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Short-Term Urban Water Demand Prediction Considering Weather Factors

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Abstract

Accurate and reliable forecasting plays a key role in the planning and designing of municipal water supply infrastructures. Recent studies related to water demand prediction have shown that water demand is driven by weather variables, but the results do not clearly show to what extent. The principal aim of this research was to better understand the effects of weather variables on water demand. Additionally, it aimed to offer an appropriate and reliable technique to predict municipal water demand by using the Gravitational Search Algorithm (GSA) and Backtracking Search Algorithm (BSA) with Artificial Neural Network (ANN). Moreover, eight weather factors were adopted to evaluate their impact on the water demand. The principal findings of this research are that the hybrid GSA-ANN (Agent=40) model is superior in terms of fitness function (based on RMSE) for yearly and seasonal phases. In addition, it is evidently clear from the findings that the GSA-ANN model has the ability to simulate both seasonal and yearly patterns for daily data water consumption.

Keywords: Australia; explanatory variables; municipal water demand and neural network model.

24 **Acknowledgements**

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27 **1 Introduction**

28 The environmental outlook of the Organisation for Economic Co-operation and Development
29 (OECD) to 2050 indicates that global demand for water is anticipated to increase by 55%,
30 depending on 2000 as a baseline. Moreover, more than 40% of the universal population may
31 be under acute water stress (Fogden and Wood, 2009). Adamowski et al. (2012) stated that
32 successive dry days with high temperatures and a low number of rainy days can play a crucial
33 role in increased water demand. Accordingly, the urban water supply infrastructure faces
34 increasing pressures related to the impact of extreme weather factors. Under these pressures,
35 the present urban water supply infrastructure is probably insufficient to meet future water
36 demands.

37 Prediction of water demand can play a significant role in optimising the design, operation and
38 management of urban water supply infrastructures. Additionally, it can minimise the
39 uncertainty that results from a rapid increase in water demand due to increasing the weather
40 variables effect. Moreover, short-term forecasting is fundamentally associated with scheduling
41 operations related to pumping and decreasing the time that water is detained in storage tanks,
42 which can improve the water quality (Bougadis et al., 2005).

43 Several previous researchers have examined water consumption considering weather variables
44 by using traditional models (Zhoua et al., 2000; Gato et al., 2005). Gato et al. (2005) developed
45 a technique based on both a simple time series and simple linear regression analysis using total
46 daily rainfall and daily maximum temperature. This study revealed that residential water
47 consumption during winter months was affected by weather. Bakker et al. (2014) applied three

48 various models: a Multiple Linear Regression, a Transfer/-noise model, and an Adaptive
49 Heuristic with and without utilising weather input. The models' outcomes demonstrated that,
50 when weather inputs are used, the average errors can be decreased by 7% and the largest
51 predicting errors by 11%. Their models can be classified into traditional and new techniques.

52 Several previous studies have investigated and compared conventional and machine-learning
53 models to predict water demand, and they found that machine-learning techniques have the
54 ability to predict water demand better than the traditional model; these studies include:

55 Jain and Ormsbee (2002) presented an artificial neural network model (MLP) and compared it
56 with two traditional models, regression and time series. The study employed the historical daily
57 data for water consumption and weather variables in Kentucky state, USA, from 1982-1992.
58 The results indicated that the simple ANN model offers a better ability for accurate prediction
59 than the conventional techniques.

60 Bougadis et al. (2005) investigated three methods: time series analysis, linear and multiple
61 linear regression, and artificial neural networks. The research adopted the historical weekly
62 data of water consumption for summer months only for the city of Ottawa, Canada, from 1993-
63 2002. In addition, it used the climate variables and antecedent water consumption as model
64 inputs. The performance of the ANN models in predicting water demand consistently
65 outperformed the traditional models.

66 Unlike many hydrological applications, it has been noted that the artificial neural network
67 technique has only limited application in terms of water demand modelling (Firat et al., 2010).
68 In addition, the majority of previous studies have adopted monthly time series data in their
69 water demand models and sometimes used weekly data; few have adopted daily time series
70 (Sarker et al., 2013).

71 Most studies of water prediction have only investigated the impact of socio-economic factors
72 or a mix of socio-economic and weather factors (Liu et al., 2003; Firat et al., 2009; Behboudian
73 et al., 2014). Few studies have adopted weather variables only in their water demand models
74 as well as employing limit variables (maximum temperature and total rainfall only) (Jain et al.,
75 2001; Jain and Ormsbee, 2002; Adamowski, 2008; Adamowski et al., 2012). Adamowski
76 (2008) advised using extra weather variables in the water demand model to include
77 evaporation, humidity, wind speed, and amount of cloud cover and sunshine.

78 Prediction of water demand is a substantial topic for policy-makers in the water industry. It is
79 still extremely challenging to achieve the expected forecasting accuracy with respect to the
80 prediction trends (Behboudian et al., 2014). Accordingly, much uncertainty still exists about
81 the relationship between the capacity of water systems and a potential rapid increase in water
82 demand resulting from acute weather factors based on seasonal and yearly base.

83 The aims of this research study are to:

- 84 a) Utilise two novel optimisation algorithms to enhance the capability of the ANN
85 technique to predict water demand with high accuracy and minimum error.
- 86 b) Use statistical techniques to select the model inputs that increase forecasting accuracy
87 compared with a trial and error approach.
- 88 c) Examine the extra weather variables employed in the model inputs to assess the weather
89 factors' impact on water demand and reduce the uncertainty, and
- 90 d) Develop two kinds of short-term models – seasonal and yearly time series daily data –
91 to explore the relationship between water demand and weather factors on both a
92 seasonal / a yearly basis and explore the uncertainty.

93 To the best of the authors' knowledge, no previous applications for the techniques in both
94 points (a) and (b) have been used in water prediction for short-term daily data time series
95 analysis.

96 **2 Studied Area and Model Data**

97 For the purpose of this study, one catchment area in Australia, the city of Melbourne, has been
98 used to develop the water demand model. Yarra Valley Water is one of three retail water
99 companies which receive municipal water from the Melbourne Water Corporation. Yarra
100 Valley Water delivers municipal water supply and sewerage services to more than 1.5 million
101 capita who live in the catchment area of the Yarra River where it flows through Melbourne.
102 Figure 1 shows the Licence Service Area of Yarra Valley Water (YVW, 2017).

103 Historical daily data of water consumption and weather variables were collected from Yarra
104 Valley Water for the areas that were served in Melbourne city from 2010-2015. This data
105 comprises water consumption (ML), Maximum Temperature ($^{\circ}\text{C}$), Mean Temperature ($^{\circ}\text{C}$),
106 Minimum Temperature ($^{\circ}\text{C}$), Rainfall (mm), Evaporation (mm), Solar Radiation (MJ/m^2),
107 Vapour Pressure (hpa), and Maximum Relative Humidity (%). Figure 2 depicts the historical
108 daily water consumption data.

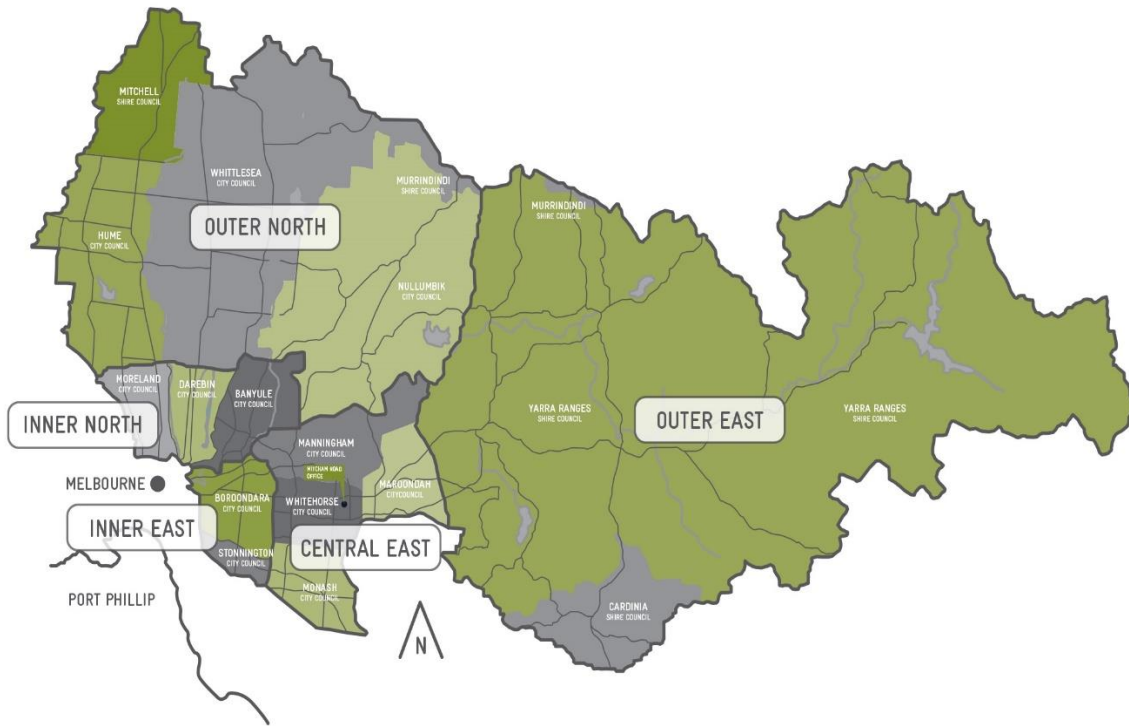


Figure 1: Yarra Valley Water's licence service area (YVW, 2017)

109

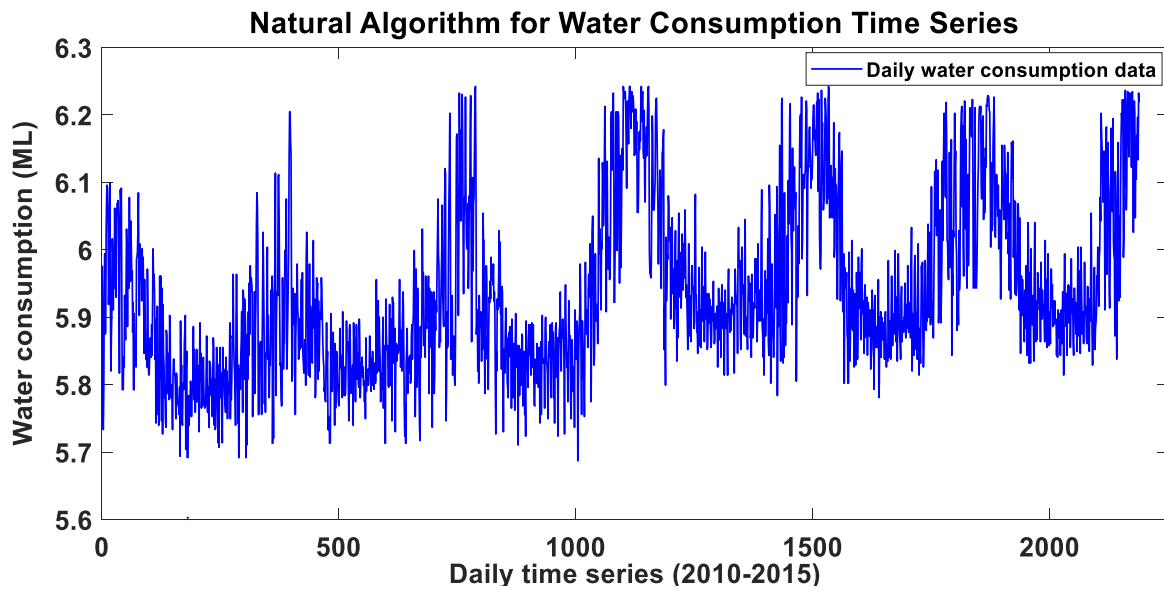


Figure 2: Daily data water consumption for Melbourne for the period 2010-2015

110 **3 Data Pre-processing Techniques**

111 Maier and Dandy (2000) stated that it is vital to pre-process data in an appropriate form before
112 it is utilised in the ANN. These techniques are essential to confirm that all the data receives
113 equal attention in the learning mode.

114 **3.1 Data Cleaning**

115 Data cleaning techniques comprise detection and removal of irrelevant or meaningless data,
116 noise or outliers, to improve the outcomes of data analysis (Xiong et al., 2006). Extreme data
117 has adverse effects on the regression solution and influences the accuracy of the model (Pallant,
118 2011). In this study, the box and whisker technique has been used to determine the outliers'
119 data and then scores changed to be within the same pattern as the rest of the data.

120 **3.2 Normalisation**

121 This approach aims to smooth the answer space and minimise the effects of noise (ASCE,
122 2000; Kotsiantis et al., 2006). Tabachnick and Fidell (2013) stated that transforming the
123 continuous variables is important in making the time series normally or near normally
124 distributed. Additionally, the results of the model are degraded, if the time series of variables
125 are not normally or near normally distributed. In this research study, natural algorithm, square
126 root, and inverse function are adopted to transfer time series data depending on the type of
127 series.

128 **4 Selection of Explanatory Variables**

129 The selection of explanatory variables influencing water demand as model input data is one of
130 the most significant stages in evolving a satisfactory forecast model (Zhang et al., 2006) .
131 Previous studies have trained many ANNs with various combinations of input variables to
132 select the model that has the best performance (Jain et al., 2001; Zhang et al., 2006; Adamowski
133 et al., 2012). A potential drawback in the above technique is that it is model-based. In other

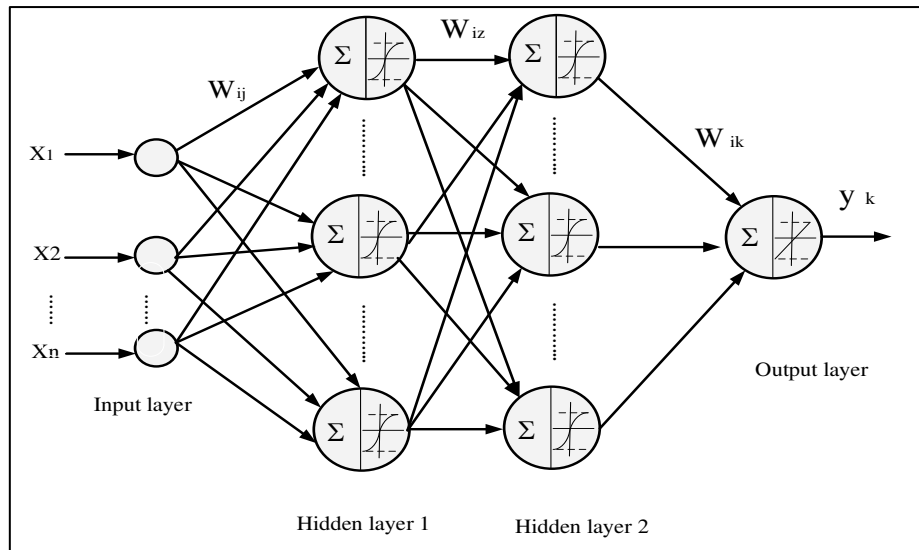
134 words, the best performance is not achieved by depending on model input variables only, but
135 also on the structure and calibration of the model (Shahin et al., 2008).

136 After the potential weather factors were identified (screened and normalised), a three-staged
137 process was adopted in this study to select the ANN model input data; this was to avoid this
138 problematic issue of choice and to reduce the uncertainty in input variables. In the first stage,
139 correlation matrix analysis will be employed to determine the strength of association between
140 the dependent and independent variables, as well as among the independent variables.
141 Accordingly, the explanatory independent variables that have a significant correlation at the
142 0.01 level (2-tailed) will be selected. In the second stage, correlation matrix analysis will be
143 adopted to investigate the effect of lag (previous values) of the independent variables that were
144 selected in the first stage on the dependent variable. In addition, an autocorrelation technique
145 will be applied for water consumption time series. The final stage of the selection process,
146 variance inflation factor (VIF), will be utilised to determine the presence of multicollinearity.
147 These stages of the process were carried out to ensure that as many of the potential variables
148 as possible were properly included in the map of the input-output relationship, to avoid
149 multicollinearity, which can lead to incorrect conclusions.

150 **5 ANN Techniques**

151 The ANN approach is a system of information processing that attempts to mimic the workings
152 of the brain's neurons by utilising a network of artificial neurons which are regular in layers. In
153 addition, it has the ability to adequately map the non-linear water demand trend (Babel and
154 Shinde, 2011). In this study, the Backpropagation Neural Network (BP-NN) kind and the
155 Levenberg-Marquardt (LM) learning algorithm were employed for training, testing and
156 validation. The LM training algorithm was adopted because it offers minimum error in addition
157 to its speed and efficiency, as proven in Payal et al. (2015). In the ANN, before achieving the

158 phases of training, testing and validation, the parameters of the number of inputs, number of
159 hidden layers, number of neurons in each hidden layer, learning rate and the number of outputs
160 must be determined. In this research, to predict the short-term daily water demand, an ANN
161 architecture with the following four layers was employed: (1) input layer; (2) first hidden layer
162 (FHL); (3) second hidden layer (SHL); and (4) output layer (Ahmed et al., 2016; Gharghan et
163 al., 2016b), as depicted in Figure 3. The input layer contains seven parameters consisting of
164 weather variables and antecedent water consumption. In the first layer, the neurons work as a
165 buffer to distribute the values of inputs to the first hidden layer. The values of inputs were
166 weighted by connections w_{ij} and collected by each neuron of the FHL to pass the output of the
167 FHL to the neurons of the SHL. The inputs of the SHL were weighted by connections w_{iz} and
168 collected by each neuron of the SHL to compute the output y_k in the fourth layer. The
169 *tansigmoidal* activation function was employed in the FHL and SHL to cover all ranges of the
170 negative input values, whilst the output layer utilised the *linear* activation functions to cover
171 the positive values of water demand. ANN parameters chosen were not secure and subject to
172 the trial-and-error technique, which does not always offer the optimal answer. Hence, the
173 learning rate and the number of neurons in the first and second hidden layers were determined
174 depending on the optimisation algorithms (GSA and BSA) with population sizes 10, 20, 30, 40
175 and 50 (Gharghan et al., 2016a). The Gravitational Search Algorithm (GSA) and Backtracking
176 Search Algorithm (BSA) are able to remedy such a problem by locating the best learning rate
177 value and the optimum number of neurons for both hidden layers of the ANN model.
178 Consequently, the ANN's performance can be improved. In this case, these algorithms could
179 be combined with the ANN to form two different types of hybrid model, the GSA-ANN
180 algorithm and the BSA-ANN algorithm, through which the ANN was capable of predicting
181 water demand with minimum error.



182

183

Figure 3: The ANN algorithm architecture

184 5.1 Heuristic Algorithms

185 Heuristic Algorithm is an approach that tries to catch a good solution (near optimal) at a
 186 plausible computational cost without the capability for undertaking either feasibility or
 187 optimality, or even in some situations to explain how close it is to the optimal solution (Rashedi
 188 et al., 2009). Because the conventional approaches provided a high water estimation error,
 189 ANN was employed in this research to improve the predicted water error. Due to the ANN
 190 technique's flexible modelling and learning abilities, it is likely to produce minimal errors in
 191 determining the future water demand. With a large amount of data and adequate ANN
 192 parameters, ANN has the ability to represent the relationship between dependent and
 193 independent variables. The heuristic algorithms, BSA and GSA, were hybridised with the ANN
 194 to select the optimum parameters of the ANN (i.e., the learning rate and number of neurons in
 195 both hidden layers). Choosing ANN parameters is not totally reliable and is dependent on trial
 196 and error, which in return gives a high level of error in water demand prediction.

197 Five population sizes, 10, 20, 30, 40 and 50, and 100 iterations were applied to let each
 198 algorithm determine the population that could attain the minimal fitness function value. In
 199 addition, the parameter settings of the heuristic algorithms were detected as $F=3$ for BSA, G_0

200 =1 and $\alpha=0.2$ for GSA (Gharghan et al., 2016a). The process of ANN training was repeated
201 many times utilising a large number of epochs (i.e., 1000 iterations) until the error between the
202 observed and predicted municipal water reached the minimum.

203 5.1.1 Backtracking Search Optimisation Algorithm (BSA)

204 BSA is a recently developed evolutionary optimisation algorithm. It has the ability to solve
205 problems of numerical optimisation in a quick and successful way by adopting a unique
206 technique to generate a trail individually. This approach has been employed to address different
207 kinds of optimisation problem in engineering fields, such as home energy management (Ahmed
208 et al., 2017), Optimisation issues (Chen et al., 2017). The BSA technique is organised into five
209 steps: initialisation, selection-I, mutation, crossover and selection-II. Additional details can be
210 found in Su et al. (2016).

211 5.1.2 Gravitational Search Algorithm (GSA)

212 Rashedi et al. (2009) proposed the GSA algorithm, which is based on the Newtonian law of
213 gravity: “Every particle in the universe attracts every other particle with a force that is directly
214 proportional to the product of their masses and inversely proportional to the square of the
215 distance between them”. The mathematical principle of the GSA is dependent on the
216 Newtonian law of gravity and the motion laws, as in the following:

$$217 \quad F = G = \frac{M_1 M_2}{R^2} \quad (1)$$

218 Where

219 F= gravitational force,

220 R = the distance between the first and second particles mass (M_1) and (M_2) respectively, and

221 G = the gravitational constant value.

222

223 Newton's second law states that "acceleration is inversely proportional to mass M and directly
 224 proportional to force F", as follows:

$$225 \quad a = \frac{F}{M} \quad (2)$$

226 Due to the influence of declining gravity, the real value of the "gravitational constant (G)"
 227 relies on the universe's real age. Eq. (3) offers a reduction of the gravitational constant with
 228 age (Gharghan et al., 2016a):

$$229 \quad G(t) = G(t_0) \times \left(\frac{t_0}{t}\right)^\beta \quad \beta < 1 \quad (3)$$

230 Where

231 $G(t)$ = the gravitational constant at time t, and

232 $G(t_0)$ = the gravitational constant at the first cosmic quantum-interval of time t_0 .

233

234 The agents' positions are initialised (i.e., the masses are chosen randomly within the offered
 235 search interval). The i^{th} agent position can be known by:

$$236 \quad X_i = (X_i^1, \dots, X_i^d, \dots, X_i^k), \quad \text{for } i = 1, 2, 3, \dots, N \quad (4)$$

237 Where

238 N = the number of agents,

239 X_i^d = the i^{th} agent position in the d^{th} dimension, and

240 k = the space dimension.

241 To compute the GSA fitness function, a root mean square error (RMSE) can be adopted to
 242 select the best and the worst fit for each iteration. The purpose of the computations was to
 243 reduce the problems and locate the masses of each agent as follows (Shuaib et al., 2015):

244

$$245 \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e^2} \quad (5)$$

246
$$best(t) = \min_{j \in \{1, \dots, N\}} fit_j(t) \quad (6)$$

247
$$worst(t) = \max_{j \in \{1, \dots, N\}} fit_j(t) \quad (7)$$

248
$$m_i(t) = \frac{fit_i(t) - Worst(t)}{best(t) - Worst(t)} \quad (8)$$

249
$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^N m_i(t)} \quad (9)$$

250 Where

251 e = the predicted water error, and

252 n = the number of samples.

253 The actual water consumption was obtained based on observation, whereas the predicted water

254 was gained using the GSA-ANN algorithm. The gravitational constant G at iteration t was

255 calculated as follows:

256
$$G(t) = G_0 e^{(-at/T)} \quad (10)$$

257 Computation of the total force in different directions for the i^{th} agent, calculation of the velocity

258 and acceleration, and the position of the agents in the next iteration are as follows:

259
$$F_i^d(t) = G(t) \frac{M_{pi} \times M_{aj}}{R_{ij} + \epsilon} (X_j^d(t) - X_i^d(t)) \quad (11)$$

260
$$F_i^d(t) = \sum_{j \in K_{best}, j \neq i} rand_j F_{ij}^d(t) \quad (12)$$

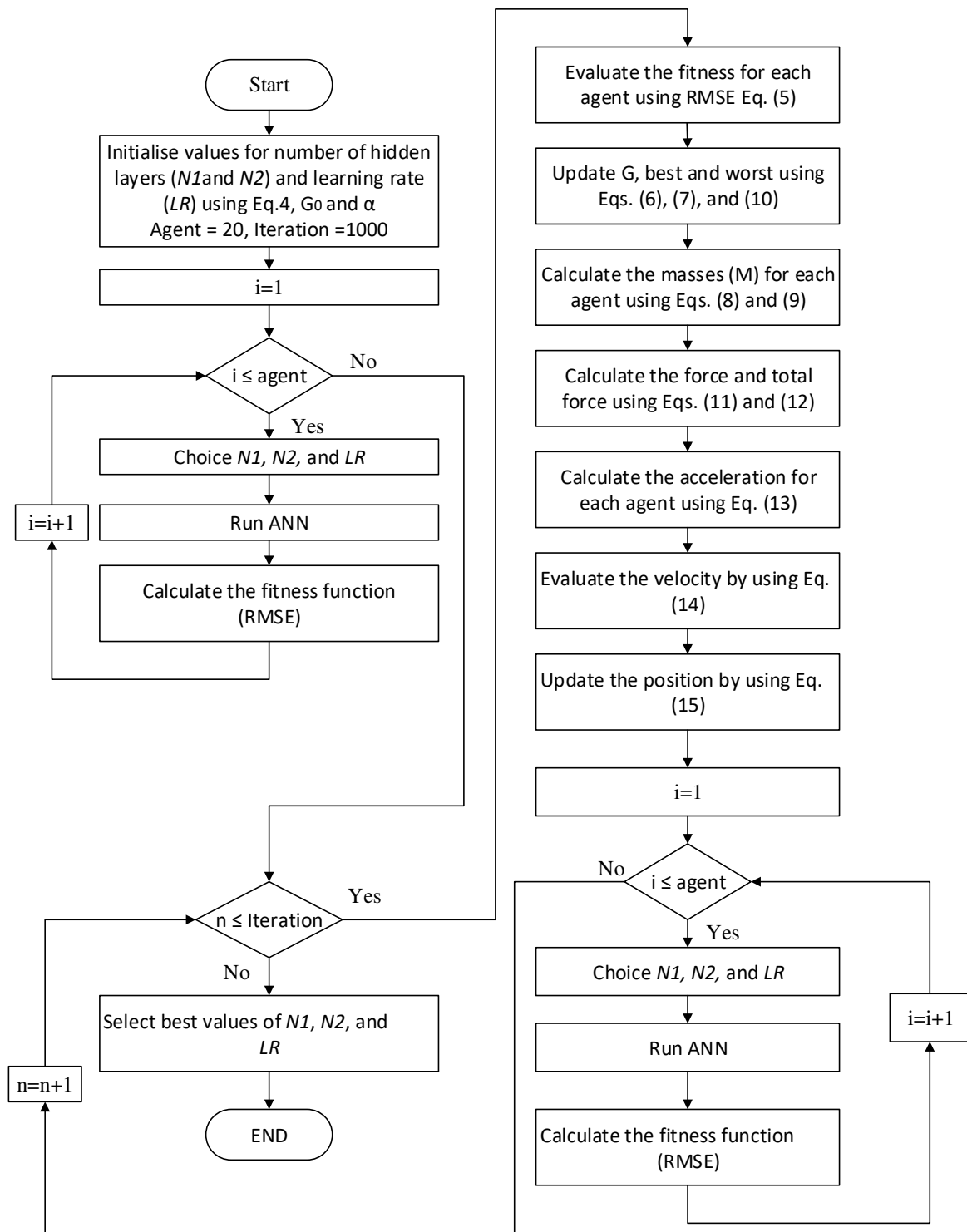
261
$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \quad (13)$$

262
$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (14)$$

263
$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (15)$$

264

265 Figure 4 presents the flowchart that shows the details of the GSA-ANN operation based on the
 266 previous equations.



267

268

Figure 4: The GSA-ANN algorithm flowchart (Gharghan et al., 2016a)

269 5.2 Data Division

270 Data division is a vital process that needs to be addressed in the ANN. It is general practice to
271 divide the obtainable data into three sub-sets, namely: learning, testing and validation. All these
272 three sets must have the same pattern because the ANN does not have the capability to
273 extrapolate outside the range of data that is employed for training (Basheer and Hajmeer, 2000).
274 In this study, data was divided randomly between the training, testing and validation sets –
275 70%, 15%, 15% respectively (Babel and Shinde, 2011; Behboudian et al., 2014).

276 6 Performance Measurement Criteria

277 The statistical criteria parameters provide a means of measuring prediction accuracy, so
278 prediction errors play a considerable role in the choice of suitable models and in providing
279 insights in advising alterations to present models to minimise deviations in future predictions
280 (Donkor et al., 2014). Several statistical parameters will be applied in the model's calibration
281 such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean
282 Squared Error (MSE), Root Mean Squared Error (RMSE) and Correlation Coefficient (R).
283 These indicators are defined in Eqs. (16) through (20).

$$284 \quad MAE = \frac{\sum_{m=1}^N |x_o - x_p|}{N} \quad (16)$$

$$285 \quad MAPE = \frac{\sum_{m=1}^N \frac{|x_o - x_p|}{x_o}}{N} \quad (17)$$

$$286 \quad MSE = \frac{\sum_{m=1}^N (x_o - x_p)^2}{N} \quad (18)$$

$$287 \quad RMSE = \sqrt{\frac{\sum_{m=1}^N (x_o - x_p)^2}{N}} \quad (19)$$

$$288 \quad R = \left[\frac{\sum_{m=1}^N (x_o - \bar{x}_o)(x_p - \bar{x}_p)}{\sqrt{\sum_{m=1}^N (x_o - \bar{x}_o)^2 \sum_{m=1}^N (x_p - \bar{x}_p)^2}} \right] \quad (20)$$

289 Where x_o = observed water consumption, x_p = predicted water demand, N = sample size, \bar{x}_p =
290 mean of predicted demand, and \bar{x}_o = mean of observed consumption.

291 Bland–Altman analysis: this scatter plot test is employed to locate the area of agreement
292 between (observed- predicted) versus $([\text{observed} + \text{predicted}]/2)$, and the percentage of data that
293 is distributed inside the limits of the agreement area

294 **7 Results**

295 **7.1 Model Development**

296 After data pre-processing, correlation coefficients and autocorrelations were detected between
297 dependent and independents variables. Additionally, variance inflation factor (VIF) technique
298 then was used to select the best model input. The values of VIF was located between (2.87-
299 4.92), which were accepted as mention in Tabachnick and Fidell (2013). Accordingly, Eq. 21
300 can express the relation between dependent and the independents variables:

$$301 \quad \text{WD} = f(\text{WD}_{t-1}, \text{Tmax}, \text{Rad}, \text{Eva}, \text{WD}_{t-2}, \text{Tmax}_{t-1}, \text{Eva}_{t-2}) \quad (21)$$

302 Where: WD = water demand, Tmax = maximum temperature, Rad = solar radiation and Eva =
303 evaporation. In addition, WD_{t-1} and WD_{t-2} represent the previous water consumption for the
304 last first and second days and so on for the rest variables. Also, Eva and Eva_{t-2} were offered
305 high correlation and less collinearity compare with Eva_{t-1} .

306 The correlation coefficients between input and output models for the best model input are 0.79,
307 0.66, 0.49, 0.64, 0.69, 0.57 and 0.52 for WD_{t-1} , Tmax, Rad, Eva, WD_{t-2} , Tmax_{t-1} and Eva_{t-2}
308 respectively. In addition, all these correlation is significant at the 0.01 level (2-tailed).

309 After selection of the best model inputs, data was divided into a seasonal (winter, spring,
310 summer and autumn) and an annual scale to assess the effect of weather factors on water

311 consumption in both seasonal and yearly data. Additionally, to examine the ability of each
312 model to predict daily water demand.

313 To get an effective prediction, four statistical criteria were used to ensure that data set for
314 training, testing, and validation have the same pattern. Table 1 provides a comparison of the
315 three data sets. The results, as shown in Table 1, indicate that all the data sets have exactly the
316 same pattern. In addition, the results of validation set will support that all sets have the same
317 pattern.

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Table 1 the statistical parameters of training, testing, and validation sets

Training set data								
	WD	WD _{t-1}	Tmax	Rad	Eva	WD _{t-2}	Tmax _{t-1}	Eva _{t-2}
\bar{X}	5.937	5.937	4.487	3.667	5.938	1.762	4.489	1.755
X_{\max}	6.242	6.242	6.245	5.568	6.242	3.162	6.245	3.131
X_{\min}	5.602	5.602	3.000	1.732	5.649	0.447	3.000	0.447
S_x	0.126	0.126	0.697	0.986	0.125	0.588	0.697	0.579
Testing set data								
	WD	WD _{t-1}	Tmax	Rad	Eva	WD _{t-2}	Tmax _{t-1}	Eva _{t-2}
\bar{X}	5.933	5.933	4.475	3.645	5.933	1.732	4.484	1.771
X_{\max}	6.234	6.242	6.205	5.568	6.242	3.066	6.205	3.162
X_{\min}	5.690	5.649	3.082	1.732	5.602	0.633	3.162	0.447
S_x	0.119	0.123	0.703	0.993	0.123	0.571	0.680	0.579
Validation set data								
	WD	WD _{t-1}	Tmax	Rad	Eva	WD _{t-2}	Tmax _{t-1}	Eva _{t-2}
\bar{X}	5.934	5.931	4.445	3.689	5.929	1.737	4.423	1.735
X_{\max}	6.242	6.234	6.124	5.385	6.242	3.066	6.124	3.131
X_{\min}	5.700	5.700	3.082	1.732	5.694	0.447	3.082	0.447
S_x	0.120	0.117	0.664	0.955	0.121	0.554	0.681	0.596

\bar{X} =mean, X_{\max} =maximum value, X_{\min} =minimum value, S_x =standard division

331

332 7.2 Hybrid Heuristic Algorithms-ANN Techniques

333 Several sizes of a population were simulated in MATLAB for the hybrids (BSA-ANN and
 334 GSA-ANN) to let each hybrid algorithm determine the optimal learning rate value and number
 335 of neurons in both hidden layers of the ANN. Thereby, the minimum value of the fitness
 336 function could be obtained as shown in Figurer 5. The figure was displayed that the GSA-ANN

337 is capable of attaining the best fitness function at the 40 population size for all seasonal and
338 yearly water consumption data. Thus, the output of the GSA algorithm has been selected to
339 develop the ANN model for water demand. Accordingly, table 2 presents the ANN factors for
340 the best population size for all data types.

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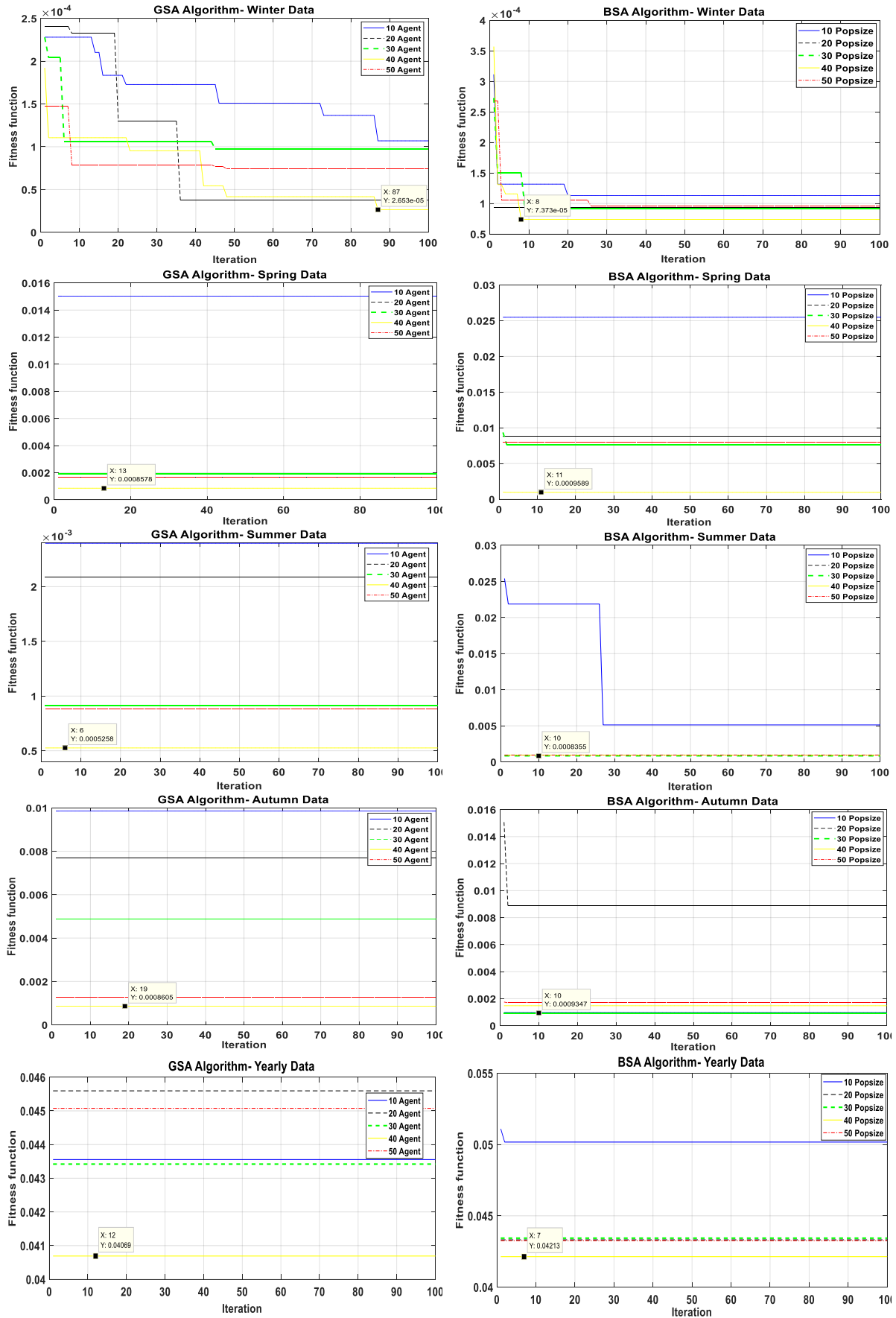


Figure 5: Fitness function versus iteration of all data kinds for GSA and BSA algorithms

Table 2: ANN parameters based on GSA-ANN algorithm for all data types

Data type	Parameters	GSA-ANN
Winter	N1	15
	N2	10
	LR	0.4434
Spring	N1	17
	N2	19
	LR	0.5198
Summer	N1	16
	N2	17
	LR	0.1477
Autumn	N1	19
	N2	19
	LR	0.9729
Yearly	N1	19
	N2	17
	LR	0.5412

N1: Number of neurons in hidden layer one, N2: Number of neurons in hidden layer two and LR: ANN's learning rate.

355

356 The regression coefficient (R) of determination between the observed and predicted municipal
357 water is a perfect indicator for the exploration of the forecast performance of the hybrid GSA-
358 ANN algorithm. In addition, R is equal to 0.99, 0.99, 0.97, 0.97 and 0.95 for winter, spring,
359 summer, autumn and yearly data respectively. It can be seen that the values of (R) for seasonal
360 data are more than the yearly data for the validation stages. These interesting findings could be

361 because the model is more able to capture the relation between input and output factors using
362 seasonal data compared to when using yearly data.

363 To examine the agreement of the model for seasonal and yearly water demand data, a Bland–
364 Altman scatter plot was employed. It has the ability to reveal the systematic and random
365 differences as well as the merit of exhibiting the variation in the outcomes. In this plot, mean
366 (m) and standard deviation (SD) of the differences were obtained by applying the T test
367 technique. In addition, $m+1.96 SD$ and $m-1.96 SD$ represent the upper and lower limits of
368 agreement. From this plot, it is quite easy to evaluate the level of (systematic) variation, the
369 scatter of the values and to display whether there is a relation between the observed and
370 predicted error.

371 The most obvious finding to emerge from the analysis is that scattered data suggests an
372 excellent distribution fit between agreement limits for seasonal and yearly data, as shown in
373 Figure 6. Table 3 shows the percentage of data distributed between the agreement limits for
374 seasonal and yearly. One of the issues that emerged from these findings was that the percentage
375 range values were from 93.8 to 95.0. In addition, Table 3 presents four statistical indicators
376 used to evaluate the model performance. These findings further indicate that no statistically
377 significant difference was observed between measured and forecasted water demand,
378 especially for winter season data.

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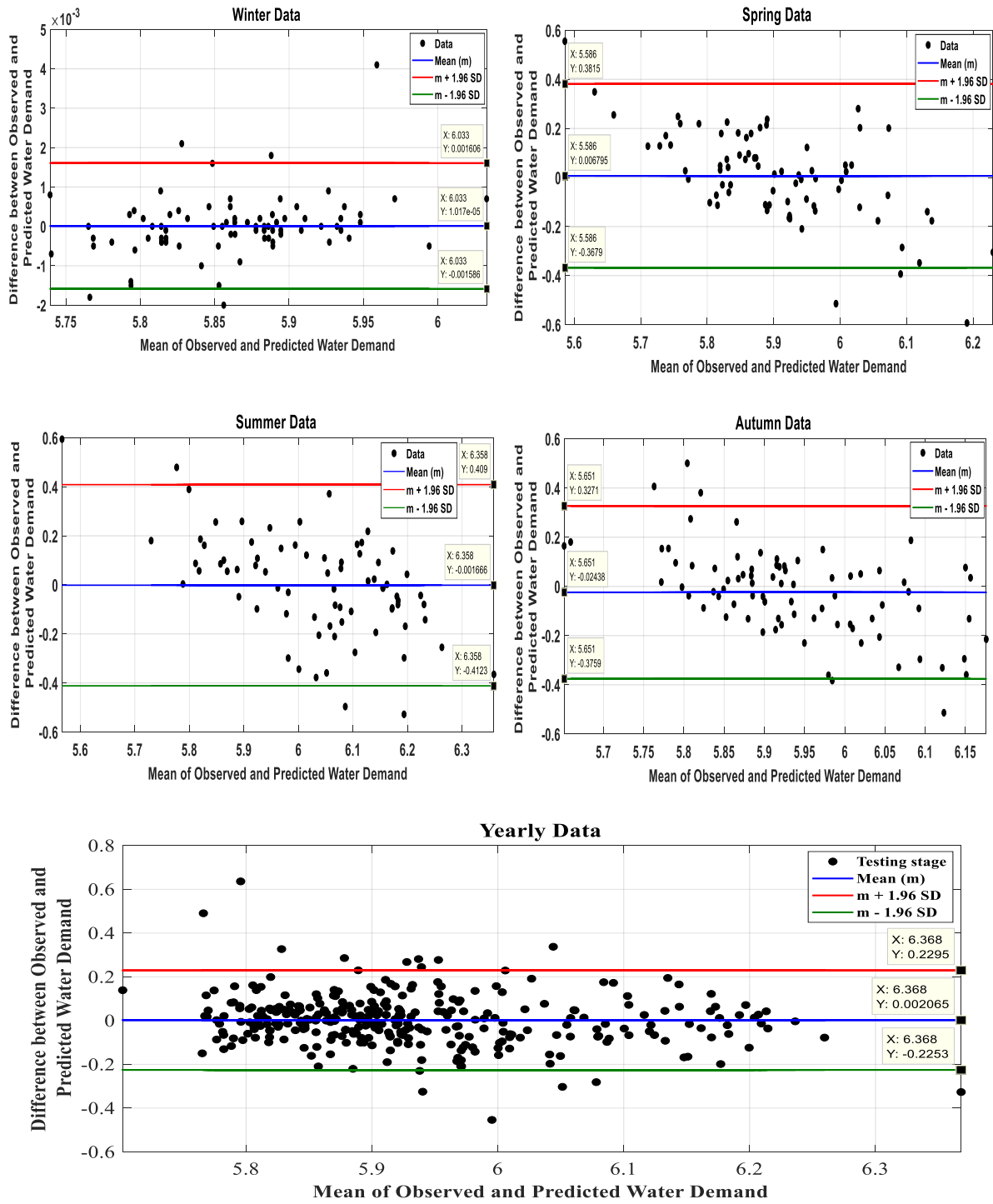


Figure 6: Bland–Altman plot of the relation between observed and predicted municipal water for seasonal and yearly data

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Table 3: Several statistical parameters for seasonal and yearly data.

Data	RMSE	MSE	MAE	MAPE	BAPA %
Winter	8.094×10^{-4}	6.551×10^{-7}	5.086×10^{-4}	2.1522×10^{-6}	93.8
Spring	0.19	0.0361	0.1449	0.0012	94.7
Summer	0.2081	0.0433	0.1612	1.4295×10^{-4}	94.7
Autumn	0.1799	0.0324	0.1363	0.0040	93.8
Yearly	0.1159	0.0134	0.0833	4.7264×10^{-4}	95.0

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RMSE: root mean square error, MSE: mean square error, MAE: mean absolute error and BAPA: Bland–Altman plot accuracy

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According to this data analysis and statistical criteria, it can be inferred that these results

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provide further support for the hypothesis that water demand is driven by weather variables. In

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addition, this study confirms that data pre-processing techniques, data division and selection

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of explanatory variables are associated with the accuracy and robustness of results. Another

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important finding was that the model’s capability to catch the pattern of time series data

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depends on seasonal data rather than yearly data. Moreover, the winter season model reveals

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more accuracy and less error compared with the rest of the models. A possible explanation for

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this might be that winter weather factors have less variability than those in other seasons.

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Furthermore, the GSA-ANN algorithm model is a robust technique which has sufficient

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capability to predict water demand considering trend and seasonal pattern for seasonal and

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yearly time series data.

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8 Conclusion

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Prediction of water demand can assist in determining convenient alternatives for ensuring the

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balance between water supply and demand. The aim of this research was to examine the

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potential input variables to select the best model input by adopting several different statistical

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techniques. These techniques consisted of data screening, cross-correlation matrix,

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autocorrelation and variance inflection factor. The second aim of this study was to determine

405 the accurate prediction of short-term future urban water demand considering weather factors.
406 To achieve these predictions, hybrid GSA-ANN and BSA-ANN algorithms were utilised. The
407 most obvious findings to emerge from this study are that: (a) statistical criteria are powerful
408 techniques for selecting appropriate model inputs, and (b) the GSA-ANN (Agent=40) hybrid
409 model is quite suitable compared with the other type of hybrid model in this study in terms of
410 water demand estimation accuracy. A key strength of this study is that selection of best model
411 inputs and ANN factors based on optimisation techniques is better than using a trial and error
412 method. This research could be further advanced by assessing the effects of extra weather
413 variables, depending on the availability of data, on water demand for different locations around
414 the world.

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