Modeling Steam Power Plant Condenser Vacuum under Off-design Conditions: A Statistical Approach

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***Abstract*—For a steam power plant, condenser vacuum is an important variable to monitor. Insufficient condenser vacuum can cause high heat rate. An approach is proposed to modeling condenser vacuum based on the autoregressive-moving-average (ARMA) combined with the generalized-autoregressive-conditional-heteroscedasticity (GARCH) technique. It makes use of data available from a generating unit of the Asam-asam Steam Power Plant over a period when the unit was running under severe off-design conditions. In that period, the unit experienced poor condenser vacuum. The data contain observations on variables, some of which are important for studying conditions regarding condenser vacuum at the unit. The resulting models can explain how condenser vacuum varies in response to changes in conditions. The predictive performance is comparable to that obtained using autoregressive neural network and support vector regression. Further remarks on the modeling issues are given.**

***Keywords*—ARMA-GARCH, condenser vacuum, off-design condition, statistical modeling, steam power plant**

I. INTRODUCTION

Steam turbines are designed to operate under fixed, assumed conditions [1] while fluctuating and deteriorating conditions occur during the lifetime of the plants. The importance of studying off-design performance of power plants cannot be understated as many suggest [2–9]. One of such conditions is insufficient condenser vacuum. Condenser vacuum is an important variable to monitor and to control in a steam power plant [10]. Any decrease in condenser vacuum (commonly caused, among others, by leakage and excessive air ingress) would increase heat rate and, therefore, operation cost [11].

Operation data from the Asam-asam Steam Power Plant in South Kalimantan Province of Indonesia reveal a period where the generating unit number 2 or Unit 2 (with rated capacity of 65 MW) of the power plant was running under rather severe off-design conditions. One indication of this is the insufficient vacuum in its shell-and-tube condenser. In that period, the best vacuum was –0.0755 MPag. This value had increased quite significantly above the required pressure, which should be around –0.09 MPag as measured when it was first commissioned in 2000. This condition, probably combined with several others, led to alarmingly high observed values of the exhaust hood temperature of the turbine with a potential to cause the entire unit to trip.

With condenser vacuum as a variable of interest, it is important to understand and to be able to explain how it behaves in response to variations in other variables and changes in conditions. Modeling the relationships among these variables is an essential step toward understanding and predicting their actual behaviors. In particular, information on such behaviors under off-design conditions may not be available during the design phase but is needed by engineers responsible for running the system.

For control purposes, several methods have been proposed for predicting condenser vacuum values as recently reported in [12–14]. Most are based on machine learning techniques such as regression techniques, neural network, and the increasingly popular long short term memory. Except for regression, a model of this type tends to behave like a 'black box' and has limited practical use when it comes to explaining the variation in condenser vacuum. Few statistical models have also been proposed, e.g., in [15–17] for monitoring power plant performance by utilizing operation data. The problem with most of them is that they assumed that observations are not autocorrelated over time. Such an assumption is prone to violation especially when the data reflect severe off-design conditions.

This paper proposes an approach toward modeling condenser vacuum by considering the nature of time series data that reflect off-design conditions. The resulting model should be capable of uncovering how condenser vacuum behaves in response to changes in conditions despite various effects in the time series data. In that way, the model can behave like a 'white box' that presents the relationships among variables based on statistical inference and in an explanatory way.

II. METHOD

A. Model Structure

Since changes in load take place randomly at all times followed by adjustments in power generation [18], other system variables are also considered in the model as explanatory variables or external regressors. The criteria for selecting such variables include the importance of their contribution to the variation in condenser vacuum and their proximity to where condenser vacuum takes place. All in all, the choice should be both theoretically sound and a reflection of operational knowledge about the system. One obvious choice in particular is the generator active power, which is the power that is eventually used to meet the load demand. It is also important to follow the parsimony principle [19].

Serial correlation or autocorrelation is first dealt with using the *autoregressive moving average* (ARMA) part [20]:

$$\left(1-\sum_{i=1}^{p}\varphi_i L^i\right)\left(y_t-\mu-\sum_{i=1}^{k}\delta_i x_{i,t}\right)=\left(1-\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \quad (1)$$

where y_t is the tth observation on condenser vacuum, $x_{i,t}$ is the tth observation on the ith of k explanatory variables or external regressors, ε_t is tth observation error, L is the lag operator such that $L^i y_t = y_{t-i}$, and parameters μ and δ_i's are the regression coefficients. Additional model parameters are φ_i's (i = 1, …, p) and θ_i's (i = 1, …, q). This *mean model* with $\mu_t = \mu + \sum_{i=1}^{k} \delta_i x_{i,t}$ as the *conditional mean* of y_t, is a demeaned version of the famous ARMA(p, q) model, where p = q = 1, 2, …. This model assumes that σ_t^2, which is the *conditional variance* of y_t, is constant, a condition known as *homoscedasticity*. This assumption is also very often violated.

Heteroscedasticity (the opposite of homoscedasticity) is taken care of by modeling variance σ_t^2 using a *generalized autoregressive conditional heteroscedasticity* (GARCH) part [21, 22]. This is the *variance model*. GARCH models are a class of statistical models successfully used in predicting the *volatility* of returns on financial assets. There is no general agreement on the definition of volatility. It can either mean conditional standard deviation or conditional variance. Three GARCH(a, b) models considered in this paper include

- The standard GARCH or sGARCH(a, b) model [22]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \varsigma_i v_{i,t} + \sum_{i=1}^{a} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{b} \beta_i \sigma_{t-i}^2 \qquad (2.a)$$

  where $v_{i,t}$ is the tth observation on the ith external regressor of the variance model, and ω, ς_i, α_i, and β_i are the model parameters.

- The Glosten-Jagannathan-Runkle GARCH or gjrGARCH(a, b) model [23]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \varsigma_i v_{i,t} + \sum_{i=1}^{a} \left(\alpha_i \varepsilon_{t-i}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2\right) + \sum_{i=1}^{b} \beta_i \sigma_{t-i}^2 \qquad (2.b)$$

  where I_t is 1 for $\varepsilon_t \le 0$ and 0 otherwise for all t, and γ_i is the 'leverage' parameter. Notice how a negative value of the previous ε_{t-1} can bring a 'shock' to σ_t^2. That is leverage.

- The exponential GARCH or eGARCH(a, b) model [24]:

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{k} \varsigma_i v_{i,t} + \sum_{i=1}^{a} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - E|z_{t-i}|\right)\right) + \sum_{i=1}^{b} \beta_i \sigma_{t-i}^2 \qquad (2.c)$$

  where $z_t = \left(y_t - \mu - \sum_{i=1}^{k} \delta_i x_{i,t}\right) / \sigma_t$ and the expectation of $|z_t|$ is given by $E|z_t| = \int_{-\infty}^{\infty} f(z_t) dz_t$. Here, $f(z_t)$ is the probability density function of the conditional distribution of z_t.

A conditional distribution is chosen for z_t. Several probability distributions are considered including the well-known normal and Student's t distributions and their skew variants [25].

Notice how the combined model handles the time series in two separate parts simultaneously: the ARMA mean model and the GARCH variance model, with each one now representing a time series. The method works because the effect of heteroscedasticity is now captured through changes in σ_t^2 in (2) and, subsequently, in z_t that has its own conditional probability chosen to fit ε_t. Without (2), (1) would be fitted regardless of changes in σ_t^2. The fact that both parts accommodate information brought by external regressors makes the modeling approach even more useful for this study.

B. Model Estimation, Testing, and Selection

All parameters in (1, 2) along with parameters of the chosen conditional distribution have to be estimated simultaneously using the method of maximum likelihood [26]. The 'rugarch' package [27] in R statistical programming language [28] offers functions for that purpose and is used in this paper. With four conditional probability distributions and three GARCH models, 12 sets of models are estimated for every unique combination of (p, q, a, b).

With all parameters in a resulting model substituted by their corresponding estimates, the tth residual, i.e., the estimate of ε_t is computed sequentially by setting initial (t = 0) observations equal to zero in (1). Fitted values are obtained by subtracting these residuals from the corresponding observations.

If an ARMA-GARCH model does fit the data, the residuals have to be independent from and identically distributed as each other (or iid). In other words, the model, in terms of its residuals, has to pass a number of significance tests.

Each resulting ARMA-GARCH model is tested for serial correlation in the residuals using the Ljung-Box test [29], autoregressive conditional heteroscedasticity using the ARCH-LM test [22], effects of leverage on residuals using the sign bias test [30], and distributional fitness using the Pearson goodness-of-fit test [31]. The stability of estimates is also tested using the Nyblom test [32]. The significance level is 0.05. The model passes a test if the test result is not significant. All the tests are covered in the R package mentioned above. To select between two competing models the Akaike Information Criterion (AIC) [33] is taken as the criterion. A low AIC is preferred.

C. Model Analysis and Performance Testing

The selected model is studied by looking at the estimates of its parameters. These estimate values should be able to reveal how condenser vacuum behaves in response to variability in operating conditions. Further tests based on the z-test (normal test, or t-test with infinite degrees of freedom) are required for these estimates to decide whether certain relationships in the model are significant or just due to mere chance. Decisions are based on a significance level of 0.05.

The prediction performance of the ARMA-GARCH model is then compared to the performance of autoregressive neural network (NNAR) [34] and the support vector regression (SVR) [35]. The 'forecast' [36] and 'e1071' [37] packages in R provide the required tools for NNAR and SVR computations, respectively, in this study. The metrics include the usual mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), median absolute error (MDAE), relative absolute error (RAE), and root mean squared error (RMSE) [38]. Small values for these metrics are preferred.

III. Results and Discussions

A. Data Description

A volume of operation data of the Asam-asam Steam Power Plant is available from a period around which relatively severe off-design conditions were experienced at Unit 2 in relation to condenser vacuum. The original observations were obtained on 138 system variables. They were taken in the interval of 2 or 3 hours resulting in 11 observations per variable every 24 hours (the company's standard log sheet format).

A batch of data containing 143 observations is available from Unit 2 (13 consecutive days: from 1 Dec 2016 to 13 Dec 2016). They are split into the first 121 observations as training data and the remaining 22 observations as testing data referred to here as Set A and Set B, respectively.

Since the original observations are not equally-spaced, they are transformed from 11 observations per day to 12 by simple interpolation. A two-hour interval is created between two adjacent transformed values. The fitted or predicted values are transformed back into 11 values per day with the original intervals.

B. Modeling Condenser Vacuum

Two other variables (k = 2) are considered as external regressors in (1) to fit the model, i.e., active power (MW) and cooling water inlet temperature (°C). Active power is a major indicator. Power is generated to meet the load demand. To stabilize supply voltage and frequency, it varies in response to demands [18]. The need to generate power dictates how other variables behave. Meanwhile, cooling water inlet temperature immediately affects heat transfer inside the condenser and, therefore, is considered as another external regressor.

The modeling focus is initially on a simple combination of (p, q, a, b), i.e., (1, 0, 1, 1). Simpler combinations either fail in a significance test or produce higher AIC values. Models obtained by adding more variables such as main steam flow, main steam temperature, and/or main steam pressure also tend to result in higher AIC values or fail in some tests. The same also happens to models that take only one external regressor.

Of the 12 models for the (1, 0, 1, 1) combination, an ARMA(1, 0)-eGARCH(1, 1) model with a Student's t distribution as the conditional distribution gives the lowest AIC of –8.4511. The variance model does not take any external regressor. The shape parameter of the conditional distribution is estimated to be $\hat{\nu}$ = 3.70598. The symbol "^" indicates the maximum likelihood estimator of the corresponding parameter. By referring to (1 and 2.c), the remaining estimates are as follows:

- $\hat{\mu}$ = –1.38599, $\hat{\delta}_1$ = 0.00465, and $\hat{\delta}_2$ = 0.01145. All are significant. This implies that the conditional mean of condenser vacuum at any time t is significantly related active power (by a factor of 0.00465) and cooling water inlet temperature (by a factor of 0.01145) at that time.
- $\hat{\varphi}_1$ = 0.71499. It is significant. This suggests that autocorrelation is present.
- $\hat{\beta}_1$ = 0.41352, $\hat{\gamma}_1$ = 0.73569, $\hat{\omega}$ = –6.61990, and $\hat{\alpha}_1$ = –0.14397, and. The first three are significant and the last one is not. This means that σ_t^2 is also serially correlated in (3.c), it implies heteroscedasticity. No significant relation is evident between σ_t^2 and y_{t-1}, where the latter is encapsulated in z_{t-1}.

After being transformed back to 11 observations per day, fitted values are plotted along with the actual observations in Fig. 1. RMSE of the fitting is 0.000536 MPa after the fitted values are transformed back into 11 observations per day.

Based on $\hat{\delta}_1$ and $\hat{\delta}_2$, it can be confirmed that condenser vacuum is systematically related to both active power and cooling water inlet temperature at Unit 2. The positive values of both $\hat{\delta}_1$ and $\hat{\delta}_2$ further suggest that an increase in any of the corresponding variables explains an increase in the expected value of condenser pressure.

Since the system works in a cycle, the relationship between condenser vacuum and its external regressors may go both ways to some extent. In a normal operation mode, however, active power is generated to meet the load demand regardless of condenser vacuum. Condenser vacuum does affect how active power is generated, that is, it affects heat rate [11].

Changing lags from (1, 0, 1, 1) does not seem to produce a successful model in term of the significance tests. Table I shows the effects of varying the lag parameters on the above ARMA-eGARCH model.

C. Predictive Performance

Although prediction is not the intension of deriving models in this study, predicting condenser vacuum y_t is quite straightforward given active power $x_{1,t}$ and cooling water inlet temperature $x_{2,t}$. Using the test data Set B, a comparison of predictive performance is made among ARMA(1, 0)-eGARCH(1, 1), NNAR, and SVR as shown in Table II and Fig. 2. The NNAR model is based on 50 networks, each of which is a 2-2-1 network with 9 weights, 1 lag, and 2 hidden

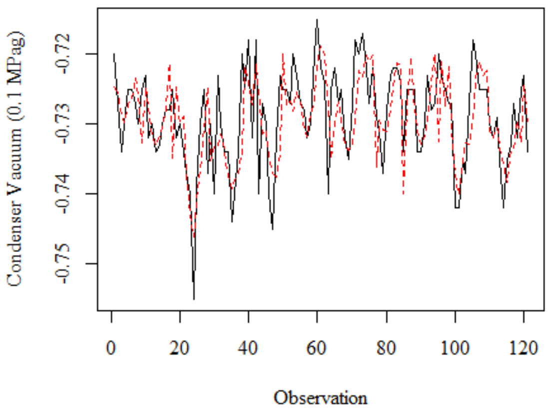

Fig. 1. Vacuum actual values (—) versus fitted (- - -)

TABLE I. VARYING LAG PARAMETERS

p	*q*	*a*	*b*	Effect
1	1	1	1	Significant in Ljung-Box, Nyblom tests
2	0	1	1	Significant in Ljung-Box, Nyblom tests
1	0	2	1	Significant in Nyblom test
1	0	1	2	Significant in goodness-of-fit test
1	0	2	2	Significant in Nyblom test
1	2	1	1	Significant in Ljung-Box, Nyblom tests
2	1	1	1	Significant in Ljung-Box test
1	2	2	1	Significant in Ljung-Box, Nyblom, goodness-of-fit tests
1	2	1	2	Significant in Ljung-Box test

nodes. It is optimized over AIC. The ε-SVR is based on radial kernel, $\gamma = 1$, tuned for ε and cost.

In real situations, $x_{1,t}$ and $x_{2,t}$ would not be available and have to be predicted as well. Table III shows results for this based on performance metrics averaged over 100 runs for each model. For the ARMA-GARCH model, active power and cooling water inlet temperature are predicted based on an ARMA(1, 1)-eGARCH(2, 2) model with a skew Student's *t* distribution and an ARMA(2, 0)-eGARCH(1, 1) model with a Student's *t* distribution, respectively. Both are without external regressors. The predictive performance of the ARMA-GARCH model is comparable to that achieved using NNAR and SVR.

D. A Comparison to a Similar Generating Unit

Another generating unit in the thermal plant is Unit 1. This is practically identical to Unit 2 and was also commissioned in 2000. It also experienced poor vacuum, though slightly better, around the same period as Unit 2. Data containing 110 observations (from 22 Dec 2016 to 31 Dec 2016) from Unit 1 are also available.

Table IV compares important statistics from Unit 1 and Set A of Unit 2. These statistics suggest that good or poor condenser vacuum is related to good or poor exhaust hood temperature and active power generation. High observed values of exhaust hood temperature often indicate heat accumulation at the low-pressure stage of the turbine. This is likely due to low-pressure steam unable to freely enter the condenser because of high pressure (poor vacuum) inside the shell. If this continues for a long period, the effect could be catastrophic for the turbine blades as well as other parts.

Although the off-design conditions at Unit 1 are not particularly impressive, they still allowed the unit to perform

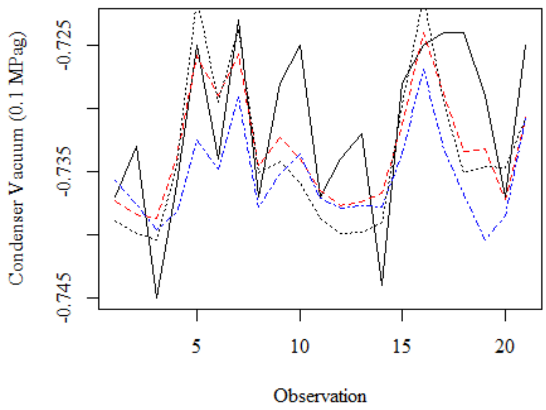

Fig. 2. Prediction based on Set B: actual (—), ARMA-GARCH(- - -), NNAR (- · -), SVR (· · ·)

relatively better than Unit 2. More importantly, they did not appear to potentially lead to a possible emergency shutdown.

Fitting another ARMA(1, 0)-eGARCH(1, 1) model of condenser vacuum at Unit 1 with active power and cooling water inlet temperature as the external regressors and a Student's *t* distribution as the conditional distribution produces an AIC value of –8.8187. The variance model takes no external regressor. The corresponding RMSE is 0.000558 MPa. Apparently, two models with the same specifications fit both data Set A and data at Unit 1 despite the difference in the severity of the off-design conditions at both units.

It is not common to assess the variation of the response variable of an ARMA-GARCH model in term of *explained variance* as in linear models. This is the proportion of variance of the response variable that is due to the mean model, while an ARMA-GARCH model represents both the mean and the variance. However, to put things in the perspective of a linear model, the proportion of variance explained by the mean model can be measured using the *coefficient of determination* as follows:

$$R^2 = 1 - \frac{n-1}{n-m} \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \tag{3}$$

where $\hat{y}_t$ is the fitted value of y_t as given by the model and $\bar{y}$ is the sample mean. With m = 1, (3) gives the (ordinary) coefficient of determination. Setting m equal to the number of parameters in the model that are estimated results in the adjusted coefficient of determination R^2_{adj}. This coefficient is computed using values that are immediately fed to and returned by the model.

The ARMA(1, 0)-eGARCH(1, 1) model at Unit 1 gives R^2_{adj} = 0.9152. This means that if the variation is seen only

TABLE II. PREDICTIVE PERFORMANCE ON SET B

Metric	ARMA-GARCH	NNAR*	SVR*
MAE$^+$	0.0055	0.0065	0.0062
MAPE	0.0075	0.0089	0.0085
MASE	0.7184	0.8499	0.8109
MDAE$^+$	0.0059	0.0069	0.0057
RAE	1.0098	1.1946	1.1398
RMSE$^+$	0.0064	0.0076	0.0071

* vary due to random weights and tuning; $^+$ in 0.1 MPa

TABLE III. AVERAGE PREDICTIVE PERFORMANCE ON SET B

Metric	ARMA-GARCH	NNAR*	SVR*
MAE$^+$	0.0050	0.0057	0.0070
MAPE	0.0069	0.0079	0.0095
MASE	0.6583	0.7494	0.9068
MDAE$^+$	0.0048	0.0044	0.0062
RAE	0.9253	1.0533	1.2746
RMSE$^+$	0.0062	0.0073	0.0086

* vary due to random weights and tuning; $^+$ in 0.1 MPa

TABLE IV. COMPARING UNIT 1 AND UNIT 2

Variable	Statistic	Unit 1	Unit 2
Condenser vacuum (0.1 MPag)	Average	–0.784	–0.729
	Median	–0.782	–0.728
Exhaust hood temperature (°C)	Average	61.6	65.9
	Median	62.0	65.8
Active power (MW)	Average	56.81	55.71
	Median	57.34	55.95

from how the conditional mean varies, the model explains 91.52 percent of the variance of condenser vacuum at Unit 1 for the operation period described by the corresponding data. By the same reasoning, the mean model explains a mere 63.01percent of the variance of condenser vacuum at Unit 2; this is based on the previous ARMA(1, 0)-eGARCH(1, 1) model with data Set A and the resulting $R^2_{\text{adj}} = 0.6301$.

Although these proportions of variance explained may not be accurate for an ARMA-GARCH model, they are quite indicative about the difference between two off-design conditions at two supposedly identical units. At Unit 1 where poor vacuum seemed to send no concerning signals in the form of high exhaust hood temperature, a high proportion of variations in condenser vacuum were adequately explained by the mean model. This was not necessarily the case at Unit 2 during the period of Set A.

Nevertheless, an ARMA-GARCH model is not a linear model. The variation in condenser vacuum should also be explained by how its volatility varies according to the variance model. The extent to which this model explains the entire variation may remain intractable as far as this study is concerned.

One can always assess the volatility of condenser vacuum by looking at its conditional standard deviation. It can be computed directly from (2). At Unit 1 the conditional standard deviation of condenser vacuum ranges from 0.0002132 MPa to 0.0007375 MPa. That behavior is less volatile than that at Unit 2 with the conditional standard deviation ranging from 0.0002490 MPa to 0.0014094 MPa.

IV. REMARKS

As demonstrated in the previous sections, the ARMA-GARCH modeling approach offers the possibility to explain the behavior of condenser vacuum toward changes in operating conditions. It enables variations in condenser vacuum to be explained by variations in other variables. In short, it helps reveal the intricate relationships between condenser vacuum and other variables.

This modeling technique is particularly suitable for off-design conditions, which saw in the case of Unit 2 a series of extreme observations that would have been considered potential to cause an emergency shutdown. Under such conditions, it reveals the sensitivity of condenser vacuum to variations in other variables.

The adequacy of the mean model in explaining the variation in condenser vacuum appears to be related to the severity of the off-design conditions. The variance model predicts a more volatile behavior under more severe off-design conditions.

With ARMA-GARCH models, fitness is achieved and interpretation is made by way of statistical inference. This is implemented through estimation and a series of significance tests. It actually requires a moderate size of data. The minimum recommended size is 100 observations per variable. Estimates of model parameters are preferred to have small standard errors, which are difficult to obtain with a small sample size.

The combination of an exponential GARCH model and the Student's t distribution as the conditional distribution is particularly recommended for modeling condenser vacuum. By slightly adjusting p and, occasionally, q of the ARMA part of the model, one may arrive at a model that passes all the required significance tests with reasonably low AIC.

Simplicity is always a concern in ensuring the practicality of deriving a model by practicing engineers. It implies a small number of external regressors, small numbers of lags (p, q, a, b), and a simple conditional distribution. Provided that the data are available, the engineer can simply experiment with several GARCH models (probably exponential ones) to arrive at the most suitable one. In that way, a monthly feed of such data should be adequate for a regular evaluation of condenser vacuum.

A more sophisticated model may be derived by using autoregressive fractionally integrated moving average (or ARFIMA) in place of ARMA. However, more sophistication could mean more complexity in searching for an optimal combination of parameters subject to the model passing all the required tests. More work should be devoted to studying the computational complexity.

V. CONCLUSIONS

The importance of studying condenser vacuum under off-design conditions has been highlighted. Modeling the relationship between condenser vacuum and other variables in the system is essential for that purpose. An approach to modeling condenser vacuum has been proposed based on the ARMA-GARCH modeling framework. Data from real world operations of a steam power plant have been used for studying the models. The results show the usefulness of the technique in unraveling from time series conflicting effects brought by serial correlation and heteroscedasticity. The resulting models are capable of separating information brought by explanatory variables on condenser vacuum despite various other effects under off-design conditions. They present relationships between condenser vacuum and other variables based on statistical inference and in an explanatory way. They enable variations in condenser vacuum to be explained by variations in these variables. Condenser vacuum is significantly related to both active power and cooling water inlet temperature. The severity of off-design conditions is somehow related to how adequate the mean model is in explaining the variation in condenser vacuum and to its volatility. The models also show predictive performance comparable to some prominent machine learning techniques tailored for that purpose. Finally, some important remarks have also been provided.

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