A Novel Approach for Predicting Monthly Water Demand by Combining Singular Spectrum Analysis with Neural Networks

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Abstract

Valid and dependable water demand prediction is a major element of the effective and sustainable expansion of municipal water infrastructures. This study provides a novel approach to quantifying water demand through the assessment of climatic factors, using a combination of a pretreatment signal technique, a hybrid particle swarm optimisation algorithm and an artificial neural network (PSO-ANN). The Singular Spectrum Analysis (SSA) technique was adopted to decompose and reconstruct water consumption in relation to six weather variables, to create a seasonal and stochastic time series. The results revealed that SSA is a powerful technique, capable of decomposing the original time series into many independent components including trend, oscillatory behaviours and noise. In addition, the PSO-ANN algorithm was shown to be a reliable prediction model, outperforming the hybrid Backtracking Search Algorithm BSA-ANN in terms of fitness function (RMSE). The findings of this study also support the view that water demand is driven by climatological variables.

Keywords

Melbourne, Neural network model, Particle Swarm Optimization, Singular Spectrum Analysis, Urban water demand, Water sustainability

1 Introduction

Climate change causes considerable problems for the ecosystem, for example, fluctuation of precipitation where scarce precipitation can lead to drought, which can, in turn, cause desertification. Freshwater resources are widely depleted, particularly in city centres, the problems this causes likely to be exacerbated because of increasing demands on freshwater (Davies and Simonovic, 2011). Hot weather conditions, extended dry periods and a general reduction in rainfall, also increase the consumption of and demand for water. As it is anticipated that climate change will cause substantial increases in temperature, a decrease in rainfall and a more droughts, it is necessary to analyse these issues and explore the relationships between climate and water consumption used to predict water demand (Zhoua et al., 2000).

Forecasting municipal water consumption, a task of considerable significance for water utilities, aims to minimise the risks involved in decision-making (Walker et al., 2015). Marlow et al. (2013) point out that accurate prediction can improve the performance of water distribution systems and encourage better water management in addition to urban water sustainability. However, the problems faced by the water sector as a result of global warming, has increased pressure on its infrastructure.

Previous studies have highlighted the importance of precise water demand predictions, several documenting that municipal water sectors depend on the development of both infrastructure and investment, making accurate advanced planning a central issue (Adamowski et al., 2012; Donkor et al., 2014).

Existing urbanised water infrastructures are coming under considerable stress because of extreme weather phenomena linked to global warming. This situation increases blue water demand and leads to high levels of uncertainty regarding mid-term projections for key drivers of climate change, during the planning process. The conventional methods used to predict these projections can lead to considerable problems for water system decision makers and cause increased operational costs (Urich and Rauch, 2014).

Previous studies have established that artificial neural network (ANN) approaches have outperformed traditional methods (e.g. regression and time series) in different fields e.g. Jain et al. (2001), Mohammadi et al. (2005) and Azadeh et al. (2007). As such, a number of studies have used ANN techniques to predict the monthly time series for urban water demand including:

a) Liu et al. (2003), proposed a combined model that included water demand forecasts and artificial neural networks (WDF-ANN). This study used historical monthly water consumption and socio-economic data for Weinan city, China, from 1991 to 2000, to establish a water prediction model. The results indicated that a WDF-ANN model has the ability to simulate monthly water consumption patterns.

b) Firat et al. (2009) evaluated three types of ANN; Generalized Regression Neural Networks (GRNN), Feed Forward Neural Networks (FFNN) and Radial Basis Neural Networks (RBNN). This study used monthly socio-economic and weather variables as the model input, from 1997-2005, for Izmir city, Turkey. The outcome, when using twenty-five different input variables, revealed that a model consisting of multiple input variables is better than a single variable input. The GRNN outperformed all other ANN techniques and Multiple Linear Regression (MLR) when predicting monthly water demand.

c) A year later, Firat et al. (2010) assessed three ANN models, including two of the techniques evaluated previously (FFNN, GRNN) and the Cascade Correlation Neural Networks (CCNN). This study also used historical monthly data from Izmir city, Turkey, over the same period (1997-2005). The model input for the ANN techniques included several combinations of previous water consumption values. The results showed that using five of these values resulted in the best model input, CCNN consistently outperforming both FFNN and GRNN.

To date, previous studies have used different types of factors as forecast model input including socio-economic data, a mixture of socio-economic and weather variables and a combination of previously recorded values of water consumption. However, no previous study has considered the impact of climate on water demand or employed a pretreatment signal technique, which has the ability to decompose the time series into different components such as trend, oscillatory behaviour (periodic or quasi-periodic components) and noise filtering. These components help to determine the effect of weather volatility on water consumption, to improve the accuracy of prediction and reduce the scale of error between observed and forecast water demand.

Different optimisation methods can be used to tackle problems in applications. The aim of optimisation algorithms is to locate the optimum values for a system's parameters, under different conditions (Ahmed et al., 2017). Recently, the backtracking search optimisation algorithm (BSA), a new evolutionary algorithm (EA), has been applied to solve a range of optimisation problems (Chen et al., 2017). It has been used to solve optimisation problems such as real-value numerical problems (Civicioglu, 2013), economic dispatch (Modiri-Delshad et al., 2016) and home energy management systems (Ahmed et al., 2017).

Ferguson et al. (2013) stated that currently, water managers and stakeholders are struggling to adapt municipal water systems to the increasingly complicated challenges of climate change. With this in mind, this paper has three aims:

1- To reduce the uncertainty of the relationship between water demand and climate variables at mid-term.
2- To identify seasonal and stochastic patterns and noise filters, for water consumption and different weather factors by applying an SSA technique.

3- To assess the capability and reliability of a hybrid PSO-ANN model to predict mid-term water demands taking climatological variables into consideration, and to assess how it compares with a hybrid BSA-ANN technique.

To the best of our knowledge, no previous study has been conducted that integrates the above three aims.

2 Study Area and Data Set

A catchment area in Australia located in Melbourne city, has been used to evaluate the water demand model. Yarra Valley Water is one of three retail water companies delivering municipal water supplies and sewerage services to more than 1.5 million people in the Yarra River catchment area. Figure 1 shows the Licence Service Area of the Yarra Valley company (YVW, 2006).

Historical monthly water consumption data and information on six weather variables were gathered from the Yarra Valley Water Company covering 2006-2015. This data comprised water consumption (Mega litre), Maximum Temperature (˚c), Mean Temperature (˚c), Minimum Temperature (˚c), Rainfall (mm), Solar Radiation (mj/m^2) and Vapour Pressure (hpa).

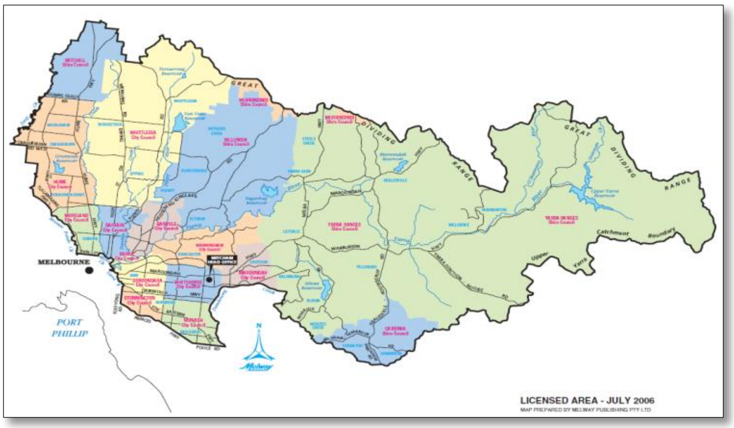

Figure 1: Yarra Valley's water licence service area (YVW, 2006)

3 Pre-processing data

Pre-processing data techniques are deemed a significant step in the data mining process. These techniques play an important role in ANNs by fostering high precision and minimal computational costs at the training stage as noisy and unreliable information that could be present in data records will adversely affect the learning phase and result in a poor model (Kotsiantis et al., 2006). Zhang and Qi (2005) used ANN to evaluate the effect of two pre-processing techniques; the detrending and deseasoning of nonlinear monthly data. Their results showed that both techniques can minimise prediction errors, the combination of both found to be the most efficient pre-processing method. In the current research, Singular Spectrum Analysis (SSA) was used for detrending, deseasoning and noise removal.

3.1 Singular Spectrum Analysis (SSA)

SSA is a powerful method used to analyse time series to uncover significant prediction characteristics. It can be used for both linear and nonlinear time series and small sample sizes. It does not rely on any statistical assumptions based on the stationarity and linearity of the series, or on the normality of the residuals (Hassani et al., 2009).

SSA has been used in different fields including medical engineering (Ghodsi et al., 2009), economics (Hassani et al., 2015) and hydrology (Marques et al., 2006) amongst others. The SSA approach consists of two stages: decomposition of the original time series into different principle components (PC_s) including trend, oscillatory components and irregular components, and noise removal and reconstruction of a new time series that has less noise (Al-Bugharbee and Trendafilova, 2016).

In the decomposition step, a signal y of length T, $y_1, y_2, \ldots, y_T$, is mapped onto a length window (L) to create the so-called trajectory matrix, the Hankel matrix, X ($L \times K$) where $K=T-L+1$ (Eq. (1)).

$$X=\begin{bmatrix} y_1 & y_2 & y_3 & \cdots & y_K \\ y_2 & y_3 & y_4 & \cdots & y_{K+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & y_{L+2} & \cdots & y_T \end{bmatrix} \quad (1)$$

The Hankel matrix (X) will be subject to singular value decomposition to get (L) eigenvectors (**U**$_i$, i= 1, 2…., L) corresponding to (L) eigenvalues (λ_i, i=1, 2…, L). Any λ_i refers to the partial alteration of the original time series in a **U**$_i$ direction. The corresponding principal components (PC_i) can be obtained by projecting the Hankel matrix onto every eigenvector:

$$PC_i(m) = \sum_{j=1}^{L} X^{'}(m+j-1) * U_i(m) \quad (2)$$

where i=1,2….L, m= 1,2…n, j=1,2…L, and the prime means transpose.

Projecting the PC_s on the eigenvectors (U) will get the primary matrices L ($EI_i=U_i\,PC'_i$) where i= 1, 2…..L and the prime denotes transposition.

In this study, L will be equal to 12 so as to extract all the seasonal components together (12, 6, 4, 3, 2.4, and 2-months harmonics), the trend and noise (Golyandina et al., 2001) .

The contribution of these primary matrix norms to the original Hankel matrix norm follows a singular values trend, meaning that the highest contribution will go to the first matrix, the lowest contribution to the last.

As mentioned above, the signals can be reconstructed via a linear combination of several, or all, the PCs. When choosing the number of PCs, there are various criteria to observe (Kilundu et al., 2011). In this study, valuable insight is offered via inspection breaks testing in the eigenvalue spectra to select the number (w) of PCs. A slight decrease in singular sequence values, indicates pure noise according to the latter test. The seasonal signal of the original sub-signal is contained in the new reconstructed signal (yr). The process of reconstruction is achieved via the diagonal averaging mechanism that is depicted below (Ghil et al., 2002).

$$yr(m) = \frac{1}{N_m} \sum_{i \in w} \sum_{j=Lm}^{Um} PC_i\,(m - j + 1) \times U_i(m) \quad ,m1,2,,,,n-1 \tag{3}$$

The normalisation factor (Nm), the upper (Um) and the lower (Lm) of sums vary for the centre and edges of the signal. They are defined as shown below:

$$\left(\frac{1}{Nm}, Lm, Um\right) = \begin{cases} \left(\frac{1}{m}, 1, m\right), & for\ 1 \le m \le L-1 \\ \left(\frac{1}{L}, 1, K\right), & for\ L \le m \le K \\ \left(\frac{1}{n-m+1}, m-n+L, L\right), & for\ K+1 \le m \le n \end{cases} \tag{4}$$

The new reconstructed signals (yr) will be utilised for seasonal forecasting.

In this study, the SSA technique has been used for the following purposes:

1- To decompose the original time series into different PCs and detect the stationary time series, and
2- To reconstruct a new seasonal time series that is less noisy.

4 Hybrid Particle Swarm Optimisation-Artificial Neural Network (PSO-ANN)

4.1 Artificial Neural Network (ANN)

ANN is an information processing technique, which aims to emulate human brain functionality by adopting the same connectivity and operations as biological neurones. It can capture nonlinear relationships by system input and output training (Ahmed et al., 2016; Cutore et al., 2008). In this research, a feed-forward neural network (FFNN), that uses the Levenberg–Marquardt (LM) learning algorithm, was employed, implemented on a MATLAB Neural Network Toolbox (Mathworks, 2017). The decision to adopt an LM learning algorithm was because of the speed, efficiency and low level of error, as shown previously by Payal et al. (2015). The ANN structure comprises three inputs representing weather factors (maximum temperature, radiation and rainfall), two hidden layers with the *tansigmoidal* function as an activation function and one output (water demand) with a *linear* activation function. Figure 2 shows the ANN architecture. The learning rate value and the number of neurones in both hidden layers can be established by applying the PSO-ANN algorithm to avoid over- or under-fitting the model.

The complete data set has been randomly divided into three sets: training (70%), testing (15%) and validation (15%) (Babel and Shinde, 2011; Bennett et al., 2013). The ANN learning process will repeat many times over an epoch (i.e., 1000 iterations), until the error between the measured and forecast municipal water reaches its minimum.

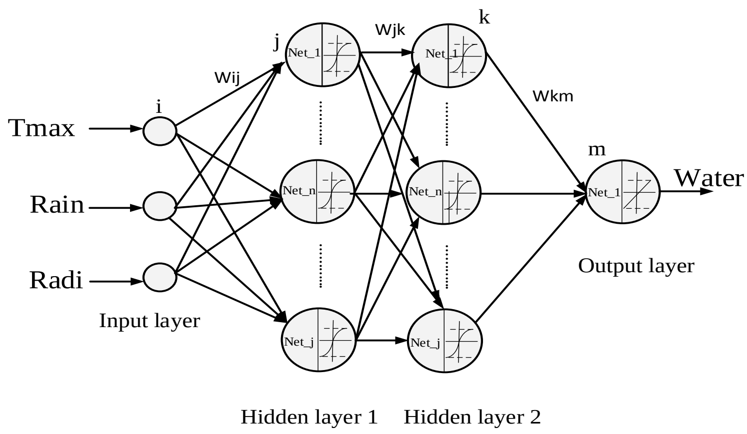

Figure 2: The architecture of ANN

4.2 Particle Swarm Optimisation (PSO)

A PSO algorithm is a computational iterative search and optimisation technique. It is biologically inspired by the social behaviour of animal societies such as birds flocking or schools of fish. This method comprises a swarm of particles where a particle denotes a possible solution (Rini et al., 2011). The PSO algorithm is commonly utilised to settle optimisation issues (Eberhart and Shi, 2001).

In each process of iteration, the velocity and position of each particle in the swarm is updated according to the two "best" values. The first one is the local best (Pbest), indicative of the particle's memory about its own best position (best fitness). The second is the global best (gbest), this denoting global knowledge of the best position, or the best position in their neighbourhood. Particle positions are altered by adding velocity and updating, this dependent on equations 5 and 6 (Wang et al. (2010); Gharghan et al. (2016). The updating process continues until either an appropriate *gbest* is attained or the pre-set number of iterations (*k*max) is reached.

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

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

Where V_{id} is the velocity of the particle, X_{id} indicating the position of the particle; k the iterations number; ω the inertia weight; $r_1(k)$ and $r_2(k)$ random values ranging between 0 and 1; c_1 and c_2 acceleration constants which 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.

Recent research has emphasised the positive use of hybrid PSO–ANN models tackling engineering issues such as improving the precision of wireless sensor localisation mechanisms (Gharghan et al., 2016). Eberhart and Shi (2001) and Lavanya and Udgata (2011) both recommend ω =0.5, and c_1= c_2 =1.494 to achieve faster convergence. Zhang et al. (2007) suggested that the swarm size could range from 20 - 50. In this research, the amount of iterations was 100 because the minimum value for the fitness function was 60, with 35 iterations for seasonal and stochastic data, respectively.

MATLAB was used to run the PSO algorithm, the fitness function for optimising the model minimising the root-mean-squared error (Wang et al., 2010). Figure 3 shows the proposed hybrid PSO–ANN algorithm flow chart used to enhance water demand prediction accuracy.

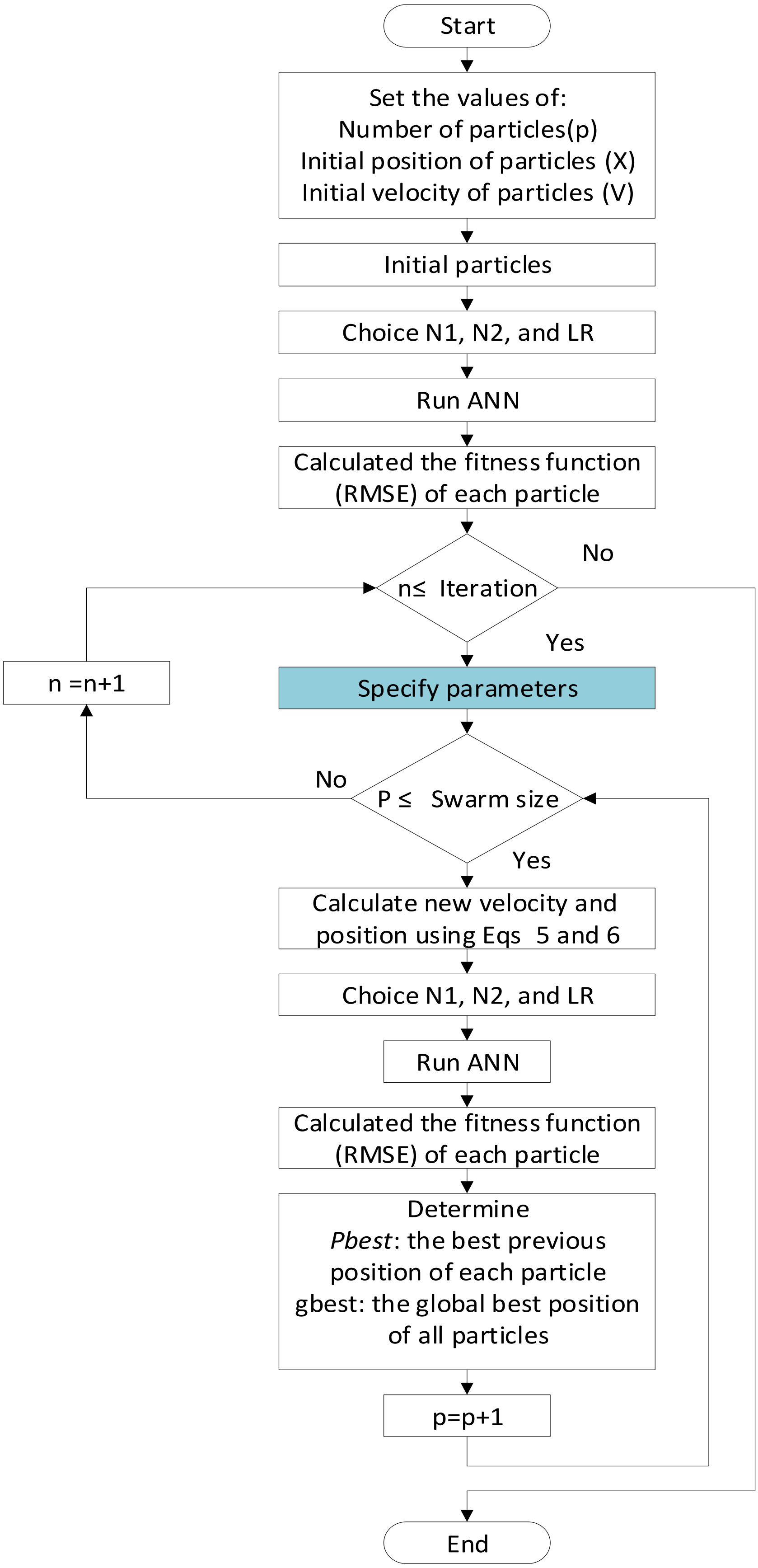

Figure 3: Flow chart of hybrid PSO–ANN algorithm, adapted from Gharghan et al. (2016)

5 Model performance and accuracy measurements

Model performance can be assessed by using several conventional statistical measures. In this study, four criteria were used to examine prediction accuracy; mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and Pearson's product moment correlation (R). The Augmented Dickey-Fuller (ADF) test and Kwiatkowski– Phillips–Schmidt–Shin (KPSS) test were also used to analyse the stationary case for the stochastic time series and residuals.

$$MAE = \frac{\sum_{m=1}^{N}|y_o - y_p|}{N} \quad (7)$$

$$MSE = \frac{\sum_{m=1}^{N}(y_o - y_p)^2}{N} \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{N}(y_o - y_p)^2}{N}} \quad (9)$$

$$R = \left[\frac{\sum_{m=1}^{N}(y_o - \overline{y_o})(y_p - \overline{y_p})}{\sqrt{\sum(y_o - \overline{y_o})^2 \sum(y_p - \overline{y_p})^2}}\right] \quad (10)$$

where y_o represents measured water consumption; y_p, forecasted water demand; N, sample size; $\overline{y_p}$, mean of forecasted demand, and $\overline{y_o}$, mean of measured consumption.

6 Results and discussion

6.1 Signal pretreatment

After treating the outliers and transforming all the time series for water consumption and the weather factors, a singular spectrum analysis was used to decompose the time series into twelve different components. Figure 4 shows the original signal and the first four components produced by the SSA for water consumption, maximum temperature, minimum temperature, mean temperature, radiation, vapour pressure and rainfall, respectively.

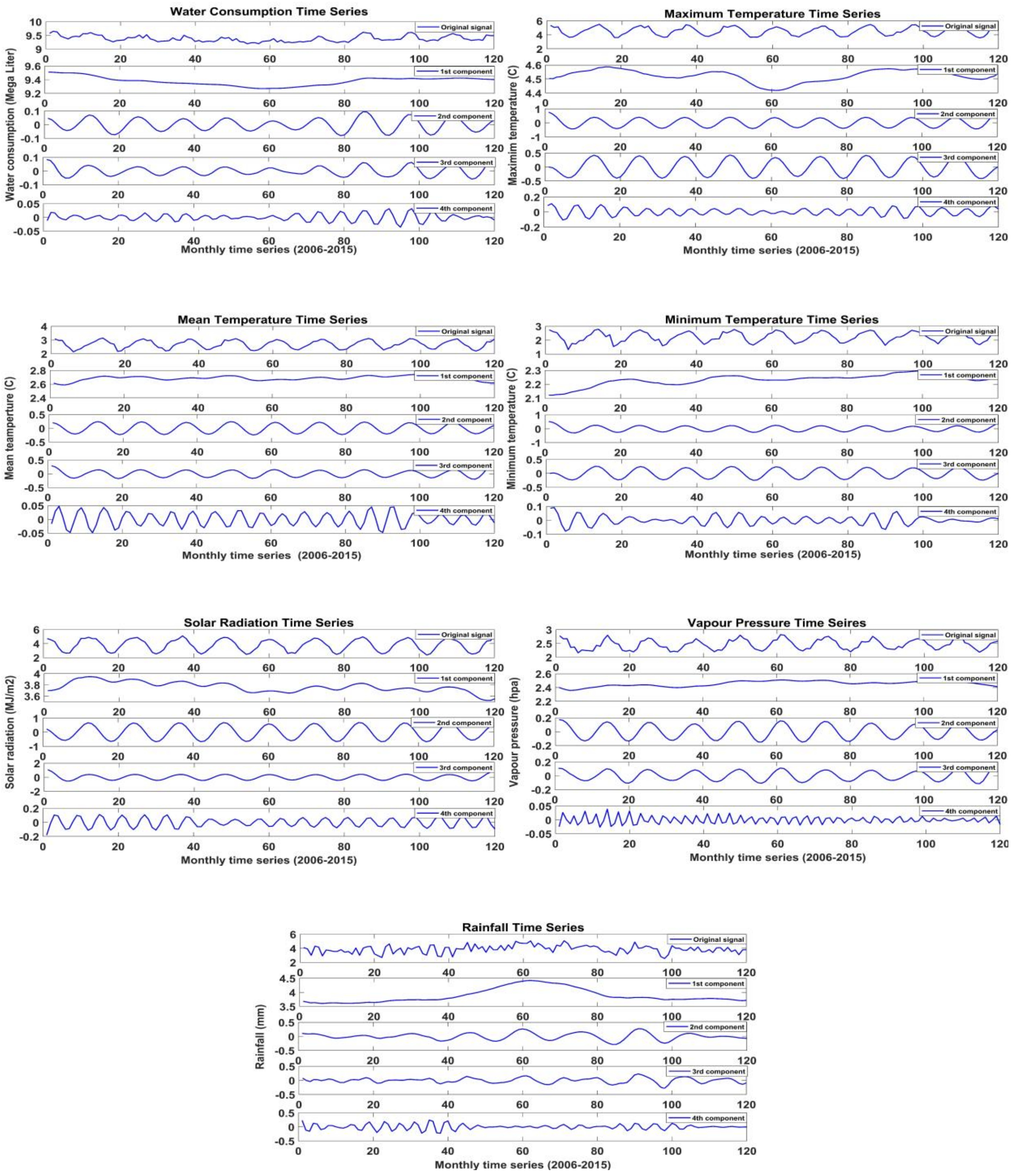

Figure 4: Original signal and the 1st four components obtained from the SSA by water consumption and all the weather variables

6.2 Reconstruction components

As a mechanism to filter particular signals, the time series has been reconstructed using only some of the principal components. The water consumption time series was reconstructed after removing the components representing trend and noise. For the weather time series, the component representing noise was removed to generate a seasonal time series.

Valuable insight is offered via an inspection breaks test in the eigenvalue spectra. A slight decrease in the singular sequence value, indicates pure noise according to the latter test. Eigenvalue spectrum breaks can therefore help to differentiate between signal eigentriples and noise. Figure 5 shows the plot of 11 eigenvalues for the water consumption time series, after removal of the trend component. For the water consumption series, the first component was omitted because it represents the trend, the new time series containing the 2nd and 3rd components. All the weather time series that have seasonal behaviour, were reconstructed using the first three components. In the case of the rainfall time series, which has irregular behaviour, the new time series comprised the 3rd component only. Figure 6 shows the new reconstructed series for all the different time series.

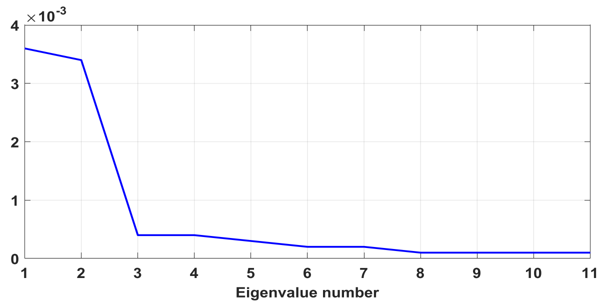

Figure 5: Eleven eigenvalues for the water consumption time series

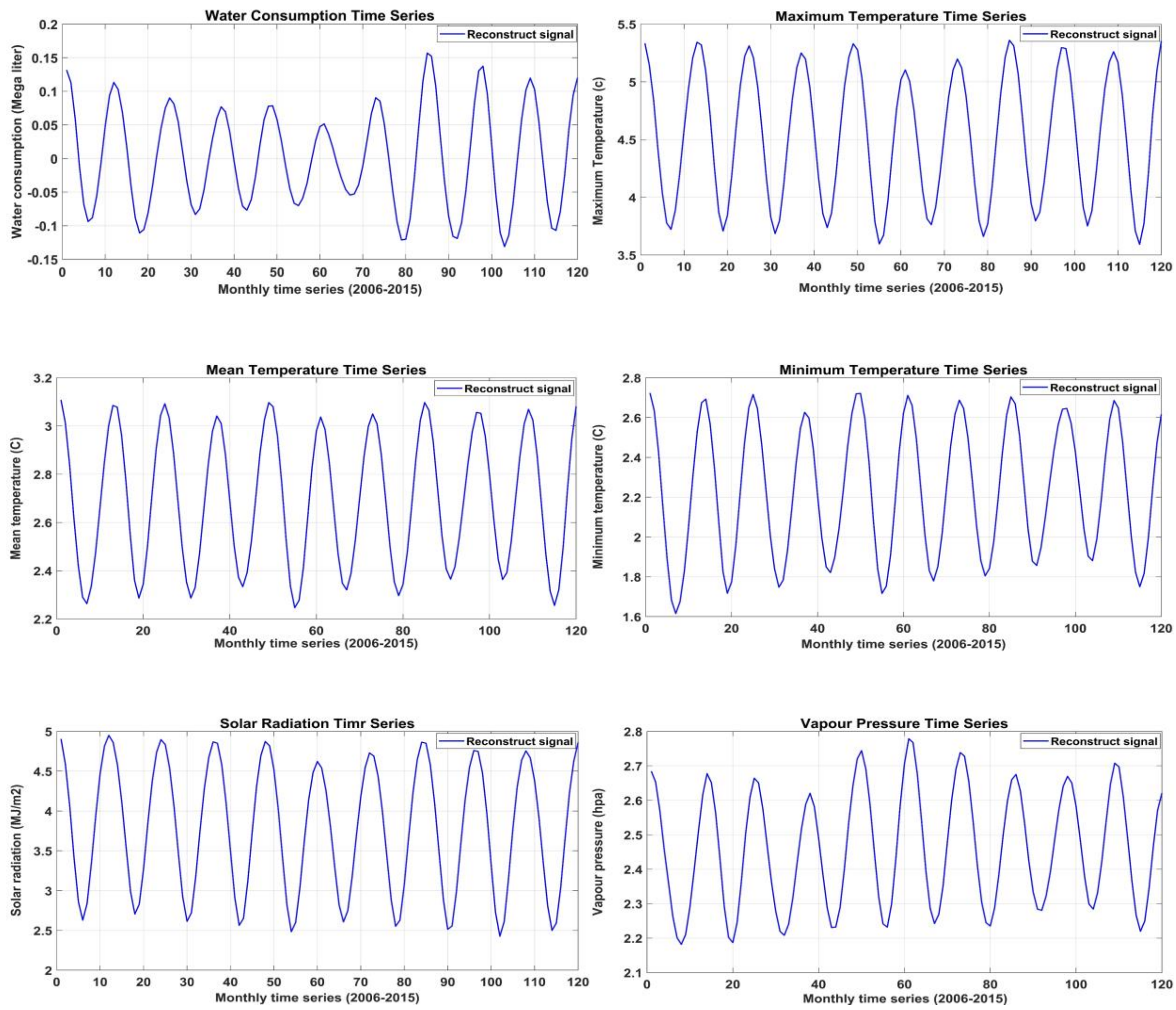

Figure 6: Seasonal time series for water consumption and all the weather factors

The original time series were decomposed into twelve components. The trend, seasonal and noise components were removed to detect the stochastic component for all time series. A stochastic component represents the 3rd component in the water time series, the 4th component in the rainfall time series and the 2nd for the remaining weather time series.

6.3 Selection of Explanatory Variables

A correlation matrix was used for water consumption and the weather variables across the raw, seasonal and stochastic phases to show the impact of the SSA on the data (Table 1). What stands out in this table is this significant increase in the correlation coefficient between water consumption and climate factors (e.g. maximum temperature correlation increase from approximately 0.72 to 0.96 after removing trend, seasonal and noise signals by using SSA). These results confirm that adopting the SSA method as a pretreatment signal, helps to improve the correlation between the dependent and independent variables, when forecasting water demand models.

Table 1: Pearson's correlation matrix analysis results for all data types

data kind	water	maximum temperature	minimum temperature	mean temperature	rainfall	radiation	vapour pressure
raw		.717**	.619**	.687**	-0.433**	.650**	.504**
seasonal	1	.945**	.901**	.933**	-0.497**	.875**	.838**
stochastic		.957**	.924**	.948**	-.616**	.900**	.877**

**. Correlation is significant at the 0.01 level (2-tailed).

Further to this, the variance inflation factor (VIF) was applied to avoid multicollinearity. Three weather variables; maximum temperature, radiation and rainfall, were selected to be input factors in both seasonal and stochastic models.

According to Tabachnick and Fidell (2013), the required sample size is based on the number of predictors as presented in equation 11.

$$N \geq 104 + m \qquad (11)$$

m= number of independent variables.

In this study the number of cases is N=120, more than the 107 required.

6.4 Application of the hybrid Algorithm technique

Different swarm sizes (20, 30, 40 and 50) were used to run a PSO-ANN algorithm in MATLAB toolbox, to establish the optimum swarm size and identify the most appropriate learning rate and number of neurons in both hidden layers. Figure 7 shows that a swarm size of 50 offers the best solution for both seasonal and stochastic time series. The best fitness function was 0.02219 after 77 iterations and 0.007689 after 35 iterations, for the seasonal and stochastic phases, respectively.

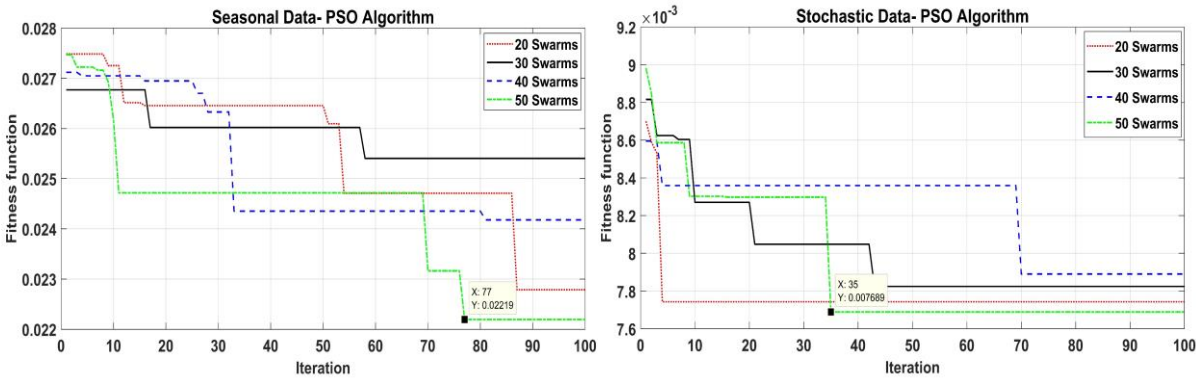

Figure 7: Fitness function of various swarm sizes for seasonal and stochastic data (PSO)

A BSA-ANN algorithm is also used to achieve the same objective for populations of 20, 30, 40 and 50 to compare to the results from the hybrid PSO-ANN, as shown in Figure 8. On close inspection of Figure 8, it can be seen that the RMSE = 0.02528 and 0.007879 for seasonal and stochastic data, respectively.

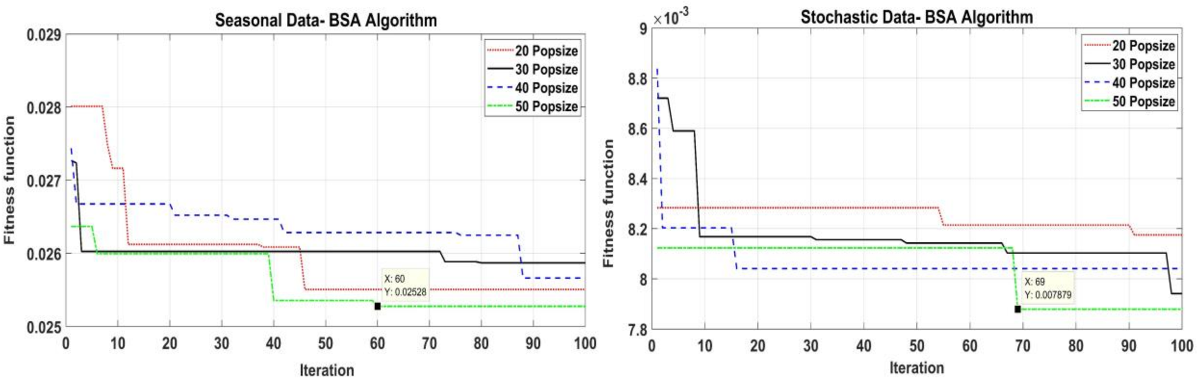

Figure 8: Fitness function of various swarm sizes for seasonal and stochastic data (BSA)

The outcomes obtained from the hybrid PSO-ANN were compared with those from the BSA-ANN in order to validate the new technique. The resulting models obtained when using PSO-ANN, have a lower RMSE in comparison to the BAS-ANN for both seasonal and stochastic data. The optimum ANN parameters obtained from the PSO-ANN technique, are given in Table 2.

Table 2: ANN parameters based on PSO-ANN algorithms for seasonal and stochastic data

Data Type	Parameters	PSO-ANN
Seasonal	N1	5
	N2	12
	LR	0.5696
Stochastic	N1	3
	N2	11
	LR	0.1594

N1, N2 = number of neurons in hidden layers one and two, respectively. LR = ANN's learning rate

To explore the predictive performance of the hybrid model, the coefficient of regression (R) was determined between the measured and predicted water demands, as shown in Figure 9. The observed water consumption (i.e., the target on the x-axis) is plotted against the predicted water demand (i.e., output on the y-axis). The combination model was significant R=0.972 and R=0.982 for seasonal and stochastic data respectively, at the validation stage. These figures emphasise the ability of the hybrid-PSO-ANN technique to accurately predict water demand for both cases, the stochastic model performing slightly better than the seasonal.

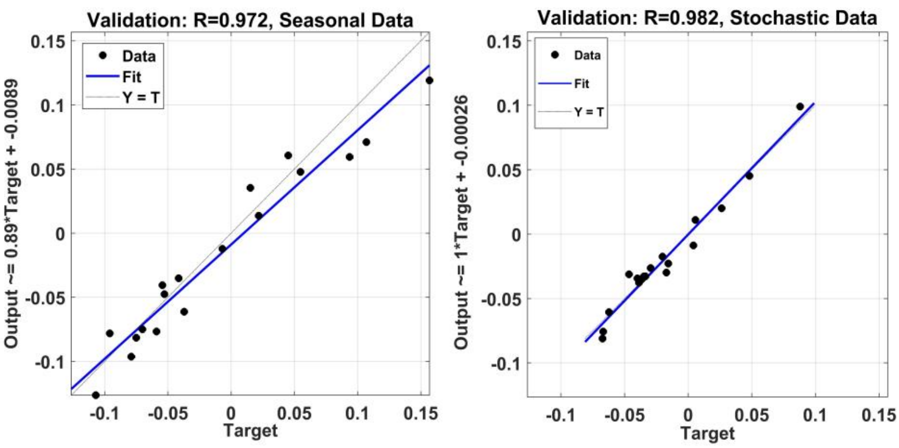

Figure 9: PSO-ANN algorithm performance for seasonal and stochastic data

In order to examine the goodness of fit of the model, an error analysis was performed. The scatter plots of error, versus a number of samples for seasonal and stochastic phases, are presented in Figure 10. In all figures, three important patterns have emerged from the data; the mean error was very close to zero, no special trend exists for the pattern of distribution and the distribution of error density for all data is regular. In addition, the stochastic data had a smaller error scale between -0.02 and 0.02 in comparison to the seasonal data scale, which was between -0.05 and 0.05 at the validation stage.

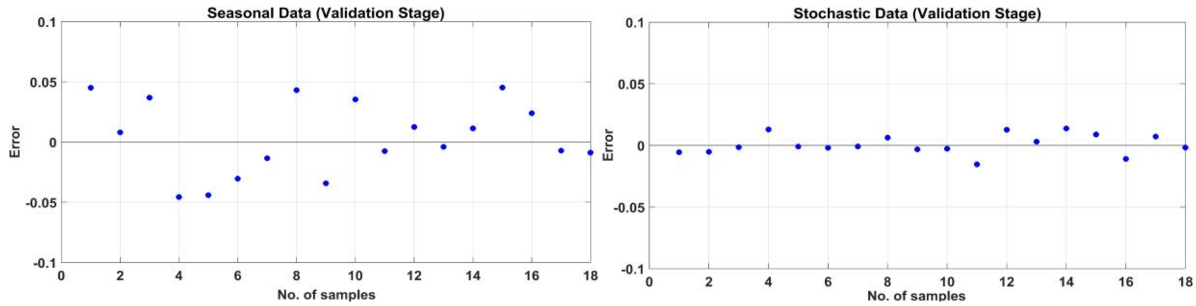

Figure 10: Residual scatterplots for seasonal and stochastic data

Both the stochastic and seasonal graphs depicted in Figure 11, show an excellent fit between actual and predicted municipal water supplies demonstrating the capacity of this model to simulate both time series accurately. This model has the ability to accurately capture the pattern of water consumption, for seasonal and stochastic data, at the validation stage. The prediction is more accurate for the stochastic time series than the seasonal, a result which is in line with the scale of error for each of these series, as detailed previously.

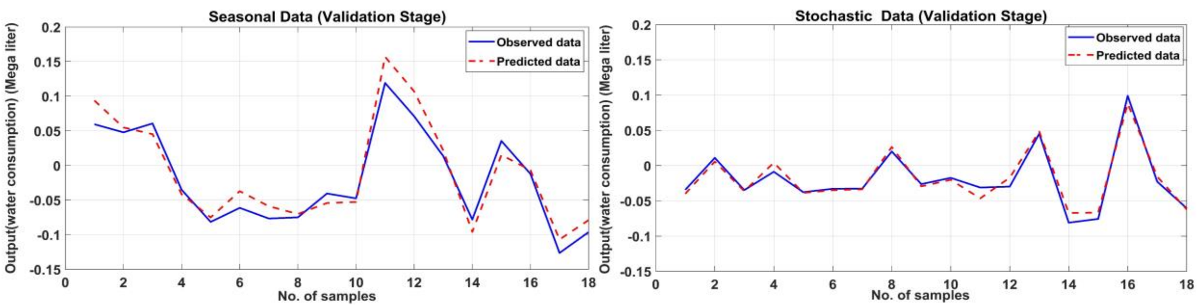

Figure 11: Measured and predicted water demand for stochastic and seasonal data

Table 3 shows the results for RMSE, MSE and MAE, used to evaluate the performance of the models. An important point that emerged from the data was the ability of both models to predict water demand. The stochastic time series was more accurate when simulating observed water data in comparison to the seasonal phase (MAE= 0.0064 for stochastic data compare with MAE= 0.0165 for seasonal data).

Table 3: Three statistical criteria for seasonal and stochastic data

Data	RMSE	MSE	MAE
Seasonal	0.0196	3,8288 e^{-04}	0.0165
Stochastic	0.0080	6.3277 e^{-05}	0.0064

RMSE: root mean square error, MSE: mean square error, MAE: mean absolute error

The use of data pre-processing, specifically the pretreatment signal technique, has played an important role in obtaining these results. The use of a hybrid PSO-ANN model has also proven to be a successful choice for this particular application. This technique has resulted in stronger correlation coefficients and less error, for the prediction of municipal water demand based only on climatic factors. The results obtained with this combination of techniques support the conceptual premise that water demand is driven by climatic factors in the mid-time period, thus deceasing the uncertainties around the impact of climate change.

7 Conclusion

The starting point of this study was the need for the precise prediction of municipal water demand for water utilities, stakeholders and policy makers. A high degree of seasonality and trend variability in municipal water demand not only intensifies this need but also creates a demand for predictive methods that are able to accurately deal with these variations. The motivation for this study was to develop a novel methodology to investigate the impact of climate change on water consumption, for a mid-term time series. This methodology comprised two sections: (1) to investigate the ability of SSA to extract tendencies, harmonic components and irregular components, as well as filtering the noise from different time series and, (2) to examine the reliability of a hybrid PSO-ANN model to forecast monthly water demand time series.

The first major finding was that maximum temperature, rainfall and solar radiation were robust predictors, able to simulate municipal water demand. The power of the SSA technique proved it able to detect both stochastic and seasonal components of the model. The PSO-ANN algorithm yielded a RMSE of 0.02219 and 0.007689 for seasonal and stochastic data. It performed better than the BSA-ANN algorithm, which yielded a RMSE of 0.02528 and 0.007879 for seasonal and stochastic data, respectively. The combination SSA and PSO-ANN technique was reliable and efficient when simulating municipal water demand based on climatic factors only, for a mid-term time series. This paired technique has correlation coefficients at the validation stage of R=0.972 and 0.982 for seasonal and stochastic data, respectively. This study may be considered evidence to encourage water companies to adopt the combined technique of a pretreatment signal with a hybrid PSO-ANN model, to predict water demand across various situations and locations.

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