Artificial Intelligence Application in Power Generation Industry: Initial considerations

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Artificial Intelligence Application in Power Generation Industry: Initial considerations

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Abstract. With increased competitiveness in power generation industries, more resources are directed in optimizing plant operation, including fault detection and diagnosis. One of the most powerful tools in faults detection and diagnosis is artificial intelligence (AI). Faults should be detected early so correct mitigation measures can be taken, whilst false alarms should be eschewed to avoid unnecessary interruption and downtime. For the last few decades there has been major interest towards intelligent condition monitoring system (ICMS) application in power plant especially with AI development particularly in artificial neural network (ANN). ANN is based on quite simple principles, but takes advantage of their mathematical nature, non-linear iteration to demonstrate powerful problem solving ability. With massive possibility and room for improvement in AI, the inspiration for researching them are apparent, and literally, hundreds of papers have been published, discussing the findings of hybrid AI for condition monitoring purposes. In this paper, the studies of ANN and genetic algorithm (GA) application will be presented.

1. Introduction

1.1. Artificial Neural Networks

Artificial Neural Network (ANN) is a fast-growing soft computing method, which has been used in different type of industries recently. ANN is a computational model inspired by natural neurons. ANN imitates the characteristic of a natural neurons by several functions, namely inputs (like synapses), which are multiplied by weights (strength of signals) and then computed by mathematical function, determining the activation of neuron. Another function will compute the output, which will sometime depend on a certain threshold. A neural network model is made up of interconnected artificial units (neurons). Neurons are arranged in different layers, including input layer, hidden layer(s), and output layer. The number of neurons and layers depends on the type of problems need to be solved and the complexity of the system to be modelled. Figure 1 shows a simple structure of a typical ANN with 4 inputs, first hidden layer with 5 neurons, second hidden layer with 3 neurons, and one output.

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Firas B. Ismail Alnaimi et al. [1] presented a detailed data preparation procedure for steam boiler fault detection and diagnosis (FDD) analysis, where real data of steam boiler are captured, identified, clustered, and sampled. The boiler behaviour was studied, and the most influencing parameters were decided. For fault detection and diagnosis neural network (FDDNN) model training-validation phase, feed-forward neural networks were used. The FDDNN model can detect and diagnose the super heater low temperature quickly and accurately, hence resulting in satisfactory performance.

Thomas Palmé et al. [2] demonstrated a solution for sensor fault detection, isolation, and accommodation by employing ANN as a classifier. Thomas Palmé et al. [3] also used nonlinear Principal Component Analysis (PCA) for early warning of gas turbine failure implemented through the use of Auto-Associative Neural Network (AANN). In this case study, the use of AANNs for early detection of abnormal engine behaviour could warn the operator a few days prior to full failure. The pros and cons of applying NN monitoring approaches are summarized in Table 1.

| Table 1. The pros and cons of applying NN monitoring approaches. |
|---------------------------------------------------------------|
| **Pros** | **Cons** |
| No detailed physical information about the GT is needed. | As in all statistical models, data covering the entire operation range is needed for training. |
| Only operational data is required. | Any new operational condition requires a retraining. |
| NN-calculation is fast and can be used for online use | |
| The interpretation is easy to understand. | |
| It can establish relationships between performance parameters and operational conditions that are difficult to model | |

1.2. Genetic Algorithm

Genetic algorithms (GA) are a class of probabilistic optimization algorithms pioneered by John Holland in the 1970’s, and became popular in the late 1980’s. They are based on ideas from Darwinian Evolution inspired by the biological evolution process, as shown in Figure 2. GA is a way of solving problems by mimicking the natural processes combination of selection, recombination and mutation to evolve a solution to a problem. GA exploits historical information to direct the search into better performance within the search parameters.
B. Kishore et al. [4] proposed an application of Adaptive GA for fault detection in machinery. The results confirm that the networks correctly diagnose faults and guarantee good performances in terms of sensitive data obtained. A. Azadeh et al. [5] proposed a flexible algorithm based on SVM, GA and particle swarm optimization (PSO) for centrifugal pumps fault diagnosis. It was also applied to noisy data to show the robustness of the proposed algorithm in noisy environments. The result showed that support vector classifier improves when hybridized with GA and PSO.

2. Case Studies

2.1. Gas Turbine Sensor Validation through Classification with Artificial Neural Networks [2]

In this study, Thomas Palmé et al. focus on detecting single sensor faults. Steam turbine data such as pressures and temperatures, were produced with a Siemens performance deck. The data from sensors is divided into 3 classes; healthy, positive sensor drift, and negative sensor drift. Based on the sensor readings, the result would be translated into ‘1’ if true and ‘0’ if false as shown in Table 2. This approach has two advantages, namely information about the direction of the drift is provided, and the NN classification capabilities are improved.

Table 2. Example of Data Preparation For ANN Classification Training [2]

| Sensor 1 reading | Sensor 2 reading | Class 1: S1 too high | Class 2: S2 too high | Class 3: S2 too high | Class 4: S1 too low | Class 5: S2 too low |
|------------------|------------------|---------------------|---------------------|---------------------|-------------------|-------------------|
| 1                | 2                | 1                   | 0                   | 0                   | 0                 | 0                 |
| 5                | 6                | 1                   | 0                   | 0                   | 0                 | 0                 |
| 1.1              | 2                | 0                   | 1                   | 0                   | 0                 | 0                 |
| 5.5              | 6                | 0                   | 1                   | 0                   | 0                 | 0                 |
| 1                | 2.4              | 0                   | 0                   | 1                   | 0                 | 0                 |
| 5                | 7.2              | 0                   | 0                   | 0                   | 0                 | 0                 |
| 0.9              | 2                | 0                   | 0                   | 1                   | 0                 | 0                 |
| 4.5              | 6                | 0                   | 0                   | 0                   | 0                 | 0                 |
| 1                | 1.6              | 0                   | 0                   | 0                   | 0                 | 1                 |
| 5                | 4.8              | 0                   | 0                   | 0                   | 0                 | 1                 |

Once a failing sensor has been identified by the classification neural network, a recovered value can be reproduced using remaining healthy sensors. This is achieved through employing individual regression neural networks using healthy sensors as inputs, and the desired parameter as output. This is further clarified when the author introduced white noise to create errors in the sensor, but the ANN predictions are near as good as those of a healthy sensor.

2.2. Using genetic algorithms to improve the thermodynamic efficiency of gas turbines [6]

Jose M. Chaquet et al. presented a method for optimizing thermodynamic efficiency of an aeronautical gas turbine. This method is based in the transformation of the original constrained optimization problem. Several tools are involved in the traditional design process of a gas turbine, which are efficiency estimator module and ThroughFlow codes. Efficiency estimator module computes the thermodynamic efficiency of a turbine design, rendering it capable of calculating the fitness function. ThroughFlow is a specific CFD code for turbo-machinery design that computes the flow variables along all the surface plane.

GA communicates with the ThroughFlow by two interfaces called export and import, which have been specifically designed to carry out our implementation. In the export process, all the data needed by the GA is generated, particularly all the fluid variables of the reference individual for computing the efficiency. After the run of the GA, the efficiency of best individual in the last generation is compared with the efficiency of the ThroughFlow model. Only three iterations are needed to obtain
the optimal configuration, as shown in Table 3. For each iteration, the thermodynamic efficiency and the total number of airfoils are given for the ThroughFlow model and the best individual in the last generation of the GA. We can check that the total number of airfoils in ThroughFlow models is similar to the one in the GA in the previous iteration. The iterative process is halted when the GA does not change the input data from the ThroughFlow. Comparing the first and last iteration, we can see that the GA has increased the efficiency by 0.36%, and reduced the total number of airfoils by 10.56%.

| Iteration | ThroughFlow | GA |
|-----------|-------------|----------------|
| η - η₀    | Num of airfoils | Efficiency | Num of airfoils |
| 1         | 0           | 0.003924     | 1334 |
| 2         | 0.003253    | 0.003480     | 1329 |
| 3         | 0.003408    | 0.003408     | 1329 |

3. Discussion and Conclusion

ANNs were shown to be robust and reliable tools. They have been utilized to solve many operational problems, especially problems of complex systems with nonlinear dynamics. In this paper, a brief overview for applications of ANNs and GA for fault detection and diagnosis was presented. The studies done in this paper are to pave the way for the author to model an intelligent condition monitoring system for steam turbine application as the next initiative. As a final note, AI will continue to develop and play an increasingly important role in the area of fault detection and diagnosis for power generation industry in the coming future.

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