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Modelling the power output from a steam power plant in Nigeria

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Abstract

Adequate supply of electricity at a competitive price is pivotal to sustainable development. More often than not, the generation of electricity which drives modern growth and development is currently powered by limited fossil fuels in many nations. Electricity generation and megawatt demand are also usually fluctuating due to several pertinent factors. In a bid to articulate the impact of inherent variations in process parameters on the performance of steam power plant at different loads, this paper presents an investigation into the efficacy of two validation strategies in predicting the net power output from the plant using GMDH Shell software. Using the combinatorial algorithm, the k-fold cross-validation strategy and the training/testing validation technique were applied to empirical data of a power plant in Nigeria. The performance of the models returned from the two validation strategies was evaluated using maximum negative error, maximum positive error, mean absolute percentage error (MAPE), root mean square percentage error (RMSPE), residual sum, the standard deviation of residuals, coefficient of determination (R^2) and correlation. For the number of folds and the training/testing split percentage considered in this study, results show that both models obtained were quite competitive, with the k-fold model having a slight edge over the other model. It is expected that the outcome of the study will be handy in researches for providing knowledge base information on choosing and setting optimum operating conditions at various load demand.

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Keywords: Power generation; Fossil fuels; Sustainability; Megawatt demands; Process variables; Artificial intelligence; Models

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1. Introduction

Sustainable development is hinged on the constant and adequate supply of energy at a competitive price [1–11]. Nigeria, with a population of over 190, 000, 000 people, has a per capita energy consumption far below what is prescribed for meaningful and sustainable development. This is not necessarily due to lack of demand but lack of means to meet the energy demand. Although several power plants have been installed across the country and there are plans for future expansion to cater for the energy needs of the populace, the installed capacity which currently stands at about 12500 MW is much lower than the required 190, 000 MW population-based projection for an economically developing nation [12]. Most of the existing power plants utilize dwindling fossil fuels and generate output below their installed capacity due to factors like inefficient operating conditions, and short supply of primary fuels.

Hence, like every other industrial process where production target is seldom static, the power generating plants regularly have to operate at off-design or partial load conditions because of short supply of fuels and periodical power demands. Changes in megawatt demand (load variation) have been reported to result in changes in the efficiency of the power plant [13,14]. This is as a result of the changes in process parameters that accompany changes in megawatt demand. Of these process parameters, change in superheated steam temperature has been reported to have the most significant effect on the efficiency of steam power plants [14]. Therefore, effective control is necessary to maintain the superheated steam at the optimum temperature. Other vital parameters also have to be precisely controlled and maintained at desired values required for the target performance of the plant.

As such, there is a need to identify operating conditions that will maximize the efficient running of the plants at a given load. Maximizing the power output from the plant for a specific amount of fuel that is fired, will ensure the conservation of the dwindling nonrenewable fossil fuels and also help in minimizing the impact of electric power generation on the environment. In other words, knowing the minimum amount of fuel and optimum values of essential process parameters required to meet a specific megawatt demand would help in curbing the waste of limited energy sources; reducing emission; lowering the cost of power generation and the price at which electric power is available to the consumers. Furthermore, it will help put the existing installed electricity capacity and the proposed ones into optimal use for meeting the energy demands of the populace. This will also assure increased returns on power generation investments, and an improved economy as a result of the ripple effect of increased supply of electricity at a reduced price.

To be able to identify optimum operational conditions and retain them at the desired set values (perhaps, at various loads), the study of the effect of changes in process variables on an output parameter of interest is imperative. As mentioned earlier, the control mechanism has to be in place. Adequate controls thrive on effective models which relate the decision and response variables involved in a process to one another. For the realization of optimum use of energy sources and the installed power capacity, accurate models which could capture the contributions of relevant input parameters to the understudied output parameters are essential. In place of rigorous models which are based on in-depth knowledge of engineering, mathematics, physics and other scientific principles inherent in the process of power generation, functional determination of the relationship between the process variables and their contribution towards various performance indices can be quickly and adequately deciphered through artificial intelligence (AI) based modelling [15]. In addition to this, incorporating AI-based data-driven model into the monitoring system of plants have been established to provide real-time anomaly detection in affected sections of a plant [16–18].

This study is, therefore set out to effectively model the net power output from a thermal power plant when certain operating conditions are varied.

2. Methodology

A steam power plant in Nigeria, which is initially designed to generate 220 MW at full capacity, was used for this study. The plant basically comprises the boiler, the turbine section, auxiliary plant equipment and power generator. Natural gas is supplied at reduced pressure to the boiler, and combustion air is delivered by two 50% duty forced draft fans to generate the heat needed to raise the temperature of feedwater and reheat steam. The turbine section is a significant part of the steam cycle of the plant. The turbine section comprises of three parts, which are the high-pressure turbine (HPT), intermediate pressure turbine (IPT) and the low-pressure turbine (LPT). The generator utilizes the mechanical energy generated by the turbines to produce alternating current. The steam condenser, air ejectors, condensate extraction pumps, boiler feed pumps and feed heating trains of low-pressure heaters & high-pressure heaters form part of the equipment that closes the steam cycle.

At full load, the heat generated from the combustion of fuel in the boiler is used to produce superheated and reheated steams from the feed water supplied by the boiler feed pump and the HPT exhaust respectively. The superheated steam coming out of the boiler at a pressure of about 12500 kPa and a temperature of approximately 540 °C turns the high-pressure turbine at a speed of 3000 rpm. Reheated steam turns the intermediate turbine whereas the exhaust steam from the intermediate turbine turns the low-pressure turbine. The generator coupled directly to the rotor of the turbine also turns at 3000 rpm. It generates a 3-phase AC power of 220 MW at full capacity through the cumulative mechanical energy from the turbines. The exhaust steam from the low-pressure turbine at a pressure of 8.5 kPa is condensed to water in the condenser. The treated flue gas is exhausted to the atmosphere through the stack after passing through the gas–air heaters.

To capture the effect of input process parameters on the plant's output when there is a departure from the designed load, working data was extracted from the steam power plant's empirical data spanning from September 1st 2018–March 21st 2019. This data was used to study how process variables such as fuel flowrate, air–fuel mass ratio (AFR), steam flow rate, temperature & pressure of steam entering the high-pressure turbine affect the net power output from the plant. A base case simulation of the steam power plant at full load was carried out with the aid of HYSYS 8.8. While other process parameters were kept constant, the five process variables listed earlier were simultaneously varied, and the net power output was obtained for each case. These datasets for each case served as input and output data for the ANN modelling of the plant's net power output. In this study, the values for the explanatory variables ranged from 30.53–50.19 T/h, 24.14–27.14 : 1, 494.00 − 653.90 T/h, 534.04 − 542.51 °C, and 12.44–12.53 MPa for fuel flowrate, AFR, steam flow rate, temperature & pressure of steam entering the high-pressure turbine, respectively

GMDH Shell DS 3.8.9 software was used for the modelling of the behaviour of the power output for changes in the input process parameters. With the aid of the neural network functionality of the software, the training/testing and the k-fold validation strategies were explored in the modelling study to obtain valid mathematical models of the net power output from the steam power plant. The combustion air for this study was taken to be 79 mole% nitrogen and 21 mole% oxygen. The composition of the fuel and the underlying combustion condition are given in Tables 1 and 2, respectively.

Table 1. Natural gas composition.

Component	CH_4	C_2H_6	C_3H_8	CO_2	N_2
Mole fraction	0.894	0.086	0.004	0.006	0.010

Table 2. Typical combustion data at full load.

Stream	Mass flow (kg/h)	Temperature (°C)	Pressure (kPa)
Air	1330356	30	865
Natural gas	50190	27	243
Combustion product	1380537	1432.172	243
Flue gas	1380537	387.87	241

3. Results and discussion

Since plants do not always operate at full capacity and process parameters are rarely constant when power plants operate off-design load, the study of the effect of pertinent process parameters on the power output from power plants is highly imperative if the process of power generation is to be carried out at optimum conditions at all megawatt demands. The effect that flow rate of superheated steam, its inlet temperature & pressure into the high-pressure turbine, fuel flow rate, and air–fuel ratio has on the net power output have been simulated with the aid of HYSYS using the extracted operational data of the steam power plant. A priori knowledge of the steam plant operation guided the selection of the process variables as the outcome of the HYSYS simulation served as the dataset for the ANN-modelling of the inherent relationships between the parameters. An inspection of the HYSYS simulation outcomes of variation in operating conditions shows that the flow rate of superheated steam into the high-pressure turbine was generally directly proportional to the net power output. Mere visual observation of the data was not sufficient to draw cogent inference on the effect of other variables on the power output in this lumped parameter study.

The k-fold and training/testing validation strategies were explored to obtain plausible & reliable descriptive & predictive mathematical relationship between the power output and the selected process parameters. In both cases, twenty percent of the dataset were held out uniformly for an unbiased evaluation of the final model fit. For the k-fold validation strategy considered in this study, the dataset was split into two parts, and the model was trained twice using one part at a time. Each time, model performance is measured using the remaining part. Finally, the residuals obtained from both testing parts were added and used for model comparison. For the training/testing validation technique, the dataset was split into two equal (50%:50%) parts. The training part was used to find model coefficients, and the remaining part was used to tune the hyperparameters of the model. The Combinatorial GMDH algorithm which gradually complicates models and selects a set of models that show highest forecasting accuracy at the previously unseen data (the holdout dataset) were applied in both the k-fold and training/testing cases.

Prediction outcomes of net power output using 2-fold validation and training/testing strategies are given in Figs. 1 and 2. Predicted values were quite close to the actual values using both strategies. Further evaluation of the modelling performance carried out using standard statistical metrics is presented in Table 3. It is observed that both strategies resulted in competitive performances both at the model fit and prediction phase. Apart from the maximum positive error and the mean absolute percentage error (MAPE) at the prediction phase, the model obtained through the 2-fold cross-validation strategy performed slightly better than the training/testing validation strategy. Based on most of the statistical metrics, the models obtained through both strategies generally performed better at the model fit phase. The maximum MAPE and RMSPE were recorded at the prediction phase. For model obtained using the test/training validation strategy, the values were 0.012% and 0.019%, respectively. The corresponding values for the model obtained through the k-fold validation strategy were 0.015% and 0.019%. Models obtained through both approaches show a perfect correlation between the net power output and the process variables. The raw model returned for the 2-fold cross-validation, and the training/testing validation strategy is given in equation (1) and (2) respectively. As indicated in the raw models, the process variables that are perfectly correlated to the net power out are superheated steam temperature & pressure into the high-pressure turbine and steam flowrate for the model obtained through 2-fold cross-validation strategy. In contrast, all the selected five process variables were correlated to the net power output in the model obtained through the test/train validation strategy.

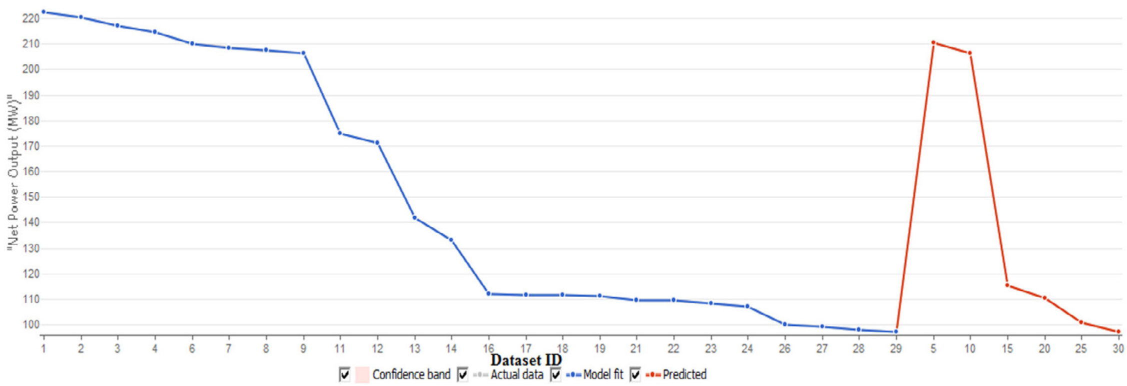

Fig. 1. The plot of predicted net power output using k-fold validation strategy.

Further analysis of the models using the impact of the process variables on the root mean square error (RMSE) indicated that the steam flowrate is the most important explanatory variable. The value 1 for the coefficient of determination for both models is an indication of a perfect fit. Thus, both models obtained through the 2-fold cross-validation and the training/testing validation techniques can equally be considered as highly reliable for a future forecast

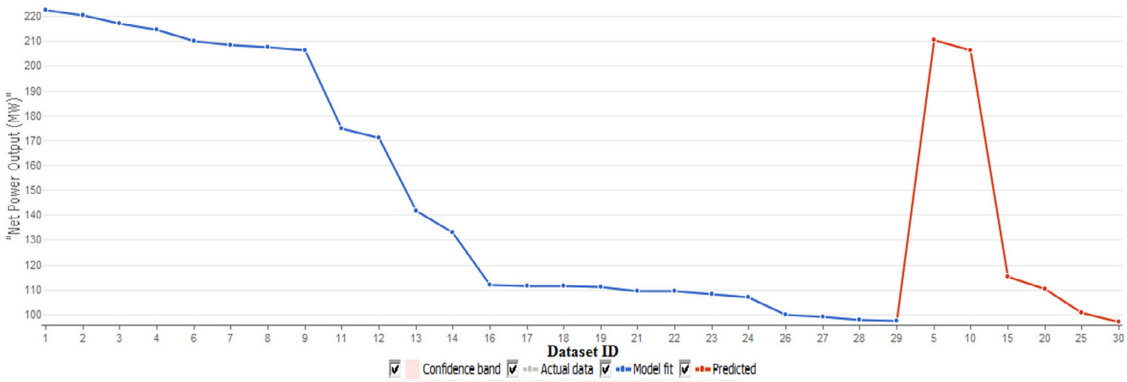

Fig. 2. The plot of predicted net power output using training/testing validation strategy.

Table 3. Model evaluation and performance.

Net power output	k-fold validation strategy		Training/testing validation strategy	
Post-processed results	Model fit	Predictions	Model fit	Predictions
Max. negative error	−0.0339205%	−0.0330088%	−0.0372871%	−0.0404245%
Max. positive error	0.0305637%	0.0282935%	0.0255463%	0.0224616%
Mean absolute percentage error (MAPE)	0.0101506%	0.0148443%	0.0103777%	0.0123703%
Root mean square percentage error (RMSPE)	0.013479%	0.0187021%	0.0140459%	0.0190458%
Residual sum	$1.91929E-12\%$	−0.00141718%	−0.00187292%	−0.00280179%
Standard deviation of residuals	0.0134789%	0.0186525%	0.0139553%	0.0187203%
Coefficient of determination (R^2)	1	1	1	1
Correlation	1	1	1	1

$$
\begin{aligned}
Y1 = {} & -287.574 + \text{“Steam Temperature (°C)”} * \text{“Steam Flowrate (T/h)”} * 0.000724232 \\
& + \text{“Steam Pressure (MPa)”} * \text{“Steam Flowrate (T/h)”} * (-0.00308803) \\
& + \text{“Steam Flowrate (T/h)”} * 0.42903
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
Y1 = {} & -287.496 + \text{“Natural Gas Flowrate (T/h)”} * \text{“AFR ”} * (-6.30851e-05) + \text{“AFR”} \\
& * \text{“Steam Temperature (°C)”} * 0.00129843 + \text{“AFR ”} * \text{“Steam Pressure (MPa)”} \\
& * (-0.0565353) + \text{“Steam Temperature (°C)”} * \text{“Steam Flowrate (T/h)”} * 0.000669839 \\
& + \text{“Steam Flowrate (T/h)”} * 0.420037
\end{aligned} \tag{2}
$$

where Y1 is the net power output from the steam power plant.

4. Conclusion

The knowledge of the role of an individual parameter in the multi-variable process of power generation is vital to achieving improved plant performance at any given megawatt demand. In this study, the k-fold cross-validation strategy and the training/testing validation technique have been explored to model the net power output of a steam power plant with a design capacity of 220 MW. Using the GMDH combinatorial algorithm, empirical data from the plant located in Nigeria was adopted for the model fit and final evaluation of the models generated. The dataset comprised of fuel flowrate, air–fuel mass ratio, steam flow rate, temperature & pressure of superheated steam into the high-pressure turbine as the input parameters, while net power output was the output parameter. The GMDH combinatorial algorithm proved to be highly effective for the predictive modelling of the net power output. Both models obtained through the validation strategies employed are deemed to possessed excellent descriptive and predictive capabilities based on the evaluation carried out using a number of standard model evaluation criteria. However, based on the evaluation measures, the model obtained via 2-fold cross-validation technique is adjudged to perform slightly better than the model obtained when an equal data split was used in training/testing validation strategy. On the other hand, while the model which was returned by the equal data split training/testing validation strategy captured the contributions of all the five input parameters to the observed output parameter, the 2-fold cross-validation model captured the contributions of superheated steam temperature, pressure and flow rate into the high-pressure turbine.

It is expected that the models that have been developed will serve as veritable tools for optimization and control studies. At a given load, the models should be able to facilitate identification of optimum values of process parameters and maintaining them at the optimum values; thereby ensuring optimum performance of existing installed capacity and increasing the chances of adequately meeting the ever-growing need for electric power with minimum energy resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Figs. 3 and 4.

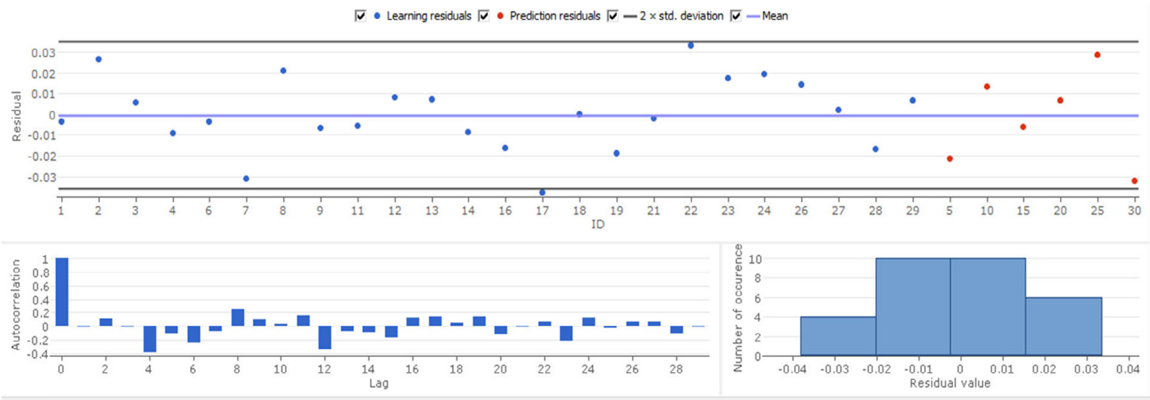

Fig. 3. Residual plot of predicted net power output using k-fold validation strategy.

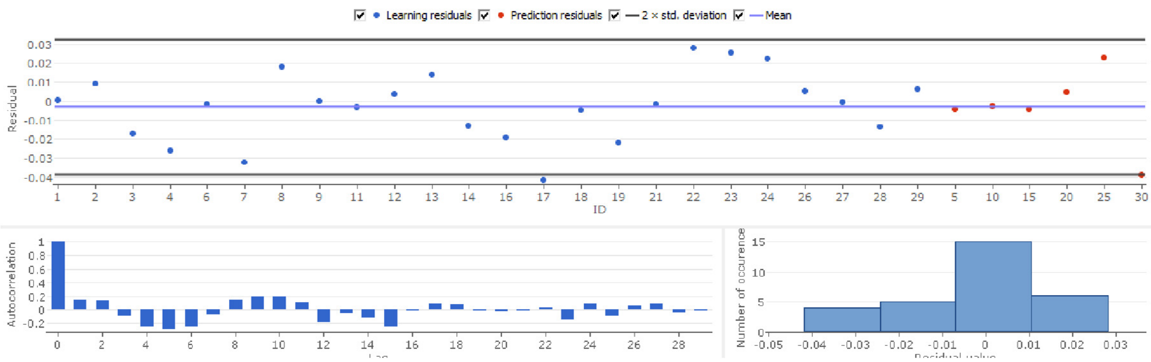

Fig. 4. Residual plot of predicted net power output using training/testing validation strategy.

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