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A novel methodology to predict monthly municipal water demand based on weather variables scenario

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ABSTRACT

This study provides a novel methodology to predict monthly water demand based on several weather variables scenarios by using combined techniques including discrete wavelet transform, principal component analysis, and particle swarm optimisation. To our knowledge, the adopted approach is the first technique to be proposed and applied in the water demand prediction. Compared to traditional methods, the developed methodology is superior in terms of predictive accuracy and runtime. Water consumption coupled with weather variables of the Melbourne City, from 2006 to 2015, were obtained from the South East Water retail company. The results showed that using data pre-processing techniques can significantly improve the quality of data and to select the best model input scenario. Additionally, it was noticed that the particle swarm optimisation algorithm accurately predicts the constants of the suggested model. Furthermore, the results confirmed that the proposed methodology accurately estimated the monthly data of municipal water demand based on a range of statistical criteria.

1. Introduction

Forecasting studies demonstrate that by 2075 about 9 billion of the world population would face water scarcity around the world, including Australia. Melbourne City suffered from several droughts in the past, and, according to the climate models, it will face a drier climate in the future. Thus, this region will be subjected to increasing water stress and water security challenges (Hemati et al., 2016). Additionally, different studies demonstrated that the continuous discharge of wastewater to the surrounding environment is intensifying the problem of water sacristy as it pollutes the freshwater resources such as Al-Marri et al. (2020), Alnaimi et al. (2020) and Alyafei et al. (2020). Toth et al. (2018) stated that municipal water consumption is driven by complicated interactions between human and natural system factors at various spatial and temporal scales, for example, it has been found that the increase of greenhouse gases concentrations intensifies the impacts of global warming with a high level of uncertainty. However, the majority of the literature has only considered economic and policy factors that are characterised by a known future evolution. A few numbers of the previous studies have focused on the weather factors that have an uncertain evolution. Therefore, additional models and methodologies are needed to assess the effects of climatic factors for short- and medium-term scenarios.

A medium-term forecast of municipal water demand can play a vital role in the water industry. For example, an accurate medium-term forecast could address the issue of uncertainty by proactively optimising the operation of water pump that enhance the quality of delivered water to the customers and minimise the power

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consumption (Ajbar and Ali, 2015; Zubaidi et al., 2018c). In this context, various methods have been employed to forecast the future water demand, but the need to find more reliable, capable and effective water demand model to optimise the operation of the existing water system has encouraged researchers to evolve innovative techniques (Adamowski et al., 2012).

Donkor et al. (2014), De Souza Groppo et al. (2019), and Rahim et al. (2020) reviewed various techniques and models that have been used in previous studies to predict urban water demand. These studies indicated that conventional models are lacking precision when predicting water demand, which can cause substantial problems in the operation system of the water supply. Additionally, the data analytic techniques have an effective impact for improving the accuracy of water demand prediction models.

Al-Sulttani et al. (2017) mentioned that utilising conventional trial-and-error procedures to calculate the constants of the prediction models is difficult and complex. Therefore, employing an optimisation technique is a considerably more effective method to tackle nonlinear problems. Recently, particle swarm optimisation (PSO) has been recognised as an innovative technique that could be successfully used to determine the coefficients of the prediction models in different fields, including, but not limited to, structural engineering (Hanoon et al., 2016), environmental engineering (Al-Sulttani et al., 2017), and electronic engineering (Jawad et al., 2020).

Araghinejad (2014) stated that hybrid techniques are being evolved to meet the new requirements of water prediction that resulted from the variability of weather factors, socio-economic factors, and policy of local authority. The hybrid technique means developing one model as a primary model and the rest to support (manipulating the data) and optimise the primary model. Hybrid models have been applied in different scenarios, and the results revealed their ability to simulate the water demand by capturing the trend and seasonality with reasonable accuracy based on the scale of error such as in Altunkaynak and Nigussie (2018), Seo et al. (2018) Zubaidi et al. (2018b), Zubaidi et al. (2020b) and Zubaidi et al. (2020a).

Brentan et al. (2017) and Gagliardi et al. (2017) mentioned that urban water demand prediction is characterised by high levels of uncertainty resulting from the natural variability of water consumption. Accordingly, there is an increasing interest to develop precise methodologies for water demand estimation to improve the planning, design and operation of the municipal water system, and to reduce the level of uncertainty.

In light of the above, this research proposes a novel methodology that combines the particle swarm optimisation (PSO) algorithm with two data preprocessing techniques, namely discrete wavelet transform (DWT) and principal component analysis (PCA) to improve the performance precision of medium-term water demand anticipating by defining the coefficients of the suggested model.

To the best of the authors' knowledge, this is the first time to use this novel methodology to predict medium-term urban water demand based on nine weather factors. This research study shows the ability of PSO technique to locate the best values of coefficients for the water demand model that gives the minimal error between the observed and predicted municipal water. Accordingly, the model can insight decision-maker with a scientific tool to assess the influence of global warming on water demand for a medium-term scale.

2. Studied area and data set

The present study used monthly data on municipal water consumption and weather factors time series for South East Water (SEW) utility. SEW is one of the retail water utility that purchases water wholesale from the Melbourne Water company in Melbourne City, Australia. SEW provides water and wastewater services to more than 1.7 million people who live in the area. The served area covers about 3640 km^2 that is a home for more than 727,000 customers, and many commercial, and industrial organisations (SEW, 2016).

The collected data included the municipal water consumption (megalitre, ML), maximum temperature (Tmax) (°C), minimum temperature (Tmin) (°C), mean temperature (Tmean) (°C), rainfall (Rain) (mm), evaporation (Eva) (mm), solar radiation (Srad) (MJ/m^2), vapour pressure (VP) (hpa), maximum relative humidity (RHmax) (%), and potential evapotranspiration (FAO56) (mm) from 2006 to 2015. Table 1 provides descriptive statistics of the significant parameters.

Table 1
The descriptive statistics of significant parameters.

Variable	Mean	Max.	Min.	Std. Dev.
Water	11,412	17,122	9432	1467
Tmax	21	30	13	5
Tmin	10	16	4	3
Tmean	15	23	9	4
Rain	55	158	1	31
Eva	4	8	1	2
Srad	15	26	6	6
VP	12	17	9	2
RHmax	50	65	32	8
FAO56	3	6	1	2

Max. = maximum value, Min. = minimum value, Std. Dev. = standard deviation.

3. Methodology

This section explains, in detail, the development of the proposed novel methodology. A number of techniques have been considered during the development of the utilized methodology, including:

1- DWT method was applied, with different orders and kinds of mother wavelet, to denoise water consumption and weather variables time series.
2- PCA technique was used to choose the optimum scenario of model input.
3- PSO approach was employed to define the coefficients of the suggested model of water demand prediction.
4- Finally, the novel methodology, for prediction of municipal water demand, was developed basing on the studied weather variables with a minimum scale of error.

To simplify the application of the developed methodology, it can be divided into three subsections: data pre-processing techniques, particle swarm optimisation algorithm, and performance evaluation criteria.

3.1. Data pre-processing techniques

Data preprocessing techniques can be categorised into three steps: normalisation, cleaning, and selecting the best model inputs.

3.1.1. Normalisation

The natural logarithm function has been widely applied in regression modelling to reduce multicollinearity among predictor variables (Zubaidi et al., 2018a). Accordingly, SPSS 24 statistics package was employed for normalising data of water consumption and weather variables via natural logarithm.

3.1.2. Cleaning

Noise and outliers may cause an undesirable influence on data analyses and consequently on the performance of the proposed model. Therefore, data cleaning is necessary to detect and remove or treat undesirable values (Tabachnick and Fidell, 2013). In this study, the box and whisker approach was used via SPSS version (24) statistics package to clean the data from outliers and this step has a substantial positive impact on the precision of the proposed prediction model. Also, the discrete wavelet transform (DWT) was employed to denoise the time series of all variables. The DWT method was used here because of its efficiency for denoising time series, and it is more appropriate for hydrology applications (Okkan and Ali Serbes, 2013). Additionally, the DWT method has been used in various disciplines such as the forecast of irrigation water (Zhang et al., 2019), estimation of relative humidity (Bayatvarkeshi et al., 2018), simulation of water demand (Adamowski et al., 2012), and simulation of evapotranspiration (Patil and Deka, 2015).

In the present study, the wavelets were considered to denoise the time series in order to increase the correlation coefficient between water consumption and weather variables data, which consequently enhances the predictive accuracy of the developed model. The basic of the wavelet transform is to contain scaling and shifting of a mother wavelet along with a time series. The mathematical representation of the DWT method is described in Eq. (1) (Dohan and Whitfield, 1997; Sekar and Mohanty, 2020):

$$DWT(m,n) = \frac{1}{\sqrt{2^m}} \sum_k x[k]\Psi\left[2^{-m}n - k\right] \tag{1}$$

where $\Psi(n)$ is the mother wavelet, while m and k are the scaling and shifting indices, respectively. The small transformation coefficients are typically considered as noise and can be removed without affecting the time series quality. The selection of the mother wavelet type is an essential step in the application of DWT method; thus, the performance of various types of wavelets was assessed. This study used five types of wavelets, namely Haar, Daubechies (db), Coiflets (coif), Symlets (sym) and Discrete Meyer Wavelet (dmey) to reduce the uncertainty of outcomes. These five types of wavelets were studied using MATLAB toolbox.

3.1.3. Selecting the best model inputs

In this research, principal component analysis (PCA) is employed to select the best scenario of predictors (weather variables) that used to simulate municipal water demand data using SPSS version (24) statistics package. PCA converts a dataset of original predictors into a new dataset of uncorrelated derived predictors that retain as much of the original variation as possible, and these predictors are named principal components (PCs). The latter are the outcomes of linear functions of the original predictors. During the PCA procedure, variances' sums are equal for both the original and derived predictors. The first PC represents the highest value of variance in the data that can be utilised to describe the original observations (Eq. (2)), and then, the second-highest variance represents by the second PC (Eq. (3)). The rest of the PCs can be gained using the same technique. In the PCA analysis, the dimensionality of the original dataset can be decreased by employing the first few PCs (Haque et al., 2018; Sarwar et al., 2019; Sonawane and Kulkarni, 2018).

$$PC1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1k}x_k = \sum_{j=1}^{k} a_{1j}x_j \tag{2}$$

$$PC2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2k}x_k = \sum_{j=1}^{k} a_{2j}x_j \tag{3}$$

where $x_1, x_2, \ldots, x_k$ refer to the original predictors in the data matrix and a_{ij} refer to the eigenvectors.

Recently, two different studies (Gedefaw et al., 2018) and (Haque et al., 2018) have proved that PCA technique plays a considerable role to locate the influential variables in urban water demand modelling compared to different statistical approaches.

According to Tabachnick and Fidell (2013), the needed size of the sample dataset (N) depends on the predictors' number as shown in Eq. (4).

$$N \geq 50 + 8\ m \tag{4}$$

m = number of predictors variables.

3.2. Particle swarm optimisation based modelling

PSO is an optimisation technique that has been successfully applied recently in different fields to choose the optimal solution, such as wireless sensor networks (Dash et al., 2019), single server optimisation (Alharkan et al., 2020), and smart agriculture (Jawad et al., 2020).

PSO is an evolutionary computation algorithm based on the natural system that is usually applied in settling optimisation problems, and it has few parameters compared with other intelligent algorithms (Banerjee and Dwivedi, 2018; Xu et al., 2018). In this study, it is applied to obtain the best coefficients of a prediction model that offers the minimum error between observed and predicted water demand as shown in Fig. 1.

In each iteration process, the velocity and position of each particle, in the swarm, is updated based on the local best (Pbest) and the global best (gbest) values. Pbest value refers to the memory of the particle about its own best position (best fitness), and gbest value is referring to the global knowledge of the optimal position, or the optimal position in their neighbourhood. The positions of the particle are changed via adding velocity and updating, this has been illustrated in Eqs. (5) and (6) (Jawad et al., 2020). The process of the PSO algorithm continues updating according to achieving an appropriate gbest or the pre-set number of iterations (kmax) is attained. The number of iterations is determined as 500 to confirm that the variances of objective functions are still constant for the long-term. The PSO algorithm has been coded before the application of the MATLAB software.

$$\begin{aligned} V_{id}(k+1) = \omega V_{id}(k) + c_1 r_1(k)(Pbest_{id} - X_{id}) \\ + c_2 r_2(k)(gbest_{id} - X_{id}) \end{aligned} \tag{5}$$

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k+1) \tag{6}$$

where V_{id} is the particle velocity, X_{id} indicates the particle position; k is the number of iterations; ω is the inertia weight; $r_1(k)$ and $r_2(k)$ are random values ranging between 0 and 1; c_1 and c_2 are acceleration constants that are often equals; $c_1r_1(k)(Pbest_{id} - X_{id})$ and $c_2r_2(k)\ (gbest_{id} - X_{id})$ representing the updating of particles. Following Jawad et al. (2020), the value of ω = 0.7, $c_1 = c_2 = 1.494$, and swarm size range from 10 to 50.

The relationship between the predicted water demand ($\widehat{Q}$) and the weather variables (X) (model input) can be expressed in Eq. (7).

$$\widehat{Q} = W_o + \sum_{i=1}^{n} W_{i+2(i-1)} \times X_i^{2i} \tag{7}$$

where W is the unknowing coefficient.

The performance criteria applied in this research are classified as absolute, relative, and dimensionless errors. These types of errors include the mean squared error (MSE), the mean absolute relative error (MARE), the coefficient of efficiency (CE) as shown in Eqs. (8), (9), and (10), respectively. Also, the Bland-Altman plot,

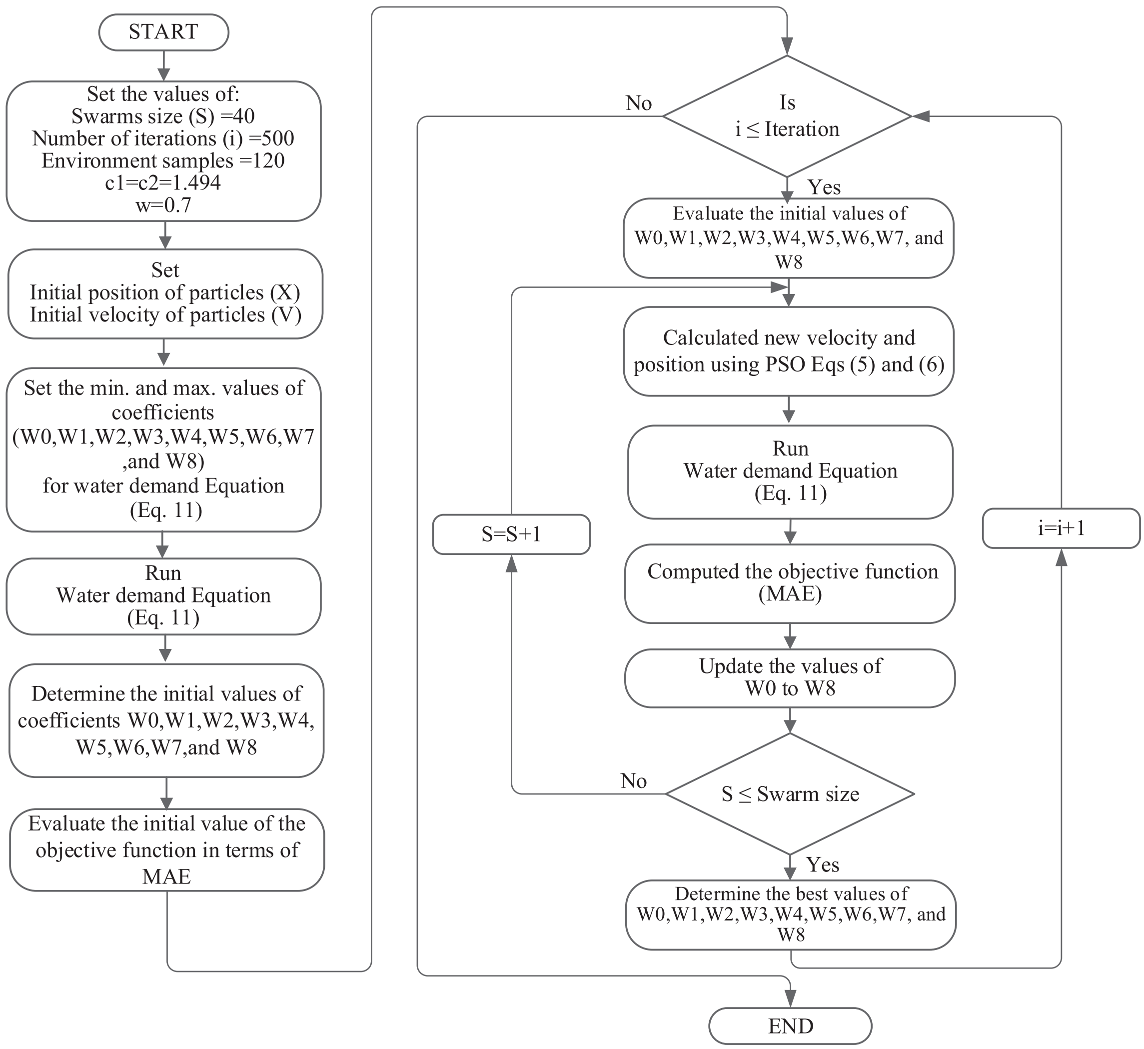

Fig. 1. Flowchart of the water demand equation based on the PSO algorithm.

chi-square goodness-of-fit test and Augmented Dickey-Fuller test were used to assess the residual analysis. Moreover, T-test was used to examine the difference between the means of the observed and predicted water demand.

$$MSE = \frac{\sum_{i=1}^{N}\left(Q_i - \widehat{Q}_i\right)^2}{N} \tag{8}$$

$$MARE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|Q_i - \widehat{Q}_i\right|}{Q_i} \tag{9}$$

$$CE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i - \widehat{Q}_i\right)^2}{\sum_{i=1}^{n}\left(Q_i - \overline{Q}_i\right)^2} \tag{10}$$

where $\widehat{Q}_i$ = predicted water demand, Q_i= observed water consumption, $\overline{Q}_i$= mean of observed water demand, N = data size.

4. Results and discussion

4.1. Input data analysis

Time series for water consumption (dependent variable) and weather factors (independent variables) were normalised and cleaned as mentioned earlier in Sections 3.1.1 and 3.1.2. Five mother wavelets (coif5, sym5, db5, dmey and Haar) were used individually for the purpose of time series denoising. Their effects on the correlation coefficient between dependent and independents data are investigated. In general, all kinds of mother wavelets improve the correlation coefficients values between water consumption and weather variables, but dmey yielded the highest R compared with the rest types of wavelets. For example, the correlation coefficient between water consumption and maximum temperature are 0.82, 0.81, 0.80, 0.80 and 0.74 for dmey, db5, sym5, coif5 and Haar, respectively. The results of the correlation analysis between water consumption and weather variables for raw and denoised data can be seen in Table 2. Apparently, the data pre-processing techniques increased the quality of data for dependent and independent time series, for example the correlation

Table 2
Correlation matrix between water demand and weather variables for denoise data.

Data	Weather variables Tmax	Tmin	Tmean	Rain	Eva	Srad	VP	RHmax	FAO56
Raw	0.72	0.62	0.69	−0.43	0.75	0.65	0.5	−0.74	0.71
Denoised	0.82	0.71	0.78	−0.6	0.83	0.72	0.57	−0.83	0.77

coefficient (R) between water consumption and Rhmax increase from −0.74 to −0.83.

After cleaning data, PCA technique was applied to select the best scenario for model inputs. PCA, as a factor analysis technique, was performed with the eigenvalue equal to one to enhance the strength of the factors. The results reveal that the value of the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) is 0.86 > 0.6 and the Barlett's Test of Sphericity value is 0.0 < 0.05, accordingly, factor analysis is suitable (Pallant, 2011). Also, the results show that two principal components (PCs) have eigenvalues more than one and explain 94.2% of the total variance.

Table 3 presents the rotated component matrix that has the independent variables heavily loaded in PC_1 and PC_2. Pallant (2011) stated that the multicollinearity exists among independent variables based on each PC if they have correlation equal to 0.9 and above. Therefore, Tmax, Eva and RHmax from PC_1 and Rain from the PC_2 were selected as the best potential scenario of prediction model inputs.

The size of the sample required for the model was calculated by using Eq. (4), which showed that $82(50 + 8 \times 4)$ were needed. In this research, the number of cases is N = 120 that is way more than the required size. The relationship between predicted water demand ($\widehat{Q}$) and the weather variables (model input) Rhmax, Tmax, Eva, and Rin can be expressed in Eq. (11).

$$\widehat{Q} = W_0 + W_1 \times (Rhmax)^{W_2} + W_3 \times (Tmax)^{W_4} + W_5 \times (Eva)^{W_6} + W_7 \times (Rin)^{W_8} \quad (11)$$

where, W_0 to W_8 are the unknowing coefficients.

The PSO optimisation algorithm was applied to find the best value of the coefficients in the next subsection.

4.2. Analysis of the PSO technique

The size of the swarm was varied to analyse the number of the particle that offered better performance for convergence and processing time. Following Jawad et al. (2020), this research applies five swarm sizes (10, 20, 30, 40, and 50-particle swarms) to gain the minimum objective functions (MAE). The results show that swarm 40 offers the minimum objective function (MAE = 0.05563) after 380 iterations as presented in Fig. 2, which reveals that the variance of the objective function becomes constant after 380 iterations that support our selection 500 iterations.

After applying the PSO algorithm (swarm 40), as shown above in Fig. 2, the coefficients of the Eq. (11) were obtained as tabulated in Table 4.

Therefore, the new values of the constants could be substituted in Eq. (11) to produce a new water prediction model, as presented in Eq. (12).

$$WD = -3.4337 \times 10^2 + 2.3664 \times 10^2 \times (Rhmax)^{-127} + 32.7605 \times (Tmax)^{-646} + 3.5268 \times 10^2 \times (Eva)^{2.1128 \times 10^{-4}} + 2.9901 \times 102 \times (Rin)^{-6.3185} \quad (12)$$

4.3. Performance evaluation

The performance of the proposed methodology was evaluated using mean squared error (MSE), mean absolute relative error (MARE) and coefficient of efficiency (CE), as presented in Table 5. The latter clearly shows that the proposed methodology offers a good scale of error based on MSE and MARE criteria, and a good coefficient of efficiency (equals to 90%) according to Dawson et al. (2007).

Also, Bland–Altman plot was considered to estimate the degree of the systematic variance, the scatter of the values, and also to

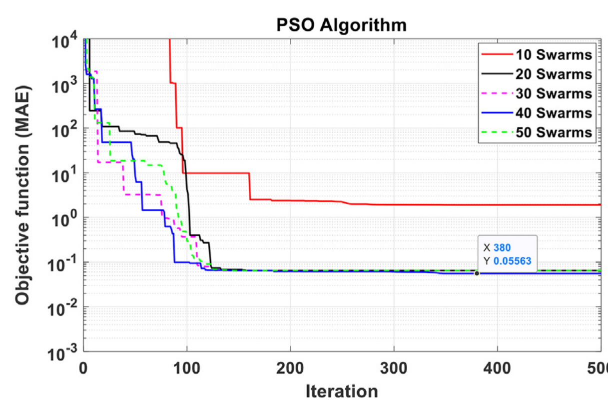

Fig. 2. Objective function versus iteration (PSO).

Table 3
Rotated Component Matrix.

Weather variables	Principal components 1	2
Tmax	**0.983**	
Tmin	0.974	
Tmean	0.980	
Rain		**0.963**
Eva	**0.88**	
Srad	0.922	
VP	0.910	
RHmax	−**0.869**	0.445
FA	0.960	

Table 4
The coefficients of the suggested equation obtained by PSO technique.

Coefficient	Value
W_0	-3.4337×10^2
W_1	2.3664×10^2
W_2	−127
W_3	32.7605
W_4	−646
W_5	3.5268×10^2
W_6	2.1128×10^{-4}
W_7	2.9901×10^2
W_8	−6.3185

Table 5
Performance evaluation tests.

MSE	MARE	CE
0.0057	0.0055	0.9

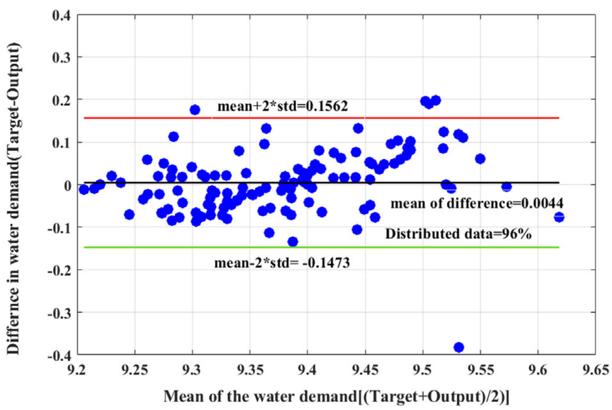

Fig. 3. Bland-Altman plot of the relationship between observed and predicted municipal water.

check whether there was a relation between the observed and predicted error, as shown in Fig. 3. What is interesting about the data in Fig. 3 is that 96% of data are distributed between bounds of acceptance range; red and green bounds ($mean \pm 2 \times std$).

Furthermore, to examine the robustness of the proposed methodology, three tests were employed for residual. First, the chi-square goodness-of-fit test was used to check the normality, while the second one was the Augmented Dickey-Fuller test that was used to examine randomness. Finally, T-test was conducted to examine the difference between the means of two groups (i.e., observed and predicted water demand). The results showed that the residuals are normally distributed and random. Additionally, the outcomes of the T-test revealed that the magnitude of P-value was more than 0.05 meaning that the null hypothesis that there was no significant difference between the observed and predicted water, i.e., time series cannot be rejected.

The results disclosed that the PSO algorithm yields excellent coefficients of water demand model. The use of a combined methodology (WDT-PCA-PSO) technique leads to a good matching between the predicted and actual water demand data.

5. Conclusion

This study proposed a novel methodology to estimate the monthly municipal water demand using ten-years data considering some weather variables in Melbourne City. The methodology encompasses three hybrid techniques, namely WDT, PCA and PSO. This hybridization proves its powerful ability to enhance the predictive accuracy of the developed model; it is capable to accurately predict the water demand basing on various statistical measures, such as MSE = 0.0057, MARE = 0.0055, CE = 0.9 and a Bland–Altman plot accuracy 96%. These findings are of great importance to both policy-makers and stakeholders in planning, reviewing and comparing the availability of water resources and the increase in water demand. Further research should be conducted to examine the effects of weather factors on the prediction of water demand using different scales.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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