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RESEARCH ARTICLE - ELECTRICAL ENGINEERING

Power System Voltage Stability Assessment Using a Hybrid Approach Combining Dragonfly Optimization Algorithm and Support Vector Regression

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Abstract
In this paper, an efficient approach based on the combination of dragonfly optimization (DFO) algorithm and support vector regression (SVR) has been proposed for online voltage stability assessment. As the performance of the SVR model extremely depends on careful selection of its parameters, the DFO algorithm involves SVR parameters setting, which significantly ameliorates their performance. In the proposed approach, the voltage magnitudes of the phasor measurement unit (PMU) buses are adopted as the input data for the hybrid DFO–SVR model, while the minimum values of voltage stability index (VSI) are taken as the output vector. Using the data provided by PMUs as the input variables makes the proposed model capable of assessing the voltage stability in a real-time manner, which helps the operators to adopt the required measures to avert large blackouts. The predictive ability of the proposed hybrid model was investigated and compared with the adaptive neuro-fuzzy inference system (ANFIS) through the IEEE 30-bus and the Algerian 59-bus systems. According to the obtained results, the proposed DFO–SVR model can successfully predict the VSI. Moreover, it provides a better performance than the ANFIS model.

Keywords Voltage stability assessment · Phasor measurement unit · Support vector regression · Dragonfly optimization algorithm

1 Introduction

Electric power systems have become larger and more complex. They operate close to their stability limits, with a small security margin. Under such a situation, any disturbance, such as generator, transformer or transmission line outages, can lead to voltage instability the cause of many blackouts in different countries [1]. The occurrence of the blackouts and their large impacts clearly demonstrate the great importance of online voltage security/stability assessment.

Owing to its ability to perform parallel data processing with high accuracy and swift response, the artificial neural network (ANN) has attained increasing importance in recent years as a tool for assessment of voltage stability [2–6]. Although ANNs have gained the attention of researchers, it has some shortcomings, particularly with respect to the relatively long time required for learning, sticking at local minima, and the fact that the learning is highly dependent on the number of training data [7]. To remedy these shortcomings, some substitute methods, such as support vector machine (SVM), have been proposed.

SVM is a novel machine learning technique introduced by Vapnik [8]. It is based on statistical learning theory and structural risk minimization. Recently, the SVM has emerged as an effective computational technique, due to its performance in solving classification and regression problems. Support vector regression (SVR), the regression version of SVM, is the widespread form of application of SVM. However, in the area of voltage stability monitoring, most of the published works use the SVM as a classification tool. Cortés et al. [9] successfully employed every single SVM that was trained to classify the situations of a power system as secure, alert and emergency. The final classification, representing a system security assessment, is extracted from the coalescence of each classifier output undertaken by utilizing the Bayesian

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rule. This approach has been applied in a relatively analogous manner with the proposed multi-class SVM used for security assessment, which has been discussed in [10]. In the proposed approach, there are four different statuses of system security which are normal, alert, emergency_1 and emergency_2. Further amelioration of multi-class SVM has been undertaken by consolidating the pattern recognition approach for security assessment [11]. SVR was introduced into voltage stability assessment by Suganyadevi and Babulal [12], it was proposed to evaluate the voltage stability of power system incorporating flexible AC transmission system (FACTS) devices. On the overleaf, a new methodology for online prediction of voltage stability margin has been introduced by deploying the SVR trained by considering the input information of real and reactive power load at all buses [13].

Notwithstanding that SVR is a robust tool to solve nonlinear regression problems, there are no general guidelines to define their parameters, which is an obstacle to the widespread of the use of SVR in manufacturing applications and scientific research. Therefore, the main concern for researchers is to reveal convenient parameter values for a given data set in SVR that can ensure high accuracy. Inappropriate SVR parameters values cause over-fitting or under-fitting problems, and various parameter settings can also lead to considerable differences in performance [14]. Traditionally, the grid search algorithm [15] and gradient descent algorithm [16] are the most commonly applied algorithms to select SVM parameters. Convergence to local minima point, computational complexity and height computational time requirement are the major drawbacks of these conventional methods [17]. With the development of meta-heuristic optimization algorithms, some of them have been adopted to determine the SVR parameters, such as genetic algorithm (GA) [18,19] and particle swarm optimization (PSO) [20]. However, the performance of these methods is imperfect; the GA has some disadvantages, for instance, the premature convergence and the poor aptitude of local search. Another problem is related to the difficulty of choosing of GA operators such as population size, selection method, crossover rate and mutation rate, which have a significant impact on the convergence to the optimum solution [21,22]. In a like manner, the effectiveness of the PSO is influenced by the particle's multiple parameters [23].

Dragonfly optimization (DFO) is a novel optimization technique proposed by Mirjalili [24]. It is inspired from the static and dynamic demeanour of a swarm of dragonflies. Compared to the other well-known optimization techniques, DFO has some advantages, such as a simple concept and easy implementation. The robustness of this new optimization method is tested and validated by authors using many standard benchmark functions. The results show that the DFO algorithm outperforms existing well-known algorithms such as GA and PSO [24]. In this paper, a new hybrid DFO–SVR model is proposed for online voltage stability assessment. In the proposed model, the DFO algorithm is deployed to seek out the optimal values of SVR parameters. The developed model was trained based on the voltage magnitudes obtained from PMU buses, for various operating conditions, as the input variables, and the minimum values of voltage stability index (VSI) as the output variables. The efficiency of the developed model is evaluated and compared with the well-known ANFIS model. Numerical results of the proposed approach are presented using the IEEE 30-bus and the Algerian 59-bus systems.

2 Development of DFO–SVR Model

2.1 Support Vector Regression (SVR)

Support vector regression (SVR), the extended version of SVM, was initially suggested by Vapnik [8]. It has become a paramount computational tool due to its effective applications in regression and prediction problems. SVR was developed for the prediction of regression functions, and it is based on the implicit nonlinear conversion of the data into a higher-dimensional feature space [25]. The fundamentals of SVR are briefly reported here considering a regression function F which is estimated based on the training data in the form of $\{(x_i, y_i)i = 1, 2, \ldots, n\}$, where x_i and y_i are the input and output sets, respectively; n is the overall number of the dataset. SVR predicts the target values by utilizing the regression function as follows [8]:

$$F = w^T \varphi(x) + b \tag{1}$$

where F is the predicted output, w is the weight vector, b is the bias, and $\varphi(x)$ is the high-dimensional input vector. Flatness in (1) means that one seeks small w. For this, it is required to minimize the Euclidean norm, i.e. $||w||^2$ [26]. The coefficients w and b were computed by minimizing the risk function, as given below.

$$R(F) = \frac{1}{2}\|w\|^2 + C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(y_i, F_i) \tag{2}$$

where

$$L_\varepsilon(y_i, F_i) = \begin{cases} 0 & \text{if } |y_i - F_i| \le \varepsilon \\ |y_i - F_i| - \varepsilon & \text{otherwise} \end{cases} \tag{3}$$

The penalty parameter C is used to identify the trade-off between function intricacy and losses. As can be seen in Fig. 1, the parameter ε is the loss function which represents the range between the actual values and the regression function. This range can be seen as a tube around the regression function. All points located on the exterior of the tube are considered as training errors. $L_\varepsilon(y_i, F_i)$ is called the ε-insensitive loss function. Equation (2) can be changed to the following constrained form [8].

$$\text{minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

$$\text{Subject to } \begin{cases} w \cdot \varphi(x) + b - y_i \le \varepsilon + \xi_i \\ y_i - (w \cdot \varphi(x) + b) \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, \quad i = 1, 2, \ldots, n \end{cases} \tag{5}$$

where ξ and ξ^* are two positive slack variables, which assume nonzero values on the exterior of the ε-tube and zero inside (Fig. 1).

The optimization problem in (4) can be solved more easily in its dual formulation. Therefore, a standard dualization technique using Lagrangian multipliers has been employed. Using the Lagrangian multipliers, this problem can be written in the dual formulation as follows [26]:

$$\text{Maximize} \left\{ -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i, \alpha_i^*)(\alpha_j, \alpha_j^*)(\varphi(x_i)\cdot\varphi(x_j)) - \varepsilon\sum_{i=1}^{n}(\alpha_i, \alpha_i^*) + \sum_{i=1}^{n} y_i(\alpha_i, \alpha_i^*) \right\} \tag{6}$$

$$\text{Subject to } \begin{cases} \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C \quad i = 1, 2, \ldots, n \\ 0 \le \alpha_i \le C \quad i = 1, 2, \ldots, n \end{cases} \tag{7}$$

where α_i, α_i^* are nonlinear Lagrangian multipliers. The SVR function can be obtained by solving the dual maximization problem in (6) as follows [26]:

$$F\left(x, \alpha_i, \alpha_i^*\right) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(\varphi(x_i)\cdot\varphi(x_j)) + b \tag{8}$$

The vector inner-product $(\varphi(x_i)\cdot\varphi(x_j))$ represents the mapping function from the input space to feature space, and it can be replaced by a kernel function $K(x_i, x_j)$. Hence, Equation (8) becomes:

$$F\left(x, \alpha_i, \alpha_i^*\right) = \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) k\left(x_i, x_j\right) + b \tag{9}$$

The prevalent kernel functions provided by the SVR are linear, polynomial, sigmoid and radial basis function. Among these functions, the radial basis function (RBF) is the most used due to its effectiveness, reliability and simplicity. The RBF is defined as follows:

$$K\left(x_i, x_j\right) = \exp\left(\frac{-\left\|x_i - x_j\right\|^2}{2\gamma}\right) \tag{10}$$

where γ represents the bandwidth of the RBF function.

2.2 Dragonfly Optimization (DFO) Technique

The dragonfly optimization (DFO) algorithm is a recently established new and efficient swarm intelligence optimization technique proposed by Mirjalili [24]. It was inspired by the dynamics of dragonflies in nature. Dragonflies are carnivorous insects that catch and eat a wide variety of small insects, from gnats and mosquitoes to wasps and butterflies. Generally, dragonfly swarms are both dynamic and static in the natural world. Dynamic swarms, or migratory swarms, form as large groups (hundreds of thousands of dragonflies) and fly in a single direction for long distances as shown in Fig. 2. During the process of static swarms, in which the dragonflies hunt prey, they fly in small groups frequently over a well-determined small area and much closer to the land as shown in Fig. 3. Naturally, the

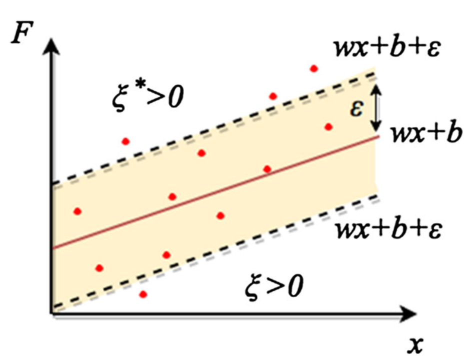

Fig. 1 Regression with the ε-insensitive tube

Fig. 2 Dynamic dragonfly swarms

Fig. 3 Static dragonfly swarms

instinct of each individual in the swarm imposes to attract to the nurturing sources and distract outward enemies. From these two conducts, the DFO algorithm is inspired. The position updating of each individual in the swarm is represented in Fig. 4 and mathematically explained as follows [24].

Separation (S) the aim of this step is to eschew the collision of individuals with their neighbours in the static swarm. This separation is expressed by the following equation.

$$S_i = \sum_{j=1}^{n} X - X_j \quad (11)$$

where X and X_j are the positions of the current individual and the jth neighbouring individual, respectively. n is the number of neighbouring individuals.

Alignment (A) the purpose of this step is to match the velocity of each individual with the other. The alignment is given by (12).

$$A_i = \frac{\sum_{j=1}^{n} V_j}{n} - X \quad (12)$$

where V_j is the velocity of neighbouring individual j.

Cohesion (C) refers to the movement of individuals towards the centre of the swarm's group.

$$C_i = \frac{\sum_{j=1}^{n} X_j}{n} - X \quad (13)$$

Attraction towards the food (F) All individuals tend to move towards the food.

$$F_i = X^{+} - X \quad (14)$$

where X^{+} shows the position of the food source.

Distraction outwards an enemy (E) is calculated as follows:

$$E_i = X^{-} - X \quad (15)$$

where X^{-} shows the position of the enemy.

The position of each dragonfly is updated based on step vector ΔX, which is calculated as follows.

$$\Delta X_i = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \quad (16)$$

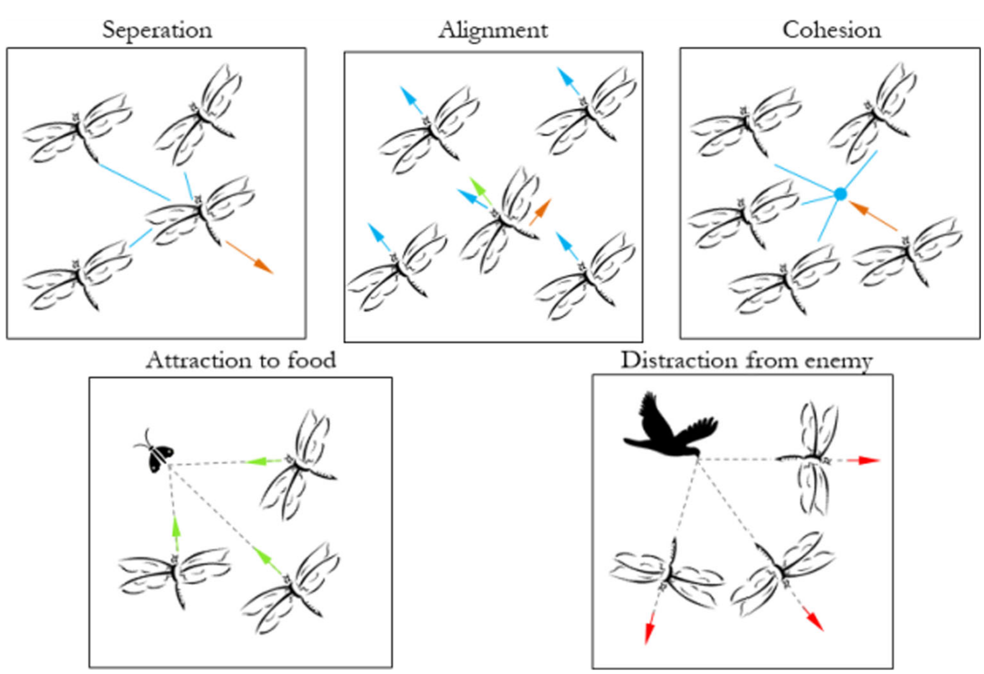

Fig. 4 Primitive corrective patterns between individuals in a swarm [24]

where $s, a,$ and c represent, respectively, the separation, alignment and cohesion weights; f and e are the food and the enemy factors, respectively; w is the inertia weight, and t is the iteration counter. The updated position vector is calculated as follows.

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{17}$$

In the case of no neighbouring solutions founded, dragonflies fly around the search space using a random walk, or Lévy flight [27], to ameliorate their randomness, stochasticity and exploration. In this case, the dragonflies update their position based on the following equation [24]:

$$X_{t+1} = X_t + \text{Lévy}\,(d) \times X_t \tag{18}$$

where t is the current iteration, and d is the dimension of the search space. Levy flight is given by [28]:

$$\text{Lévy}\,(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{19}$$

where r_1 and r_2 are the random numbers in the range of [0,1], β is a constant, and σ is given by (20).

$$\sigma - \left(\frac{\Gamma\,(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)} \right)^{\frac{1}{\beta}} \tag{20}$$

where $\Gamma(x) = (x-1)!$.

2.3 The Hybrid DFO–SVR Algorithm

In order to obtain an effective SVR model with a good predictive ability, there are three parameters that necessitate being chosen carefully [29]. These parameters include the penalty parameter C, the non-sensitivity coefficient ε and the kernel parameters (bandwidth of the Gaussian RBF kernel γ in this study). These parameters have a great importance in the regression accuracy and generalization performance of the SVR model [29]. Hence, a robust and efficient optimization method is coveted to select the above-mentioned parameters. In this study, the recently developed dragonfly algorithm has been deployed to optimize the SVR parameters. The proposed hybrid DFO–SVR algorithm can be briefly described by the following steps (Fig. 5).

Step 1 Set the values of DFO parameters such as:

- The number of dragonflies (candidate solutions);
- The maximum number of iterations;
- The upper and the lower bounds of C, γ and ε.

Step 2 Initialize the step vectors $\Delta X_i (i = 1, 2, \ldots, n)$, the values of s, a, c, f, e and w, and the values of SVR parameters (C, γ, and ε).

Step 3 Train the SVR model using the training set and compute the fitness value of every dragonfly. The root mean square error (RMSE) was used as a fitness function. The fitness function is in the form of:

$$\text{Fitness} = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(a_i - p_i)^2} \tag{21}$$

where α and P are the actual output and the predicted output, respectively, and n is the overall number of data.

Step 4 Update the values of s, a, c, f and e.

Step 5 For all individuals, calculate the values of S, A, C, F and E using (11)–(15).

Step 6 Update the neighbouring radius.

Step 7 If the dragonfly has at least one neighbouring dragonfly, the velocity and the position of the dragonfly are updated based on (16) and (17). Otherwise, the position vector is updated using (18).

Step 8 Correct the new positions taking into account the upper and lower values of variables C, γ and ε.

Step 9 Check the stop criterion: if its criterion is achieved, go to the Step 10. Otherwise, loop to Step 3.

Step 10 The best position for all individuals comprising the optimized SVR parameters is selected, and then the SVR model was tested and evaluated.

3 Voltage Stability Assessment

Voltage stability assessment is one of the important parts in the planning and operating of power systems. This assessment is for objective to identify whether the current operating point is secure or not, as well as to determine how close the system is to the voltage instability. Several methods have been introduced to assess the voltage stability and to determine the stability margins such as minimum eigenvalue, tangent vector and continuation power flow [30]. However, the high computational requirements make these methods inadequate for online application. To overcome this problem, several indices have been proposed to evaluate the voltage stability such as line stability factor (LQP) [31], line stability index (L_{mn}) [32], fast voltage stability index (FVSI) [33] and voltage stability index (VSI) [34]. These indices do not require computational effort and are suitable for fast analysing the voltage stability. A comparative study of these indices has been presented in [35]. Based on this comparison, the VSI is found to be the best index since the mathematical formulation is derived considering all of the system mar-

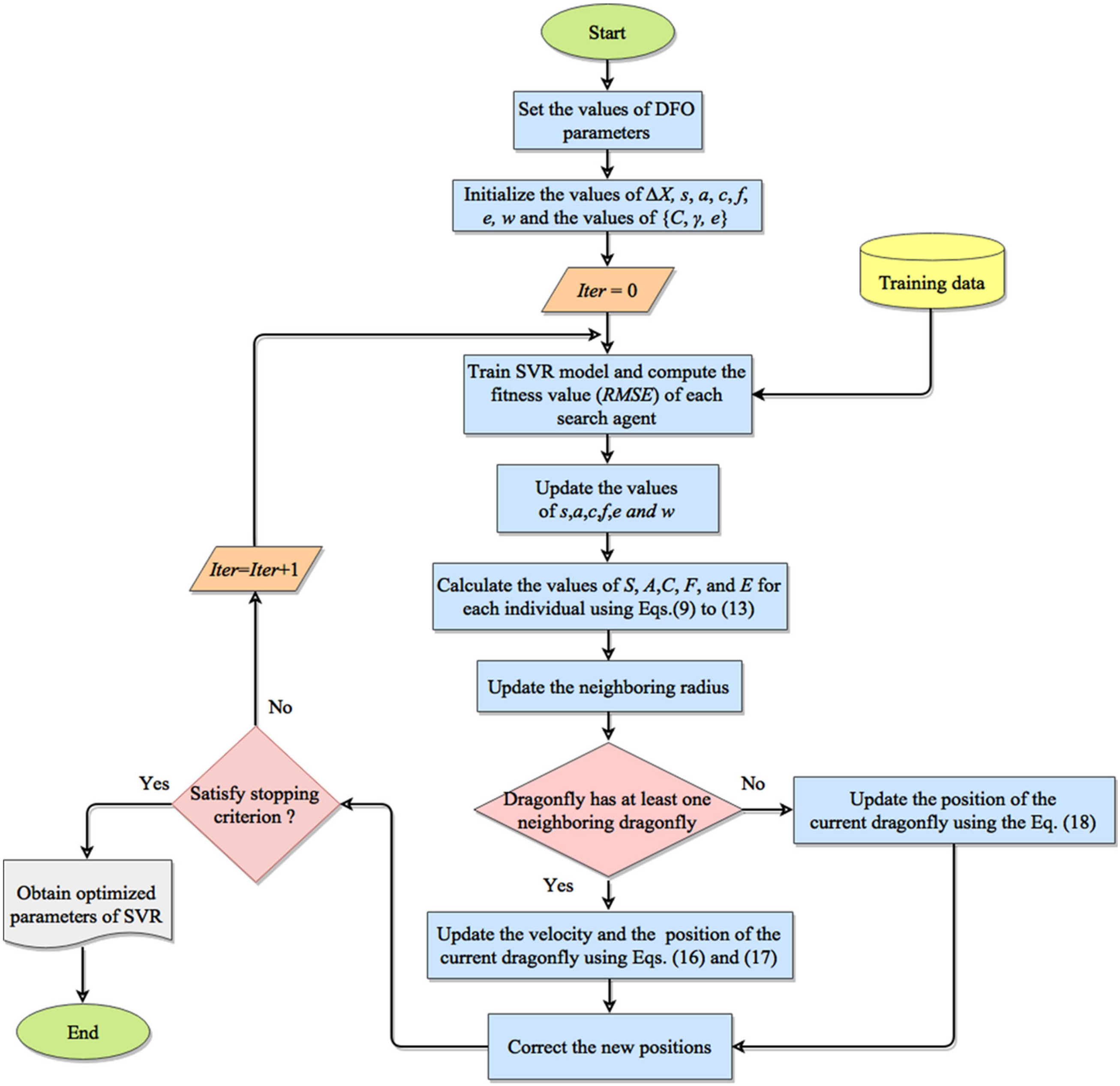

Fig. 5 The flowchart of the proposed DFO–SVR model

gins, including active, reactive and apparent power margins. The VSI can be calculated in a real-time manner to predict the power system operating condition. The derivation of VSI formulation is originated from a 2-bus system illustrated in Fig. 6.

The current I that flows in the line given by:

$$I = \frac{V_s \angle \delta_s - V_r \angle \delta_r}{R + jX} \tag{22}$$

The apparent power S at receiving end bus can be written as:

$$S_r = V_r I^* \tag{23}$$

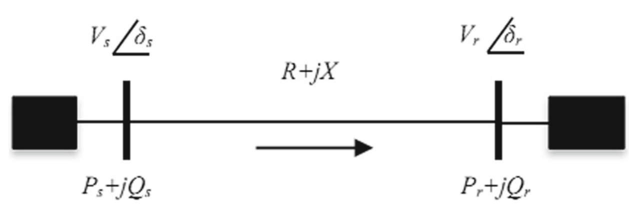

Fig. 6 Single transmission line model

Rearranging (23) yields:

$$I = \left(\frac{S_r}{V_r}\right) = \frac{P_r - jQ_r}{V_r \angle - \delta_r} \tag{24}$$

Equating (22) and (24)

$$\frac{V_s\angle\delta_s - V_r\angle\delta_r}{R + jX} = \frac{P_r - jQ_r}{V_r\angle - \delta_r} \tag{25}$$

Separating the real and imaginary parts yields:

$$V_s V_r \cos\delta - V_r^2 = RP_r + XQ_r \tag{26}$$

And,

$$-V_s V_r \sin\delta = XP_r + RQ_r \tag{27}$$

where $\delta = \delta_s$-δ_r.

From (26) and (27), the real and reactive powers at the receiving end bus can be given by:

$$P_r = \left[(V_s\cos\delta - V_r)\frac{R}{R^2+X^2} + V_s\sin\delta\frac{X}{R^2+X^2}\right]V_r \tag{28}$$

$$Q_r = \left[(V_s\cos\delta - V_r)\frac{X}{R^2+X^2} - V_s\sin\delta\frac{R}{R^2+X^2}\right]V_r \tag{29}$$

Combining (28) and (29) by removing δ, as a result, the voltage V_r can be expressed by (30).

$$V_r = \sqrt{\frac{V_s^2}{2} - (Q_rX + P_rR) \pm \sqrt{\frac{V_s^4}{4} - (Q_rX + P_rR)\,V_s^2 - (P_rX + Q_rR)^2}} \tag{30}$$

where V is the voltage magnitude; s and r are the sending and receiving buses, respectively; R and X are the line resistance and reactance, respectively. The maximum transmitted power $S_{\max}$ through the line is attained when the internal root phrase equals to zero [35]. There is a unique solution for V_s and V_r located at the collapse point. The maximum transferred active power $P_{\max}$, the maximum transferred reactive power $Q_{\max}$ and the maximum transferred power $S_{\max}$ can be expressed by (31)–(33), respectively:

$$P_{\max} = \frac{Q_rR}{X} - \frac{V_s^2R}{2X^2} + \frac{|Z_L|\,V_s\sqrt{V_s^2 - 4Q_rX}}{2X^2} \tag{31}$$

$$Q_{\max} = \frac{P_rX}{R} - \frac{V_s^2X}{2R^2} + \frac{|Z_L|\,V_s\sqrt{V_s^2 - 4P_rR}}{2R^2} \tag{32}$$

$$S_{\max} = \frac{V_s^2\,[|Z_L| - (\sin(\theta)\,X + \cos(\theta)\,R)]}{2\,(\cos(\theta)\,X - \sin(\theta)\,R)^2} \tag{33}$$

where θ is the load power angle, $\theta = \tan^{-1}\left[\frac{Q_r}{P_r}\right]$.

These equations can be simplified by supposing high X to R ratio.

$$P_{\max} = \sqrt{\frac{V_s^4}{4X^2} - Q_r\frac{V_s^2}{X}} \tag{34}$$

$$Q_{\max} = \frac{V_s^2}{4X}\frac{P_r^2X}{V_s^2} \tag{35}$$

$$S_{\max} = \frac{(1 - \sin(\theta))\,V_s^2}{2\cos(\theta)^2\,X} \tag{36}$$

Therefore, based on these relations, the total VSI can be defined by [34]:

$$VSI = \min\left(\frac{P_{\max} - P_r}{P_{\max}}, \frac{Q_{\max} - Q_r}{Q_{\max}}, \frac{S_{\max} - S_r}{S_{\max}}\right) \tag{37}$$

A small value of VSI indicates that the voltage magnitude at the load bus is approaching to its collapse point. Once the voltage magnitude at a load bus has reached its collapse point, consequently the VSI is equal to zero.

4 Implementation of DFO–SVR Model Based PMU Data in Online Voltage Stability Assessment

PMU is a smart metering device that measures a voltage phasor of the power system's bus, as well as, the current phasor of the lines emanating from that bus, with consideration of the global time reference offered by the GPS of satellites [36]. The network of PMUs together with the new communication systems is called wide area measurement system (WAMS) [37], which is considered as one of the key technologies in smart grids. The fundamental aims of WAMS are the monitoring, centralized control and protection of power systems [38]. The simplified architecture of WAMS is represented in Fig. 7. The distributed PMUs send the time synchronized data taken from throughout the system to control centre. The precise and accurate real-time measurements offered by the PMU devices help the operators to take the required control action. In the present study, the gathered data from PMU buses, under different power system operating conditions, were used to train the developed DFO–SVR model, which was then employed in online prediction of VSI. Figure 8 shows the schematic representation of the DFO–SVR model applied to VSI prediction.

4.1 Generation of Training and Testing Data

To train and evaluate the performance of the proposed DFO–SVR model, appropriate training and testing data must first be prepared. These data are generated through off-line simu-

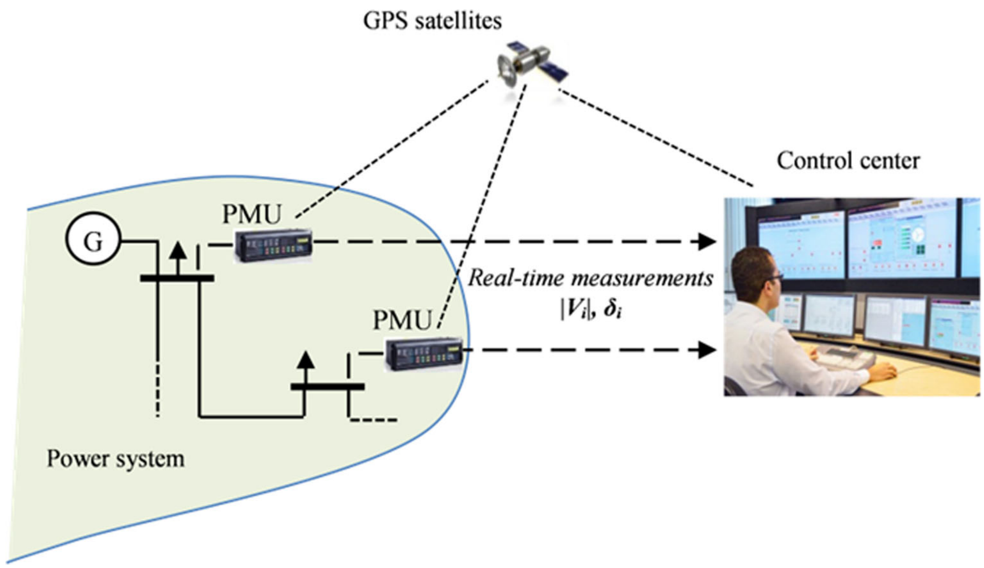

Fig. 7 Simplified architecture of WAMS

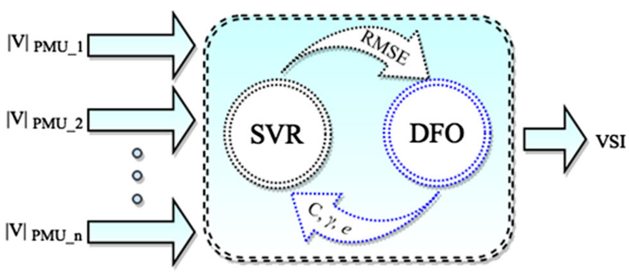

Fig. 8 Schematic representation of DFO–SVR model applied to VSI prediction

lation processes by varying both the active and reactive power at each load bus in the system. The load is increased randomly from the base case until the system reaches the collapse point, and then the VSI is computed for each operating point using (37). In turn, to meet the increased power demand, the active and reactive powers of all generators should be adjusted. The adjustment of the generator output can be achieved using distributed slack bus [39] or optimal power flow (OPF) methods [40]. Here, the OPF-based technique has been used. The voltage magnitudes of PMU buses ($|V|_{\mathrm{PMU}}$) obtained by solving the conventional load flow for every load-generating sample are taken as the input variables of the DFO–SVR model. The minimum VSI values at each operating point are used as the output variables.

4.2 Performance Evaluation

The evaluation of DFO–SVR model was undertaken with the aid of three statistical indices. These indices are the correlation coefficient (R), the root mean square error (RMSE) and the percentage RMSE (PRMSE). R and RMSE are given by (38) and (39):

$$R = \frac{\sum_{i=1}^{n}(a_i - \overline{a})\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{n}(a_i - \overline{a})^2 \sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2}} \tag{38}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(a_i - p_i)^2} \tag{39}$$

where a and P represent the actual and the expected outputs, respectively; n denotes the overall data; $\overline{a}$ and $\overline{P}$ are the rate of the actual and the expected values, respectively. The prediction model is considered as robust in its performance if the correlation coefficient R reached 1 and the RMSE close to 0.

The PRMSE is described as follows:

$$\mathrm{PRMSE} = \frac{\mathrm{RMSE}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} p_i^2}} \times 100 \tag{40}$$

Different levels of PRMSE can be defined to determine the model accuracy:

- Excellent for PRMSE $< 10\%$;
- Good for $10\% <$ PRMSE $< 20\%$,
- Reasonable for $20\% <$ PRMSE $< 30\%$;
- Low for PRMSE $> 30\%$.

5 Simulation and Results

This section presents the details of the simulation study carried out on IEEE 30-bus and Algerian 59-bus test systems shown in Figs. 9 and 10, respectively. The IEEE 30-bus power system contains 30 buses, 6 generators, 24 loads and

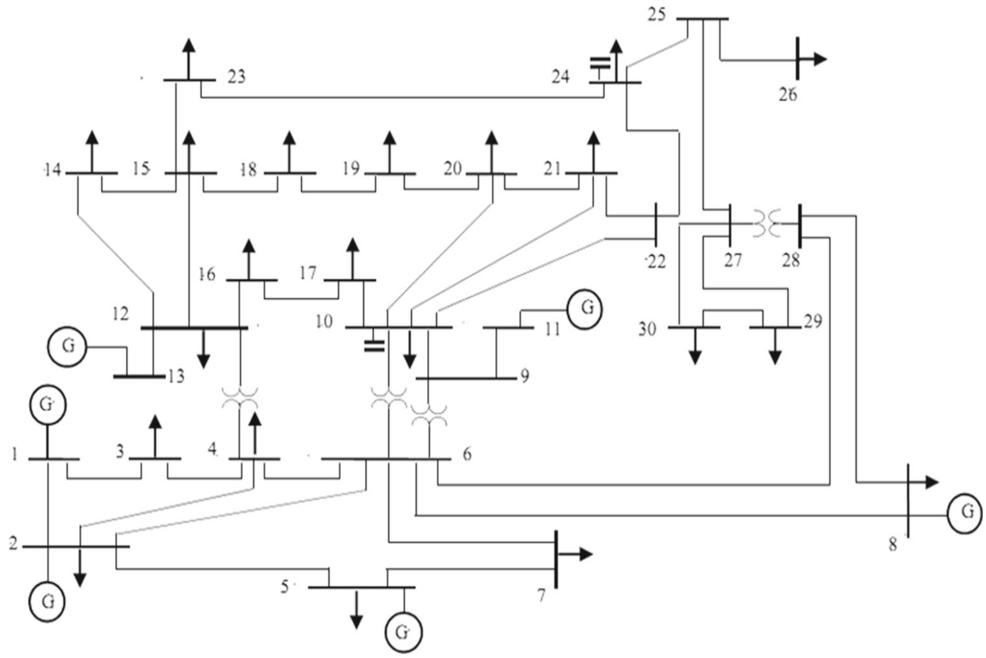

Fig. 9 Single line diagram of the IEEE 30-bus test system

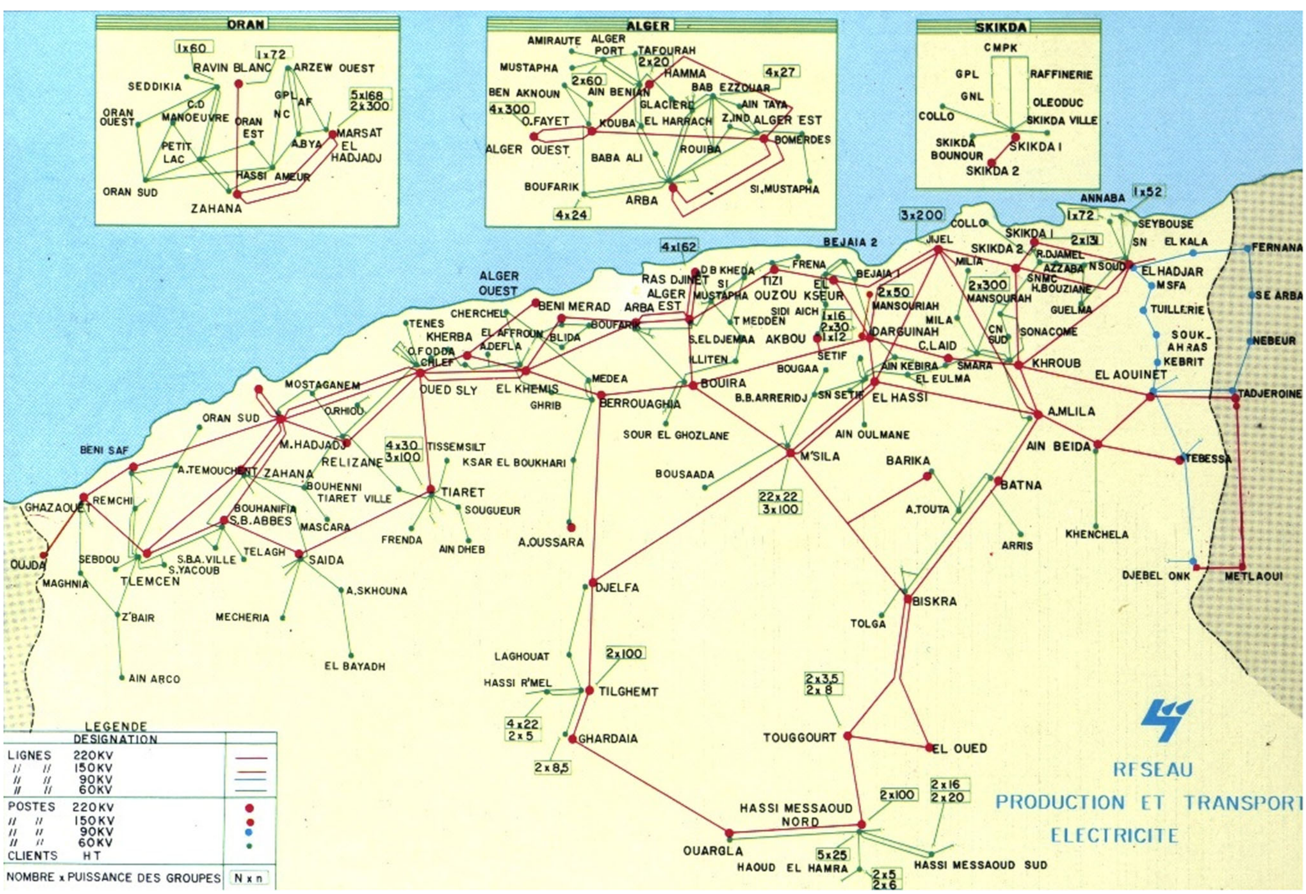

Fig. 10 Topology of the Algerian 59-bus power system [42]

Table 1 Number and locations of the required PMUs

System	Number of required PMUs	Locations of PMUs
IEEE 30-bus	7	3, 5, 10, 12, 19, 23, 27
Algerian 59-bus	12	5, 12, 20, 27, 29, 33, 34, 40, 43, 44, 56, 58

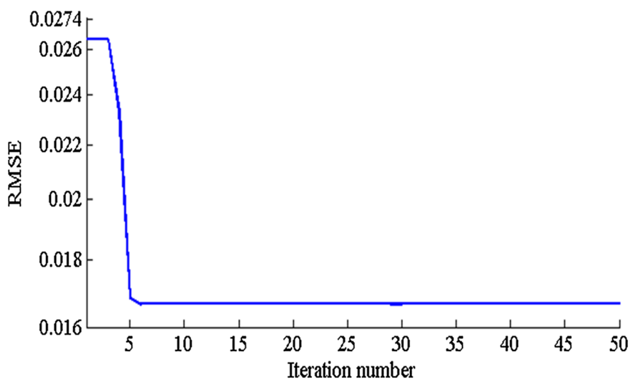

Fig. 11 Convergence curve of the DFO algorithm in the case of IEEE 30-bus system

41 branches [41]. The Algerian 59-bus system comprises 59 buses, 10 generators, 36 loads and 83 lines [42]. In the online assessment of voltage stability based phasor measurement technology, the optimal number and location of PMUs should be determined beforehand. In the present paper, the optimal number and locations of PMUs for both systems are obtained using PSAT software [43]. The attained results are illustrated in Table 1.

As mentioned above, the gathered voltage magnitudes by the distributed PMUs will be used in an online manner as the input information for the DFO–SVR model to estimate the VSI. To train the model, the dataset is generated using the conventional power flow by varying the load at each load bus from the base case to the collapse point. As much as 80% of the generated data is used as training samples, while the rest is used to test the proposed model. To implement the hybrid DFO–SVR model for predicting the VSI, the MATLAB software was used. The Dragonfly optimization algorithm searches for the optimal values of the C, γ and ε parameters. The number of dragonflies (candidate solutions) and the maximum number of iterations were taken as 30 and 50, respectively. The RMSE was considered as a fitness function in the optimization process. Moreover, the stop criterion in this study is the set number of maximum iterations. The ranges of the C, γ and ε parameters are [1 1000], [0.0001 0.1] and [0.1 1], respectively. The iterative RMSE trend of the DFO search of the SVR optimal parameters in the training stage is displayed in Figs. 11 and 12. The optimal values of the C,

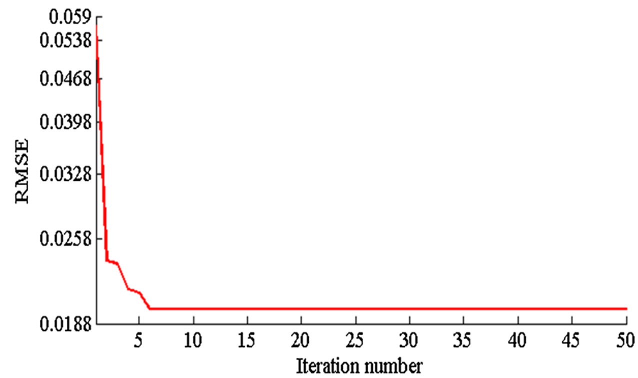

Fig. 12 Convergence curve of the DFO algorithm in the case of Algerian 59-bus system

Table 2 Optimal parameters of the SVR model found using DFO algorithm

SVR parameters	Optimal values of SVR parameters	
	IEEE 30-bus	Algerian 59-bus
C	971.9378	985.561
γ	0.1	0.1
ε	0.0001	0.0001

γ and ε parameters found for both systems are shown in Table 2.

Once the optimal parameters of the SVR model are obtained, its ability to predict the VSI was evaluated. The actual values of VSI, calculated using conventional load flow, and the predicted values by DFO–SVR model in training and testing phases are plotted in Figs. 13 and 14. Figure 13a, b shows that the DFO–SVR model provides the results that are in agreement with the actual values. This is referring to the case study of the IEEE 30-bus system. The above-mentioned discussion is similar to the compendium representing the outcome of the DFO–SVR model for the case study of the Algerian 59-bus system, as shown in Fig. 14a, b.

Figures 15 and 16 show the correlation plots of predicted values versus actual values of VSI for both systems in the training and testing processes. For the IEEE 30-bus system (Fig. 15a, b), the statistical characteristics of $R = 0.99641$ and RMSE = 0.0166 were obtained in the training phase and $R = 0.98776$ and RMSE = 0.0273 in the testing phase. For the Algerian 59-bus system (Fig. 16a, b), the proposed technique managed to yield $R = 0.98968$ and RMSE = 0.0198 in the training phase and $R = 0.91369$ and RMSE = 0.0565 in the testing phase. According to the obtained results, it can be noted that the proposed DFO–SVR model has a good predicting performance.

In order to further evaluate the superiority of the DFO–SVR technique and extract a more crucial conclusion, their

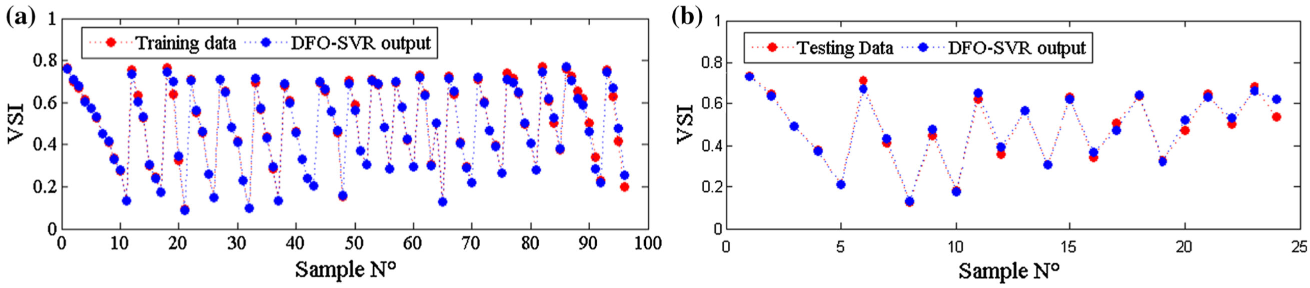

Fig. 13 Comparison between predicted and actual values of VSI in the case of IEEE 30-bus system: **a** training phase and **b** testing phase

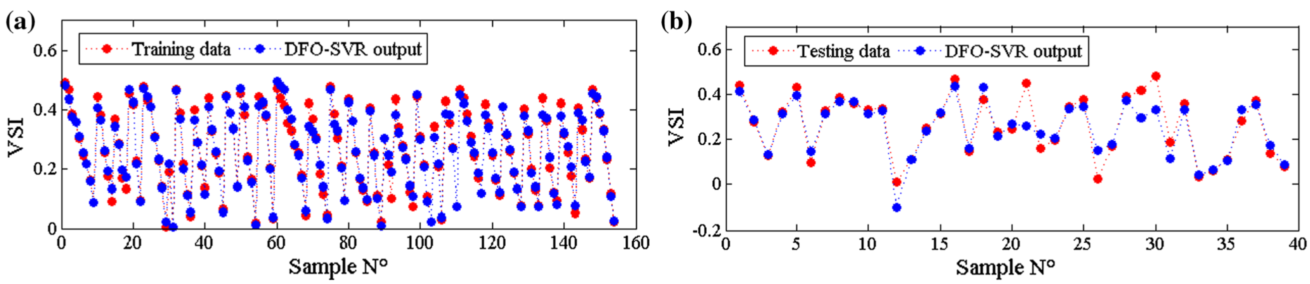

Fig. 14 Comparison between predicted and actual values of VSI in the case of Algerian 59-bus system: **a** training phase and **b** testing phase

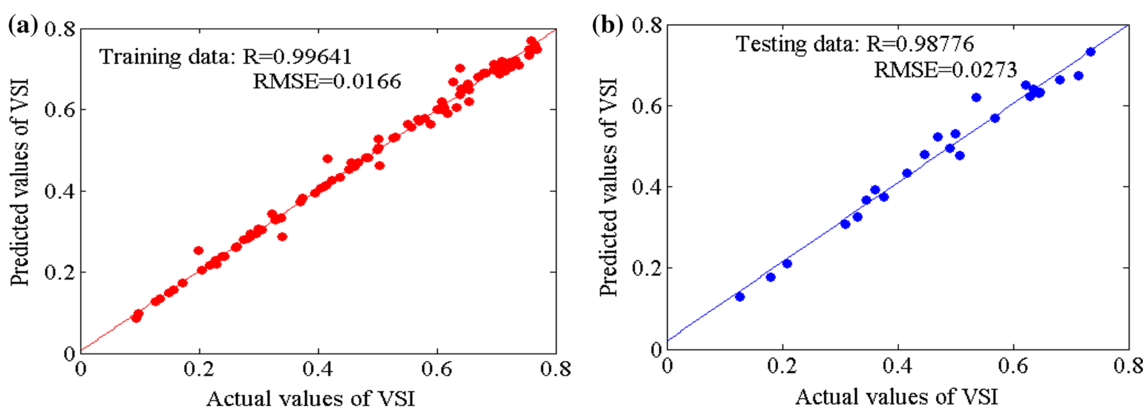

Fig. 15 Correlation plots of actual versus values predicted of VSI in the case of IEEE 30-bus system in **a** training phase and **b** testing phase

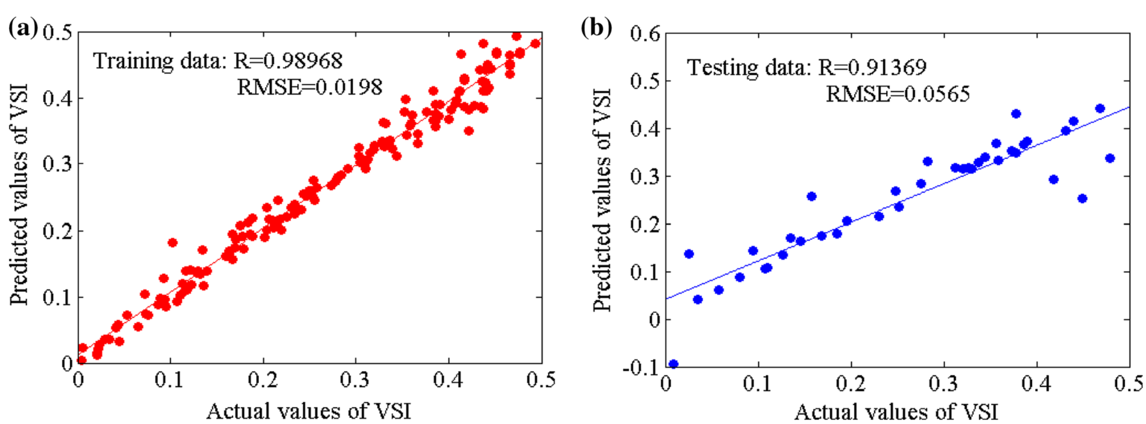

Fig. 16 Correlation plots of actual versus predicted values of VSI in the case of Algerian 59-bus system in **a** training phase and **b** testing phase

Table 3 Optimal values of ANFIS cluster radius

Test system	Performance indices	Value of cluster radius			
		0.2	0.3	0.4	0.5
IEEE 30-bus	RMSE	0.0464	0.0435	**0.0381**	0.0433
Algerian 59-bus	RMSE	0.1008	0.1063	**0.0909**	0.1049

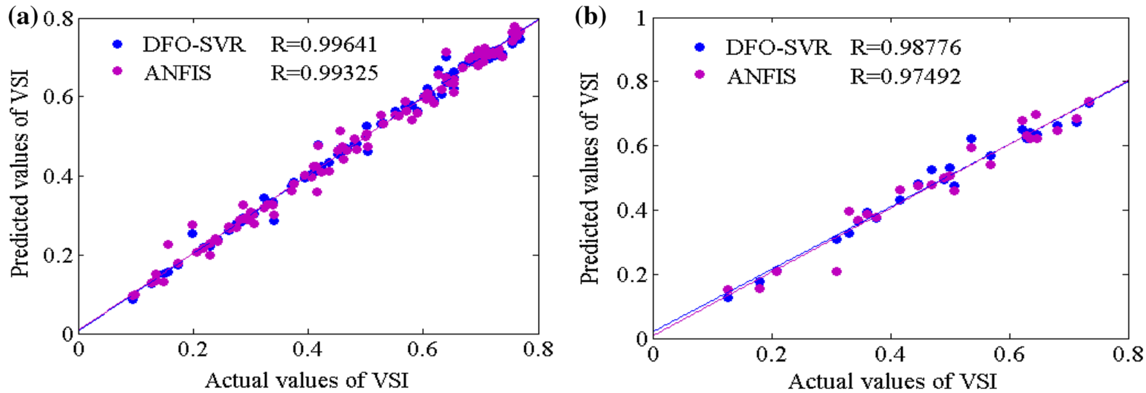

Fig. 17 Correlation plots of actual versus predicted values of VSI via DFO–SVR and ANFIS in the case of IEEE 30-bus system in **a** training phase and **b** testing phase

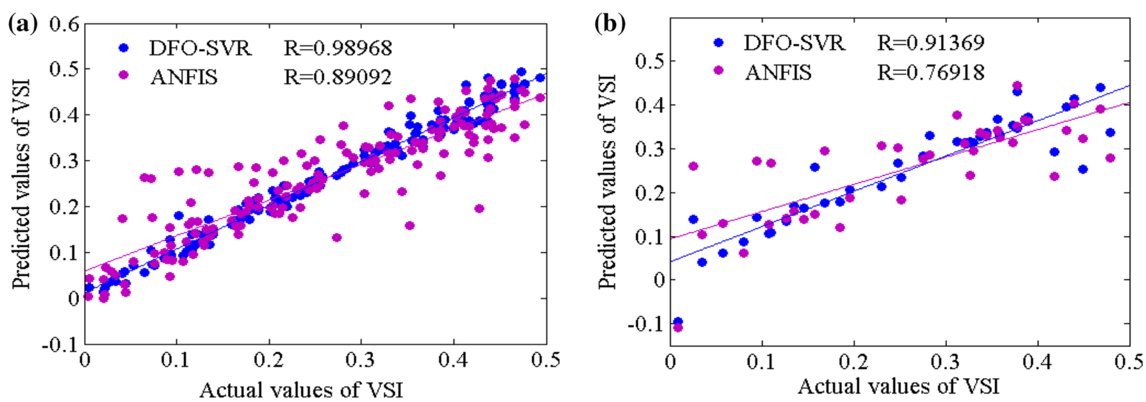

Fig. 18 Correlation plots of actual versus predicted values of VSI via DFO–SVR and ANFIS in the case of Algerian 59-bus system in **a** training phase and **b** testing phase

performance is compared to the ANFIS model. For the ANFIS model development, a subtractive clustering (SC) technique [44] has been used to generate the fuzzy rules. In order to generate fuzzy rules using SC technique, it is required to determine the adequate value of the cluster radius [45]. According to [45], the opportune values for the cluster radius are customarily between 0.2 and 0.5. To compare the predicting results of different cluster radius and to set the adequate value for each training data set, the RMSE indicator was used. Table 3 shows the values of RMSE obtained, for both test systems, by varying cluster radius in the previous range with 0.1 increment value. According to the obtained results, the minimum values of RMSE for both test systems were found with a cluster radius of 0.4.

Figure 17a, b, in the form of scatter plot, represents the predicted outputs via DFO–SVR and ANFIS models against the actual ones in the case of the IEEE 30-bus system. From this figure, it can be noted that the proposed DFO–SVR model has a better prediction performance in both training and testing phases compared to the ANFIS model. In the training phase, these predictions result in a correlation coefficient $R = 0.99641$ obtained by the DFO–SVR model and $R = 0.99325$ obtained by the ANFIS model. In the testing phase, the R obtained by DFO–SVR model was found to be 0.98968, while that obtained by the ANFIS model was 0.97492. Similarly, the DFO–SVR predictions in the case of the Algerian 59-bus system plotted in Fig. 18a, b are better than the ANFIS ones. Table 4 shows a comparison between the obtained R, RMSE and

Table 4 Performance of the DFO–SVR model compared to ANFIS model

Model	IEEE 30-bus system			Algerian 59-bus system		
	R	RMSE	PRMSE	R	RMSE	PRMSE
DFO–SVR						
Training	0.99641	0.0166		0.98968	0.0198	
Testing	0.98776	0.0273		0.91369	0.0565	
ANFIS						
Training	0.99325	0.0228		0.89092	0.0620	
Testing	0.97492	0.0385		0.76918	0.0876	

PRMSE by both models in the training and testing steps. From the obtained results, it is clear that the DFO–SVR model acquired relatively smaller RMSE and larger R. The proposed hybrid model also outperforms the ANFIS model in terms of PRMSE in both test systems. In the IEEE 30-bus system, it can be seen that the PRMSE value of the DFO–SVR is 5.6225%, in the testing phase, which is smaller than that of the ANFIS model which is 7.9798%. For the Algerian power system, the PRMSE values of DFO–SVR model are dramatically smaller than those obtained by the ANFIS model. The deference in PRMSE is up to 16% in the training phase and 12% in the testing phase. We can conclude from the results that the proposed DFO–SVR model is more suitable for the prediction of VSI than the ANFIS model.

6 Conclusion

In this paper, a hybrid approach is proposed for online voltage stability assessment. The proposed approach is based on the amalgamation of the dragonfly optimization (DFO) algorithm with support vector regression (SVR). The DFO is adopted as a search strategy to obtain the optimal parameters of SVR. The developed model was trained based on the voltage magnitudes obtained from PMU buses, for different operating conditions, as the input vector and the minimum values of voltage stability index (VSI) as the output vector. The DFO–SVR model was successfully implemented to estimate VSI, which means that DFO is a potential optimization technique that can be employed to determine the appropriate SVR parameters and to ameliorate its prediction accuracy. Compared with the well-known ANFIS model, the proposed hybrid DFO–SVR model is confirmed to have a better performance. For future work, the DFO algorithm can be incorporated with other machine learning techniques to develop powerful tools that can be exploited in a wide variety of problems. Furthermore, other advanced optimization methods could be amalgamated with the SVR model to improve its performance.

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