Adaptive Salp Swarm Algorithm as Optimal Feature Selection for Power Quality Disturbance Classification

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Abstract: Power quality disturbance (PQD) is an influential situation that significantly declines the reliability of electrical distribution systems. Therefore, PQD classification is an important process for preventing system reliability degradation. This paper introduces a novel algorithm called “adaptive salp swarm algorithm (SSA)” as an optimal feature selection algorithm for PQD classification. Feature extraction and classifier of the proposed classification system were based on the discrete wavelet and the probabilistic neural network, respectively. The classification was focused on the 13 types of power quality signals. The optimal number of selected features for the proposed classification system was firstly determined. Then, it demonstrated that the optimally selected features resulted in the highest classification accuracy of 98.77%. High performance of the proposed classification system in the noisy environment, as well as based on the real dataset was also verified. Furthermore, the proposed SSA indicates a very high convergence rate compared to other well-known algorithms. A comparison of the proposed classification system’s performance to existing works was also carried out, revealing that the proposed system’s accuracy is on a high-range scale. Hence, the adaptive SSA becomes another efficient optimal feature selection algorithm for PQD classification.

Keywords: power quality disturbance; power quality disturbance; probabilistic neural network; feature selection; salp swarm algorithm

1. Introduction

Electricity is widely regarded as a critical factor in economic growth, as increased usage is required to serve a diverse range of load types, including industrial, commercial, and residential customers [1–4]. Renewable energy sources have been widely used to improve the capacity of electrical generation, particularly in the last few decades [5–7]. Power quality disturbance (PQD) has been a highly concerning problem in power systems since it can essentially degrade the system’s performance. In particular, this problem becomes more serious in the system having several non-linear loads and renewable energy distributed generators since these factors typically have high uncertainty [8]. Typically, PQD can occur in different forms, i.e., voltage sag, swell, interruption, harmonic, spike, transient, notch, or their combination [9–11]. To prevent the damage to the power system due to PQD, several tools have been proposed to identify the type of disturbances [12–16]. Signal processing is the main technique used in PQD classification since it is capable of accurately characterizing the type of signals [17].

Feature extraction is extensively known as an effective signal processing technique to classify the type of PQDs through their features [18–23]. In the literature, there were many signal processing methods performed in the feature extraction. Fourier transform (FT) is the famous frequency domain signal analysis that can extract the spectrum of stationary signals at specific frequencies. However, the FT has low performance in extracting the feature of non-stationary signals due to its fixed window function [24]. Short time
Fourier transform (STFT) is a reform of FT in which the time-frequency window of temporary transient signal localization is improved from FT. Later on, the discrete wavelet transform (DWT) was developed by improving the fixed resolution issue of the STFT. Therefore, this extraction method is capable of providing a short window function at high frequency phases while maintaining a long window function at low frequency phases [25].

Since the feature extraction based signal processing can distinguish only the characteristics of signals, the additional tool called classifier has been widely used to increasingly improve the accuracy of PQD classification by classifying the type of PQD signals [26–28]. In previous studies, several techniques have been performed as a classifier for PQD classification, for example, artificial neural networks (ANN), support vector machines (SVM), expert systems, fuzzy logic [29–35]. In particular, many previous studies claimed that the ANNs have a competently higher potential for classifying PQD than the other classifier tools [36–38]. Furthermore, the feature selection process has extensively been used in PQD classification research, aiming to improve the performance of the classification system [39–41]. The main goal of this process is to optimally select the appropriate data of feature extracting data, so that the processing time and classification accuracy can be improved by eliminating unnecessary data [40,41].

Many research works in the literature have implemented feature selection techniques for PQD classification, demonstrating that this tool can significantly improve classification accuracy, as following detail. In 2009, B. Biswal et al. proposed the optimal feature selection algorithm for PQD classification using the adaptive particle swarm optimization (PSO) method, while the STFT was used as feature extraction and the fuzzy C-means was performed as a classifier. It was found that this system could provide a classification accuracy of 96.33% [42]. In 2013, the PQD classification system using the k-means with an Apriori algorithm as optimal feature selection and WT as feature extraction was introduced, while the least squares support vector machine (LS-SVM) was performed as a classifier to classify five PQD signals [43]. It showed that 98.88% classification accuracy can be obtained. Next, R. Ahila et al. presented a combination of PSO algorithm and DWT in PQD classification based on the extreme learning machine (ELM) classifier, it was demonstrated this system could achieve 97.60% classification accuracy [44]. In 2016, A. A. Abdoos et al. proposed the PQD classification system that uses the sequential forward selection algorithm for optimal features selection, STFT with variational mode decomposition (VMD) for feature extraction, and SVM as a classifier. It was shown that this system could reach a classification accuracy of up to 99.66% for nine PQD signal types [21].

In 2017, T. Chakravorti et al. showed that the PQD classification with the Fischer linear discriminant analysis algorithm for optimal feature selection, VMD as feature extraction, and reduced kernel extreme learning machine (RKELM) as a classifier could provide a classification accuracy of 98.82% [45]. Recently, Lei Fuei et al. performed the permutation entropy and the Fisher score algorithm for finding the optimal features of PQD classification using VMD for feature extraction, and one-versus-rest support vector machine (OVR-SVM) for a classifier [46]. Classification accuracy of 97.6% was demonstrated.

From the literature surveys, it shows that numerous recent works focus mainly on developing the ability of feature selection to improve the performance of PQD classification system. We also noticed that this process strongly influences the signal’s features before entering the classifier. Rather than state of the art in PQD classification, our hypothesis was the performance of the existing PQD classification system can be improved increasingly, especially system accuracy and convergence rate. Therefore, the contribution of this work is to introduce the PQD classification system based on a novel algorithm, namely, the adaptive salp swarm algorithm (SSA) as the feature selection algorithm. This new algorithm is supposed to reach a higher classification performance than the previous studies. The proposed approach was inspired by the fact that the SSA can efficiently find the solution of optimization problems within a short time due to its great exploration, which are typically the required properties in PQD classification. Another research gap was that, despite the high capability of SSA in solving many optimization problems in
power systems, the use of this algorithm in power quality classification had not yet been reported. The proposed classification system performed DWT as feature extraction, while the probabilistic neural network (PNN) was used as the classifier. The verification of our proposed system was made based on the real dataset of distribution system. The performance of proposed classification system was compared to that of the previous PQD classification systems.

The rest of this paper is arranged as follows: A synthesis of power quality signals using mathematic equations under specific constraints is shown in Section 2. Section 3 describes the feature extraction process, while Section 4 explains the classifier based on a probabilistic neural network. Section 5 expresses the mechanism of the adaptive SSA as optimal feature selection. Then, Section 6 shows the simulation results including the related discussions. Finally, the results are concluded in Section 7.

2. Power Quality Disturbance Signals

In this research, the PQD signals were generated following the IEEE-1159 standard. We focused on 13 types of PQD signals consisting of 10 single types, which are pure sine, sag, swell, interruption, harmonic, impulsive transient, oscillatory transient, flicker, notch, and spike, and 3 combined signals including sag with harmonic, swell with harmonic, and interruption with harmonic. All signals were randomly generated within their constraints at 50 Hz, 1 p.u. of amplitude, 10 cycles, 2000 sampling points at 10 kHz. The mathematic equations and parameter constraints of all signals are shown in Table 1.

| Label | Disturbance Classes# | Mathematic Equations | Constraints |
|-------|-----------------------|----------------------|-------------|
| C1    | Pure sine             | \( y(t) = A \sin(\alpha t) \) | \( A = 1 \) |
| C2    | Sag                   | \( y(t) = A[1-\alpha(u(t-t_i)-u(t-t_f))]\sin(\alpha t) \) | \( 0.1 \leq \alpha \leq 0.9; \ T \leq t_2 - t_1 \leq 9T \) |
| C3    | Swell                 | \( y(t) = A[1+\alpha(u(t-t_i)-u(t-t_f))]\sin(\alpha t) \) | \( 0.1 \leq \alpha \leq 0.8; \ T \leq t_2 - t_1 \leq 9T \) |
| C4    | Interruption          | \( y(t) = A[1-\alpha(u(t-t_i)-u(t-t_f))]\sin(\alpha t) \) | \( 0.9 \leq \alpha \leq 1; \ T \leq t_2 - t_1 \leq 9T \) |
| C5    | Harmonic              | \( y(t) = A[a_1 \sin(\omega_1 t) + a_2 \sin(3\omega_1 t) + a_3 \sin(5\omega_1 t) + a_4 \sin(7\omega_1 t)] \) | \( 0.05 \leq a_i, a_\alpha, a_\beta \leq 0.15; \ \sum a_\alpha^2 = 1 \) |
| C6    | Impulsive transient   | \( y(t) = A[1-\alpha(u(t-t_i)-u(t-t_f))]\sin(\alpha t) \) | \( 0 \leq \alpha \leq 0.414; \ T / 20 \leq t_2 - t_1 \leq T / 10 \) |
| C7    | Oscillatory transient | \( y(t) = A[\sin(\omega t) + \alpha^{-(t_2-t_1)^2/2}] \sin(\omega(t-t_i)(u(t)-u(t_f))] \) | \( 0.1 \leq \omega \leq 0.8; \ 0.5T \leq t_2 - t_1 \leq 3T; \ 8 \leq \tau \leq 40ms; \ 300 \leq f_s \leq 900Hz \) |
| C8    | Flicker               | \( y(t) = A[1+\alpha_f \sin(\beta \omega t)]\sin(\omega t) \) | \( 0.1 \leq \alpha_f \leq 0.2; \ 5 \leq \beta \leq 20Hz \) |
| C9    | Notch                 | \( y(t) = \sin(\omega t) - \text{sign}(\sin(\omega t)) \) | \( 0 \leq t_i, t_f \leq 0.5T \) |
| C10   | Spikes                | \( y(t) = \sin(\omega t) - \text{sign}(\sin(\omega t)) \) | \( 0.01T \leq t_2 - t_1 \leq 0.005T; \ 0.1 \leq K \leq 0.4 \) |
| C11   | Sag with harmonic     | \( y(t) = A[-u(t-t_i)-u(t-t_f)] \) | \( 0 \leq \alpha \leq 0.9; \ T \leq t_2 - t_1 \leq 9T \) |
| C12   | Swell with harmonic   | \( y(t) = A[1+u(t-t_i)-u(t-t_f)] \) | \( 0 \leq \alpha \leq 0.8; \ T \leq t_2 - t_1 \leq 9T \) |
| C13   | Interruption with harmonic | \( y(t) = A[-u(t-t_i)-u(t-t_f)] \) | \( 0.9 \leq \alpha \leq 1; \ T \leq t_2 - t_1 \leq 9T \) |

Table 1. Power quality disturbance’s mathematical equations, adapted from: [9].
3. Feature Extraction

The overall process of PQD classification is shown in Figure 1. After the PQD signals generation, the signals were separated into training and testing data and passed through the feature extraction which is the process of creating the features of PQD signals. In this work, the signal’s characteristics were firstly extracted from the raw dataset of PQDs using the WT, as explained in Section 3.1. Then, the wavelet coefficients were obtained through the multi-resolution analysis (MRA), as detailed in Section 3.2. The procedure to create the feature vectors based on the their existing wavelet coefficients and statistical parameters is described in Section 3.3.

![Figure 1. PQD classification scheme.](image)

3.1. Wavelet Transform

In the PQD classification research, several signal processing techniques have been used for characterizing the characteristics of signals, i.e., wavelet transform, DWT, S-transform, VMD, etc. [18,42,43,46,47]. In this work, we used the DWT for extracting the signal characteristics due mainly to its flexible time-scale and high conservation of information without reduced resolution [17,48]. This method has also been used extensively in many applications for power systems, such as fault detection and localization, classification of the shunt compensated transmission line, islanding detection technique, and PQD classification [48–51]. The DWT is transformed from the WT based on a discrete wavelet scales. The expression of DWT is given as following equation;
\[ DWT(m, n) = \frac{1}{\sqrt{a_0^m}} \sum f(k) \psi \left( \frac{n - kb_0}{a_0^m} \right) \]  

where the parameter \( m \) indicates the frequency localization, \( n \) is the time localization, \( a_0^m \) represents the scaling parameter that repeats the length of wavelet as a function of \( m \), \( b_0 \) is the translation parameter, \( f(k) \) is the discrete point sequence of signal. The \( \psi \) represents the mother wavelet based on the fourth-order Daubechies, since its suitability for PQR classification was claimed in several previous studies [52, 53].

### 3.2. Multi-Resolution Analysis

The MRA is the process that uses the scaling function and orthogonal wavelet function to decompose and reconstruct signals at various resolution levels. This process benefits for filtering the propitious information of input signals, so the resulting signals are easier to be further implemented and require less execution memory [22]. In this work, we used the MRA for decomposing the PQD signals before constructing the feature vectors. The procedure of MRA can be described as follows; the continuous-time PQD signals are passed through the filtering system that consists of low-pass (LP) and high-pass (HP) filters at different resolution levels. The high-frequency component having the first detail coefficient (D1) was obtained by HP filtering the down-sampling signal. Likewise, a low-frequency component having the first approximation coefficient signal (A1) is obtained by LP filtering the down-sampling signal. Afterwards, the output of A1 is decomposed before calculating the second detail coefficient (D2) and approximation coefficient (A2). This process was repeatedly operated until eight decomposition levels were achieved since it was confirmed in the previous study that this desired value is appropriate for extracting the characteristics of the PQD signals [53]. The feature vector of PQD signals, \( F(k) \), is then constructed from the obtained coefficients, as written in Equation (2):

\[ F(k) = [D_1, D_2, D_3, D_4, D_5, D_6, D_7, A_8] \]  

### 3.3. Feature Vector Arrangement

After nine signal characteristics of PQD signals were obtained by the MRA process, the statistical parameters of signals were evaluated based on the signal’s characteristics. In this work, we focused on 11 statistical parameters including the energy (E), entropy (Ent), standard deviation (s), mean value (m), kurtosis (KT), skewness (SK), root-mean square (RMS), range (RG), log-energy entropy (LEnt), crest factor (CF), and form factor, as shown in Table 2. \( i, j = 1, 2, 3, ..., l \) are the wavelet decomposition numbers at level \( l \). \( N \) is the signal coefficient quantity in each decomposed data. \( X \) is the signal collected from eight detailed signals (D1, D2, ..., D8) and one approximate signal (A8).

**Table 2. Equations for statistical parameter**

| Parameter         | Statistical Equation | Parameter          | Statistical Equation |
|-------------------|----------------------|--------------------|----------------------|
| Energy \( E_i \)  | \[ E_i = \sum_{j=1}^{N} \left[ X_j^2 \right] \] | RMS                | \[ RMS_i = \left( \frac{1}{n} \sum_{j=1}^{N} X_j^2 \right)^{\frac{1}{2}} \] |
| Entropy \( Ent_i \) | \[ Ent_i = -\sum_{j=1}^{N} X_j^2 \log X_j^2 \] | Range              | \[ RG_i = \max(X_j) - \min(X_j) \] |
| Standard deviation \( \sigma_i \) | \[ \sigma_i = \left( \frac{1}{n-1} \sum_{j=1}^{N} \left( X_j - \mu_i \right)^2 \right)^{\frac{1}{2}} \] | Log-energy entropy \( LEnt_i \) | \[ LEnt_i = -\sum_{j=1}^{N} \log(X_j^2) \] |
| Mean \( \mu_i \)  | \[ \mu_i = \frac{1}{n} \sum_{j=1}^{N} X_j \] | Crest factor \( CF_i \) | \[ CF_i = \frac{X_{\text{max}}}{RMS_i} \] |
The feature vector of each statistical parameter was then constructed by the 11 detailed signals and one approximate signal, as shown in Table 3. It is shown that the overall features having 99 data are organized based on the type of statistical parameters.

Table 3. Creation of feature vectors from statistical parameters, adapted from: [54].

| Feature Vector |
|----------------|
| \( F_1 = \{E_{d1}, E_{d2}, E_{d3}, E_{d4}, E_{d5}, E_{d6}, E_{d7}, E_{d8}, E_{a1}\} \) |
| \( F_2 = \{\text{Ent}_{d1}, \text{Ent}_{d2}, \text{Ent}_{d3}, \text{Ent}_{d4}, \text{Ent}_{d5}, \text{Ent}_{d6}, \text{Ent}_{d7}, \text{Ent}_{d8}, \text{Ent}_{a1}\} \) |
| \( F_3 = \{\sigma_{d1}, \sigma_{d2}, \sigma_{d3}, \sigma_{d4}, \sigma_{d5}, \sigma_{d6}, \sigma_{d7}, \sigma_{d8}, \sigma_{a1}\} \) |
| \( F_4 = \{\mu_{d1}, \mu_{d2}, \mu_{d3}, \mu_{d4}, \mu_{d5}, \mu_{d6}, \mu_{d7}, \mu_{d8}, \mu_{a1}\} \) |
| \( F_5 = \{KT_{d1}, KT_{d2}, KT_{d3}, KT_{d4}, KT_{d5}, KT_{d6}, KT_{d7}, KT_{d8}, KT_{a1}\} \) |
| \( F_6 = \{SK_{d1}, SK_{d2}, SK_{d3}, SK_{d4}, SK_{d5}, SK_{d6}, SK_{d7}, SK_{d8}, SK_{a1}\} \) |
| \( F_7 = \{\text{RMS}_{d1}, \text{RMS}_{d2}, \text{RMS}_{d3}, \text{RMS}_{d4}, \text{RMS}_{d5}, \text{RMS}_{d6}, \text{RMS}_{d7}, \text{RMS}_{d8}, \text{RMS}_{a1}\} \) |
| \( F_8 = \{\text{RG}_{d1}, \text{RG}_{d2}, \text{RG}_{d3}, \text{RG}_{d4}, \text{RG}_{d5}, \text{RG}_{d6}, \text{RG}_{d7}, \text{RG}_{d8}, \text{RG}_{a1}\} \) |
| \( F_9 = \{\text{LEnt}_{d1}, \text{LEnt}_{d2}, \text{LEnt}_{d3}, \text{LEnt}_{d4}, \text{LEnt}_{d5}, \text{LEnt}_{d6}, \text{LEnt}_{d7}, \text{LEnt}_{d8}, \text{LEnt}_{a1}\} \) |
| \( F_{10} = \{CF_{d1}, CF_{d2}, CF_{d3}, CF_{d4}, CF_{d5}, CF_{d6}, CF_{d7}, CF_{d8}, CF_{a1}\} \) |
| \( F_{11} = \{FF_{d1}, FF_{d2}, FF_{d3}, FF_{d4}, FF_{d5}, FF_{d6}, FF_{d7}, FF_{d8}, FF_{a1}\} \) |

Since the feature vectors calculated from the statistical parameters might have a large difference in scale, they have to be normalized before passing through the classifier, as given in Equation (3):

\[
Z_i = \frac{F_i - F_{\text{min}}}{F_{\text{max}} - F_{\text{min}}} \quad (3)
\]

where \( Z_i \) is the normalized data, \( F_i \) is the feature vectors, \( F_{\text{min}} \) and \( F_{\text{max}} \) are the feature vectors having the minimum and maximum value. Therefore, the overall feature set can be obtained using Equation (4).

\[
\text{Feature} = [F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_{10}, F_{11}] \quad (4)
\]

4. Probabilistic Neural Network as a Classifier

In the PQD classification, the classifier is a process that classifies the power quality signal type. From the literature, many approaches have been performed as the classifier in power quality classification research [55–57]. PNN, which is one type of ANN, is a very well-known machine learning technique that has been extensively performed in several classification research [58]. The PNN uses the probabilistic model to operate the neural network for the pattern recognition [58]. Advantages of PNN include its high ability to achieve the results of non-linear learning algorithms with preserving high precision, as well as its simple implementation because the weights and network’s number of hidden layers are defined automatically by the network via the spread constant. PNN is also known as a powerful tool to solve various classification problems [59–61]. Our hypothesis was that the PNN could be highly appropriate for the proposed classification system according to its merits; thus, the PNN was used as classifier in this work. As shown in Figure 2, the PNN scheme contains the input and output layers separated by the hidden layer.
Initial weight of each node is initialized automatically. The distribution value or probability density function is used to classify the input dataset. Then, the probability density function is used to determine the output hidden layers. The same probability as the category unit in which the model units contribute to a signal is addressed. A Gaussian based on the associated training dataset creates the test dataset. The neural network is supplied by the summation of these local estimates calculated in the relevant category unit.

According to the PQD classification scheme depicted in Figure 1, after the optimally selected features were obtained from feature selection, they were passed through the PNN-based classifier. The dataset was then trained and used for classifying the power quality signal types.

5. Proposed Adaptive Salp Swarm Algorithm for Optimal Feature Selection

As extensively demonstrated in several literature surveys, the optimal feature selection in PQD classification is a procedure that could significantly improve the performance of the classification system [42–46]. It is a process that selects the optimal features from feature extracting data before passing those features through the classifier. Accordingly, this process can efficiently eliminate the redundant features of extracting data, yielding better classification accuracy, as well as faster computational time. Referred to Figure 1, we used the feature selection process to optimally select features before passing through the PNN classifier. As mentioned in the introduction, there were plenty of previous studies that developed many optimization algorithms for optimal feature selection in PQD classification. Especially, it was claimed in many literature surveys that the swarm intelligence algorithm such as PSO, comprehensive learning PSO, modified PSO and SSA are effective for solving real-world applications [62,63]. However, we noticed that the SSA could be another capable algorithm for optimal feature selection since it has many required properties in PQD classification such as good convergence acceleration, accelerated process in getting high precise solution, great neighborhood search characteristic, simple implementation, reasonable calculating time, and a parameter tuning [64–66]. We used the SSA for optimal feature selection in our PQD classification system, and it was performed using the proposed adaptive techniques for ability improvement of this algorithm.

5.1. Salp Swarm Algorithm

In 2017, the SSA was proposed and claimed as another high-ability algorithm for solving optimization problems [64]. The SSA was introduced by simulating the swarming movement of salps. The advantages of this algorithm are their fewer control parameters, simple expression, qualitative global exploration, fast convergence rate, accelerated process in getting high precise solution, and small required data storage. The SSA is used...
extensively in many past optimization research [67–70]. We also noticed that its advantages are suitable for PQD classification. For this reason, we proposedly performed the SSA as an optimal feature selection algorithm in PQD classification. The mechanism of SSA is the salps moving in a chain pattern. The salp chain is made up of two salp groups: leader salps and follower salps. The leader, which is responsible for exploration of the food location, determines the direction of movement by taking the first position in front of the chain. The followers follow the leader and move after the leader movement. The expression of leader’s position is given in the following equation;

\[
x^j_i = \begin{cases} 
F_j + c_i \left((ub_j - lb_j)c_i + lb_j \right) & c_i \geq 0.5 \\
F_j - c_i \left((ub_j - lb_j)c_i + lb_j \right) & c_i < 0.5
\end{cases}
\]

(5)

where \(x^j_i\) is the leader position at \(j\) dimension. \(F_j\) represents the food position. \(ub_j\) and \(lb_j\) are the upper and lower boundaries. \(c_2\) and \(c_3\) are the random numbers between 0 and 1. \(c_i\) represents a movement of the leader toward the food, defined as the following equation;

\[
c_i = 2e^{-\left(\frac{t}{\tau_{max}}\right)^2}
\]

(6)

where \(t\) is the current iteration and \(\tau_{max}\) is the maximum number of iterations. The position of followers can be updated using Newton’s law of motion, as shown in Equation (7);

\[
x^j_i = \frac{1}{2}ay^2 + v_0y
\]

(7)

where \(x^j_i\) is the position of following salp of \(i\)-th follower in \(j\) dimension \((i \geq 2)\), \(a\) is the acceleration value, \(y\) is time, \(v_0\) is an initial speed. Then, the position of followers can be updated using Equation (8).

\[
x^j_i = \frac{1}{2}(x^j_i + x^{j-1}_i)
\]

(8)

5.2. Proposed Adaptive Salp Swarm Algorithm

In this work, we performed two approaches to improve the ability of SSA as the feature optimal selection algorithm. Section 5.2.1 describes the first approach to modifying salp movement behavior while searching for a food source, meanwhile Section 5.2.2 describes the adaptive technique to improve the performance of SSA.

5.2.1. Proposed Approaches for a Modification of Salp Movement

The salp movement for the SSA begins with the leader exploring the food position, while the followers move in a chain pattern. The leader’s position updates depending on the food location, which requires the calculated boundaries. This mechanism usually decreases the direct interaction between the leader and the food. The follower’s chain pattern depends only on the position of the leader. These mentioned behaviors of SSA sometimes cause a poor development between exploitation and exploration in case that the leader falls into the local optimum, which results in its low precision. Therefore, we propose a new parameter to control the convergence speed of a leader while searching for food, it is called “searching control parameter, \(x\)”. This proposed parameter is supposed to improve the balance between exploitation and exploration of SSA to avoid the local optimum. The \(x\) is included in the conventional expressions for salp positioning of SSA, and then those equations can be rewritten as Equations (9) and (10).
\[x_j' = \begin{cases} 
\lambda_j F_j + c_1 \left((ub_j - lb_j)c_2 + lb_j\right) & c_1 \geq 0 \\
\lambda_j F_j - c_1 \left((ub_j - lb_j)c_2 + lb_j\right) & c_1 < 0 
\end{cases} \] (9)

\[x_j' = \frac{1}{2} \left(x_j' + \lambda_j x_j^{-1}\right) \] (10)

In addition, we also proposedly adjust the moving direction of the leader to have wider spreading behavior through the parameter \(c_1\) of the leader’s movement of each iteration, as shown in Equation (11).

\[c_1 = \left(\frac{0.5}{\sqrt{f}}\right) \sin\left(10 \pi \frac{t}{t_{\text{max}}} + 2\right) \] (11)

5.2.2. Proposed Adaptive Salp Swarm Algorithm

Since we noticed, from a literature review, that the main disadvantage of SSA is their local optima issue. Then, we propose the adaptive technique to solve this weakness of SSA by improving its development ability between exploitation and exploration. The idea of this proposed technique is to enlarge the searching space of the salp while finding the new salp’s position, which may possibly be located nearby. The procedure of the PQD classification using the adaptive SSA as the feature selection algorithm is described in following detail, while its pseudo code is illustrated in Figure 3.

**Input:** A feature vector containing 99 feature data

**Output:** 12 optimal features

1. Initialize the salp population
2. While maximum iteration is not reached
   - Compute the objective function for each salp
   - Update the best position of salp (food source)
   - Update the parameter \(c_1\)
   - For each salp
     - For each dimension
       - If salp is the leader
         - Update the leader salp’s position using Equation (9)
       - Else (follower)
         - Update the follower salps’s position using Equation (10)
     - End if
   - End for
   - Evaluate the fitness value
3. End while
4. Select the feature vector having the highest accuracy
5. Find the nearby salp’s position using the adaptive method shown in Equation (12)

**Return best fitness**

**Figure 3.** Pseudocode of the proposed adaptive SSA.

Step 1: Initialize the number of salp population, dimension of the feature extracting data and iteration parameters;
Step 2: Create the feature vector randomly based on the setting upper and lower boundaries, defined dimension, and salp initialization;

Step 3: Pass the feature vector through the classifier. Calculate the percentage classification accuracy by a correctly classified signal types divided by the total test signals. Memorize the feature vector having the highest accuracy in the current population;

Step 4: Update the parameter $c_i$ according to each iteration using Equation (11), and then randomly generate the parameters $c_2$ and $c_3$;

Step 5: Evaluate the leader’s position based on the parameters $c_1$, $c_2$, and $c_3$ obtained from Step 4 using Equation (5). Then, the follower’s position based on the existing leader position is determined using Equation (8). Once all dimensions are built, calculate the accuracy;

Step 6: Perform the proposed adaptive technique, as the following detail. Select the feature vector having the highest accuracy at current iteration to enter the adaptive process. This process aims to further find the new position of salp nearby the current position which might has better accuracy than the existing one. At the each iteration of adaptive process, the adaptive coefficient value of the previous iteration, $\beta_i^{\text{old}}$, is randomly generated for calculating the adaptive coefficient value of the current iteration, $\beta_i^{\text{new}}$, with taking into account the initial weight, $w_{\text{max}}$, and the final weight, $w_{\text{min}}$, as expressed in Equation (12). The weight parameters developed in this work are used to determine the search space of the feature data in each iteration of adaptive process, $C$ is the current iteration of the adaptive method, $C_{\text{max}}$ is the maximum iteration number of the adaptive process. $i$ is the iteration number of SSA process. After that, the feature vector of the adaptive process, $x_i^{\text{new}}$, is obtained based on the salp’s current position having the highest accuracy, $x_i$, with taking into account the $\beta_i^{\text{new}}$ and the $x_i^{\text{random}}$, as expressed in Equation (13). Where $x_i^{\text{random}}$ is the random feature vector between lower and upper boundaries of feature extracting vector, generated to indicate the data range of adaptive process compared to the $x_i$;

$$\beta_i^{\text{new}} = \beta_i^{\text{old}} - \frac{C(w_{\text{max}} - w_{\text{min}})}{C_{\text{max}}}$$

(12)

$$x_i^{\text{new}} = x_i + \beta_i^{\text{new}} \left( x_i^{\text{random}} - x_i \right)$$

(13)

where $j$ is the feature dimension. The feature vector obtained from the adaptive process is passed through the PNN classifier, and then the classification accuracy is calculated;

Step 7: Repeat the adaptive process until the its maximum iteration is reached. Collect the feature vector of adaptive process indicating the highest classification accuracy;

Step 8: Compare the classification accuracy obtained from the adaptive process to that existed in iterations of SSA, then collect the feature vector that has the highest classification accuracy;

Step 9: Repeat Step 3 to 8 until the maximum number of iterations is reached. Obtain the optimal feature vectors.

6. Results and Discussion

In this section, the performance of the proposed classification system is shown and discussed based on the 13 types of power quality signals. The system feature extraction was based on the DWT, while the classifier was based on the PNN. The results were based on the SSA’s control parameters including number of salp = 10, iteration = 40, run 3 times, 20 independent runs, $\lambda_1 = 0.5$, and $\lambda_2 = 0.1$. MATLAB environment was performed in the simulations. The section is organized as follows: Section 6.1 investigates the optimal number of selected features for the proposed classification system. The accuracy of the
PQD classification based on the proposed adaptive SSA is discussed in Section 6.2. The classification accuracy under a noisy situation is demonstrated in Section 6.3. The convergence property of the classification systems is indicated in Section 6.4. The simulations based on the real dataset are demonstrated in Section 6.5. Finally, Section 6.6 shows a performance comparison of the proposed classification system to the previous studies.

6.1. Optimal Number of Selected Features for the Proposed Classification System#

Since the number of selected features obtained from the feature selection process typically has an impact on the classification accuracy, we firstly investigated the optimal number of selected features for our PQD classification. Table 4 shows the classification accuracy of various numbers of selected features, with the results based on the adaptive SSA. This table indicated that with over 5 selected features, higher precision than 1 to 4 selected features is obtained. In particular, the highest classification accuracy of 98.77% can be achieved with 12 optimally selected features. In addition, Table 5 shows further detail of classification accuracy at each iteration having different selected features by the adaptive SSA. It shows that the highest accuracy with the optimally selected features indicated is achieved at iteration 79. The results displayed in the next sections are based on these 12 optimal features.

| Number of Feature Data | Feature Selected | Accuracy (%) |
|------------------------|------------------|--------------|
| 1                      | 37               | 65.62        |
| 2                      | 72 21            | 75.30        |
| 3                      | 36 1 14          | 92.15        |
| 4                      | 7 16 20 14       | 94.77        |
| 5                      | 18 37 14 8 7     | 95.62        |
| 6                      | 2 40 5 16 7 58   | 97.31        |
| 7                      | 40 6 7 17 16 8 2 14 | 98.23    |
| 8                      | 32 7 10 16 40 21 9 19 | 97.31    |
| 9                      | 70 18 10 4 17 2 85 41 9 | 97.08    |
| 10                     | 2 10 7 2 6 9 9 40 6 5 16 | 97.62    |
| 11                     | 51 7 40 16 11 4 39 6 12 4 12 | 97.77    |
| 12                     | 41 38 43 27 40 9 29 7 16 47 26 18 | 98.77    |
| 13                     | 54 7 63 38 40 54 19 13 24 17 22 57 18 | 97.92    |

| Iteration | Selected Features | Classification Accuracy (%) |
|-----------|-------------------|----------------------------|
| 75        | 7 8 14 1 11 90 8 15 49 16 | 3 10 | 92.15 |
| 76        | 7 92 9 18 17 33 15 30 28 8 89 14 | 92.00 |
| 77        | 9 70 27 8 12 16 38 20 17 5 52 7 | 78.46 |
| 78        | 20 31 14 49 44 12 31 16 9 3 35 4 | 94.31 |
| 79        | 41 38 43 27 40 9 29 7 16 47 26 18 | 98.77 |
| 80        | 24 22 29 13 24 6 12 4 11 25 9 6 | 89.00 |
| 81        | 13 15 15 7 12 4 22 13 15 10 9 3 | 93.23 |
| 82        | 8 9 7 4 6 3 7 13 12 51 90 5 | 88.38 |
| 83        | 8 6 43 3 4 13 4 10 8 25 26 2 | 79.46 |
6.2. PQD Classification Accuracy Using the Adaptive SSA#

To look closer into the mechanism of the adaptive SSA in PQD classification, Table 6 demonstrates the classification accuracy using the adaptive SSA and without feature optimal selection. The difference in performing different statistical parameters in classification was also taken into account. It is seen that using a single statistical parameter has poor capability in classification. Meanwhile, the classification accuracy improves when using a greater number of statistical parameters. This finding indicates that multiple statistical parameters are typically required to achieve high accuracy in PQD classification. The 94.38% accuracy was obtained for a case with all statistical parameters included excluding the optimal feature selection process. The highest accuracy was demonstrated for a case using 13 statistical parameters with the proposed adaptive SSA at optimal feature selection algorithm.

Table 6. Classification accuracy using different statistical parameters.

| Type of PQD          | Classification Accuracy (%) | 1 Type (Energy) | 1 Type (Entropy) | 1 Type (Kurtosis) | 3 Types (Energy, Entropy, S.D.) | 5 Types (Energy, Entropy, S.D., Mean, Kurtosis) | All Types Adaptive SSA |
|----------------------|----------------------------|-----------------|------------------|-------------------|--------------------------------|------------------------------------------------|------------------------|
| Pure sine            | 100                        | 100             | 100              | 100               | 100                            | 100                                           | 100                    |
| Sag                  | 73                         | 76              | 77               | 86                | 96                             | 98                                            | 96                     |
| Swell                | 82                         | 89              | 56               | 95                | 98                             | 99                                            | 98                     |
| Interruption         | 81                         | 96              | 60               | 96                | 100                            | 99                                            | 100                    |
| Harmonic             | 97                         | 100             | 99               | 100               | 100                            | 100                                           | 100                    |
| Sag with harmonic    | 59                         | 66              | 72               | 81                | 89                             | 78                                            | 93                     |
| Swell with harmonic  | 86                         | 94              | 68               | 95                | 98                             | 96                                            | 97                     |
| Interruption with harmonic | 67               | 93              | 97               | 93                | 99                             | 93                                            | 100                    |
| Flicker              | 72                         | 84              | 99               | 92                | 99                             | 100                                           | 100                    |
| Oscillatory transient | 75                        | 92              | 97               | 97                | 100                            | 100                                           | 100                    |
| Impulsive transient  | 74                         | 85              | 100              | 90                | 100                            | 100                                           | 100                    |
| Periodic notch       | 100                        | 53              | 100              | 100               | 100                            | 77                                            | 100                    |
| Spike                | 47                         | 73              | 26               | 61                | 77                             | 87                                            | 100                    |
| Overall accuracy     | 77.92                      | 84.69           | 80.85            | 91.23             | 96.61                          | 94.38                                         | 98.77                  |

6.3. Classification Performance under a Noisy Environment#

A noisy condition is a situation that typically occurs in a practical distribution system. Therefore, the performance of the proposed classification system under a noisy environment was tested and compared to the conventional SSA, as well as the well-known methods, which are the conventional particle swarm optimization (PSO) and the Genetic algorithm (GA), as feature selection algorithms. The expression of these comparative algorithms was adopted from references [33,44,64]. The key parameters of PSO were set as follows; population size = 10, max inertia weight = 0.9, min inertia weight = 0.4, acceleration factor = 0.9, maximum number of iterations = 40, maximum needed number of runs = 20. The key parameters of GA were set as follows; population size = 10, max number of generations = 40, number of binary bits per design variable =10, crossover rate = 0.9, mutation rate = 0.1, transition probability = 0.01, maximum number of runs need to be = 20. Meanwhile, the key parameters of SSA were set similarly to the its adaptive. White noise with a signal-to-noise ratio of 10 to 50 dB were identically added to all power quality signal types. From Table 7, it is seen that the classification system based on the adaptive SSA optimal feature selection is qualitatively more resistant to noise than a system without an optimal feature selection, using conventional SSA, using PSO and using GA as optimal
feature selection. Therefore, the proposed system could be efficiently operated in a noisy environment.

Table 7. Accuracy of PQD classification under a noisy environment.

| Noise Magnitude | Classification Accuracy (%) |
|-----------------|----------------------------|
|                 | All Features | PSO   | GA   | SSA  | Adaptive SSA |
| Without noise   | 94.38        | 98.46 | 97.85| 96.85| 98.77        |
| 10 dB           | 55.26        | 72.31 | 69.38| 60.55| 72.86        |
| 20 dB           | 74.89        | 88.43 | 77.85| 81.17| 89.11        |
| 30 dB           | 87.20        | 93.60 | 92.38| 89.66| 93.91        |
| 40 dB           | 90.03        | 94.46 | 89.85| 90.52| 94.95        |
| 50 dB           | 91.45        | 95.94 | 96.31| 91.63| 96.37        |

6.4. Convergence Rate

As mentioned earlier, one of the outstanding advantages of the SSA is its very fast convergence property. It is, therefore, necessary to examine the convergence profile of the proposed algorithm. In this work, we compared the convergence rate of our proposed system to the convergence rates of other well-known algorithms, such as PSO and GA. Figure 4 shows a comparison of the convergence rate of the PQD classification system using different algorithms for optimal feature selection, while the detail of accuracy and required iterations is summarized in Table 8. It was found that the system based on the adaptive SSA had the highest convergence rate to reach the classification accuracy of 98.77% at iteration 79. The conventional SSA can provide 96.85% accuracy at iteration 105. Meanwhile, the accuracy of 98.46% was reached by the PSO at iteration 80 and of 98.15% was reached by the GA at iteration 106. Then, the classification system using the adaptive SSA is not only able to provide very high accuracy, but it also has a rapid convergence rate.

Figure 4. Convergence rate of classification system using different feature selection algorithms.
Table 8. Detail of classification performance using different feature selection algorithms.

| Feature Selection Algorithms | Overall Accuracy (%) | Required Iterations |
|------------------------------|-----------------------|---------------------|
| PSO                          | 98.46                 | 80                  |
| GA                           | 97.85                 | 106                |
| SSA                          | 96.85                 | 105                 |
| Adaptive SSA                 | 98.77                 | 79                  |

6.5. Classification Performance Based on the Real Dataset

To validate the accuracy of the proposed classification system, it was tested using the real dataset of the practical distribution network. The dataset was adopted from the PQube equipment, which is a tool used for real-time monitoring the power quality and electrical signal phenomena [71]. We focused on a case study of the distribution system located in Singapore, China, Sweden, and South Africa. Table 9 displays the classification system’s accuracy when using adaptive SSA as the optimal feature selection. It was found that the classification system proposed in this work provides 98.5% accuracy for identifying 5 types of power quality signals, which is consistent with that obtained by using the synthetic waveforms (98.8%).

Table 9. Classification accuracy using the real dataset.

| Signal Type   | Classification Accuracy (%) |
|---------------|-----------------------------|
| Pure sine     | 97.5                        |
| Sag           | 100                         |
| Swell         | 100                         |
| Interruption  | 95                         |
| Harmonic      | 100                         |
| Overall accuracy | 98.5                      |

6.6. Comparison of Classification Performance to the Existing Works

To compare the performance of our proposed PQD classification to the other existing works, Table 10 shows a list of the accuracy of PQD classification appeared in the literature. Noted that accuracy of each mentioned system is adopted from those references. It is seen that the 98.77% classification accuracy of our proposed system is classified as very high value compared to the existing works. Additionally, our classification system can classify power quality signals of up to 13 different types, which is more than most research in this field. Furthermore, the classification system using the SSA as an optimal feature selection algorithm can quickly provide a solution. Hence, the classification system proposed in this work is another capable method for PQD classification and is appropriate for use in practical distribution systems.

Table 10. Comparison of classification accuracy to the existing works.

| Reference | Number of PQD Types | Feature Extraction Type | Classification Technique | Optimal Feature Selection Algorithm | Overall Accuracy (%) |
|-----------|----------------------|-------------------------|--------------------------|-------------------------------------|----------------------|
| [43]      | 5                    | DWT                     | LS-SVM                   | k-means +Apriori algorithm           | 98.88                |
| [72]      | 8                    | Modified frequency slice wavelet | PNN                      |                                     | 97.70                |
| [73]      | 8                    | Hilbert–Huang transform | NN                       |                                     | 97.90                |
| [74]      | 9                    | Time-time transform     | Decision tree            | Ant Colony Optimization             | 95.97                |
| [42]      | 9                    | ST                      | Fuzzy C-means            | Adaptive PSO                        | 96.33                |
| [21]      | 9                    | ST + VMD                | SVM                      | Sequential forward selection        | 99.66                |
| [75]      | 9                    | VDM                     | Decision tree            |                                     | 98.56                |
| [44]  | 10   | DWT | extreme learning machine | PSO | 97.60 |
| [76]  | 10   | DWT + FFT | Threshold |  | 90.04 |
| [46]  | 13   | VMD | OVR-SVM | Permutation Entropy + Fisher Score | 97.6 |
| [77]  | 13   | hyperbolic S-transform | Decision tree | GA | 99.5 |
| [45]  | 15   | VDM | Fast reduced kernel extreme learning machine | Fischer linear discriminant analysis | 98.82 |
| This work | 13   | WT | PNN | Adaptive SSA | 98.77# |

7. Conclusions

In this work, we introduced a new algorithm called the adaptive SSA as a feature selection algorithm for PQD classification. The classification system’s feature extraction was based on the DWT and the classifier uses probabilistic neural network. The adaptive approaches were proposedly performed to enhance the ability of SSA for classification. It was found that the presented system indicated the best performance through 12 optimally selected features. The results showed that the highest accuracy in the classification of 13 types of signal power quality of 98.77% was achieved. Additionally, the proposed classification system can greatly operate in the noisy situation and the real dataset. The convergence rate of the system based on adaptive SSA was very high compared to the SSA, PSO, and GA. Considering the classification accuracy of previous studies reveals that the proposed classification system’s accuracy falls on a high-range scale, implying that it is capable of being another efficient PQD classification system.

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