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AI Adoption for Steam Boiler Trip Prevention in Thermal Power Plants

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ABSTRACT

This study introduces two advanced artificial intelligence systems designed to model and predict various boiler trips, playing a pivotal role in maintaining boilers' normal and safe functioning. These AI systems have been meticulously developed using MATLAB, thus offering sophisticated tools for diagnosing boiler trip occurrences. Real-world operational data from a coal-fired power plant, encompassing a comprehensive range of thirty-two operational variables tied to seven distinct boiler trips, was harnessed for these innovative systems' training, validation, and analysis. The first intelligent system capitalizes on a pure Artificial Neural Network (ANN) approach, leveraging the insights drawn from plant operators' decision-making processes concerning the key variables influencing each specific boiler trip. On the other hand, the second system takes a hybrid approach, incorporating Genetic Algorithms (GAs) to emulate the decision-making role of plant operators in identifying the most influential variables for each trip. Moreover, different topology combinations were explored to pinpoint the optimal diagnostic structure. The outcomes of our investigation underline the impressive capabilities of the ANN system, successfully detecting all six considered boiler trips either before or concurrently with the detection by the plant's control system. Furthermore, the hybrid system exhibited a marginal improvement of 0.1% in Root Mean Square error compared to the pure ANN system. These findings collectively emphasize the potential of AI-driven methods in enhancing early detection and prevention of boiler trips, thereby contributing to improved operational safety and efficiency.

1. INTRODUCTION

Intelligent monitoring systems (IMSs) are efficient and successful tools for identifying equipment malfunctions [1]. Enhanced performance and precision are observed when adopting a fusion of multiple IMSs, like the combination of “Artificial Neural Network" (ANN) and “Genetic Algorithm” (GA), resulting in the formation of hybrid “artificial intelligent systems” (AIS). An area of notable significance for their application lies in the context of steam boilers within small to medium industries and “Thermal Power Plants” (TPP). The early detection of faults and anticipating potential undesired incidents significantly contribute to a more secure and dependable industrial operation [2]. Consequently, the detection and diagnosis of faults are imperative to uphold the safety standards of power plants.

Muselli and Ridella [3] introduced a method that melds GA with simulated annealing to generate and select a set of points within the network connection weight space. This integration accelerates the reliability and convergence of the IMS. The resulting system, aptly named “interval genetic algorithm”, was tailored for applications encompassing boilers, superheaters, and turbines. In a similar vein, Guglielmi et al. [4] harnessed “multilayer feed-forward” (MFF) and radial basis function NN to address prevailing fault detection and diagnosis challenges within an online 320 MW power plant system, inclusive of four feed heaters along the high-pressure water line.

Zhou et al. [5] presented a novel fault diagnosis methodology that intertwines GA and “Classical Probability” techniques, drawing from expert knowledge and data derived from a comprehensive 950 MW Beijing nuclear power plant. Meanwhile, Shi et al. [6] employed a combination of RBF neural network and GA to devise an automated fault diagnosis system for a nuclear power plant, thereby enhancing the accuracy and practicality of the diagnostic process, particularly in cases characterized by non-typical scenarios.

Agrawal et al. [7] introduced an online model for fault detection and diagnosis, employing “Fuzzy Logic” (FL) to evaluate residuals and a Bayesian network for troubleshooting. The findings underscore the positive impact of integrating FL with the Bayesian network in enhancing fault detection and diagnosis. Romeo and Gareta [8] devised an algorithm using NN to monitor a biomass boiler, highlighting the advantages of NN in this context. Rusinowski and Stanek [9] established an NN-based model for steam boilers, utilizing operational measurement data for material and energy balances. Alnaimi et al. [10] constructed an IMS integrating four distinct ANN algorithms. This IMS was evaluated using real-time data sourced from a Malaysian power plant, and the results were juxtaposed with corresponding "Root Mean Square" (RMS) calculated values. Notably, the optimal NN structure was identified using the "Broyden-Fletcher-Goldfarb" (BFG) "Quasi-Newton Training Algorithm".

Fast and Palme [11] implemented an online system for monitoring and diagnosing "Combined Heat Power" (CHP) plant components, leveraging ANN. This system was smoothly incorporated into the control unit of the plant alongside a power generation and information management server. They developed a user-friendly graphical interface embedded in the CHP information management system. Nistah et al. [12] designed a boiler fault prediction model, striving for minimal misclassification rates and mean squared errors through ANN. They trained the ANN with a set of operational parameters and validated the model against real fault values from an operational plant, achieving an average accuracy of 92%.

Ismail et al. [13] devised an AIS model to predict tube leakage in steam boilers using ANN, training, and validating the model with operational data from a TPP. Their results underscored the superiority of employing a single hidden layer over a two-layer configuration in the feed-forward with backpropagation architecture. Selvi et al. [14] compared a static and dynamic ANN-based model for predicting water levels in a boiler drum. The static model, constructed with a feed-forward architecture containing a single hidden layer of 28 neurons, was juxtaposed with the dynamic model utilizing "NARX Architecture," with a single hidden layer featuring 9 neurons. Both models were validated and assessed using real operational data obtained from an Indian plant, revealing superior prediction accuracy in the case of the dynamic model.

Panchal and Kumar [15] proposed implementing a FL methodology and formulated a model for a plant's reliability and risk analysis. The authors propose that the limitations often encountered when employing outdated "Failure Modes and Effects Analysis" (FMEA) can be surmounted using a decision support system grounded in FL. Smrekar et al. [16] constructed an ANN framework using plant-derived data to predict upcoming steam properties. The insights of plant operators influenced the original input parameters, and the final selection of input parameters was fine-tuned for optimal performance. Iliyas et al. [17] successfully crafted a predictive model for NOx and O_2 emissions using an RBF neural network, validating this model against actual data from an operational plant.

De et al. [18] detailed a "feed-forward with backpropagation" (FFBP) ANN model designed for biomass and coal-fired CHP plants. This model was trained using data from the plant to predict its performance. Moreover, in their comprehensive review paper, Nistah et al. [19] analysed current techniques in developing IMS for "Coal-fired Power Plants". Their conclusion endorsed the viability of incorporating remote accessibility and seamless interaction between plant operators and the control system interface, highlighting the IMS's accurate trip prediction capabilities.

Victor et al. [20] embarked on the development of an AI model for a "Pressurized Water Reactor" (PWR) within a "Nuclear Power Plant".

They fashioned an FL controller for the PWR pressurizer, the parameters of which were modelled through ANN. Data from a 2785 MW thermal Westinghouse 3-loop PWR simulator was employed to validate the pressurizer ANN model and the FL controllers. Simulation outcomes demonstrated a reasonable agreement between the developed ANN model's responses and the simulated power plant, showcasing the FL controllers' enhanced performance compared to conventional ones.

Mayadevi et al. [21] had recently provided a comprehensive survey encompassing diverse applications of expert systems within power generation plants. The publication highlights the notable technological progression of expert systems and their harmonization with contemporary methodologies, including FL, NN, machine learning, and computerized data acquisition systems. The study affirms that expert systems possess substantial potential to alleviate the operational burden on plant operators and experts, effectively serving as fault diagnosis and maintenance experts for the plant. Furthermore, the integration and fusion of various intelligent systems have expanded the problem-solving capabilities of expert systems, contributing to an enriched scope of solutions.

It can be deduced that prior research has predominantly employed a one-hidden layer (1HL) architecture for ANNs in the context of fault detection and diagnosis. Additionally, the training of IMSs has largely relied on simulation data. Some studies have incorporated the insights of plant operators as inputs for NNs. However, a comprehensive hybrid intelligent system framework combining NN and GA has not been previously formulated for diagnosing steam boiler trips within TPPs. It is noted that a standardized approach for real data preparation in IMSs, elucidating the nature of boiler operational variables, has not yet been established. Furthermore, the topologies of NN-based IMSs have received little attention.

The primary objective of the current study is to devise two IMSs to diagnose steam boiler trips within a three-unit 700 MW coal-fired thermal power plant (CFTPP). The case study encompassed six instances of steam boiler trips. The initial AIS, designated as IMS-I, employs a pure ANN configuration with influential variables selected based on the expertise of plant operators. The second AIS, referred to as IMS-II, adopts a hybrid structure combining ANN and GA. In IMS-II, GA substitutes the plant operators' decision-making process to identify the most influential variables for each of the six trips. Real operational data associated with the six steam boiler trips and relevant operational variables were collected to train and validate the two developed IMSs. The research also outlines the data acquisition and processing procedure instrumental in training and validating both pure and hybrid AIS.

The article is organized into four distinct sections. The first section conducts a review to identify gaps and delineate the problem statement concerning boiler trip diagnosis. The second section delves into problem identification and presents specifications relevant to the power plant. Section 3 comprehensively elaborates on the methodology and procedures adopted, encompassing data acquisition, manipulation, and the creation of the two IMSs. Section 4 showcases and analyses the diagnostic outcomes and compares the performance of the developed IMSs. Finally, the article concludes in Section 5, summarizing the insights gained and accomplishments derived from the case study.

2. CASE STUDY FORMULATION

The chosen CFTPP for the present case study is a TPP fuelled by bituminous coal. It encompasses three identical power units. Each unit can produce 700 MW of electrical power. The boilers have a sub-critical pressure of about 22.12 MPa, or 221.2 bar, and operate with a pulverized coal supply. The normal operating pressure range for these steam boilers is between 10 MPa (100 bar) and 19 MPa (190 bar). Subcritical plants usually operate below the critical pressure of 22.12 MPa. These boilers feature a combustion system comprising a furnace with direct tangential firing facilitated by a balanced draught. Light fuel oil burners facilitate initial furnace ignition. A low NOx combustion burner system, incorporating cover fire airports, controls NOx emissions effectively.

An Electrostatic Precipitator is employed at the boiler outlet to eliminate particulate matter from the flue gas. At the same time, a wet "Flue Gas Desulphurization" plant is responsible for scrubbing the flue gas to regulate SO_2 emission levels at the stack. The main supporting components include three boiler circulating pumps, two forced draft fans, two steam air pre-heaters, a soot-blowing apparatus, and two "electrostatic precipitators". Refer to Figure 1 for an illustration of the selected CFTPP schematic.

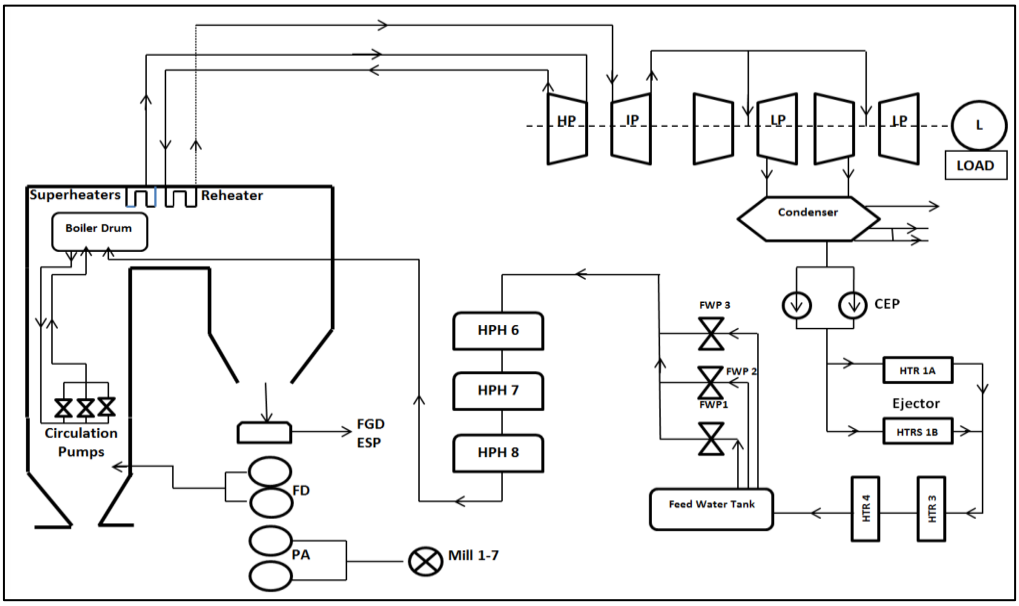

Figure 1. Schematic layout of a 700 MW CFTPP

2.1 Influential variables

The control room monitors and records a comprehensive set of 1800 real measurement data, which had been subsequently reduced. The reduction was performed in three stages. First, by excluding any measurements related to furnaces and fans; second, through evaluation by a power plant expert; and third, by averaging the respective sensor readings. Various methods were adopted to assess the importance of each measurement relative to one another and to understand their relationship to previously recorded faults based on historical fault reports archived in the plant documents. Within the scope of boiler monitoring, a total of 32 variables are examined, measured by utilizing 177 sensors. In such scenarios, the approach involves calculating the mean value through summation and subsequent averaging. While this calculation does not compromise accuracy, it serves to simplify computations. Following the counsel of the plant operator, certain variables deemed insignificant were omitted. Consequently, the definitive count of variables that contributed to boiler trips and were employed as input for the developed IMSs stands at 32, as outlined in APPINDEX-A. The data, spanning three years with a time interval of one minute, was segregated into two parts: 70% for training and 30% for validation.

2.2 Trips identifications

This case study is conducted under a contractual arrangement to create an artificial system that aids operators in reducing the frequency of shutdown occurrences. The choice was made to actively monitor the plant operations over a designated timeframe and gather pertinent operational data on the boiler. This dataset encompassed values of 32 distinct variables, as enumerated in Table 1. Throughout the monitoring period, specific trips were considered, involving instances where the power unit underwent a shutdown.

Table 1. Identification of boiler trips

Trip Code	Identification of Trip
Trip-1	low-temperature superheater
Trip-2	boiler drum level low (a)
Trip-3	boiler drum level low (b)
Trip-4	boiler feed pump
Trip-5	boiler drum level high
Trip-6	high-temperature superheater

3. METHODOLOGY

The primary objective of this case study is to assess the performance of the "pure ANN (IMS-I)", "hybrid ANN-GA (IMS-II)", and the corresponding IMS-I and IMS-II systems in diagnosing various types of steam boiler trips. The underlying hypothesis posits that the hybrid AIS developed would exhibit superior sophistication to the pure AIS for these diagnostic tasks. This automated approach aims to surmount challenges intrinsic to human intervention within the pure AIS, such as entrapment in local minima or inadequate search exploration.

The methodology employed In the research Is visually delineated in Figure 2, commencing from acquiring data within the TPP and extending through four distinct phases to culminate in the generated outcomes. The code development for modelling the power plant's boiler is executed across these four sequential phases, as graphically depicted in Figure 2.

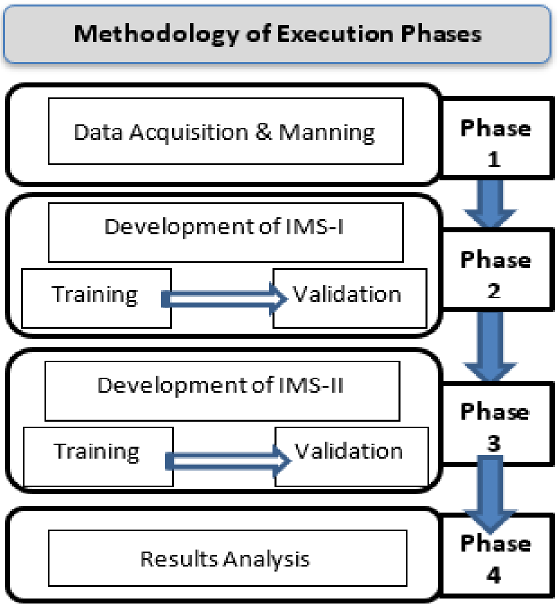

Figure 2. Phases of methodological execution

3.1 Phase 1: Data acquisition and manning

Due to the significance of plant data preparation, a structured framework has been introduced for six prevalent boiler trips. These specific trips, identified by experienced plant engineers as the most recurrent culprits behind the occurrences of trips, are associated with relevant operational variables. The schematic representation of the modelling procedure is provided in Figure 3. The comprehensive interpretation of plant data involves the following procedural steps:

Step 1: Data Identification for Preliminary Analysis – The operational variables of the boiler are pinpointed and collected for each distinct boiler trip, as listed in Table A1.

Step 2: Data Preprocessing – During this phase, the data is subjected to preprocessing, encompassing the filtration of noisy and defective data points, followed by their normalization within the range of one to zero. Manual intervention was employed to identify and remove any data points deviating beyond the ± 0.8 thresholds, regarded as noise. It's important to note that numerous instances exhibited no scattering of signals beyond the ± 80% range of the sensor's mean value.

Step 3: Data Post-analysis – This phase involves segmenting the data into two separate sets for each trip: Data-set-A and Data-set-B. Data set A constitutes 70% of the complete data set for each trip, utilized for the initial training of the developed ANN. On the other hand, Data Set B, comprising 30% of the total trip data, is reserved for validation purposes. It is pertinent to mention that the chosen percentage allocation results from iterative experimentation. Notably, every phase of the plant data preparation incorporates distinct inter-phases, contributing to the overall process.

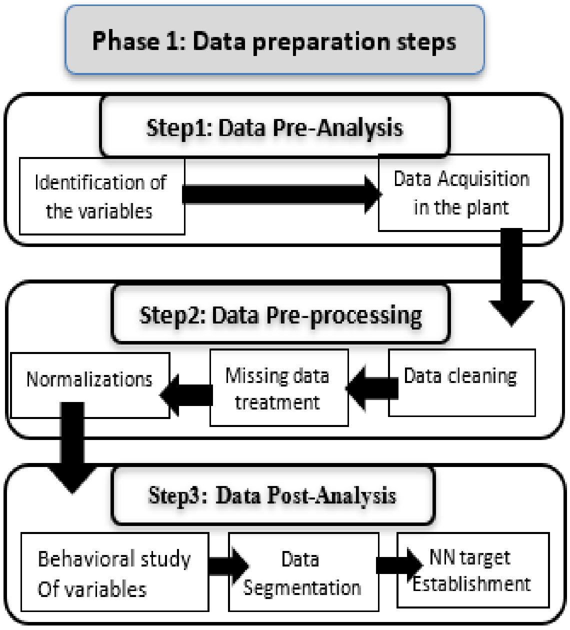

Figure 3. Data preparation scheme

3.2 Phase 2: Development of IMS-I (Pure ANN)

The fundamental training approach employed in this study is the FFBP Training Algorithm. This multidimensional minimization algorithm has undergone several adaptations to reduce errors effectively.

3.2.1 IMS-I structure

As elucidated in the preceding section, the thirty-two variables of steam boilers are designated as the inputs for the ANN. Each individual ANN model encompasses two outputs, where "0" signifies normal operation, and "1" denotes a malfunctioning state (an operational trip). Throughout the training and validation of the pure IMS, the outputs manifest as continuous values ranging between 0 and 1. Consequently, based on the outcomes yielded by the ANN model, a decision-making process is employed to determine the optimal meaningful threshold value that distinguishes between faulty and normal operations.

Numerous ANN configurations were investigated, encompassing 1 and 2 hidden layers, 1 to 10 neurons for each hidden layer, 3 distinct activation functions, and 4 training algorithms. To ascertain the accuracy of IMS-I, the "Root Mean Square Error" (RMSE) of the NN outputs (an indicator of steam boiler trips) is scrutinized against a novel dataset that hasn't been employed in the NN model's training. This procedure called the validation of the developed IMS-I, ensures the reliability of the model's performance. The training of IMS-I was conducted utilizing the tools available in MATLAB. The structure of IMS-I, incorporating its input and output parameters, is visually depicted in Figure 4.

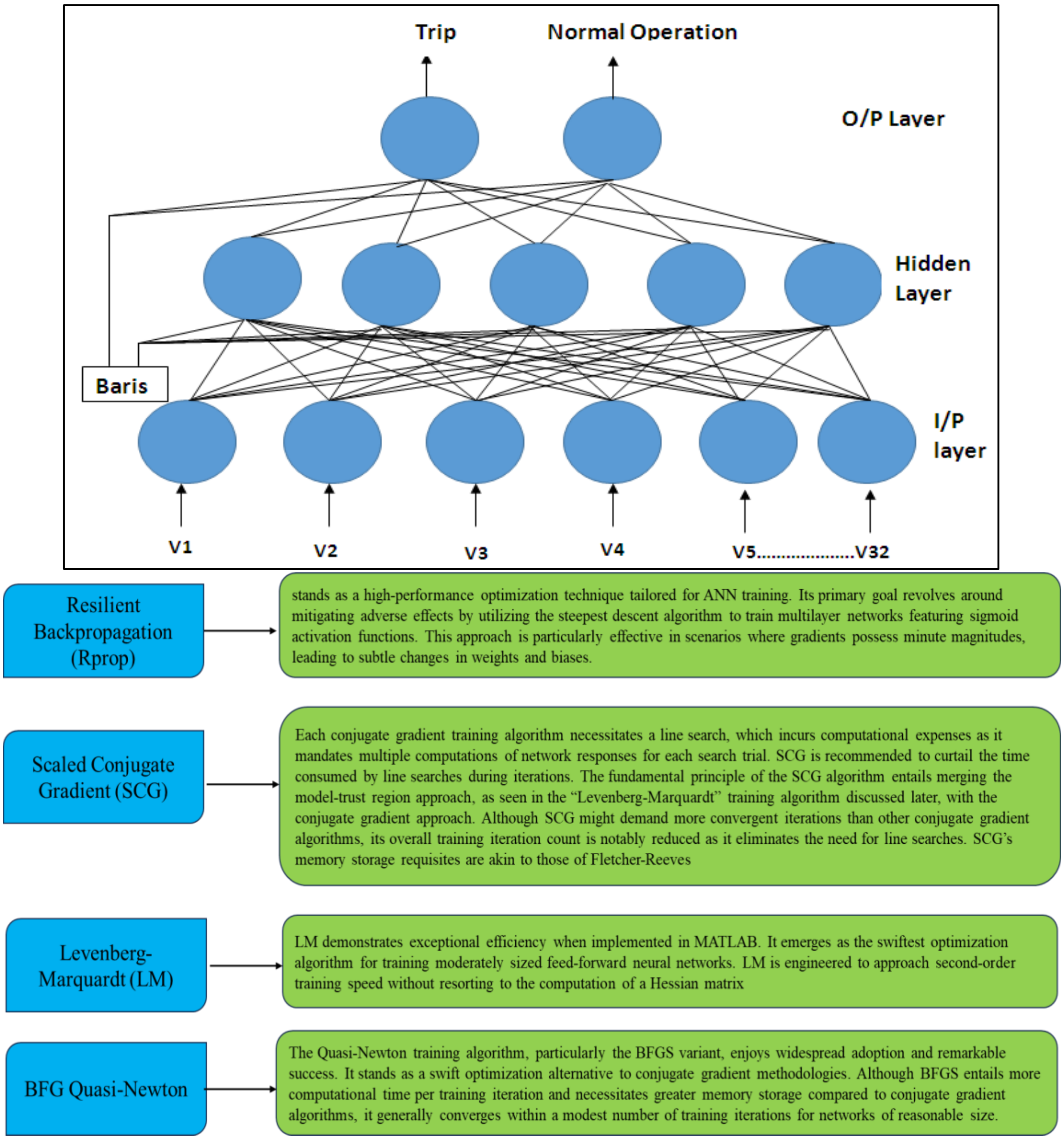

Figure 4. Top: IMS-I architecture, Bottom: computational times selection process

3.2.2 Training algorithms

Within the context of multidimensional minimization algorithms aimed at error reduction, the backpropagation training algorithm has undergone several adaptations.

Table 2. Convergence times for nine widely recognized Back Propagation accelerated training algorithms

Activation Function	Techniques	Time	Epochs	Mflops
traingdx	Variable Learning Rate	57.71	980	2.50
trainRprop	**Rprop**	**12.95**	**185**	**0.56**
trainscg	**Scaled Conj. Grad.**	**16.06**	**106**	**0.70**
traincgf	Fletcher-Powell CG	16.40	81	0.99
traincgp	Polak-Ribiere CG	19.16	89	0.75
taincgb	Powell-Beale CG	15.0.3	74	0.59
trainoss	One-Step-Secant	18.46	101	0.75
trainbfg	**BFGS quasi-Newton**	**10.86**	**44**	**1.02**
trainlm	**Levenberg-Marquardt**	**1.87**	**6**	**0.46**

Table 2 presents the convergence times observed for nine widely recognized Back Propagation accelerated training algorithms addressing a specific problem.

Only four types of minimization algorithms, as indicated in bold in Table 2, have been considered in this study. The selection process was informed by the computational times reported by Demuth et al. [22], as detailed in the subsequent sub-sections. It is worth mentioning that Mayadevi et al. [21] endorsed Rprop due to its expedited nature compared to standard steepest descent optimization methods.

3.3 Phase 3: Development of hybrid IMS-II (ANN+GA)

Gas operates as search methods inspired by the principles of natural genetics. Over time, gas has gained substantial popularity as an optimization technique, largely due to its demonstrated success in identifying optimal solutions, often outperforming more conventional optimization algorithms. According to Sivanandam and Deepa [23], typical operational characteristics of a genetic algorithm encompass:

3.3.1 Structure of the IMS-II

IMS-II represents a hybrid system that integrates GA selection for determining influential variables within the ANN, contrasting the conventional approach of relying on plant operator decisions. Numerous instances have demonstrated the robust search capabilities inherent in Gas. The process employed by Gas involves generating new populations through selection, recombination, and mutation operators.

The GA Selection Process initiates the creation of a breeding pool composed of strings with above-average fitness from the current population. This pool forms the foundation for generating new population members. Specifically, the Tournament Selection method is adopted, wherein the population is repeatedly subdivided into random tournaments, each comprising two population members. This study includes the fittest individual from each tournament in the reproducing pool. This process continues until the size of the reproducing pool matches that of the population. A notable advantage of Tournament Selection is its independence from the range of fitness values, and its concurrent implementation is straightforward.

In the context of binary-encoded Gas, the typical recombination operator is crossover. A "crossover probability" (Pc) is applied, usually between 0.6 and 0.9. This operator involves taking two strings from the reproducing pool and exchanging contiguous segments of their structures to generate two offspring. Various techniques exist for executing the crossover operation. A single-point crossover method is employed for the GA at hand, with the site along the string selected randomly.

Within the framework of the binary-encoded GA, the mutation operator introduces randomness by occasionally replacing a "Bit" with another bit through a minor mutation probability. Each string within the population might share the same value in each Bit. Consequently, crossover might not introduce any deviation from these predefined values. The mutation operation safeguards, ensuring that lost values are reintroduced, thereby maintaining diversity within the GA population.

3.3.2 Process of the hybrid system

Chromosomes serve as the representation of primary ANN topologies and the boiler's operational variables slated for optimization. These chromosomes are encoded as binary strings referred to as "genes". Consequently, a chromosome contains as many genes as the number of ANN topologies and boiler operational variables earmarked for optimization. Figure 5(a) illustrates the Binary representation characteristic of the hybrid IMS-II.

The gene optimization process entails the creation of an initial population comprising a specified count of chromosomes, each assigned "1" or "0" to its genes at random. Within the context of selecting ANN topologies and boiler operational variables, a gene encompasses a single-bit string indicating the presence or absence of a specific plant variable.

The design of the fitness function plays a pivotal role in the application of the GA, as it dictates the optimization objective of the GA. In this study, the initial GA population is generated randomly, except for one chromosome, configured to encompass all ANN topologies and boiler operational variables. Subsequently, the generated chromosomes are assessed using the Fitness Function. This evaluation begins with encoding the chromosomes into NNs, where "1" signifies utilizing a specific boiler operational variable, and "0" signifies its omission. These NNs are then subjected to training and validation with fresh datasets. In this context, the fitness of each string is gauged by the root mean square error (RMSE), culminating in the ultimate fitness value calculation:

$$(\mathrm{RMSE})_{ps} = \sqrt{\sum_{i}^{n} \frac{(d_i - o_i)^2}{n}} \tag{1}$$

where, I = 1, 2, 3, …., n, ps is the number of training data set, and d_i and o_i are the desired and predicated outputs of node i.

Furthermore, an integral aspect of the evolutionary system involves encoding the various potential configurations of NN topologies and boiler operation variables into distinct genotypes. These NN topologies encompass factors like activation functions within hidden layers and output nodes. The training process employs multidimensional algorithms in conjunction with the backpropagation technique.

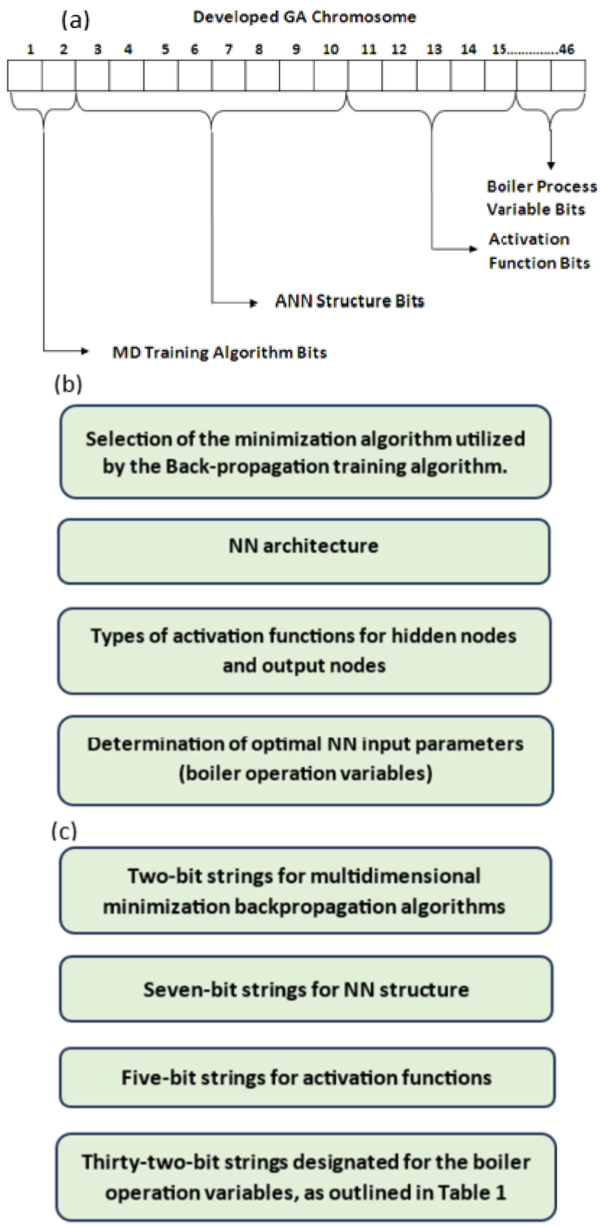

Figure 5. (a) GA binary representation, (b) WSR encompasses four essential aspects of ANN design, (c) proposed individual, comprising a total of 46 strings

A genotype is a binary sequence comprising either 0s or 1s and uniquely corresponding to a phenotype. In this context, a phenotype encompasses a set of thirty-two boiler operation variables. The "Weak Specification Scheme" (WSR), innovated and implemented within this study, employs specific associations between designated binary strings and predefined network architectures, as stipulated by the user. WSR encompasses four essential aspects of ANN design illustrated in Figure 5(b). Each genotype within the GA distinctly represents a particular phenotype, encompassing both NN topologies and training parameters. Figure 5(c) presents and explains the proposed individual, comprising a total of 46 strings.

4. RESULTS AND DISCUSSION

To diagnose boiler trips, this study introduced two intelligent monitoring systems, IMS-1 and IMS-2. Both systems were developed within the MATLAB environment and employed the "Feed-forward" ANN approach. The construction of a boiler trip detection system hinges on recognizing aberrant operations through datasets that exclusively feature instances of faults. The discussion centres on identifying optimal NN topology configurations and each trip's most influential boiler operation variables.

This section is categorized into two subsections for comprehensive coverage. The initial subsection entails the presentation and deliberation of results stemming from IMS-I. The subsequent subsection delves into the outcomes achieved by the hybrid IMS

4.1 Training results of IMS-I (Pure ANN)

IMS-I is trained using operational data gathered from the CFTPP, encompassing instances of both regular and faulty boiler operations. The dataset, spanning approximately 2 continuous days leading up to each trip, constitutes the foundational training and validation sets. These data points are captured at intervals of 1 minute.

The training process comprises two integral modes. The initial mode, known as preliminary training, ascertains the optimal combination of network architecture and training algorithms. This determination is accomplished by subjecting numerous potential network topologies, both 1-hidden layer (1-HL) and 2-hidden layer (2-HL) configurations, employing four distinct training algorithms. Comparative analysis of the outcomes of preliminary training guides the selection of the most suitable combination. The subsequent phase, referred to as the basic training process, is dedicated to training the identified superior combination of architecture and algorithms. This training framework evaluates diverse values of the "Coefficient of Momentum" (λ). Additionally, "hyperbolic P", "tangent T", "logistic L", and linear summation activation functions are tested.

Existing literature suggests that no universal amalgamation of ANN topologies can be universally applied to all boiler trips. The outcome of the preliminary training, gauged by the lowest RMSE, underscores the efficacy of the logistic activation function for the output node within both 1-HL and 2-HL architectures for the six boiler trips. The same inference was claimed by Chernykh et al. [24] in their application of the ANN to predict electric energy consumption.

Their investigation revealed that altering the number of neurons within the network's hidden layer has a negligible impact on the prediction magnitude. Conversely, adjusting the number of neurons in the input layer substantially influences the outcomes generated by the network. Notably, particular attention should be directed towards the two-layer network configuration featuring a solitary neuron in the input layer.

4.2 Analysis of IMS-I diagnosis (Pure ANN)

Six distinct collections of actual data were meticulously curated for the purpose of validation. The initial five sets encompassed genuine faulty data, serving to assess the swiftness with which the suggested IMS-I identifies anomalies. In contrast, the final set exclusively comprised genuine data from regular boiler operations, allowing for an appraisal of the system's functionality under standard operational conditions. A comprehensive breakdown of the validation process for these real data sets is comprehensively presented in Table 3.

Table 3. Description of the actual data for each trip

Data Set	Fault Status	Starting Date/Time	End Date/Time	No. of Intervals	An Interval That Fault Was Introduced
1	Trip 1	05.06.2008 01:56:00	05.06.2008 06:29:00	275	251
2	Trip 2	06.06.2008 7:23:00	06.06.2008 12:54:00	333	17
3	Trip 3	19.12.2008 21:19:00	20.12.2008 01:03:00	326	50
4	Trip 4	30.01.2009 03:39:00	30.01.2009 08:31:00	293	118
5	Trip 5	05.05.2009 10:20:00	05.05.2009 16:22:00	364	239
6	Trip 6	31.05.2009 20:24:00	31.05.2009 23:59:0	216	38

The reaction of IMS-I to the corresponding dataset of trip (1) is represented in Figure 6, which identified as a "low-temperature superheater" trip. When the steam temperature drops below the designated threshold, an elevation in moisture content within the produced steam travels to the turbine. This situation poses a risk of erosion in the guiding passages, leading to damage in headers and steam tubes, ultimately resulting in steam leakage. The turbine's stop valves, steam chests, and the structural integrity of the initial rotating stage within the steam turbine may be compromised.

A rapid decline in steam temperature can transpire due to water carryover from the boiler to the superheater header or due to malfunctions in the attemperator system. An early alert mechanism is essential through an Advanced AIS to promptly notify operators, enabling swift action to mitigate water carryover and uphold normal operating temperatures.

Given the absence of an early detection and diagnosis system, operators are compelled to halt unit operations. In the context of this case study, data sampling from the plant covers 275 minutes before the shutdown event. The dataset initiation features a period of typical boiler operation, with the introduction of faulty operation commencing at the 251st interval. The devised IMS-1 identifies the anomaly within the 235th interval, marking a sixteen-minute lead over the plant's monitoring system. With an IMS-I output value of 0.57, it is categorized as a subtle fault indication, lying near the defined threshold range.

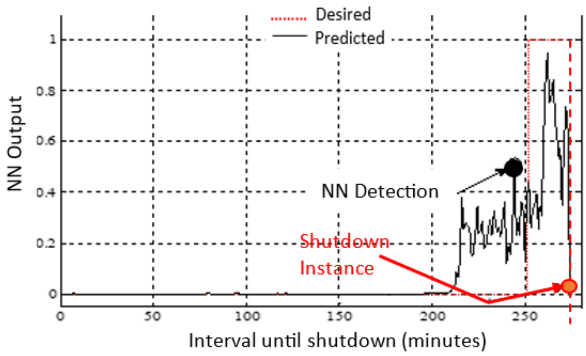

Figure 6. IMS-I predicted outputs and actual plant data for trip (1), low-temperature superheater

The boiler drum's water level is typically slightly below its geometric center. A low water level within the drum could lead to severe consequences for the boiler tubes. An automated protection system is in place to regulate the water level. However, in cases where this automated protection system fails to operate within a designated timeframe, it becomes imperative to have an alarm system within the control room. This alarm system alerts operators, enabling them to conduct the necessary inspections and take appropriate measures. In instances where there is no early detection and alarm system in place, a critically low drum water level can become extremely hazardous. A fault in this scenario could result in the overheating of water tubes, leading to localized tube melting and water leakage into the furnace resulting into "fish mouth" tube deformations within the water wall. Such failures have been known to cause furnace explosions under specific conditions, often contingent on the location of the failure. Water mix with coal generates a combustible gas that may lead to a boiler furnace explosion.

Figure 7 illustrates the outputs from IMS-I for trip (2), denoted as "boiler drum level low". The total duration of data sampling covers a span of 334 minutes preceding the shutdown event. In this instance, the shutdown transpired due to the plant's absence of an alarm system. Operators were compelled to halt unit operations to address the underlying cause and avert a potential explosion. The fault initiation occurred during the 17th interval. Notably, IMS-I successfully identifies the fault 10.0 intervals before the plant's monitoring system does, featuring an output value of 0.65. The IMS-I output dips below the threshold of 0.5, indicative of normal boiler operation, within five minutes of the fault occurrence and maintains this range for several ensuing intervals.

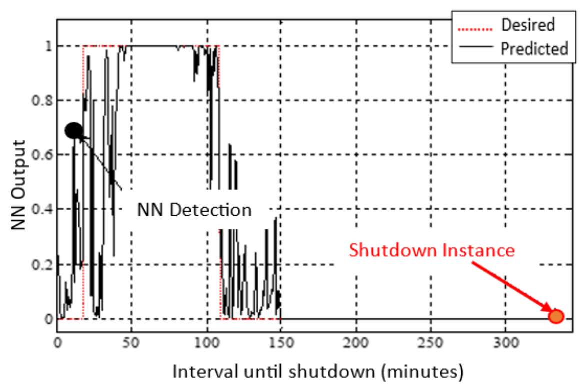

Figure 7. IMS-I predicted outputs and actual plant data for the trip (2), boiler drum level low

As previously indicated, the power plant comprises three identical units. The prediction for the trip (3), depicted in Figure 8, bears resemblance to trip (2), which is characterized as a "boiler drum level low" trip. However, this event occurred within Unit 3 of the CFTPP. The IMS-I output for this event is illustrated in Figure 8. The timeframe encompassed in the total data sampling interval extends to 327 minutes prior to the shutdown event. The fault was introduced during the 50th interval. Notably, IMS-I adeptly identified the fault. Remarkably, even as early as the 40th interval, the system strongly signalled the presence of a fault with an output value of 0.65. It is worth mentioning that continuous fault detection by the intelligent system after initial detection is not of paramount importance. The swiftness with which the system can detect anomalies holds significance in fault detection.

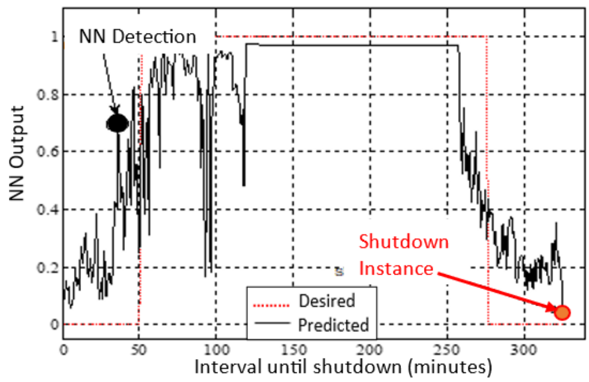

Figure 8. IMS-I predicted outputs and plant data for the trip (3), boiler drum level low

Figure 9 illustrates the IMS-1 output during the fourth set of real data for the "boiler feed pump" trip (4). The time span covered by the total data sampling interval is 293 minutes leading up to the shutdown event. The monitoring of the data commences with a regular boiler operation, while the occurrence of a faulty operation takes place in the 118th interval. IMS-I identified the fault concurrently with the plant monitoring system interval (118th step), yielding an output of 0.53. Subsequently, the IMS-1 output surged into the high-high alarm zone, reaching a value of 0.96, which can be considered a robust indication. It is worth noting that, amid a fault event, the system's output experiences an abrupt drop before the fault begins to subside. As mentioned earlier, this sudden drop is not considered a network shortcoming. Rather, the pivotal factor in fault detection lies in the speed at which detection occurs.

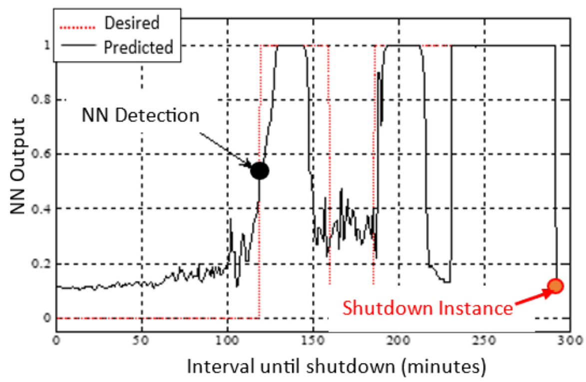

Figure 9. IMS-I predicted outputs and plant data for the trip (4), boiler feed pump

Controlling the water level in a steam drum of a boiler is a complex task due to the inherent instability of the "water level", which is a dynamic mix of water and steam bubbles that undergoes fluctuations in response to pressure changes. As the demand for steam increases, the pressure within the boiler decreases, causing the water level to rise. Additionally, when fresh water is supplied from the feed tank, it has a cooling effect on the drum water, leading to the collapse of steam bubbles and a sudden drop in the water level.

Figure 10 illustrates the IMS-1 prediction and the results obtained from the fifth real data set of a "boiler drum level high" trip (5). The total data sampling interval covers 365 minutes leading up to the shutdown event. The monitoring of boiler data began under normal operating conditions, and the fault was introduced during the 239th interval. The intelligent system effectively detected the faulty operation a mere 5 minutes before the plant monitoring system did, with the IMS-I output registering a value of 0.71. Notably, the intelligent system's output strongly indicated abnormal boiler operation, as evidenced by the higher values observed towards the end of the fault period.

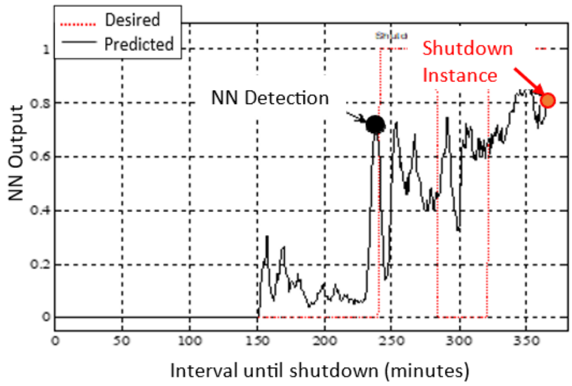

Figure 10. IMS-I predicted outputs and actual plant data for the trip (5), boiler drum level high

Figure 11 depicts the output of IMS-I in response to the sixth real data set, representing a "high-temperature superheater" trip. The complete data sampling interval encompasses the 217 minutes leading up to the shutdown event. The graph demonstrates that while the intelligent system successfully detects the fault, there are instances where the system output momentarily returns to the range associated with normal operation. This phenomenon occurred twice during the primary phase of the particular fault and towards the fault period's conclusion (after interval 78). The periodic oscillation observed in the NN output values can be attributed to the inherent characteristics of sensor or actuator faults. This fault was replicated by introducing periodic noise to the readings of the boiler wall water tube sensors and actuators, which was modelled as a sine function. The system exhibited remarkable speed in detecting the fault within 15 intervals (approximately 23 minutes prior to the plant monitoring system). The output value of IMS-I was 0.78, signifying a robust indication of the presence of faulty boiler operation.

4.3 Analysis of IMS-II diagnosis (hybrid ANN-GA)

The optimal selections made by the GA search for all six boiler trips are presented in Figure 12. The outcomes highlight those networks with two hidden layers generally outperformed those with a single hidden layer, except for trip (3). The hybrid system consistently exhibited a lower error value of less than 0.5. Additionally, a specific set of operational variables was identified as ANN inputs. The results indicate that, in most instances, the BFGS Quasi-Newton and resilient backpropagation training algorithms yielded superior performance compared to the other two training algorithms.

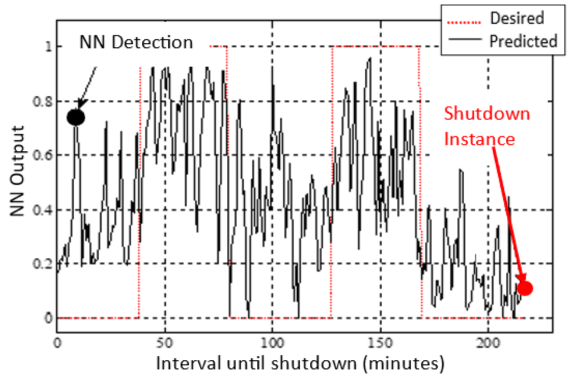

Figure 11. IMS-I predicted outputs and actual plant data for the trip (6), high-temperature superheater

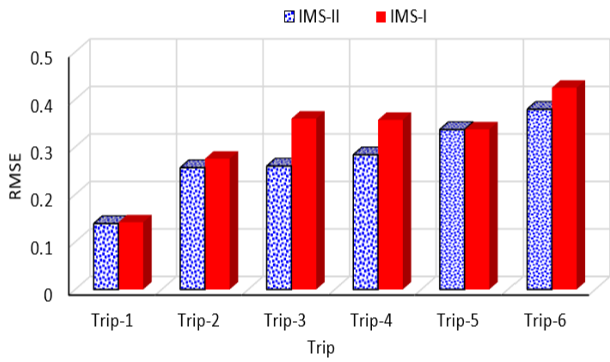

Figure 12. RMSE VS. trips for IMS-I and IMS-II

4.4. Comparison between pure and hybrid systems

The Problem Space addressed in this study encompasses a total of 246 potential combinations. Each combination necessitates multiple training iterations with varying initial conditions. Considering this, conducting an exhaustive search is notably challenging, rendering the sole use of the pure NN technique somewhat unclear. A sophisticated optimization technique has been integrated with the NN approach to address this complexity, resulting in a hybrid intelligent system. This hybrid system possesses the capability to intelligently navigate extensive problem spaces, a feat that would be infeasible with an exhaustive search. Consequently, the processing power of this approach is significantly superior to that of an exhaustive search, and the resultant solutions are more likely to approach optimality than those generated solely by a pure NN system.

IMS-II was introduced to optimize and automate the selection of optimal combinations of NN topologies and boiler operation variables for specific boiler trips. The outcomes of trip detection predictions by both IMS-1 and IMS-2 are detailed in Table 4. The results obtained underline that IMS-I effectively detected the occurrence of specific boiler operation trips before the faults manifested, which is deemed satisfactory. Conversely, the findings from IMS-II highlight its ability to identify optimal solutions, leading to a satisfactory level of accuracy in the NN training and validation processes, as evident from the RMSE values depicted in Figure 12 across different trips.

While the pure NN technique does address numerous spatial issues, these can be mitigated by constraining the choices of accessible NN topologies and operational variables. However, as the problem space expands, the likelihood of a substantial reduction in probability becomes evident.

Table 4. The optimal solution as given by the IMS-I and IMS-II Boiler operation trips best GA selection interpretations

Trip	HSG.	RMSE Fitness	Selected Input Variables	No. of Inputs	ANN Topologies Training Algorithm	Architecture	Activation Function
1	G30	0.30004	V2, V8, V11	3	LM	7HL1-4HL2	L+P+L
2	G11	0.18381	V1, V3, V9, V12	4	Rprop	10HL1	L+P
3	G14	0.13598	V1, V2, V3, V4, V5, V6, V9	7	BFGS	3HL1-5HL2	L+T+T
4	G11	0.44721	V3, V7, V10, V11, V12, V17, V22, V23, V26	9	SCG	2HL1-10HL2	P+L+L
5	G2	0.27943	V8, V11	2	BFGS	4HL1-6HL2	L+T+P
6	G4	0.31126	V2, V7, V10, V11, V12, V14	5	BFGS	5HL1-7HL2	T+L+L

5. CONCLUSIONS

This study developed and evaluated two artificial intelligent monitoring systems designed to detect boiler trips within a coal-fired thermal power plant. The first system, referred to as IMS-1, employs a pure ANN approach, while the second system, named IMS-2, hybridize GA techniques with ANN. These systems' efficacy was assessed using operational data obtained from six distinct trip events within the thermal power plant.

The outcomes of the investigation underscore the capability of the feed forward NN methodology to systematically explore optimal NN topology configurations for each trip, guided by the NN performance indicator, RMSE. Additionally, the integration of GA successfully facilitated the selection of superior NN topologies and specific boiler operational variables for individual boiler trips, effectively replacing subjective human judgment with a structured optimization process.

Comparing the two systems, IMS-II, which relies on optimization properties, emerges as a preferable option in many instances due to its automated approach, as opposed to IMS-I. Notably, both IMS-I and IMS-II exhibit enhanced trip detection performance compared to the actual plant control unit. However, the pure AI system, IMS-I, showcased marginally higher ability to detect all six boiler trips prior to the intervention of the plant control system. Consequently, IMS-I holds potential as an online, dependable monitoring system for TPPs.

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REFERENCES

[1] Du, B., Ye, J., Zhu, H., Sun, L., Du, Y. (2023). Intelligent monitoring system based on Spatio-temporal data for underground space infrastructure. Engineering, 25: 194-203. https://doi.org/10.1016/j.eng.2022.07.016

[2] Valh, D., Tovornik, B., Furman, J., Vukić, Z. (2000). Introduction to steam boiler fault detection and insulation analyses. IFAC Process, 33(13): 549-554. https://doi.org/10.1016/s1474-6670(17)37248-8

[3] Muselli, M., Ridella, S. (1992). Global optimization of functions with the interval genetic algorithm. Complex Systems, 6: 193-212.

[4] Guglielmi, G., Parisini, T., Rossi, G. (1995). Fault diagnosis and neural networks: A power plant application. Control Engineering Practice, 3(5): 601-620. https://doi.org/10.1016/0967-0661(95)00037-U

[5] Zhou, Y.P., Zhao, B.Q., Z., Wu, D.X. (2000). Application of genetic algorithm to fault diagnosis in nuclear power plants. Reliability Engineering & System Safety, 67(2): 153-160. https://doi.org/10.1016/S0951-8320(99)00061-7

[6] Shi, X.C., Xie, C.L., Wang, Y.H. (2006). Nuclear power plant fault diagnosis based on genetic-RBF neural network. Journal of Marine Science and Application, 5: 57-62. https://doi.org/10.1007/s11804-006-0064-1

[7] Agrawal, V., Panigrahi, B.K., Subbarao, P.M.V. (2016). Intelligent decision support system for detection and root cause analysis of faults in coal mills. IEEE Transactions on Fuzzy Systems, 25(4): 934-944. http://doi.org/10.1109/TFUZZ.2016.2587325

[8] Romeo, L.M., Gareta, R. (2006). Neural network for evaluating boiler behavior. Applied Thermal Engineering, 26(14-15): 1530-1536. https://doi.org/10.1016/j.applthermaleng.2005.12.006

[9] Rusinowski, H., Stanek, W. (2007). Neural modelling of steam boilers. Energy Conversion and Management, 48(11): 2802-2809. http://doi.org/10.1016/j.enconman.2007.06.040

[10] Alnaimi, F.B.I., Ali, M.A., Al-Kayiem, H.H., bin Mohamed Sahari, K.S. (2014). On-line condition monitoring system for high level trip water in steam boiler's drum. In MATEC Web of Conferences, p. 03011. https://doi.org/10.1051/matecconf/20141303011

[11] Fast, M., Palme, T. (2009). Application of Artificial Neural Networks to the condition monitoring and diagnosis of a combined heat and power plant. Energy. 35(2): 1114-1120. https://doi.org/10.1016/j.energy.2009.06.005

[12] Nistah, M., Nurnie, N., Lim, K.H., Gopal, L., Alnaimi, I., Basim, F. (2018). Coal-fired boiler fault prediction using Artificial Neural Networks. International Journal of Electrical & Computer Engineering, 8(4): 2486-2493. http://doi.org/10.11591/ijece.v8i4.pp2486-2493

[13] Ismail, F.B., Singh, D., Maisurah, N., Musa, A. B.B. (2016). Early tube leak detection system for steam boiler

at KEV power plant. In MATEC Web of Conferences, p. 00006. https://doi.org/10.1051/matecconf/20167400006
[14] Selvi, B.T., Kalpana, D., Thyagarajan, T. (2017). Modeling and prediction of boiler drum in a thermal power plant. In 2017 Trends in Industrial Measurement and Automation (TIMA), pp. 1-6. https://doi.org/10.1109/TIMA.2017.8064820
[15] Panchal, D., Kumar, D. (2015). Stochastic behaviour analysis of power generating unit in thermal power plant using fuzzy methodology. Opsearch, 53(1): 16-40. https://doi.org/10.1007/s12597-015-0219-4
[16] Smrekar, J., Assadi, M., Fast, K., Kustrin, M., De, S. (2009). Development of Artificial Neural Network model for a coal-fired boiler using real plant data. Energy, 34(2): 144-152. https://doi.org/10.1016/j.energy.2008.10.010
[17] Iliyas, S.A., Elshafei, M., Habib, M.A., Adeniran, A.A. (2013). RBF neural network inferential sensor for process emission monitoring. Control Engineering Practice, 21(7): 962-970. https://doi.org/10.1016/j.conengprac.2013.01.007
[18] De, S., Kaiadi, M., Fast, M., Assadi, M. (2007). Development of an Artificial Neural Network model for the steam process of a coal biomass cofired combined heat and power (CHP) plant in Sweden. Energy, 32(11): 2099-2109. https://doi.org/10.1016/j.energy.2007.04.008
[19] Nistah, N.N.B.M., Motalebi, F., Samyudia, Y., Alnaimi, F. (2014). Intelligent monitoring interfaces for coal fired power plant boiler trips: A review. Pertanika Journal of Science and Technology, 22(2): 593-601.
[20] Victor, M., Oliveira, D., Aleida, J.C.S. (2013). Modeling and control of a nuclear power plant using AI techniques. In 13th International Nuclear Atlantic Conference-INAC, Recife, Brazil, Vol. 2013, pp. 1-15.
[21] Mayadevi, N., Vinodchandra, S.S., Ushakumari S. (2014). A review on expert system applications in power plants. International Journal of Electronics and Computer Engineering, 4(1): 116-126. http://doi.org/10.11591/ijece.v4i1.5025
[22] Demuth, H., Beale, M., Hagan, M. (1992). Neural network toolbox. For Use with MATLAB. The MathWorks Inc.
[23] Sivanandam, S., Deepa, S. (2007). Introduction to Genetic Algorithms. Springer Verlag.
[24] Chernykh, I., Chechushkov, D., Panikovskaya, T. (2014). The prediction of electric energy consumption using an Artificial Neural Network. Energy Production and Management in the 21st Century: The Quest for Sustainable Energy, 190: 1109. http://doi.org/10.2495/EQ140121

NOMENCLATURE

AIS	Artificial Intelligent System
ANN	Artificial Neural Network
CHP	Combined Heat Power Plant
GA	Genetic Algorithm
IMS	Intelligent Monitoring System
MW	Mega Watt
NN	Neural Network

APPENDIX

Table A1. Influential boiler operation variables

Code	Variables	No. of Sensors	Unit	Criteria
V_1	Total Steam flowrate	1	t/h	
V_2	Feedwater flowrate	1	t/h	
V_3	Drum pressure	4	Bar g	$= 1/4\sum_1^4 V3_4$
V_4	Superheater steam pressure	1	Bar g	
V_5	Superheater steam temperature	1	°C	
V_6	Re-heater outlet temperature	4	°C	$= 1/4\sum_1^4 V4_4$
V_7	Superheater exchange metal temperature	4	°C	
V_8	Intermediate superheater exchange metal temperature, A	4	°C	$= 1/4\sum_1^4 V8_4$
V_9	Superheater inlet header metal temperature	4	°C	$= 1/4\sum_1^4 V9_4$
V_{10}	Final superheater outlet temperature	6	°C	$= 1/6\sum_1^6 V10_6$
V_{11}	Superheater steam pressure transmitter	7	bar	$= 1/7\sum_1^7 V11_7$
V_{12}	Feedwater valve station	8	t/h	$= 1/8\sum_1^8 V12_8$
V_{13}	Feedwater control valve position	4	%	$= 1/4\sum_1^4 V13_4$
V_{14}	Drum level corrected	1	mm	
V_{15}	Drum level compensated	1	mm	
V_{16}	Feedwater flow transmitter	1	%	
V_{17}	Boiler circulation pump1 pressure	1	bar	
V_{18}	Boiler circulation pump 2 pressure	2	bar	$= 1/2\sum_1^2 V18_2$
V_{19}	Low superheater left wall outlet before superheater dryer	4	°C	$= 1/4\sum_1^4 V19_4$
V_{20}	Low superheater right wall outlet before superheater dryer	2	°C	$= 1/2\sum_1^2 V20_2$
V_{21}	Low superheater left wall after superheater dryer	2	°C	$= 1/2\sum_1^2 V21_2$
V_{22}	Low superheater right wall exchange metal temperature	1	°C	
V_{23}	Intermediate superheater exchange metal temperature, B	1	°C	
V_{24}	Intermediate superheater outlet before superheater dryer	1	°C	
V_{25}	Intermediate superheater header metal outlet temperature	2	°C	$= 1/2\sum_1^2 V25_2$
V_{26}	High superheater outlet header metal temperature	6	°C	$= 1/6\sum_1^6 V26_6$
V_{27}	Steam pressure at the re-heater outlet	2	bar	$= 1/2\sum_1^2 V27_2$
V_{28}	Superheated steam outlet pressure	11	bar	$= 1/11\sum_1^{11} V28_{11}$

V_{29}	Superheater water injection compensated flow	10	ton/hr	$= 1/10 \sum_{1}^{10} V29_{10}$
V_{30}	Water pressure at economizer inlet	6	bar	$= 1/6 \sum_{1}^{6} V30_{6}$
V_{31}	The temperature at the economizer inlet	1	℃	
V_{32}	The temperature at the economizer outlet	1	℃	