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Forecasting Water Demand With the Long Short-Term Memory Deep Learning Mode

Junhua Xu, Zhejiang Tongji Vocational College of Science and Technology, China*

ABSTRACT

Traditional methods often fall short in modeling the nonlinear, seasonally variable nature of urban water demand. This proposed solution is an integrated ARIMA-LSTM deep learning model, combining ARIMA's proficiency in linear trend and seasonal modeling with LSTM's strength in capturing nonlinear time dependencies. In these experiments, the authors trained and evaluated using daily water demand data from 2015 to 2020, with its performance validated for the year 2021. The ARIMA-LSTM model demonstrates promising results, outperforming individual models in terms of accuracy. In validation, it achieves a high coefficient of determination (R^2) of 0.98 and a significantly low root mean square error (RMSE) of 2.94. These metrics indicate an excellent fit to the data and a high level of precision in its predictions. The significance of this research lies in its potential to advance the field of urban water demand forecasting, ultimately contributing to better water resource management and sustainability in urban areas.

KEYWORDS

ARIMA, Deep Learning, LSTM, Urban Water Demand, Water Resource Management

INTRODUCTION

The rapid expansion of urban areas underscores the increasing necessity for intelligent urban water supply systems, which are crucial for the development of modern smart cities (Wu et al., 2018). A key component of such systems is the prediction of urban water demand, a task that is both significant and challenging. Accurate predictions of water demand are essential for optimal operation of valves and pumps in waterworks and for identifying potential leakages in the supply network. Effective water demand forecasting can not only lower water supply costs but also ensure that urban water needs are met. However, few models are practically applicable to urban water demand prediction. This task is complex due to the multifaceted influencing factors and inherent unpredictability of urban water demand (Du et al., 2021).

The accurate forecasting of urban water demand is a critical aspect of sustainable urban development and efficient resource management. As urban populations grow and climate patterns

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*Corresponding Author

change, the need for robust forecasting models becomes even more pronounced. In recent years, the integration of machine learning and deep learning techniques in this field has shown promising results, leading to more accurate, adaptive, and efficient forecasting models (Khozani et al., 2022; Xu et al., 2022). Urban water demand forecasting is not just a technical challenge but also a key component in addressing broader issues such as water conservation, infrastructure development, and environmental sustainability (Butler & Memon, 2005; Donkor et al., 2014). Accurate forecasting helps in reducing wastage, optimizing distribution, and planning for future needs, particularly in the context of climate change and urban expansion (Zubaidi et al., 2020). The deep learning models commonly used in the field are as follows (Adamowski & Karapataki, 2010): Linear Regression models are the most basic form of predictive analysis and are used for their simplicity and interpretability (Pulido-Calvo et al., 2007; Sebri, 2016). However, they often fail to capture complex nonlinear relationships inherent in water demand data. ARIMA (auto-regressive integrated moving average) is a popular traditional statistical model for time series forecasting, which is effective for data with a clear trend or seasonal pattern but struggles with non-linear data (Pulido-Calvo et al., 2007). Support vector machines (SVMs) are effective for classification and regression challenges. SVMs work well with high-dimensional data but can be computationally intensive and less effective with very large datasets (Peña-Guzmán et al., 2016). The random forest is an ensemble learning method that is robust to overfitting and can handle both linear and nonlinear data (Chen et al., 2017). However, it can be less interpretable and may require a significant amount of data for optimal performance. The LSTM (long short-term memory network) is a type of recurrent neural network (RNN) particularly well-suited for time series data due to its ability to capture long-term dependencies. However, LSTMs can be complex to tune and train and may require substantial computational resources (Kühnert et al., 2021).

Banjac et al. (2015) developed a water demand prediction system utilizing ANNs, which was a significant step towards understanding the complex dynamics of water demand series. Further, Yin et al. (2018) demonstrated the superiority of ANNs over traditional statistical models in water-energy demand forecasting, highlighting the enhanced predictive accuracy and capability of ANNs in handling complex datasets. Additionally, other machine learning methods have also been explored and applied in the field of water demand forecasting, signifying a shift towards more sophisticated, data-driven approaches in this area. However, these methods, particularly those with shallow architectural designs commonly found in classic intelligent models, face limitations in efficiently handling large-scale data. This restriction hinders their ability to effectively mine and interpret complex data features, presenting a significant challenge in the field of predictive analytics, where understanding and leveraging intricate data patterns is crucial (Du et al., 2021).

Given the limitations of traditional models in capturing the complexities of urban water demand, there is a clear need for models that can assimilate both linear and nonlinear patterns efficiently. This led to the proposal of combining ARIMA and LSTM into a cohesive model, aiming to utilize the strengths of both methods: ARIMA's efficiency in modeling linear aspects and seasonality and LSTM's prowess in capturing complex, long-term nonlinear dependencies. The ARIMA-LSTM model is designed as a hybrid approach, where initially, ARIMA is employed to model and remove the linear trends and seasonality from the time series data. This processed data is then fed into an LSTM network to model the residual (non-linear) components. The ARIMA component handles the linear and seasonal aspects of the time series data, making the residuals more stationary and easier for the LSTM to model. The LSTM component focuses on the non-linear patterns in the residuals, leveraging its recurrent nature and long-term memory capabilities. By combining these two approaches, the ARIMA-LSTM model aims to provide a more comprehensive and accurate forecast of urban water demand, addressing both short-term fluctuations and long-term trends. This hybrid approach is expected to outperform traditional models, especially in scenarios with complex demand patterns influenced by multiple factors such as weather, urban activities, and policy changes.

The main contribution of this article lies in introducing an integrated approach that combines the traditional ARIMA time series model with the deep learning LSTM model. This integration

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