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The use of band similarity in urban water demand forecasting as a new method

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ABSTRACT

Water consumption and demand by persons vary from time to time and from location to location depending on countless factors, notably, population, socio-economic and climatic variables. Today, studies that create models of water consumption of persons, using numerous methods including artificial neural networks and regression models in this regard and ensure that ongoing projections are made. In this study, parameters affecting water consumption were examined within the scope of the study area, and the parameter reduction was realized with the help of Factor Analysis. Then, as a new method, the Band Similarity method was used together with the Artificial Bee Colony optimization algorithm, urban water demand models were produced and the temporal dependence of the relevant variables was examined. As a result of the study, it was seen that the Band Similarity method improved the results obtained with the optimization algorithm and helped to understand the temporal dependencies of the variables. The fact that the Band Similarity method, which was put forward for the first time in its field, worked successfully and produced results, can be said to be the main contribution of this study to existing knowledge.

Key words: artificial bee colony, band similarity, factor analysis, optimization, water demand forecasting

HIGHLIGHTS

- Band Similarity method developed by the author was applied in a problem for the first time and successful results were obtained.
- In addition to the Band Similarity method, Factor Analysis, which is a multivariate statistical analysis method, and an optimization method were applied together.

INTRODUCTION

According to data of the United Nations, 55.3% of the world's population lived in cities in 2018. It is estimated that this rate will go up to 60% by 2030. Besides, migration and influx of refugees has made cities even more sensitive. Under current conditions, there is no doubt that meeting drinking water needs is the most important among many services that need to be rendered so that urban life can be maintained in a healthy manner. Apart from the population density, which gets bigger and bigger in cities, the fact that the need for water is now higher given that the quality of life has improved increases the importance of this subject matter more and more.

In this framework, it is of paramount importance, with regards to efforts for water supply in cities, to determine the character and behaviour of the water demand as well as to what extent it is affected by which parameters, both in terms of the design phase and operation phase. Water demand and consumption is a parameter that can largely vary from time to time and from location to location, yet it can be affected by countless variables. Many parameters such as level of education, cultural behaviour patterns, form of settlement and water price including, notably, population, climatic and socio-economic variables, may have an impact upon the water demand to a different extent. It is suggested that climate, economy, urban design, and demographics are the most important among such parameters (Corbella & Pujol 2009), and in another study, it is emphasized that the main components having an impact upon the water consumption are water price, income and household composition (Peters & Chang 2011). Parameters may differ in general depending on the characteristic properties of the region. For instance, although under normal conditions the water price is not a very important parameter, a dramatic hike in the water price in a region suffering from scarcity of water with a view to limiting the use may make this parameter important.

In order to be able to model the water demand more precisely, it is known that there is a rather high increase in the number of studies conducted in recent years (Ghalehkhondabi & Ardjmand 2017; Vijia & Sivakumar 2018). In general, it may be seen that studies so conducted are differing from one another and grouped in terms of parameters, methods, time period and horizon used.

It may be said that the parameters most frequently used during the studies conducted include temperature, precipitation, per capita income and family structure (Peters & Chang 2011). Besides, in regions with high levels of pool use (Domene & Saurí 2006; Wentz & Gober 2007) or garden watering (Domene & Saurí 2006; Fox *et al.* 2009), effects of such variables were researched. Besides, even if the water price was used as a parameter in most of the studies conducted, it is observed that changes in the water price do not have an impact upon the consumption to a great extent (Peters & Chang 2011).

On the other hand, it is seen in the literature that hourly (Jentgen *et al.* 2007; Herrera *et al.* 2010), daily (Levin *et al.* 2006; Cutore *et al.* 2008), weekly (Jain *et al.* 2001; Adamowski & Karapataki 2010), monthly (Brekke *et al.* 2002; Altunkaynak *et al.* 2005; Firat *et al.* 2009) or annual water consumption data (Wei *et al.* 2010) were used. What matters in this regard is being aware of the fact that parameters which may be influential are also likely to change depending on the time period chosen (Donkor *et al.* 2014). During the studies conducted, long-, mid- and short-term forecasts were made (Tamada *et al.* 1993; Jain *et al.* 2001; Ghiassi *et al.* 2008). In this scope, forecasts covering a period longer than two years were defined as long-term forecasts, forecasts covering a period from three months and two years as mid-term forecasts and forecasts covering a period shorter than three months as short-term forecasts (Donkor *et al.* 2014).

While methods such as Multiple Regression and Time Series analysis were first (Maidment & Parzen 1984) used in studies conducted on this subject matter, in later years, Artificial Neural Networks (Campisi-Pinto *et al.* 2012; Shirkoohi *et al.* 2021) and soft computing methods such as Support Vector Machines (Ji *et al.* 2014; Shabani *et al.* 2017) were used, but especially today, optimization algorithms, notably metaheuristic methods, are being used in this regard (Ji *et al.* 2014; Candelieri *et al.* 2019). It is seen in the literature that especially Particle Swarm Optimization (Zhou & Yang 2010; Sun *et al.* 2012) and Genetic Algorithm (Chen 2009; Shirkoohi *et al.* 2021) methods are used in water demand estimation in this area. It may be said that, from among studies conducted, more successful results were achieved in general when methods were used in hybrid versus standalone use (Ghalehkhondabi & Ardjmand 2017).

In the present study, the optimization algorithm Artificial Bee Colony (ABC), not commonly used in this subject matter, was applied concomitantly with the Band Simulation (BS) method as a new method and the water demand was forecast. To that end, meteorological data, per capita income and population values as well as monthly domestic water consumption pertaining to Yazır district in the city of Konya, Turkey, for 2008–2017 were used. Parameters so used were first subjected to Factor Analysis (FA) and parameter reduction was made, and forecast models were created with the ABC algorithm, using parameters so derived. Lastly, ABC results were improved with the BS method. As a result of the study conducted, it was observed that the BS method improved ABC results by around 32%. Additionally, it has been observed that the BS method helps to understand the temporal dependence. It was seen that the most successful models were formed according to the 3-month change in percentages among the data.

The present study is thought to contribute to the knowledge in terms of being a successful application of the Band Similarity method, which is introduced for the first time, and the first application of the ABC method in water demand forecasting.

METHODS

Yazır district, chosen for the present study, lies within the province of Konya, Turkey, and its population is, as of the end of 2019, 63,773 persons. The relevant district has a dense settlement. For this study, 16 parameters for a period covering 120 months were used, which included 120 months' of 13 meteorological parameters pertaining to the period of 2008–2017 for the province of Konya (Maximum Actual Pressure, MaxAP; Maximum Relative Humidity, MaxRH; Maximum Temperature, MaxT; Maximum Precipitation, MaxP; Minimum Actual Pressure, MinAP; Minimum Relative Humidity, MinRH; Minimum Temperature, MinT; Average Actual Pressure, AvAP; Average Relative Humidity, AvRH; Average Wind Speed, AvWS; Average Temperature, AvT; Average Water Vapour Pressure, AvWVP; Total Precipitation, TP) and Per Capita Income (PCI) values as well as Monthly Demand (MD) and Population (P) values pertaining to Yazır district. Parameters so used and statistical information pertaining to such parameters are given in Table 1 below.

In the present study, first of all, in order to eliminate with little impact upon water consumption and simplify the study from a procedural point of view, FA was applied to the 16 parameters shown in Table 1. According to FA results, after

Table 1 | Statictical values of parameters

	MaxAP hPa	MaxRH %	MaxT °C	MaxP mm = kg ÷ m²	MinAP hPa	MinRH %	MinT °C	AvAP hPa	AvRH %	AvWS m ÷ sn	AvT °C	AvWVP hPa	TP mm = kg ÷ m²	P Person	PCI TL	MD m^3
Max	916.7	100.0	40.1	46.6	897.3	37.0	17.6	908.5	83.2	1.9	27.9	13.0	114.2	59,111	35,174.7	2,08,946.0
Ave	906.9	94.2	26.2	12.2	889.0	14.4	2.7	899.1	55.0	1.3	13.4	7.9	29.5	44,147	19,105.2	1,20,592.5
Min	899.6	62.0	8.4	0.0	875.4	1.0	−16.6	894.2	27.4	0.8	−2.6	3.8	0.0	21,980	9,946.3	44,144.0
Std. Dev.	4.0	8.8	8.3	10.1	4.2	7.5	9.0	2.7	15.4	0.3	8.5	2.3	25.8	10,835	7,179.5	44,471.7

identification of parameters with the highest impact upon water consumption, forecasting models giving the water consumption were created with the aid of the ABC optimization algorithm, using these parameters. Then, ABC testing results were improved using the BS method. Summarized information on the methods used is given below.

FA

FA is a statistical analysis type with multiple variables used in order to render complex information masses more comprehensible. Using the FA, parameters with high interaction are grouped in certain manners and the problem is freed from the additional transaction load caused by variables that have no or less impact upon the parameter that is desired to be analyzed. It may be possible to observe how data affect one another in a simpler manner. In other words, the factor analysis can be said to be a method of dimension reduction and destroying the structure of dependence (Harman 1976).

Prior to the start of the analysis, it is necessary to analyze whether data are suitable for FA with different tests. The Kaiser Meyer Olkin (KMO) coefficient and Bartlett Sphericity test are frequently used in connection with this topic. FA employs eigenvalues and eigenvectors in order to reveal the relationship structure between data whilst carrying out operations. At this stage, although different methods are used, eigenvalues and eigenvectors are derived with the aid of Principal Component Analysis to the greatest extent. Eigenvalues help identify number of factors capable of explaining the total data in a meaningful manner with the least possible information loss.

Once factors are identified, the factor structure matrix expressing the relationship of variables with factors plays a crucial role in identification of factors' characters, showing at which factor variables have a higher weight. In some cases, the relationship in the data set may not be expressed clearly, and an operation called factor rotation is carried out in order to derive more meaningful results in such cases. By using methods such as varimax, equamax or quartimax, it is possible to carry out the factor rotation operation.

As a result, it becomes possible to name or define factors, taking the identification of factors and characters of parameters grouped within factors as the starting point. Now, each factor is considered a new variable different from other factors with a character separate from other factors. Thus, the problem is freed from the additional operation load and clutter that may be caused by parameters pertaining to a factor other than the factor linked to the parameter desired to be analyzed.

In the present study, it is possible to easily determine to what extent 15 parameters apart from the water consumption affected the water consumption with the aid of FA. Thus, variables pertaining to factors with a weak relationship to water consumption are not used at the model creation phase.

ABC

Since, in recent years, Meta-Heuristic methods, modeling behaviors of living creatures in particular, have led to successful results in problems, different methods have been proposed in this subject matter. One of them is the ABC optimization algorithm. Inspired by the food search behavior of bees in nature, ABC was developed by Karaboga (2005) and it is implemented in numerous fields.

At this algorithm, first of all, places of starter food sources are identified. Scout bees randomly spread to the near vicinity and look for sources of food. This modeling corresponds to the random starting points generated when starting the solution. Random points between upper and lower limits of parameters at the search space are determined as the starting point of the solution, using Equation (1). Here, FN (FoodNumber) is the number of food sources and D (Dimension) is the number of parameters to be optimized. x_j^{min}, is the lower limit of the parameter j., whereas x_j^{max} is the upper limit of the parameter j.

$$x_{ij} = x_j^{min} + rand(0, 1)(x_j^{max} - x_j^{min})\mathrm{i} = 1 \ \ldots \mathrm{FN}, \mathrm{j} = 1 \ \ldots \mathrm{D} \tag{1}$$

After finding sources of food, for each source, fitness values are calculated, as shown in Equation (2), with Z being the objective function (Equations (6)–(8)). Here, f is the value derived with Z objective function pertaining to each source.

$$fitness_i = \left\{ \begin{array}{ll} 1/(1 + f_i) & f_i \geq 0 \\ 1 + abs(f_i) & f_i < 0 \end{array} \right\} \tag{2}$$

At this phase of the model, fitness values represent the quality of the nectar at the solution point. Behaviors demonstrated by real bees for choosing a source with abundant nectar of high quality were modeled with the aid of a fitness operator. The one with the highest quality of first solutions so generated is recorded to the common memory of the colony in this way.

Scout bees leaving the hive and randomly looking for food sources are now employed bees. At the employed bee phase, food sources with higher quality are searched by scout bees using Equation (3) adjacent to randomly determined food sources.

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{3}$$

Each source is shown with an x, by changing one parameter of this source, i.e. solution, source v_i adjacent to x_i is found. Equation (3) is a whole number randomly generated within the range of j, [1,D]. While changing the randomly selected j parameter, differences of parameter j. of the randomly changed x_k neighbor solution and parameter j. of the existing source are taken and such difference is added to the parameter j. of the existing source after weighting it with the number φ_{ij} which randomly takes a value within the range of [−1,1] (Akay 2009). Again, objective function results and fitness values pertaining to new solution points generated are calculated (Equation (2)). After the employed bee phase, as is the case with the end of every phase, if a better food source adjacent to former food sources is found, the new best food source is recorded in place of the former one. Otherwise, the trial counter is incremented by one. At this stage, the search for a better food source around the food sources found by bees is modeled. That is, efforts are made to improve solutions so generated.

At the onlooker bee phase, the next phase, probability values pertaining to each source are calculated with the aid of Equation (4) and a random number is generated within range of [0, 1] for each source. If the value p is bigger than such number generated, the onlooker bee generates a new solution at this source area, using Equation (3). The quality of the source is evaluated and, if better than the previous solution, it is memorized, if a solution better than the former solution has not been generated, the former solution is memorized and the trial counter is incremented by one. At this stage, transfer by bees of information on quality food sources to one another through dancing was modeled. Researches conducted center upon the source of the food with the highest quality at this phase.

$$p_i = \frac{fitness_i}{\sum_{i=1}^{FN} fitness_i} \tag{4}$$

The scout bee phase starts when the trial counter of any source exceeds a predefined limit value; in such a case, it is understood that the food pertaining to the relevant food source is used up. A new scout bee leaves the hive and starts looking for a new source with the aid of Equation (1). The limit value is mostly determined as FNxD. In the ABC algorithm, a certain iteration number or a cost value previously defined as a target may be used as an interruption criterion (Akay 2009).

Each source must have an attendant bee as per the assumption in the algorithm. The number of attendant bees and number of food sources are equal to one another. That is, half of the colony is composed of employed bees, and the other half is composed of onlooker bees. If the problem can be improved at each phase (employed bee, onlooker bee, scout bee phases), the new best solution found is recorded in the common memory of the colony in place of the previous one; if it cannot be improved, that is to say, if better food cannot be found, the trial counter that was 0 at the beginning is incremented by one, if the said counter exceeds the predefined limit value, it is understood that the nectar pertaining to the relevant source is used up and a new scout bee leaves the hive and starts a random search for a new food source. By proceeding as described, efforts are made to find the most suitable solution for the problem in the search space (Akay 2009).

With regards to water demand forecast problem in particular, the model desired to be generated may be established, for example, for a linear behavior, as seen in Equation (5). Depending on distribution of data, non-linear or exponential models may be created, too. At this stage, the user may manipulate the model in any way she/he pleases.

$$\hat{y} = a_1.x_1 + a_2.x_2 + a_3.x_3 + \ldots + a_t.x_t \tag{5}$$

Here, t, shows the number of independent variables required to be found at the model, $\hat{y}$ is the dependent variable and shows water consumption values derived from the model for the problem studied. In this respect, with y_i; being the water consumption values observed and $\hat{y}_i$ water consumption values generated as a result of model, Z objective function may be created in different forms as shown in Equations (6), (7) or (8) below. Where n is the number of data set used.

$$Z_1 = \mathrm{MSE}(y_i, \hat{y}_i) = \frac{1}{n} \cdot \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{6}$$

$$Z_2 = \mathrm{R}^2(y_i,\ \hat{y}_i) = \frac{\left[\sum (y_i\hat{y}_i) - \left(\sum y_i\right)\left(\sum \hat{y}_i\right)/n\right]^2}{\left(\sum y_i^2 - \frac{\left(\sum y_i\right)^2}{n}\right) \cdot \left(\frac{\sum \hat{y}_i{}^2 - \left(\sum \hat{y}_i\right)^2}{n}\right)} \tag{7}$$

$$Z_3 = \frac{MSE}{R^2}(y_i, \hat{y}_i) \tag{8}$$

where MSE refers to Mean Square Error; R^2 refers to correlation coefficient. When the objective function is chosen as Z_1 or $Z_{3,}$ the problem goes to minimization and, if Z_2 is chosen, it goes to maximization. The model, which determines the relationship between model results and real results in the best way according to the selected objective function, is determined by the analysis. That is, in a nutshell, coefficients a_1, a_2, a_3, ……, a_t in the equation, which are given in Equation (5) and expresses the best relationship among values of measurement are established.

BS

Optimization algorithms such as ABC include randomness due to their structure and, mostly, they cannot reach the same solution point when two solutions in succession are done. Although the stability of the results varies from method to method, in general, solutions differ from each other due to randomness. This randomness structure is used in BS method. As seen in Figure 1 below, assuming that, for one data set, 5 different models are created with the ABC algorithm at the training stage;

Of 5 different models so created, it is assumed that the most successful relationship has been built with Model1. Although Model1 is the most successful one, as seen in the Figure 1, at point A Model2, at point B Model4, at points C and D Model5 and Model3, respectively, generated results close to values locally observed. In line with data derived, what is normally

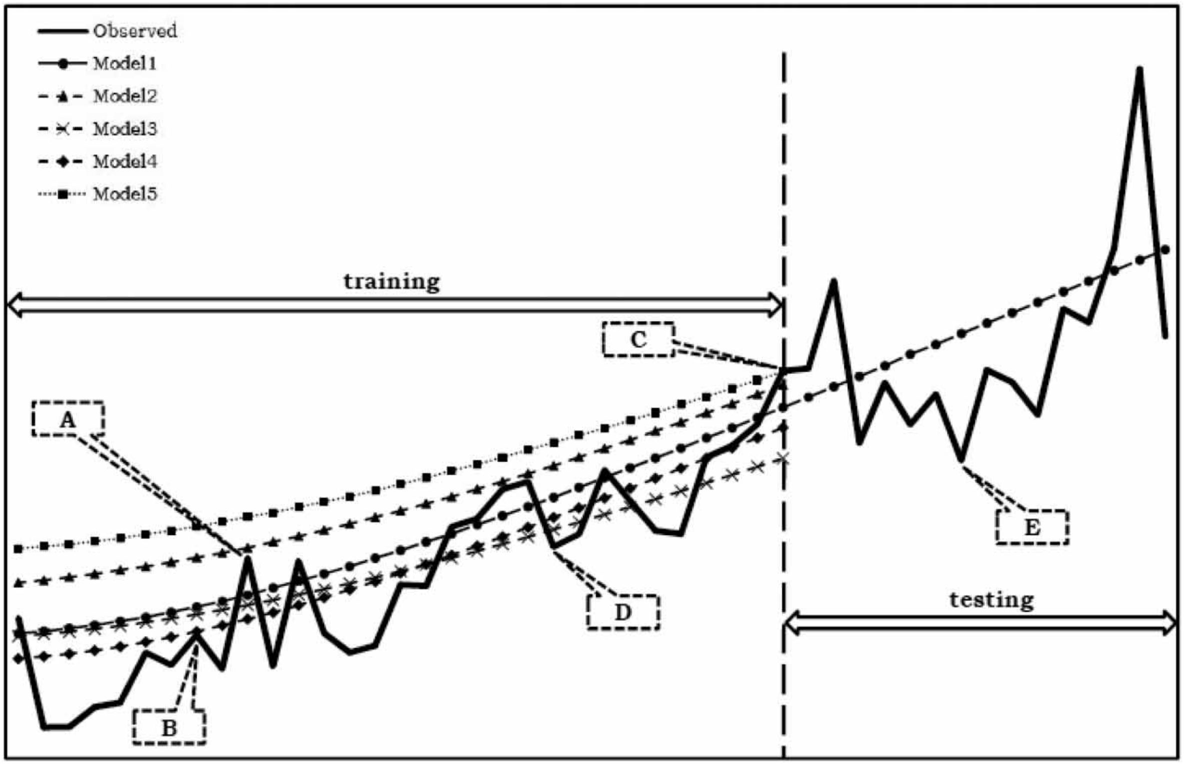

Figure 1 | Behavior of BS method.

required to be done is applying Model1 to all test individuals. At this stage, a correlation is built with the BS method which, for instance, reflects the character of the point E. If the character of point E is similar to that of any one of points A, B, C or D (or from among other training individuals), the model that is successful at the relevant point is used for point E. If no point similar to character of point E can be found, a solution will be generated using Model1, the best model for point E. BS method is completed by repeating the same operations for all test individuals in this way.

In order to ensure that such operations can be carried out, firstly, a Band Structure that will reflect the character of the test data of which the result is searched is created. $K_{i,j}$ values of Band Structure can be calculated, as seen in Equation (9).

$$K_{i,j} = f(x_{i,j}) i = 1, 2, 3, \dots p \quad j = 1, 2, 3, \dots t \tag{9}$$

Here, it is assumed that m pcs of p pcs data will be used for the training and n pcs data will be used for the test. $K_{i,j}$ values can be calculated as a function of x_t independent variables, given in Equation (5). Different patterns of behavior can be taken into consideration here. Six different simulation models used in the present study are shown below.

Simulation was established according to the ratio of standardized data in Equation (10); differences of data from values of r months ago in Equation (11); according to percentage of change in relation to the value of r months ago in Equation (12); according to rate of change based on values of r months ago in Equation (13); according to difference values of standardized data in Equation (14) and, finally, rate values of standardized data in Equation (15).

$$f(x_{i,j}) = \frac{s_{i,j}}{\sum_{j=1}^{t} s_{i,j}} s_{i,j} = \frac{x_{i,j} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{10}$$

$$f(x_{i,j}) = x_{i,j} - x_{i-r,j} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{11}$$

$$f(x_{i,j}) = \frac{x_{i,j} - x_{i-r,j}}{x_{i-r,j}} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{12}$$

$$f(x_{i,j}) = \frac{x_{i,j} - x_{i-r,j}}{r} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{13}$$

$$f(x_{i,j}) = s_{i,j} - s_{i-r,j} s_{i,j} = \frac{x_{i,j} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{14}$$

$$f(x_{i,j}) = \frac{s_{i,j} - s_{i-r,j}}{r} s_{i,j} = \frac{x_{i,j} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad i = 1, 2, 3, \dots p; \quad j = 1, 2, 3, \dots t \tag{15}$$

It will be ascertained if residual data are similar to one another based on $K_{i,j}$ values. The length of this Band Structure must be equal to the number of independent variables used in the model. The width of the Band Structure is expressed with a μ value set by the user. Limits of Band Structure can be calculated as shown in Equation (16). The value μ is chosen so that the best result is generated among μ^u and μ^l values from different μ values according to properties of the data.

$$V_{1,j} = K_{i,j} + \mu; \quad V_{2,j} = K_{i,j} - \mu \quad i = m+1, m+2, \dots, p; \quad j = 1, 2, \dots, t \tag{16}$$

Then, individuals entering the Band Structure searched within training data sets. If, within the training data set, any individual is able to enter the Band Structure of the relevant test structure, the model that is the most successful in the relevant training individual is used for the relevant test individual. If, within all training individuals, no individual is able to enter the Band Structure, the best model derived for the training data set is used for the relevant test individual. The BS method is completed by repeating the same operations for all test individuals. Figure 2 shows how the band similarity works.

RESULTS AND DISCUSSION

Firstly, FA was applied on 16 variables of the present study and parameters that affected the monthly domestic water consumption the most were ascertained. Then, forecasting models were generated with the aid of ABC optimization

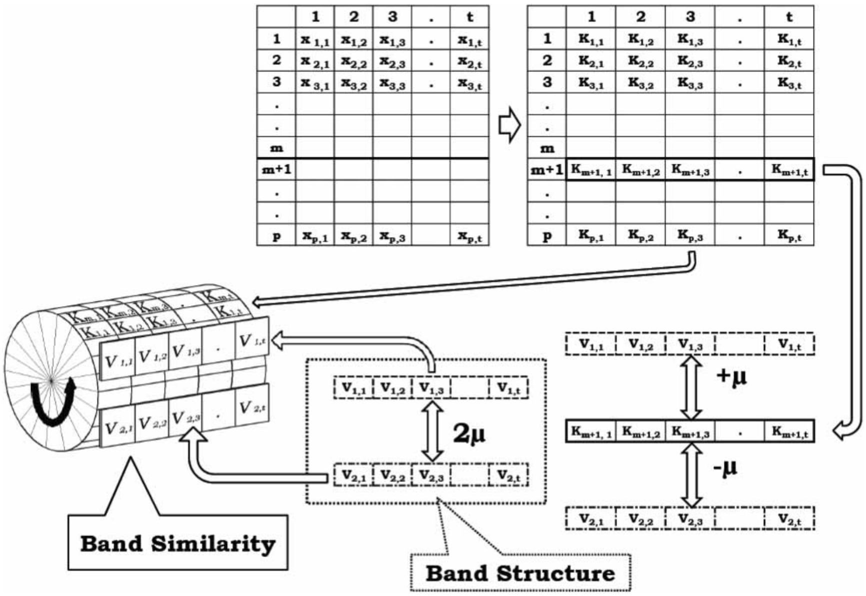

Figure 2 | Mechanism of BS method.

algorithm. At those models generated, of the data set of 120 months, the first 80 months were used for the training and the remaining 40 months were used for the test. Finally, test results derived from the ABC method were improved with BS analysis. Necessary information pertaining to studies conducted is given below for each and every method.

FA application

For the purpose of FA application, 16 parameters of statistical information which are given in Table 1 were used. No standardization was conducted on the data, and Principal Component Analysis was chosen for deriving eigenvalues. Prior to start of the analysis, it was analyzed whether data were suitable for FA with KMO coefficient (KMO $= 0.783$) and Bartlett Sphericity ($P = 0 < 0.05$) test, and it was found that the data were suitable. During the study, Factor Rotation was applied and factors were rotated with the quartimax method. As a result of FA application, it was seen that three factors account for 76.79% of the total data (Table 2).

In the subsequent stages of FA application, factor structure matrix rotated with quartimax method was derived, as seen in Table 3. Upon review of Table 3, it was seen that meteorological variables, predominantly, concentrated in Factor 1, variables including water consumption concentrated in Factor 2 and variables associated with precipitation concentrated in Factor 3. Factors account for 43.7%, 18.8% and 14.2% of the total information, respectively (Table 2).

As seen in Table 3, five variables in total, which include the water consumption (AvAP, MD, PCI, P, MinAP), aggregated in Factor 2. In this respect, it is understood that the water consumption in the relevant area predominantly interacts with variables AvAP, PCI, P and MinAP. Thus, it was decided to use these variables when creating forecasting models in ABC application. Forecasting models were created in three different forms and in line with Equation (5) and are shown in Equations (17)–(19) (Table 4).

$$\widehat{y_A} = a_{A1}.P + a_{A2}.PCI \tag{17}$$

$$\widehat{y_B} = a_{B1}.MinAP + a_{B2}.P + a_{B3}.PCI \tag{18}$$

$$\widehat{y_C} = a_{C1}.AvAP + a_{C2}.MinAP + a_{C3}.P + a_{C4}.PCI \tag{19}$$

ABC application

At this stage of the study, three linear models seen in Table 4 were trained with the ABC method. MSE minimization was materialized for all of the three models with the objective function Z_1 given in Equation (6). No standardization was carried out on data. Models A, B and C were analyzed as 2-, 3- and 4-dimensions, respectively. The number of bees or FN value were determined as four

Table 2 | Eigenvalues and cumulative variance description shares

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.261	45.383	45.383	7.261	45.383	45.383	6.994	43.715	43.715
2	3.008	18.800	64.183	3.008	18.800	64.183	3.014	18.838	62.553
3	2.017	12.607	76.790	2.017	12.607	76.790	2.278	14.236	76.790
4	1.412	8.822	85.612						
5	0.614	3.840	89.451						
6	0.475	2.966	92.417						
7	0.389	2.433	94.850						
8	0.290	1.810	96.660						
9	0.164	1.024	97.684						
10	0.119	0.742	98.427						
11	0.084	0.528	98.955						
12	0.076	0.474	99.429						
13	0.038	0.239	99.668						
14	0.030	0.184	99.852						
15	0.020	0.124	99.977						
16	0.004	0.023	100.000						

Table 3 | The values for transformed factors

	Component		
	1	2	3
AvT	0.966	*	*
MaxT	0.953	*	*
MinT	0.942	*	*
MaxAP	−0.913	*	*
AvRH	−0.873	*	0.353
AvWVP	0.832	*	*
MinRH	−0.720	*	*
AvAP	−0.715	0.271	−0.251
AvWS	0.684	*	*
MaxRH	−0.568	*	0.493
MD	*	0.970	*
PCI	*	0.951	*
P	*	0.905	*
MinAP	*	0.384	−0.288
TP	−0.263	*	0.899
MaxP	*	*	0.897

*values less than 0.25.

times the problem dimension for Models A, B and C, as 8, 12 and 16. Limit values shown in Equation (1) (x_j^{min} and x_j^{max}) were assumed as +5 and −5. The limit value used in production of the scout bee was established for Models A, B and C as FNxD as 16, 36 and 64, respectively, and 10 solutions per model were made. The iteration number was assumed as 500 for each solution.

Table 4 | Water demand forecasting models for study area

Model	Input parameters	Output parameter
A	P, PCI	MD
B	MinAP, P, PCI	MD
C	AvAP, MinAP, P, PCI	MD

Parameter coefficients pertaining to the most successful solutions derived for each and every model and R^2 values are given in Table 5 below. Graphs of the most successful solutions for each of the three models are shown in Figure 3. The convergence graphs showing how MSE values pertaining to the most successful solutions for each one of the three models decline along the iterations are given in Figure 4.

When models given in Table 5 are examined, per capita income seems to be the parameter that had the greatest impact upon water consumption for the relevant area. The population is the second most effective parameter after the per capita income. To conclude, it was seen that socio-economic variables of the relevant region had a greater impact upon the water consumption than the climatic variables. Of the climatic variables, the air pressure seems to be the most effective parameter.

BS application

For the ABC application, ten linear equations were generated for Models A, B and C, and values pertaining to the most successful equation for each model are shown in Table 5. For the BS application, first of all, simulation models were used in 6 different forms, as shown in Equations (10)–(15), in order to be able to calculate K_{ij} values used in determination of the character of data.

With 6 different simulation methods used, the highest Test R^2 values derived for Models A, B and C are shown as $R^2_{BS\_A}$, $R^2_{BS\_B}$ and $R^2_{BS\_C}$, respectively, in Table 6. For μ values associated with band width used in deriving these values, upper and lower limits were shown as μ^1 and μ^u, μ values whereby the highest Test R^2 values were derived are shown in Table 6 as μ_{BS_A}, μ_{BS_B} and μ_{BS_C}.

Upon examining Table 6, it is seen that the highest Test R^2 values were derived with Equation (12) from among three models. Here, a simulation is established according to percentage of change of each piece of data in relation to what they were like r months ago. The highest relation was derived within each of the three models with the change percentage of 3 months. Test R^2 values derived for Model A, B and C with pure ABC application were 0.620, 0.622 and 0.614, respectively, whereas Test R^2 values were derived, for Models A, B and C, as 0.823, 0.822 and 0.824, respectively as a result of BS analysis created with the change percentage of 3 months.

At this stage, BS analysis produced beneficial results in terms of ability to observe the temporal relation between data. In the solution where the highest R^2 values were derived, the fact that a simulation model of 3 months was used makes one think that seasonality may be effective among data. As a result, as seen in Table 7, it is observed that the BS method improves test results derived from Pure ABC method by around 32%. On the other hand, as seen in Table 6, it may be seen that BS method improved results in most of the analyses if other equations were used, too. Figure 5 shows, as a graph, relations derived with ABC method for each of the three models and how the BS analysis improved results.

CONCLUSIONS

In the present study, it was understood that parameters such as per capita income and population for the relevant region were the two variables that had the highest impact upon the water consumption, and the air pressure from among climatic variables

Table 5 | Best results belong to ABC applications over models

Models	Coefficients	Training R^2	Testing R^2
A	$\widehat{y_A} = y_A^{best} = 0.832xP + 4.368xPCI$	0.914	0.620
B	$\widehat{y_B} = y_B^{best} = -2.506xMinAP + 0.875xP + 4.337xPCI$	0.913	0.622
C	$\widehat{y_C} = y_C^{best} = -3.444xAvAP - 2.938xMinAP + 0.742xP + 4.992xPCI$	0.914	0.614

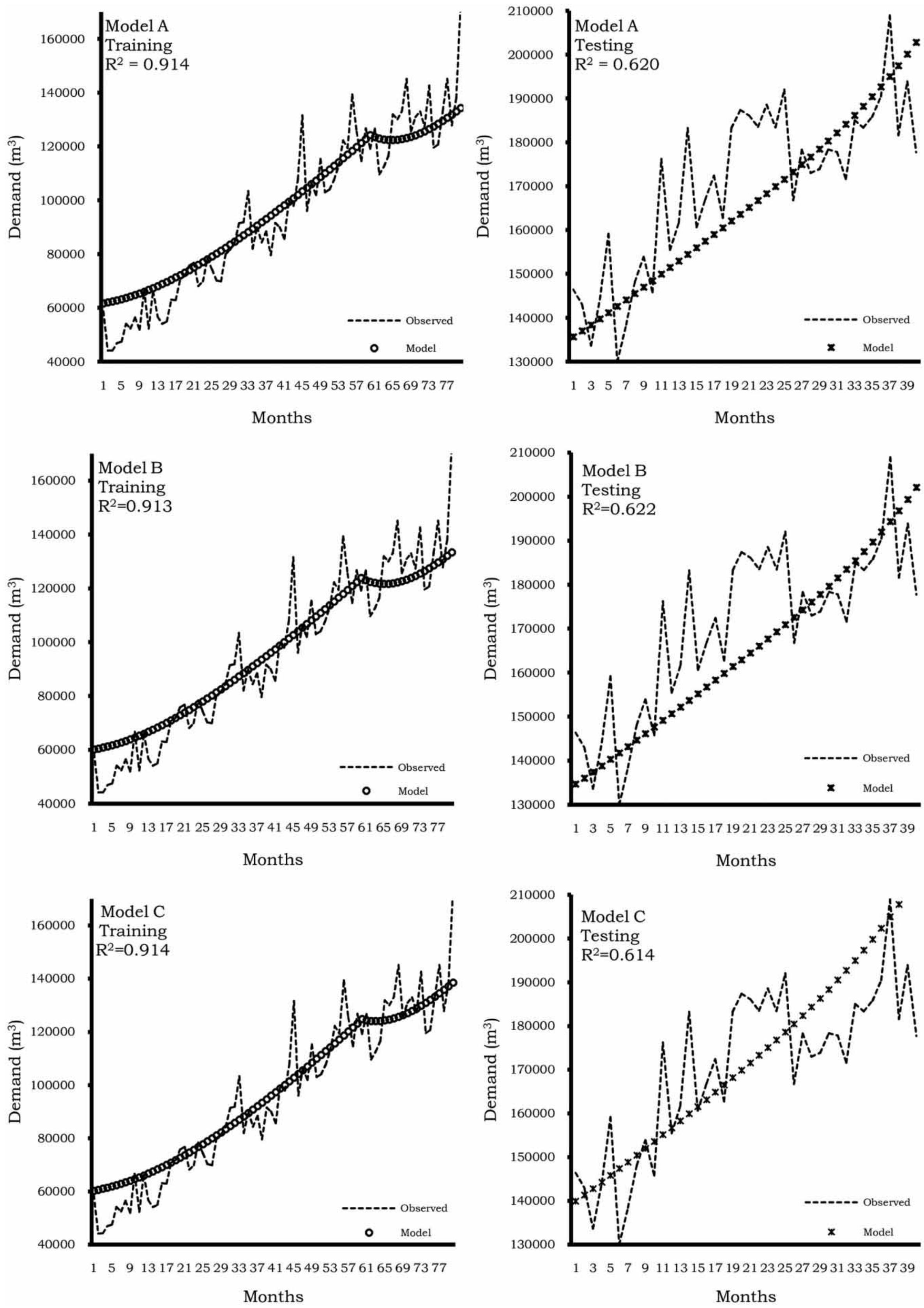

Figure 3 | Best solutions for ABC application.

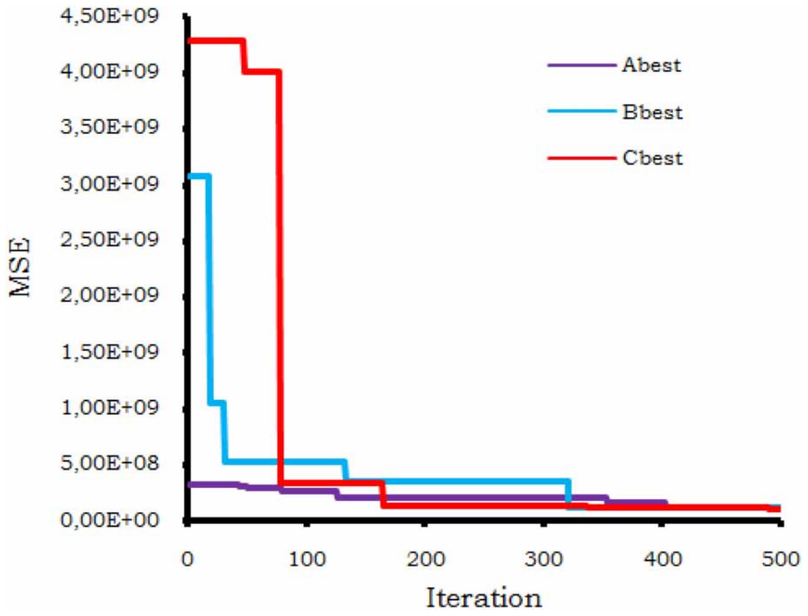

Figure 4 | Convergence graph of best solutions for ABC application.

Table 6 | Testing R^2 and μ values of BS analysis for Model A, B and C

Equation (10) $\mu^l = 0$ $\mu^u = 20$												
$R^2_{BS\_A}$	0.691											
μ_{BS_A}	20											
$R^2_{BS\_B}$	0.662											
μ_{BS_B}	0.6											
$R^2_{BS\_C}$	0.656											
μ_{BS_C}	20											
Equation (11) $\mu^l = 0$ $\mu^u = 500$												
r	**r = 1**	**r = 2**	**r = 3**	**r = 4**	**r = 5**	**r = 6**	**r = 7**	**r = 8**	**r = 9**	**r = 10**	**r = 11**	**r = 12**
$R^2_{BS\_A}$	0.758	0.702	0.676	0.688	0.675	0.623	0.622	0.620	0.620	0.620	0.623	0.625
μ_{BS_A}	170	370	265	455	460	475	435	55	75	150	265	235
$R^2_{BS\_B}$	0.725	0.703	0.707	0.671	0.643	0.635	0.633	0.635	0.622	0.627	0.624	0.634
μ_{BS_B}	175	370	450	380	450	305	280	390	75	435	265	235
$R^2_{BS\_C}$	0.710	0.692	0.681	0.668	0.635	0.630	0.625	0.617	0.636	0.617	0.630	0.678
μ_{BS_C}	170	370	220	310	445	385	470	290	370	305	500	500
Equation (12) $\mu^l = 0$ $\mu^u = 5$												
r	**r = 1**	**r = 2**	**r = 3**	**r = 4**	**r = 5**	**r = 6**	**r = 7**	**r = 8**	**r = 9**	**r = 10**	**r = 11**	**r = 12**
$R^2_{BS\_A}$	0.807	0.807	**0.823**	0.777	0.666	0.640	0.620	0.620	0.627	0.639	0.643	0.662
μ_{BS_A}	1.15	2.3	3.45	4.55	0.5	1.6	0.3	0.7	2.55	2.7	3.05	3.35
$R^2_{BS\_B}$	0.760	0.807	**0.822**	0.777	0.654	0.664	0.626	0.644	0.625	0.623	0.640	0.679
μ_{BS_B}	1.15	2.3	3.45	4.55	1.5	1.65	2.3	2.65	2.55	2.7	2.8	3.35
$R^2_{BS\_C}$	0.762	0.808	**0.824**	0.779	0.700	0.701	0.693	0.672	0.732	0.657	0.645	0.658
μ_{BS_C}	1.15	2.3	3.45	4.55	2	2.9	3.35	3.9	5	4.7	3.4	4.45

(*Continued.*)

Table 6 | Continued

Equation (13) $\mu^l = 0$ $\mu^u = 100$

r	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6	r = 7	r = 8	r = 9	r = 10	r = 11	r = 12
$R^2_{BS\_A}$	0.665	0.671	0.666	0.670	0.675	0.635	0.622	0.622	0.620	0.620	0.623	0.625
μ_{BS_A}	98	80	89	82	92	87	95	6	8	15	24	19
$R^2_{BS\_B}$	0.670	0.680	0.666	0.671	0.643	0.635	0.633	0.637	0.622	0.628	0.626	0.634
μ_{BS_B}	71	81	84	95	90	51	40	48	8	54	76	19
$R^2_{BS\_C}$	0.644	0.645	0.639	0.624	0.614	0.614	0.614	0.616	0.630	0.617	0.629	0.677
μ_{BS_C}	34	44	57	28	28	30	21	35	39	30	43	51

Equation (14) $\mu^l = 0$ $\mu^u = 10$

r	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6	r = 7	r = 8	r = 9	r = 10	r = 11	r = 12
$R^2_{BS\_A}$	0.698	0.671	0.667	0.633	0.628	0.625	0.623	0.620	0.620	0.620	0.623	0.625
μ_{BS_A}	4.6	3.1	8.2	9.6	9.2	6.7	7.9	2.1	2.7	4	7.2	6.4
$R^2_{BS\_B}$	0.622	0.669	0.622	0.622	0.623	0.622	0.622	0.622	0.622	0.622	0.622	0.622
μ_{BS_B}	1.3	10	7	9.1	10	10	7.4	9.1	10	10	10	10
$R^2_{BS\_C}$	0.614	0.631	0.614	0.614	0.614	0.614	0.614	0.614	0.614	0.614	0.614	0.614
μ_{BS_C}	8.7	10	10	10	10	10	10	10	10	10	10	10

Equation (15) $\mu^l = 0$ $\mu^u = 10$

r	r = 1	r = 2	r = 3	r = 4	r = 5	r = 6	r = 7	r = 8	r = 9	r = 10	r = 11	r = 12
$R^2_{BS\_A}$	0.698	0.698	0.700	0.683	0.674	0.667	0.661	0.656	0.632	0.634	0.623	0.625
μ_{BS_A}	4.6	6.3	6.3	3.5	6.2	6.2	6.2	6.2	6.4	7	0.6	0.5
$R^2_{BS\_B}$	0.622	0.669	0.622	0.683	0.646	0.640	0.649	0.622	0.625	0.631	0.632	0.624
μ_{BS_B}	1.3	5.5	2.3	4.3	2.3	3.1	3.9	1.1	2.9	1.3	1.4	1.7
$R^2_{BS\_C}$	0.614	0.644	0.614	0.617	0.614	0.614	0.644	0.614	0.630	0.614	0.661	0.661
μ_{BS_C}	8.7	7.4	6.7	7.1	4.1	3.4	5.8	3.3	6	1.9	4.6	4.6

Table 7 | Performance of BS analysis for models

	Pure ABC		BS Analysis	
Model	**Training R2**	**Testing R2**	**Testing R2**	**Improvement**
A	0.914	0.620	0.823	%32.7
B	0.913	0.622	0.822	%32.1
C	0.914	0.614	0.824	%34.2

had a greater impact upon the water consumption in comparison to the other variables. Findings derived were evaluated particularly for the study area, and do not include a general statement, because temporal and position-wise difference can be seen in variables that have an impact upon the water consumption. The important portion of the relevant study is the fact that ABC optimization algorithm was used in the water consumption forecast and results derived with BS analysis were improved.

Advantages of using ABC optimization algorithm, basically, include ease of use and ability to adjust the objective function in any manner. The objective function may be expressed with relations such as linear, non-linear or exponential, and so on, depending on the distribution of data. Besides, undesired solutions likely to arise during operations may be easily eliminated with the aid of a penalty cost to be added to the objective function. Other optimization algorithms such as ABC are able to promise successful solutions in that processes can be easily manipulated at the solution phase in particular.

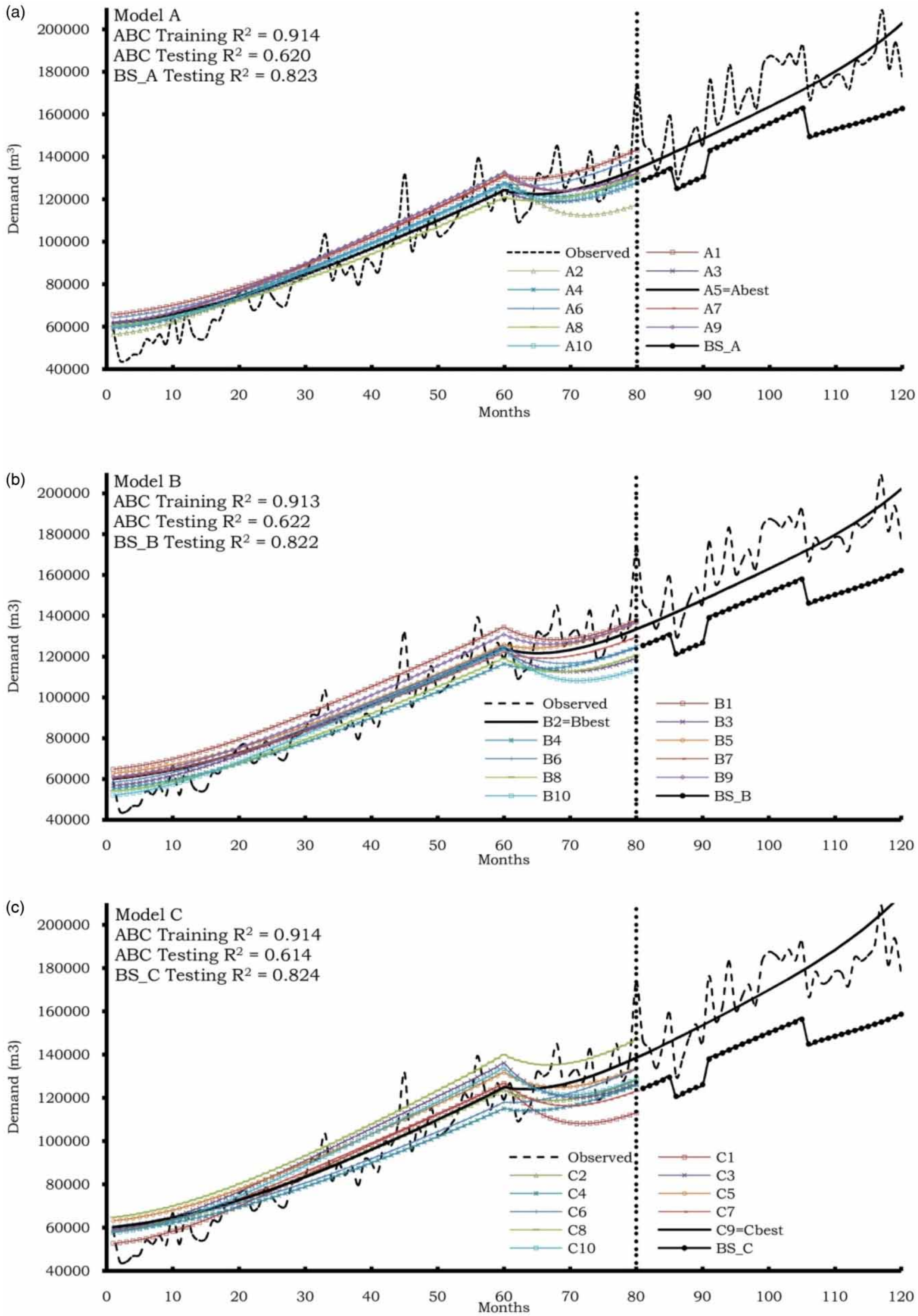

Figure 5 | Relationships belong to ABC and BS analysis for Model A (a), Model B (b) and Model C (c).

One of the criteria in evaluation of ABC and other optimization algorithms is stability of methods. Although the ABC method exhibits a stable structure in general, there may be differences in solutions due to its intrinsic randomness. The BS analysis makes use of that difference structure. In the present study, it was observed that results were improved to a great extent with BS analysis based on the principle of using the model that is successful for a set of training data similar to the character of any test data. On the other hand, it was seen that the BS analysis is a method that can be used for revealing the temporal relationships between data. Taking the aforesaid reasons as the starting point, the ABC optimization algorithm used in conjunction with the BS method is thought to be an alternative model to other models when it comes to model production and forecasting. Application of the BS method with different optimization algorithms may be submitted to researchers conducting studies in this subject matter as a proposal.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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