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An Industrial Fire Prediction System Based on Artificial Intelligence Technology

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ABSTRACT

A predictive system using artificial intelligent (AI) technique called the Particle Swarm Optimization (PSO) to predict fire outbreaks caused by electrical faults in Industrial environment was developed. The PSO technique belongs to a class of computing called Swarm Intelligence, and it is aimed at solving minimization problems. Results prove that PSO can be used to predict fire outbreak. Further work, the system has not been integrated into real time hardware.

KEYWORDS

Particle swarm optimization; Fire outbreaks; Swarm-based heuristic; Fault resistance, Population size and max iteration.

1. Introduction

Particle Swarm Optimization algorithm (PSO) is a population-based stochastic search algorithm, which is used as a solution for optimization drawbacks. The PSO algorithm was introduced by James Kennedy and Russell Eberhart in 1995 [1]. It is inspired by simulation of the social behavior and movement dynamics of insects, bird flocking and fish. The PSO method basically learned from animal's activity to solve optimization problems. In PSO, each member of the population is called a particle and the population is called a swarm [2]. The PSO algorithm consists of three steps, which are evaluation of fitness for each particle, update individual and global bests and update velocity and position of each particle [3]. The key advantages of PSO (particle Swarm Optimizer) are easy to implement, while calculation in PSO method is very simple and very efficient global search algorithm [4].

Particle swarm optimization method has been applied or used for predictive systems or uncertainty situation like Optimizer Solution to Supply Chain Network Architecture by [5], Particle swarm optimization (PSO) with ant colony optimization (ACO)] was used for multiprocessor job scheduling by [6] and GA-PSO-Optimized was used on Neural-Based control scheme for adaptive congestion control to improve performance in multimedia applications by [7] are all works done using Particle swarm optimization. However, Particle swarm optimization method has not been used in predicting fire outbreaks caused by electrical faults in industrial environment. In Nigeria, there have been increases in damages due to fire outbreaks caused by electrical faults particularly in industrial and busy environments. Industrial fires and explosions cost companies and governments billions of naira every year.

In this paper, a predictive system was developed, using Particle swarm optimization method (PSO) to predict fire outbreak caused by electrical faults in Nigeria. Specifically a modification of the PSO with an adaptive objective function will be used to automate the optimization procedure.

The remainder of the paper is as follows. The following session provides; 2. Brief overview of related works, 3. Particle swarm optimization (PSO) 4. Electrical faults detection using Particle swarm optimization Algorithm 5. Results and Discussion. Finally, a conclusion is drawn.

2. Related Works

A microstrip tapered transformer design was done using Particle Swarm Optimization [8]. This type of problem is a multiobjective optimization drawback with an objective function that needs to be optimized and with the condition about the elements of the objective function to be in a decreasing order. The acquired results are confirmed using PUFF simulator and PSO finds the solution to this problem in less than 1000 iterations. Simulated results also prove that results that were acquired gives the matching that is desired. Particle swarm optimization can be applied for the design of microstrip tapered transformers.

The interfacing of hydroPSO with PHREEQC was successfully done to estimate surface complexation constants for uranium (VI) species on quartz [9]. Thermodynamic values acquired with hydroPSO provided a superior match to observation sorption rate in comparison to those obtained with PEST, using the same input data. This is recognized by the higher coefficient of determination for the results based on hydroPSO.

In [10], a modified PSO technique was proposed based on the simulated annealing algorithm. The modified PSO has a superior performance in stability and global convergence; although the modified PSO do some modifications to two particle's position and velocity, but its convergence rate for the multi-peak function is much quicker as compared with the second improvement. In the modified PSO method, the maximum and minimum velocity of particles has clear impact on the convergence rate.

3. Particle Swarm Optimization (PSO)

1. Randomly initialized population and moving in randomly chosen directions, each particle goes through the searching space and remembers the best previous positions of itself and its neighbors.

2. Evaluate each particle's position according to the objective function, which are associated with the best solution (fitness) that has achieved so far. This value is called pbest).

3. If a particle's current position is better than its previous best position, update it

4. Determine the best particle, best value obtained so far by any particle in the neighbors of the particle. This value is called gbest [11].

5. Update particles velocities of each particle toward its pbest and the gbest position at each time step, using this Equation.

$$v(t+1) = c0 * v[t] + c1 * rand(\quad) * [pbest[t] - present[t]] + c2 * rand(\quad) * [gbest[t] - present[t]]$$

t Time, c0 inertial coefficient (0.3-1.2),c1, c2 are acceleration coefficients, rand() - random values, v[t] is the particle's velocity at time t, present[t]is the particle's position at time t, pbest[t] − is the particle's individual best solution as of time t and gbest[t] is the swarm's best solution as of time t [12].

6. Each particle's position is updated using this Equation:

$$present[t + 1] = present[t] + v[t + 1]$$

7. Go to step 2 until maximum iteration or minimum criterion is met [13].

4. Electrical Faults Detection Using Particle Swarm Optimization

The system uses an artificial intelligence (Particle swarm optimization) to evolve a set of system parameters from which context is built and predictions are made. The design includes the use of real time data from the field. The system consists of input layer, optimization layer and decision layer [14].

Input layer: This is where to input the attribute range specifications like the maximum iteration, population size, Fault resistance, etc. Optimization layer: uses the AI technique (PSO) to find the set of parameters that gives least cost, the least error as defined by an objective function which will be used by the decision layer for prediction. Decision layer: takes decisions based on the condition of input against a reference value that will be used to predict if there is danger of fire or no fire. The Architecture of the Predictive/decision making system is shown in figure 1.

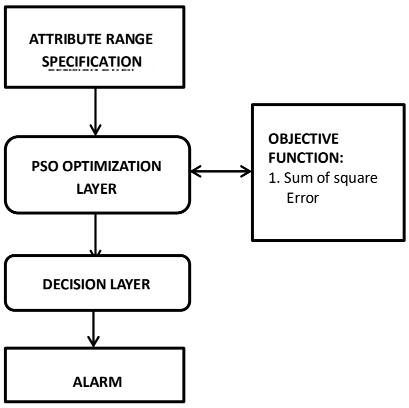

Figure 1. Architecture of Proposed PSO fire predictive/decision making system

Table 1 shows Input/output Specifications for the PSO predictive/decision making system. The Bolted fault current, Protected bolted fault current, Arcing fault current and Protected arcing fault current can be caused by some other faults like Soil resistance, Metallic resistance condition (conductor clashing), Weather resistance lighting (lighting strike),wind, tree falling across bus line etc. Bolted fault current is when there is maximum available fault current at some point in an electrical system. Arcing fault current is when system voltage is high and an electric arc will form between power systems conductors. Protective Device Bolted fault is bolted fault current that flows through a given protective device. Protective Device Arcing fault is the current flowing through the protective device feeding the Arc fault. Protective device Name is the device that is used to protect the power system from faults.

The PSO Technique searches the Impedances of the different faults, using the Actual fault resistance which is the decision parameter and the control resistance which is the reference to get the decision that will be used for prediction. Particle Swarm Optimization method uses the different particle's to search the impedances for the different faults and check which one has the likelihood to cause danger using an objective function.

Table 1. Sample Input/output Specifications for the PSO predictive/decision making system, source SPDC field Data

Bus Name	Protective	Bus	Prot Dev	Prot Dev
	Device	Voltage	Bolted	Arcing
	Name	kV	Fault	Fault
			(kA)	(kA)
BUS-0001	MaxTripTime	11.00	65.71	61.77
BUS-0002	MaxTripTime	11.00	64.65	60.79
BUS-0003	MaxTripTime	11.00	64.65	60.79
BUS-0004	MaxTripTime	10.97	9.89	5.76
BUS-0005	MaxTripTime	10.97	9.89	5.76

5. Result and Discussion

Two Experiments were conducted; prediction estimates are read and recorded for each run. The first Experiment (Exp. 1) prove that using Max iteration of 5 and Population size of 20, PSO will have all faults occurring at the same time at 0.3 ohm – 0.0 ohm fault resistance while using Max iteration of 50 and Population size of 100 for the second experiment, PSO will have all faults occurring at 0.35 ohm – 0.0 ohm fault resistance. The two Experiments were performed with 26 test simulations each using different fault resistances values, Population size and Max iteration. The results from Simulation of Experiment 1 using PSO are given in Table 2.

The results show good performance of the predictive PSO system for average convergence at 2.05 at 26 trials and its unique capability to make multiple predictions.
Rule: Rule used for the prediction is when Z of context state of I is less than or equal to Z context state threshold (0.4 kilo ohm) there is a fault in the system, and it will show Danger.

Table 2. Results from simulation of experiment 1

Max iteration = 5		**Population Size = 20**			
Fault Resistance	Bolted Fault	Arcing Fault	Protected Bolted	Protected Arcing	Bus Voltage
4	5.76	9.80	42.09	5.76	11
3.9	5.76	56.51	10.74	6.05	11
3.7	16.0	17.07	16.09	5.76	11
3.5	25.44	9.80	9.89	5.76	11
3.3	20.0	13.0	12.0	19.0	11
3.1	32.99	9.80	9.89	5.76	11
2.9	11.4	9.90	54.34	6.04	11
2.7	5.76	49.42	33.32	5.76	11
2.5	5.76	43.53	9.89	25.11	11
2.3	15.0	57.0	22.0	6.00	11
2.1	5.76	58.59	9.89	5.76	11
1.9	5.76	9.80	27.32	5.84	11

1.7	5.76	29.04	9.89	5.76	11
1.5	9.64	9.82	10.36	7.45	11
1.3	10.1	12.1	11.1	15.1	11
1.1	17.0	19.0	21.0	23.0	11
0.9	9.76	16.95	10.98	21.08	11
0.7	15.0	12.87	15.91	41.5	11
0.5	19.69	21.53	21.9	31.28	11
0.3	**40.49**	**36.44**	**36.91**	**39.85**	**11**
0.28	38.12	43.55	38.87	40.84	11
0.25	43.69	43.02	43.72	44.35	11
0.2	56.11	55.65	56.12	55.55	11
0.1	59.18	65.7	53.64	45.88	11
0.05	48.2	65.7	65.71	61.77	11
0	61.77	65.7	65.71	60.33	11

Results from Simulation of Exp. 1 shows different fault resistance tested with a constant Population size of 20 (area of search) and max Iteration of 5 (maximum number of iteration). It also shows the bus voltage and different faults current. Arcing fault produces a very high current during the experiment, which can cause fire outbreak. The Results prove that between 0.3 ohm – 0.0 ohm (fault resistance), all faults will show danger and should be attended to on time before it will lead to fire outbreak. 26 test simulations were performed using different fault resistances values. The PSO Prediction Graph of Experiment 1 is shown in Figure 2.

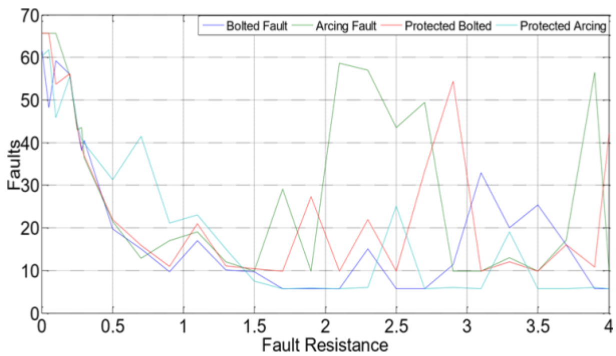

Figure 2. PSO prediction graph of experiment 1

The PSO Prediction Graph of Exp. 1 shows the different faults e.g. bolted fault current, arcing fault current, protected bolted fault current and the protected arcing fault current against different fault resistance values, which is from 0.0 ohm – 4.00 ohms. At 0.00 ohm – 1.00 ohm fault resistance, Protected Bolted fault has a current of 65.71 kA and Arcing Fault has a current of 65.70 kA which has the likelihood to cause fire outbreak, while Bolted Fault has current of 9.76 kA which is normal and will not cause harm. At 1.00 ohm -2.00 ohms fault resistance, Protected Bolted fault has a current of 27.32 kA and Arcing fault has a current of 29.04 kA which has the likelihood to cause hazard, while Protected Arcing Fault has current of 5.76 kA which is normal. At 2.00 ohms -3.00 ohms fault resistance, Arcing fault has a current of 57.00 kA which could lead to hazard, while Protected Arcing Fault has current of 5.76 kA which is normal. At 3.00 ohms -4.00 ohms fault resistance, Arcing fault has a current of 56.51 kA which could lead to fire outbreak, while Protected Arcing Fault has current of 5.76 kA which is normal and will not cause harm. The prediction results from Experiment 1 are tabulated in Table 3. It also shows the faults current that is in danger and the fault current that are normal.

The prediction table of Exp. 1 shows different fault resistances that have been tested on the different monitoring Impedance (MOZ), the bus voltage divided by its fault current gives the Impedance. Bolted fault

MOZ, Protected Bolted fault MOZ, Arcing Fault MOZ, and Protected Arcing Fault MOZ monitors the context state of I, if it is less than or equal to 0.4 kilo ohm, means there is fault in the system that will lead to fire outbreak and it will show Danger else it should show Normal. At 0.3 ohm – 0.00 ohm fault resistance, all monitoring Impedance are likely to show danger and should be attended to immediately before it will lead to fire outbreak. Arcing Fault MOZ shows danger from 2.7 ohms – 2.1 ohms fault resistance, which can cause fire outbreak. At 1.7 ohms fault resistance, bolted fault MOZ, Protected bolted fault MOZ and protected Arcing Fault MOZ are normal, which will not lead to fire outbreak, while Arcing fault MOZ is in danger and has the likelihood to cause fire.

Table 3. Prediction table results of experiment 1

Max iteration = 5		**Population Size = 20**	
Fault Resistance	Bolted Fault MOZ	Protected Bolted fault MOZ	Protected Arcing fault MOZ
4	Normal	Danger	Normal
3.9	Normal	Normal	Normal
3.7	Normal	Normal	Normal
3.5	Normal	Normal	Normal
3.3	Normal	Normal	Normal
3.1	Danger	Normal	Normal
2.9	Normal	Danger	Normal
2.7	Normal	Danger	Normal
2.5	Normal	Normal	Normal
2.3	Normal	Normal	Normal
2.1	Normal	Normal	Normal
1.9	Normal	Danger	Normal
1.7	Normal	Normal	Normal
1.5	Normal	Normal	Normal
1.3	Normal	Normal	Normal
1.1	Normal	Normal	Normal
0.9	Normal	Normal	Normal
0.7	Normal	Normal	Danger
0.5	Normal	Normal	Danger
0.3	Danger	Danger	Danger
0.28	Danger	Danger	Danger
0.25	Danger	Danger	Danger
0.2	Danger	Danger	Danger
0.1	Danger	Danger	Danger
0.05	Danger	Danger	Danger
0	Danger	Danger	Danger

The results from Simulation of Experiment 2 are given in Table 4, showing different current, voltage, Max Iteration of 50 and Population Size of 100.

Exp. 2 result shows different fault resistance tested with a constant Population size of 100 (area of search) and max Iteration of 50 (maximum number of iteration). It also shows the bus voltage and different faults current. The Results prove that from 0.35 ohm – 0.00 ohm fault resistance all faults will show danger and should be attended to on time before it will lead to fire outbreak. 26 test simulations were performed using different fault resistances values. The PSO Prediction Graph of Experiment 2 is given in Figure 3.

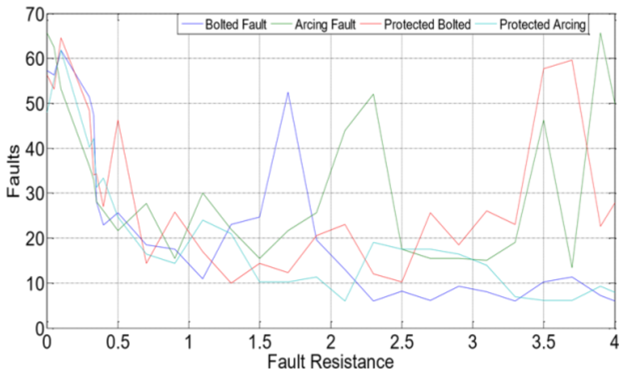

Figure 3. PSO prediction graph of experiment 2

The PSO Prediction Graph of Exp. 2 shows the different faults against different fault resistance. At 0.00 ohm – 1.00 ohm fault resistance, Bolted Fault, Arcing Fault and Protected Bolted fault has a current of 57.29 kA, 65.63 and 56.25 kA respectively, which has the likelihood to cause hazard, while Protected Bolted Fault and Protected Arcing Fault has current of 14.40 kA and 14.38 kA respectively which is normal. At 1.00 ohm -2.00 ohms fault resistance, Bolted Fault and Arcing Fault has current of 52.41 kA and 30.00 kA respectively, which has the likelihood to cause hazard, while Protected Bolted fault and Protected Arcing Fault has current of 10.00 kA and 10.29 kA respectively, which is normal. At 2.00 ohms -3.00 ohms fault resistance, Arcing Fault has current of 52.00 kA which has the likelihood to cause fire outbreak, while Bolted Fault, Protected Bolted fault and Protected Arcing Fault has current of 6.00 kA, 10.29 kA and 16.45 kA respectively, which is normal. At 3.00 ohms -4.00 ohms fault resistance, Arcing Fault and Protected Bolted fault has current of 65.70 kA and 59.61 kA respectively, which has the likelihood to cause fire outbreak, while Bolted Fault and Protected Arcing Fault has current of 6.02 kA and 6.17 kA respectively, which is normal.

The prediction table of Exp. 2 shows different fault resistances that have been tested on the different monitoring Impedance (MOZ), the bus voltage divided by its fault current gives the Impedance. Bolted fault MOZ, Protected Bolted fault MOZ, Arcing Fault MOZ, and Protected Arcing Fault MOZ monitors the context state of I, if it is less than or equal to 0.4 kilo ohm, means there is fault in the system and it will show Danger else it should show Normal. At 0.35 ohm – 0.00 ohm fault resistance, all monitoring Impedance are likely to show danger and should be attended to immediately before it will lead to fire outbreak. At 4.0 ohms – 0.5 ohm fault resistances, Protected Arcing Fault MOZ is showing normal which will not lead to fire outbreak.

6. Conclusion

In conclusion, a predictive system using artificial intelligent (AI) technique called the Particle Swarm Optimization (PSO) to predict fire outbreaks caused by electrical faults in Industrial environment was developed. The PSO technique belongs to a class of computing called Swarm Intelligence, and it is aimed at solving minimization problems. Results prove that PSO can be used to predict fire outbreak. Further work, the system has not been integrated into real time hardware.

References

Sushanta, K., M. (2005). Particle Swarm Optimization (PSO) Algorithm and Its Application in Engineering Design Optimization, Slide presentation retrieved from School of Information Technology, Indian Institute of Technology Kharagpur, September 9.

Zhijie, L., Xiangdong, L., and Xiaodong, D. (2010). Comparative Research on Particle Swarm Optimization and Genetic Algorithm, Computer and Information Science, vol. 3, No. 1.

James, B. (2017). Particle Swarm Optimization Applications in Parameterization of Classifiers, Slide presentation retrieved from Armstrong Atlantic State University.

Riccardo, P., James, K., and Tim, B. (2007). Particle swarm optimization: An overview, Swarm Intell, Springer Science + Business Media, LLC.

Rajeshwar, S., K. (2013) Optimization Solution to Supply Chain Network Architecture Using New-PSO Algorithm. Ind Eng Manage, doi:10.4172/2169-0316.1000e114.

Thanushkodi, K., and Deeba, K. (2012). Hybrid intelligent algorithm [improved particle swarm optimization (PSO) with ant colony optimization (ACO)] for multiprocessor job scheduling, Scientific Research and Essays, Vol. 7(20), pp. 1935-1953, 30 May.

Mansour, S., Ehasn, H., and Reza, S. (2012). GA-PSO-Optimized Neural-Based Control Scheme for Adaptive Congestion Control to Improve Performance in Multimedia Applications, Majlesi Journal of Electrical Engineering, Vol. 6, No. 1, March.

Ezgi, D., U. and Sad?k, U. (2014). Application of Particle Swarm Optimization to Microwave Tapered Microstrip Lines, Computer Science & Engineering: An International Journal (CSEIJ), Vol. 4, No. 1, February.

Ramadan, A., Broder, J., M., Mauricio, Z., and Sreejesh, N. (2017). Particle Swarm Optimization for Surface complexation with the PHREEQC geochemical model, Geosci. Model Dev. Discuss., Manuscript under review for journal Geosci. Model Dev.

Ai-Qin M., De-Xin, C., and Xiao-Hua, W. (2009). A Modified Particle Swarm Optimization Algorithm, Natural Science, Vol.1, No.2.

Dian, P. R., Siti, M. S., and Siti, S. Y. (2011). Particle Swarm Optimization: Technique, System and Challenges, International Journal of Computer Applications, Vol. 14- No.1, January.

Hugo, J. E., Manuel, M., and Luis, E., S. (2009). Particle Swarm Model Selection, Journal of Machine Learning Research, Vol. 10, pp. 405-440.

Vu, T., V. (2012). A Comparison of Particle Swarm Optimization and Differential Evolution, International Journal on Soft Computing (IJSC), Vol.3, No.3, August.

Nuka, D. N., and Okpu, E. O., (2018). Predicting Fire Outbreak Caused by Electrical Faults using Artificial Bee Colony Algorithm, International Journal of Computer Applications, Vol. 179, No.14.