Journal Pre-proof

Artificial Intelligence driven smart operation of large industrial complexes supporting the net-zero goal: Coal power plants

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PII: S2772-5081(23)00037-6
DOI: https://doi.org/10.1016/j.dche.2023.100119
Reference: DCHE 100119

To appear in: *Digital Chemical Engineering*

Received date: 16 May 2023
Revised date: 18 July 2023
Accepted date: 3 August 2023

Please cite this article as: Waqar Muhammad Ashraf , Vivek Dua , Artificial Intelligence driven smart operation of large industrial complexes supporting the net-zero goal: Coal power plants, *Digital Chemical Engineering* (2023), doi: https://doi.org/10.1016/j.dche.2023.100119

Highlights

- Demonstrating the potential of AI model for the industrial competitiveness.
- AI model-based analysis enhances the performance of coal power plant.
- 1.3 % improvement in thermal efficiency and 50.5 kt/y of emissions are reduced.
- The power generation capacity of the plant is reduced on the tighter emissions constraint.
- The improvement in the plant-level performance indicators contributes to net-zero goal.

Artificial Intelligence driven smart operation of large industrial complexes supporting the net-zero goal: Coal power plants

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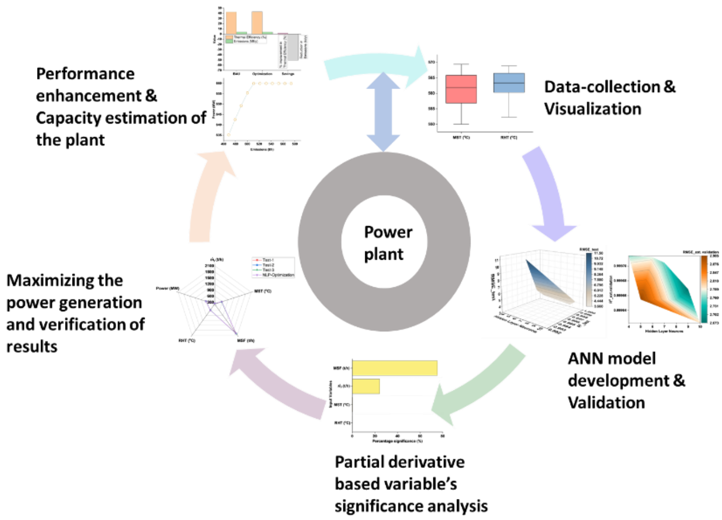
Abstract

The true potential of artificial intelligence (AI) is to contribute towards the performance enhancement and informed decision making for the operation of the large industrial complexes like coal power plants. In this paper, AI based modelling and optimization framework is developed and deployed for the smart and efficient operation of a 660 MW supercritical coal power plant. The industrial data under various power generation capacity of the plant is collected, visualized, processed and subsequently, utilized to train artificial neural network (ANN) model for predicting the power generation. The ANN model presents good predictability and generalization performance in external validation test with R^2 = 0.99 and RMSE =2.69 MW. The partial derivative of the ANN model is taken with respect to the input variable to evaluate the variable' sensitivity on the power generation. It is found that main steam flow rate is the most significant variable having percentage significance value of 75.3 %. Nonlinear programming (NLP) technique is applied to maximize the power generation. The NLP-simulated optimized values of the input variables are verified on the power generation operation. The plant-level performance indicators are improved under optimum operating mode of power generation: savings in fuel consumption (3 t/h), improvement in thermal efficiency (1.3 %) and reduction in emissions discharge (50.5 kt/y). It is also investigated that maximum power production capacity of the plant is reduced from 660 MW to 635 MW when the emissions discharge limit is changed from 510 t/h to 470 t/h. It is concluded that the improved plant-level performance indicators and informed decision making present the potential of AI based modelling and optimization analysis to reliably contribute to net-zero goal from the coal power plant.

Keywords

Coal power plant; artificial intelligence; net-zero; energy efficiency; CO_2 reduction

Graphical abstract



Introduction

In the industry 4.0 era, the advancement in the information communication technologies has led to the measurement, communication and storage of the data collected by the state-of-art sensors installed at the various locations of the industrial processes. The data stored in the supervisory information systems is precious since it contains the key information of the industrial processes carried out under the sustained operating constraints. The artificial intelligence (AI) based modelling algorithms are presented to mine the value out the stored volumes of data (new oil) [1]. However, at the best, the management of the industrial complexes graphically visualizes the hyperdimensional process and make the conservative decisions owing to limited cognitive abilities of human brain to visualize and analyse few dimensions, traditionally qualified performance engineers not trained with the advanced analytics and lack of industry-academia liaison. Furthermore, AI-driven conclusions drawn from the lab-scale and polit plant studies are of limited relevance to large industrial complexes since their design space and operation modes are significantly different. Thus, the true potential of AI-based modelling algorithms is critical to be exploited for the large industrial complexes like coal power plants to contribute to the solutions of big problems like climate change, net-zero and sustainability.

Coal based power generation systems contribute a major share in the national energy mix of the emerging and underdeveloped economies [2]. The global political instability can drive the higher share of coal for the energy needs in the developed countries especially in Europe [3]. The electrical sector accounts for 50 % of total CO_2 emissions and out of it, coal alone causes a total 40% of CO_2 emissions [4]. The International Energy Agency (IEA) has estimated that the existing energy infrastructure can peak the CO_2 emissions up to 650 Gt (30% more than CO_2 budget corresponding to 1.5 ^{o}C limit with 50% probability) from 2020 to 2050 if the fossil-based energy assets are operated until the end of their lifetime in a similar way to that in the past [4]. Furthermore, IEA also suggests the smart operation of the existing fossil-based plants to support the net-zero goal.

Maintaining the energy-efficient and smart operation of coal power plant can be quite challenging given the coordinated and integrated operation of energy devices from component (pumps, compressors, belts, conveyors etc.) to system level (boiler, steam turbines, generator etc.). The operating space becomes truly hyperdimensional, and the nonlinearity and interactions among the variables further complicate the management of the power generation. Therefore, the development of accurate first-principle models to such level of complexity and operational level is difficult and the model-based optimization analysis can be computationally prohibitive. To overcome this problem, the data-driven AI-based models are widely deployed by the research community that are computationally cheap to develop and can speed up the predictive and optimization analyses [5]. However, the quality of data, selection of modelling algorithm, evaluation of modelling performance and the optimization analysis guided by domain knowledge are the key challenges to exploit the true potential of AI-based models.

Amongst the available modelling algorithms, artificial neural network (ANN) is the excellent functional approximator and can effectively construct the functional mapping between the hyperdimensional input space and the output variable [6]. The algorithm can also mine the nonlinearity and develop the causal relationships among the variables from the volumes of data. The algorithm is computationally inexpensive, requires less memory storage, and can be fed with medium to large size dataset for the model development [7]. These key features of the ANN algorithm can deal with the complexity of power generation operation of coal plant and thus is utilized to model the power production under various generation capacities of the power plant.

Research studies modelling the power generation using AI models are reported in literature. Elkhawad Ali Elfaki [8] predicted the electrical power production from a combined cycle power plant by ANN model. The ambient air conditions like pressure, temperature, humidity and the condenser vacuum were deployed for the task. However, the impact of operating parameters like fuel supply and heat recovery steam generators can be studied to evaluate their impact on the power production. Naveen Kumar [9] studied the impact of excess air ratio and different fuels on the performance of power plant using ANN approach. 30% reduction in coal consumption and 1.3% improvement in the energy efficiency were reported. Yasin Tunckaya [10] modelled the power production operation from a 660 MW power plant using various machine learning (ML) techniques. Thirty-seven variables taken from different operating systems were included for the task. In another study, Ravinder Kumar [11] also modelled the power production operation of a 660 MW plant on large number of operating parameters using ANN. Ashraf. et al [12]. modelled the power generation from a 660 MW power plant by support vector machine and extreme learning machine. The response surface methodology technique was applied to simulate the operating values of the input variables for the efficient power production.

Liu et al. [13] developed a fuzzy neural network for a 1000 MW ultra-supercritical power plant based upon large number of operating variables. The model exhibited good merit of efficacy in modelling the hyperdimensional power generation operation. Haddad et al., [14] performed multi-objective optimization analysis for the parametric optimization of the coal based power plant. Genetic algorithm and particle swarm optimization techniques were utilized for the analysis. Zhang et al., [15] developed a stacked autoencoder simulating model for a 1000 MW ultra-supercritical boiler-turbine system. The model exhibited better predictive performance in comparison with the multi-linear regression.

In the literature studies, the research focus has been to model the power production from the power plants by AI models. However, the deployment of the model for conducting the plant-level performance analytics and estimating the improvement in the power generation operation is missing. Thus, the true potential of AI based models for the performance enhancement of coal power plants is essentially lacking in literature that needs to be investigated and the findings backed by the domain knowledge should be communicated to the industrial community. Furthermore, the step-by-step methodology explaining the details / procedure in conducting the AI-based modelling and optimization analysis on the industrial data should be presented that the industry may benefit with to support the smart operations of their industrial complexes and contributes to the industry 4.0 vision of smart operation management.

This study presents the utilization of AI based modelling and optimization analysis for conducting the performance enhancement of a 660 MW supercritical coal power plant that is the novelty of this work. The industrial data of the power generation operation is taken and deployed for the development of ANN model. The partial derivative of the ANN model is taken with respect to the input variable to compute its significance on the power generation that also contributes to novel aspects of this work. An optimization problem with the embedded ANN model and the applied operation constraints is solved by a deterministic optimization technique, i.e., nonlinear programming. The determined optimized values of the input variables for maximum power production are verified on the power generation operation that is main novelty of this work thereby demonstrating the reliability of AI based modelling and optimization analysis. The improvement in the plant-level performance measures like thermal efficiency and the reduction in emissions (CO_2, CH_4, N_2O, SO_2 and Hg) discharge are also calculated signifying the utilization of AI model for the industrial competitiveness. Moreover, optimization problem considering the maximum power production and the emissions discharge constraint is solved by NLP technique and the maximum power production of the power plant is estimated that is the novel AI model-based analysis to estimate the capacity of the power generation. The operation excellence, performance enhancement and informed decision making based on AI based modelling and optimization analysis contributes to the net-zero goal from the coal power plant that constitutes the key novelty of this work depicting the potential of AI models for big industrial complexes.

Methodology

A comprehensive and step-by-step methodology followed in this study for carrying out data-driven modelling and optimization analysis to maximize the power generation under optimum operating conditions is presented in Figure 1. The key stages involved in the analysis are as follows: a) variables' selection, data-collection & visualization, b) ANN model development & Validation, c) sensitivity analysis & variables' significance, d) maximizing power generation under the optimum operating conditions, e) verification of the optimization results, f) performance enhancement of the power generation system, and g) investigating the maximum power generation capacity on the emissions discharge limit. The details associated with each analytical stage is provided in the next sections.

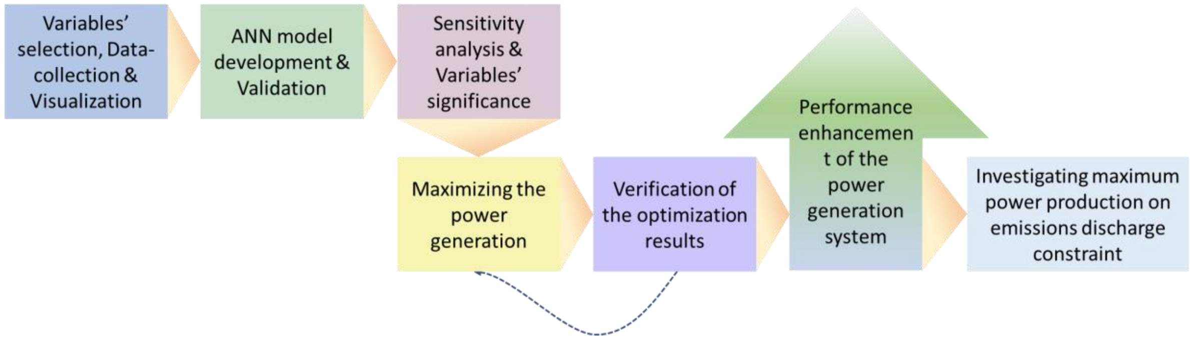


Figure 1. The proposed methodology for the data-driven modelling and optimization of power generation from a coal power plant. The key stages on the optimum operating conditions for the maximum power generation, verification of the optimization results on the power generation operation and the performance enhancement of the power generation system are included in for the comprehensive ML enabled modelling and optimization analysis.

Variables' selection, data-collection & visualization

The power generation operation of a 660 MW supercritical coal power plant is maintained under the synchronized operation of a number of energy devices and systems like boiler, steam turbines, generator, flue gas system, feed water regenerative heating system, and auxiliary systems etc. The control space is essentially hyperdimensional and there exists nonlinearity and interactions among the operating variables of the systems. Thus, the selection of the operational relevant and significant operating variables for modelling the power generation requires to consult with the operation engineers (domain-knowledge) and conduct the literature survey.

Having identified the input variables with respect to the power generation, the data for the input-output variables is collected. The supervisory information system, also known as the data-storage bank, stores the data measured by the sensors installed at different locations of the power plant. The data should be collected corresponding to the different operating modes of the power plant to cover the wide range of the operating variables, capturing the pattern for the ramp-up and ramp-down, and the diversity in the data. The data-distribution across the ranges of the input variables should be visualized to ensure the reasonable data-spread and density. Thus, the quality of the collected data is ensured and the dataset in transformed into equal scale. Data-processing is crucial to ensure the efficient working of AI models for two reasons: 1) the significantly different operating range of a variable may dominate the mapping between the output and input variables and the contribution of the input variables having small operating ranges might be negligible towards establishing the relationship with the output variable, and 2) the parameters embedded in the AI modelling algorithm might not achieve optimal values during the model development phase owing to different scales of the input variables [16]. In the literature, data is generally scaled into -1 to 1 and the mathematical expression for the data-transformation is given as:

$$x_i' = \frac{(x_i - x_{min})\,(b-a)}{x_{max} - x_{min}} + a \tag{1}$$

here, x_i is the operating variable having observations, i = 1,2,3,…N and is transformed in to x_i' on the [-1,1] scale. x_{min} and x_{max} are the minimum and maximum value x_i, whereas a and b are taken as -1 and 1 respectively.

ANN model development & validation

Artificial neural network (ANN), also known as a multi-layered perceptron, is a computationally fast and efficient algorithm for data-driven modelling problems. The working of ANN mimics the information processing in the human brain and the algorithm has demonstrated excellent performance to approximate the complex function space [17]. Thus, ANN is one amongst the powerful modelling algorithms of AI and it can capture the hidden patterns and dig hard-to-extract nonlinearity and interactions in the hyperdimensional designed space consisting on heap of data. The generic working of ANN can be found in [16].

The number of hidden layer neurons is the key parameter to be optimized for the effective working of the ANN [17]. The number of hidden layer neurons control the complexity introduced in the ANN model for constructing the functional mapping between the input-output variables. Another parameter for the development of optimal ANN architecture is the number of hidden layers. It is proved in literature that a single hidden layer ANN model can well approximate the nonlinear function given that appropriate number of hidden layer neurons are provided in [6]. Thus, for the initialized architecture of ANN (number of hidden layers and number of hidden layer neurons), the parameters like weights and biases are tuned via iterative training process that is governed by training algorithms like Levenberg Marquardt, scaled conjugate gradient and Newton's method etc. Levenberg Marquardt algorithm is generally used for the parametric optimization of ANN (the loss function is minimized corresponding to the parameters: weights and biases) since it is computationally efficient, and has stable and fast convergence performance [18].

Evaluation Criteria

The modelling performance of the ANN model is evaluated on rigorous statistical measures. Coefficient of determination (R^2) and root-mean-squared-error (RMSE) are introduced as evaluation criteria for gauging the modelling performance of ANN [19]. The mathematical expression of the two terms included in the performance matrix is given as:

$$R^2 = 1 - \frac{\sum_i^N (y_i - \hat{y}_i)^2}{\sum_i^N (y_i - \bar{y}_i)^2} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \quad (3)$$

here, y_i is the true output variable's value whereas $\hat{y}_i$ is the model-simulated output variable's value; i = 1,2,3,…,N equal to total number of observations. The value of R^2 varies from zero to one thereby showing the accuracy scale. Similarly, RMSE computes the deviation between the true and model-simulated output variable's value and should be minimized thereby indicating good predictive performance of the trained model.

Validation of the trained ANN model

The generalization and predictive performance of the trained ANN models need to be evaluated before deploying the model for subsequent analyses. For this purpose, the external validation test in conducted as reported in literature studies [20, 21]. The external validation test comprises on deploying the trained ANN model to predict the external validation dataset that is essentially unseen to the model. Thus, the external validation test serves to evaluate the effectiveness of the functional mapping between the input-output variables constructed by the network by predicting the unseen dataset having the operating ranges of the variables similar as that of the dataset deployed for developing the ANN model. The predictive accuracy is measured on the performance matrix incorporating R^2 and RMSE terms. The performance comparison based on external validation test is conducted to select a better ANN model having good predictive and generalization performance.

Sensitivity analysis & variables' significance

ANN is essentially a black-box model, and it is quite challenging to explain the predictability of the model. At the same time, it is important to get insights about the working of the system being modelled by the ANN thereby fostering the need towards its explainability. To this end, researchers have reported various sensitivity analysis techniques to evaluate the sensitivity of the output variable towards the input variables, calculating the variables' significance on the output variables, and getting an insight about the system's working. Neural interpretation diagram, Garson's method, Olden's method, input perturbation etc. are some sensitivity analysis techniques reported in literature [22]. However, these techniques lack in providing the comprehensive information about the interpretability of the AI model.

On the other hand, partial derivative-based sensitivity analysis computes the partial derivative of the output variable with respect to the input variable at each sample of the dataset. Thus, the explicit expression for the sensitivity analysis of the ANN model can be obtained using partial derivative approach and it provides the robust diagnostic information about the variables' sensitivity compared with the previously mentioned techniques. Therefore, in this study, partial-derivative based sensitivity analysis technique is applied for the sensitivity analysis of the developed ANN model, and subsequently, the input variable's significance in predicting the responses of the output variable is calculated.

Maximizing power generation under the optimum operating conditions

In this work, data-driven ANN model is constructed and integrated within the optimization environment. The data-driven model makes the optimization analysis fast and accurate optimized results for the system under consideration can be obtained. The power generation process is essentially nonlinear and there exists nonlinear relationships between the variables. Therefore, in this work, nonlinear programming technique is applied for maximizing the power production modelled on the input variables. The mathematical expression of the NLP based optimization problem incorporating the ANN model is written as:

$$\text{Objective Function: } \max f(x)$$

subject to:

$$\begin{gathered} h(x) = 0 \\ x = \{\, x_1, x_2, \dots, x_n \,\} \\ x \in X \subseteq R^n \\ x^L \le x \le x^U \end{gathered} \tag{6}$$

here, $f(x)$ is the objective function representing the power generation from the power plant that is to be maximized. $h(x)$ is the equality constraint representing the developed ANN model [23] and x is the set of input variables. Whereas, x^L and x^U are the lower and upper bounds applied on x. The NLP based optimization problem is solved and the optimum operating values of the input variables are determined corresponding to the maximum power production from the coal power plant.

Verification of the optimization results

The computed optimized results corresponding to the maximum power production need to be verified to check their experimental accuracy. For this purpose, the operating values of the input variables are maintained around the NLP based optimized values such that maximum power (660 MW) is generated from the power plant. The maximum power generation on the set-value of the input variables verifies the effectiveness of the computed optimized results. Otherwise, the failure in the experimental verification requires to re-calculate the optimized values of the input variables corresponding to maximum power production and the verification of the optimized results should be made.

Performance enhancement of the power generation system

The successful implementation of the optimized results for the maximum power production may result in improvement in the performance parameters of the power plant. The savings in the fuel consumption and improvement in the thermal efficiency as the result of the maximum power production under the optimized values of the input variables are calculated. Furthermore, the accumulated reduction in emissions (CO_2, SO_2, N_2O, CH_4 and Hg) is also calculated on annual basis. The enhanced performance of the power generation system achieved under data-driven modelling and optimization analysis would contribute to net-zero goal from the coal power plant.

Maximum Power generation under the emissions discharge constraint

The power generation from the power plant under the limit on the emissions discharge is investigated. The emission constraint is introduced considering the emissions discharge regulation that can be introduced by environmental protection agency for the power production from coal power plant. The optimization problem for the maximum power production and the applied emissions constraint is defined within the framework of NLP that is written as:

$$\text{Objective Function: } \max f(x)$$

subject to:

$$\begin{gathered} h(x) = 0 \\ g(x) < 0 \\ x = \{ x_1, x_2, \dots, x_n \} \\ x \in X \subseteq R^n \\ x^L \leq x \leq x^U \end{gathered} \tag{7}$$

here, $g(x) < 0$ is an inequality constraint that is incorporated to represent the emissions discharge limit from the power plant. The rest of the components of the optimization problem is same as described in eq. (6). The NLP based optimization problem is solved to maximize the power generation that also satisfies the applied constraint of the emissions. The Pareto front for the problem can depict the response of the power generation under the restriction of the emissions discharge.

Results & Discussion

Variables' selection, data-collection and visualization for power generation

The power generation operation of a 660 MW supercritical coal power plant is governed under the synchronized and integrated operation mode of a number of systems like flue gas system, feed water regenerative heating system, steam production system, water treatment system, auxiliary systems etc. These sub-systems are controlled by the coordinated operation management of large number of component level devices like pumps, compressors, conveying belts etc., thereby maintaining the enterprise level performance measures like power generation is a difficult task for the operators. Moreover, the operation of power generation from a large capacity coal-fired power plant undergoes complex, non-linear, interactive, and high-dimensional process and the listing of truly significant variables is a challenging task. To this end, domain knowledge of the system guides to consider critically relevant operating variables out of the large input space of the power plant. Furthermore, a detailed literature survey is conducted to identify the significant operational parameters for the power generation operation [24-26]. Thus, the input variables considered for modelling the power production from a coal power plant are: coal flow rate (t/h), main steam temperature (^{o}C), main steam flow rate (t/h) and reheat steam temperature (^{o}C). Coal flow rate ($\dot{m}_f$) is one amongst the critically controlled operation parameters as it accounts for thermal energy spent in the boiler. Similarly, $\dot{m}_f$ is adjusted at the sustained power generation capacity corresponding to the condition of feed water and air supply (primary and secondary) entering the boiler. The thermal energy contained in the hot flue gas is transferred to the feedwater in various heating surfaces for producing the steam at the specified conditions. Smrekar et al., [24] deployed the feed water conditions to construct the AI model for predicting the steam conditions at the outlet of the boiler. However, there exists a strong linear correlation among the conditions of feed water at the entrance of the boiler and $\dot{m}_f$ that is also supported by the domain-knowledge regarding the power production [12]. Thus, feed water conditions are not considered for modelling the power production. Similarly, main steam temperature (MST) and main steam flow rate (MSF) represent the steam conditions before the high-pressure steam turbine. The high temperature steam with the specified flow rate expands in the high-pressure steam turbine and then, is passed through rehetaer to reheat the steam. Thus, the reheat steam temperature (RHT) is the temperature of steam recovered in the reheater and the steam expands the intermediate steam turbine. The heat transfer from the flue gas to the reheat steam increases the thermal efficiency of the Rankine cycle [26]. Generally, steam conditions at the entrance of the steam turbine greatly influence the power production, thus the variables associated with the sub-systems like feed water regenerative heating system, deaerator system, condenser vacuum etc., are inter-dependent on the steam conditions [12, 20]. Considering the variables dependency and discussions made with the operation engineer of the power plant, the selected variables are the critically controlled that have significant impact on the power generation. It is important to mention here that end-state variables drive higher modelling accuracy of AI algorithms without needing to incorporate the state and inter-dependent variables [27]. However, domain knowledge of the system should be consulted during the selection of the input variables for modelling the output variables taken from the industrial-scale engineering systems [24].

The power production operation from an industrial complex is maintained upon the coordinated and complex network of sensors installed at various points on the power generation processes, thereby facilitating the operators to maintain the operating values within the controlled limits. The state-of-art sensors are used on the newly installed power plant to ensure the quality of the measurements being recorded and thereby communicated to the control systems for the operation management. Thus, the measured data is stored in the supervisory information system of the power plant and utilized for conducting the operation analysis and decision making for the system. The sensor make, model and uncertainty level in the recorded observation are mentioned in Table 1. The uncertainty level of the sensors is reasonably small indicating the reliable working of the sensors and the accurate measurement made by the sensors.

Table 1. Summary of sensors' make, model number and uncertainty

Sensor	Unit	Make	Model Number	Uncertainty
Coal Flow Rate ($\dot{m}_f$)	t/h	Vishay Precision Group (USA)	3410	< 1 %
Main Steam Temperature (MST)	^oC	Anhui Tiankang China Thermocouple	WRNR2 (K TYPE)	± 0.004%
Main Steam Flow Rate (MSF)	t/h	Emerson, Rosemount, USA	-	± 0.04%
Reheat Steam Temperature (RHT)	^oC	Anhui Tiankang China Thermocouple	WRNR2 (K TYPE)	± 0.004%
Power	MW	Nanjing Suatak Measurement and Control System	STM3-WT-3-555A4BY	0.5 MW

The data for the power production and the corresponding input variables is taken from the supervisory information system of a coal power plant installed in Sahiwal, Pakistan [28]. 2017 hourly-averaged observations for the operating variables are taken during which power production from the power plant is varied according to the energy demand in the national grid. The continuous variation in the power generation is associated with the careful adjustment in the input variables to sustain the power production operation. Thus, there exists variation in the data-distribution for all the operating variables as shown in Figure 2. Referring to Figure 2, good data-distribution profiles for the input variables are observed for the extracted dataset. $\dot{m}_f$ is varied from 126 t/h to 252 t/h with the standard deviation of 47.9. It is important to mention here that the fluctuation in the heating value of the coal utilized at the power plant is reasonable, i.e., 23 ± 1 MJ/kg. Thus, coal flow rate indicates the amount of the energy brought to the boiler that would be transferred to the heating surfaces after fuel combustion. Whereas, MSF undergoes an increase from 997 t/h to 2134 t/h and has the standard deviation of 430. MST and RHT are generally controlled within tight operating windows during the power plant operation and in the extracted dataset, the two temperatures are almost varied from 550 ^oC to 570 ^oC and the standard deviation among their observations is 4.95 and 4.22 respectively. The operating range for the MST and RHT is comparable with the one reported in literature [29]. Similarly, power is produced from the power plant in the range of 354 MW to 660 MW that represents the half load to full load power generation capacity of the power plant. The dataset considered for the power production operation presents the good data-distribution profiles as well as the wide operating ranges for the operating variables. This feature of the extracted dataset is particularly desirable from the perspective of developing an efficient and flexible data-driven machine learning model predicting the power generation states of the power plant under different operating values of the input variables and subsequently, can provide effective optimization solution for the maximum power production. Having visualized the data-distribution space, the operating ranges of the variables are scaled into -1 to 1 using eq. (1).

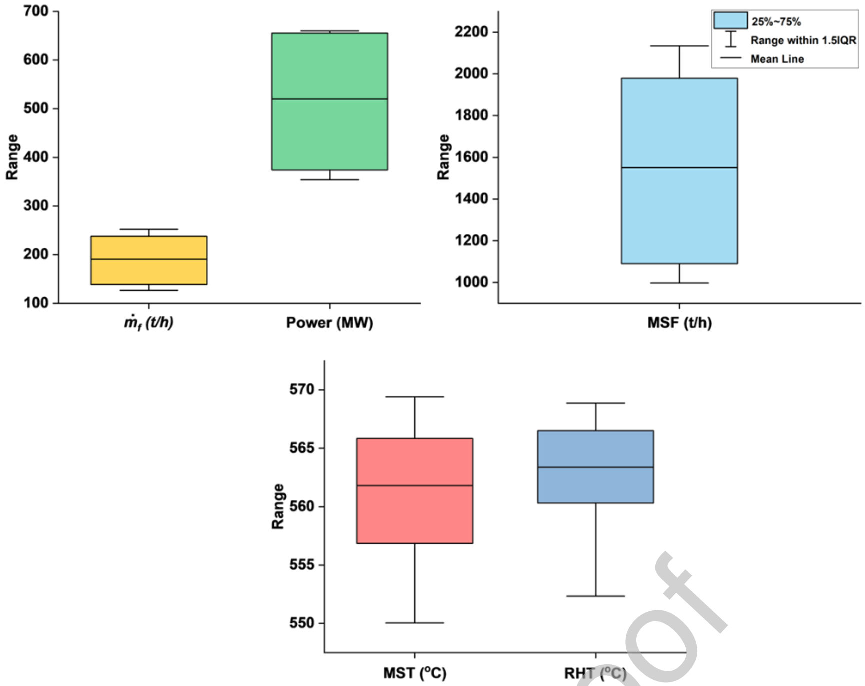


Figure 2. Data distribution space of input operating variables (coal flow rate ($\dot{m}_f$ (t/h)), main steam temperature (MST (°C)), main steam flow rate (MSF (t/h)), and reheat steam temperature (RHT (°C)) and output variable (Power (MW)). The data is distributed in the wide operating range of the input variables.

Development of ANN model for power generation and its external validation

In this work, a shallow multi-layered ANN model is developed. The split ratio of 0.8, 0.1 and 0.1 is taken for training, testing and validation data for the model development respectively. The number of hidden layer neurons are varied from 4 to 10. Levenberg Marquardt algorithm and sum-of-squared error is deployed for the parametric optimization of ANN. The activation function applied on hidden and output layer of ANN is logistic sigmoidal and linear respectively. The learning rate is set to 0.01 which is reasonable concerning with the computational time and smooth tuning of the parameters during the network development. The early stopping criteria is also established as: minimum gradient achieved = 1.0 x 10^{-20}, maximum validation failure = 6 and training epochs = 10000. The network training is stopped when either condition of the stopping criteria is met.

Figure 3 shows the modelling performance of the ANN model constructed for the power production. The performance matrix is computed during the training, testing and validation phase with respect to hidden layer neurons of the network. A high R^2 value, i.e., approximately 1 is computed for all the ANN models (having hidden layer neurons from 4 to 10). Another merit of performance, i.e., RMSE, introduced in the performance matrix, is a bit different for the constructed models. The external validation test is carried out to evaluate the prediction and generalization performance of the developed ANN models and thereby to select a better model for the power generation.

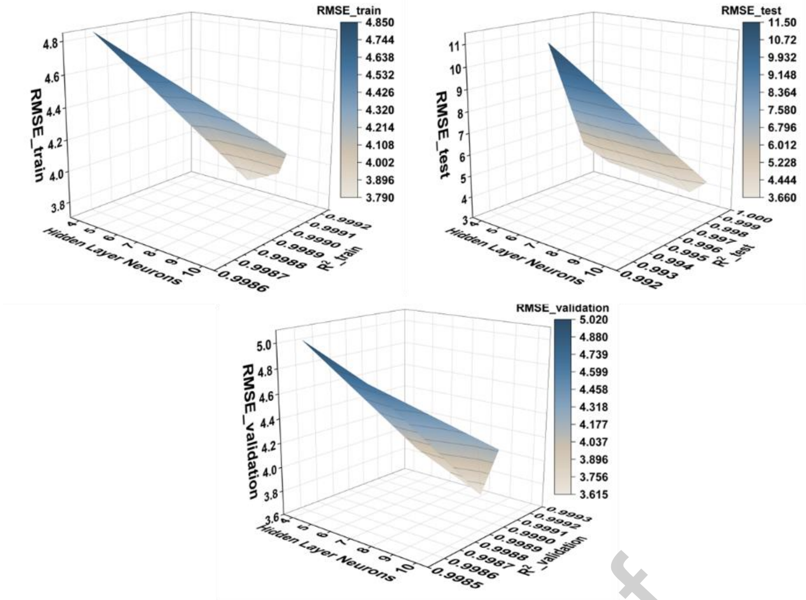


Figure 3. Development of ANN model for the power production. R^2 and RMSE are measured during the training, testing and validation phase corresponding to hidden layer neurons. ANN model having 9 hidden layer neurons demonstrates the better performance with comparatively higher R^2 value and minimum RMSE.

The dataset for the external validation test comprises on 134 randomly selected observations for the input variables and the power generation that lie within their operating ranges. The dataset is deployed to be predicted by the developed ANN models and the performance metrices are calculated. Figure 4 shows the performance metrices (R^2 & RMSE) calculated for the developed ANN models based on external validation dataset. The ANN models exhibit closed values of R^2, i.e., approximately one. However, RMSE with respect to ANN model having nine hidden layer neurons is comparatively lower, i.e., 2.43 MW. Thus, nine hidden layer neurons make the optimal configuration for the ANN model for the power generation as confirmed by the external validation test. The value of R^2 & RMSE for the ANN model during the model development in training, testing and validation phase are 0.99 & 3.90 MW, 0.99 & 3.96 MW and 0.99 & 4.38 MW respectively. Therefore, the model is selected for conducting the subsequent analyses as mentioned in the next sections.

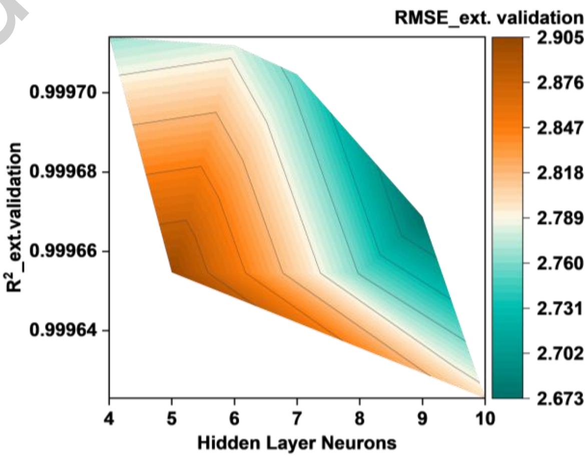


Figure 4. External validation of the developed ANN models. The external validation test confirms the better prediction and generalization performance of ANN model having nine neurons in the hidden layer.

Model comparison in the literature

Ashraf et al., [12] constructed the AI based models like support vector machine (SVM) and extreme learning machine (ELM) for modelling the power generation from a 660 MW supercritical coal power plant. The measures of performance, i.e., R^2 and RMSE were measured corresponding to the external validation dataset. The SVM model was coupled with response surface methodology technique to estimate the operating values of the input variables ensuring the efficient power generation.

Figure 5 compares the performance metrices for modelling the power generation by ANN with the ones reported in [12]. It is apparent that ANN model, developed in this study for modelling the power generation from a 660 MW power plant, has lower RMSE compared with those of SVM and ELM model. Though R^2 value is same for the three models, however RMSE_ANN = 2.69 MW < RMSE_SVM = 2.96 MW < RMSE_ELM = 7.81 MW thereby indicating the better generalization and predictability of ANN model towards the unseen dataset compared with SVM and ELM.

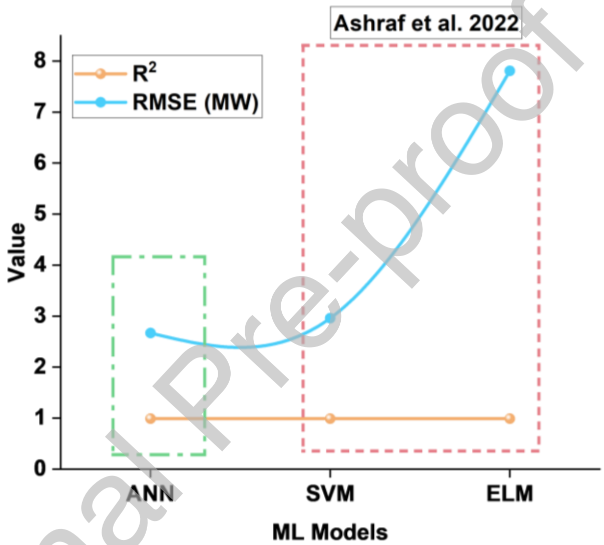


Figure 5. The performance comparison of ANN model developed in this study with SVM and ELM models reported in literature. ANN model has improved performance measures (R^2 = 0.99 and RMSE = 2.69 MW) than of SVM (R^2 = 0.99 and RMSE = 2.96 MW) and ELM (R^2 = 0.99 and RMSE = 7.81 MW).

Partial derivative-based sensitivity analysis of ANN model

The partial-derivative based sensitivity analysis is carried out on the developed ANN model to evaluate the sensitivity of the power generation towards the input variable. The information received at any hidden layer neuron (h) can be written as:

$$S_h = N_p w_{hp} + \sum_{i \neq p} N_i w_{hi} + b_h \quad (7)$$

where, N_p is the input variable whose sensitivity on the output is to be evaluated. w_{hp} is the connection weight from N_p to a neuron of the hidden layer; N_i is the set of other input variables having connection weights w_{hi} with the hidden layer neuron (h).

The activation function ϕ_h applied on S_h is written as:

$$N_{h(t)} = \phi_h(S_h) \quad (8)$$

here, N_h represents the information signal forwarded to the output layer from the hidden layer of ANN. The information processing at the output layer is given as:

$$S_o = N_h\, w_{oh} + \sum_{j \neq h} N_j w_{oj} + b_o \quad (9)$$

$$N_o = \phi_o(S_o) \quad (10)$$

here, b_o is the bias applied at the output layer; ϕ_o is the activation function applied on the output layer of ANN; 'j' denotes the neuron in the hidden layer; and N_o is the value simulated by ANN for the given values of the input variables. Also, we have:

$$\frac{\partial S_h}{\partial N_p} = w_{hp} \quad (11)$$

$$\frac{\partial S_o}{\partial N_h} = w_{oh} \quad (12)$$

The first-order partial derivative of output variable with respect to the input variable X_p ($N_i = X_p$) is:

$$\frac{\partial N_o}{\partial X_p} = \frac{\partial N_o}{\partial N_p} = \frac{\partial N_o}{\partial N_h}\frac{\partial N_h}{\partial N_p} = \left(\frac{dN_o}{dS_o}\frac{\partial S_o}{\partial N_h}\right)\left(\frac{dN_h}{dS_h}\frac{\partial S_h}{\partial N_p}\right) \quad (13)$$

Considering eqs. (8) and (10):

$$\frac{dN_o}{dS_o} = \phi_o'(S_o) \quad (14)$$

$$\frac{dN_h}{dS_h} = \phi_h'(S_h) \quad (15)$$

Eq. (13) can be expressed as:

$$\frac{\partial N_o}{\partial X_p} = \phi_o'(S_o) w_{oh} \phi_h'(S_h)\, w_{hp} \quad (16)$$

Since, the hidden layer consists of more than one neuron, the general form of partial derivative-based input sensitivity of three-layer multi-layered perceptron-based ANN model for 'nh' hidden layer neurons is expressed as:

$$\frac{\partial N_o}{\partial X_p} = \sum_{h=1}^{nh} \phi_o'(S_o) w_{oh} \phi_h'(S_h)\, w_{hp} \quad (17)$$

In this work, the activation function applied on the hidden and output layer is logistic sigmoidal ($\phi_h(S_h) = 1/(1+\exp(-S))$) and linear ($\phi_h(S_o) = S_o$) respectively. Therefore, first-derivative of logistic sigmoidal function is given as:

$$\phi'(S) = (1-\phi(S))\phi(S) = (1-N)N \quad (18)$$

Thus, eq. (17) can be expressed as:

$$\frac{\partial N_o}{\partial X_p} = \sum_{h=1}^{nh} w_{oh}((1-N)N) w_{hp} \quad (19)$$

The eq. (19) describes the absolute sensitivity on output variable N_o for per unit change in input variable X_p which can be deployed to identify the significant input variables for the power generation.

The training dataset is deployed for the evaluation of the output variable's sensitivity towards the input variable [22]. Subsequently, the variance in the sensitivity responses is calculated and normalized to evaluate the percentage significance of the input variables. The mathematical expression for the percentage significance is given as:

$$\text{Percentage significance} = \frac{\sigma^2_{y_i|x_i}}{\sum_{i=1}^{c} \sigma^2_{y_i|x_i}} \times 100 \qquad (20)$$

here, $\sigma^2_{y_i|x_i}$ refers to the variance produced in output variable y_i with respect to the input variable x_i; $\sum_{i=1}^{c} \sigma^2_{y_i|x_i}$ is the summation of the variance produced in the output variable with respect to input variables; $i = 1, \ldots, c$ equals to number of input variables. Thus, percentage significance measures the contribution of the input variable in explaining the variance of the output variable.

Higher the value of percentage significance, the significant is the variable towards the output variable and vice versa. In this work, eq. (19) is used to compute the partial-derivative based sensitivity responses with respect to the input variable and eq. (20) is utilized to calculate the percentage significance of the input variable. Figure 6 presents the percentage significance of the input variables on the power generation calculated by partial derivative-based sensitivity analysis. MSF is termed out to be the most significant variable on the power generation having the percentage significance value of 75.3 %. The second significant variable is $\dot{m}_f$ that shares the percentage significance of 24.3% followed by MST and RHT with percentage significance value of 0.3 % and 0.1 % respectively. The sensitivity of MSF on the power generation can be explained by the operational knowledge of the power plant since the amount of steam expanding in the series of the turbines drives the steam turbines rotor to rotate, and matches the grid frequency, which in turn drives the generator shaft for the power production. Furthermore, the order of significance of the input variables on the power production is comparable with the studies reported in literature [12] (response surface methodology analysis was conducted to investigate the variable's significance).

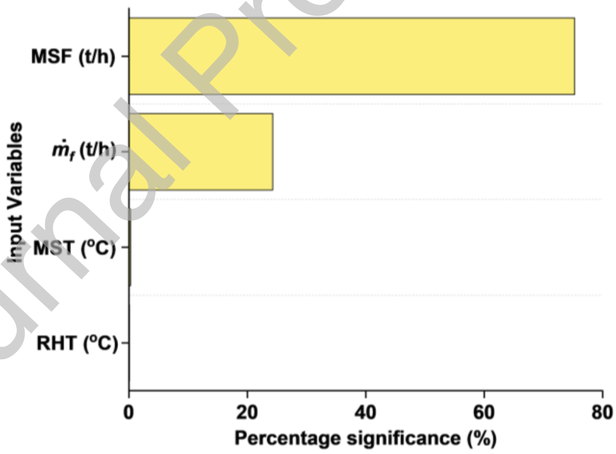


Figure 6. Percentage significance of the input variables on the power generation calculated by partial derivative-based sensitivity analysis. MSF is the most significant variable on the power generation followed by $\dot{m}_f$, MST and RHT.

NLP based analysis for maximizing the power generation and its verification

The developed ANN model is integrated in the optimization environment to determine the optimum operating values of the input variables corresponding to the maximum power production. Due to nonlinear and non-convex characteristics of the power generation, nonlinear programming technique is utilized for the optimization purpose. The operating ranges of the input variables are the constraints within which the optimized values of the input variables are to be determined. Interior point solver is used for the NLP based optimization analysis under different initial conditions. Starting from the initial point, the optimizer converges to a feasible solution ensuring the maximum power generation (660 MW) under the applied constrains. The optimized values determined for the maximum power generation are as follows: $\dot{m}_f$ = 235 ± 1 t/h, MST = 569 ± 0.2 ^{o}C MSF = 1994 ± 7 ^{o}C, and RHT = 567 ± 0.2 ^{o}C.

The NLP based optimized values of the input variables are verified to evaluate their effectiveness for the maximum power production. The operating values of the input variables are tried to be maintained around the optimized values of the input variables given the hyperdimensional and complex nature of the power production. The operating conditions are maintained for an hour corresponding to maximum power production and the hourly-averaged observations are recorded for the input and output variables. The procedure is repeated three times and the experimental values of the input variables along with the NLP based optimized values are presented in Figure 7. The % deviation of the optimized values of the input variables with those of actual values (testing phase) corresponding to the maximum power production is calculated. The % deviation among the actual and optimized values of the input variables is as follows: $\dot{m}_f$ (t/h) = 0.28 %, MST (^{o}C) = -0.87 %, MSF (t/h) = 0.10%, and RHT (^{o}C) = - 0.32 %. The negative sign indicates that the experimental values are maintained below the optimized values of the input variables and vice versa. The % deviation values for the input variables is reasonable corresponding to the maximum power production that signifies the effectiveness of the optimized values of the input variables computed by NLP technique having ANN model embedded in.

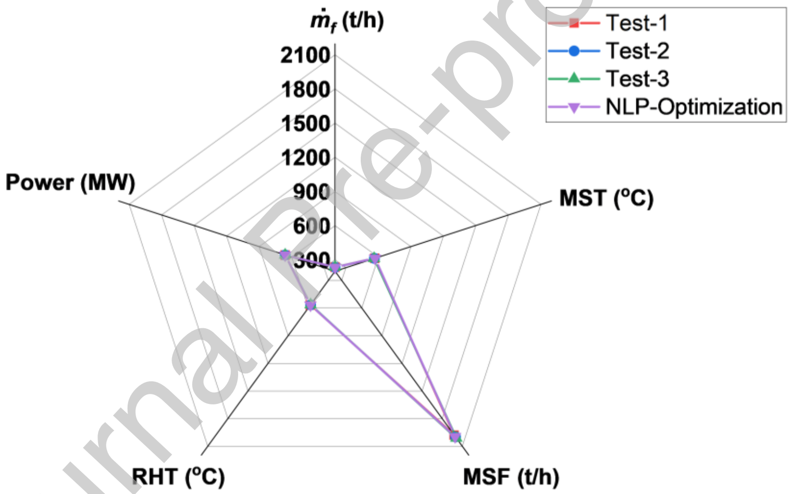


Figure 7. NLP based optimal solutions are investigated on the power generation operation of the power plant. The computed solutions are tested three times named as test-1, test-2 and test-3. A close agreement between the NLP-simulated optimized conditions and the experimental observations is observed for the maximum power generation (660 MW).

Performance analysis for the power generation system

The NLP-simulated optimized values of the input variables are compared with the power generation operation. For this purpose, the historical operational data of the power plant corresponding to the maximum power production (660 MW) is taken and the data-distribution profiles for the input variables ($\dot{m}_f$, MST, MSF and RHT) are presented in Figure 8. The data-distribution profiles are essentially nonlinear indicating the complexity of the power generation operation. The average values of the historical data for $\dot{m}_f$, MST, MSF and RHT is 238 t/h, 565 ^{o}C, 1996 t/h, and 566 ^{o}C respectively and are compared with NLP-driven optimized values of the input variables. It is found that 3 t/h savings in $\dot{m}_f$ is possible for 660 MW power generation by maintaining the power generation operation around the optimized values of the input variables. The identified fuel savings are significant for the same quantity of energy produced by the power plant that can increase the plant-level performance indicators.

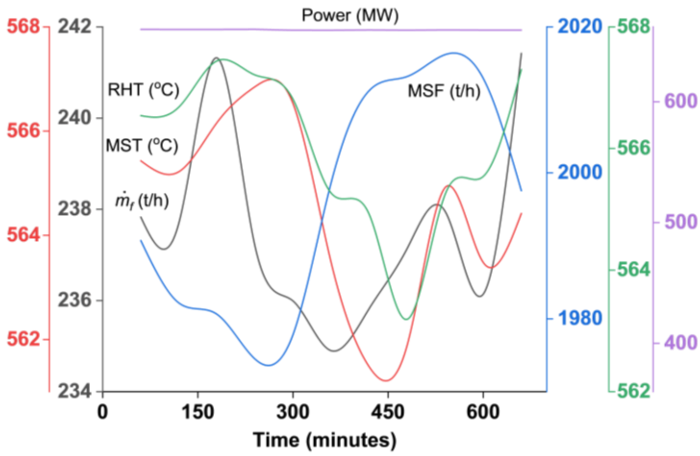


Figure 8. Input variables' data-distribution profiles corresponding to maximum power production (660 MW) based on the historical operational data of the power plant.

Two operating modes, i.e., business as usual (BAU) and the maintaining the power generation operation at optimized values of the input variables (Optimization mode) are considered and the plant-level performance indicators like thermal efficiency and the accumulated emissions discharge comprising on CO_2, N_2O, CH_4, SO_2, and Hg are calculated corresponding to the two operating modes. The emissions discharge is calculated on annual basis and the annual shut down hours, as committed with the power purchasing agency by the power plant management, are not considered for estimating the emissions discharge.

The thermal efficiency of the power plant corresponding to maximum power generation (660 MW) is calculated under two operating modes, i.e., BAU and Optimization. Furthermore, the annual emissions discharge (CO_2, CH_4, N_2O, SO_2 and Hg) from the power plant is calculated according to the Environment Protection Agency (EPA) and European Commission DG Environment guidelines [30-32] for the two operating modes. The formula for calculating the concentrations of emissions (CO_2, CH_4, N_2O, SO_2 and Hg) from the coal-fired power plant is as follows [30, 32-34]:

$$\text{Emission (metric ton)} = Coal\ Quantity\ (pound) \times \text{Lower Calorific Value of coal} \left(\frac{\text{mmbtu}}{\text{metric ton}}\right)$$

$$\times\ Emission\ Factor \left(\frac{\text{kg}}{\text{mmbtu}}\right) \times \left(\frac{1\ metric\ ton}{2204.6\ \text{pound}}\right) \times \left(\frac{1\ metric\ ton}{1000\ kg}\right) \tag{21}$$

For Bituminous coal used at the power plant (24.265 mmBtu/ton heat content), CO_2, CH_4 and N_2O emissions factor taken corresponding to the EPA [31] guidelines are 93.28 kg CO_2/mmBtu, 11 g CH_4/mmBtu and 1.6 g N_2O/mmBtu respectively; SO_2 emissions factor is 417 g/GJ [35] and Hg emission factor is 4.88 mg/mmBtu taken with reference to European Commission DG Environment [32].

Figure 9 presents thermal efficiency (%) and annual emissions discharge (Mt/y) calculated for the two operating modes, i.e., BAU and Optimization, and the savings thermal efficiency, and emissions discharge (kt/y) are also estimated. The thermal efficiency of the power plant corresponding to BAU and Optimization modes is 42.48 % and 43.02 % thereby 1.3% improvement in thermal efficiency of the power plant is achieved relevant to BAU approach. The accumulated emissions discharge from the power plant under BAU and Optimization mode is calculated and is 4.01 Mt/y and 3.96 Mt/y respectively. The savings in emissions discharge is identified and is approximately 50.5 kt/y shown in negative direction on Figure 9. The plant-level performance indicators are improved by maintaining the power generation operation under Optimization mode. The improvement in thermal efficiency and reduction in emissions discharge achieved through smart operation management contributes to net-zero goal from the coal power plant.

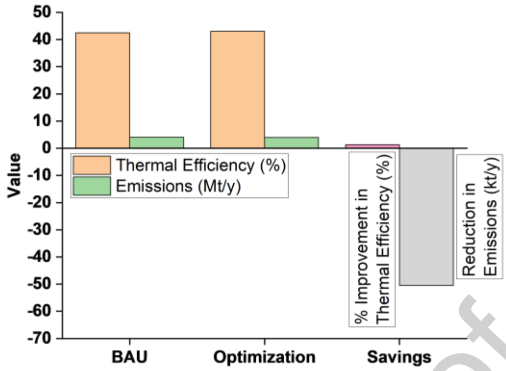


Figure 9. Plant-level performance indicators like thermal efficiency and emissions improved as the result of power generation under optimum operating conditions. The performance indicators are measured corresponding to business as usual (BAU) approach and optimized mode of power generation.

Maximum power generation on the constraint of emissions discharge from the power plant

The optimization problem considering the maximum power generation capacity on the condition of the emissions discharge limit is solved by NLP technique. The upper limit on CO_2, CH_4, N_2O, SO_2 and Hg emissions discharge is calculated to be around 570 t/h considering the maximum consumption of $\dot{m}_f$ and the emissions coefficient, i.e., 2.275 is calculated according to the guidelines by the Environment Protection Agency (EPA) and European Commission DG Environment guidelines [30-32]. The NLP based optimization problem for the maximum power production is solved on emissions discharge limit varying from around 470 t/h to 570 t/h and the Pareto front is presented in *Figure 10*. It is observed that power plant can produce maximum power generation, i.e., 660 MW for the emissions discharge constraint up to 510 t/h. It is explained by the fact that the maximum power, i.e., 660 MW can be produced under different coal consumption rate depending upon how the operator maintains the power generation operation. Thus, we have different operating conditions for the maximum power generation in the training dataset the model is trained on. Moreover, the other input variables also have an impact on the power generation. Thus, the optimized values are determined for the maximum power generation corresponding to the applied emissions constraint under multi-objective optimization analysis. However, decreasing the limit on the emissions discharge, i.e., from 510 t/h to 470 t/h results in the reduction in the maximum power generation from 660 MW to 635 MW. Thus, the maximum power generation capacity of the power plant can be calculated on the applied emissions constraint using the developed ANN model that can enhance the operation excellence and promotes the informed and effective decision making for the power generation operation of the power plants.

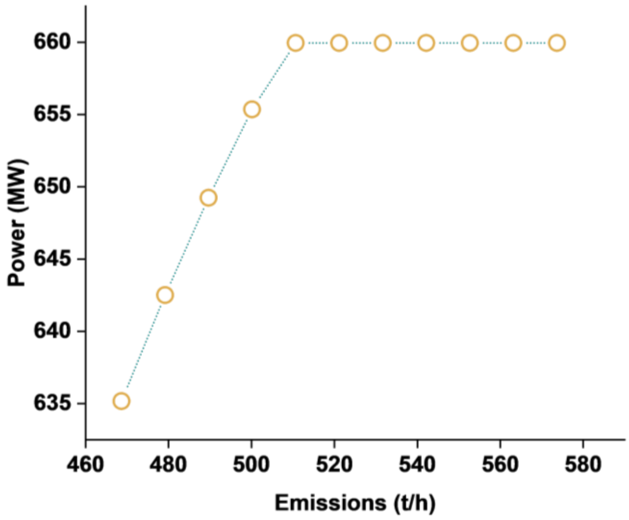


Figure 10. Pareto front for the maximum power generation under the constrained emissions discharge from the power plant.

Conclusions

The energy-efficient power generation operation from the coal power plant is complemented with higher energy efficiency and reduced emissions discharge supporting the net-zero goal from coal power plant. However, the hyperdimensional input space comprising the synchronized operations ranging from component to system level devices presents the challenges to accurately analyse the power generation operation. Therefore, in this work, ANN model is constructed to model the power generation from a 660 MW supercritical coal power plant on the operational relevant input variables, i.e., $\dot{m}_f$, MST, MSF and RHT. A well-performing ANN model is constructed under rigorous hyperparameters tuning, and the model also qualifies the external validation test thereby indicating its good prediction and generalization capacity. Furthermore, the developed ANN model has superior performance measures compared with SVM and ELM model reported in literature.

The partial-derivative based sensitivity analysis is carried out on the developed ANN model. The analysis reveals that MSF is the most significant variable on the power generation bearing the percentage significance value of 75.3 % followed by $\dot{m}_f$, MST and RHT having percentage significance value of 24.3 %, 0.3 % and 0.1 % respectively.

The developed ANN model is integrated in the rigorous optimization environment and the objective (power generation) is maximized by nonlinear programming technique. The optimized values of the input variables corresponding to maximum power production are determined and verified on the power generation operation of the power plant. A good agreement between the actual and NLP-simulated optimized values of the input variables is found corresponding to maximum power generation (660 MW) from the power plant.

3 t/h savings in $\dot{m}_f$ are identified as the result in optimum power generation operation. The plant-level performance measures are investigated corresponding to BAU and Optimization mode of the power plant. 1.3% improvement in thermal efficiency, and 50.5 kt/y accumulated reduction in emissions (CO_2, CH_4, N_2O, SO_2 and Hg) from the coal-fired power plant is estimated. Furthermore, the maximum power generation capacity of the power plant on the applied emissions constraint is also estimated by solving the optimization problem. It is found that maximum power generation capacity of the plant is reduced from 660 MW to 635 MW when emissions discharge constraint is changed from 510 t/h to 470 t/h.

This paper presents the detailed and step-by-step procedure in conducting the data-driven modelling and optimization analysis for the smart power generation operation of the coal power plant. The methodology can be applied on different power generation systems like natural gas, furnace oil etc. In the future work, the global emissions reduction potential estimated by AI based data-driven models integrated in the optimization environment would be investigated for coal and gas power plants and the contribution to the net-zero goal would be made.

Declaration of Competing Interest

The authors declare no competing financial benefits and personal relationships have influenced the findings of the paper.

Acknowledgment

The authors acknowledge the support and resources received from Sahiwal Power Plant to conduct this research. The feedback and knowledge-sharing of the operation engineers is appreciated.

Funding

WMA declares to have received the funding from Punjab Education Endowment Fund (PEEF) to pursue his PhD at University College London.

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Conflict of Interests

The authors declare no competing financial benefits and personal relationships have influenced the findings of the paper.