

Article

Optimization of a 660 MW_e **Supercritical Power Plant Performance—A Case of Industry 4.0 in the Data-Driven Operational Management** *Part 1. Thermal Efficiency*

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Received: 27 September 2020; Accepted: 22 October 2020; Published: 26 October 2020



Abstract: This paper presents a comprehensive step-wise methodology for implementing industry 4.0 in a functional coal power plant. The overall efficiency of a 660 MW_e supercritical coal-fired plant using real operational data is considered in the study. Conventional and advanced AI-based techniques are used to present comprehensive data visualization. Monte-Carlo experimentation on artificial neural network (ANN) and least square support vector machine (LSSVM) process models and interval adjoint significance analysis (IASA) are performed to eliminate insignificant control variables. Effective and validated ANN and LSSVM process models are developed and comprehensively compared. The ANN process model proved to be significantly more effective; especially, in terms of the capacity to be deployed as a robust and reliable AI model for industrial data analysis and decision making. A detailed investigation of efficient power generation is presented under 50%, 75%, and 100% power plant unit load. Up to 7.20%, 6.85%, and 8.60% savings in heat input values are



identified at 50%, 75%, and 100% unit load, respectively, without compromising the power plant's overall thermal efficiency.

Keywords: combustion; supercritical power plant; industry 4.0 for the power sector; artificial intelligence; thermal efficiency

1. Introduction

With the development of information and communication technology (ICT) in the last decade, the industrial sectors generate large volumes of data that possess an undiscovered source of information. The key challenges industries are facing today are data collection, storage, integration, processing, and analysis. The scientific literature addressing these problems is scarce [1,2]. The analysis of such raw industrial data using advanced data analytics and AI algorithms can identify significant operational savings and suggest areas of useful technological improvements, i.e., the optimum industrial outputs, better product quality, and sustainable growth of the industries. Such an approach is truly in line with the industrial revolution we live through that is recently being termed industry 4.0.

The growth rate of electricity consumption is a direct indicator of industrialization, economic growth, and a country's gross domestic product. By the end of June 2019, Pakistan's planned electricity generation capability was 26,887 MW_e (electric power), while 63.96% of the electricity demand was met by thermal power plants [3,4]. The energy conversion efficiency, fuel consumption, and hazardous emissions from thermal power plants on the environment are critical issues of concern in research in industrial and regulatory circles in the last decade [5–8]. Various retrofits, technology improvements, and state-of-the-art air pollution control devices are integrated at the power complexes to ensure cleaner energy production with minimal emissions from the power plants that comply with various national and international standards [9–25].

A large number of operating parameters govern the $\eta_{thermal}$ of a running coal power plant. The operating parameters have a non-linear, inter-dependent, and complex relationship with the $\eta_{thermal}$ [26]. An extensive set of assumptions should be made to help derive the analytical equations for such a complicated process analytically, and thereby, the correct response of the process cannot be accurately described [27,28].

AI-based process models such as the least square support vector machine (LSSVM) and artificial neural network (ANN) are widely used to model such ill-defined and complex problems using real operational data of the process [29–34]. An extensive process of data of high quality, the data visualization tests, and the validation of AI process models are essential for reliable AI utilization. Moreover, the response of a useful AI process model under certain operating conditions of an actual process establishes guidelines for optimizing the industrial performance without conducting the costly hit and trial technological changes. The incorporation of real industrial data, computational software tools, and AI algorithms for the improved performance of industrial outputs help realize the real implementation of industry 4.0.

Researchers have reported a novel Nelder-Mead approach for optimizing the objective function of a complex process. Three different direct search approaches, i.e., Nelder-Mead, Rosenbrock, and Hooke-Jeeves, have represented the potential to locate the optimal objective function value against the influence of several decision variables [35–37]. The Nelder-Mead approach is primarily designed for the un-constrained nature of the problem. The algorithm is computationally time-consuming to achieve the optimum results under the influence of many decision variables and the big volume of the process's operation data [35]. However, AI process modeling techniques like ANN and LSSVM have proved to be computationally inexpensive and efficient to model the complex process and find the optimal solution of the objective function [38–40].

The new generation of artificial intelligence, called AI 2.0, had seen a rapid development worldwide, especially in smart energy and electric power systems (Smart EEPS) and fueling its enormous applications in operation, optimization, control, and management of Smart EEPS [41,42]. Moreover, a comprehensive review of machine learning tools for energy efficiency objectives was presented based on the published forty-two research articles. Machine learning tools were potentially used for the energy utilization improvement demands of petrochemical industries, but limited applications were reported in other industries [43]. The process data analytics platform was built around the concept of industry 4.0 for studying the syngas heating values and flue gas temperatures in waste to energy plants. A neural network-NARX model developed to evaluate the performance of waste to the energy system well described the dynamic behavior of the system compared with conventional statistical techniques [1].

Complex data mining methods were utilized to minimize the net coal consumption rate (NCCR) of a 1000 MW_e power generation. Such an approach allowed us to determine the benchmark values of the power plant's key operation parameters. The proposed result served to adjust the critical operating parameters for an energy-efficient plant operation [44]. A cross-feature convolutional neural network was employed for generalizing the boiler load fluctuations behavior to ensure optimal energy utilization efficiency and ethylene production in the petrochemical industry. The average relative generalization error was reduced to 2.86%, and energy utilization efficiency was increased by 6.38% [45]. LSSVM-based hybrid models were developed for forecasting the energy demand of the grid [46] as well as the energy consumption of complex industrial processes to ensure the efficient operation management and control of the cement industry [47]. In other studies, ANN and LSSVM were used for dynamic optimization of a pilot-scale entrained flow gasifier operation [48]. They allow monitoring the stability of a gas combustor [49], improving the energy conversion, optimization, and thermal efficiency of coal-fired utility boiler [50,51], gas turbine operation performance evaluation, and fault diagnosis [52], and for predicting the boiler thermal efficiency of a 660 MW_e ultra-supercritical coal power plant [53].

Power generation from a power complex is governed by the demand and stability of the national grid. The operating regimes of the key-controllable operation parameters are adjusted according to the various unit loads defined within the power generation capacity of the power complex offering an opportunity to optimize the controllable operating parameters for energy-efficient and techno-economic power generation. The power plant's efficient operation control can be assessed by the power plant's $\eta_{thermal}$. Since a power plant's $\eta_{thermal}$ is defined as the ratio of electric power produced (MW_e) to the energy supplied (MW) by the fuel, the improved heat transfer to the heating surfaces and effective operational control of the power plant offers optimal energy spent on the power production. Consequently, the power plant's $\eta_{thermal}$ can be simultaneously improved. The increase in thermal efficiency offers many benefits, i.e., reduced operation cost, optimal fuel consumption, and reduced power plant emissions.

In this paper, operational data of the initially selected input control variables were taken from the Supervisory Information System (SIS) of the 660 MW_e supercritical coal-fired power plant under the continuous power generation mode for developing the AI process models for $\eta_{thermal}$. A histogram and self-organizing feature map (SOFM) of control variables were constructed to visualize the data's health, distribution, and quality. Monte Carlo experiments on ANN and LSSVM and an interval adjoint significance analysis (IASA) were performed to eliminate the insignificant variables from the list of control variables. Effective and experimentally validated ANN and LSSVM process models were developed, and the performance of the two models was compared comprehensively. The ANN process model proved to be significantly more effective; especially, in terms of the capacity to be deployed as a robust and reliable AI model for industrial data analysis and decision making. The 360 MW_e, 495 MW_e, and 660 MW_e that corresponded to 50%, 75%, and 100% unit load of the power plant were taken into account in the study. Finally, some control variables that affected the power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit loads were constructed with a 95% confidence interval. Extensive investigations of

the power plant's various operational strategies were conducted using the ANN approach and the Monte Carlo technique.

Two fundamental objectives were considered: (a) the pursuit of minimum potential energies spent (conveniently translatable in various useful measures like the monetary cost of power generation or fuel cost of power generation), and (b) achieving those above while maintaining or enhancing the $\eta_{thermal}$ of the power plant. The savings in heat input values at 50%, 75%, and 100% unit load relative to the power plant's optimal $\eta_{thermal}$ were calculated for the power plant's energy-efficient operation control.

Big data analytics, industrial internet of things, and simulation were the three technologies prioritized and incorporated in the study to achieve the power plant's operational excellence by embracing the industry 4.0 digital transformation approach. The process modeling based on process data, process optimization, and data-driven strategy development for the improved process control lead to an increase in the thermal efficiency of the power plant that offers many benefits, i.e., reduced operating cost and optimal fuel consumption. The utilization of advanced and sophisticated technologies dedicated to the implementation of industry 4.0 in the industrial complexes for higher productivity and effective operation control is in line with the objectives of the industry, innovation, and infrastructure program of the united nations sustainable development goals and the Paris agreement to fulfill the nations' commitment for sustainable growth and environment [54,55].

2. Overview of a Coal Power Plant Operation

Power plants can be classified into sub-critical, critical, supercritical, and ultra-supercritical based on the steam conditions [56]. At critical condition, water is directly converted to steam and no longer exists in separate phases. The critical state of water is defined at 22.1 MPa, and 374 °C. Steam conditions in sub-critical power plants are generally around 16.5 MPa and 538 °C, while the steam parameters in supercritical power plants are generally maintained between 22.1 MPa to 28.9 MPa, and below 600 °C. There is no uniform definition for ultra-super-critical steam conditions. However, steam conditions of 28.9 MPa or higher and 600 °C or higher are generally maintained in ultra-supercritical power plants.

Supercritical power plants have higher thermal efficiency, stable combustion, better fuel economy, reduced emissions, faster load following response than the sub-critical power plants, and are generally employed for electrical power generation systems [57].

The 660 MW_e supercritical coal-fired boiler model # HG-2118/25.4-HM16 is manufactured by Harbin Boiler Plant Co., Ltd. at Harbin, China and installed at the Sahiwal Coal Power Plant, as shown in Figure 1. The modern and advanced design features of the boiler include a π -shaped structure, once-through technology (no steam drum), an intermediary reheating system, sliding pressure, balanced draft, wet bottom ash with a single furnace, ultra-sonic leakage detection system, full steel frame, full suspension structure arranged in the open air, and is also equipped with two rotary tri-sector air preheaters (APH). The boiler's sliding pressure ability allows it to continuously provide steam ranging from 330 MW_e to 660 MW_e unit load.

The boiler furnace consists of diaphragm walls designed to improve the wall water tightness and bear the high structural loads. The lower furnace water walls and hopper adopt spiral coils and have enough cooling capacity under different boiler loads to effectively compensate for the thermal deviation of furnace circumambient. Above the spiral tubes, vertical tubes are used to ensure the heat transfer for fast response characteristics. The intermediary mixing header used for the transition between spiral tubes and vertical tubes also balances the pressure across four sides of water walls.

The furnace and fuel burners' operation is synchronized to ensure the flame burning until burnout, higher combustion efficiency, and minimal NO_x formation. The boiler's burning system is equipped with a medium-speed direct-fired pulverizing system with cold and hot primary air. Twenty-four direct-flow fuel burners are arranged, four at the corners in a layer, and a total of six layers for six coal mills. The fuel burner at the bottom of the furnace is provided with a micro oil gun system to save



fuel during start-up and support the combustion. In addition to that, three layers of big oil guns are provided, consisting of 12 burners.

Figure 1. Schematic diagram of the boiler.

Fuel Burne

Oil Burner
 Fuel Burn

Secondary Air Burner

Fuel Burner With Micro Oil Gur

Scanner for Micor Oil Gun

Scanner for Coa

Scanner for Oil

The efficiently designed tangentially fired fuel burners ensure smooth and gradual pulverized coal combustion in the furnace with the combustion chamber's uniform temperature field. The tangential combustion system ensures uniform heat distribution and stable combustion under varying boiler loads.

The fuel burners adopt a low NO_x , horizontal rich, and lean burner. The fuel burner's secondary air is fired in the furnace 5° away from the primary air to form the air-enclosure-coal arrangement and oxidation near the water wall zone. Fuel burners are divided into upper and lower groups within a specific distance to reduce the burner zone's thermal load and slagging. Separated over-fire air (SOFA) nozzles are arranged near the furnace's exit and above the burners to supply air for the late combustion and implement efficient combustion to reduce furnace temperature level and to control NO_x emissions. The flame detection system is installed with every fuel burner to prevent flameout phenomenon, which detects flame strength both by digital and analog signals. Two sets of temperature sensing thermocouples are installed at a high-temperature position for each fuel burner to prevent the burners melting by high temperature. Moreover, infrared flue gas temperature measuring devices are set on the right and left sides of the furnace outlet to monitor the furnace outlet's flue gas temperature. The boiler is also equipped with the ultrasonic leakage detection system, and the flame observation cameras on both sides of the boiler monitor the combustion. It is necessary to mention that the advanced and reliable combustion control systems installed at the power plant ensure the boiler's stable and reliable operation for the power generation. The manufacturer designed the boiler's operating parameters at boiler maximum continuous rating (BMCR), listed in Table 1.

Parameters	Unit	BMCR Load
Superheated steam flow	t/h	2118
Superheater outlet steam pressure	MPa	25.4
Superheater outlet steam temperature	°C	571
Reheat steam flow	t/h	1752
Reheater steam inlet pressure	MPa	5.6
Reheater steam outlet pressure	MPa	5.4
Reheater steam inlet temperature	°C	345
Reheater steam outlet temperature	°C	569
Feed-water pressure	MPa	29
Feed-water temperature	°C	300

Table 1. Designed operating parameters of the boiler.

The schematic diagram of the coal power plant operation is shown in Figure 2. Coal is supplied by a coal feeder, while primary air is provided by the primary air fan (PAF) to the boiler. Coal and primary air are fed to the coal mill for producing pulverized coal, which is injected into the boiler via coal burners.



Figure 2. Schematic diagram of coal power plant operation.

The pulverized coal burns in the boiler with the secondary air provided by the forced draft fan (FDF). The hot flue gas produced by the pulverized coal combustion is used for heat transfer to the heating surfaces in the boiler, as shown in Figure 2. An induced draft fan (IDF) is used for the flue gas suction from the boiler, which helps to maintain the desired furnace pressure and discharges flue gas to the ambient environment through the stack. Upon leaving the boiler, flue gas is passed through the APH to heat the primary and secondary air and enter the electrostatic precipitator (ESP) and flue gas desulphurization (FGD) system particulate matter and sulfur oxides removal, respectively. Finally, through strict control of emission parameters, flue gas is discharged to the ambient environment through the stack.

Feed-water can be considered the power plant's blood and is converted to superheated steam in the boiler. The condensate pump directs feed-water, now also called condensate water in the condenser, to the low-pressure heaters (LPH) for the feed-water heating. After passing through the LPH, feed-water is passed through a deaerator where deoxygenation is applied to the feed-water. The feed-water pump builds up the feed-water pressure and forces it to the series of high-pressure heaters (HPH) for further feed-water heating. The steam extractions heat feed-water in the HPH and LPH from high-pressure (HP) and intermediate-pressure (IP) turbines. After passing through the HPH, feed-water passes through a series of heating surfaces like the economizer (ECO), low-temperature superheater (LTSH), division platen superheater (DPSH), and the final superheater (FSH), etc. for producing superheated main steam by the heat transfer from the flue gas. The superheated main steam is expanded in the HP turbine, where its temperature and pressure are dropped during expansion. After leaving the HP turbine, steam is directed to the low-temperature re-heater (LT REHEATER) and final re-heater (FRH) for reheating the steam. Attemperation water flow is used to control the temperature of the main steam and reheat steam. The reheat steam is expanded in the IP turbine and is directed to lowpressure (LP) turbines A and B for further expansion. The steam, after expanding in LPA and LPB turbines, is condensed to condensate water in the condenser, and the cycle continues. The expansion of superheated and reheated steam in HP, IP, and LP turbines is used for the rotor rotation, coupled with the generator (G) for electricity generation.

The Sahiwal coal power plant was commissioned in 2017 and has been operational and integrated with the national grid since then. It is equipped with state-of-the-art measuring sensors as well as an SIS data storage system. All the sensors measuring the control variables involved in this study are hard sensors measuring the power plant's different operating parameters. The data generated constitute a large number of variables, with each variable having randomly distributed values. It has been extensively reported in the literature that mining causal relationships out of such data is beyond the capability of any type of multi-variate regression technique. AI-based data analytic techniques perform significantly better for modeling such scenarios [39,58]. The sensors' location for measuring the power plant's different operating parameters is shown with numbers in Figure 2. The sensors make and model numbers are mentioned in Table 2.

Sensors	Make	Model Number
Coal flow rate	Vishay Precision Group (USA)	3410
Air flow rate	Siemens (Germany)	7MF4433-1BA22-2AB6-Z
Furnace pressure	Siemens (Germany)	7MF4433-1DA22-2AB6
APH air outlet temperature	Anhui Tiankang (China) Thermocouple	WRNR2 (K type)
% O ₂ in flue gas at boiler outlet	Walsn (Canada)	0AM-800-R
APH outlet flue gas temperature	Anhui Tiankang (China) Thermocouple	WRNR2 (K type)
Feed-water temperature	WIKAI (China) Thermocouple	TC10-3(IEC 60584) (K type)
Main steam pressure	Siemens (Germany)	7MF4033-1GA50-2AB6-Z
Main steam temperature	Anhui Tiankang (China) Thermocouple	WRNK2 (K type)
Reheat steam temperature	Anhui Tiankang (China) Thermocouple	WRNK2 (K type)
Candanaan	Siemens	
Condenser vacuum	STTRANS D PS III (Germany)	7MF4233-1GA50-2AB6-Z
Attemperation water flow rate	Siemens (Germany)	7MF4533-1FA32-2AB6-Z
Turbine speed	Braun (Germany)	A5S

Table 2. Details of sensors measuring the control variables.

3. AI-Based Data Visualization and Process Modeling

AI-based process models are developed to learn the complex, non-linear, and interacting relationship between the system's input and output variables [59–61]. ANN and LSSVM are considered the most efficient approximation tools of AI and can generalize the relationship between input and output variables. These AI tools also have the proven ability to mine the hidden details in the training data, thereby ensure their reliable applications in real-world problems [40,62,63].

3.1. Variables Selection for AI Process Modeling

In this paper, thirteen control variables were initially selected to model the 660 MW_e supercritical coal power plant's η_{thermal} in Sahiwal, Pakistan. The variables were selected based upon the recommendation of experienced plant managers of the power plant and a comprehensive literature review [33,64–68]. Some control variables were controllable by the operator, e.g., the main steam temperature (MST), reheat steam temperature (RST), and oxygen content in flue gas at the boiler outlet (O₂). On the other hand, some control variables were uncontrollable during the power plant operation, e.g., turbine speed (N). The coal properties measured under the air-dried basis are listed in Table 3.

LHV MJ/kg	Properties of Coal/wt.%					
04.00	Moisture	Volatile Mater	Ash	Sulfur	Fixed Carbon	
24.23	2.5	23.73	16.6	0.55	57.66	

Table 3. Properties of coal (air-dried basis).

A total number of 27,267 data points were taken from the SIS of the power plant. Each data point constitutes thirteen of the control variables' numerical values and the output variable's corresponding values. All the variables have continuous numeric values, and the respective distributions are shown in Figure 3. The data points were taken at intervals of one minute during the power plant's controlled continuous operation. It is important to note here that the power plant's load varied from 50% to 100% rated load of the unit as per the requirement and stability of the national grid of Pakistan to which the power plant is connected to by a 500 kV transmission line. The statistics of training data of the initially selected control variables for the development of AI process models are shown in Table 4. The operation parameters that were essential for the stability and effective control of combustion include the coal flow rate (M_c), the air flow rate (M_a), furnace pressure (P_f), the APH air outlet temperature (T_a), % O_2 in flue gas at the boiler outlet (O₂), the APH outlet flue gas temperature (T_{fg}), feed water temperature (FWT), main steam pressure (MSP), main steam temperature (MST), reheat steam temperature (RST), condenser vacuum (P_{vac}), attemperation water flow rate (AWF), and turbine speed (N). It is evident from Table 4 that control variables possess wide operating ranges of the power plant control parameters, which contain not only all possible operating modes of the power plant but also possess the detailed and comprehensive information of the plant operation required for the development of a generalized AI process model.

The histograms of the control variables are shown in Figure 3a–m. M_c values in the operating range, as mentioned in Table 4, correspond to the various unit load generation from the power complex and are shown in Figure 3a. Figure 3b represents air consumption in the boiler during different load generation. Figure 3c shows a nearly normal distribution of P_f , while Figure 3d illustrates the distribution of T_a . T_a was selected as the training parameter to better account for the heat recovery from the flue gas after its exhaust from the boiler and the subsequent benefit for improving the power plant's $\eta_{thermal}$.

Figure 3e represents the % O_2 in the flue gas exhaust from the boiler. T_{fg} was a very critically controlled and sensitive parameter for the boiler operation as it was one of the critical parameters of the boiler operation for ensuring its effective operation control. The variation in T_{fg} is shown in Figure 3f. The increase in T_{fg} indicated that heat transfer from flue gas to the heating surfaces decreased, which might be caused due to soot accumulation on the heating surfaces, high flame center, or large access air coefficient of combustion re-burning of un-burnt carbon in the tail of the boiler.



Figure 3. Cont.



Figure 3. Histograms of initially selected control variables, (**a**) coal flow rate (M_c), (**b**) the air flow rate (M_a), (**c**) furnace pressure (P_f), (**d**) the APH air outlet temperature (T_a), (**e**) % O₂ in flue gas at the boiler outlet (O₂), (**f**) the APH outlet flue gas temperature (T_{fg}), (**g**) feed water temperature (FWT), (**h**) main steam pressure (MSP), (**i**) main steam temperature (MST), (**j**) reheat steam temperature (RST), (**k**) condenser vacuum (P_{vac}), (**l**) attemperation water flow rate (AWF), (**m**) turbine speed (N).

Parameters	Unit	Min	Avg	Max
Coal flow rate (M _c)	t/h	122	167	239
Air flow rate (M_a)	t/h	1315	1850	2590
Furnace pressure (P _f)	Pa	-229	79	69
APH air outlet temperature (T _a)	°C	307	325	350
% O ₂ in flue gas at boiler outlet (O ₂)	%	3.5	4.8	5.9
APH outlet flue gas temperature (T_{fg})	°C	110	132	154
Feedwater temperature (FWT)	°C	259	276	298
Main steam pressure (MSP)	MPa	12.9	17.6	24.5
Main steam temperature (MST)	°C	543	563	572
Reheat steam temperature (RST)	°C	550	565	572
Condenser vacuum (Pvac)	kPa	-95.5	-92.6	-89.5
Attemperation water flow rate (AWF)	t/h	0	20	98
Turbine speed (N)	Rpm	2969	3007	3033
Overall thermal efficiency $(\eta_{thermal})$	%	37.25	40.39	42.75

Table 4. Statistics of data for artificial neural network (ANN) process modeling of $\eta_{thermal}$ of the power plant.

A regeneration system was installed at the power plant. Three HPH and four LPH utilized the steam extractions from the HP and IP turbines for heating the feed-water. The distribution of FWT achieved by regenerative heating is shown in Figure 3g. Figure 3h represents the operating range of the MSP. The MSP was a critical parameter for the unit load generation. Similarly, the MST controllable range was critically controlled as it affected the thermal efficiency, safety, and stable power plant operation. The distribution of the MST is depicted in Figure 3i. As mentioned in Table 4, the MST working range was a good operating range for evaluating its effect on the $\eta_{thermal}$ of the power plant. The reheat system positively influenced the $\eta_{thermal}$ of the power plant. The distribution of RST is shown in Figure 3j. Figure 3k represents the variation in vacuum maintained in the condenser, while Figure 3l shows the distribution of AWF data in the input space used to control the MST and RHT. Lastly, Figure 3m represents the variation in N during power plant operation. It is evident from Figure 3a–m that the distribution of control variables data points across their operating ranges was wide and meaningful and thus can be confidently used to develop AI process models of the $\eta_{thermal}$ of the power plant.

3.2. Elimination of Insignificant Control Variables

Each selected control variable's significance on the output variable ought to be investigated to train effective AI models. For physical system modeling through equations representing a process, many input variables are required to describe an output variable accurately. In contrast, AI process models have an excellent, proven ability to model such a system with fewer significant variables. The selection of significant variables for AI process models development is crucially important, and therefore, sensitivity analysis was performed to eliminate insignificant control variables that had a minimal or negligible effect on the output variable [64].

3.2.1. Monte Carlo Experimentation for Significance Analysis

Monte Carlo experimentation was used to determine each variable's effect on the output variables considering the uncertainties in the control variables' data set. Monte Carlo experiments operate by generating the random values between the control variables [69,70]. The detailed description of the working of Monte Carlo experimentation for the variable elimination purpose is described below.

- 1. A control variable is represented as x_i where, i = 1, 2, ..., 13.
- 2. Each input vector containing all control variables x_i can estimate output variable y_o where, $o = 1,2,3, \ldots, m$, where m is equal to the number of input vectors in the training data set.

- 3. The Monte Carlo experimentation can be illustrated by considering a control variable x_i and all other control variables as x_j , were (i \neq j). As an example, let $x_i = x_1$ and $x_j = x_2$, ..., x_{13} , where (i \neq j).
- 4. Create n equal divisions (k) for x_i between its range $(x_{imax}-x_{imin})$ where, k = 1,2,...,n.
- 5. Generate M random values for each division k (k = 1,2,3,..., n) by keeping x_{ik} , at a constant value. All other input control variables for these M replications are generated so that the probability (P) of any value (u) between x_{jmin} and x_{jmax} is equal. The Mth input vector will be $[x_{1kM}, x_{2u}, x_{3u}, x_{4u}, ..., x_{13u}]$, and the corresponding output will be y_{okM} .
- 6. The output value y_{okM} is obtained by ANN and LSSVM prediction for the Mth input vector $[x_{1kM}, x_{2u}, x_{3u}, x_{4u}, \dots, x_{13u}]$. Compute a mean value (µ) for each y_{okM} having M replications, which will give y_{ok} for each x_{ik} .
- 7. Repeat step number iii to step number vi for all remaining control variables
- 8. Compute Δy_i where $\Delta y_i = y_{okmax} y_{okmin}$ for all control variables x_i and compute the summation value Y for all Δy_i

$$Y = \sum_{i=1}^{13} \Delta y_i \tag{1}$$

9. Compute the percentage significance (r_i) of each x_i by dividing Δy_i with Y and multiplying it by 100

$$r_i = \left(\frac{\Delta y_i}{Y}\right) \times 100\tag{2}$$

The least insignificant variables obtained from Monte Carlo experimentation performed on ANN and LSSVM are shown later in the paper. The elimination of insignificant control variables is essential to develop a useful process model based on ANN and LSSVM. This elimination of insignificant control variables is usually obtained by coupling an algorithm (in our case, Monte Carlo experimentation) to ANN and LSSVM. Therefore, the significance of control variables obtained by Monte Carlo experimentation is confirmed with the Interval Adjoint Significance Analysis (IASA) method.

3.2.2. Interval Adjoint Significance Analysis (IASA)

The sensitivity-based method is advantageous in finding out the significance of control variables in a given sample [71,72]. The deviation in output Δy caused by the deviations in the input is defined as sensitivity [71]. By finding out the sensitivities of given control variables, we can find out their significance. In this sub-section, intervals are represented by uppercase letters (e.g., *A*, *B*, *C*, ...) and scalars are represented by lower case letters (e.g., *a*, *b*, *c*, ...). The interval is defined as $X = [x^l, x^u]$, where *l* and *u* represent the lower and upper limit of the interval, respectively.

Interval arithmetic (IA) [73] is used to evaluate a function f[X] in a given range over a domain and it gives us a guaranteed enclosure $f[X] \supseteq \{f[x] | x \ni [X]\}$ that contains all possible values of f(x)for $x \ni [X]$. Similarly, interval evaluation yield enclosures $[V_i]$ for all intermediate variables V_i . Reverse mode (also; adjoint mode) of algorithmic differentiation (AD) [74,75] can be applied here to evaluate this interval function. Because reverse mode AD not only computes the primal values of intermediate and output variables, but it also computes their derivatives $(\frac{\delta Y}{\delta X_i}, \frac{\delta Y}{\delta V_i})$. Significance can also be calculated here by taking the absolute maximum of first-order derivative $max |\nabla_{[x_i]}[y]|$ of an input interval X_i and multiplying it by the width $w[X_i] = x_i^u - x_i^l$ of that interval [76].

$$S_Y(X_i) = w[X_i] * max \left| \nabla_{[x_i]}[y] \right|$$
(3)

To illustrate the basic working of the interval adjoint method, here is an example of significance analysis on a very simple interval function $f(X) = log(X_0 \cdot X_1)/10 + X_1/100$. Let $X = \{X_0, X_1\} \in \mathbb{R}^2$, where $X_0 = [1, 36, 000], X_1 = [1, 36, 000]$. The computational graph for function f is given in Figure 4a, and a possible code list of f is listed in Table 5.

Table 5. A possible code list.

V ₀	=	$X_0 \cdot X_1$
V_1	=	$log(V_0)$
Ŷ	=	$V_1/10 + X_1/100$

After the reverse mode, AD significance values are generated based on Equation (3) (see the computational graph given in Figure 4b). Note the significance value of the intermediate node V_1 is equal to 2.098, which is way below the significance values of the other nodes. This node and the preceding nodes connecting to V_1 are removed and replaced with the mean value of interval V_1 as shown in Figure 4c.



(a) Computational graph of f(X) with primal values (forward mode of AD).

(b) Computational graph of f(X) with first order derivatives (reverse mode of AD), and significance values.



Figure 4. Computational graphs for $f(X) = log(X_0 \cdot X_1)/10 + X_1/100$; (a) computational graph of f(X) with primal values (the forward mode of AD), (b) computational graph of with first-order derivatives (reverse mode of AD), and significance values, (c) new computational graph of f(X) after the significance analysis.

Some authors used IASA to determine the significance of the trained network's input parameters and hidden parameters based on Equation (3) [77]. After selecting insignificant nodes/parameters, insignificant nodes can be removed from the network, and bias for the next layer parameters/nodes is updated. Using the IASA method of finding out the ranking of significant nodes defined in [77] of a trained network, we find out variables O_2 , N, and P_f are the least significant and impact on the network's overall performance is negligible. The significance ranking is given in Figure 5c.





Figure 5. Cont.



Figure 5. Comparison of variables elimination techniques (**a**) Monte Carlo-ANN variables elimination (**b**) Monte Carlo- least square support vector machine (LSSVM) variables elimination (**c**) interval adjoint significance analysis (IASA)-variables elimination.

The results of both Monte Carlo experimentation for variables elimination and IASA indicated that the control variables O_2 , N, and P_f were relatively insignificant variables and could be eliminated from the data set of control variables for the sake of decreasing the computational time, eliminating the redundant control variables, and achieving accurate results [69]. Therefore, ten control variables out of thirteen initially selected control variables highlighted in blue in Figure 5a–c were finalized for training the AI process modeling of the power plant's $\eta_{thermal}$.

3.3. Self-Organizing Feature Map

A self-organizing feature map, also known as the Kohonen feature map, is primarily used in data visualization techniques. An unsupervised learning machine maps the underlying possible statistical features in training data on to the nodes in the two-dimensional lattice. Owing to its excellent ability to distribute the control variables data on the nodes in the form of homogenous groups, SOFM is used in many real-life applications [78–80]. In this work, a two-dimensional output layer carrying 10 × 10 nodes was created, and the distribution of control variables data points are shown in Figure 6. The *z*-axis represents the frequency of occurrence of data points on a node. It is evident from Figure 6, that control variables data points were well-distributed on the 10 × 10 nodes on the output layer and confidently directed the construction of the AI process models for the η_{thermal} of the power plant.



Figure 6. Self-organizing feature map of control variables.

3.4. Development of ANN Process Model

The multilayer perceptron (MLP) consisted of three layers. The first input layer consisted of neurons, which number corresponded to the number of control variables. The MLP may consist of one or more hidden layers, depending on its architecture, and the optimum one is determined by hit and trial methods [58]. It was proved that one hidden layer was enough to approximate the nonlinearity present in the data provided enough number of neurons were present in the hidden layer [81]. The neurons' number in the output layer was equal to the number of outputs. The optimal ANN, thus trained, had ten neurons in the input layer, 17 neurons in the hidden layer, and one neuron in the output layer. The MLP architecture is represented as [10-17-1] and shown in Figure 7.

The feed-forward backpropagation network algorithm was used to develop a process model for the power plant's η_{thermal} . It has a well-established ability to dig and learn the complex nonlinearities and interactions out of high dimensional and complex input space data [82–84]. Gradient descent with momentum was employed as a training function, and tangent hyperbolic was used as a transfer function between the layers of MLP for the neural network model development [64,85].

The ANN training was carried out until one of the two stopping criteria was met, i.e., either a 0.0000001 change in convergence error or a maximum number of epochs was reached. The best MLP architecture is represented as [10-17-1] and shown in Figure 7. The trained ANN achieved a good correlation coefficient (R) value, i.e., 0.917 for training, 0.911 for validation, and 0.92 for testing purposes during ANN development.

3.5. Development of LSSVM Process Model

The support vector machine is a powerful machine learning tool and is utilized for non-linear classification, function approximation, and density estimation [86–88]. LSSVM can be trained more effectively for modeling a system based on the structural risk minimization (SRM) principle. The Gaussian kernel function is generally used for mapping the complicated non-linear relationship between the input and output variables onto the feature space [40]. It is essential to mention here that the training data set should be standardized for developing a useful LSSVM model. Bayesian optimizer and expected improvement per second plus acquisition function was used to optimize the regularized

constant (C) and epsilon (ϵ) parameters for LSSVM [89–92]. Thus, the optimal value for C and ϵ for the developed LSSVM model was 305.30 and 0.0057, respectively. The R-value for the developed LSSVM model was equal to 0.922.



Figure 7. Structure of Multi-Layer Perceptron.

3.6. Evaluation Criteria

The performance of the developed AI process models can be assessed based upon the prediction error against the validation data set that was unseen to the networks during their development phase. Root-mean-square error (RMSE), normalized RMSE (NRMSE), and mean absolute percentage errors (MAPE) were calculated on the models predicted values to evaluate their robustness and effectiveness for modeling the $\eta_{thermal}$ of the power plant. The definitions of the error criteria are given below:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$
(4)

$$NRMSE = \frac{RMSE}{y_{\max} - y_{min}} * 100\%$$
(5)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| * 100\%$$
(6)

where *n* is the sample size, \hat{y}_i and y_i are the predicted and actual values, y_{max} and y_{min} are the maximum and minimum value of y_i , respectively.

3.7. External Validation Case of Trained AI Process Models

After training the ANN and LSSVM process models using the control variables dataset consisting of 27,267 observations, the developed models were externally validated using a new operating data of the power plant that was "unseen" to ANN and LSSVM models during their development. An additional 28,460 observations of the control variables that serve as a characteristics data set for external validation cases were taken from the SIS to compare the ANN and LSSVM models' predictions with the power plant's actual η thermal. The ANN and LSSVM predicted response for actual vs. predicted η_{thermal} , and the corresponding residuals are shown in Figure 8a,b. Comparing the ANN and LSSVM models' responses, as shown in Figure 8a,b, the ANN model had more effectively predicted the external validation data set than the LSSVM model. The spread of residuals for the ANN model was comparatively smaller than the one for the LSSVM model. The performance comparison of ANN and LSSVM models for predicting the power plant's η_{thermal} , in terms of the evaluation criteria, is presented in Table 6.



Figure 8. External validation of ANN and LSSVM models. (a) ANN prediction (b) LSSVM prediction.

M. 1.1	RMSE	NRMSE	MAPE
Niodel	(%)	(%)	(%)
ANN LSSVM	0.5051 0.7164	8.2159 11.6538	1.016 1.2819

Table 6. Comparison of ANN and LSSVM model prediction performance.

It is clear from Table 6 that various error estimations, i.e., RMSE, NRMSE, and MAPE for the ANN predicted response was 0.5051%, 8.2159%, and 1.016% respectively, which was lower than the ones for LSSVM model predictions, i.e., 0.7164%, 11.6538%, and 1.2819%, respectively. It confirmed that the ANN process model had effectively modeled the power plant's $\eta_{thermal}$ concerning the control variables compared to LSSVM. The ANN presented a good generalization ability to model the complex power plant operation with better network robustness, confirming its superior efficacy for data analysis and decision making.

4. Results and Discussion

Generally, power generation from a power plant is either 50%, 75%, or 100% of unit load capacity, as determined by the national grid's demand. The control variables' operating regimes are different under the different power generating capacity of the power plant. The minimum, average, and maximum control variables at 50%, 75%, and 100% unit load are listed in Table 7.

	T T •.	50%	50% Unit Load		75% Unit Load			100% Unit Load		
Parameters	Unit	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
Mc	t/h	128	134	140	170	178	185	219	227	235
Ma	t/h	1326	1386	1456	1896	1973	2076	2206	2303	2395
Ta	°C	315	320	330	320	330	335	335	342	350
T_{fg}	°C	110	113	125	123	125	138	118	123	130
FWT	°C	259	260	261	280	281	282	295	296	297
MSP	MPa	13.1	13.6	13.9	18.4	18.9	19.1	24.0	24.2	24.4
MST	°C	550	567	570	550	562	570	550	567	570
RHT	°C	550	567	570	550	564	570	550	567	570
P _{vac}	kPa	-94.7	-94.6	-94.5	-92.1	-92.0	-91.9	-91.1	-91.0	-89.9
AWF	t/h	0	18	82	0	15	85	0	15	87

Table 7. Operating ranges of parameters at 50%, 75%, and 100% unit load.

It was crucial to evaluate the effect of selected control parameters on the output variable by keeping remaining control variables at the select value (generally the mean values) corresponding to the specific unit load to simulate the power plant operation's actual operating scenario. The individual or combined effect of the essential control variables on the $\eta_{thermal}$ was evaluated.

The detailed procedure for creating the experiments is discussed below:

- 1. Let x_i be the control variable(s) where $i = 1, 2, 3 \dots ., 10$, whose effect is to be studied, and x_j ($i \neq j$) represents the remaining control variables.
- 2. Let yo represent the output value corresponding to x_i where o = 1.
- 3. Divide the range of x_i (x_{imax} - x_{imin}) in n equal step size (d) where d = 1,2, ..., n
- 4. Keep the remaining control variables xj constant at the selected value at every step size d. The input vector with x_i say, i = 1, step size d and remaining input control variables x_j is represented as [x_{1d}, x_{2d}, x_{3d}, x_{4d}, x_{5d}, x_{6d}, x_{7d}, x_{8d}, x_{9d}, x_{10d}]. Create "m" replications for the input vector for every step size d.
- 5. Generate "m" Gaussian noise values (g) from the 1% range value of control variables x_i and x_j . Add g with the input vector for all step size d.

- 6. Predict the developed ANN process model from an input vector and compute mean (μ) and standard deviation (σ) of the predicted values y_{od} against x_{id} input vector, which is represented as μ_{yod} and σ_{yod} relative to x_{id} input vector, respectively.
- 7. Calculate upper control limit (UCL = μ_{yod} + 2* σ_{yod}) and lower control limit (LCL = μ_{yod} 2* σ_{yod}) and plot mean, UCL and LCL against x_i.

4.1. Effect of MST and RST on $\eta_{thermal}$ of Power Plant

MST and RST are critically and simultaneously controlled power plant operating parameters. The power production was generally maintained at either 50%, 75%, or 100% unit load, which depends on the connected national grid's demand and stability. MST and RST parameters under such an operation scenario should be effectively controlled within the operating control limits to ensure economical, safe, and fuel-efficient power production from the power plant.

To evaluate the effect of MST and RST on the power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit load, MST and RST were varied from 550 to 570 °C. The remaining control parameters were set at the corresponding average values at 50%, 75%, and 100% unit load, as mentioned in Table 7. Thus, the experiments were used to evaluate the combined effect of MST and RST on the power plant's $\eta_{thermal}$.

The operating range of MST (x_1) and RST (x_2) was divided into ten equal divisions (d) in order to conduct experiments according to the procedure described in Section 4. MST and RST remained constant in each division, while the other control variables ($x_j = 3,4,5,6,7,8,9,10$) were set at their average values, as mentioned in Table 7. A total of 100 replications (m) of the control variables were created and added with the Gaussian noise values (g). The constructed experiment was simulated using the ANN process model of η_{thermal} of the power plant and mean (μ_{yod}), and the standard deviation (σ_{yod}) of the predicted values of η_{thermal} (y_o) was calculated. The procedure was repeated for remaining division values (d), and mean UCL and LCL trend lines against MST and RST were plotted for 50%, 75%, and 100% unit load and represented in Figure 9a–c.

Figure 9a–c relates to the effect of the MST and RST on the power plant's $\eta_{thermal}$. A general increasing trend of the power plant's $\eta_{thermal}$ was observed when MST and RST increased from 550 °C to 570 °C. The power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit load had, on average, a relative increase of 1.50%, 1.50%, and 1.32%, respectively, with every 10 °C rise in MST and RST. The upper control limits of the temperatures were restricted by material properties [93].

Figure 9d compares the effect of the MST and RST on the power plant's n_{thermal} at 50%, 75%, and 100% unit load. It was apparent from Figure 9d that the n_{thermal} of the power plant at 100% unit load was higher than 50% and 75% unit load efficiencies. It was because the heart rate of the power plant was improved at 100% unit load. Moreover, the power plant operating mode was also supercritical under which the boiler operation was fuel-efficient, stable, and economical [56,93]. The heat inputs to produce 50%, 75%, and 100% unit load at 550 °C, 560 °C, and 570 °C MST and RST are mentioned as MW values on each trend in Figure 9d. The heat inputs required to sustain the highest n_{thermal}, i.e., 39.78%, 41.05%, and 41.59% at 50%, 75%, and 100% unit load at higher temperature limit (570 °C) of MST and RST were 905 MW, 1206 MW, 1587 MW respectively. Meanwhile, at a lower temperature limit (550 °C) of MST and RST, the overall thermal efficiencies achieved were 38.62%, 39.85%, and 40.51% at 50%, 75%, and 100% unit load. The corresponding energies spent to keep the plant operational were 932 MW, 1242 MW, 1629 MW, respectively, which were comparatively higher heat inputs for the same power production. Therefore, it was advantageous to maintain the MST and RST at a higher temperature limit to ensure the fuel-efficient and optimum power plant operation for sustainable power production.



Figure 9. Effect of main steam temperature (MST) and reheated steam temperature (RST) on $\eta_{thermal}$ of power plant. The parameters of other input control variables: (a) $M_c = 134 \text{ t/h}$, $M_a = 1386 \text{ t/h}$, $T_a = 320 \text{ °C}$, $T_{fg} = 113 \text{ °C}$, FWT = 260 °C, MSP = 13.6 MPa, $P_{vac} = -94.6 \text{ kPa}$ and AWF = 18 t/h (b) $M_c = 178 \text{ t/h}$, $M_a = 1973 \text{ t/h}$, $T_a = 330 \text{ °C}$, $T_{fg} = 125 \text{ °C}$, FWT = 281 °C, MSP = 18.9 MPa, $P_{vac} = -92.0 \text{ kPa}$ and AWF = 15 t/h (c) $M_c = 227 \text{ t/h}$, $M_a = 2303 \text{ t/h}$, $T_a = 342 \text{ °C}$, $T_{fg} = 123 \text{ °C}$, FWT = 296 °C, MSP = 24.2 MPa, $P_{vac} = -91.0 \text{ kPa}$ and AWF = 15 t/h (d) $\eta_{thermal}$ comparison at 50%, 75% and 100% unit load.

4.2. Effect of T_{fg} on the $\eta_{thermal}$ of Power Plant

 T_{fg} is a critically controlled operating parameter of the boiler operation. It indicates the efficiency of fuel combustion and heat transfer to the heating surfaces inside the boiler, thereby directly influencing the power plant's $\eta_{thermal}$. The increase in this temperature beyond its normal controllable operating range, as mentioned in Table 7, indicates that heat transfer from the flue gas to the heating surfaces is decreasing, which might be caused by soot accumulation on the heating surfaces, high flame center, large access air coefficient of combustion and burning of unburned carbon in the tail of boiler. This is an indicator of poor control of boiler operation resulting in the power plant's reduced $\eta_{thermal}$.

The effect of T_{fg} on the power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit load is given in Figure 10a–c. The $\eta_{thermal}$ of the power plant decreased with the increase in T_{fg} . With every 5 °C rise in the T_{fg} , the relative decrease in the power plant's $\eta_{thermal}$ was an average of 0.65%, 0.25%, and 0.28% at 50%, 75%, and 100% unit load respectively.

Figure 10d compares the effect of T_{fg} on the power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit load. At 100% unit load, the power plant's $\eta_{thermal}$ was relatively higher than 75% and 50% unit load due to the improved heat transfer conditions. At 50% unit load, there was a sharp decreasing trend of the power plant's $\eta_{thermal}$ with increased flue gas temperature after APH. Thus, the temperature should be effectively controlled mainly at 50% unit load as it had a relatively more significant adverse impact on the power plant's $\eta_{thermal}$. This was explained by the fact that the increase in T_{fg} indicated the decreased heat transfer from flue gas to the heating surfaces, which was responsible for the decrease in the η_{thermal} of the power plant. The temperature was critically controlled by the significant soot blowing on various heating surfaces in the boiler, improved fuel combustion, lower irreversibility losses in the boiler, and significant operational control. The lower limit of the temperature was strictly controlled as it may cause corrosion to the downstream equipment due to the condensation of flue gas containing various acidic gases [93–95].



Figure 10. Effect of T_{fg} on $\eta_{thermal}$ of the power plant. The parameters of other input control variables: (a) $M_c = 134$ t/h, $M_a = 1386$ t/h, $T_a = 320$ °C, FWT = 260 °C, MSP = 13.6 MPa, MST = 567 °C, RHT = 567 °C, $P_{vac} = -94.6$ kPa and AWF = 18 t/h (b) $M_c = 178$ t/h, $M_a = 1973$ t/h, $T_a = 330$ °C, FWT = 281 °C, MSP = 18.9 MPa, MST = 562 °C, RHT = 564 °C, $P_{vac} = -92.0$ kPa and AWF = 15 t/h (c) $M_c = 227$ t/h, $M_a = 2303$ t/h, $T_a = 342$ °C, FWT = 296 °C, MSP = 24.2 MPa, MST = 567 °C, RHT = 568 °C, $P_{vac} = -91.0$ kPa and AWF = 15 t/h (d) $\eta_{thermal}$ comparison at 50%, 75% and 100% unit load.

The heat inputs required to achieve the power plant's overall thermal efficiencies at 50%, 75%, and 100% unit load are shown in Figure 10d. At the highest η_{thermal} of the power plant, i.e., 39.97%, 40.96%, and 42.23% at 50%, 75%, and 100% unit load, the corresponding heat inputs were 901 MW, 1208 MW, and 1563 MW, respectively. The possible lowest overall thermal efficiencies, i.e., 39.18%, 40.66%, and 41.87% at 50%, 75%, and 100% unit load, were 919 MW, 1218 MW, and 1576 MW, respectively. Resultantly, heat input values at lower thermal efficiencies caused by the increased temperature of flue gas after APH were comparatively higher for the same unit load generation. It accounted for the effective control of the flue gas temperature after APH near the lower controllable limits, as mentioned in Table 7, to achieve optimal η_{thermal} under various power plant operating modes.

4.3. Effect of T_a and T_{fg} on the $\eta_{thermal}$ of Power Plant

 T_a and T_{fg} is an essential pair of power plant control parameters for the effective boiler operation and improved $\eta_{thermal}$ under various power plant operating modes. Flue gas leaving the boiler had some thermal energy depending upon the boiler thermal efficiency, which would otherwise be lost if not recovered and decrease the power plant's $\eta_{thermal}$. A part of this energy was recovered by the air passing through the APH. Thus, the pre-heated air improved the power plant's $\eta_{thermal}$ and helped coal combustion at high air temperature for producing high-quality steam. The combined effect of rising T_a and falling T_{fg} represented the flue gas's waste heat recovery system.

The operating ranges of two temperatures were divided into ten equal divisions to evaluate the combined effect of T_a and T_{fg} . T_a was varied systematically in the ascending order, while T_{fg} was decreasing systematically. The remaining operating parameters were kept at the average values corresponding to the 50%, 75%, and 100% unit load, as mentioned in Table 7. The further treatment for constructing the experiment's design for evaluating the effect of T_a and T_{fg} on the power plant's $\eta_{thermal}$ was executed as per the procedure described in Section 4.

The combined effect of T_a and T_{fg} at 50%, 75%, and 100% unit load on the power plant's $\eta_{thermal}$ is represented in Figure 11a–c. As expected, an increasing trend in the power plant's $\eta_{thermal}$ was observed at 50%, 75%, and 100% unit load with the increase in T_a and fall in T_{fg} . The relative increase in the $\eta_{thermal}$ of the power plant on an average was 0.43%, 0.44%, and 0.42% at 50%, 75%, and 100% unit load respectively against every 5 °C rise in T_a and 5 °C fall in T_{fg} . It is essential to mention here that the extent of waste heat recovery was limited to the dew point temperature of flue gas and the APH material metallurgy [96,97].



Figure 11. Effect of T_a and T_{fg} on the $\eta_{thermal}$ of power plant. The parameters of other input control variables (**a**) $M_c = 134 \text{ t/h}$, $M_a = 1386 \text{ t/h}$, MSP = 13.6 MPa, MST = 567 °C, RHT = 567 °C, $P_{vac} = -94.6 \text{ kPa}$ and AWF = 18 t/h (**b**) $M_c = 178 \text{ t/h}$, $M_a = 1973 \text{ t/h}$, FWT = 281 °C, MSP = 18.9 MPa, MST = 562 °C, RHT = 564 °C, $P_{vac} = -92.0 \text{ kPa}$ and AWF = 15 t/h (**c**) $M_c = 227 \text{ t/h}$, $M_a = 2303 \text{ t/h}$, FWT = 296 °C, MSP = 24.2 MPa, MST = 567 °C, RHT = 567 °C, P_{vac} = -91.0 \text{ kPa} and AWF = 15 t/h (**d**) $\eta_{thermal}$ comparison at 50%, 75% and 100% unit load.

Figure 11d compares the combined effect of T_a and T_{fg} on the power plant's $\eta_{thermal}$ at 50%, 75%, and 100% unit power generation capacity. At 100% unit power generation capacity, the power plant's $\eta_{thermal}$ was relatively higher than 50% and 75% unit power generation capacity because of its improved heat rate.

Trend lines in Figure 11d show the heat inputs to achieve the power plant's thermal efficiency at 50%, 75%, and 100% unit load. At the highest $\eta_{thermal}$ of the power plant, i.e., 39.77%, 41.08%, and 42.29% at 50%, 75%, and 100% unit load, the corresponding heat inputs were 905 MW, 1205 MW, and 1561 MW, respectively. The possible lowest overall thermal efficiencies at 50%, 75%, and 100% unit load would be 917 MW, 1221 MW, and 1580 MW, respectively. The lowest heat inputs corresponding to the power plant's highest $\eta_{thermal}$ at 50%, 75%, and 100% unit load was possible due to improve heat recovery from the flue gas leaving the boiler. The effective operation control of T_a and T_{fg} promised the boiler's efficient operation and the improved $\eta_{thermal}$ of the power plant.

4.4. Effect of Change in All Control Variables on the $\eta_{thermal}$ of Power Plant

In this sub-section, first, the power plant's possible worst operating scenario during which overall thermal efficiencies of the power plant may drop to the lowest value at 50%, 75%, and 100% unit load was constructed. Further, in the Monte Carlo experiments, certain adjustments in operating parameters were simulated to recover the power plant's $\eta_{thermal}$. This strategy of adjusting operating parameters can be practically implemented to achieve the maximum overall thermal efficiencies at various power plant operation modes.

AWF controls the temperature of the MST and RST. Low adjustment of AWF, i.e., the exceptionally high flow rate, may significantly drop the MST and RST. However, the MSP may have a little increase depending upon the AWF and unit load. Moreover, MST and RST drop may also be linked with lower heat transfer to the boiler's heating surfaces, indicated by higher T_{fg} . In such an operating scenario, FWT would also drop, and the P_{vac} would be slightly increased. Meanwhile, the M_c , M_a , and AWF were adjusted to recover the plant operation to the stable operating conditions at any unit load. The operational ranges of all the control variables within which the corresponding variables' values were systematically changed at 50%, 75%, and 100% unit load are s mentioned in Table 7.

To conduct the experiments for optimizing the η_{thermal} of the power plant at 50%, 75%, and 100% unit load, M_c, M_a, T_{fg}, T_a, MSP, P_{vac}, and AWF were varied from maximum to average values as mentioned in Table 7. FWT was varied from minimum to average, while MST and RST were changed between the minimum and the maximum operating limits. The operating ranges of all variables were divided into ten equal divisions. To evaluate the response of the power plant's η thermal under such an operating scenario, we applied the procedure as described in Section 4.

The effect of changes in control variables (MST and RST are conveniently represented along the lower and upper x-axes while the operating range of remaining control variables is mentioned in the description of Figure 12) on the power plant's η_{thermal} at 50%, 75%, and 100% unit load is shown in Figure 12a–c. At 50% unit load, the power plant's η_{thermal} was initially stagnant (~550 °C ~555 °C MST), and then it started increasing. On the other hand, at 75% and 100% unit load, an increasing trend of the power plant's η_{thermal} was observed. For 550 °C to 560 °C and 560 °C to 570 °C of MST and RST with the corresponding changes in remaining control parameters at 50%, 75%, and 100% unit load, the relative increase in the η_{thermal} of the power plant on an average was equal to 3.36%, 3.21%, and 4.29% respectively.



Figure 12. Effect of change in all operating parameters on $\eta_{thermal}$ of power plant (**a**) $M_c = 140 - 133 \text{ t/h}$, $M_a = 1456 - 1386 \text{ t/h}$, $T_a = 330 - 320 \text{ °C}$, $T_{fg} = 125 - 113 \text{ °C}$, FWT = 259 - 260 °C, MSP = 13.9 - 13.6 MPa, $P_{vac} = -94.5 - -94.4 \text{ kPa}$ and AWF = 82 - 0 t/h (**b**) $M_c = 185 - 178 \text{ t/h}$, $M_a = 2075 - 1973 \text{ t/h}$, $T_a = 335 - 330 \text{ °C}$, $T_{fg} = 138 - 125 \text{ °C}$, FWT = 280 - 281 °C, MSP = 19.1 - 18.9 MPa, $P_{vac} = -92.1 - -92.0 \text{ kPa}$ and AWF = 85 - 0 t/h (**c**) $M_c = 236 - 227 \text{ t/h}$, $M_a = 2421 - 2303 \text{ t/h}$, $T_a = 350 - 342 \text{ °C}$, $T_{fg} = 130 - 123 \text{ °C}$, FWT = 295 - 296 °C, MSP = 24.4 - 24.2 MPa, $P_{vac} = -91.1 - 91.0 \text{ kPa}$ and AWF = 93 - 0 t/h (**d**) $\eta_{thermal}$ comparison at 50%, 75% and 100% unit load.

Figure 12d compares power plant thermal efficiencies against the changes in all control variables at 50%, 75%, and 100% unit load. At 100% unit load, the power plant's thermal efficiency was higher than 75% and 50% unit load. It explained that the heat rate was generally improved at the power plant's supercritical operating mode.

The heat input values for achieving the thermal efficiencies against the changes in control variables at 50%, 75%, and 100% unit load are mentioned as MW values in Figure 12d. It is observed from Figure 12d that at a specific unit load, heat input values at higher operating limits of the control variables were significantly reduced as compared to lower operating limits of the control parameters. The heat input values corresponding to the power plant's maximum thermal efficiencies, i.e., 40.48%, 41.35%, and 42.20% at 50%, 75%, and 100% unit load, were 889 MW, 1197 MW, and 1564 MW, respectively. On the other hand, the possible lowest thermal efficiencies, i.e., 37.9%, 38.8%, and 38.8% at 50%, 75%, and 100% unit load, were 958 MW, 1285 MW, and 1711 MW. The difference in heat input values at a specific unit load reflects the savings in heat input energy ensured under the power plant's optimal operating conditions. Such savings can be safely interpreted as the total energies spent to produce output electricity and, therefore, be directly related to savings in the cost of power plant operation.

Table 8 compares the percentage savings or losses in the heat input values for power plant operation concerning the operating ranges of control parameters at 50%, 75%, and 100% unit load.

		50% Unit Load			75% Unit Load			100% Unit Load	1
Parameters	Operating Range	Heat Input Range	% Energy Savings/Losses	Operating Range	Heat Input Range	% Energy Savings/Losses	Operating Range	Heat Input Range	% Energy Savings/Losses
Unit	°C	MW	%	°C	MW	%	°C	MW	%
MST and RST	550-570	934–907	2.94	550-570	1219–1183	2.95	550-570	1598–1557	1.16
T _{fg}	110-125	903-921	-1.99	123-138	1186-1194	-0.75	118-133	1561-1567	-0.85
T _a and T _{fg}	315-330	919–907	1.27	320-335	1196–1183	1.31	335-350	1567-1554	1.24
* All Control Variables	550-570	952–901	7.20	550-570	1252-1185	6.85	550-570	1643–1521	8.60

 Table 8. Energy savings/losses in heat input values for power plant operation.

* All control variables are the operating parameters of the power plant, as mentioned in Table 7.

The energy savings were achievable by the effective operational control of the combustion that ultimately influenced power plant operation. The energy savings or energy losses were expressed in % of heat input values and were mentioned against the operating parameters, i.e., MST and RST, T_{fg} , T_a and T_{fg} , and all control variables, as discussed in Sections 4.1–4.4, respectively. The energy savings or energy losses for any control variable at a specific unit load were calculated from the heat input values corresponding to the control variable's operating range, as mentioned in Figures 9d, 10d, 11d and 12d. (+) the sign indicates the % energy savings while the (–) sign indicates the % energy losses in heat input values against the control variable in its operating range. At 50%, 75%, and 100% unit load, MST and RST indicated energy savings in heat input values of 2.94%, 2.92%, and 2.59%. T_a and T_{fg} noted energy savings of 1.27%, 1.31%, and 1.25%, respectively. All control variables showed significant energy savings of 7.20%, 6.85%, and 8.60%, respectively, whereas, T_{fg} expressed energy losses of 1.99%, 0.70%, and 0.35% in heat input values for the operation of the power plant.

5. Conclusions

In this work, industrial operation data, advanced data analytic tools, and AI algorithms are incorporated to formulate the step-wise methodology in the spirit of industry 4.0-data analytics to optimize the power plant's η_{thermal} for sustainable power generation from a power complex.

The quality of operation data is ensured by employing data visualization techniques like histograms and SOFM. Monte-Carlo experiments on ANN and LSSVM process models and IASA were performed to eliminate insignificant variables from the list of initially selected control variables.

At 50%, 75%, and 100% unit load, for every 10 °C rise in MST and RST, the power plant's $\eta_{thermal}$ on average had a relative increase of 1.50%, 1.50%, and 1.32%, respectively.

For every 5 °C rise in T_{fg} , the relative decrease in the power plant's $\eta_{thermal}$ was an average of 0.65%, 0.25%, and 0.28%, respectively, under 50%, 75%, 100% unit load.

For every 5 °C rise in T_a and 5 °C fall in T_{fg}, the relative increase in the η_{thermal} of the power plant on average was 0.43%, 0.44%, and 0.42%, respectively, under 50%, 75%, and 100% unit load.

From 550 °C to 560 °C and 560 °C to 570 °C MST and RST with the corresponding changes in remaining control variables, the relative increase in the η_{thermal} of the power plant on an average was 3.36%, 3.21%, and 4.29% respectively at 50%, 75%, and 100% unit load.

At 50%, 75%, and 100% unit load: the savings in heat inputs corresponding to the highest overall thermal efficiencies, for MST and RST were 2.94%, 2.92%, and 2.59% respectively, for T_a and T_{fg} are 1.27%, 1.31%, and 1.25% respectively, for all control variables were 7.20%, 6.85%, and 8.60% respectively. Energy losses in heat inputs corresponding to the lowest overall thermal efficiencies at 50%, 75%, and 100% unit load, for T_{fg} were 1.99%, 0.70%, and 0.35%, respectively.

The true implementation of industry 4.0 built by the modern data analytics tools for power plant operation ensured the increase in the power plant's thermal efficiency and, therefore, the techno-economic benefits that offer reduced operation cost, optimal fuel consumption, and effective operational control.

Big data analytics, industrial internet of things, and simulation were the three technologies prioritized and incorporated in the study to achieve the power plant's operational excellence by embracing the industry 4.0 digital transformation approach.

The process modeling based on process data, process optimization, and data-driven strategy development for improved process control using sophisticated technologies dedicated to the implementation of industry 4.0 in the industrial complexes for higher productivity and effective operation control is in line with the objectives of the industry, innovation, and infrastructure program of the united nations for sustainable development and the Paris agreement allowing to fulfill the nations' commitment to sustainable growth and the environment.

The effect of auxiliaries' system operation, separately or combined, on the power plant's $\eta_{thermal}$ needs to be evaluated in the future.

Author Contributions: Conceptualization, W.M.A., G.M.U., S.M.A., J.K.; methodology, S.A., A.H.K.; supervision, G.M.U., L.B.X., S.C.; validation, M.A., M.H.K., J.K.; data curation, W.M.A., A.J., A.A.; formal analysis, W.M.A., S.A., M.W.R., U.N.; investigation, S.G.N., H.J.; writing—original draft, W.M.A., A.A.; writing—review and editing, G.M.U., L.B.X., S.C., J.K.; visualization, I.A.C., N.H., J.K.; project administration, W.M.A., G.M.U. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The research activity is based on the data collection from the Sahiwal Coal Power plant. The power plant is installed by Huaneng Shandong Ruyi Pakistan Energy Private limited- a joint venture of China Huaneng Group and China Ruyi group. The author is obliged to the power plant management and professional engineers to carry out the research activity for their support, supervision, and wisdom.

Conflicts of Interest: The author declares no conflict of interest concerning this work.

Nomenclature

attemperation water flow rate (°C)
Feed-water temperature (°C)
air flow rate (t/h)
coal flow rate (t/h)
main steam pressure (MPa)
main steam temperature (°C)
energy supplied
electric power
turbine speed (rpm)
$\% O_2$ in flue gas at boiler outlet (%)
furnace pressure (Pa)
condenser vacuum (kPa)
reheat steam temperature (°C)
APH air outlet temperature (°C)
APH outlet flue gas temperature (°C)
overall thermal efficiency (%)
epsilon

Abbreviations

AD	algorithmic differentiation
AI	Artificial Intelligence
ANN	Artificial Neural Network
APH	air preheater
С	regularized constant
DPSH	division platen superheater
ECO	economizer
ESP	electrostatic precipitator
FDF	forced draft fan
FGD	flue gas desulphurization
FRH	final re-heater
FSH	final superheater
G	generator
HP	high pressure
HPH	high-pressure heaters
IA	interval arithmetic
IASA	Interval Adjoint Significance Analysis
ICT	information and communication technology
IDF	induced draft fan
IP	intermediate pressure
LP	low pressure
LPA	low-pressure turbine A

LPB	low-pressure turbine B
LPH	low-pressure heaters
LSSVM	Least Square Support Vector Machine
LT REHEATER	low-temperature re-heater
LTSH	low-temperature superheater
MAPE	mean absolute percentage error
MLP	multilayer perceptron
NCCR	the net coal consumption rate
NRMSE	normalized RMSE
PAF	primary air fan
R	correlation coefficient
RMSE	root mean square error
SIS	Supervisory Information System
Smart EEPS	smart energy and electric power system
SOFM	self-organizing feature map
SRM	structural risk minimization

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