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ARTICLE

APPLICATION OF INTELLIGENT COMPUTATIONAL TECHNIQUES IN POWER PLANTS: A REVIEW

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ABSTRACT

Growing worldwide demand for energy leads to increasing the levels of challenge in power plants management. These challenges include but are not limited to complex equipment maintenance, power estimation under uncertainty, and energy optimisation. Therefore, efficient power plant management is required to increase the power plant's operational efficiency. Conventional optimisation tools in power plants are not reliable as it is challenging to monitor, model and analyse individual and combined components within power systems in a plant. However, intelligent computational tools such as artificial neural networks (ANN), nature-inspired computations and meta-heuristics are becoming more reliable, offering a better understanding of the behaviour of the power systems, which eventually leads to better energy efficiency. This paper aims to provide an overview of the development and application of intelligent computational tools such as ANN in managing power plants. Also, to present several applications of intelligent computational tools in power plants operations management. The literature review technique is used to demonstrate intelligent computational tools in various power plants applications. The reviewed literature shows that ANN has the greatest potential to be the most reliable power plant management tool.

KEY WORDS

Intelligent Computational Tools, Power Plant, Energy Efficiency, Artificial Neural Networks, Genetic Algorithms, Hybrid Intelligent Systems.

1. INTRODUCTION

Since energy demand continues to increase, related issues to power plants such as equipment breakdown and fault detection are most likely to occur. The failures in power plants are varied and are extremely difficult to be understood without thorough monitoring of the behaviour of parameters involved. For example, sensors in power plants monitor several processes where an alert alarm is triggered when operating parameters exceed their typical values or limits. However, every plant measurement has to be monitored individually based on fixed setpoints or statistical limits taking into account the relationships between parameters. It is possible that while a variable of a correlated pair is within the safe range, a connected relationship escalates from the normal range. Abnormal measurements exceeding the acceptable range indicates that a particular component in the system is not operating as intended. This could be caused by a failure or damage in certain parts of the component. The repeated failures and shutdowns would eventually reduce the efficiency of the power plant to produce the maximum amount of output.

Conventional optimisation tools involve analytic computational codes that consist of complicated algorithms, and complex differential equations cannot determine the abnormal behaviour of an individual or combined components within a system effectively as they are computationally expensive [1]. Therefore, intelligent computational tools could play a significant role in efficient energy management as prediction, monitoring and classification of individual and combined operating components in power plants are possible using such intelligent tools. This is attributed to the latter having intelligent feature modelling that captures the component's behaviour. This ultimately leads to improving the overall efficiency of the operating plant.

Frequent electrical power outages have tremendously disrupted the operational cost and production process of most industries. The accumulative effects of unscheduled power outages incur costs in power restoration, interrupted production loss, equipment maintenance and protection. These factors of unscheduled power outage are mainly due to a sudden shortfall of electrical load failure and frequency drop in the electrical power plant. A series of electrical standards set by the Energy Commission has to be carried out to restore the operation of the power plant [2]. One of the standards requires a time-lapse after the system inspection before start-up can be safely administered.

This delay can cause cost setbacks to small businesses, office equipment's failure, and even traffic flow interruption. Hence, it becomes more apparent to consider improving the existing equipment monitoring system for a more stable contingency plan for power recovery. The current monitoring system continuously tracks the plant's equipment's operating condition [3,4]. Any identified features that affect the availability, capacity, safety and quality of the energy production will be displayed on the plant monitoring system. This displayed information helps plant operators report the scheduled maintenance data as part of the action items. Generally, most of the tell-tale signs of an equipment's degradation will be overlooked until the maintenance is carried out. As a result, additional costs and time are required to carry out the necessary equipment overhaul.

In this paper, the application of intelligent computational tools in power plant applications, including prediction of trips in various components of power plants, fault diagnosis, condition monitoring, modelling, power estimation, efficiency optimisation, and simulation of systems, are reviewed.

The main objective of this review paper is to summarise the study related to intelligent computational tools using Artificial Neural Networks (ANNs) and compare their network architectures, to identify the principles of hybridisation through a combination of ANN with other expert systems, and to compare and analyse the recent applications and development of intelligent computational tools in power plants.

This review paper is divided into the following sections starting with section 2, which describes ANN. Section 3 explains expert systems applied with ANN for hybridisation. Section 4 involves the applications of intelligent computational tools in power plants. Discussions and findings are provided in section 5, and the paper is concluded in section 6.

2. INTELLIGENT COMPUTATIONAL TOOLS IN POWER PLANTS

In this section, ANN application in power plants is demonstrated along with the achieved plant efficiency.

2.1 ANN in power stations efficiency prediction

A feedforward backpropagation neural network was proposed by [5] to predict refuse plastic fuel-fired boiler performance. The temperature, pressure, and mass flow rate of steam were predicted using the following input parameters: feed water pressure, feed water temperature, incinerator exit temperature and conveyor speed. Figure 1 showed that the ANN model proposed had good prediction capability. The capability of the predictive model was based on the mean absolute percentage error between the model fitted and actual plant data. They were determining the absolute average sensitivity values allowed for sensitivity analysis on input parameters. The incinerator exits temperature's average sensitivity was higher than the feed water pressure, feed water temperature, and conveyor speed. Thus, the change of incineration exit temperature had a significant influence on the selected outputs. It was also highlighted that fluctuations of the measured data, which usually occurs in real-time operations, caused errors in some of the predictions [5].

ANN and neuro-fuzzy were applied by [6] to detect and predict leaks in fluidised-bed boilers. The developed system was applied on six blocks of professional power plants. The diagnostic and prediction task were divided into two stages: early fault detection by virtual sensors and leak isolation using classifiers of fault state. In the first stage, the residual value *r*, which signals a faulty state of the process, was determined as the difference between the measured process signal (y_s) and the output of the respective model ($\hat{y}_s$). Figure 2 represents leak isolation with the pattern recognition method in which u represents the input variables and $\hat{x}_i$ represent the expected values of a subset of internal process variables that are sensitive to fault occurrences. Fault state classifiers are developed using data during the correct state and data before the shutdown period. Separate classifiers were developed for different system locations, including the steam superheaters, economiser, and furnace chamber. The results of fault detection for four models using ANN and neuro-fuzzy were tabulated in table 1. Based on the number

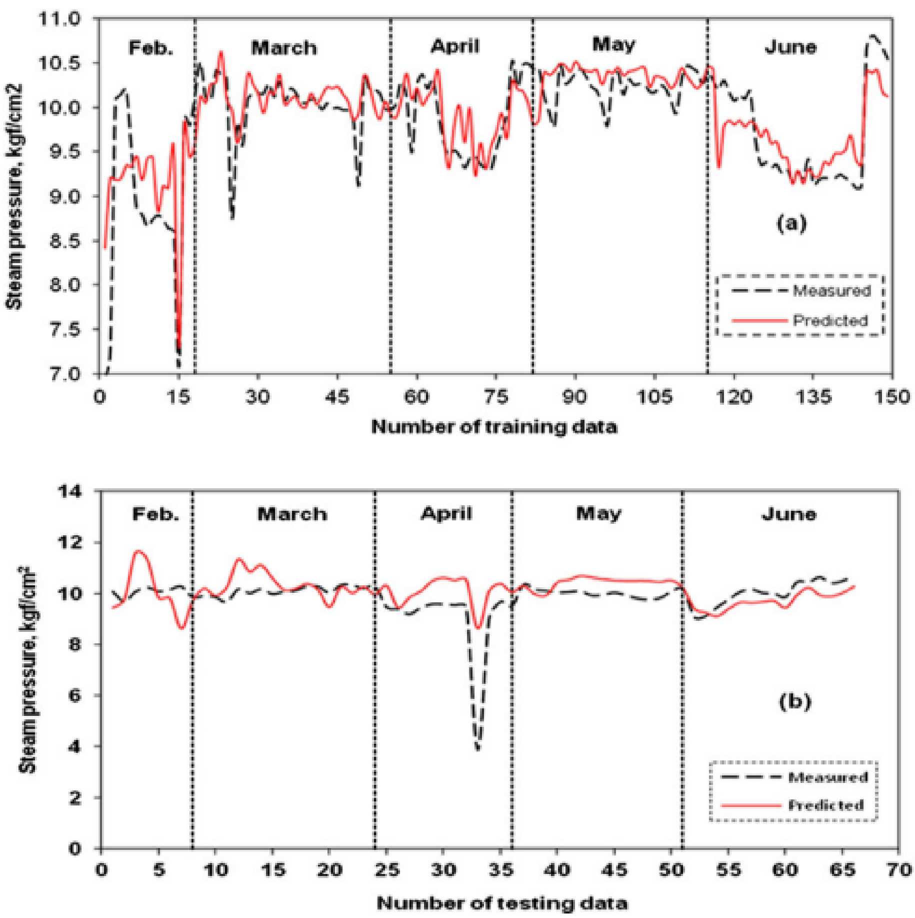

Figure 1: ANN model predictions: (a) during training and (b) during testing [5].

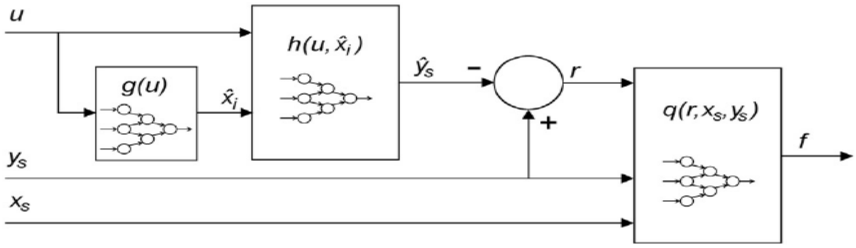

Figure 2: Fault isolation with pattern recognition [6].

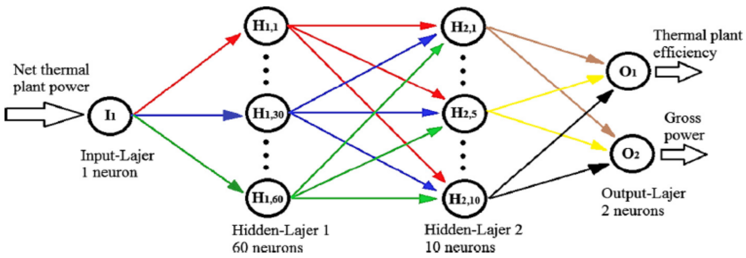

Figure 3: The architecture of the net-gross power and efficiency ANN design [7].

of faults detected, ANN models performed better than neuro-fuzzy structures. In 11 out of 12 cases, the system detected the fault 2-9 days before a shutdown. The developed classifier of the fault state distinguished between different classes of leaks [6].

The development of ANN to predict high-efficiency boiler steam generation was investigated by [7] based on real data obtained from a coal-fired Slovenian power plant. The output data includes electrical power, industrial steam power, power thermal substation 1 and thermal substation 2. Based on Figure 3, the ANN design consisted of one input layer representing the ambient temperature. The three hidden layers contain 20, 8 and 2 neurons. The actual process boilers efficiency was 90.722%, whereas the model provided an efficiency of 90.018%, showing that the model has good prediction capability. The prediction ability of the model allowed for cost reduction of steam production.

ANN was applied by [7] to predict new steam properties using real plant data. The input parameters were first selected based on expert knowledge and previous experience. Eventually, sensitivity analysis was done in order to optimise the input parameters. Results of the sensitivity analysis are summarised in Figure 4. Each input parameter was removed for each trial to examine its effect on the accuracy of the ANN. Eventually, three input parameters were considered optimum: fuel mass flow rate, valve openings at the boiler outlet, and feed water pressure at the valve outlet. The prediction of fresh steam temperature, pressure and flow was done with acceptable accuracy.

2.2 Condition monitoring and diagnostic using ANN

The crucial requirement in the design and implementation of the fault detection system is its ability to discover the fault symptoms as early as possible, to give the staff enough time to change the control policy; repair the faulty device; or eventually, to shut down the process in a safe manner. Fault diagnosis methods can be based on the following approaches, (i) Signal processing, when spectral analysis, principal component analysis (PCA), wavelet transforms, fast Fourier transforms (FFTs) are used to analyse the system and identify faults; (ii) Model-based methodologies, when knowledge of the system (in the form of physical, balance and chemical equations; or a black-box or a grey-box model) is employed to detect and analyse faults; (iii) Artificial intelligence, when neural networks, fuzzy systems, expert systems, Gray correlation or support vector machines (SVMs) are used to develop a diagnostic system that, once trained, can identify specific faults [9].

Four different ANN models were developed by [10] to monitor and diagnose a combined heat and power plant. Each model was developed separately for gas turbine, heat recovery steam generator, boiler and steam turbine. Each component had its inputs and outputs. The power output and the feedwater temperature were predicted accurately [11]. Based on the best model structure, the prediction performance of the model is illustrated in Figure 5.

De et al. [11] proposed developing an ANN model for the steam process of coal biomass cofired combined heat and power (CHP) plant. Developing an ANN simulator for the whole steam process was divided into two modules. The first module is for the boiler, whereas the second one is for the steam turbine. The first module was trained to predict the exhaust gas characteristics, whereas the second module predicted the power output from the steam turbine. The modules of the steam cycle for ANN model development is illustrated in Figure 6. Based on the excellent prediction accuracy of power output for both the models, an online monitoring system for the plant and the assessment of degradation of the plant performance can be implemented [10].

Firas & Hussain [12] applied an artificial neural network to diagnose steam boiler trips based on superheater parameters observation. In this paper, the boiler mentioned was a coal-fired, sub-critical pressure, single reheat and controlled circulation type. The methodology implied three execution phases: plant data acquisition, plant data preparation and parameters selection, and training validation phase. In the first phase, actual data of steam boiler are captured, identified, clustered and sampled. Boiler behaviour was studied to determine the most influencing parameters. In this study, the feedforward methodology of the neural network was used. A total of 32 parameters were considered, in which 30 days of data at an interval of 1 minute were collected. The feedforward backpropagation training algorithm had been modified based on a multidimensional minimisation algorithm that minuses the error estimator. The minimisation algorithm applied were Rprop, BFGS quasi-Newton, Scaled Conj. and Levenberg-Marquardt algorithm. Binary strings were used for the values of the outputs for training. The number ‘0’ represented non-existing fault-normal operation, while ‘1’ represented the existence of the fault-faulty operation. The performance indicator from the fault detection and diagnosis of neural network was Root Mean Square Error(RMSE). The new model obtained could detect

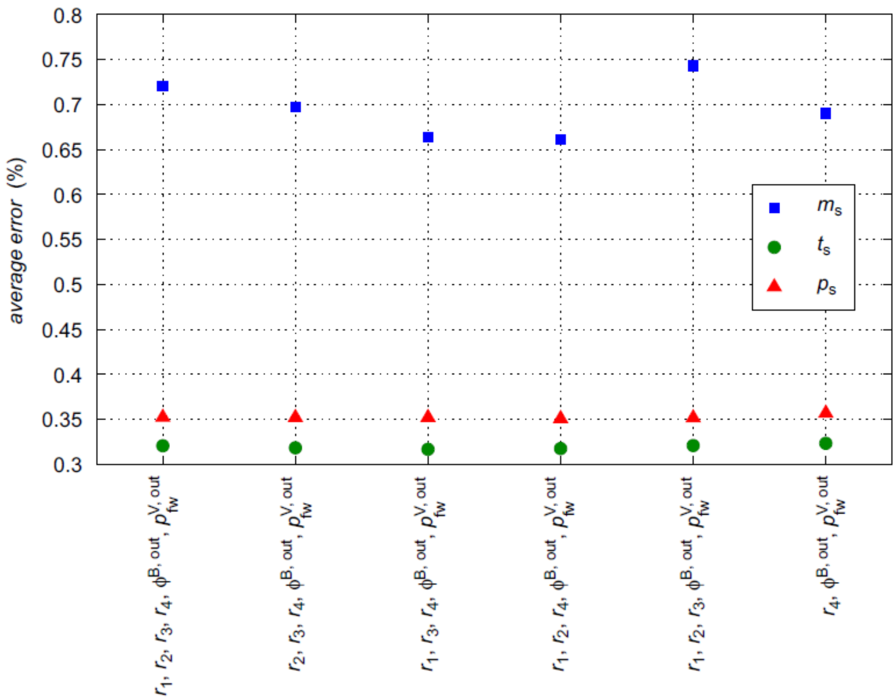

Figure 4: Sensitivity analysis results for alternate models [8].

Table 1: Detection of fault for four variables sensitive to leak [6].

Fault No.	Fault label: f1–steam superheaters f2–feedwater heater f3–combustion chamber	Concentration of O_2 before a chimney	Flux of the air for combustion	Flux of the feedwater	Pressure at the sunction of the flu gas fans
1	f3				
2	f3				
3	f3	x			
4	f3		x	x	
5	f3	x	x	x	
6	f1	x	x		
7	f1	x			x
8	f1	x	x		x
9	f2	no model	x	x	x
10	f2	no model	x	x	x
11	f3	no model	x		x
12	f1,f3	no model	x		x
Defected faults	ANN	5 of 8	8 of 12		7 of 12
	NF	6 of 8	6 of 8	3 of 84 of 12	5 of 8

and diagnose the low superheater temperature precisely before the actual trip occurred.

An artificial intelligence monitoring system was used in [13] for steam boiler high-temperature superheater trip. In this study, the neural network topologies were developed to get the final architecture. This included one and two hidden layers, one to ten neurons for each hidden layer, three different activation functions and two multidimensional minimisation training algorithms. The approach towards the neural networks topologies was based on trial and error. In this case, one-hidden layer(1HL) and two hidden layers (2HL) networks with activation function of logistic (Logsig), hyperbolic tangent (Tansig) and linear summation (Purelin) were applied. It was concluded that the lowest RMSE was achieved from one hidden layer with four neurons using the BFGS training algorithm, which provides the optimum neural network structure. However, the backpropagation training algorithm's speed (computational time) in which the learning converges or learns has been criticised.

An online plant data was used in [14] for the application of the condition monitoring system. The online plant data was pre-processed, in which 93 variables were shortlisted to 32 variables through the plant operator experience. The data were divided into three groups for ANN training. 60% of the data were used for training, whereas 15% were used for the validation process and used for testing. The proposed pure intelligent system detected the fault 10 minutes before the actual trip with an ANN output value of 0.65.

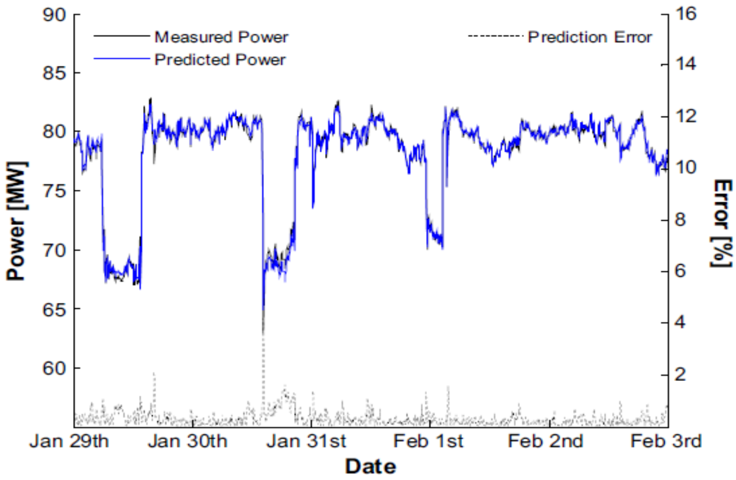

Figure 5: Steam turbine power output [11].

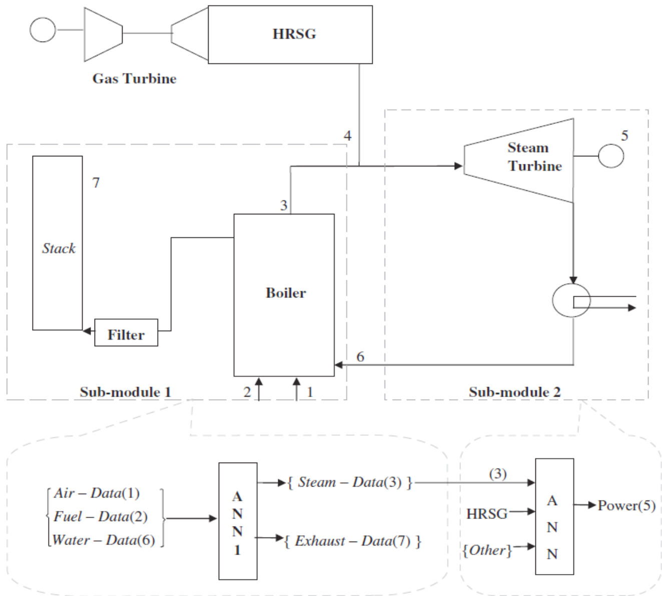

Figure 6: Sub-modules of the steam cycle for ANN model development [10].

2.3 Intelligent failure detection

Ismail & Thiruchelvam (2013) [15] applied backpropagation ANN for fault detection of condenser failure in thermal power plants. This study highlighted that a large number of data input reduces the root mean square error. Therefore, a total of 1817 input vectors with 241 conditions have been used by the author. Initially, the weight is in the random condition. However, once the suitable weights were found, the performance errors decreased linearly, as shown in Figure 7. After 2152 epochs, the program managed to reach its performance goal of 0.0025.

Demand-side management (DSM) techniques were applied by [7] using ANN to optimise power system management in real-time. The data were collected from digital meters, and load curves were formed and used to train and validate the network. ANN was used to classify new data based on the defined patterns. The satisfactory performance of the network in rating the load curves was presented. This information can be used to implement policies that optimise the management of the power system [16].

The ANN and GA as a hybrid system were applied in [17] to model and optimise unburned carbon in a coal-fired boiler. The unburned carbon characteristic is investigated in this study through parametric field experiments. The effects of excess air, coal properties, boiler load, air distribution scheme and nozzle tilt on unburned carbon were studied. GA was applied to determine the optimum level process parameters that were used in the ANN model. The experimental data were used to relate the operational parameters with the unburned carbon in the bottom ash. Figure 10 shows the unburned carbon concentrations calculated by GA through various generations. The graph illustrates that the unburned carbon in the bottom ash was reduced after the combustion optimisation [17].

Azadeh et al. (2011) [18] combined an adaptive network-based fuzzy inference system (ANFIS) with GA for the performance assessment and improvement of conventional power plants. The ANFIS-GA algorithm was able to find a stochastic frontier based on a set of input-output observational data without any explicit assumptions on the functional structure of the stochastic frontier. The performance of the ANFIS-GA was compared with the conventional algorithm and ANN fuzzy C-means algorithm based on Table 2. The analysis from the table shows that the proposed algorithm had several advantages over other methods [18].

Wu et al. (2014) [19] used the Artificial Bee Colony (ABC) algorithm to optimise boiler combustion efficiency. This was set up based on the heat loss of boiler combustion. Another optimisation process was done using GA. The results of both the optimisation process were graphed and compared in Figure 9. Based on the comparison, the optimal global value was achieved after 20 iterations using the ABC algorithm, whereas it took 30 iterations for GA. It was concluded that the ABC algorithm was

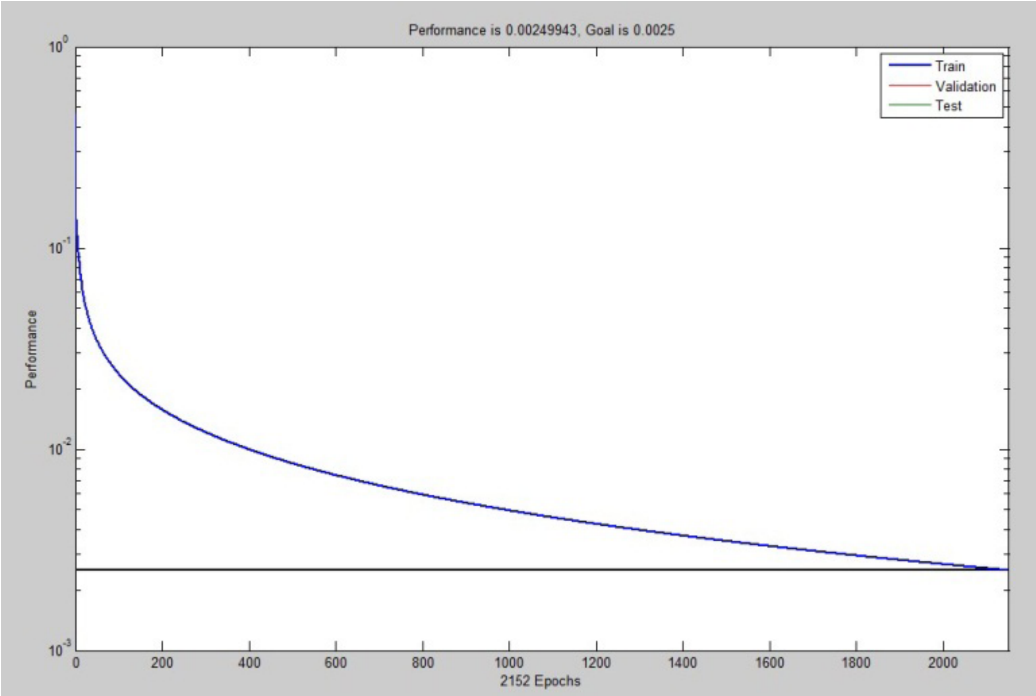

Figure 7: The plot performance of the training [15].

Table 2: Comparison between the proposed algorithm versus other algorithms [18].

Method/ approaches	Features							
	Crisp Data	Non Crisp Data	Handling Data Linearity	Handling Data Nonlinearity	Clustering Ability	Handling outlier and noise data	Handling clustering sensitivity to initial points	Determination of the optimum number of clusters
Data envelopment analysis	*		*					
Artificial neural network	*	*	*			*		
Principal component analysis	*	*						
Numerical taxonomy	*		*		*			
Stochastic frontier analysis	*		*					
ANN-Fuzzy C-Means		*	*	*	*	*		
The integrated ANFIS-GA-clustering ensemble	*	*	*	*	*	*	*	*

faster and more efficient for this application [19].

Fengqi et al. (2009) [20] proposed optimising coal-fired boiler and selective catalyst reaction (SCR) systems using modified support vector machine models and genetic algorithms. The optimisation was done with a population size of 240, crossover probability of 0.9, mutation probability of 0.1 and maximum generation of 30. Figure 10 shows the optimisation results for a particular set of data. The optimal combination of boiler parameters at different levels of target SCR inlet for NOx emission rate was achieved [20].

A genetic algorithm has also been applied to operational plan combined heat and power (CHP) plants. Based on this study, ambient temperature and operating load had the most effect on the plant energy efficiency. A genetic search was applied only on 0-1 variables, and a gradient search was applied on continuous variables. The genetic algorithm method proposed is more consistent in finding feasible integer solutions. GA was also able to find solutions with lower optimality gaps with minimum computational time. When applied in the system, it increased the plant energy efficiency by 5-11% [21].

Boilers are essential components in power, chemical and oil refinery

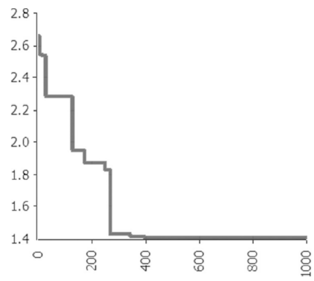

Figure 8: The unburned carbon concentrations calculated by GA under various generations [17].

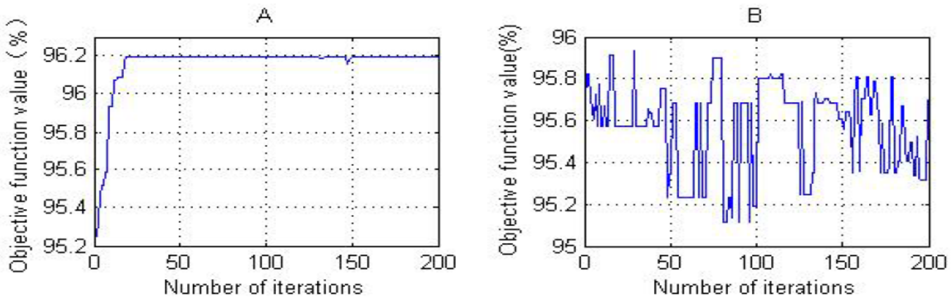

Figure 9: The comparison of the optimisation process between ABC algorithm (a) and GA (b) [19].

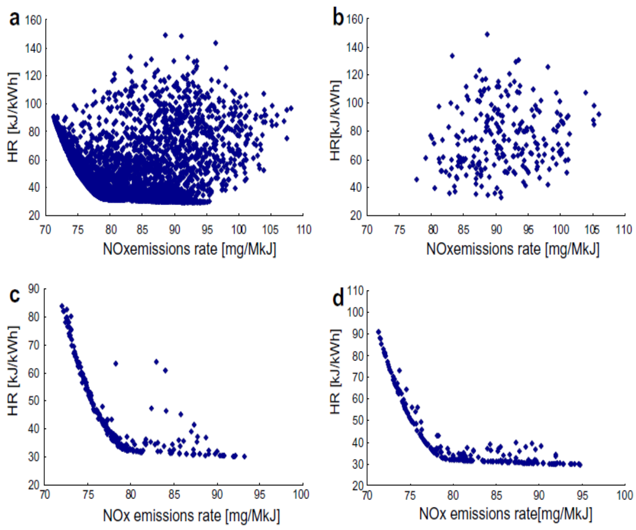

Figure 10: Optimisation results for Set (12): (a) Feasible solutions, (b) Initialisation of first-generation, (c)Pareto front of 15th generation, (d) Pareto front of 30th generation [20].

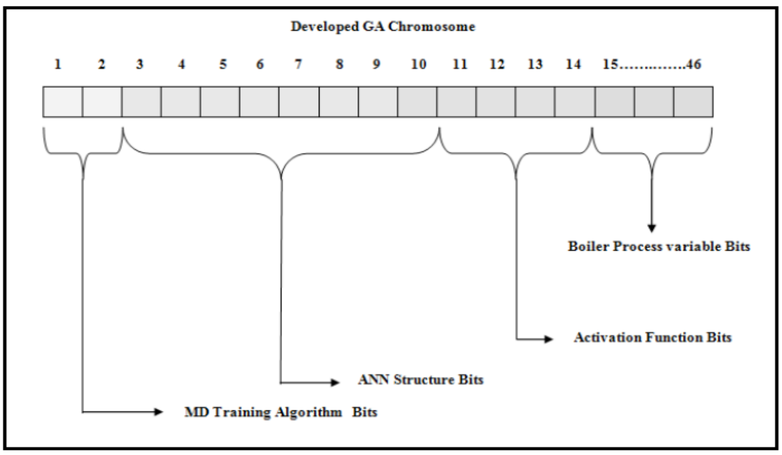

Figure 11: GA binary representation [23].

industries; they transform water into steam for power generation or other industrial applications. A common boiler fault is the tube leak in the riser and downcomer sections due to ageing (corrosion) and thermal stress (e.g., overheating) [22]. Early detection of such faults in operation is crucial because it helps in reducing possible damage to equipment and productivity loss caused by (otherwise) unscheduled boiler shutdown and ensures safety for operators. Several leakage detection methods in a boiler pipeline system have been described in the literature; however, some cannot be easily applied in industrial practice, especially in a plant designed and equipped over fifteen years ago and working under certain technical and economic conditions.

Another application of a hybrid intelligent monitoring system for steam boiler high-level drum trip was researched [23]. MATLAB coding has been used for two artificial monitoring systems, including a pure artificial neural network and genetic algorithms. The weak specification scheme was used to incorporate four tasks of the NN design: the selection of minimisation algorithm, the architecture of the NN, the types of activation function of the hidden nodes and the selection of optimal NN input parameters. The Binary representation of the hybrid system was represented in Figure 11. This study concluded that lower root mean square error was achieved using a pure intelligent system than the hybrid neural network system.

An integrated machine learning-based model with an optimal sensor selection scheme was proposed [24] to analyse boiler water's wall tube leakage. A real steam power plants case was employed to validate the proposed model's effectiveness. The work outcomes indicate that the proposed model can successfully detect water wall tube leakage with improved accuracy vs other comparable models.

3. DISCUSSION AND FINDINGS

Several types of research involving intelligent computational tools in the power plant sector have been reviewed. The highlights and important information regarding the development of these systems have been reviewed in this paper. All the applications of intelligent computational tools in power plants have been summarised in Table 3 in the appendix. The feedforward neural network has been popular in previous studies. Several researchers in the past have applied backpropagation algorithms in constructing the neural network structure. They include minimisation algorithms such as the resilient backpropagation, scaled conjugate gradient, BFGS Quasi-Newton, and Lavernberg-Marquardt algorithms. Based on this summary table, the most commonly used activation function for the neural network is the hyperbolic tangent function. Other activation functions such as the logistic function and the linear summation function have also been used in some cases. Researchers also preferred using a multilayered perceptron network over the radial basis function.

Review from other researches has also shown that the selection of data set for training of the network is crucial as it eventually affects the performance and result of the system. Large data sets have to undergo missing data treatment and noise removal to achieve a quality data set. It is essential to process the data set to remove unwanted and erroneous information as it will increase the computational time of processing these data. The data collected varies depending on the application. However, most researchers have opted to use data with a 1-minute interval. This is because it provides a more sensitive and accurate result. The input for each application varies based on the desired outputs. Each variable's behaviour must be studied and understood so that only variables that affect output are considered. Several pieces of research have adopted the sensitivity analysis for the selection of imported inputs. The hybridisation of ANN in previous studies has proven that the combination of ANN with other expert systems has enhanced the intelligent system's abilities. Genetic algorithm has been most commonly used for optimisation process in power plants.

This review paper covers the applications of intelligent computational tools in power plants. A comparison of the current review paper with related reviews on the applications of intelligent computational systems is presented in Table 4 in the appendix. Based on Table 4, a multilayered feedforward neural network is the most common ANN model for various applications. Backpropagation is the typical learning algorithm, whereas GA and fuzzy logic have been often applied for optimisation even in other applications.

The results from several pieces of research have shown that the implementation of the intelligent computational system in finding the most optimum solution has increased the efficiency of various power plant components. An optimised operation eventually leads to an increase in energy efficiency for power plants. It can be concluded that ANN and its hybridisation proves to be an effective alternative methodology for applications in power plants.

4. CONCLUSION

This article presents an overview of recent development and research in the power plant sector. Various applications of intelligent computational tools in power plants were summarised. Suitable Expert systems for hybridisation with ANN were also identified. From the present study, it can be concluded that in most cases, the feedforward neural network with a backpropagation algorithm is used for prediction and modelling in power plants. The most common neural model consists of the multilayer perceptron (MLP) network. In developing an intelligent system for power plants, the selection of accurate data is essential. The selection of the training data set eventually determines the performance of the intelligent system. Several hybrid systems have been applied to enhance the conventional neural networks. Genetic algorithms have been widely used for optimisation, including optimising the input variables and the neural network topologies. With the increasing popularity of ANN applications, this review will be helpful to researchers working on prediction, forecasting, modelling and fault diagnosis in power plants.

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Table 3: Summary of intelligent computational tools application for power plants.

Ref	Type of intelligent computational tool	Activation Function	Objective	Results	Data Collection Period	Input Parameters	Output parameters	Hybridisation
5	ANN (Back-propagation with gradient decent)	Hyperbolic tangent function (Sigmoid)	Prediction of RPF-fired boiler performance	The network provided excellent predictions. However, fluctuation caused errors in certain cases.	5 months (1 min)	Water temperature, water pressure, incinerator exit temperature, conveyor speed.	Temperature, pressure and mass flow rate of steam	-

6	ANN (Backpropagation)	Gaussian function	Prediction of leaks in fluidised-bed boilers	11 faults out of 12 were able to be detected 2-9 days before the shutdown.	8 years (for 12 faults)	Set points of four coal suppliers, the active power of a unit, the temperature of the flue gas, temperature of the feedwater, temperatures of the superheated steam, flux of the flue gas, temperatures of a fluidised bed, temperature of the live steam, O2 in a combustion chamber, pressures of steam.	Concentration of O_2 in the flue gas before a chimney, primary air flux to the boiler, flux of the feedwater, pressure at the suction of the flue gas fans.	-
7	ANN (Back-propagation)	Linear activation function	Prediction of high-efficiency boiler steam generation and distribution	Steam production costs were reduced through the controlled distribution of generated steam.	1 year	Ambient temperature	Electrical power, industrial steam power, power thermal substation 1 and 2.	-
8	ANN (Back-propagation)	Hyperbolic tangent transfer function	Prediction of fresh steam properties for the coal-fired boiler.	Both models show good accuracy and proved suitable for use in real operations.	12 days (1min)	Mass flow rate of fuel, Temperature of water, Pressure of water (in & out)	The mass flow rate of steam, Temp of steam and Pressure of steam	-
11	ANN (Back-propagation)	Hyperbolic tangent transfer function	Development of ANN model for performance prediction of biomass and coal-fired plant.	The first model predicted exhaust and emission characteristics, and the second model estimated the power output with reasonable accuracy.	1 month (5 min average)	Mass flow rate of coal, biomass, air and water. Temperature of air, water and burner. The pressure of water.	The mass flow rate of steam and exhaust gas. The temperature of the steam and exhaust gas. The pressure of steam. Percentage of O_2 and NO_x .	-
10	ANN (Back-propagation)	Hyperbolic tangent function	To create an online system for condition monitoring and diagnosis of a combined heat and power plant.	High prediction accuracies for all major CHP plant components (gas turbine, heat recovery steam generator, boiler, steam turbine)	3 months (5 min average)	Boiler: Feedwater temperature, feedwater pressure. Varying inputs for other components	Boiler: Steam flow rate, Steam temperature, pellets flow rate. Variable outputs for each component.	-
12	ANN (backpropagation)	Hyperbolic tangent (Tansig), logistic (logsig), linear summation (purelin)	To develop an artificial intelligence system for steam boiler diagnosis (Prediction of boiler tube leak trip)	The low superheater temperature which causes the trip was detected 10 minutes earlier by the proposed model	30 days (1min interval)	32 boiler-related parameters	Specific trip conditions and regular operation.	-

13	ANN (backpropagation)	Hyperbolic tangent (Tansig), logistic (logsig), linear summation (purelin)	Detection of possible boiler trip using multidimensional minimisation training algorithms for steam boiler high-temperature superheater trip.	The one hidden layer with four neurons using the BFGS training algorithm provided the best optimum NN structure.	1 month (1 min interval)	32 boiler-related parameters	Specific trip conditions and regular operation.	-
14	ANN (backpropagation)	Hyperbolic tangent (Tansig), logistic (logsig),linear summation (purelin)	To develop an online condition monitoring system for high-level water trips in the steam boiler's drum.	Two hidden layer structures performed better with RMSE of 0.118 compared to two hidden layers with RMSE of 0.154	1 month (1 min)	32 boiler-related parameters	Specific trip conditions and normal operation.	-
11	ANN (back-propagation)	Hyperbolic tangent (Tansig), logistic (logsig), linear summation (purelin)	Fault detection of condenser failure in thermal plant.	With 2152 epochs, the performance goal of 0.0025 was achieved.	-	1817 input vector with 241 conditions	Specific trip conditions and regular operation.	-
16	ANN (learning vector quantisation algorithm)	Hyperbolic tangent.	To optimise power system management with the application of demand-side management using ANN.	Satisfactory performance in rating the load curves.	1 month	96 measurements for 2000 low-voltage consumers.	Load curves rating	-
17	ANN (Back-propagation)	-	Modelling of the coal combustion process to predict and minimise unburned carbon in bottom ash of a large capacity coal-fired boiler.	The highest boiler efficiency is achieved from operation optimisation.	-	Damper position, 0xygen in flue gas, unburned carbon in fly ash, burner tilt, carbon oxide (PPM).	Unburned carbon in bottom ash	GA is used to achieve the optimum operation parameters yielding the best-unburned carbon in bottom ash.
18	Adaptive network-based fuzzy inference system (ANFIS) with GA	-	Proposed non-parametric efficiency frontier analysis methods based on ANFIS and GACE for performance assessment and improvement of conventional power plants.	The proposed algorithm provided far better results and more robust units than the conventional algorithm and ANN Fuzzy C-means algorithm.	4 separate data set from 1997 to 2004.	Install capacity, internal consumption, fuel consumption and gross production.	Electric power is generated from thermal power plants in each decision-making unit.	The clustering ensemble method was used to find the best number of clusters
19	Artificial Bee Colony (ABC) algorithm and GA.		To optimise boiler efficiency based on the model of boiler combustion efficiency.	Boiler efficiency was better using the ABC algorithm at 96.19% compared to GA, which had an efficiency of 95.3%	-	Enthalpy of coal slag, exhausted gas temperature	Boiler efficiency	Optimisation processes were done using both the ABC algorithm and GA for comparison.

20	Modified support vector machine model and GA	-	Optimisation of coal-fired boiler and selective catalyst reaction (SCR) system	The optimal solution for the lowest unit heat rate and lowest NOx emissions were achieved. The modified AOSVR performed better with an MAE of 1.65 than the batch-wise SVR, an MAE of 9.92.	3 days (1 min)	Excess O2, Average top selected coal flow rates overfire opening and tilt, burner tilt, the coal flow rate of the top mill, ammonia flow rate and damper position.	Heat rate and NOx emission	GA was used to obtain a functional relationship between the lowest achievable heat rate and boiler outlet.
21	GA for mixed 0-1 nonlinear programming	-	Short term operational planning in CHP plants for district energy applications to improve its efficiency.	The proposed scheduling strategy increased energy efficiency by 5-11%.	24 hours (1-hour interval)	Ambient temperature, turbine output and burner input.	Heat transfer efficiency of heat recovery steam generator.	GA was applied to determine 0-1 variables.
23	ANN and GA	Hyperbolic tangent (Tansig), logistic (logsig),linear summation (purelin)	Early steam boiler high-level drum trip monitoring.	The pure ANN system performed better with an RMSE of 0.229 with two hidden layers than the hybrid model with an error of 0.279.	2 days (1-minute interval)	32 steam boiler drum variables	Specific trip conditions and regular operation.	A chromosome presented the NN topologies and boiler drum operation variables for GA optimisation.

Table 4: Comparison of previous related review papers with the current review paper.

Ref	Authors	Year	Popular network model	Popular learning algorithm	Optimisation techniques	Subject
35	A.R. Soroush et al.	2009	Recurrent NN	Backpropagation	Fuzzy logic	Review on applications of ANN in supply chain management and its future
27	Mi X. et al.	2004	Multilayer feedforward NN	Backpropagation	-	A general review of applications of artificial neural networks to the water industry
34	S.A. Kalogirou	2000	Multilayer feedforward NN	Backpropagation	-	Application of ANN for energy systems (Solar energy)
29	S.A. Kalogirou	2003	Multilayered feedforward NN, Recurrent NN	Backpropagation	GA, Fuzzy logic	Artificial intelligence for the modelling and control of combustion process: a review
30	A. Mellit et al.	2008	Multilayer feedforward NN, Radial basis function network	Backpropagation	GA, Fuzzy logic	Artificial intelligence techniques for photovoltaic applications: A review
26	S.A. Kalogirou	2001	Multilayer feedforward NN	Backpropagation	-	ANN in renewable energy systems applications: a review
31	S. Jebaraj	2004	-	Backpropagation	Fuzzy logic	A review of energy models
32	R. Banos et al.	2011	-	-	GA, PSO, Pareto-optimisation technique	Optimisation methods applied to renewable and sustainable energy: A review
33	T. Rakesh	2015	Multilayer feedforward NN	Backpropagation	-	Application of ANN in hydrology- A review
-	Current	2016	Multilayer feedforward NN	Backpropagation	GA, Fuzzy logic	Application of intelligent computational tools in power plants.

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