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# DEVELOPMENT OF INTELLIGENT EARLY WARNING SYSTEM FOR STEAM TURBINE

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**Abstract**

Fault detection and diagnosis is a critical element in the power generation sector. Early faults detection ensures that correct mitigation measures can be taken, whilst false alarms should be eschewed to avoid unnecessary cost of operation, interruption and downtime. Modern power plant is equipped with thousands of sensors for monitoring, diagnosis and sensor validation application. By utilizing these features, we can use the collected operational data to develop a data-driven condition monitoring method. Intelligent Early Warning System (IEWS) represented by Artificial Neural Network (ANN), which was developed by training the network with real operational data, can be proven useful for real-time monitoring of a power plant. In this work, an integrated data preparation method was proposed. The ANN models and the hybrid artificial intelligence (AI) of ANN with Genetic Algorithm (GA), which is able to detect steam turbine trip for Malaysia Jana Manjung (MNJ) power station were developed. The AI models adopting ANN and GA were trained with real data from the MNJ station. The developed models were capable of detecting the specific trip earlier before the actual trip occurrence was detected by the existing control system. The AI model provides a good opportunity for further research and implementation of AI in the power generation industry especially in fault detection and diagnosis initiatives.

Keywords: Artificial intelligence, Artificial neural network, Genetic algorithm, Steam turbine, Warning system.

## 1. Introduction

Predictive maintenance as one of the optimization actions has emerged as an excellent method to provide condition-based early warning. In power generation industry, it provides early warning on the failure of assets such as combustion turbines, steam turbines, boiler feed water pumps and cooling water pumps [1]. One of the most important elements in a thermal power plant is its steam turbine. Steam turbine trip can lead to the entire plant shutdown, thus, it is very critical to ensure that the turbine is at normal operation.

Standard operating procedures of modern power plants ensure that the operating parameters are measured and saved in databases, which can be used for historical data analysis and performance analysis. A detailed analysis of these data requires time and extensive resources. A data-driven, Intelligent Early Warning Systems (IEWS) approach would truly be benefitted from the effective use of the measured data and thus lead to full utilization of the capabilities and opportunities provided by the historical records of the system operating behaviour.

By developing an IEWS for steam turbine trips, the causes of turbine trips can be identified and mitigation steps can be taken to maintain the normal and safe operating condition of the turbine. The operational data of the steam turbine, which will be used to drive the algorithm used in the IEWS [2-6], need to be studied and measured to detect the tripping trends. Typically, IEWS for steam turbine continuously evaluates the operation state and parameters of a steam turbine by collecting data from various sensors within the turbine. By diagnosing the state of the turbine, IEWS determines the condition of the turbine. IEWS can then perform several thousand of fault detection steps every second.

The main benefit of IEWS includes giving the user the ability to detect early symptoms of a developing problem thus enabling condition-based maintenance. With the early warning system, the maintenance team will be able to troubleshoot and bring the turbine back online as quickly as possible. There are also several preferred features for modern IEWS such as comprehensive graphics data, data visualization, detailed replaying of data, remote access, automated reports, and notification via email or Short Message Service (SMS). In this work, a few research objectives to be achieved are to investigate and analyse the operational data of steam turbine in JanaManjung (MNJ) power plant and to prepare an integrated data preparation method for future data. Furthermore, this work aims to analyse the operational behaviour trends that lead to turbine trips and to propose an operational threshold to determine the operating states of the steam turbine and to develop an Intelligent Early Warning System for steam turbine trips by the application of artificial neural network and a hybrid application (artificial neural network + genetic algorithm).

## 2. Artificial Intelligence, Artificial Neural Network, Genetic Algorithm, Steam Turbine

For the last few decades, there has been an explosion of interest in Artificial Intelligence (AI) application for thermal power plant especially with the rapid development in the area of ANN. ANN is based on simple principles but takes advantage of their mathematical nature, non-linear iteration to demonstrate powerful problem-solving ability. With the massive possibility and room for improvement in AI, the inspiration to carry out research in this area is apparent and literally, hundreds of papers have been published to discuss and present the findings of hybrid AI for condition monitoring purposes. Explanation on the core element of AI particularly in the field of ANN and GA and the studies of other hybrid AI application including their characteristics will be elaborated. Finally, it provides an overview and justification of the methodology chosen in this research.

Typically, a power plant operation will be monitored by a control system. This system consists of several thousands of sensors placed in the various critical and strategic area throughout the power plant. These sensors feed the control system with various parameter reading, which will then be used by the control system to diagnose the power plant current operating state. IEWS should be able to perform condition-based maintenance. By detecting early symptoms of a developing problem, it can improve the power plant reliability and reduce unnecessary plant shut down. During the fault, the IEWS should be able to pinpoint the exact location of the faulty area. This will improve fault troubleshooting and corrective action can be implemented precisely. Modern IEWS typically have several other features such as comprehensive graphical user interface, wireless remote access, automated fault report generation, and notification via email or text messages.

## 2.1. Artificial intelligence

Development of AI has been initiated since the early 1950s. The critically acclaimed yet widely used Expert Systems (ES) have been introduced in the 1970s from their first generation of DENDRAL, MYCIN, and PROSPECTOR [7]. ES technology continues to develop following the next decade and contributes towards Knowledge Engineering (KE) that pioneered the Intelligence System (IS). Kishore et al. [8] explained that, AI quickly gained another resurgence of popularity among researchers during the 1980s particularly in the field of ANN with the introduction of fuzzy set theory and soft computing along with the high processing capabilities of the computer during that time. There is a various artificial intelligent system, which can be adopted for an early warning system. Described in this section are some of the most relevant methods for the research scope.

## 2.2. Artificial neural network

This subsection summarizes the application and development of artificial intelligence systems particularly with ANN technique in thermal power plants throughout the years 2010 to 2015. ANN is a fast-growing soft computing method, which has been used in different types of industries recently. ANN is a computational model that is inspired by natural neurons. A neural network model is made up of interconnected artificial units (neurons). Neurons are arranged in different layers, including an input layer, hidden layer(s), and an 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.

## 2.3. Genetic algorithm

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. Furthermore, based on studies by Benazzouz et al. [7], GA exploits historical information to direct the search into better performance within the search parameters. GA exploits the historical information to direct the search into better performance within the search parameters. Compared to the traditional way of exploring each of the probability for a solution, GA performs exceptionally well in finding the most optimal solution or combination of sequence, especially within a huge data. It is widely used in many fields such as business, science and engineering to provide solutions for optimization, search problems, scheduling and timetabling [8, 9].

**Application of Genetic Algorithm**

Table 1 summarizes the literature review on ANN optimization by adopting hybrid ANN with GA application.

**Table 1. Summary of previous researches on ANN hybrid with GA.**

| Author | Optimization | Types of data | Application area |
|---|---|---|---|
| **Proposed research** | **Parameter selection, ANN structure** | **Real data** | **Steam turbine** |
| **Kishore et al. [ 8]** | Parameter selection | Real data | Production line |
| **Wu [9, 10]** | Parameter selection | Real data | Automatic car assembly |
| **Fritzen et al. [11]** | Parameter selection | Real data | Centrifugal pump |
| **Huang et al. [12]** | Parameter selection, weights and bias | Real data | Power transformers |
| **Tang et al. [13]** | ANN structure | Simulation | Gear |
| **Guolian et al. [14]** | ANN structure | Simulation | Wind turbine |
| **Li et al. [15]** | ANN structure, weights and bias | Simulation | Voltage source inverter |
| **Yang et al. [16]** | Parameter selection | Simulation | Gear box |
| **Zhang et al. [17]** | ANN structure | Simulation | Automobile engine |
| **Xiao-qin [18]** | ANN structure, weights and bias | Simulation | Chemical reactor |
| **Gui-li et al. [19]** | ANN structure | Real data | Motor |

## 2.4. Steam turbine

Modern steam turbine was invented in 1884 by Sir Charles Parsons. He created a turbine capable of using compounded steam that turned a dynamo at 18,000 revolutions a minute. In 1890, his steam turbine and accompanying electric generator were installed in the Forth Banks power station. According to Keysen [20], Parsons' steam turbine made cheap and plentiful electricity possible and the technology quickly spread afterwards.

In today’s modern power generation, steam turbine continues to be the major driving technology throughout the world. Even nuclear power plants are using a steam turbine, generating power from steam produced by heat generated from controlled nuclear chain reaction. Due to the importance of steam turbine, power producers are forced to continuously investigate various means of maintaining and increasing steam turbine efficiency, reliability, availability and maintainability. To increase its availability, steam turbine maintenance can be scheduled based on condition monitoring rather than operating hours. Reliability can be improved by using monitoring tools that alert plant operators to take mitigation action before faults are fully developed.

## 2.5. Characteristics and specification

The characteristic and specification of a steam turbine can be summarized in Table 2 [20].

**Table 2. Characteristic and specification of steam turbine.**

| Characteristics | Specifications |
|---|---|
| **Fuel flexibility** | Steam turbines have a wide range of fuel flexibility. It uses a variety of fuel sources in the boiler including coal, oil, natural gas and biomass |
| **Reliability and lifetime** | Steam turbine's lifetime is very long. There are steam turbines that have been in service for over 50 years. Overhaul intervals are measured in years. |
| **Availability** | Steam turbines are considered to have high availability with more than one year needed between shutdowns for maintenance and inspections |
| **Size range** | Steam turbines are available in different sizes from under 100 kW to over 250 MW |
| **Emissions** | Emissions are dependent upon the fuel used by the boiler, boiler furnace combustion design, and the boiler exhaust cleanup systems |

## 3. Design and Modelling of Intelligent Early Warning System

Trips in power plants occur when a certain parameter exceeds their normal values or limits and an alert alarm is triggered. The boiler records the highest number of trips compared to other components of power plants. Boiler tube failures ranked as the number one equipment problem in coal-fired power plants [21, 22].

The design and modelling of the proposed IEWS were developed with the help of MATLAB. The type of intelligent system used was a feed-forward ANN that is described later in details. In this research, two IEWS approaches were adopted. The first approach used pure ANN model while the second used hybrid AI approach to optimize the ANN structure with GA. For the first ANN approach, the development procedures focused on the topology selection and training of the ANN. On the other hand, the second approach focused on the genetic algorithm operators, GA design parameter, encoding process and the hybrid AI scheme.

### 3.1. IEWS_I (Pure ANN)

Choosing a good topology is a crucial task for the success of any ANN modelling. The topology selection influences the learning process, time, and its classification. The selection criteria in this research were based on its impact on the network performance. The main NN topologies include; training algorithms, learning rate, momentum coefficient, activation functions, the number of hidden layers, and the number of hidden layer neurons. Table 3 shows the list of the algorithm used with descriptions.

**Table 3. Training algorithm description.**

| Algorithm | Description |
|---|---|
| **trainscg** | • Scaled conjugate gradient backpropagation<br>• Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables<br>• Uses less memory |
| **trainlm** | • Levenberg-Marquardt backpropagation trainlm is often the fastest backpropagation algorithm in the toolbox and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms |
| **trainbr** | • Bayesian regulation backpropagation |

- It minimizes a combination of squared errors and weights and then determines the correct combination to produce a network that generalizes well. The process is called Bayesian regularization
- Takes longer time but may be better for challenging problems

### 3.1.1. Design of IEWS_I (Pure ANN)

The IEWS_I is a pure ANN condition monitoring system. The feed-forward methodology was adopted to develop the IEWS_I. The ANN inputs are listed in Table 4, thus, the network had thirty-two inputs as shown in Fig. 1. The number of neuron in each hidden layer was determined by trial and error. The proposed IEWS_I was formed to have a fuzzy outputs ranging from 0 to 1 according to the threshold determined with the help of the plant expert and after analysing the variable behaviour, which were: normal operation below 0.3, medium alarm warning was between 0.3-0.5, high alarm warning was between 0.5-0.7, and high-high alarm warning was above 0.7. The codes for IEWS_I were built using MATLAB.

**Table 4. Influential operation variables.**

| Variables | Description | Unit |
|---|---|---|
| **v1** | Steam flow | ton/hr |
| **v2** | FW flow | ton/hr |
| **v3** | drum pressure | Barg |
| **v4** | SH steam pressure | Barg |
| **v5** | SH steam temperature | °C |
| **v6** | E inlet temperature | °C |
| **v7** | HT Re-heater outlet temperature | °C |
| **v8** | HT SH exchange metal temperature | °C |
| **v9** | SH exchange metal (A) temperature | °C |
| **v10** | HT SH inlet header metal temperature | °C |
| **v11** | Final SH outlet temperature | °C |
| **v12** | SH steam (control) pressure | Bar |
| **v13** | FW valve station flow | ton/hr |
| **v14** | FW control valve position | % |
| **v15** | E inlet pressure | Bar |
| **v16** | Drum level corrected | Mm |
| **v17** | Drum level compensated | Mm |
| **v18** | E outlet temperature | °C |
| **v19** | FW flow transmitter | % |
| **v20** | Boiler circulation pump1 pressure | Bar |
| **v21** | Boiler circulation pump 2 pressure | Bar |
| **v22** | LT SH left wall outlet temperature | °C |
| **v23** | LT SH right wall outlet temperature | °C |
| **v24** | LT SH left wall temperature | °C |
| **v25** | LT SH right wall exchange metal temperature | °C |
| **v26** | SH exchange metal (B) temperature | °C |
| **v27** | Intermediate SH outlet temperature | °C |
| **v28** | Intermediate SH outlet header metal temperature. | °C |
| **v29** | HT SH outlet header metal temperature | °C |
| **v30** | HT Re-heater outlet steam pressure | Bar |
| **v31** | Superheated steam pressure | Bar |
| **v32** | SH water injection flow | ton/hr |

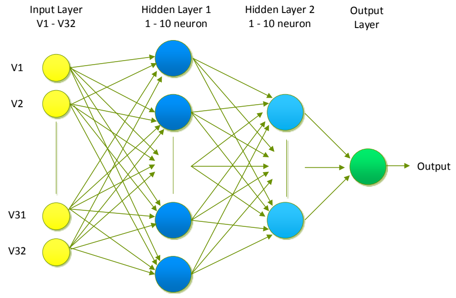


**Fig. 1. Basic representation of Input Layer, Hidden Layer 1, Hidden Layer 2 and Output for the proposed ANN.**

#### 3.1.2. Training, testing and validation of IEWS_I (Pure ANN)

The ANN training was done in order to find out the optimal NN topology combination. A trip data sets (Faulty data) were used as an input to the IEWS_I. The data sets were segmented as 70% for training, 15% for testing and the remaining 15% for validation. Various candidates of NN topologies were investigated for both 1 Hidden Layer (HL) and 2HL. Several numbers of neurons for each hidden layer ranging from one to ten were tested. Thirty-two boiler operation variables were considered as network inputs. The training results were compared based on the Root Mean Square Error (RMSE) as a network performance indicator.

### 3.2. IEWS_II (Hybrid ANN+GA)

In developing IEWS_I model, we have adopted trial and error approach in determining the best ANN topology structure. GA can be adopted in optimizing the ANN model thus creating a hybrid AI of ANN and GA (ANN+GA). There are several proposed optimization techniques by GA, which generally fall into three categories.

- Input parameter selection
- ANN structure optimization
- Bias and weight optimization

#### 3.2.1. IEWS_II design

In binary coding, the strings are made up of 1's and 0's. The length of the strings were determined by the number of solution probability. To simplify the structure, for comparison and in continuity with the previous pure ANN IEWS model, 1HL and 2HL model were separated into two different coding sets. In this research, the parameters that were optimized and their number of probabilities are shown in Table 5.

**Table 5. String bit features probability.**

| Features/character to be optimized | Number of probabilities | |
|---|---|---|
| | 1 Hidden layer | 2 Hidden layer |
| **Training algorithm** | 3 | 3 |
| **Activation function** | 9 | 27 |
| **Number of hidden layer neurons** | 10 | 100 |
| **Input variables** | $2^{32}$ = 4,294,967,296 | $2^{32}$ = 4,294,967,296 |

#### 3.2.2. IEWS_II Scheme

GA approach for any particular problem must have the following components.

- A genetic representation for the potential solutions to the problem, which is the encodings.
- A way to create an initial population of the potential solutions.
- An evaluation function to rate the individuals called fitness function.
- Genetic operators that alter the composition of the offspring.
- Values for the various parameters that GA uses. (Population size, the probability of genetic operators, number of generations).

The scheme consists of three major sections: the user section where the user enters the input, the GA section where the optimization process occurs, and the ANN section for ANN training process. Initially, the ANN training dataset ($T$), the number of generations ($G_n$), the size of population ($P_z$), the probabilities of crossover ($P_c$), and the mutation probability ($P_m$) were provided by the user. The initial population ($X_{init}$) of several binary strings, each of which represents a specific network topology and the NN training parameters were set.

Next, the user inputs were passed to the main GA optimization part. The internal function namely the "GA decoding" receives the population of binary strings in order to decode each string of binary into explicit information on the five parts, which are: Training algorithms (*algo*), neuron number (*archit*) , activation function of hidden layer 1 (*activf1*), activation function of hidden layer 2 (a*ctivf2*) and the NN Training Parameters (*Tp*). The information was then transferred to an internal function named as "NN train". The RMSE for each individual was calculated after each training and sent to the internal function, named as "GA fitness". Next, GA operators produced new children for the next generation. The individuals were subjected to crossover and mutation operations of the GA, followed by the formation of the new population ($X_{new}$). This process was repeated until ($G_n$) reached the maximum limit of 100.

## 4. Results and Discussion

Two intelligent monitoring systems were proposed to diagnose turbine trips. The results of the proposed IEWS together with some additional information about their performance will be discussed in this section. The discussion will be focused on determining the best NN topology combination. To get the results, several NN topologies were trained for the 1HL case and a 2HL case. The training results of both cases were compared based on the RMSE performance indicator. Different numbers of neurons for each of the hidden layer cases ranging from one to ten were tested.

### 4.1. Result of IEWS_I (Pure ANN) 1 hidden layer

The training process took place in order to determine the best NN topology combination. Several candidate NN topologies were trained for both the 1HL and 2HL cases. Thirty-two steam turbine operation variables were considered as the number of NN inputs and the training results were compared based on the NN performance indicator of RMSE. The neuron numbers in each of the hidden layers were set to be in range of one to ten hidden neuron.

Table 6 summarizes the results for NN with 1HL. Based on the results, it was proven that trainlm was the fastest training algorithm and from the observation, the average computation time for trainbr was the slowest and some of the training reached the maximum epoch of 10,000 iterations. In comparing the best performance for each training algorithm, trainbr has the best RMSE of 0.0351, followed by trainlm with RMSE of 0.1354, and trainscg with RMSE of 0.1593.

**Table 6. Result summary for 1HL NN.**

| TA | Act | AF | RMSE | NoI |
|---|---|---|---|---|
| **trainscg** | 6HL1 | T+T | 0.0254 | 27 |
| **trainlm** | 4HL1 | P+T | 0.0183 | 5 |
| **trainbr** | 2HL1 | T+P | 0.0012 | 18 |

## 4.2. Result of IEWS_I (Pure ANN) 2 hidden layer

The result for NN with two hidden layers is summarized in Table 7. Based on the result, it was shown that trainbr was the fastest training algorithm and there were plenty of results with a very low error RMSE. In comparing the best performance for each training algorithm, trainbr has the best RMSE of 0.0200, followed by trainlm with RMSE of 0.1114, and trainscg with RMSE of 0.00197. It is clear, from the results discussion, that ANNs with 2HL have better performance compared to that of 1HL.

**Table 7. Result summary for 2HL NN.**

| TA | Act | AF | RMSE | NoI |
|---|---|---|---|---|
| **trainscg** | 7HL1-10HL2 | P+T+T | 0.1404 | 21 |
| **trainlm** | 1HL1-5HL2 | T+P+T | 0.1114 | 12 |
| **trainbr** | 1HL1-10HL2 | T+T+T | **0.0200** | 10 |

## 4.3. Result of IEWS_ II (hybrid ANN+GA) 1 HL

Since there was no trial and error process involved in optimizing the model with GA, the result with the highest performance from each training algorithm was produced as shown in Table 8. It was proven that trainlm was the fastest training algorithm with only 8 iterations needed to achieve the desired performance. In comparing the best performance for each training algorithm, trainbr has the best RMSE of 0.0300, followed by trainscg with RMSE of 0.2298, and trainlm with RMSE of 0.2478. Table 9 shows the bit string representation of the best result from 1HL IEWS_II, which was achieved by trainbr training algorithm.

**Table 8. Result summary for 1HL IEWS_II.**

| TA | Act | AF | RMSE | NoI |
|---|---|---|---|---|
| **trainscg** | 9HL1 | T+T | 0.2298 | 13 |
| **trainlm** | 9HL1 | L+T | 0.2478 | 8 |
| **trainbr** | 4HL1 | T+T | **0.0300** | 29 |

**Table 9. Network topology bit string representation for best 1HL IEWS_II.**

| TA | | AF | | | | HLN | | | |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |

## 4.4. Result of IEWS_ II (hybrid ANN+GA) 2 hidden layer

Since the NN structure of IEWS II was optimized by GA, the trial and error procedure was reduced significantly. The results with the highest performance from each training algorithm were generated and they are shown in Table 10. In comparing the best performance for each training algorithm, trainbr has the best RMSE of 0.0153, followed by trainlm with RMSE of 0.0504, and trainscg with RMSE of 0.1816. In comparison, hybrid ANN+GA with 2HL have better performance compared to that of 1HL. Table 11 shows the bit string representation of the best result from 2HL IEWS_II, which was achieved by trainbr training algorithm.

**Table 10. Result summary for 2HL IEWS_II.**

| TA | Act | AF | RMSE | NoI |
|---|---|---|---|---|
| **trainscg** | 8HL1-8HL2 | P+T+T | 0.1816 | 26 |
| **trainlm** | 4HL1-6HL2 | T+P+T | 0.0504 | 17 |
| **trainbr** | 8HL1-9HL2 | T+T+T | **0.0153** | 16 |

**Table 11. Network topology bit string representation for best 2HL IEWS_II.**

| TA | | AF | | | | HLN | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |

The results for both systems, IEWS_I and IEWS_II are summarized in Tables 12-15. By analysing the results, advantages and drawbacks of each design parameters can be elaborated. These tables also show the detection capability of each model compared to the existing control and what the corresponding output/alarms were in each case. When comparing between the training algorithms, we can conclude the followings:

- **Trainscg**: It works best when adopted in IEWS -II, although the accuracy was reduced, the output was increased and the detection was earlier compared to IEWS -I. Trainscg has good prediction ability. The earliest detection was achieved by 1HL IEWS -II using trainscg. It manages to detect the trip 58 minutes before the actual fault occurrence with an output of 0.59 considered as a high warning.
- **Trainlm**: In average, this training algorithm was the fastest. The iteration to achieved the desired goal rarely exceeds 20 epochs. Most suitable when computer processing power is a limitation. The fastest result was achieved by 1HL IEWS -I using trainlm. The model achieved the desired performance goal after only 5 iterations.
- **Trainbr**: The slowest training algorithm but it is also the most accurate. The prediction ability of this training algorithm was also the slowest. During the trial and error procedure, it was found that the training commonly exceeds the training limit of 10,000 epoch. Most suitable for application where accuracy is the utmost important and superior computer processing power is available. The highest accuracy was achieved by 2HL IEWS -II using trainbr. The RMSE for this model was only 0.0153.

After analysing the output validation graph, it was confirmed that all of the proposed IEWS gives a high - high warning in a period of around 20 minutes before the actual fault occurrence except for 1HL IEWS-II using trainscg. Even though this model gives the earliest detection, it only gives a medium warning until the actual fault occurrence where it does give high-high alarm at those particular instances.

Although by only adopting IEWS-I the objective of detecting the turbine trip was already achieved, the development and structure selection of the ANN itself requires huge trial and error effort. To duplicate IEWS-I method for other equipment or plant would also be hard because of the complexity of the model itself. The biggest advantage of IEWS-II was the simplicity of the ANN after it was optimized by GA. The best structure will be optimized by GA since the topology selection and input variable selection will be automated. Without trial and error process and less input variable needed for training, the AI model will be further simplified thus making the duplication of IEWS-II method for other equipment or plant much more hassle free.

Two IEWS; pure ANN and hybrid ANN+GA were proposed in this research. The results of both IEWS were presented and their advantages and drawbacks were discussed in details. The advantages for each training algorithm were highlighted and the benefits of adopting the hybrid approach was also explained. After analysing the results, the proposed IEWS was proven to be a very viable approach to be applied on-line as a feasible control system for a thermal steam turbine since all the results manage to detect the trip at least 20 minutes before the plant control system. Furthermore, the method is general and can be duplicated for other thermal plant.

**Table 12. Result summary for IEWS_I 1HL NN.**

| TA | Act | AF | RMSE | NoI | Det | O/P | Am |
|---|---|---|---|---|---|---|---|
| **trainscg** | 6HL1 | T+T | 0.1593 | 27 | -31 | 0.57 | High |
| **trainlm** | 4HL1 | P+T | 0.1354 | **5** | -32 | 0.52 | High |
| **trainbr** | 2HL1 | T+P | **0.0351** | 18 | -32 | 0.47 | Medium |

**Table 13. Result summary for IEWS_I 2HL NN.**

| TA | Act | AF | RMSE | NoI | Det | O/P | Am |
|---|---|---|---|---|---|---|---|
| **trainscg** | 7HL1-10HL2 | P+T+T | 0.1404 | 21 | -38 | 0.67 | High |
| **trainlm** | 1HL1-5HL2 | T+P+T | 0.1114 | 12 | -38 | 0.60 | High |
| **trainbr** | 1HL1-10HL2 | T+T+T | **0.0200** | 10 | -32 | 0.44 | Medium |

**Table 14. Result summary for IEWS_II 1HL NN.**

| TA | Act | AF | RMSE | NoI | Det | O/P | Am |
|---|---|---|---|---|---|---|---|
| **trainscg** | 9HL1 | T+T | 0.2298 | 13 | **-58** | 0.59 | High |
| **trainlm** | 9HL1 | L+T | 0.2478 | 8 | -39 | 0.49 | Medium |
| **trainbr** | 4HL1 | T+T | **0.0300** | 29 | -38 | 0.33 | Medium |

**Table 15. Result summary for IEWS_II 2HL NN.**

| TA | Act | AF | RMSE | NoI | Det | O/P | Am |
|---|---|---|---|---|---|---|---|
| **trainscg** | 8HL1-8HL2 | P+T+T | 0.1816 | 26 | -38 | 0.75 | $High^2$ |
| **trainlm** | 4HL1-6HL2 | T+P+T | 0.0504 | 17 | -20 | 0.88 | $High^2$ |
| **trainbr** | 8HL1-9HL2 | T+T+T | **0.0153** | 16 | -20 | 0.97 | $High^2$ |

## 5. Conclusions

Two Intelligent Early Warning System (IEWS) were proposed in this research, motivated by the need to develop an early warning for steam turbine trips. IEWS_I adopted a pure artificial neural network (ANN) technique whilst IEWS_II adopted the hybrid ANN with genetic algorithm (GA) technique. The data utilized to carry out the IEWS training and validation was captured from MNJTPP power station in Lumut and the process of acquiring and preparing the data was explained. The trip considered was a turbine trip due to a sudden steam temperature fall. An integrated data preparation method was also introduced for future usage.

The IEWS was modelled using MATLAB and the computational tool used to perform the early warning was feed-forward ANN. The main reason for selecting this tool was because of the robustness and reliability of the tool in fault prediction and classification for power generation application.

Four development phases have been proposed and executed to achieve the objectives of the research, which consist of:

- Plant data preparation phase.
- Data analysis and variable behaviour study.
- Development of IEWS_I (Pure ANN) phase.
- Development of IEWS_II (ANN+GA) phase.

There are several outcomes achieved from this research as shown below: -

- By adopting feed-forward ANN, the IEWS model was proven as reliable because all the models were capable of detecting the turbine trip earlier or around at the same time with the target, which is 20 minutes before the actual fault detected by existing plant control system. To determine the best model, a performance comparison was made using RMSE as a performance indicator.
- In general, ANN with 2HL produced a more accurate result with lower error compared to 1HL ANN.
- GA optimization was successfully adopted in IEWS_II approach. Optimization was done to eliminate the trial and error procedure of IEWS_I in deciding the best topology structure for the ANN. In most cases, IEWS_II approach is more preferable since the method is automated thus easier to be duplicated and adopted.

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**Nomenclatures**

| | |
|---|---|
| *activf1* | Activation function of hidden layer 1 |
| *activf2* | Activation function of hidden layer 2 |
| *algo* | Training algorithm |
| *archit* | Neuron number |

| | |
|---|---|
| $G_n$ | Number of generations |
| $P_c$ | The probabilities of crossover |
| $P_m$ | The mutation probability |
| $P_z$ | Size of population |
| $T$ | Training dataset |
| $T_p$ | The NN training parameter |
| $X_{init}$ | Initial population |
| $X_{new}$ | Formation of new population |

**Abbreviations**

| | |
|---|---|
| Act | Architecture |
| AF | Activation Function |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| Am | Alarm |
| Det | Detection |
| E | Economizer |
| ES | Expert Systems |
| FW | Feedwater |
| GA | Genetic Algorithm |
| HL | Hidden Layer |
| HLN | Hidden Layer Neuron |
| HT | High Temperature |
| IEWS | Intelligent Early Warning System |
| KE | Knowledge Engineering |
| LT | Low Temperature |
| MNJ | Jana Manjung |
| MNJTPP | Jana Manjung Thermal Power Plant |
| NN | Neural Network |
| NoI | Number of Iterations |
| O/P | Output |
| RMSE | Root Mean Square Error |
| SH | Superheater |
| SMS | Short Message Service |
| TA | Training Algorithm |

## References


1. Alnaimi, F.B.I.; and Al-Kayiem, H.H. (2011). Artificial intelligent system for steam boiler diagnosis based on superheater monitoring. *Journal of Applied Sciences*, 11(9), 1566-1572.
2. Alnaimi, F.B.I.; and Al-Kayiem, H.H. (2010). Multidimensional minimization training algorithms for steam boiler drum level trip using artificial intelligent (AI) monitoring system. *Proceedings of the International Conference on Intelligent and Advanced Systems (ICIAS)*. Kuala Lumpur, Malaysia, 1-6.
3. Fast, M.; Palme, T. (2010). Application of artificial neural network to the condition monitoring and diagnosis of a combined heat and power plant. *Energy*, 35(2), 1114-1120.

4. Fast, M.; Palme, T. (2010). Application of artificial neural network to the condition monitoring and diagnosis of a combined heat and power plant. *Energy*, 35(2), 1114-1120.
5. Palme, T.; Fast, M.; and Thern, M. (2011). Gas turbine sensor validation through classification with artificial neural networks. *Applied Energy*, 88(11), 3898-3904.
6. Bell, D.R. (2001). The hidden cost of downtime: A strategy for improving return on assets. *Maintenance Technology*, 14(7), 28.
7. Benazzouz, D.; Benammar, S.; and Adjerid, S. (2011). Fault detection and isolation based on neural networks case study: Steam turbine. *Energy and Power Engineering*, 3, 513-516.
8. Kishore, B.; Satyanarayana, M.R.S.; and Sujatha, K. (2013). Adaptive genetic algorithm with neural network for machinery fault detection. *International Journal of Advances in Engineering and Technology*, 6(4), 1639-1646.
9. Wu, Q. (2011). Hybrid fuzzy support vector classifier machine and modified genetic algorithm for automatic car assembly fault diagnosis. *Expert Systems with Applications*, 38(3), 1457-1463.
10. Wu, Q. (2011). Car assembly line fault diagnosis model based on triangular fuzzy gaussian wavelet kernel support vector classifier machine and genetic algorithm. *Expert Systems with Applications*, 38(12), 14812-14818.
11. Fritzen, P.C.; Cardoso, G.; Zauk, J.M.; de Morais, A.P.; Bezerra, U.H.; and Beck, J.A.P. (2010). Alarm processing and fault diagnosis in power systems using artificial neural networks and genetic algorithms. *Proceedings of the IEEE International Conference on Industrial Technology*. Vina del Mar, Chile, 891-896.
12. Huang, Y.-C.; Huang, C.-M.; Sun, H.-C; and Liao, Y.-S. (2010). Fault diagnosis using hybrid artificial intelligent methods. *Proceedings of the IEEE Conference on Industrial Electronics and Applications.* Taichung, Taiwan, 41-44.
13. Tang, J.-l.; Cai, Q.-r., and Liu, Y.-j. (2010). Gear fault diagnosis with neural network based on niche genetic algorithm. *Proceedings of the International Conference on Machine Vision and Human-Machine Interface*. Kaifeng, China, 596-599.
14. Guolian, H.; Pan, J.; Zhentao, W.; and Jianhua, Z. (2010). Research on fault diagnosis of wind turbine control system based on artificial neural network. Proceedings *of the 8th World Congress on Intelligent Control and Automation*. Jinan, China, 4875-4879.
15. Li, H.; Li, C.; and Wang, W. (2010). Artificial neural network classifier design using genetic algorithm and wavelet transform in fault diagnosis. *Proceedings of the 2nd International Conference on Information Engineering and Computer Science*. Wuhan, China, 1-4.
16. Yang; Z.; Hoi, W.I.; and Zhong, J. (2011). Gearbox fault diagnosis based on artificial neural network and genetic algorithms. *Proceedings of the International Conference on System Science and Engineering*. Macau, China, 37-42.
17. Zhang, W.; Zhu, J.; and Kong, L.F. (2011). Gradient genetic algorithm-based performance fault diagnosis model. *Proceedings of the 2nd International*

*Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC).* Dengleng, China, 3059-3062.

18. Xiao-qin, L. (2011). A method for fault diagnosis in chemical reactor with hybrid neural network and genetic algorithm. *Proceedings of the International Conference on Electronic and Mechanical Engineering and Information Technology*. Harbin, China, 4724-4727.
19. Gui-li, Y.; Shi-wei, Q.; and Mi, G. (2013). Motor fault diagnosis of RBF neural network based on immune genetic algorithm. *Proceedings of the 25$^{th}$ Chinese Control and Decision Conference*. Guiyang, China. 1060-1065.
20. Keysen, P. (1992). A new look at Heron's "steam engine". *Archive for History of* Exact *Sciences*, 44(2), 107-124.
21. Jayapriya, P.; and Harikrishnan, P. (2015). Detection of air leakage in boiler rectangular duct using simulation. *National Conference on Research Advances in Communication, Computation, Electrical Science and Structures (NCRACCESS).*
22. Behera, S.K.; Rene, E.R.; Kim, M.C.; Park, H.-S. (2014). Performance prediction of an RPF-fired boiler using artificial neural networks. *International Journal of Energy Research*, 38(8), 995-1007.