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Study of the Evaluation Functions of PSO for Reconfiguration of Electrical Power System

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Abstract. This paper proposes the analysis of Sigmoid, Hyperbolic Tangent and Elliot functions in the PSO algorithm for reconfiguration of electrical system. The aim of reconfiguration is to reduce losses in the electrical system. The optimization algorithm used the binary PSO heuristic method and was developed in MATLAB© software using the MATPOWER toolbox to solve the power flow. The reduction of real losses is the objective function, where each particle is the state of the branch switch, open or closed. The methodology was applied to the IEEE-30 Bus, IEEE-118 Bus and to a Planned Example Case of a Brazilian Power Distribution Company. It was observed that the Hyperbolic Tangent and Elliot function performed well in optimizing the power system reconfiguration to reduce losses in the IEEE-30 bus, IEEE-118 bus and 138 kV planned example case.

Keywords: Elliot function, losses, Hyperbolic Tangent, Binary PSO.

1 Introduction

The reconfiguration of electrical systems can be used as a control tool for operation of the distribution and transmission power system to ensure the continuity of supply or the system parameters adaptation. The aim of reconfiguration can be the losses reductions, load distribution or regulation of voltage level. The reconfiguration problem is solved from the best combination of the system switches. The high number of switches in the power system increase the complexity of the problem, because each combination of switches represents a topology for the system that can be implemented. The reconfiguration of electrical systems with heuristic methods aimed at reducing active losses was discussed by Shirmohammadi and Hong [1]. The method employed involved calculating the power flow to the system with all switches closed and then opening switches that had the lowest circulating current with the verification and maintenance of compliance with all loads and operational limits. The bio-inspired heuristic methods search optimal solutions through probabilistic rules.

The particle swarm optimization (PSO) method was first described by Kennedy and Eberhart [2], which were based on concepts of artificial intelligence, bird clustering theory, schooling behavior and theories of particle swarms. The PSO was used to reconfigure radial power flow with 33-bus. Shetty and Ankaliki [3] used the PSO to reduce losses and improve the voltage profile of the radial system. Nasir [4] proposed the PSO to optimize the network by reconfiguration of the radial system and the allocation of distributed generation. And Khalil [5] considered the application of the PSO to optimize the allocation of capacitors with the system reconfiguration.

This paper proposes the application of Sigmoid, Hyperbolic Tangent and Elliot functions in the PSO to the reconfiguration problem of electrical systems. The motivation of this paper is to analyze the behavior and the viability of these functions in the binary PSO algorithm with application in electrical power system. The methodology aims to be applied in meshed electrical systems with automated switches available in each branch of the system, operating them individually or together in search of the optimal system configuration to reduce real technical losses. This paper is divided in Background, Particle Swarm Optimization (PSO), Results and Conclusion.

2 Background

2.1 Power Flow

The power flow is performed to control the system in real time and to study expansion projects of the electric power system. The mathematical model of the electrical system considers the modelling of the transmission lines through their resistance, inductance and susceptibility; the substations as connection points between lines, loads, generation and reactive compensation devices; loads and generations by real and reactive power values.

The power flow calculation has as input the lines impedances, transformer impedances and the specification of the values of real and reactive demand in each bus. The Newton-Raphson (NR) iterative method works with four electrical quantities: the voltage magnitude (V_k), voltage argument (δ_k), real (P_k) and reactive (Q_k) power in the bus k under steady state. The real and reactive power is computed in (1) and (2), respectively, where the terms of the admittance matrix are written by magnitude (Y_{kn}) and argument (θ_{kn}). The admittance matrix is composed of the admittances of the systems branches. The bus is named according to the input variables. The Vδ bus is considered a slack bus, PQ is the load bus and PV is the bus with controlled voltage.

$$P_k{}^{(i)} = \sum_{n=1}^{N} |V_k \cdot V_n \cdot Y_{kn}| \cdot \cos(\theta_{kn} + \delta_n - \delta_k) \tag{1}$$

$$Q_k{}^{(i)} = -\sum_{n=1}^{N} |V_k \cdot V_n \cdot Y_{kn}| \cdot \sin(\theta_{kn} + \delta_n - \delta_k) \tag{2}$$

The difference between the specified and calculated values for real and reactive power is given in (3) e (4), respectively. The voltage magnitude and argument are computed in (5).

$$\Delta P_k{}^{(i)} = P_{k,specified} - P_{k,calculated}{}^{(i)} \tag{3}$$

$$\Delta Q_k{}^{(i)} = Q_{k,specified} - Q_{k,calculated}{}^{(i)} \tag{4}$$

$$\begin{bmatrix} \delta_k^{(i+1)} - \delta_k^{(i)} \\ V_k^{(i+1)} - V_k^{(i)} \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial V} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \Delta P_k \\ \Delta Q_k \end{bmatrix} \tag{5}$$

2.2 System Reconfiguration

System reconfiguration can be performed to accommodate variations in load and generation values, at the request for new entrants to the system or by seasonality. Typically, system reconfiguration is used to find an optimal topology of the system given a load profile. The reconfiguration problem is solved using the best combination of the various switches. The high number of switches in the systems increases the complexity of the problem, since each combination of switches represents a topology that this system can assume. Some combinations cannot be used, as they do not comply with voltage and load parameters, in addition to which, in some situations, points in the system are without power supplies as shown by Shirmohammadi and Hong [1]. The total number of possible combinations between the system switches is 2^n, where n represents the total number of switches.

3 Particle Swarm Optimization (PSO)

The particle swarm optimization technique is used to explore a determined search space and find solutions capable of achieving the defined objective for the particles.

In the PSO, each particle represents a solution to a given problem, this particle is a vector (x_{np}^{i}) that corresponds to the particle's position in the search space. At each iteration, the particles update their positions according to their previous position, velocity, position of the best performance of the particle (*pbest*) and position of best performance of the whole cluster (*gbest*). Where np is the particle number, i is the number of the current iteration and $i+1$ is the number of the new iteration.

Velocities are updated by the sum of the cognitive term, inertia term and the social learning term according to (6). The inertia term depends on the velocity in the previous iteration (v_{np}^{i}) and a weighting factor of inertia (ω). The cognitive term has a random number (r_1), a cognitive parameter (c_1) and the variation between the point of best individual performance (*pbest*) and the current point of the particle. The social learning term has a random number (r_2), a social learning rate (c_2), the variation between the point of best global performance (*gbest*) and the current point of the particle. The position of the particle is computed in (7).

$$v_{np}^{i+1} = \omega v_{np}^{i} + r_1 c_1 \left(pbest - x_{np}^{i} \right) + r_2 c_2 \left(gbest - x_{np}^{i} \right) \tag{6}$$

$$x_{np}^{i+1} = x_{np}^{i} + v_{np}^{i+1} \tag{7}$$

The PSO can operate with discrete binary variables, for this, the particles start to change their trajectory according to the probability that coordinate must assume the value 1 or 0 as shown by Kennedy and Eberhart [6]. In this variation, the velocity function stops defining the direction in which the particle will go and becomes a decision agent. The higher the velocity function, the more likely it is that the particle will assume a value of 1. The velocity function in (6) remains unchanged and therefore it is necessary to apply a normalization function over its final value. The sigmoid function is used to ensure that the velocity function is translated as probability and that its value is in the range [0,1]. The particles are updated by comparing the sigmoid function in (8) and a vector of the random numbers $\rho_{\mathrm{np}}^{\mathrm{i+1}}$ between 0 and 1 according to (9).

$$f(v_{np}^{i+1}) = \frac{1}{1 + exp^{-(v_{np}^{i+1})}} \tag{8}$$

$$x_{np}^{i+1} = \begin{cases} 1, \text{ if } \rho_{\mathrm{np}}^{\mathrm{i+1}} < f(v_{np}^{i+1}) \\ 0, otherwise \end{cases} \tag{9}$$

The classical and binary PSO present different results for variation of velocity. In the classic PSO, the higher values of the velocity function represent a positive factor for increasing exploration in the search space. And in the binary PSO, the increase in velocity brings with it the probability that the particle takes on a value and does not change, restricting the exploration of the search space. Therefore, the binary PSO has limits for the velocity function so as not to allow the sigmoid function to approximate to the value 0 or 1 as shown by Khanesar [7].

3.1 Binary PSO for System Reconfiguration

This paper applied the binary PSO to reduce losses in the meshed electrical system. Each particle is composed of vector of size n, which contains the combination of commands for the n switches of the system. The approach considers that all interconnections in the system have a switch, to test the performance of the algorithm. Therefore, the number of switches n is equivalent to the total number of connections available. The particles were started by a random function and the initial velocity was set to 1 for all particles, that is, all switches were in the closed state. The state of the open switch was set to 0.

The MATPOWER toolbox, created by Zimmerman [8], was used to calculate the power flow using the Newton-Raphson method. In this algorithm, voltage limits of 95 and 105% of the nominal voltage as voltage levels for systems operating above 69 kV according to Brazilian regulatory agency ANEEL [9].

The objective function used was the real losses of the system in (10). Where I_{AB} is the current in the branch AB and R_{AB} is the resistance in the branch AB.

$$|P_t| = \sum {I_{AB}}^2 \cdot R_{AB} \tag{10}$$

The velocities values are updated in each iteration according to (6). The velocity limits were defined as [-4,4] so that to prevent the normalized velocity function from approaching 1 or 0, limiting the algorithm search space as shown by Khanesar [7].

The particles are updated at each iteration through (9), where a comparison is made between a random value and the value of the velocity function using its representation of probability calculated using the sigmoid function in (8). This paper proposes the use of the hyperbolic function in (11) and the Elliot function in (12) in the binary PSO to reconfiguration of the electrical system. The flowchart of the algorithm is shown in Fig.1.

$$f(v_{np}^{i+1}) = \frac{tanh\,(v_{np}^{i+1})\ +1}{2} \tag{11}$$

$$f(v_{np}^{i+1}) = \frac{\frac{v_{np}^{i+1}}{1+|v_{np}^{i+1}|}+1}{2} \tag{12}$$

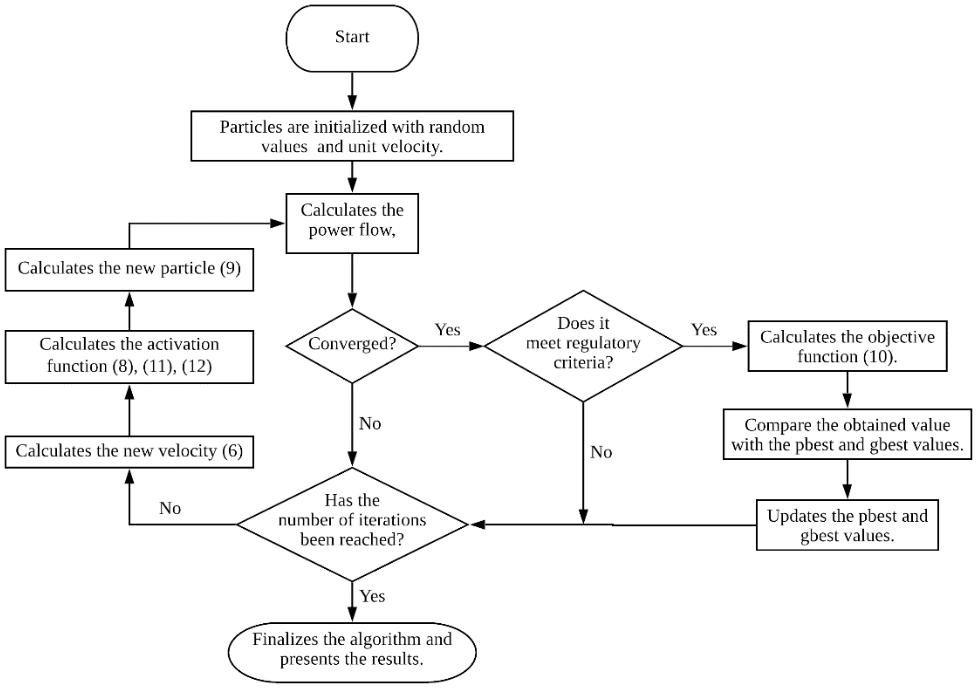

Figure 1. Binary PSO flowchart for the electrical system reconfiguration.

4 Results

4.1 Electrical systems

The paper proposal was applied to reduce losses in the IEEE-30 bus, IEEE-118 bus and 138 kV planned example case of a Brazilian Power Distribution Company. The mathematical model of the IEEE-30 and IEEE-118 bus system is available in the MATPOWER toolbox. Initially, it was considered that all branches have a switch and the initial state was normally closed. The IEEE-30 bus system has a Slack bus, 5 PV buses, 24 PQ buses and 41 branches as described by Christie [10]. The total number of switches combinations is approximately 2.2 trillion possibilities. The IEEE-118 bus system has a Slack bus, 53 PV buses, 64 PQ buses and 186 branches as described by Christie [11]. The total number of switches combinations is approximately $9.81{\times}10^{55}$ possibilities.

The algorithm was used to propose a new configuration to a meshed electrical system and designed to operate in the energy distribution at voltage level of 138 kV of a Brazilian Power Distribution Company. Figure 2 presents the diagram of the system that has 34 branches connecting 28 substations. In this system, each bus represents a substation, where generation supply and load are connected. This system is based on a project to expand a real distribution system, the generation and load values used were extracted from the system in operation. The total number of switches combinations is approximately 17 billion possibilities.

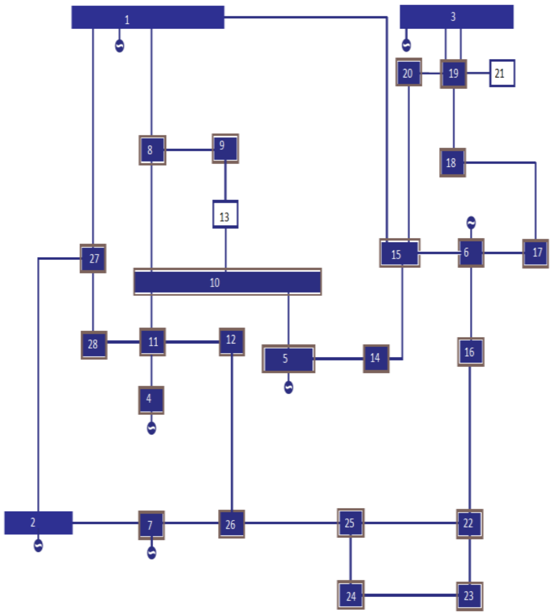

Figure 2. Diagram of the 138 kV power distribution system.

4.2 Analysis of Results

The inertia coefficient (ω) was defined as 1 to prevent the normalized values of the normalized velocity function from tending to one of the limits according to Khanesar [7]. In this paper, the algorithm used the value 1 for the cognitive parameter (c_1) and the social learning rate (c_2) allowing the influence of these components to be defined by random number r_1 and r_2. The binary PSO of this paper was written in MATLAB© and were performed using an Intel® Core™ i7-8565U, CPU @1.80 GHz and11.9GB of RAM.

The best result for loss reduction in the IEEE-30 bus system was obtained using the sigmoid function. In these terms 5,000 particles are evaluated, where each of the initial 50 particles is reconfigured with 100 iterations. Real losses were reduced by 6.47% considering the switches open in the branches 12-15, 14-15, 16-17 and 24-25. The Hyperbolic Tangent function presented a loss reduction of 6.38% and the Elliot function maintained the same loss value as the initial condition.

The best result for loss reduction in the IEEE-118 bus system was obtained using the Hyperbolic Tangent function. In these terms 50,000 particles are evaluated, where each of the initial 50 particles is reconfigured with 1,000 iterations. Real losses were reduced by 4.64% considering the switches open in the branches 1-2, 13-15, 14-15, 12-16, 23-24, 25-26, 31-32, 27-32, 15-33, 52-53, 56-57, 51-58, 61-64, 65-66, 47-69, 49-69, 68-69, 70-75, 68-81, 77-82, 94-100 and 105-106. The Sigmoid function presented a loss reduction of 3.81% and the Elliot function, 0.15%. Figure 3 shows the voltage profile within the regulatory limits for IEEE-118 bus.

The optimal loss value for the 138-kV planned example case system was 2.69% with Sigmoid and Hyperbolic Tangent functions. In these terms 50,000 particles are evaluated, where each of the initial 50 particles is reconfigured with 1,000 iterations. The optimal configuration has the switches open in the branches 6-15, 8-10, 16-22, 23-24 and 11-28. The Elliot function presented a loss reduction of 2.62%. Figure 4 shows the voltage profile within the regulatory limits for 138-kV planned example case system. The reconfiguration proposed reduces the real losses of this system by approximately 0.18 MW. This value represents around 1.58 GW per year of reduction in technical losses. These values contribute to the analysis of economic viability and can be used as a decision factor for improvement for this distribution system.

Table 1 presents the losses, percentage loss reduction, runtime, and convergent combinations for the Sigmoid, Hyperbolic Tangent and Elliot functions for IEEE-30 bus, IEEE-118 bus and 138-kV planned example case.

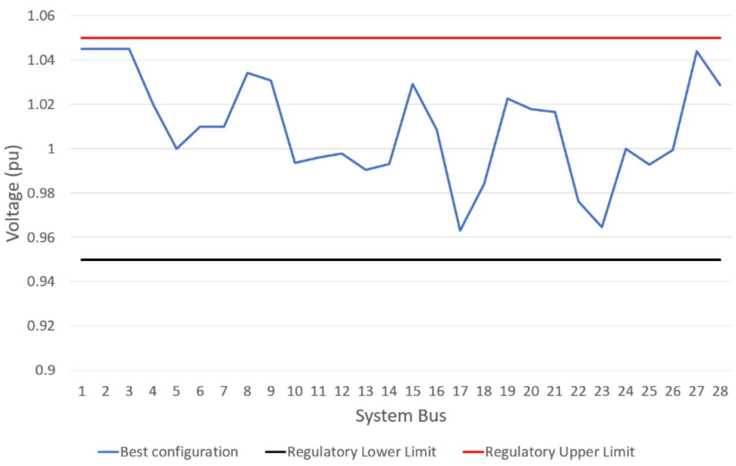

Figure 3. Voltage profile of IEEE-118 bus system.

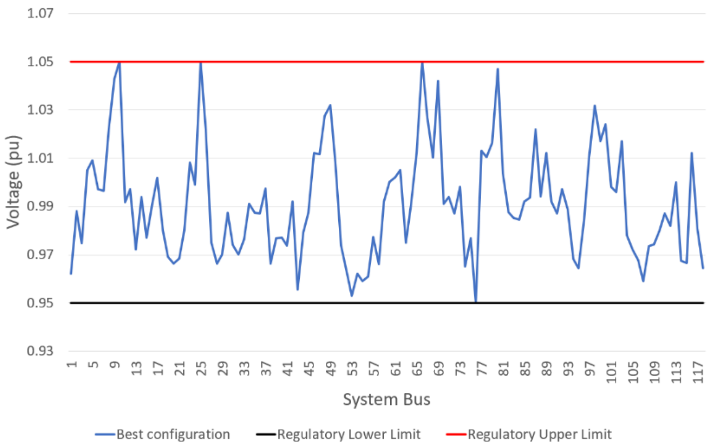

Figure 4. Voltage profile of 138-kV case.

Table 1. Coefficients in constitutive relations

	Initial condition	Sigmoid	Hyperbolic Tangent	Elliot
IEEE-30 Bus System				
Real Losses (MW)	2.4438	2.2856	2.2877	2.4438
Loss Reduction (%)	-	6.47	6.38	0
Runtime (s)	-	60.33	69.45	73.84
Convergent Combinations	-	2,274	636	347
IEEE-118 Bus System				
Real Losses (MW)	132.8629	127.7959	126.6943	132.6548
Loss Reduction (%)	-	3.81	4.64	0.15
Runtime (s)	-	1476.5	1530.1	1128.27
Convergent Combinations	-	30,769	9,119	5,812
138-kV Planned Example Case of Brazilian Power Distribution Company				
Real Losses (MW)	6.8351	6.6508	6.6508	6.6556
Loss Reduction (%)	-	2.69	2.69	2.62
Runtime (s)	-	62.57	73.58	73.22
Convergent Combinations	-	2,769	2,680	569

5 Conclusions

This paper proposed the analysis of the Sigmoid, Tangent Hyperbolic and Elliot functions in the binary PSO for reconfiguration of electrical power system. The feasibility of application of the Tangent Hyperbolic and Elliot functions to the binary PSO algorithm for reducing losses in the electrical system was observed. The optimization packages can offer the user option to choose among the Sigmoid, Hyperbolic Tangent and Elliot functions for system reconfiguration. The reason is that the characteristics of the electrical system can influence losses and each function can obtain a different scenario for optimizing the electrical system.

It was observed that for the IEEE-30 bus system there was a reduction of losses of 6.47% with the application of the Sigmoid function and 6.38% for the Hyperbolic Tangent function. The reduction of losses was 3.81% with the Sigmoid Function and 4.64% for the Hyperbolic Tangent Function for the IEEE-118 bus system. And for the planned example case, the reduction of losses was 2.69% with the application of Sigmoid and Hyperbolic Tangent function. For this case, the Elliot function reduced losses by 2.62%. The Hyperbolic Tangent function showed results with less convergent combinations.

For future work, study the impact of load variation throughout the day for different systems reconfigurations and evaluate the functions in the binary PSO considering the reconfiguration with distributed generation.

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