. Concept of the proposed PPSO algorithm

Perturbation in the velocity vector of each particle needs to be performed whenever the particles get struck into a local optimum. Normally, this situation occurs when the solution (Gbest of the swarm) does not improve for a prespecified number of iterations, such as when the tolerance or a stopping criterion (other than maximum iteration) is met. Therefore, the velocity vector of each particle needs to be reset, so that particles can get a big thrust that pushes them to escape from the local optimum. Mathematically, the perturbation concepts of velocity for each particle can be expressed as follows:

$$V_{p,q}^{k+1} = pbest_{p,q}^{k} \tag{12}$$

Furthermore, the tolerance limit needs to be relaxed, so that the swarm can get another chance to resume the search for a minimum number of iterations. Additionally, such perturbation may be allowed a certain number of times. Consequently, the proposed perturbation in the velocity vector of each particle allows the particles to keep exploring the search space in order to escape from the local optimum. A typical distribution pattern of each particle with a larger length of arrows in PPs is shown in Figure 2.

The PPSO algorithm can be expressed using the following steps:

1: Set parameters and initialize X and V of each particle of the population;

2: Evaluate the fitness of each particle $F_p^k = f(X_p^k)$, and find the best particle index b;

3: Select $Pbest_p^k = X_p^k$, $\forall$p and $Gbest^k = X_b^k$;

4: Set iteration count k = 1 and tolerance tol = 1;

5: Update the velocity and position of each particle;

6: Evaluate the updated fitness of each particle $F_p^{k+1} = f(X_p^{k+1})$, $\forall$p and find the best particle index b1;

7: Update the Pbest of each particle $\forall$p.

If $F_p^{k+1} < F_p^k$, then $Pbest_p^{k+1} = X_p^{k+1}$, else $Pbest_p^{k+1} = Pbest_p^k$

8: Update the Gbest of the population.

If $F_{b1}^{k+1} < F_b^k$, then $Gbest^{k+1} < Pbest_{b1}^{k+1}$ and set b = b1, else $Gbest^{k+1} < Gbest^k$.

9: If tol < tol_max, then V = Pbest and tol = 1. Go to Step 10, else tol = $F_b^k - F_{b1}^{k+1}$ and go to Step 10.

10: If k < Maxite then k = k + 1. Go to Step 5 or Step 11.

11: Optimum solution is obtained. Print the results of optimum solution as $Gbest^k$.

5. The PPSO-based SVM for fault classification

The overall structure of the proposed PPSO-based SVM approach is shown in Figure 3. In the work, a 127-bit PRBS disturbance is injected into the distribution feeder under test at a frequency (f) of 1 MHz. The reflected responses are caused by any electrical fault on feeder and laterals, and are then cross-correlated with the incident impulse with Eq. (7). The reflected voltage, current magnitudes, and the CCR peaks between reflected and incident waves are chosen as the input features of the SVM classifier, and the fault types are chosen as the output features. Therefore, the total number of derived features is 12 and comprises a feature vector $V = [v_1\ v_2 \ldots v_{12}]^T$, where v_1–v_6 are the reflected voltage values (v_a, v_b, v_c) and reflected current values (i_a, i_b, i_c), and v_7–v_{12} are the peaks of CCR functions between reflected and incident waves of voltage and current. Then this input data set is divided into two groups, known as the training and testing data set. Next, the optimization of SVM parameters, using the PPSO algorithm, is performed on the training data set, whereas the testing data set are used to calculate the sum of mean square error (MSE) with the target testing data set. This process is repeated until the MSE becomes the least, which occurs at the point of optimum SVM parameters. Finally, once SVM is trained, the optimum values of regularization parameter C and kernel function parameter γ are obtained, and then SVM that possess these parameters are used to classify fault types in the testing data set.

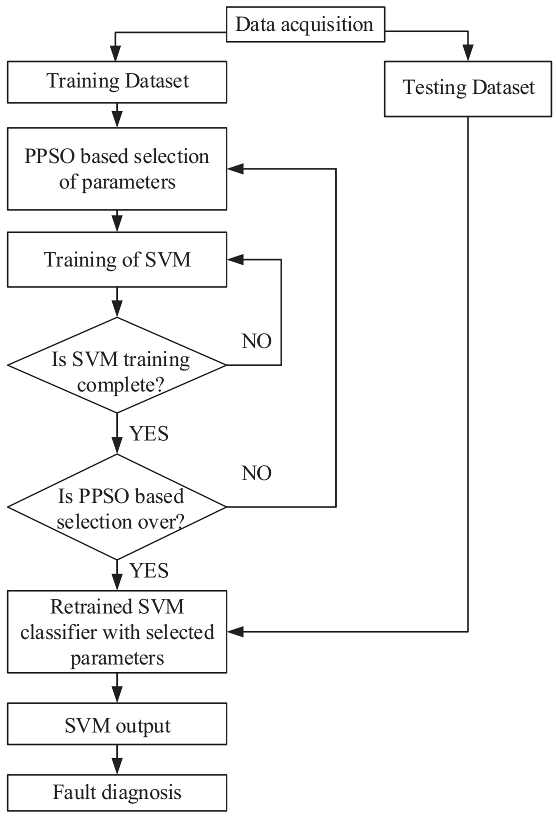

Figure 3. Flowchart of the proposed PPSO algorithm for optimizing SVM parameters.

6. Test results and discussion

The proposed PPSO algorithm was validated on five benchmark problems and was then used to optimize SVM parameters for the purpose of fault diagnosis in distribution systems. For this purpose, the following parameters were considered for three different variants of PPSO: perturbed C-PSO (PC-PSO), perturbed T-PSO (PT-PSO), and perturbed K-PSO (PK-PSO) algorithms, respectively. It is worth noting that these parameters were selected after performing repeated runs by varying them.

- Swarm size is taken as 10;
- Lower and upper limits of inertia weight are taken as 0.4 and 0.9, respectively (PC-PSO algorithm);
- Acceleration factors c_1 and c_2 are taken as 1.5 and 2.5, respectively (PC-PSO algorithm);
- Lower and upper limits on acceleration factors c_1 and c_2 are taken as 2.025, 2.075 and 2.025, 2.075, respectively (PT-PSO algorithm);

- Acceleration factors c_1 and c_2 are taken as 2.05 and 2.05, respectively, and constriction factor K as 0.729 (PK-PSO algorithm);
- Number of instants is 3 after the velocity perturbation is applied;
- Maximum iteration is set to 1000.

The programs were developed in MATLAB environment and executed on an Intel Core i7 processor and 2.66-GHz clock frequency with 8192 MB RAM.

6.1. Testing the proposed PPSO algorithm on benchmark problems

The proposed PPSO algorithm was tested on five benchmark problems, given in Table 1, to prove the effectiveness of the developed algorithms in solving complex optimization problems. The obtained results of three newly developed PPSO algorithms with different population sizes are given in Table 2.

Table 1. Five benchmark unconstrained optimization problems.

Name	Function	Dimension	Variable range	Optimum values
Beale function	$f1 = (1.5 - x_1 - x_1x_2)^2 + (2.25 - x_1 - x_1x_2^2)^2 + (2.625 - x_1 - x_1x_2^3)^2$	2	[–10, 10]	$f(3, 0.5) = 0$
Levi function	$f2 = \sin^2(3\pi x_1) + (x_1^2 - 1)^2\left(1 + \sin^2(3\pi x_2)\right) + (x_2^2 - 1)^2\left(1 + \sin^2(3\pi x_2)\right)$	2	[–10, 10]	$f(1, 1) = 0$
Booth function	$f3 = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$	2	[–10, 10]	$f(3, 0) = 0$
Sphere function	$f4 = \sum_{i=1}^{n} x_i^2$	10	[–20, 20]	$f(0, 0, ..., 0) = 0$
Ackley function	$f5 = 20 + e - 20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)$	10	[–20, 20]	$f(0, 0, ...0) = 0$

From Table 2, it is observed that the three developed PPSO algorithms successfully solved the benchmark problems. PT-PSO gives the least values of f1 and f2 using population sizes 10 and 20, respectively, PC-PSO gives the least value of f3 using population size 50, whereas PK-PSO gives the least values of f4 and f5 using population sizes 100 and 20, respectively.

6.2. Testing the proposed PPSO algorithm for optimizing the parameters of SVM fault classifier

For the purpose of fault classification, the proposed PPSO-based SVM classifiers are performed on a two-lateral radial distribution system, as given in Figure 4. A total of 5600 fault cases, with 12 features for each type of fault, have been simulated using the TDR method with PRBS stimulus. It is noted that 560 samples have been recorded for each type of fault by varying the fault distance from the substation to the end of the line.

Table 2. Optimum results of the proposed PPSO algorithms on benchmark problems.

Function	Algorithm	Population size					
		10	20	30	40	50	100
f1	PC-PSO	1.95e–13	1.39e–17	2.56e–16	3.22e–16	6.15e–19	1.33e–15
	PT-PSO	7.81e–21	4.99e–13	4.15e–17	5.98e–18	1.74e–16	1.45e–15
	PK-PSO	2.75e–15	4.68e–17	8.56e–15	4.17e–18	1.46e–15	9.13e–18
f2	PC-PSO	2.38e–18	2.69e–15	2.72e–16	2.01e–17	6.81e–16	9.05e–16
	PT-PSO	6.42e–17	5.49e–20	5.63e–16	1.74e–17	4.22e–17	1.22e–13
	PK-PSO	2.57e–16	2.14e–18	9.02e–20	1.51e–16	1.62e–18	2.66e–17
f3	PC-PSO	1.59e–16	1.21e–15	1.12e–17	4.17e–16	3.90e–19	7.66e–19
	PT-PSO	2.48e–14	2.01e–17	2.49e–16	1.10e–16	8.33e–17	3.92e–18
	PK-PSO	2.04e–17	1.51e–18	2.55e–17	1.87e–17	2.81e–17	6.44e–18
f4	PC-PSO	1.14e–14	5.33e–17	1.65e–19	2.95e–20	8.60e–23	1.25e–24
	PT-PSO	7.74e–17	1.67e–20	1.58e–23	1.30e–23	2.83e–24	1.57e–28
	PK-PSO	2.98e–24	6.24e–27	1.86e–28	2.88e–31	2.61e–30	2.05e–32
f5	PC-PSO	5.11e–06	2.72e–08	6.05e–10	2.96e–10	9.76e–12	3.82e–14
	PT-PSO	4.76e–08	2.29e–11	9.14e–11	4.89e–12	2.17e–12	1.33e–14
	PK-PSO	6.22e–15	2.66e–15	2.66e–15	2.66e–15	2.66e–15	2.66e–15

Additionally, it is noted that this data set has been divided into training and testing data sets in the ratio of 4:1, and has then been input into the SVM for the purpose of classification.

Table 3 gives the classification results for the SVM classifier, whose parameters are selected by nonoptimization and optimization algorithms.

Table 3. Performance with nonoptimization and optimization algorithms.

Classifier	C	γ	Classification accuracy (%)
Nonoptimization SVM	100	0.33	85.98
PSO-SVM	97.22	8.23	96.16
GA-SVM	3.42	3.10	96.42
PPSO-SVM	186.75	0.92	97.23

As can be clearly seen from Table 3, optimization algorithms are capable of improving the performance of the SVM classifier. If there is no optimization algorithm, the successful rate of the SVM classifier is 85.98%. Meanwhile, the obtained result when using the proposed PPSO algorithm is 97.23%, which is higher than that obtained using PSO (96.16%) and GA (96.42%). The optimum parameters of the PPSO-based SVM classifier are C = 186.75 and γ = 0.92.

Furthermore, the results obtained using the proposed PPSO algorithms are compared to those obtained using the original PSO variants, as shown in Table 4. The corresponding convergence characteristics of the PSO and PPSO algorithms are shown in Figure 5.

It can be clearly seen from Table 4 that the developed PPSO algorithms give better results compared

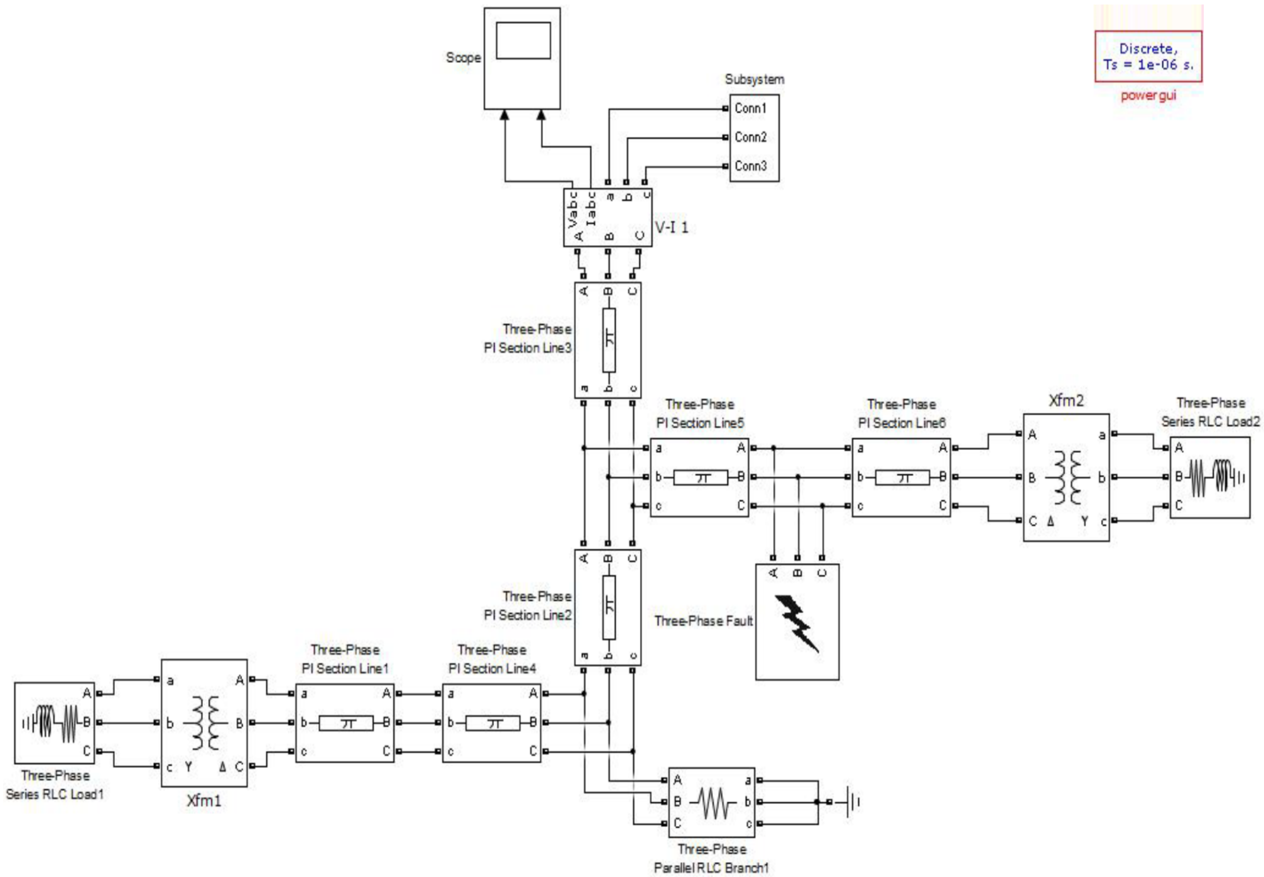

Figure 4. Simulation model of a two-branched distribution system.

Table 4. Performance with the novel PPSO algorithms and the original PSO variants.

SVM	Optimum SVM parameters		Accuracy	Run time
	C	γ	(%)	(seconds)
With PC-PSO	304.04	0.50	96.25	122.5
With PT-PSO	221.21	2.85	96.96	119.9
With PK-PSO	186.75	0.92	97.23	102.0
With C-PSO	107.17	1.10	96.16	142.8
With T-PSO	206.17	3.75	96.87	112.1
With K-PSO	384.85	0.61	96.87	109.3

to the original PSO variants, in which PK-PSO gives the highest accuracy of 97.23%. Additionally, Table 4 shows that PK-PSO takes 102 s to converge, whereas the simulation time is 122.5 s for PC-PSO and 119.9 s for PT-PSO. It can be concluded that PK-PSO gives the highest classification accuracy in the shortest time.

From Figure 5, it can be observed that the characteristics of the PPSO algorithms are better (lower) than those of basic PSO algorithms, in which the characteristic of the PK-PSO is optimal.

6.3. Effects of different division of training and testing data sets

This subsection studies the effects of different ratios of diving, training, and testing data sets on classification accuracy. For this purpose, the entire data set has been divided into two different ratios for the training and testing data set: 3:1 and 4:1.

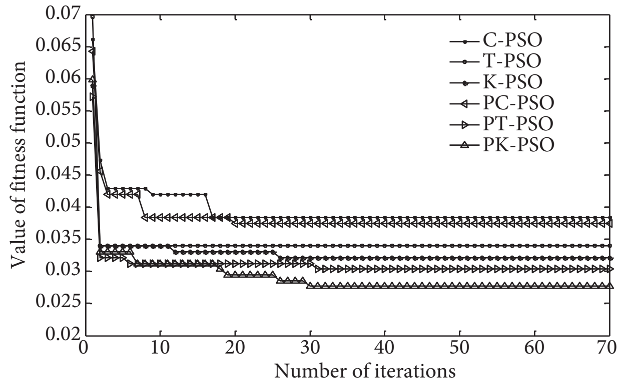

Figure 5. Comparative convergence characteristics of various PSO algorithms.

Since the PK-PSO variant gives the best result, it has been applied to test the classification performance of these two data set divisions. Table 5 shows the results for the PK-PSO-based SVM classifier with the different divisions of the data set.

Table 5. Results of the PK-PSO-based SVM classifier using various data set divisions.

Data set division	C	γ	Classification accuracy (%)	Training time (s)
3:1	122.38	0.41	96.67	102.68
4:1	186.75	0.92	97.23	102.00

It can be observed from Table 5 that the performance of the proposed classifier gives the highest accuracy in the training and testing data set division with a 4:1 ratio. In other words, a higher training data set gives better results as opposed to the use of a lower data set.

7. Conclusion

In this paper, three PPSO algorithms were developed to select the parameters of the SVM for the purpose of classifying the fault types in distribution systems. The results obtained by nonoptimization and other optimization algorithms were compared. Furthermore, time-domain reflectometry (TDR) with pseudo-random binary sequence (PRBS) stimulus has been utilized for generating the reliable fault data set. Overall, the following conclusions can be drawn from this study:

1) The optimization algorithms are capable of solving benchmark problems and improving the performance of the SVM fault classifiers.

2) The novel PPSO algorithms give better results than the original PSO variants and the GA.

3) The PP-PSO variant gives the highest classification accuracy in the shortest time among the newly developed algorithms.

4) Provision of a higher training data set gives better results compared to that performed with a lower data set.

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