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TABLE OF CONTENT

PART 1: MATHEMATICS

PART 2: STATISTICS

PART 3: COMPUTER SCIENCE & INFORMATION TECHNOLOGY

PART 4: OTHERS

WATER DEMAND PREDICTION USING MACHINE LEARNING: A REVIEW

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Water is important and critical sources of life. Even though some countries enjoy tropical weather year-round with plenty of water resources like Malaysia, they are still facing scarcity issue. Water demand is influenced by various factors such as population, climate change and water utilization. This study reviews 45 Scopus articles from year 2015 to 2021 on predicting water demand using Machine Learning (ML) methods which include: neural network, random forest, decision tree, and hybrid optimisation models. The summary of ML methods on the evaluation of their performance in water demand prediction is identified by a comprehensive analysis of the literature. The narrative search of the most relevant literature is classified according to method, prediction type, prediction variables and accuracy rate. The review identified several machine learning methods that are commonly used which include decision tree, neural network, random forest and hybrid method. In conclusion, the study reports that the accuracy of the method varies according to types of prediction variables used.

Keywords: Water demand, Machine learning, Neural network, Decision tree

1. Introduction

Water is one of the important element and a critical source of life. With the growing of population as well as higher standard of living, the demand of water in daily use has also increased (Ali et al., 2014). However, some countries are still facing some problems with water scarcity issues even though they enjoy tropical weather year-round with plenty of water resources. Water demand is influenced by various factors such as population, climate change and water utilization (Ali et al., 2014).

Forecasting water demand with higher accuracy is useful to various parties for effective long-term planning in order to manage water systems efficiently and accommodating the increase in water demand. There are many uncertainties in predicting water demand and some of the challenges evolve from the relationship between human and natural systems in urban environments (House-Peters and Chang, 2011). Traditional methods such as time series and regression model were firstly used in forecasting water demand, however, the approaches have less accuracy (Zubaidi et al., 2020c). Recently, machine learning methods which include random forest, neural network, and support vector machine has been widely employed in the prediction of water demand.

There are limited studies done in Malaysia regarding water demand forecasting especially using machine learning method. Ali et al. (2014) and Mohd Firdaus and Talib (2016) investigated the pattern of water supply and demand in Langat catchment and Selangor area using Water Evaluation and Planning (WEAP) System. The Stockholm Environment Institute (SEI) created WEAP, a unique water resources and planning software that stimulates hydrologic patterns based on climatic input. This is a critical tool for informing society about climate change adaptation and policy making. WEAP also allows users to create scenarios using assumptions about water demand, infrastructure, and regulation, such as an increase in temperature or heavier rainfall. WEAP can combine all human activities in order to predict water shortages and water quality based on a model scenario. The latest study by Anang et al. (2019) used the pooled Ordinary Least Squares (OLS) to determine the availability of water resources for 13 states in Malaysia. The pooling technique used compared changes in cross-sectional units to changes in individual units over time. It allows for more complex analysis than either cross-section or time series analysis alone. Furthermore, pooled regression uses pooled data sets to handle a larger number of data points.

This study reviews the current studies on the prediction of water demand. The review covers the application of ML methods (including optimization and hybrid models) and the discussions on the evaluation of their performance in water demand prediction. Narrative reviews of relevant literatures are classified according to method, prediction type, prediction variables and accuracy rate. The discussion and the conclusion of the reviews are presented in the last section of this paper.

2. Research Methodology

The SCOPUS online database has been assessed to identify the related documents on water demand forecasting using ML approaches. The database had been explored by using the advanced document search with keyword: (TITLE-ABS-KEY ("water demand") AND TITLE-ABS-KEY ("machine learning" OR "Deep learning" OR "ANN" OR "MLP" OR "ELM" OR "neural network" OR "ANFIS" OR "decision tree")).

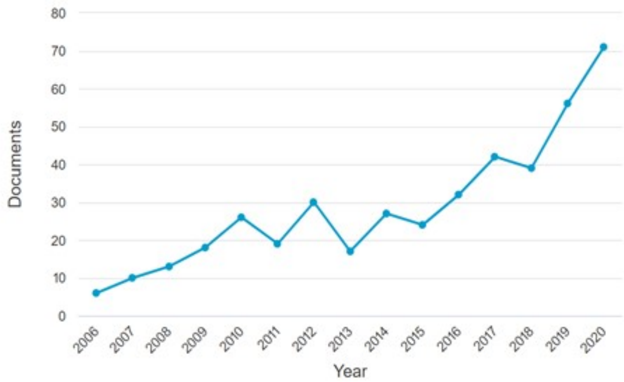

Figure 1: The number of SCOPUS publication in water demand prediction using Machine Learning approaches.

Figure 1 represents the number of SCOPUS publications in water demand prediction using ML approaches since 2006. The database shows an increment in the number of manuscripts published from year to year. In this paper, 46 relevant papers issued from 2015 to 2021 are reviewed. The revised papers are then categorised based on the ML model used which are Neural Network, Decision Tree, Random Forest, Hybrid, and Optimization models as illustrated in Section 3.

3. Machine Learning Models

The ML models presented in this paper include: 17 Artificial Neural Network, 9 Decision Tree, 4 Random Forest, 15 Hybrid and Optimisation. The review takes into consideration of the year the papers were published, the prediction variables and prediction type used in water demand analysis, the region in which the data were taken from, and lastly, the accuracy rate of the ML models chosen.

3.1 Artificial Neural-Network (ANN)

ANN is a computing system design that resembles the way human brain works where it takes the preceding examples into consideration to create a system of neuron hence makes a new decision. In modelling complex data pattern, ANN model is more practical and precise as the technique involved non-linear applications. ANN has been broadly used in various areas especially in prediction and classification. The extensive reviews of water demand forecasting using ANN is as in Table 1.

Table 1: Papers Review on Water Demand Analysis using ANN model.

References	Prediction Variable	Prediction Type	Region	Accuracy Rate
Carvalho et al. (2021)	Water demand	N/A	Fortaleza, Brazil	N/A
Xenochristou et al. (2020)	Water demand	1-7 days into the future	Southwest of England	MAPE $= 3.2\% - 17\%$, for a reduction in group size from 600 to 5 households.
Sidhu et al. (2020)	Crop water demand	Daily	Karnal in Haryana, India	Average accuracy rate of 71%
Xenochristou and Kapelan (2020)	Water demand	Daily	Southwest of England	$R^2 = 74.1\%$
Pesantez et al. (2020)	Water demand	Hourly	Cary, North Carolina, USA	Median RMSE $= 9.5 - 16$ gph of water
Ibrahim et al. (2020)	Water demand	Daily	Kuwait	Support Vector Linear Regression MAPE $= 0.52$, RMSE $= 2.59$, ARIMA MAPE $= 1.8$, RMSE $= 9.4$
Chen et al. (2020)	Evapotranspiration for cabbage farmland	Daily	Hunan Province	$R^2 = 0.78 - 0.81$
Smolak et al. (2020)	Short-term water demand	24hours forecast Weekly forecast	Wroclaw, Poland	MAPE $= 90.4\%$
Rahim et al. (2020)	N/A	N/A	N/A	N/A
Lee and Derrible (2020)	Water Demand	Daily	USA	$R^2_{adj} = 0.60$
Mouatadid et al. (2019)	Water irrigation flow	Daily	Palos de la Frontera	Wavelet-bootstrap using ANN: $R^2 = 0.9432$, Bootstrap using Machine Learning: $R^2 = 0.9190$
Vonk et al. (2019)	Climate change and vacation absence	Yearly, daily	Netherlands and Belgium	The average demand increased between -0.2% and $+3.1\%$, The peaking factor increased between -2.9% and 21.3%.
Duerr et al. (2018)	Portable water billing records water usage data from TBW	Short term, Long term	Tampa Bay Water, Florida (Hills-borough, Pasco, and Pinellas)	N/A
Candelieri (2017)	Water demand	Hourly	Milan	N/A
An et al. (2015)	Building water demand	Area Precipitation per Demand Ratio (APDR)	Hong Kong	N/A
Safavi et al. (2015)	Baseline scenario	Annually	Iran	N/A
Liu et al. (2015)	Urban water use	Yearly	China	NSE $= 0.87$

3.2 Decision Tree

Decision tree uses supervised machine learning algorithms where the data analysis technique divides the data into many possible entities related to a given parameter. A decision tree has two main components which are nodes and leaves. The supervised learning approach analyses an item's observation in the branches to determine the item's goal value in the leaves. The leaves reflect the results, whereas the decision nodes represent the data splitting. One of the benefits of decision trees is that their outputs are simple to read and analyze without the need for statistical expertise. However, the main problem of the decision tree is generally leading to overfitting of the data which ultimately leads to wrong predictions. The summary of water demand studies using decision trees are as in Table 2.

Table 2: Papers Review on Water Demand Analysis using Decision Tree model.

References	Prediction Variable	Prediction Type	Region	Accuracy Rate
Ahcene and Saadia (2019)	hourly water request	Hourly	Rassauta, Algeria	$R = 0.95$
Oyebode (2019)	weather and socioeconomic variations	N/A	City of Ekurhuleni, South Africa	Pearson correlation-based ANN model produced the highest R^2 and NSE values at 0.9233 and 0.9001
Shah et al. (2018a)	temperature, rainfall, snow, snow depth, number of customers, median income, holidays and day of the year	Daily and monthly	Indiana, USA	mMLR = -12.73%, mFFNN = -6.45%, mMRNN = -3.84%
Yin et al. (2018)	total population, urban population, and the primary, secondary, and tertiary industry gross domestic product, annual precipitation	Yearly	Wuxi City, China	Mean relative error: ANN $= -2.14\%$, MLR $= -3.96\%$
Shah et al. (2018b)	Weather conditions	Daily	Indiana	Average error 2.31% and 1.90% with threshold values of 10% and 5%
Shabani et al. (2018)	Water demand	short term	Milan, Italy	$R^2 = 0.95$ and 0.93 for training and testing data set
Farias et al. (2018)	RBF-ANN Drinking water demand	Hourly, daily, weekly	Barcelona	RMS $= 0.0559$
Loureiro et al. (2016)	Water demand	Daily	Portugal	Relative error, $= 7\% - 21\%$
Ji et al. (2016)	Water supply operation	Monthly	China	83%

3.3 Random Forest

Random forest is made up of huge number of individual decision trees that work together as an ensemble. Each tree in the random forest produces a class prediction and the class with the most votes becomes the prediction model. Its popularity is due to its ease of use and adaptability as it can handle both classification and regression problems. Besides, it reduces overfitting in decision trees and helps to improve the accuracy. However, Random Forest creates a lot of trees and combines their output. In order to do so, this algorithm requires much more computational power and resources. The summary of water demand studies using random forest are presented in Table 3.

Table 3: Papers Review on Water Demand Analysis using Random Forest Model.

References	Prediction Variable	Prediction Type	Region	Accuracy Rate
Villarin and Rodriguez-Galiano (2019)	Domestic water consumption per capita	N/A	Seville, Andalusia	RMSE = 22.06 L/day/inhabitant, $R^2 = 0.46$
Park and Lee (2019)	daily usage of water per person, water price, population, and the information of the water source	Seasonal	Korea	N/A
Tulbure et al. (2016b)	Surface water dynamics	Long term trends	Australia	99.9%(0.02% standard error) with 87%(3%) and 96%(2%)
Tulbure et al. (2016a)	Surface water (SW)	Yearly	Australia	99.94%

3.4 Hybrid and Optimization

Hybrid model is a method to overcome the weakness of an original approach by combining two or more techniques. This model works significantly more efficient and has better predictive performance. Optimization approache is a process of modifying the hyperparameters. The aims of optimization algorithm are to identify the best parameter values under various conditions. This method has been used to solve problems in numerous applications domains. Table 4 presented the reviews on hybrid and optimization methodologies for prediction of water demand.

Table 4: Papers Review on Water Demand Analysis using Hybrid and Optimization models.

References	Prediction Variable	Prediction Type	Region	Accuracy Rate
Pandey et al. (2021)	Water demand	Hourly and monthly	Spanish and India	Spanish RMSE $= 11.67\% - 62.38\%$, Indian RMSE $= 52.19\% - 70.12\%$
Zubaidi et al. (2020a)	Urban water demand	Monthly	Southeast Water Utility in Melbourne	$R^2 = 0.9$
Zubaidi et al. (2020b)	Municipal water demand	Monthly	Melbourne City	ANFIS CE $= 0.974$, CSA-ANN CE $= 0.971$
Zubaidi et al. (2020d)	Long-term Municipal Water Demands	Monthly	Australia, Greater Melbourne, Victoria,	$R^2 = 0.96$, RMSE $= 0.0025$
Zubaidi et al. (2020c)	Urban water demand	Monthly	Gauteng Province, South Africa	BSA – ANN: RMSE = 0.0099 Mℓ, CE $= 0.979$
Kazemi et al. (2020)	Water resources allocation	Monthly	North of Iran	$R^2 = 0.78 - 0.9$, RMSE $= 2.35 - 4.26$
Peng et al. (2019)	growth period of crops, irrigation values (light intensity, soil moisture, soil electrical conductivity, and air temperature)	Long term	China	$R = 0.98963$, Mean Square Error (MSE) $= 0.00857724$
Zhang et al. (2016)	Water demand	Annually	China	RMSE $= 42.8\%$, MAE $= 7.6\%$

Hou et al. (2016)	Water demand	Annually	China	N/A
Safavi and Enteshari (2016)	Water extraction quantities	Monthly	Iran	$R^2 = 0.86 - 0.99$
Abdullah et al. (2015)	Evapotranspiration (ET)	Daily	Iraq	$R^2 = 0.982$
Tiwari and Adamowski (2015)	Water demand	Weekly and monthly	Canada	$R^2 = 0.70 - 0.85$
Rahmani and Zarghami (2015)	Water resources management	Monthly time scale	Iran	$R^2 = 0.82 - 0.98$
Perea et al. (2015)	Irrigation water demand	Daily	Spain	$R^2 = 0.93$
Tiwari and Adamowski (2017)	Water demand	Daily	Canada	$R^2 = 0.78 - 0.92$

4. Discussion

This study has reviewed papers on water demand using machine learning from 2015 to 2021. It is found that, most of the studies focus on short-term demand forecasting and very few studies address medium and long-term forecasting. An extensive literature review revealed that the most used machine learning method to predict water demand was Artificial Neural Network. Finding the best method that can provide the best results can be a difficult task because it depends on the predictive variables included and data that the studies used.

The accuracy of the predictive models was evaluated using variety of methods including accuracy rate, R^2 and error rate such as RMSE and MAPE. The comparative assessment of the prediction models showed that the hybrid and optimized methods can be considered as the best assessment to predict future water demands.

5. Conclusion

In the previous six years, the adoption of machine learning models has increased. The reviewed found that the most machine learning method used is Artificial Neural network, Support Vector Machine, Random Forest and Decision Tree. According to the study, the method's accuracy varies based on the type of prediction variables applied. In addition, the use of hybrids and optimization methods has risen considerably in recent years. The researchers have proven that hybrid and optimization models can improve accuracy and efficiency of the models. The research's next step is to create hybrid and optimization models with improved accuracy.

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