Modelling Domestic Water Demand and Management Using Multi-Criteria Decision Making Technique

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Abstract

Sustainable water consumption is considered as one of the key factors for the successful management and development of every institution. In selecting the most appropriate forecasting technique for an institution, it is necessary to consider not only the planning needs but also the balance of the benefits arising from adopting a more sophisticated technique against the cost of data acquisition and analysis. However, there is a lack of an analytical tool that matches the needs and capability of the institution in dealing with multifaceted problems based on the selected criteria for water management. In this premise, this study aims to provide an appropriate prediction model in the short and midterm of water demand forecasting based on institution-specific criteria. There were two steps used to perform decision making in selecting the water demand forecasting. First, a multi-criteria decision making technique was applied to obtain weights in each criterion and was used in all models. Second, each model utilized a 10-fold cross-validation to evaluate prediction models by dividing the dataset into a training and a test set. Mean absolute percentage error was used to assess the performance of the models. Based on the result, the support vector machine was the most preferred model. In the short-term water demand forecasting, it only used one variable to predict the water demand. The most preferred model was autoregressive integrated moving average.

***Keywords**:* water demand, multi-criteria decision making, decision support system

1. Introduction

Water is considered at the core of sustainable development and is essential in everyday social and economic activities. The available water resources must be reliable and predictable at the place where the user needs to support the services they provide (World Water Assessment Programme, 2015). In any institution or organization, having sustainable water consumption is one of the critical factors for successful management and achieving goals. However, sustainable water consumption and water scarcity are significant challenges as the global population increases. These challenges may damage our ecosystems, and the distribution of water resources available make it critical in many regions.

The cost of water supply has further increased rather than alleviated the problem of sustainable water consumption and water depletion (Pfister and Ridoutt, 2016). At present, most of the institutions are focused on identifying potential gaps between water demand and supply at a future date. These gaps can be eliminated by developing a detailed plan that could benefit the institution such that guaranteed water supplies are provided to the user, and where there is a stable supply for estimated water demands. These plans typically include projections of water use based on socioeconomic factors, land area use, and other variables that affect water demand. Usually, institutions use a demand forecasting method for their planning and operational strategy level.

Forecasts can help anticipate potential revenue shortfalls related to usage reductions. In the water industry, forecasting is helpful because it can fix costs and represent a massive proportion of the overall cost. It also suggests that an unforeseen reduction in demand will likely decrease revenues compared to the total cost in a short period. Reliable and accurate forecasting is vital so that institutions can better plan the building of new infrastructure that will function to serve the future demand and avoid the financial burden of capital investments and maintenance, and other costs of assets due to failure in planning (Sahin *et al.*, 2017). Having accurate forecasts can help utility companies avoid budget deficits by more effectively managing costs and rates. This is only achievable if the appropriate variables for the development of the water demand forecasting model are identified. Haque *et al.* (2018) suggest that these variables must create high intercorrelation with the independent variables.

When selecting a forecasting method, a variety of qualitative factors must also be considered. These include the purpose and goal of the forecast, ability to perform forecasting horizons and periodicities, and availability of data. Other approaches to select a forecast model are structured judgment, validation sample, and information criteria (Kourentzes, 2016).

Identifying the appropriate forecasting model is highly critical and significantly influenced by the type of industry. Decision makers are also expected to use the most sophisticated and applicable model that would fit the organization's financial capacity. At present, finding an appropriate analytical tool that connects the preferences of an institution and its capability in handling problems of water management is still an issue. The water demand is also increasing rapidly, while only a few options available for new development or strategy on utilizing the limited water resources of freshwater and conservation of groundwater. Moreover, regardless of the water demands, there are excessive growth projections that lead to investment in excess water supply capacity that also means higher cost.

Like many other decision-based problems, applications of decision support system (DSS) help decision makers improve their evaluations for water management. DSS has been widely used in water resources management to facilitate decision-making in the competing demand from irrigation, industry, water supply, hydropower, environment, and climate change (Anzaldi *et al.*, 2014). A suitable multi-criteria decision-making (MCDM) tool is necessary to attain the success and effectiveness of water supply systems, considering the importance of water resources and the various criteria that must be taken into account in decision-making (Garfí *et al.*, 2011).

Some studies have used various MCDM methods or group decision-making on water resources management. Among others, analytic hierarchy process (AHP) was used for water supply scheduling (Ilaya-Ayza *et al.*, 2017); preference ranking organization method for enrichment evaluations (PROMETHEE) in water network segmentation (Fontana and Morais, 2017); elimination and choice expressing reality (ELECTRE)-II for water allocation (Kumar *et al.*, 2016) and voting procedure in network maintenance (Almeida-Filho *et al.*, 2017). While these works did not address the problem, they demonstrated the applicability of MCDM in solving water management problems.

Meanwhile, there are various methods implemented for water demand forecasting, including standard methods like water quota and conventional tendency approaches. There are also multiple linear regression approach, system dynamics approach, the gray model and artificial neural network approach (Sebri, 2016; Ghalehkhondabi *et al.*, 2017; Tan *et al.*, 2017). Recently, many researchers adopted the linear regression model to develop water demand forecasting models (Al-Musaylh *et al.*, 2018; Candelieri *et al.*, 2018), for long-term forecasting. However, neural networks and hybrid models are found to be more suitable for short-term forecasting (Haque *et al.*, 2018).

In this study, a decision-support system, designed and developed for forecasting domestic water demand and management, is proposed. This system incorporates an MCDM technique to assist the selection of the most appropriate demand forecasting methodology and conservation measures based on various criteria for institution-specific. Furthermore, this study discussed the domestic water usage patterns, bridge the gap between present and future domestic water demand and management. The sample data used was taken from the Asian Institute of Technology (AIT) through the Office of Facilities and Asset Management (OFAM) to demonstrate the system capability.

2. Methodology

This section presents the steps of building a model for water demand and management. The steps include data gathering, identifying of MCDM evaluation criteria, selecting of forecasting method, testing of datasets and generating the results. Figure 1 shows the proposed flow in building an institution's own model tested in this study.

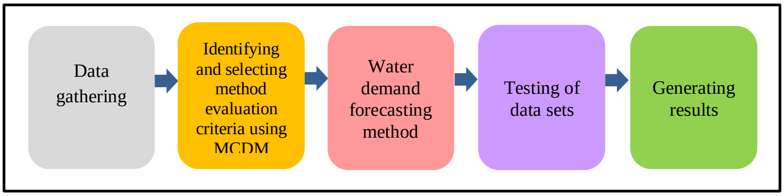

Figure 1. Process flow diagram of the water demand and management of the institution

2.1 Proposed System Architecture

Figure 2 shows the proposed system architecture. There were three components involved in the project, namely the MCDM technique, prediction model, and visualization. The MCDM aids in identifying the appropriate forecasting method to be used by the institution based on its preferences. The institution sets their criteria and weight to choose the forecasting method. Furthermore, the institution decides what type of prediction model based on the result in MCDM. The dataset is then loaded to the identified prediction software tool to generate a dataset.

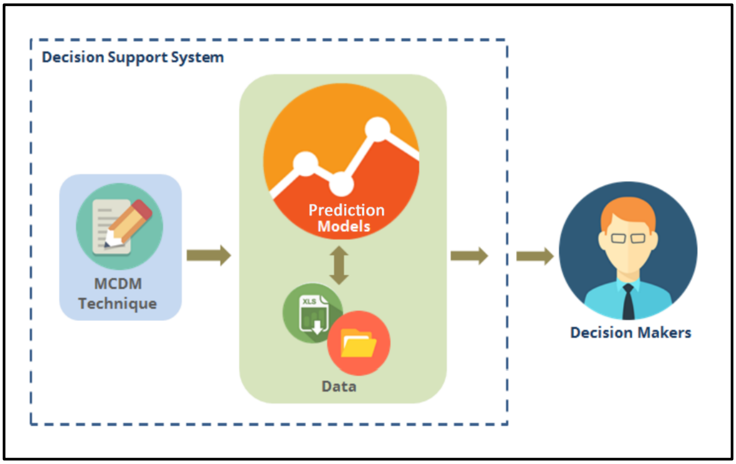

Figure 2. Proposed system architecture for water demand management of the institution

2.2 Data Collection and Criteria

In terms of the planning level, many institutions used varied approaches for water demand forecasting exercises. This study focused on the short and midterm water demand using forecast variables. These variables were categorized into socioeconomic (past water demand [2012-2016] and current population) and weather forecast (average temperature, total amount of rainfall, number of days of raining, average relative humidity, maximum energy from sunray, and average ground level temperature). The socioeconomic variables are usually applied for the long-term effects on water demand, while weather forecast variables are used for short-term water demand (Oyebode and Ighravwe, 2019). Data were sourced from the 2012-2016 AIT and Pathum Thani weather station records, which contained two socioeconomic and six weather forecast variables. More specifically, the data in socioeconomic variables consists of monthly and annual water consumption in each building, while weather forecast variables are on a monthly basis.

In this system, the institution can choose or design their criteria in selecting the models to forecast the water demand and supply. There is a possibility that every institution has different sets of criteria. The criteria below were based on the preferences of the AIT OFAM.

Criteria 1: Forecast accuracy – this implies that an institution should make forecasts close to real figures so that the real picture of demand can be determined.

Criteria 2: Data requirements – the forecasting methods should depend on the availability of the data. When there is no data available or irrelevant to the forecast, then qualitative forecasting methods must be used.

Criteria 3: Speed – this means the fast execution time of the forecasting method in the entire process.

Criteria 4: Required resources – these include the time and cost to build (including data collection, verification, and validation), run and analyze the results of the model, and the model's hardware requirements (e.g., computer memory).

Criteria 5: Ease of use – the method should be user-friendly and understandable in most cases. The methods should be such that the institution does not face any complexities, too much time and manual labor involved in preparing the forecasts.

Criteria 6: Flexibility – this indicates that the forecasts must be adjustable and adaptable to changes. It gives management the flexibility necessary to use non-numerical data sources, such as the intuition and judgment of the experienced user.

2.3 Application of MCDM Approach

The MCDM, which incorporates multiple criteria, is a method to solve decision and planning problems. Using the MCDM, the institution can attain an optimal solution to solvable problems using common models. Some other widely used MCDM methods are AHP (Saaty, 1994), the ELECTRE (Benayoun *et al*., 1966), and the technique for order of preference by similarity to ideal solution (TOPSIS) (Hwang and Yoon, 1981). In this study, AHP was used in selecting forecasting method. The AHP has a particular application in group decision making and is used around the world in a wide variety of decision situations in the government, business, industry, healthcare, and education. Rather than prescribing a correct decision, the AHP helps decision makers find one that best suits their goal and their understanding of the problem. It further provides a comprehensive and rational framework for structuring a decision problem; representing and quantifying its elements; relating these elements to the overall goals; and evaluating alternative solutions (Giri and Nejadhashemi, 2014).

2.4 Construction of Water Demand Forecasting Models

In short-term forecasting, the data can get in less than a year and offer forecasts of hourly, daily, weekly or monthly demand. These short-term forecasts assist water utilities with day-to-day system management and optimization (Donkor *et al*., 2014). This study utilized the autoregressive integrated moving average (ARIMA) model for forecasting time series to predict the water demand for the next month using AIT OFAM's historical record of water consumption. The ARIMA model was used and integrated into other models including hybrid model 1 ARIMA - artificial neural network (ANN) and hybrid model 2 ARIMA - SVM. These hybrid models both have linear and nonlinear patterns for forecasting water demand. There are two steps applied in each hybrid model. First, an ARIMA model is used to analyze and predict the linear values for future value. Second, the residual obtained from the ARIMA is entered to ANN or SVM model. Since the ARIMA model cannot capture the nonlinear structure of the data, the residuals of linear model would contain information about the nonlinearity. The results from the ANN or SVM model could be used as predictions of the error terms for the ARIMA model.

The midterm forecast can generate data from one to 10 years with monthly or annual horizons. It allows the water utility to develop revenue forecasts and plan investments (Donkor *et al.*, 2014). This study used a linear regression model, and both the neural network and SVM for midterm water demand forecasting model to predict the next one to three years of water demand.

2.5 Model Optimization and Evaluation

To maximize the model performance, this study applied model optimization through sensitivity analysis. All models were evaluated using 10-fold cross-validation strategy. Each sub data set was randomly divided into sets in which nine sets were dataset training and one set was dataset testing. This process was repeated 10 times. Mean absolute percentage error (MAPE) was used to measure the forecast error of each model.

3. Results and Discussion

3.1 AHP Model

Figure 3a and 3b show the screenshot of the AHP model, preferred water demand forecast methods for short-term and midterm period. There are three levels in each model where every node in a level is the parent of every node in the next level down. The model starts from the goal and moves down systematically. A set of criteria in the next to the last level is connected only to those elements for which pairwise comparison makes sense in the bottom level. Decision-maker may assign value to compare a pair of elements that give a meaningful weight vector.

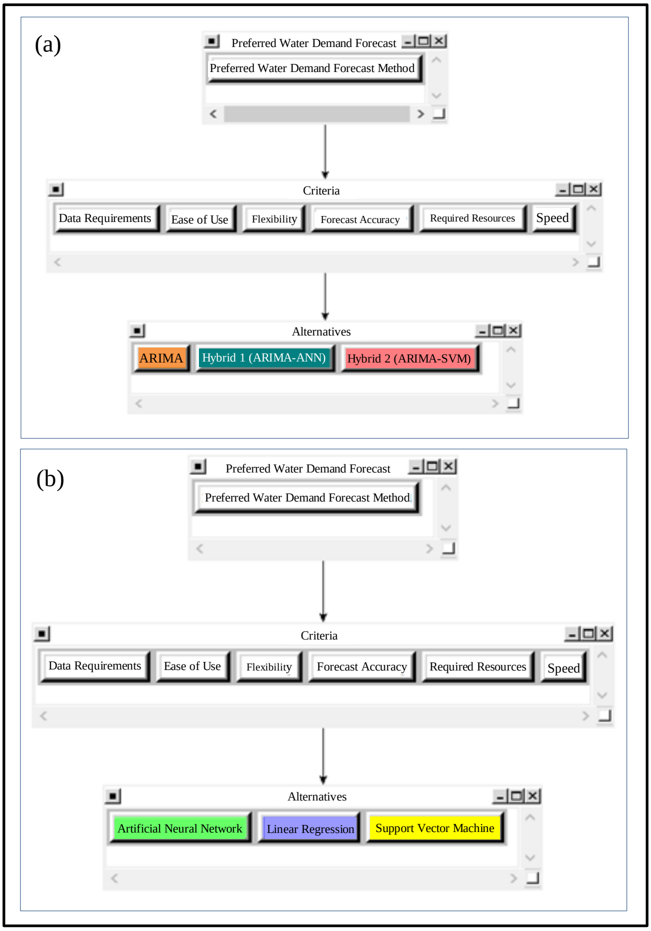

Figure 3. Screenshots of created AHP mode:
water short-term demand (a) and midterm water demand (b)

3.2 Criteria Weight Results

Table 1 shows the weights of each water demand forecasting criteria. Forecast accuracy has the highest weight of 0.39. The second highest weight is the data requirements with 0.26. This is followed by speed and required resources with a weight of 0.17 and 0.10, respectively. The lowest weight is ease of use (0.03) and flexibility (0.05). The inconsistency index 0.089 is desirable to be less than 0.1. This was kept in mind while performing the pairwise comparison for all the items.

Table 1. Water demand forecasting criteria

Criteria	Weights	Rank
Forecast Accuracy	0.39	1
Data Requirements	0.26	2
Speed	0.17	3
Required Resources	0.10	4
Flexibility	0.05	5
Ease of Use	0.03	6
Total	1.00	

Inconsistency: 0.089

3.3 Performance of Models

In the construction of the model, cross-validation was used to measure the model's performance using 2016 data as test set. Lewis (1989) classified models: best model – MAPE is less than 10%, good model – MAPE is between 10% to 20%, acceptable model – MAPE is 20% to 50%, and false or unacceptable model – MAPE is 50% and above. In the short-term level, it only needs a historical record of water consumption to predict the water demand for the next month. Referring to Table 2, all models were considered as the best model. ARIMA has the lowest MAPE value (4.09%) compared to two hybrid methods. In the midterm level, it applied optimization to select suitable attributes every model. In Table 3, SVM generated the lowest MAPE value (5.47%), followed by neural network with 6.89% MAPE value. Linear regression is still considered a good model with MAPE value of 12.90%.

Table 2. Comparison of short-term water demand forecasting model

Methods	10 Folds-Cross Validation MAPE	Year 2016 Test set MAPE
ARIMA	6.82%	4.09%
Hybrid ARIMA ANN	7.02%	4.62%
Hybrid ARIMA SVM	6.99%	4.36%

Table 3. Comparison of models in sensitivity analysis and optimization

Model	No. of Attributes		10-Fold Cross-Validation			2016 Year Test Set		
	Unoptimized	Optimized	Unoptimized MAPE	Optimized MAPE	Improve (%)	Unoptimized MAPE	Optimized MAPE	Improve (%)
Linear Regression	6	2	8.18%	7.74%	5.38%	4.95%	4.31%	12.90%
Neural Network	6	2	8.07%	7.79%	3.46%	4.71%	4.39%	6.89%
SVM	6	3	7.59%	7.46%	1.72%	4.39%	4.15%	5.47%

3.4 Comparison of Water Demand Forecasting Models

Table 4 summarizes the overall priority of water demand for short-term water demand period. The table also shows the average weights of each water demand factors or operational planning model. Based on the result, ARIMA is 0.49 or 100% – the most preferred model, followed by hybrid 2 (ARIMA-ANN) with 0.29 or 59.1%, and hybrid 1 (ARIMA-ANN) with 0.22 or 44.7%.

Table 4. Overall priority weights for water demand forecasting in short-term period

Criteria	ARIMA	Hybrid 1 (ARIMA-ANN)	Hybrid 2 (ARIMA-SVM)
Preferred Model	*0.49*	*0.22*	*0.29*
Forecast Accuracy	0.59	0.16	0.25
Data Requirements	0.41	0.26	0.33
Speed	0.33	0.33	0.33
Required Resources	0.53	0.14	0.33
Flexibility	0.55	0.21	0.24
Ease of Use	0.49	0.31	0.20
Rank	1	3	2

Table 5 shows the overall priority of water demand for midterm water demand period. Also, it shows the average weights of each water demand factors. Results revealed that SVM is 0.46 or 100%, which means that it is the most preferred model for midterm water demand period or tactical planning level. ANN is 0.29 or 55.2% (good as the most preferred model). Lastly, the linear regression is 0.25 or 51.9% (still good as the most preferred model).

Table 5. Overall priority weights for water demand forecasting in midterm period

Criteria	ANN	SVM	Linear Regression
Preferred Model	*0.29*	*0.46*	*0.25*
Forecast Accuracy	0.29	0.57	0.14
Data Requirements	0.14	0.57	0.29
Speed	0.16	0.25	0.59
Required Resources	0.57	0.33	0.10
Flexibility	0.52	0.33	0.14
Ease of Use	0.25	0.60	0.15
Rank	2	1	3

4. Conclusion and Recommendation

There are different factors and priorities that need to be considered in seeking the right water demand forecasting model to be used by each institution. In this study, AHP method was used to obtain weights of identified water demand forecasting model criteria. The accuracy had the highest weight of 0.39, considered as important criteria. It was followed by the data requirements (0.26), speed weight (0.17), required resources (0.10), ease of use (0.05) and flexibility (0.03). AHP helped in selecting an appropriate forecasting model and resolved the MCDM problems of the institution.

Furthermore, this study utilized two out of three levels of short-term and midterm periods wherein each period was applied to the three models. Each model was optimized and used 10-fold cross-validation to evaluate prediction models by dividing the dataset into training and test sets. The error measure used in the study is the MAPE – the most widely adopted in the water demand forecasting. There was a significant improvement of the model's accuracy from the construction of a model to deploying the data set.

In short-term water demand forecasting, it only used one variable to predict the water demand. ARIMA is 0.49 or 100% – the most preferred model for operational planning level. The most preferred model can be used for short-term water demand period or operational planning level. As for the midterm water demand forecasting, it applied sensitivity analysis and model optimization. These were used to determine the input variables that contribute the most to the output behavior and the non-influential inputs or to ascertain some interaction effects within the model. Based on the result, SVM is 0.49 or 100% – regarded as the most preferred model for tactical planning level that can be used for both midterm and long-term water demand.

It is recommended that the institution should collect enough data needed in the decision support system for water demand and use a forecasting model that fits into the institution's need. Aside from AHP, the institution can likewise use other MCDM techniques such as ELECTRE, PROMETHEE and analytical network process. The institution can also add or modify the criteria based on the needs of goals of the institution. Moreover, the socio-demographic data must also be included as variables of the forecasting model. Lastly, mean absolute deviation, mean squared deviation, and other statistical techniques to compare the fits of different forecasting and smoothing methods should be employed.

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