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# THE LONG SHORT-TERM MEMORY MODEL AS THE NEURAL NETWORKS APPROACH IN MODELING WATER SUPPLY STRUCTURAL PRODUCTION

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**Abstract:** Almost all cities in Indonesia are moving to find alternatives for providing clean water as the population increases, so the demand for clean water volume is also increasing. Water wastage issues arise as water production continues to rise, highlighting the need for accurate predictions of future water production levels. Modeling clean water supply structural movements as an effort to predict water needs in a city in the future is important. This can be done by considering water usage data over time and factors that trigger clean water demand. This research proposes a long short term memory (LSTM) model that adopts a neuro informatics model as the neural networks approach for modeling water supply. The architecture of the LSTM used in this research employs one hidden layer with 32 neurons. The findings demonstrate that LSTM model can predict water production levels accurately with mean absolute percentage error (MAPE) less than 5% both for training and testing data set. These results categorize the LSTM model as a reliable forecasting tool for water production levels. Therefore, modeling using the LSTM method is a preferable choice for predicting water production aiding relevant parties in planning clean water resources tailored to the needs

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of population.

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## 1. INTRODUCTION

The global water crisis has reached a critical point, supported by data from the United Nations (UN) in 2023, which reported that 2.2 billion people, or one-quarter of the world's population, lack access to water for daily consumption [1]. According to a report from Indonesian National Development Planning Agency (NDPA), water availability in most areas of Java and Bali is currently categorized as scarce to critical [2]. The main problems related to the availability of clean water are the quantity, management methods, and sources of water. In addition, natural factors often affect the condition of clean water in Indonesia, making it difficult to get access to clean water. Climate change has a serious impact on the availability of clean water in Indonesia due to increasingly irregular rain accompanied by floods and landslides. This disrupts water sources and clean water infrastructure. In addition, long dry seasons can also cause droughts that affect the availability of clean water in certain sources.

Due to the crucial need for water, addressing issues related to water availability is essential. One of the major cities in Indonesia is Jakarta, which requires a substantial supply of clean water [3,4]. In meeting this water demand, the government must consider the quantity of water to be distributed to the public due to issues related to water needs [5,6]. One of the problems is that if the amount of water produced and distributed exceeds the water demand, companies will face water wastage issues. Conversely, if the amount of water produced and distributed is insuficient or does not meet consumer needs, there will be a shortage of water volume, which will harm consumers [7,8,9]. Therefore, accurate predictions are needed to estimate the amount of water production distributed to the local community, commercial, and agricultural activities.

The data on water production is available monthly as the time series data, many methods can be used to predict this time series data such as the basic model of autoregressive and moving average model. This model is a forecasting method that is usually very efective for short-term forecasting. However, the method has limitations because it requires a large amount of historical data to produce accurate predictions. The fractionally autoregressive model with the effect of long memory is advancement of the autoregressive and moving average model [10,11,12,13,14,15]. Furthermore, the nonlinear models involve numerical or iterative processing on large datasets, thereby enabling accurate estimation of the actual values. Due to this limitation, a deep learning method was developed to address the issue of short-term data. Deep learning models as neoro informatics approach, especially those using neural networks as the hybridization of time series model, excel at identifying complex and subtle patterns and relationships that are often missed by classical methods [16,17]. Furthermore, the flexibility of deep learning allows it to adapt to a wide range of time series forecasting tasks such as predicting exchange rate [18,19], stock market trends [20,21], and to forecasting weather patterns [22,23], deep learning models can be tailored to meet the specific needs of various domains including clean water supply forecasting [24,25,26].

The recurrent neural network (RNN) method is introduced to process time series data specically designed to process sequential data. However, RNN has limitations in predicting long-range data. To address this issue, a long short-term memory (LSTM) model is used to minimize errors and avoid long-range dependency problems in RNN [27,28,29]. Based on these studies, it can be seen that the LSTM method anticipates epochs and batch sizes. Additionally, the excellent performance of the LSTM method has led to extensive research on this method. However, there are very few studies that apply LSTM models to predict quantitative water parameters (in this case, water production quantities) [30,31]. Therefore, predictions are made using this method for the water production quantity, specically in the Jakarta as the capital city of Indonesia.

## 2. Material and Methods

### 2.1 Material and Data Source

The data on the amount of tap water production in Jakarta is sourced from the official website of the Central Statistics Agency of Jakarta (CSA Jakarta) from website https://jakarta.bps.go.id, the data is covering the period from January 2013 to December 2024 with adjusted the area of Jakarta as the capital city of Indonesia.

**2.2 Conceptual and Theoretical Approach**

This research uses the LSTM method that adopts a neuro informatics model as the neural networks approach to predict clean water production in Jakarta. As the deep learning approach, this issue meet the algorithm to predict time series model with recognizing existing data by utilizing existing algorithms. This learning process can be conducted through three options: supervised learning, semi-supervised learning, andunsupervised learning [23,24,30,32]. Supervised learning allows machine learning algorithms to learn from available and sufficient data. In contrast, semi-supervised learning is based on existing but incomplete data, and unsupervised learning relies on machine learning algorithms to learn without any input data.

Several methods employ deep learning techniques. The RNN method as a neural networks specically designed with feedback connections to process sequential or time series data [28,29,33]. In RNN, the generated output is feedback into the network as input, along with new data at each time step. The feedback connections allow the neural network to retain information from the past while processing subsequent outputs. This characteristic describes a repetitive process; its architecture is called a RNN. However, RNN suffers from vanishing and exploding gradient problems, where the gradient values change consequences as they propagate from one layer to the next within an architecture [28,29]. The vanishing gradient problem occurs when the gradient values become increasingly smaller over time, resulting in insignificant parameter adjustments in the RNN. The exploding gradient problem occurs when the gradient values become increasingly larger over time, which can lead to issues with using sigmoid activation functions [28,29,34]. The formulas for RNN can be seen in Equations (1) and (2) as follows,

$$h_t = f(x_t W_{xh} + h_{t-1} W_{hh}), \tag{1}$$

$$y_t = W_{hy} h_t, \tag{2}$$

where $h_t$ is the output value of the $t$-th order, $h_{t-1}$ is the output value before the $t$-th order, $x_t$ is the input value at time $t$, $W_{xh}$ is the weight for $x$, $W_{hh}$ is the weight for $h$, $W_{hy}$ is the weight for $y$, and $y_t$ is the final output value.

### 2.3 Methodology and Algorithm

The LSTM is a model in deep learning that falls under the RNN category. This deep learning model is benecial for handling complex tasks such as time series forecasting, handwriting recognition, speech detection, and other evaluation task. The LSTM was introduced to address the vanishing gradient problem commonly encountered in RNN architectures when storing long-term memory information [34,35]. The uniqueness of LSTM lies in its neurons' ability to learn when to open and close gates within the network, thus e ectively managing error propagation consistently throughout the network [35].

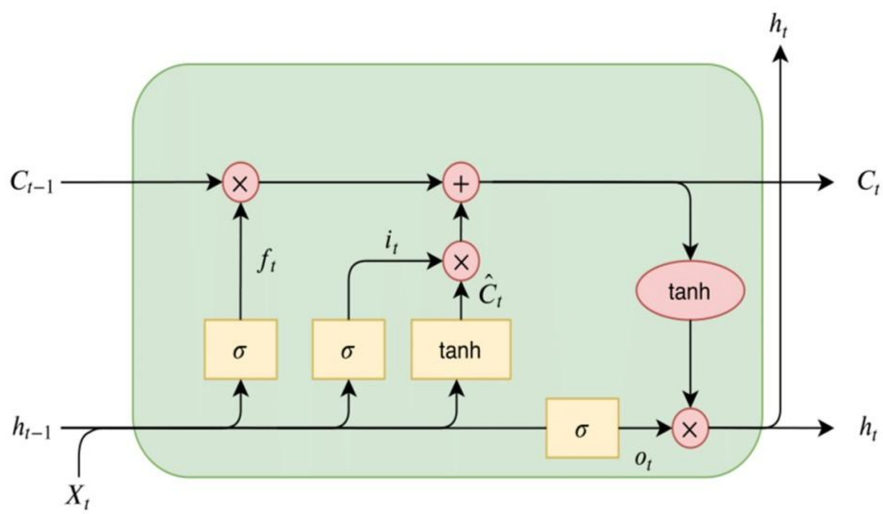



Figure 1. Long Short Term Memory (LSTM) Architecture.

The LSTM generally has an architecture (see Figure 1) consisting of a memory cell, forget gate, input gate, and output gate. The memory cell is a type of cell that can store information or data for reuse when needed. Three sigmoid layers and one tanh layer exist within each memory cell. The sigmoid and tanh functions can be seen in Equations (3) and (4) as follows,

$$\sigma(x) = \frac{1}{1+e^{-x}}, \tag{3}$$

$$\tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}, \tag{4}$$

where $\sigma(x)$ is the sigmoid activated function, $\tanh(x)$ is tangent hyperbolic function, and $x$ is input data.

The forget gate function determines which information needs to be retained and which must be discarded from the memory cell. The input gate is a component of LSTM that controls how much information will be stored in the memory cell. The input gate consists of 2 gates that use sigmoid activation functions to update information and the tanh activation function to store new values in the memory cell [36]. The property of activation functions is obtained by using the characterization of infinitely divisible distribution such as exponential and gamma distribution [37,38]. The equations for the forget gate and the two gates within the input gate can be seen in Equations (5), (6), and (7) as follows,

$$f_t = \sigma((W_f\ h_{t-1}) + (W_f\ x_t) + b_f), \tag{5}$$

$$i_t = \sigma((W_i\ h_{t-1}) + (W_f\ x_t) + b_i), \tag{6}$$

$$\tilde{C}_t = \tanh((W_c\ h_{t-1}) + (W_c\ x_t) + b_c), \tag{7}$$

where $f_t$ is the forget gate, $\sigma$ is the sigmoid activation function, $W_f$ is the weight value at the forget gate, $h_{t-1}$ is the output value before the $t$-th order, $x_t$ is the input value at time step-$t$, $b_f$ is the bias value at the forget gate, $i_t$ is the input gate, $W_i$ is the weight value at the input gate, $b_i$ is the bias value at the gate input, $\tilde{C}_t$ is the new cell candidate that can be added to the memory cell, $W_c$ is the weight value at the new cell candidate, and $b_c$ is the bias value at the new cell candidate.

The combined result from the input gate is called the cell state. Next, the output gate controls how much of the current information in the cell will be retained or discarded. Sigmoid activation functions are used to generate initial data that will be further processed through the tanh activation function, and the result will be multiplied by the output of the sigmoid activation function to produce the final output [16]. The equations for the cell state and the output gate can be seen in Equations (8), (9), and (10) as follows,

$$C_t = (f_t\ C_{t-1}) + (i_t\ \tilde{C}_t), \tag{8}$$

(9) $$O_t = \sigma((W_O \; h_{t-1}) + (W_O \; x_t) + b_O)\,,$$

(10) $$h_t = O_t \; \tanh(C_t),$$

where $C_t$ is the memory cell, $\tilde{C}_t$ is the new cell candidate that can be added to the memory cell, $f_t$ is the forget gate, $i_t$ is the input gate, $O_t$ is the ouput gate, $\sigma$ is the sigmoid activation function, $h_{t-1}$ is the output value before the $t$-th order, $x_t$ is the input value at time step-$t$, $b_0$ is the bias value at the output gate, and $W_o$ is the weight value at the output gate.

The model has been developed by using LSTM, then evaluted by accuracy procedure. The root mean square error (RMSE) is used to calculate the magnitude of error in predicting a dataset. RMSE indicates how much the data differs from the best regression line. The smaller the value of RMSE, the better the prediction results of the model. While, the mean absolute percentage error (MAPE) can be interpreted as a relative accuracy measure used to determine the percentage deviation from the predicted results. The smaller the percentage value of MAPE, the better the prediction results of the model. The calculation of RMSE and MAPE can be seen in Equation (11) and (12) as follows,

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

(12) $$MAPE = \sum_{i=1}^{n} \frac{\frac{|\,y_i - \hat{y}_i\,|}{y_i}}{n} \times 100\%,$$

where $n$ represents the number of data, $\hat{y}_i$ denotes the predicted value, and $y_i$ signifies the actual data value.

The following steps complete the prediction using the LSTM method.

(1) Input the data of tap water production in cubic meters.

(2) Preprocessing the data.

(a) Normalization.

(b) Segmentation

(3) Splitting the data into training data and testing data.

(4) Constructing the LSTM model.

(5) Evaluating model optimization.

(6) Performing LSTM prediction.

(7) Calculating accuracy scores on the training data and testing data.

## 3. MAIN RESULTS

The tap water production data consists of 10 years of data, divided into two sets: training data and testing data, with a ratio of 80% and 20%. This data will be normalized using min-max scaling in Equation (13) to ensure that calculations involving various variable values can be performed by scaling all values into the range [0,1] as follows,

$$Y' = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}}. \tag{13}$$

Next, testing is conducted using hyperparameters such as 1000 epochs, 32 neurons, a batch size of 16, 1 hidden layer, an Adam optimizer, and activation functions tanh (for the LSTM input layer) and sigmoid (for the output layer). Table 1 shows that the model has one hidden layer where 32 neurons are formed, resulting in 4352 parameters. A dense layer in the output layer is formed, indicating that this layer has one output value, the target value (Y). The resulting model has a total of 4385 weights and biases parameters overall.

TABLE 1. LSTM Model Structure for Water Supply.

| **Layer (Type)** | **Output Shape** | **Paramater** |
|---|---|---|
| LSTM | (None, 12, 32) | 4352 |
| Dense | (None, 1) | 33 |
| Total Paramater: 4385 | | |
| Trainable parameter: 4385 | | |
| Non-trainable parameter: 0 | | |

Based on the division of training data starting from January 2013 to December 2020, while testing data starts from January 2021 to December 2023. Data division is made based on the year order to make it easier to compare and this data is time series data so it cannot be randomized. Based on Figure 2 shows that the normalized data for training data is green while testing data is red with data division of 80% and 20% respectively. Clean water supply in Jakarta as the capital city of Indonesia, has shown an upward trend until 2019, this is in line with the need for clean water for the ever-increasing population, in addition to the needs for rapidly growing industry and agriculture that require supply water. Since COVID-19 spread, water use has decreased during 2019-2020 and has increased again and returned to normal since 2021 until now. This shows the need for a strategy to meet the increasing demand of water for various types of needs.

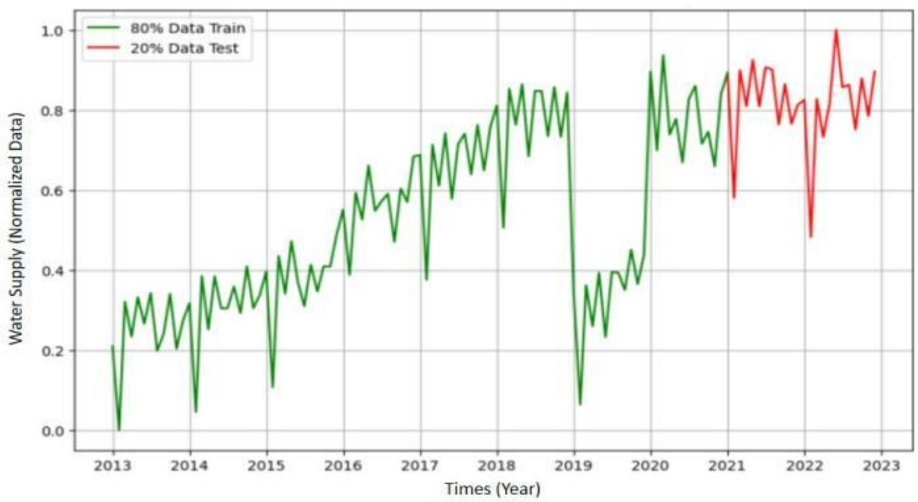



FIGURE 2. Normalized Data on 80% Training for Green Line and 20% Testing for Red Line.

During the data processing process, the value of the loss function for each epoch on the training and testing data is shown in Figure 3, this indicates that the loss function value during testing signicantly decreases from 0.10 to converge to 0.03 in the LSTM neural network. Furthermore, during the training process, the loss function value for each epoch is lower than the loss function value during testing. In the training process, the loss function value shows a signicant decrease from 0.05 to 0.02, indicating better performance than in the testing process. Therefore, this process demonstrates that the training data's loss function value will be smaller than the testing data's. Based on these results, the constructed LSTM neural network successfully identifies new data and achieves actual values through numerical processing.

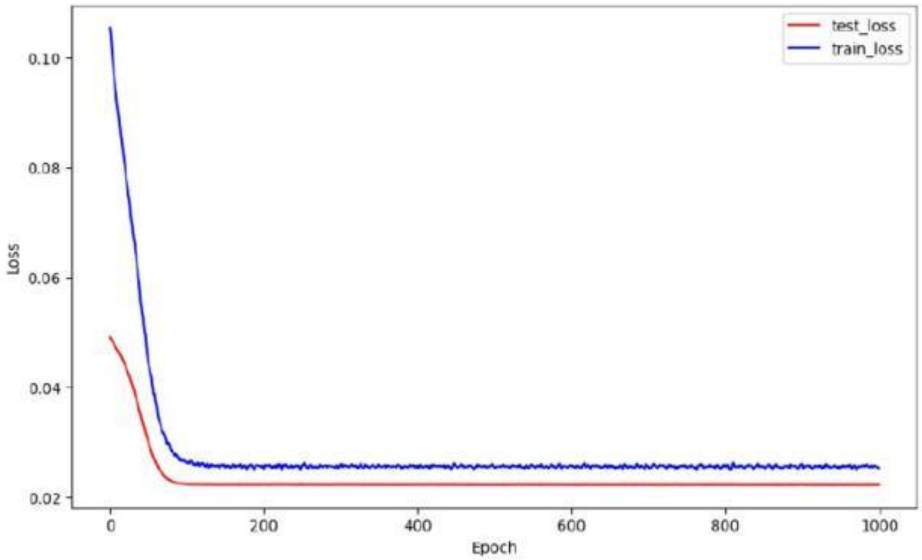



FIGURE 3. Lost function for simulation using LSTM.

In the next process, analytical calculations are carried out using equations (5), (6) and (7) in the LSTM architecture to produce water supply predictions. The water supply prediction model includes the calculation of forget gates, input gates, output gates, cell states, and hidden states. The bias and weight values for each gate are determined randomly because the researcher does not initialize the initial quantities. It is the translation of the example LSTM model calculation using one iteration. The calculation for day 1 in January 2013 on the water production quantity with $h_{t-1}$=0 and $C_{t-1}$=0 explained as initial value. Modeling to predict water supply using LSTM by using initial value of variable and parameter is done in stages using 2 time steps as in Table 2. The first is done at $t$ = 0 and continued at $t$ = 1 by using Equation (5), (6), (7) and Equation (8), (9), (10). The result of this process is presented in Table 3.

TABLE 2. LSTM Manual Proccessing for Initial Values.

| **Variabel/Parameter** | **Initial Values** | |
|---|---|---|
| | ***t*=0** | ***t*=1** |
| $Y_t$' = normalized actual data | 0.2095 | 0.0000 |
| $W_f$ = the weight value at the forget gate | 0.7000 | 0.1000 |
| $W_i$ = the weight value at the input gate | 0.8000 | 0.0000 |
| $W_c$ = the weight value at the new cell candidate | 0.7000 | 0.1000 |
| $W_o$ = the weight value at the output gate | 0.4000 | 0.6000 |
| $b_f$ = the bias value at the forget gate | 0.9000 | 0.4000 |
| $b_i$ = the bias value at the input gate | 0.7000 | 0.6000 |
| $b_c$ = the bias value at the new cell candidate | 0.0000 | 1.0000 |
| $b_i$ = the bias value at the output gate | 0.5000 | 0.2000 |

TABLE 3. LSTM Manual Proccessing for Results.

| **Variabel/Parameter** | **LTSM Results** | |
|---|---|---|
| | ***t*=0** | ***t*=1** |
| $f_t$ = forget get | 0.7401 | 0.6082 |
| $i_t$ = input gate | 0.7042 | 0.6547 |
| $\tilde{}C_t$ = the new cell state candidate | 0.1456 | 0.7778 |
| $C_t$ = cell state | 0.1033 | 0.5715 |
| $O_t$ = the weight value at the new cell candidate | 0.6419 | 0.5596 |
| $h_t$ = the weight value at the output gate | 0.0661 | 0.2890 |

The calculations for prediction of water supply production in Table 3 by using LTSM manual processing is performed on the first two data points from normalized water production quantity data in Jakarta. The calculation steps described above are carried out at each time step, resulting in new information in the form of values *Ct* and $h_t$, where these values are carried over to the next time step and the value $h_t$ is stored as the output of that time step. This calculation process continues until the best predicting model is obtained according to the parameters formed. Subsequently, the model is used in the testing process to obtain predicted values on target values. The complete prediction results can be seen in Figure 4.

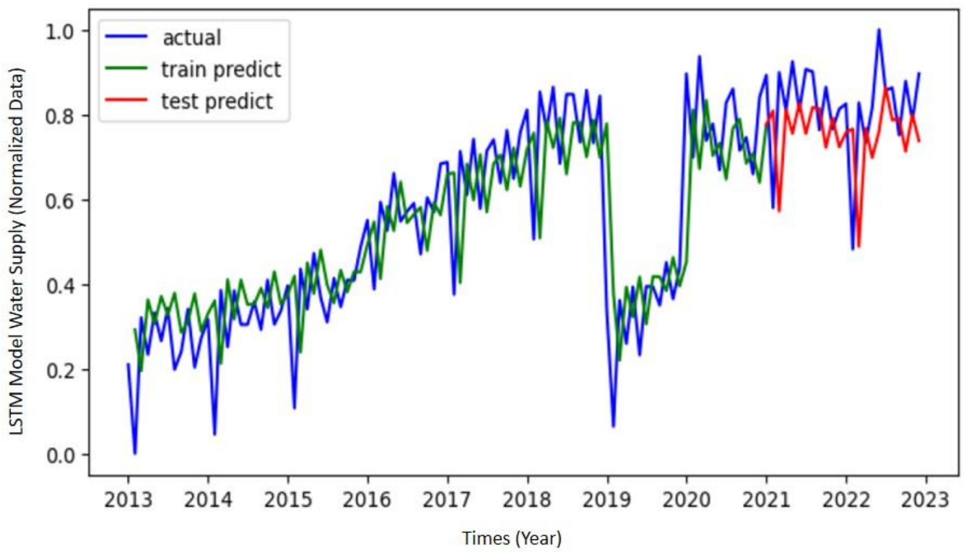



FIGURE 4. Predicting Model of Water Supply (Normalized Data) with LSTM.

It can be observed that the prediction graph follows the pattern of the actual data graph. The accuracy scores of this predictions will be calculated based on the LSTM model. The accuracy calculation results can be seen in Table 4. It is evident that the model is optimal because the mean absolute percentage error (MAPE) value on the testing data is smaller than that on the training data. Therefore, it can be concluded that forecasting using this model is considered good.

The growing population in Jakarta, along with the expansion of contemporary industrial and agricultural activities, has raised the demand for clean water. Research demonstrates that the need for clean water is growing yearly, which is evidence that have to face the quantity of water supply. Next, strategic planning has historically received minimal attention in the infrastructure industry because there is anly a little to no-competition in the market and the public or captive customers are ready to take on the investment risks.

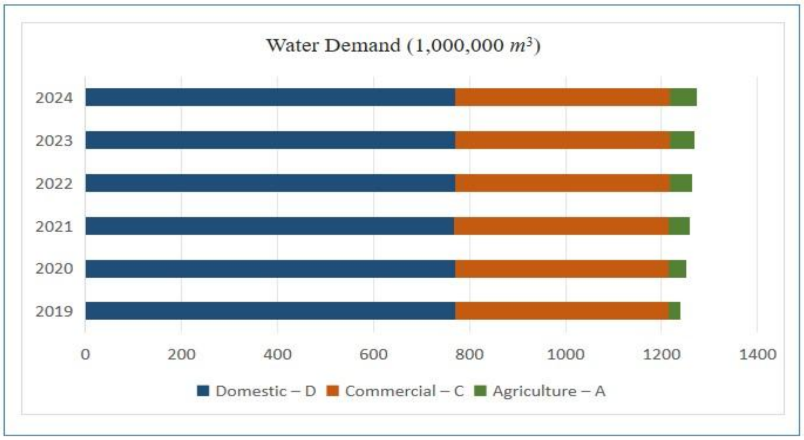
Water and hygiene for the sector policy strategy and planning, monitoring, and review are the two fundamental components that are connected to strategic planning. All of these are acknowledged as necessary elements for the water and sanitation industry to run well. Understanding the resource situation is essential for planning because it can indicate who utilizes the water in a certain area with demand and supply analysis is a good place to start.

The Table 5 described water demand and supply in Jakarta based on expended results of LSTM modeling of water supply structural movements from 2019 until 2024. The demands is related to the use of water for residents, commuters and also for domestic, commercial and agriculture. While, the supply is relied for piped/surface water, ground water and smart water management system (SWMS), where real-time operational data processing is accomplished by the SWMS, a drinking water management system that makes use of sensors and information technologies. The efficient and effective control of water use is the goal of this system, so that it is possible to reprocess and utilize waste water.

TABLE 5. Water Demand Supply (1,000,000 $m^3$) Based on LSTM Model.

| Demand-Supply | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|---|
| **Demand (1.000.000 m$^3$)** | | | | | | |
| Residents | 674.17 | 674.39 | 674.59 | 674.68 | 674.77 | 674.86 |
| Commuters | 95.02 | 95.06 | 95.09 | 95.10 | 95.11 | 95.12 |
| Domestic-D | 769.14 | 769.45 | 769.67 | 769.77 | 769.88 | 769.98 |
| Commercial-C | 446.10 | 446.28 | 446.41 | 446.47 | 446.53 | 446.59 |
| Agriculture-A | 23.58 | 35.35 | 43.89 | 47.64 | 51.66 | 55.59 |
| **Total Demand D+C+A** | 1,238.82 | 1,251.08 | 1,258.97 | 1,263.88 | 1,268.07 | 1,272.16 |
| **Supply (1.000.000 m$^3$)** | | | | | | |
| Piped/Surface Water-P | 372.19 | 342.40 | 378.64 | 363.78 | 373.34 | 369.34 |
| Groundwater-G | 866.09 | 908.14 | 879.79 | 899.56 | 894.19 | 902.28 |
| SWRS-S | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 |
| **Total Suply P+G+S** | 1,238.82 | 1,251.08 | 1,258.97 | 1,263.88 | 1,268.07 | 1,272.16 |

Jakarta relies on a variety of clean water sources, including seawater, surface water (both imported and local), and groundwater. Based on the LSTM model, we computed the supply for six consecutive years using the Jakarta water utility data as a baseline. The LSTM model was used to determine the water supply and demand shown in Figure 5. This demonstrates how Jakarta's groundwater basin provides the majority of the city's water needs at a level that puts it at risk of experiencing significant land subsidence because of restricted access to piped water. In order to enhance household access to piped water, a program that decreases reliance on untreated groundwater consumption and controls groundwater over-abstraction through the development of new infrastructure and an expansion of raw water supply is crucial.



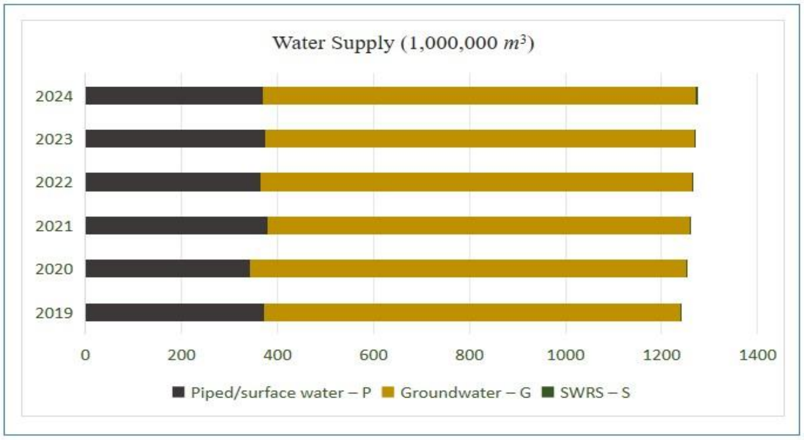




FIGURE 5. The Movement of Water Demand and Supply (1.000.000 $m^3$) Based on LSTM Model.

The groundwater still provides the majority of Jakarta's water supply, it is followed by piped or surface water accounting for around half of groundwater and also a tiny portion coming from shower water reuse system (SWRS) sources. The water supply in Jakarta needs to be stabilized. Since many locals utilize the contaminated groundwater and may be exposed to toxins like dangerous chemicals and germs on a daily basis, Jakarta must first prioritize managing the groundwater basin by improving its quality. The advantages of treating wastewater rather than dumping it straight into waterways must be understood by the community. To lessen the contamination of surface and groundwater, each building in an area where a sewage pipe is placed is required to dispose of its wastewater into the pipe via a parcel connection pipe. Second, using river water that satisfies environmental and health standards and decentralizing the supply system will increase the amount of surface water available. To provide services in specific locations, light-material rainwater tanks with a small water treatment system can be constructed. Third, it is crucial to take steps to regulate the groundwater consumption of large enterprises, particularly those situated in industrial parks, because excessive deep groundwater removal might result in a decline in shallow groundwater due to the dropping water table. Because shallow groundwater is used for daily drinking, this condition has concerns for access fairness.

Other management measures aimed at surface water are necessary, which include promoting consumer demand for water-saving technologies across commercial enterprises, government buildings, and households, as well as ensuring proper system maintenance and renovation. All these measures should be complemented by an affordable tariff scheme applicable to all segments of society. Additionally, it's important to implement a policy that ensures basic free water for daily needs specifically targeting disadvantaged populations. The improvement of clean water supply and services throughout Jakarta should be guided by a strategic planning approach in line with the new framework that needs to be developed. Establishing a new institutional structure, enhancing capacity, and creating a new governance framework are essential for managing a system that can deliver safe and affordable water to all residents. The insights provided by this study can serve as a foundation for strengthening Jakarta's water system to ensure equitable access for everyone.

## 4. CONCLUSION

Almost all cities in Indonesia are seeking alternatives to provide clean water in response to the growing population and the corresponding increase in clean water demand. As water production continues to rise, issues of water wastage emerge, underscoring the necessity for accurate forecasts of future water production levels. It is crucial to model the structural changes in clean water supply to predict a city's future water needs. This can be achieved by analyzing historical water usage data and identifying factors that influence clean water demand. The LSTM method's predictions for water production are regarded as optimal when using an 80:20 ratio of training to testing data. This is reinforced by several important hyperparameters, resulting in good accuracy values marking it as an effective forecasting model. Therefore, the LSTM approach is a superior choice for modeling to predict water production, which will assist the relevant parties in planning clean water resources that can adapt to the needs of the population. The groundwater continues to account for the majority of Jakarta's water supply, followed by piped or surface water, which represents about half of the groundwater amount. Additionally, a small portion comes from SWRS sources. To stabilize the water supply in Jakarta, it is essential to prioritize managing the groundwater basin, utilize river water that meets environmental and health standards, decentralize the supply system, and regulate groundwater consumption by large enterprises. This situation raises concerns regarding the sustainability of the water supply for Jakarta in the future.

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## CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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