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Water Demand Prediction for Touristic Mecca City in Saudi Arabia using Neural Networks

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***Abstract*—**Saudi Arabia is an arid country which depends on costly desalination plants to satisfy the growing residential water demand. Prediction of water demand is usually a challenging task because the forecast model should consider variations in economic progress, climate conditions and population growth. The task is further complicated knowing that Mecca city is visited regularly by large numbers during specific months in the year due to religious occasions. In this paper, a neural networks model is proposed to handle the prediction of the monthly and yearly water demand for Mecca city, Saudi Arabia. The proposed model will be developed based on historic records of water production and estimated visitors' distribution. The driving variables for the model include annually-varying variables such as household income, household density, and city population, and monthly-varying variables such as expected number of visitors each month and maximum monthly temperature.

***Keywords*—**Water demand forecast; Neural Networks model; water resources management; Saudi Arabia.

I. Introduction

PROPER planning and management of water resources requires good estimates of the water future demands. The projections of urban water consumption are essential for scheduling future requirements of water supply, distribution and wastewater systems. In this regard, short-term forecasting is useful for operation and management of existing water supply systems within a specific time period, whereas long-term forecasting is important for system planning, design, and asset management [1,2]. The forecast of water demand becomes necessary in regions where natural water resources are limited. The county of Saudi Arabia, for instance, is an arid country characterized by a scarcity of its water resources. The country has no perennial rivers or lakes, and its renewable water resources total 95 cubic meters per capita, well below the 1,000 cubic meters per capita benchmark commonly used to denote water scarcity. The growing population of the nation forced the kingdom to rely on desalination plants to satisfy around half of the water demand. Building desalination plants is, however, a costly and time consuming process. Authorities and policy makers are interested in having a reliable estimate of the long term water demand in order to implement the appropriate investments in the development plans and to avoid any shortage in the domestic water supply. Similarly, short-term (monthly) water demand prediction is equivalently important for municipal authorities to optimize the water production based on rigorous analysis of the effect of visitors on the total water consumption.

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There are several factors known as drivers or explanatory variables affect the water demand forecast. These include socioeconomic parameters (population, population density, housing density, income, employment, water tariff, etc), weather data (temperature, precipitation, etc), as well as cultural factors such as consumer preferences and habits. Different methods for water demand forecast are proposed in the literature. The available data for water production and consumption plays an important role in the selection of the forecast methodology. The common methodologies for the forecast include end-use forecasting, econometric forecasting and time series forecasting [2,3]. End use prediction depends on the prediction of uses for water, which requires a considerable amount of data and assumptions. The econometric approach uses statistics to build a historical relationships between the independent explanatory variables and water consumption, assuming that these relationships will persist into the future. Time series approach, on other hand, forecasts water consumption directly without having to predict other factors on which water consumption depends [3,4].

The econometric approach is usually used for long term predictions because it depends largely on variables that change on a yearly basis or at least can not be estimated on monthly basis. However, for a city like Mecca, it is important to have a model capable for monthly forecast to account for the monthly varying number of visitors within one year.

In this paper, a neural networks model will be developed. The model will be based on annually-changing data such as city population, housing density, and personal income, and monthly-varying data such as average monthly temperature and number of visitors. Neural networks are well known tools for pattern recognition and trend detection. Usually NNs can be used for data regression with high nonlinearity [5]. ANN has been used for water demand forecast by Liu et al [6]. However, their model was used only for annual water demand predictions. Further theoretical background on the field of artificial neural networks can be found elsewhere [7].

The proposed NN model has the capability for long term (annual) and short term (monthly) water demand prediction for the city of Mecca. Neural networks model is chosen because its structure allows using inputs with mixed time scales.

II. Econometric Water Demand Model

The common functional population model for estimating the total water use is adopted here [8]:

$$Q_y = Nq \tag{1}$$

Q_y is the total annual water use, N the population number and q is the water use per capita. The water use (q) is assumed to depend on a number of explanatory variables. For example q can be defined as follows:

$$q = f(I, H, T, V) \tag{2}$$

where I denotes the annul income, H the household size, T the monthly average temperature and V the number of city visitors. Of course, (2) may include other variables if necessary. Another drawback is that the model does not allow using inconsistent time-scale variables. For example, N, I and H vary annually while T and V changes monthly. In this case, implementation of (1) and (2) is somewhat ad hoc. In this paper, a Neural Networks model is proposed to develop a black box model for water production in the form of:

$$Q = f(N, I, H, T, V) \tag{3}$$

that can handle mixed time0scale variables directly.

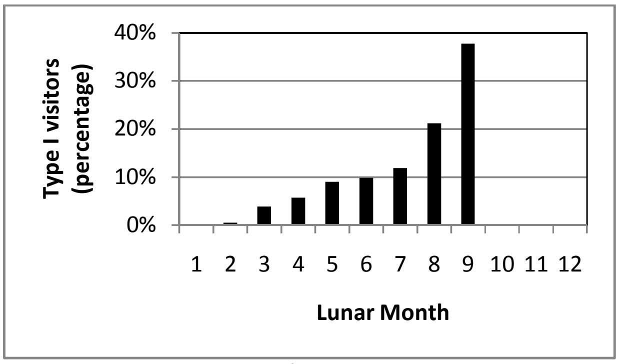

Fig. 1 Distribution of type I visitors by month

III. Estimates Of The City Visitors And Monthly Temperature

There are basically two types of visitors, here forth called type I and type II. The distinction between these visitors is important for the estimation of their number. Briefly, type I visitors can come to the city during any month of the year except the 10^{th} to 12^{th} months to perform one type of religious ritual (called *Umbra*). This ritual reaches its climax on the 9^{th} month of the lunar calendar and the number of visitors reaches a peak during this month. Another peak is reached during the 12^{th} month where type II visitors come to perform another religious ritual (called *Haj*). The population number can increase in this month to reach around three times the original local population. The distinction between the visitors is important since while there is a cap (through visa restrictions) on the number of type II visitors, while there no limit on the number of type I visitors. Fig. 1 shows a typical monthly distribution of the number of type I visitors (CDSI, [9]). The total number of type I visitors has reached 3 millions in 2010 but is expected to increase by 3% according to the predictions of the planning authorities. Setting the target for the Umrah visitors to 3 millions and using the expected distribution in Fig.1, a rough estimate of average monthly number of this type of visitors can be obtained.

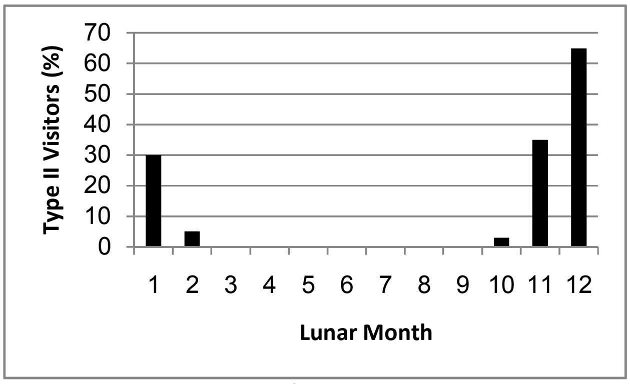

Fig. 2 Distribution of type II visitors by month

Regarding type II visitors, their total number is fixed at 2.5 millions per year, by assigning a fixed quota to each country. This type of visitors starts coming to the city in the beginning of 10^{th} month, perform the ritual in the second week of the 12^{th} month and leave the country within two months. However, the rates of visitor's accumulation and departure are largely uncertain. Local visitors from inside the country, who make up one third of the visitors, come usually one day before the ritual and leave few days after, while the rest of visitors from outside the country may stay longer. For these reasons, a rough distribution for this type of visitors was also assumed (CDSI, [9]). For months 3 through 9, the number of visitors is almost zero with very minor variations to allow for left over visitors from the previous year. For months 10 to 12, the mean values were taken to be 3%, 35% and 65% of the target value of 2.5 millions. According to historical records, most of type II visitors depart within two months following the event month. Therefore, the mean value for month 1 and 2 were taken to be 30% and 5% of the target value, respectively. Fig 2 Shows a typical distribution of type II visitors. Fig. 3 shows the estimate of the average number of total visitors (Type I and Type II) in each month of the year.

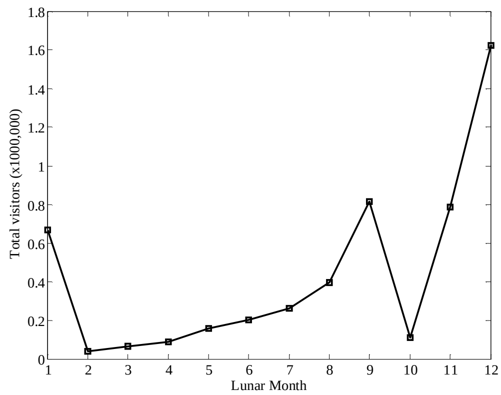

Fig. 3 Distribution of total visitors by month

Maximum monthly temperature records are available according to the Gregorian calendar. The average monthly temperature for Mecca city as function of the solar months is shown by the solid line in Fig. 4. This monthly temperature trend will remain almost the same for any Gregorian year because Gregorian calendar is related to the solar system which controls the four seasons of the year. This is not the case for the lunar month because it is related to the moon phases. Therefore, the lunar month does not match exactly the solar month and this mismatch changes every consecutive year. Consequently, the average monthly temperature is not consistent for the lunar calendar. However, water demand prediction has to be according to lunar months because of the two specific occasions that occur at 9th and 12th months of the lunar calendar. In this case, the average monthly temperature for the lunar month will be interpolated from the given temperature profile for the solar months using well known correlation between the lunar and solar calendar. Fig. 4 illustrates the lunar monthly temperature determined by interpolation for past four years that correspond to the historical training data to be used for developing the NN models.

TABLE I
GROWTH RATE VALUES

Growth rate for socioeconomic variables	
R_I	0.022
R_H	0.0238
R_N	0.021

IV. NEURAL NETWORKS MODEL

Neural network (NN) is a useful tool that uses an experimental data to produce a mathematical relationship between input variable and output variable. Neural network field is well established and has several applications other than data fitting. A typical neural network topology also known as multilayer perceptron (MLP) is shown in Fig. 5. The activation function, $f(\bullet)$ is used in the hidden layer in the form of sigmoid function:

$$f(x) = \text{logisitc}(x) = \frac{1}{1+\exp(-x)} \tag{4}$$

The last layer in Fig. 5 is the output layer which contains a number of output neurons each of which is a weighted linear combination of the hidden layer neurons. Therefore, a specific output can then be written mathematically as:

$$y = \sum_{i=1}^{m} q_i f\left(\sum_{j=1}^{p} w_{ij} u_j + w_{i0}\right) + w \tag{5}$$

Common MLP structure contains several unknown parameters such the input weights w_{ij}, the perceptron weights q_i and bias w_k. The MLP parameters are the unknown model parameters that can be estimated by solving the following optimization problem:

$$\min_{\theta} \sum_{k=1}^{N} e_k^2 = \sum_{k=1}^{N} (y_k - \tilde{y}_k)^2 \tag{6}$$

TABLE II
BASE VALUE FOR SOCIOECONOMIC VARIABLES

Variable	*Value at 2004*
City population	1,277,744
Household size	5.22
Income (SR)	42,300

where θ denotes the entire space of MLP parameters, y is the MLP output, $\tilde{y}$ is the output measurement (water demand in this case) and N is the number of observations. The solution of the above cost function is carried out by numerical techniques using MATLAB software.

The specific NN structure for water demand prediction is depicted in Fig. 6. In this case 27 input variables are used. One hidden layer with 15 neurons is employed. Three hidden neurons combine the effect of the socioeconomic inputs such as the population, household density, and household income. The other 12 neurons are interconnected to the number of visitors and maximum temperature for the twelve months of the year. All hidden layer neurons are connected to all output neurons collectively. The output layer consists of 12 output neurons which represent the water demand for each month of the lunar calendar.

A primary step before start fitting the data is to use proper scaling of the input and output variables. This was performed by the following scaling rule:

$$x = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

The proposed NN structure is trained with the water production data for the years 2003 to 2006. When developing the model, the monthly interpolated temperature shown in Fig. 4 and number of visitors shown in Fig. 3 are used over the four year span of the training horizon. The other variables such population count (N), household density (H), and household income (I) changes every year according to the growth formula given below:

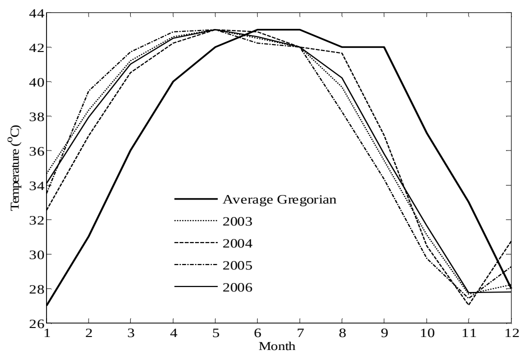

Fig. 4 Maximum monthly temperature distribution

$$N_{y_2} = N_{y_1} e^{R_N n} \tag{8}$$

$$H_{y_2} = H_{y_1}(1 + R_H n) \tag{9}$$

$$I_{y_2} = I_{y_1}(1 + R_I n) \tag{10}$$

The growth rate for each variable (R_N, R_H, R_I) is given in Table 1. The term n is the difference between the prediction year (y_2) and the base year (y_1). The base value of these variables is taken at the base year 2003 and is listed in Table 2. The prediction of the NN model is shown in Fig. 7 which presents excellent agreement with the training data. There is minor mismatch particularly for the months 2 to 8 in each year. The training data itself contains unpredictable behaviour of the water production. This behaviour may be attributed to the irregular variation on the number of Type I visitors during these months of the year. The NN model showed remarkable capability for capturing the climax periods and interim fluctuation The NN model is further validated with the 2009 and 2010 water production data as illustrated in Fig. 8. In this case, the same visitors' trend estimated before is used. The lunar temperature trend for 2009 and 2010 is calculated by interpolation as mentioned earlier. The other variables are calibrated according to equations 5 to 7. It can be seen that the NN model predictions in good agreement with the validation data, but it could not track the validation data adequately. In fact, the water consumption record in these years does not follow the same pattern of the previous years. In 2009, the water consumption during months 1 to 8 remained almost constant with a minor increase at month 9. This can be attributed to the lingering number of visitors due to the fear of swine flu epidemic. On the other hand, the water consumption jumped in the 6th month for the year 2010. The rationale behind this incident is not clear.

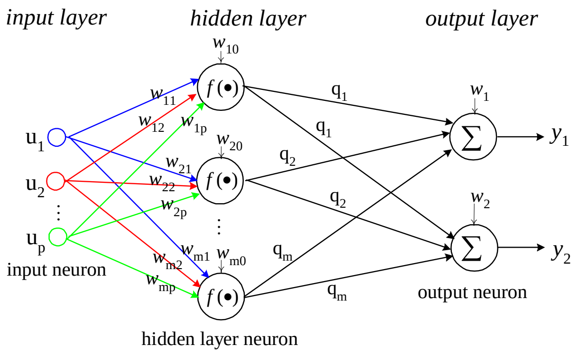

Fig. 5 Schematic of neural network

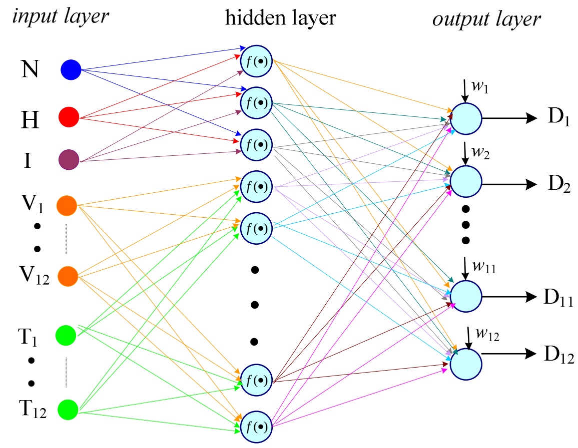

Fig. 6 Neural Network structure for Water Demand Prediction

V. Concluding Remarks

In this paper a model capable for providing short-term and long-term forecast of water demand for the city of Mecca in Saudi Arabia is developed. The model addresses the challenge imposed by the irregular visitor flux to the city during each year. The investigation of the historical data indicated peaks for water use that occur at specific months of the lunar calendar. The peaks match tow specific religious occasions. The data also demonstrated steady annual increment in the water demand. For this purpose, a neural networks model is developed for the forecast of monthly and annual water demand in the city. The neural network model found to be useful in the sense of resembling the transient water consumption both in the short and long terms. A well trained NN model can be a useful tool in the hand of decision makers to analyze the effect of input perturbation on future forecast of the water demand. This may help in operating the urban water systems optimally. However, the realistic water data contains abnormalities due to leaks in the system, changing policies and/or social habits. These irregularities cannot be captured by deterministic variables.

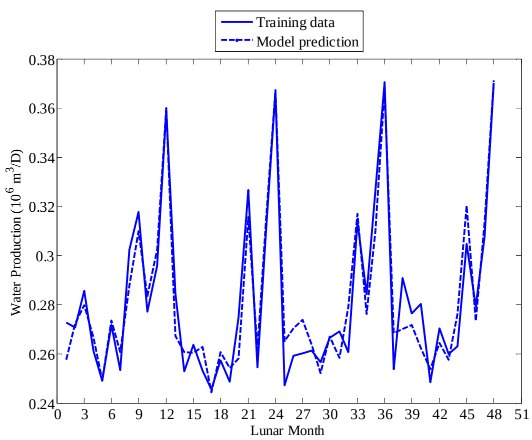

Fig. 7 Neural model training result

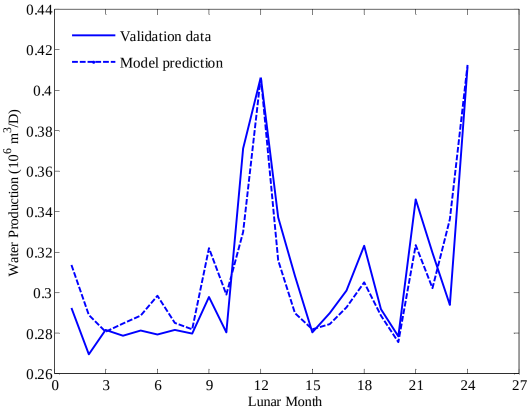

Fig. 8 Neural Networks model validation using 2009 and 2010 data

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