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UNIVARIATE TIME SERIES MODELS FOR FORECASTING ENERGY-WATER EFFICIENCY AT WATER TREATMENT PLANT

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Abstract

Water treatment is improving water quality by passing it through various processes in water treatment plants. One of the vital management in water treatment plants requires planning and strategy of water production volume, energy consumption, and energy-water efficiency. Besides, accurate energy-water efficiency forecasting results are an essential monitoring strategy for reducing electricity consumption per meter cubic of water production. However, without accurate and fast forecast results, decision-making and planning in water treatment plant management will be difficult. The univariate time series model is one option for management to cater to the time-consuming and low accuracy of forecasting problems. Therefore, this study investigates energy-water efficiency using six univariate forecasting models. The models were Naïve, Recursive Simple Average (RSA), 3-point Moving Average, 4-point Moving Average, 5-point Moving Average and Simple Exponential Smoothing models. The result shows that the RSA forecasting model is more accurate than the other five, with 0.24% mean absolute percentage error (MAPE), 0.00014 mean squared error (MSE) and 0.00897 mean absolute deviation (MAD). These three measurement errors are a measure of the forecasting accuracy of a forecasting method in statistics. Moreover, the RSA forecasting model shows the simple calculation and cheapest indicator to measure the energy-water efficiency of water treatment plants.

Keywords: Energy-Water Efficiency, Forecasting, Recursive Simple Average, Univariate Time Series, Water Treatment Plant

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1. Introduction

Water and energy are necessarily the same and beneficially connected resources because fulfilling energy needs requires water. In this study, since the relationship between energy consumption in the water treatment plant (WTP), we named this nexus as energy-water efficiency because water makes energy production so useful, and these interrelationships mean that saving water saves energy, and saving energy saves water (Othman et al., 2022). The term energy-water nexus is thus used to represent the interactions and interrelationships between water and energy, which implies that water restrictions can transform into energy constraints or vice versa (DeNooyer et al., 2016). The majority of the energy used for water-related purposes is in electricity form. For example, the generation of thermal energy has been engaging in a large amount of water for cooling and removing a huge amount of primary energy because of inefficiency in converting thermal energy into electricity. A lack of understanding of the interdependencies between water and energy may lead to overuse and mismanagement of the resources. Therefore, future strategies or practices for water resource management are suggested to consider the concept of energy-water nexus for sustainability planning and development, such as in WTPs.

Water treatment plants are essential for providing safe and reliable drinking water to communities, and they play a crucial role in public health and sanitation. A WTP is a facility that processes raw or untreated water from various sources, such as rivers, lakes, or groundwater, to produce safe and clean drinking water for human consumption. The treatment process involves several steps to remove impurities, contaminants, and harmful substances that may be present in the water. The process typically includes several stages, such as coagulation, flocculation, sedimentation, filtration, disinfection, and sometimes, other processes, such as softening, pH adjustment, and fluoridation. These processes may vary depending on the source water's quality and the plant's specific treatment goals. The treated water is then distributed to homes, businesses, and other users through a network of pipes and storage tanks.

However, there are some issues in WTPs, such as issues in energy consumption (Biswas & Yek, 2016), measuring and monitoring data (World Pumps, 2017), and energy-saving technologies (World Pumps, 2017). Water treatment plants consume large amounts of energy to operate the treatment process, which can contribute to greenhouse gas emissions and operational costs (Biswas & Yek, 2016). Besides, in measuring and monitoring issues, since many water treatment facilities were installed without much thought about data acquisition, treatment plant managers must ensure they are measuring and monitoring the proper efficiency parameters (World Pumps, 2017). Moreover, energy efficiency optimization is essential for water treatment plants because of increased energy costs. The optimisation of energy efficiency will be accomplished by integrating energy recovery from water treatment plant processes and energy-saving technologies (World Pumps, 2017). Therefore, by realizing the importance of overcoming the issue of improving energy efficiency in WTP, this study was conducted to integrate water and energy information and to produce an energy-water efficiency forecasting model that can be an alternative instrument as an assistant tool in decision-making and planning at WTPs.

Forecasting is the future value prediction based on historical data. There are some significant roles of forecasting in water treatment plants. Accurate forecasts can provide valuable information to WTP managers, engineers, and operators to make informed decisions and plan for the future. In WTPs, forecasting can help predict changes in water demand and supply and changes in water quality parameters

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such as pH, turbidity, and dissolved oxygen levels. Plant operators can adjust their treatment processes and operations by forecasting these variables to ensure they meet regulatory requirements and customer demand.

Moreover, forecasting can help in planning maintenance activities, such as replacing equipment or repairing pipelines, by predicting when such maintenance is likely to be required. The forecasting activities can help WTP managers allocate resources effectively and avoid costly emergency repairs. However, the scope of this study is to use the crucial two pieces of information only; the time series data of energy consumption and water production volume in forecasting energy-water efficiency. By providing accurate and reliable predictions, energy-water efficiency forecasting can help WTP managers and operators make informed decisions to ensure the reliable performance of WTPs. Therefore, this study aims to identify the best univariate time series model for forecasting energy-water efficiency at one of the WTPs in Kedah, Malaysia.

2. Methodology

2.1. Univariate time series models

The word uni refers to one. Meanwhile, the word variate is referring to the variable. Therefore, the word univariate model means the model types which require only one variable to be formulated. Univariate time series (UTS) models use historical values of a single variable over time to make predictions about future values of that same variable. The goal of UTS forecasting is to identify patterns or trends in the historical data that can be used to make accurate predictions of the behavior of the variable. However, Ismail et al. (2016) suggested conducting an exploratory data analysis for time series data to obtain an in-depth understanding pattern of time series data.

The dependent variable in UTS forecasting is the variable being predicted, which is typically denoted by Y in mathematical models. The independent variable is time, which is typically denoted by t in mathematical models. The value of Y at any given point in time is influenced by the values of Y at previous points in time, as well as other factors that may be external to the time series itself.

Applying the UTS model as a forecasting tool provides several advantages over the more complex models. Besides the advantage of the modelling simplicity, the UTS models are less costly to develop and easy to understand (Lazim, 2013). Hence, statistical and non-statistical UTS models were widely used in forecasting various types of data, including electricity load demand (Mansor et al., 2020; Mansor et al., 2021), electricity consumption (Mansor, Zaini et al., 2019), water production volume and energy efficiency (Othman et al., 2022; Othman & Mansor, 2022) in water treatment plants and stock price (Mansor, Kasim et al., 2019; Mansor & Zaini, 2023; Zaini et al., 2020). Four types of popular univariate models used for forecasting are the naive model, simple average model, moving average model, and exponential smoothing model. Each of these models has its strengths and weaknesses, and the decision of the best forecasting model in this study depends on the comparison results of measuring forecasting errors.

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2.2. Energy water efficiency

Electricity cost is expected to increase over the years as the changes in energy tariff rates are based on actual activity at the WTP. Therefore, this study used energy consumption (EC) in units measured as kilowatts per hour (kWh) and water production volume (WP) in units measured in meter cubic (m^3). By formulating these two pieces of information, this study defines the overall energy-water efficiency (OEE) as an indicator of the electricity used per water production unit (kWh/m^3). The OEE can be presented as in Equation (1) (Othman et al., 2022). The OEE formula is also used in the International Bank for Reconstruction and Development report (Liu et al., 2012) and previous research by Othman et al. (2022).

$$OEE = \frac{EC}{WP} \qquad (1)$$

2.3. The framework of the study

The EC data were collected from the Department of Mechanical and Electrical. Meanwhile, WP data was provided by the Department of Production. Both departments are the primary unit at the Headquarters of Syarikat Air Darul Aman (SADA) Sdn. Bhd, Kedah, Malaysia. The 32 monthly EC and WP data points were collected from January 2017 until August 2019. Exploratory data analysis was conducted to identify the reason behind the time series pattern. Based on Equation (1), these EC and WP data are formulated as OEE. Before finding the best model, the data need to be split into two parts: modeling and evaluation (Lazim, 2013). The last three of the data were defined as the evaluation part. The framework of the methodology is shown in Figure 1.

Based on Figure 1, the time series pattern is identified based on the modeling part of the data. Then three types of forecasting methods: Simple average, moving average, and Simple exponential smoothing forecasting methods were constructed based on the existence of a time series pattern. This study used the Recursive Simple Average model (RSA) to represent the model from the Simple Average method. Meanwhile, 3-point, 4-point and 5-point Moving Average models (MA3, MA4, and MA5) represent the Moving average method, and the Simple Exponential Smoothing model (SES) represents the Exponential smoothing method. The Naïve model is a benchmark of the forecasting models in this study. The six models are stated in Table 1.

Then, by using the evaluation part of the data, the best model from the best forecasting performance was identified based on three types of measurements error; mean squared error (MSE), mean absolute deviation (MAD), and mean absolute percentage error (MAPE). These three measurement errors measure the forecasting model's accuracy. The model with the lowest error was selected as the best forecasting OEE model. Then continue to the last step, applying the best OEE forecasting model to forecast future OEE.

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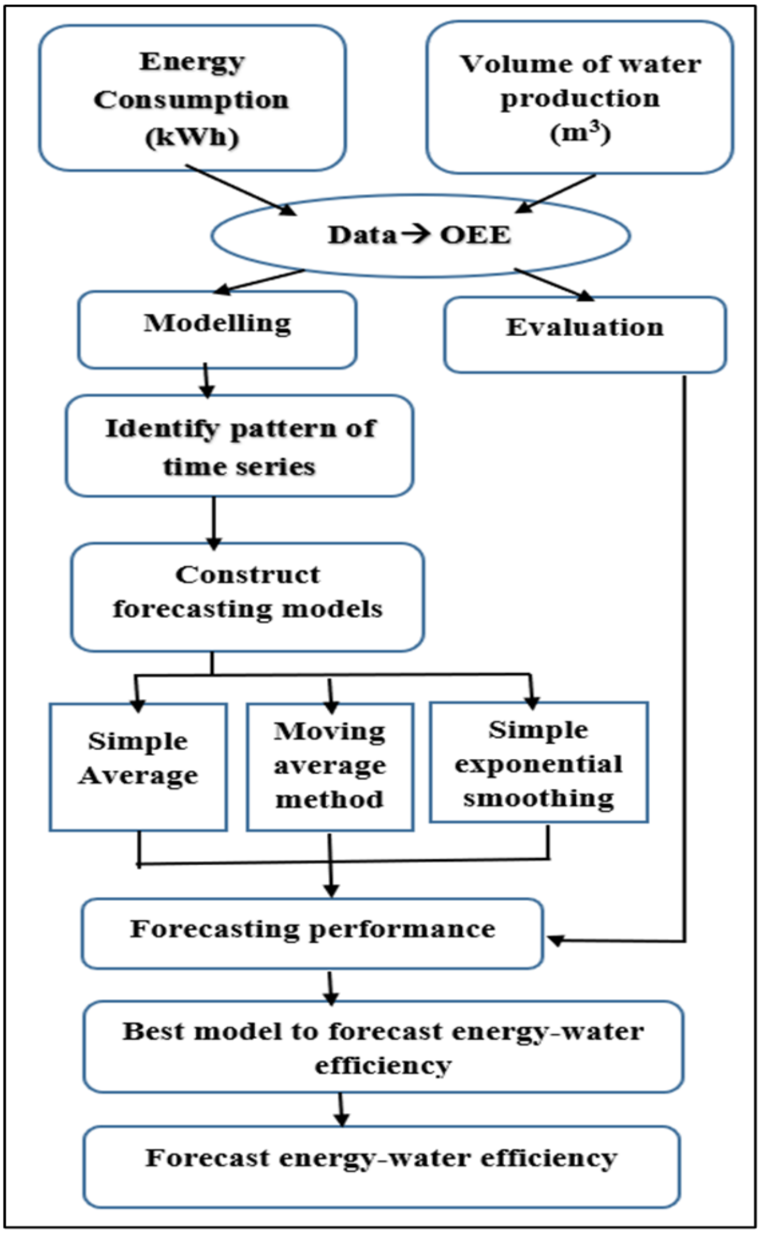

Figure 1. Framework of study

Table 1. List of univariate forecasting models used in this study

Model	Forecasting model
Naïve	$OEE_{t+1} = y_t$
Recursive Simple Average (RSA)	$OEE_{t+1} = \frac{\sum \quad (all\ data\ values)}{n}$
Moving Average (MA3)	$OEE_{t+1} = \frac{\sum \quad (most\ recent\ 3\ data\ values)}{3}$
Moving Average (MA4)	$OEE_{t+1} = \frac{\sum \quad (most\ recent\ 4\ data\ values)}{4}$
Moving Average (MA5)	$OEE_{t+1} = \frac{\sum \quad (most\ recent\ 5\ data\ values)}{5}$
Simple Exponential Smoothing (SES)	$OEE_{t+1} = \alpha y_t + (1-\alpha)F_t\,, \quad 0 \le \alpha \le 1$

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3. Results and Discussion

The results from this section are more on OEE univariate time series forecasting. Figure 2 shows the monthly OEE from 2017 to August 2019 with 32 data points. In the line graph, the time series data was shown. The Y-axis represents the OEE, while the X-axis represents the month. Based on Figure 2, it clearly shows there is a dramatic increase in the movement of OEE value starting from February 2018 until March 2018 because of the upgrading WTP system. Therefore, selecting 18 observation data after upgrading the WTP system from March 2018 to August 2019 is more significant. Hence, for splitting the data step, 15 observation data were for the modelling part (March 2018 to May 2019), and the remaining three were for the evaluation part (June 2019 to August 2019), as shown in Figure 3.

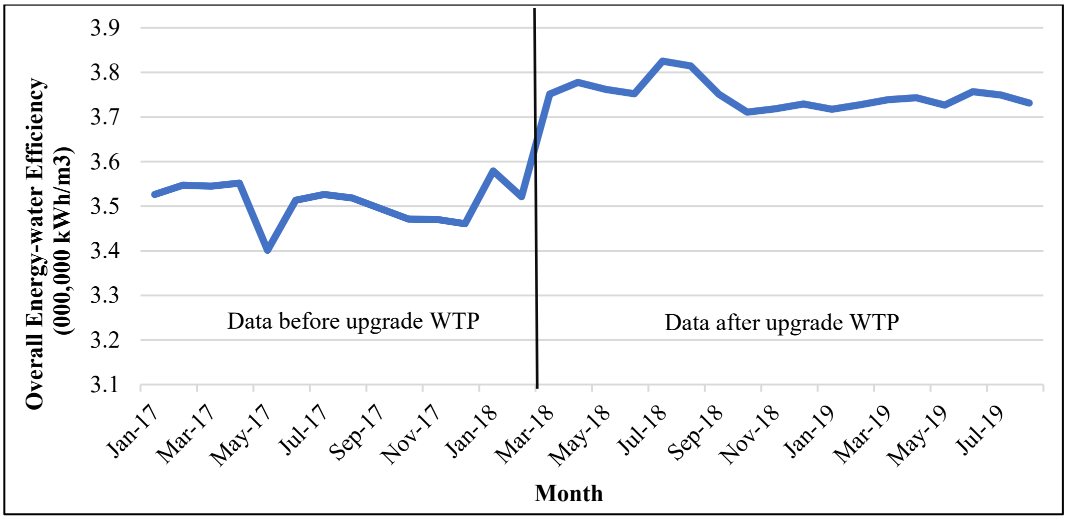

Figure 2. OEE time series data

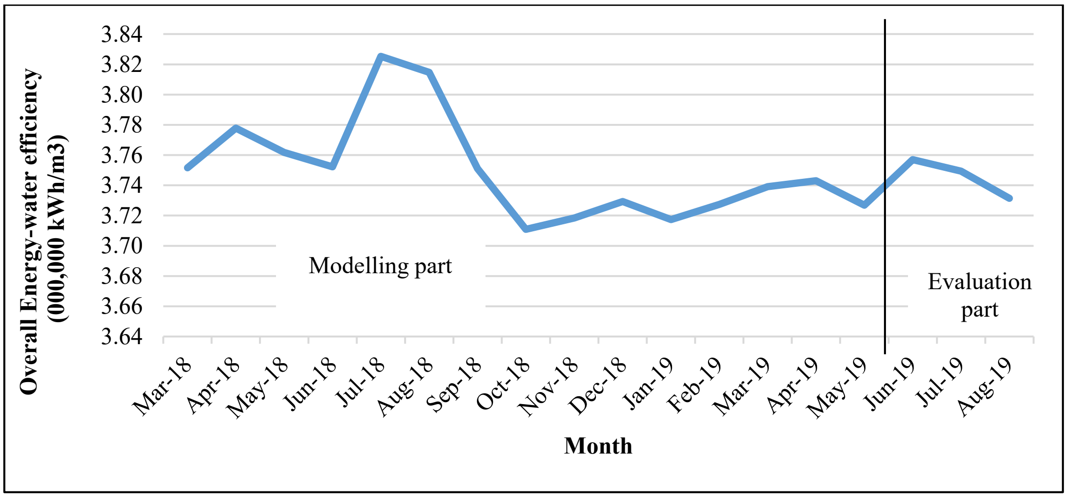

Figure 3. OEE time series data after upgrade WTP

The time series pattern was identified based on Figures 2 and 3. By referring Figure 2, shows the OEE better before upgrading the WTP since the OEE data values increase after upgrading the WTP system. It shows a stationary pattern. Also, from autocorrelation (ACF) and partial autocorrelation

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(PACF), the correlograms in Figures 4 and 5 show that the OEE after upgrading the WTP system time series is a stationary time series pattern. ACF is a visual way to show serial correlation in data that changes over time. Meanwhile, PACF gives the partial correlation of a stationary time series with its own lagged values, regressed the values of the time series at all shorter lags Therefore, RSA, MA, and SES methods suit stationary forecasting methods.

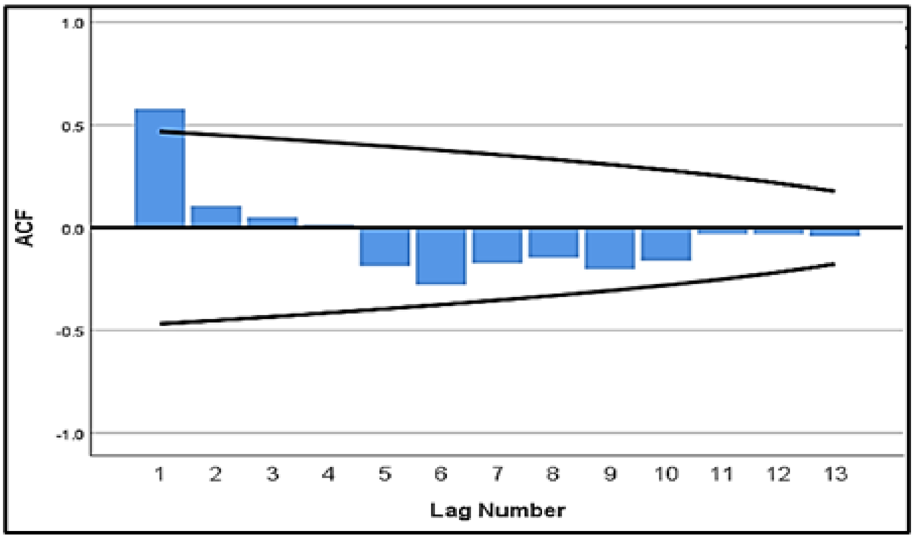

Figure 4. ACF correlogram

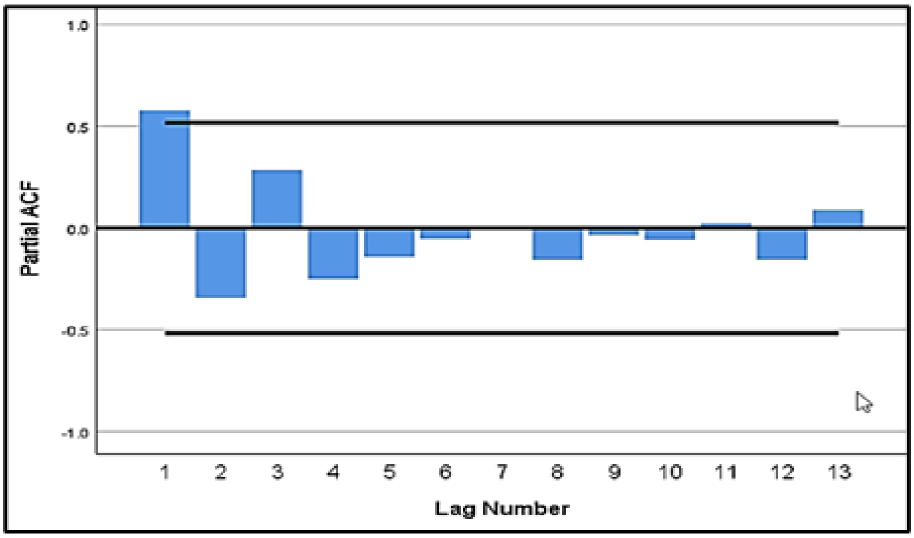

Figure 5. PACF correlogram

The following results are obtained from the forecasting model as stated earlier in mathematical formulation using MS Excel.

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Table 2. Model performance in the modelling part of data

Model	MSE	MAD	MAPE
naive	**0.00087**	**0.02076**	0.59129
RSA	0.00126	0.02946	0.78530
MA3	0.00141	0.02753	0.73336
MA4	0.00152	0.03118	0.83082
MA5	0.00132	0.03028	0.81017
SES	0.00095	0.02132	**0.56708**

Table 3. Model performance in the evaluation part of data

Model	MSE	MAD	MAPE
naive	0.00043	0.01860	0.74437
RSA	**0.00014**	**0.00897**	**0.23978**
MA3	0.00022	0.01357	0.36215
MA4	0.00025	0.01448	0.38630
MA5	0.00031	0.01620	0.43222
SES	0.00038	0.01665	0.44437

Three forecasting errors were calculated in the data of modeling and evaluation part to evaluate the performance of the OEE forecasting model. To see the performance of all models in the modeling part, refer to Table 2. However, this study selects the best model through the lowest forecasting error value in the data evaluation part, refer to Table 3. The reason for choosing the lowest forecasting error in the evaluation part as an indicator to choose the best forecasting performance is the process forecasting in the evaluation part mimics the actual forecasting scenario, and the data selected for the evaluation part are very close to the future value. Therefore, the RSA model was chosen as the best forecasting model to forecast OEE since RSA showed better performance than other univariate models; naïve, MA3, MA4, MA5, and SES. As a result, by referring to equation RSA in Table 1, OEE for next month (September 2019) is

$$OEE_{t+1} = \frac{\sum \quad (all\ data\ values)}{t}$$
$$= \frac{\sum_{18}^{1} \quad x}{18} = 3.7492kWh/m^3$$

This OEE value is better than the previous month (August 2019). It indicates that the RSA plays a better role in forecasting OEE time series data with the small size of data points rather than moving averages and exponential smoothing models in the stationary data pattern.

4. Conclusions

Univariate forecasting techniques involve using historical data to predict future events or trends. This technique can help operators anticipate issues and take preventive measures to ensure the plant's continued operation and the delivery of safe drinking water.

OEE univariate forecasting models for the Malaysia Jenun Baru water treatment plant (WTP) have been conducted. It found that the nonstationary pattern of the OEE time series from the year 2017 to 2019 is due to the upgrading activity at WTP. Even nowadays, Kedah State Government approves some amount to upgrade the WTP. The project will upgrade the WTP from 55 million liters per day (MLD) to

110 MLD (Jabatan Kerja Raya Negeri Kedah, 2021). The project is expected to be completed in 2023 as a target to resolve water supply disruptions.

OEE can measure the electricity required to produce one cubic meter of water. The smaller the OEE value, the more efficient the energy used. For a given level of service and regulatory compliance, a reduction in those OEE numbers indicates improvement in EE of water service delivery. Therefore, the OEE forecasting model from this study is a worthwhile contribution to the energy-water nexus field in planning and monitoring the effectiveness of EC management in WTP. The OEE is also linked to energy consumption (EC) and water production (WP) at the WTP. OEE can measure the electricity required to produce one cubic meter of water. The smaller the OEE value, the more efficient the energy used. For a given level of service and regulatory compliance, a reduction in those OEE numbers indicates improvement in EE of water service delivery

Besides, the RSA forecasting model shows the simple calculation and cheapest indicator to measure the OEE of WTP. It means that the forecasting results are highly accurate using univariate modelling only. It also shows no need for a complicated univariate forecasting model methodology to get low forecasting errors. These results are also in line with the statement from In and Jung (2022) that the averaging forecasting model is an effective way to improve forecast accuracy.

Hence, this forecasting approach is a worthwhile contribution for academics and practitioners in the energy-water nexus field management. However, some limitations exist, such as the indicator used in this study, EE first, the mismatch of energy and water. Often, energy use per unit of water, OEE, produced is used as an indicator instead of water delivered. Doing so leaves out a vital efficiency factor, physical losses in the network. Therefore, in the future, the study should come out with water efficiency as an indicator of physical losses in the network where the assumption of how much a certain WTP can produce the amount of water is efficient according to physical water treatment techniques in WTPs. There are many techniques in physical water treatment, including conventional and modern techniques.

The second is incomparable operating conditions and processing technologies between utilities or WTP. It is because different WTP has different system operation conditions in some factors. The factors include the different geography factors, the mix of water sources, and the gravity that can cause the WTP to need more energy to palm the water. Therefore, we suggest EE monitoring at each step in the water treatment process for further research.

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