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Adaptive Particle Swarm Optimization with Neural Network for Machinery Fault Detection

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Abstract— Rotating machines are one of the most important elements in almost all the industries and continuous condition monitoring of these crucial parts is essential for preventing early failure, production line breakdown, improving plant safety, efficiency and reliability. Faults may also be developed over a long period of time or even suddenly. However manual fault detection techniques are error prone. This paper identifies and utilizes the distribution information of the population to estimate the evolutionary states. Based on the states, Adaptive control strategies are developed for the inertia weight and acceleration coefficients for faster convergence speed. The Particle Swarm Optimization (PSO) is thus systematically extended to Adaptive Particle Swarm Optimization (APSO), so as to bring about outstanding performance when solving global optimization problems. This paper proposes an adaptive particle swarm optimization with adaptive parameters. Adaptive control strategies are developed for the inertia weight and acceleration coefficients for faster convergence speed.

Index Terms—Artificial Neural Network, Adaptive Particle swarm Optimization (APSO), Fault detection, Particle swarm Optimization (PSO).

I. INTRODUCTION

Rotating machine fault diagnosis is becoming a challenging role for the researchers. McCormick et al classified the condition of rotating machines [1], [2]. .Neural networks process information in a similar way the human brain does. It composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks can be trained through some examples. Artificial neural networks cannot be programmed to perform a specific task. Since the performance of the neural network depends on the training, the selection of training examples should be more and more careful.

Generally computers use a kind of approach to problem solving where the solutions are existed and the method of approach. Accordingly we need to train with proper instructions to obtain the expected outcome. Then those instructions can be converted into programming and of course into the machine code. The outcome from the computers can be approximate solutions only. In general Artificial Neural networks and the programmed computers are not equal but complement each other.

The common basic operations that we can execute both in computers and with the neural networks arithmetic operations and tasks related to classifications. Furthermore a lot more tasks, require systems that use a combination of the two approaches (Generally a conventional computer is used to organize the neural network) in order to obtain more accuracy and efficiency.

Particle swarm optimization (PSO) is one of the swarm intelligence algorithms that was first introduced by Kennedy and Eberhart in 1995 [3], inspired by swarm behaviors such as birds flocking and fishes schooling. Since its inception in 1995, PSO has been seen rapid development and improvement, with lots of successful applications to real-world problems. Much work focused on parameters settings of the algorithm and on combining various techniques into the PSO. However, most of these improved PSOs manipulate the control parameters or hybrid operators without considering the varying states of evolution. Hence, these operations lack a systematic treatment of evolutionary state and still sometimes suffer from deficiency in dealing with complex problems. This paper identifies and utilizes the distribution information of the population to estimate the evolutionary states. The PSO is thus systematically extended to APSO, so as to bring about outstanding performance when solving global optimization problems.

II. VIBRATION DATA AND FEATURE EXTRACTION

The main air blower system (MAB) setup illustrated in figure 2 in the sulfuric acid plant. It intakes air from filters through the drying tower in which the air mixes with the sulfuric acid in the counter current direction reducing its temperature. The MAB is turbine driven and runs at a rated speed of 5000rpm. The turbine and blower are connected by flexible metallic coupling i.e., a spring plate coupling. The blower and the turbine are lifted by a total of five journal bearings as shown in the figure. They are located at various locations like Turbine non drive end, Turbine drive end, Blower thrust end, Blower drive end and Blower non drive end.

All the bearings are five piece babbitt bearings with four portals for lubrication inlet points. The steam enters the turbine at a temperature of 350^0C. The turbine is driven by a 2 step starting process. First an auxiliary oil pump drives the main oil pump which then starts the turbine. Once the main oil pump comes on line, turbine starts pumping the steam thus rotating the blower.

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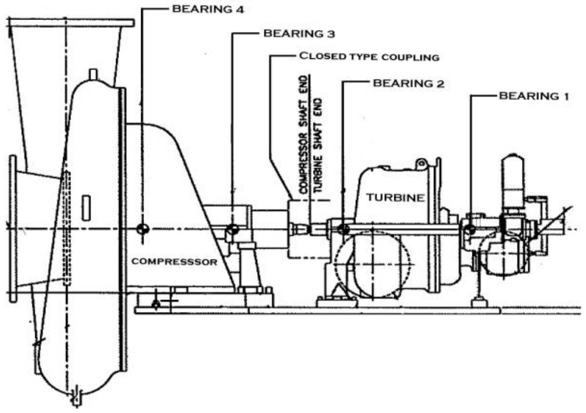

Figure 2: The main air blower system setup

Condition monitoring is done on the main air blower via vibration measurement. It is done through online and manual observation. Manual vibration analysis is done using software PRISM 4. CMVA 65 MICROLOG DATA COLLECTOR is used to collect and analyze the vibrations of the rotating equipment. Its frequency range is up to 40 KHz.

A magnetic sensor receives the vibrations when placed on the bearing housing. The sensor is placed in horizontal (H), vertical (V), axial (A) locations on the housing to observe the vibrations and analyze the condition properly. The readings are uploaded in the software and it displays the spectrum of the vibrations. By studying the spectrum and observing physically the condition of the equipment, its condition and abnormality can be detected. The maximum limit of vibrations to this blower is 7mm/sec. The various problems that this blower undergoes are Misalignment, Imbalance (system induced), Unbalance (by default), Surging, Bearing wear, Coupling failure etc.

III. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is an artificial intelligence (AI) technique [4] – [6] that can be used to find approximate solutions to extremely difficult or impossible numeric maximize and minimization problems. When using PSO, a possible solution to the numeric optimization problem under investigation is represented by the position of a particle. In addition to that, each and every particle has a current velocity, which specifies the direction and magnitude towards a new better solution/position. Each particle will have the measure of position and velocity of its current location and the better identified position.

Algorithm: PSO

Step 1 : Create a ‘population’ of agents (called particles) uniformly distributed over X .

Step 2 : Based on the objective function estimate each particle’s position.

Step 3 : Update the position of the particle if current position is better than its previous best position.

Step 4 : Determine the best particle (according to the particle’s previous best positions).

Step 5 : By using Equation 1 update particles’ velocity.

$$V_i^{t+1} = V_i^t + \varphi U_1^t (pb_i^t - X_i^t) + \varphi_2 U_2^t (gb_i^t - X_i^t) \quad (1)$$

Step 6 : Base d on equation 2 move particles to their new positions.

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

Step 7 : Repeat from step 2 till stopping criteria is satisfied.

Step 8 : End

PSO is a loop based system. On every iteration, based on the particle’s global and local information its current velocity is updated. Then, each particle’s position is updated using the particle’s new velocity. PSO is easy to implement, and only few parameters have to be adjusted. Unlike the GA, PSO has no evolution operators [7], [8] such as crossover and mutation. In PSO, only global best particle (gbest) gives out information to the others. PSO can be more efficient and robust when compared to genetic algorithms. PSO often finds the solution with fewer objective function evaluations and has the flexibility to control the balance between global and local exploration of the search space.

IV. ADAPTIVE PARTICLE SWARM OPTIMIZATION (APSO)

As evolution goes on, the swarm might undergo an undesired process of diversity loss. Some particles become inactively while lost both of the global and local search capability in the next generations. For a particle [9], the lost of global search capability meaning that it will only be flying within a quite small space, which will be occurs when its location and pbest is close to gbest (if the gbest has not significant change) and its velocity is close to zero (for all dimensions) according to the equation (1);and the updated position will get based on the equation 2.The lost of local search capability meaning that the possible flying cannot lead perceptible effect on its fitness. From the theory of self-organization if the system is going to be in equilibrium, the evolutionary process will be stagnated. If gbest is located in a local optimum, then the swarm becomes premature convergence as all the particles become inactively. To stimulate the swarm with sustainable development, the inactive particle should be replaced by a fresh one adaptively so as to keeping the non-linear relations of feedback efficiently by maintaining the social diversity of the swarm. The advanced version of PSO is adaptive particle swarm optimization (APSO) initially proposed by Shi and Eberhart in 1998 [10]. The APSO can be described as follows:

$$V_i^{t+1} = wV_i^t + \varphi U_1^t (pb_i^t - X_i^t) + \varphi_2 U_2^t (gb_i^t - X_i^t) \quad (3)$$

and $X_i^{t+1} = wX_i^t + V_i^{t+1}$ (4)

However, it is hard to identify the inactive particles, since the local search capability of a particle is highly depending on the specific location in the complex fitness landscape for different problems. Fortunately, the precision requirement for fitness value is more easily to be decided for the specified problem.

Step 1. Initialization of the swarm: For a population size m, the particles are randomly generated between the minimum and maximum limits of the design variables.

Step 2. Initialization of pbest and gbest: The fitness values obtained above for the initial particles of the swarm are set as the initial pbest values of the particles. Gbest can be identified

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as the best value among all the pbest values.
Step 3. Evaluation of adaptive inertia weight and acceleration factors: The inertia weight and acceleration factors are computed.
Step 4. Evaluation of velocity: The new velocity of each particle is computed.
Step 5. Update the swarm: The particle position is updated and the values of the fitness function are calculated for the updated positions of the particles. The new value is set to pbest if the new value is better than the previous pbest. Similarly, gbest value can be updated as the best of pbest.
Step 6. Stopping criteria: A stochastic optimization algorithm is usually stopped either based on the tolerance limit or when the maximum number of generations is reached. The number of generations is used as the stopping criterion in this paper

V. NEURAL NETWORKS

Feed forward neural networks [11],[12] become more and more popular with their remarkable ability to derive meaning from complicated data. Now a day's these are using to extract patterns and detect trends which are too difficult to be noticed by either human beings or conventional computer algorithms. Artificial neural networks can be treated as expert systems in the domain of pattern classification. This expert systems can be used to provide projections given new situations of interest and answer "what if" questions.

VI. NEURAL NETWORK WITH ADAPTIVE PSO IMPLEMENTATION (NNAPSO)

In the proposed method the neural network learns using adaptive particle swarm optimization algorithms. This means that the weights and biases of all the neurons are joined to create a single vector. A particular set of vector can be identified as the best optimized solution to the classification problem. One of these vectors is found to be the best using an APSO. The flowchart for the Neural Network with Adaptive PSO (NNAPSO) is as shown in figure 3.

The modern world is utilizing artificial neural networks for different kind of complicated problems. They are very powerful and flexible because of their ability of learning from examples. The major advantage of artificial neural networks is that there is no need to prepare any algorithms to perform any task i.e., there is no need to understand the structure or mechanism of the network. Because of its parallel architecture [13] – [15] they are widely using in the practical problems of the manufacturing industries.

We implemented a NNAPSO with 3 inputs and 1 output with a sample database whose values are gathered from industry. The input for the NNAPSO is Velocity, Speed, and Displacement of air blower. The first network is trained by using training samples. The impact of textual indication of the learning process is presented on the standard output during the learning.

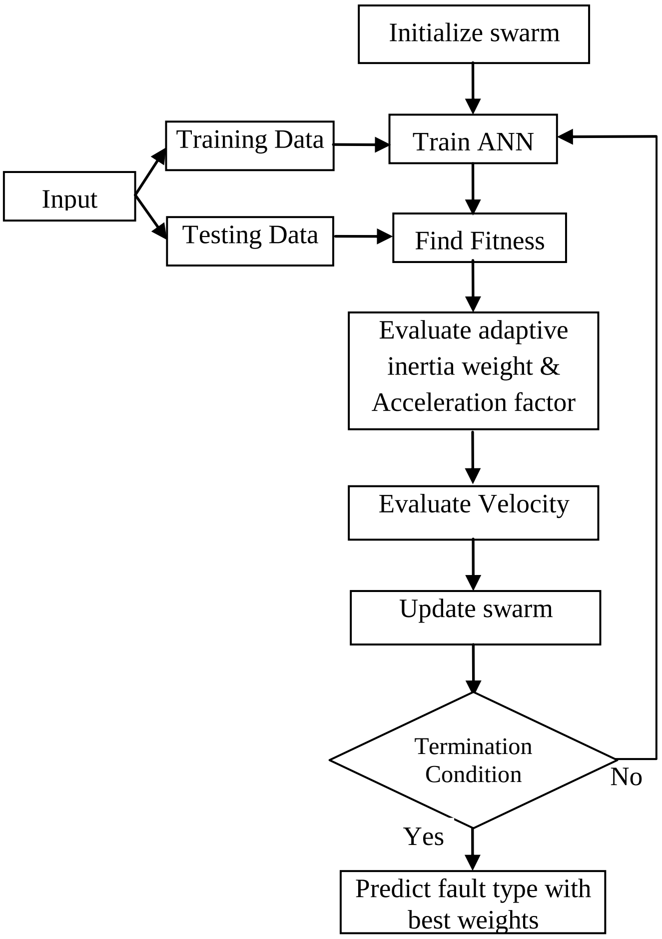

Figure 3 : Neural Network with Adaptive PSO Implementation (NNAPSO) Process

Table 1 : Optimized weights with PSO and APSO

Weight No	NNPSO	NNAPSO	Weight No	NNPSO	NNAPSO
1	0.44488	1.19811	16	0.86172	1.83878
2	1.5247	2.64612	17	0.87917	0.49493
3	0.5237	0.3653	18	1.2652	0.46824
4	0.02875	1.17886	19	0.45113	1.27385
5	0.05436	0.25268	20	1.82438	0.94018
6	0.36037	1.0671	21	1.79915	0.06967
7	0.36144	1.58843	22	1.6746	1.71168
8	0.71302	0.40626	23	0.10504	0.95005
9	0.52468	1.84048	24	0.65675	0.54123
10	0.16875	1.21306	25	0.3414	1.15763
11	0.8101	2.19068	26	0.07413	0.02264
12	0.44031	1.03494	27	0.43901	0.9888
13	0.1266	0.5364	28	0.71032	0.52845
14	0.28111	0.19603	29	0.50573	1.73378
15	0.33314	0.60927	30	0.14891	2.16012

On each generation it includes the Individual best fitness in each population and for every 50 generations a schematic textual division of the plane, to allow the

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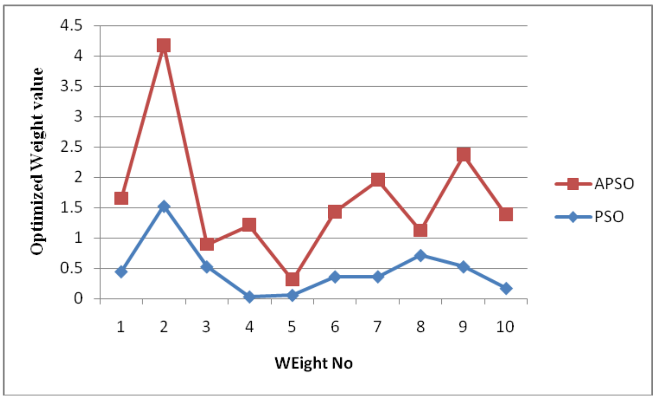
user to inspect the progress. Then testing is performed and this network is found to be more accurate and efficient compared to Neural Network with PSO. Obtained optimized values are tabulated in the table1 for fist 30 values out of 100 values and the comparison is given in figure 4.

VII. RESULTS

We implemented a NNAPSO with 3 inputs and 1 output with a sample database whose values are gathered from industry. The input for the NNAPSO is Velocity, Speed, and Displacement of air blower. The first network is trained by using training samples. While the learning takes place, a textual warning of the learning process is presented on the standard output; this includes the fitness of the best individual in each population on each generation, and a textual separation of the plane once every 50 generations, to allow the user to examine the progress.

Then testing is performed and this network is found to be more accurate and efficient compared to Neural Network with PSO. Obtained optimized values are tabulated in the table1 for fist 30 values out of 100 values and the comparison is given in figure 3.



PSO optimized weights

We obtained the values of Sensitivity, Specificity, Accuracy and Time for PSO: 0.30556, 0.65278, 0.53704and 98.1577 Seconds respectively and for APSO: 0.33333, 0.66667, 0.55556 and 97.2631Seconds respectively The best weights through PSO and APSO analyzed by using signal processing Window Visualization (WV tool box) Technique and the results are plotted in figure 4 and figure 5 respectively.

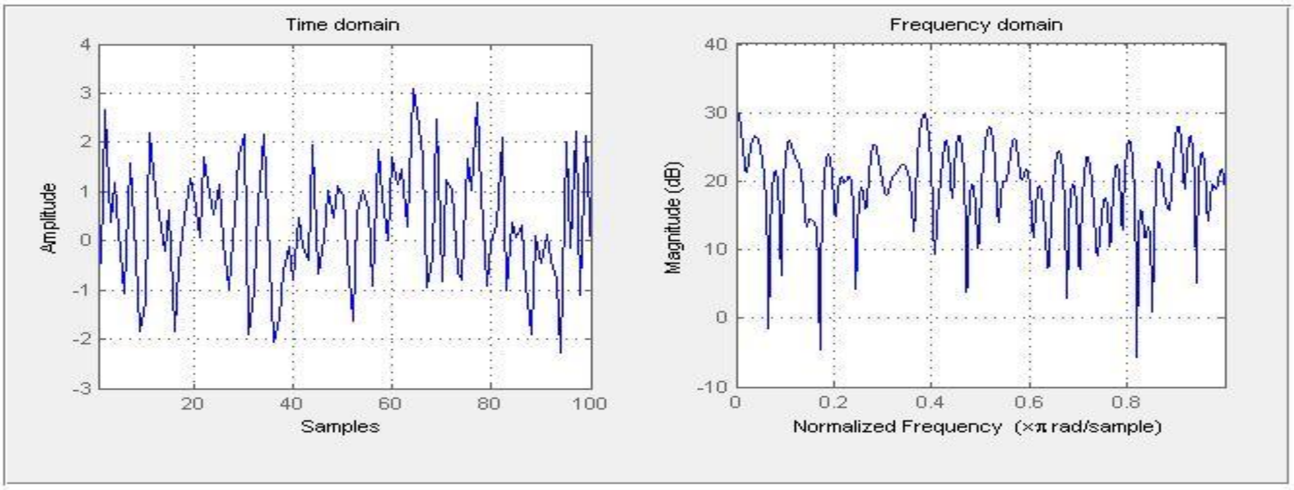


Figure 4: PSO Best Weight analysis using the WV tool box

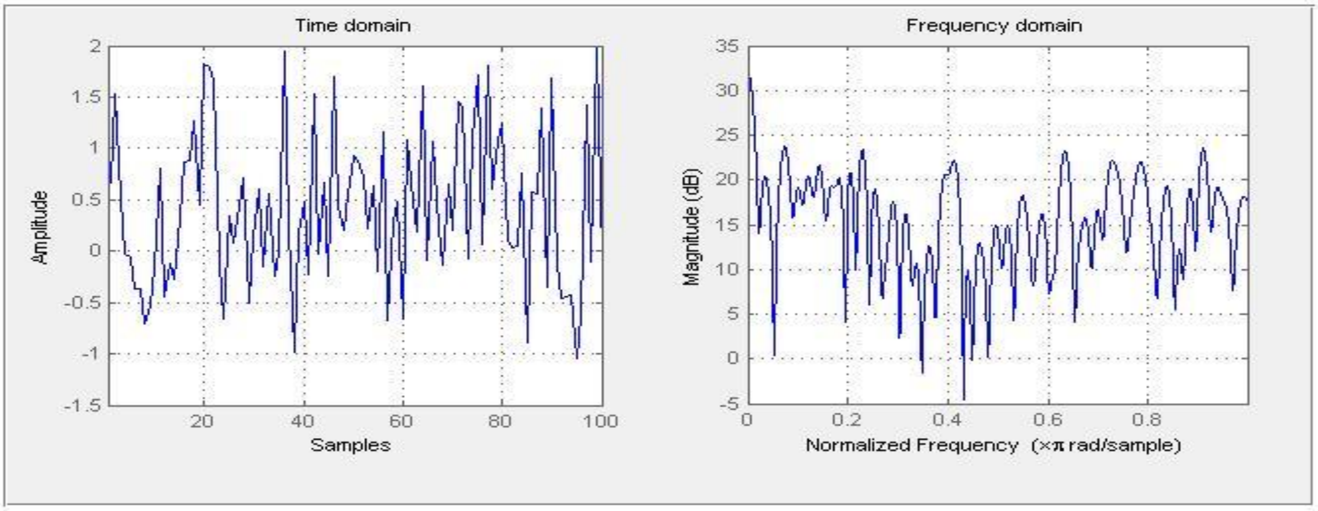


Figure 5: APSO Best Weight analysis using the WV tool box

VIII. CONCLUSION

In this paper, an adaptive particle swarm optimizer was introduced to improve the performance. The adaptive criterion is appended on an individual level. Since the critical constant e is decided by the precision requirement for fitness, it is more easy to be decided for different problems. Three benchmark functions have been used for testing. The simulation results illustrate the performance of adaptive PSO can improve the performance. The adaptive particle swarm optimization (APSO) approach has been proposed for solving the complex condition monitoring problems.

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