Single Input Single Output Time Series Artificial Neural Network Models for Free Residual Chlorine Forecasting in Water Distribution Networks

Selcuk Soyupak[1], Hurevren Kilic[2], Ibrahim Ethem Karadirek[3] and Habib Muhammetoglu[3]
[1]*Civil Engineering Dept., KTO Karatay University, Akabe Mah. Alaaddin Kap Cad. No:130, 42020, Karatay, Konya, Turkey*
[2]*Department of Computer Engineering, Gediz University, Seyrek Kampusu, 35665, Menemen, Izmir, Turkey*
[3]*Environmental Engineering Department, Akdeniz University, Dumlupinar Bulvari, 07058, Kampus, Antalya, Turkey*

Keywords: Single Input Single Output Artificial Neural Networks, Time Series, Water Distribution Networks.

Abstract: The aim of this study is to investigate the utilization of Single Input Single Output Time Series Artificial Neural Networks models as a forecasting tool for estimating Free Residual Chlorine levels at critical locations of fairly complex Water Distribution Systems. The response surface methodology was adopted in identifying performance and precision trends as a function of number of steps used as inputs and number of steps ahead to predict (Horizons). The utilized response surfaces were for coefficient of determination and mean absolute error. The creation of response surfaces was achieved by developing Artificial Neural Network models for several combinations of number of steps used as inputs and number of steps ahead to predict that enable the calculations of coefficient of determination and mean absolute error for the selected combinations. Then these results have been assembled to obtain contour maps by distance weighted least square technique. The maximum attained coefficient of determination levels were within the range 0.656 to 0.974, while minimum achievable mean absolute error levels were within the range 0.0080 to 0.0284 ppm. The achieved mean absolute error is very low when compared with the followings: a) the applied Free Residual Chlorine levels from the source which is about 0.5 ppm and b) the minimum detection limit of the chlorine analyzers given as 0.01 ppm.

1 INTRODUCTION

Data driven artificial intelligence techniques provide alternative solutions to deterministic approaches for controlling and providing acceptable levels of Free Residual Chlorine (FRC) levels in Water Distribution Systems (WDSs). The reason for shifting to data driven approaches from deterministic approaches lies in the following facts: i) decay kinetics of chlorine within water is nonlinear and it is very complex to formulate while it is being transported to consumption points (Gibbs et al., 2003; May et al., 2004; Bowden et al., 2006; May et al., 2008), ii) because of the mentioned complexity, the dynamics of decay kinetics are usually oversimplified by modelers to obtain solutions, that reduce predictive powers of deterministic models and consequently guarantees only low levels of precision. One additional weakness of deterministic models is the problem of unnecessary computational efforts even for small WDSs (Polycarpou et al., 2002). Finally, a major drawback of deterministic models lies in the difficulties of accurately predicting the future water demands as emphasized by (May et al., 2008).

Milestone research within this field goes back to the beginning of last decade (Rodriguez and Serodes, 1999; Serodes et al., 2001). The data requirement of Artificial Neural Network (ANN) approach by these investigators includes the past records of FRC levels at critical points, and at chlorine dosing and application locations. They also needed the past records of variables at dosing points that were expected to influence chlorine decay in WDSs. The literature indicates adoption of a variety of data driven approaches under different application conditions. A control oriented model using ANN methodology has been developed and compared with autoregressive moving average (ARMA)

Soyupak S., Kilic H., Karadirek I. and Muhammetoglu H..
Single Input Single Output Time Series Artificial Neural Network Models for Free Residual Chlorine Forecasting in Water Distribution Networks.
DOI: 10.5220/0004171105880593
In *Proceedings of the 4th International Joint Conference on Computational Intelligence* (NCTA-2012), pages 588-593
ISBN: 978-989-8565-33-4

approaches as forecasters; ANN gave better results (May et al., 2004). A multi-layer perceptron (MLP) ANN with back-propagation has been developed by selecting the inputs required with adoption of three different techniques (Gibbs et al., 2003, Sharma, 2000). The MLP model performed better than traditional linear regression (Gibbs et al., 2003). Further MLP ANN was indicated to be implemented as an online tool to aid in the determination of chlorine levels (Gibbs et al., 2003). A general regression neural network (GRNN) model for forecasting FRC levels within a WDS has also been developed (Bowden et al., 2006). The GRNN model was shown to perform better than a multiple linear regression (MLR) model as a forecaster. Some investigators have emphasized the importance of the Input Variable Selection (IVS) for modeling and forecasting the residual chlorine dynamics within WDSs (Serodes et al., 2001; Gibbs et al., 2006). In recent years, some progress has been achieved as related to solving IVS problem. Wrapping and filtering are two basic classes of approaches to IVS problem (May et al. 2008 b). The wrapping methodology as a search process has the objective of obtaining best performance of the calibrated model (Serodes et al., 2001). Filtering methodology is a model-free approach where linear correlation coefficient and mutual information have been proposed as two measures of dependence for input variable selection (Sharma, 2000; May et al. 2008 b). A recent study has shown that multiple input ANN models with high predictive power and precision can be developed for WDSs supplied with high quality waters; however, these models can be utilized only for forecasting purposes. The study has further questioned the applicability and validity of multiple input ANN models as control instruments for FRC levels for systems similar in nature to the system investigated within the scope of this earlier work (TUBITAK, 2009).

In this particular research, we have investigated the possibility of developing Single Input Single Output Time Series Artificial Neural Networks (SISO-TS-ANN) that utilize appropriate Number of Steps Used As Inputs (NSUAI) and number of steps ahead to predict (H), so that the developed models can be utilized as an efficient and economical forecasting instrument. The question of selecting appropriate NSUAI and appropriate number of H has been answered by utilizing response surfaces for coefficient of determination (R^2) and Mean Absolute Error (MAE). The coefficient of determination (R^2) and mean absolute error (MAE) are commonly utilized statistical entities for judging model validity or quality of fit (StatSoft's STATISTICA Electronic Statistics Textbook, 2012). R^2 values are calculated using model predictions and measurements as variables. In order to realize the goals of the research, a WDS operated by ASAT (Antalya Water and Wastewater Administration, Turkey) has been selected as pilot. The following sections first present the properties of the studied WDS and monitoring program, as a summary. Secondly, the details of the adopted SISO-TS-ANN modeling approach and the adopted response surface methodology are given. The methodology gives general guidelines to select the best location specific NSUAI and H combinations for models with high predictive power and precision. Finally, results are presented and discussed in detail.

2 METHOD

2.1 Antalya Konyaalti WDS

The SISO-TSS-ANN models have been developed for Antalya Konyaalti Water Distribution System (KWDS) operated by ASAT, as depicted in Figure 1. The pilot network is one of the major sub-networks of Antalya water supply system. The area that being served by KWDS has the following properties: i) It can be operated independently, ii) The area has supervisory control and data acquisition system (SCADA) infrastructure, iii) The WDS is relatively new. The raw water source is groundwater which is pumped to the network after chlorination at Bogacay Pumping Station and Reservoir. Chlorination is not applied at any other location within KWDS. There is one balancing reservoir and eight monitoring stations operated with the existing SCADA system to collect on-line data to achieve the goals of this specific research.

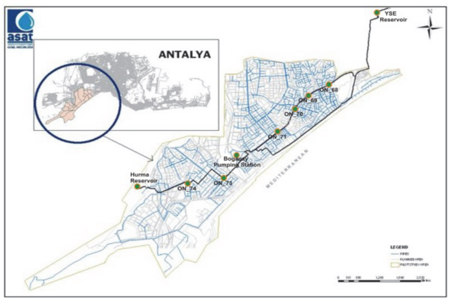


Figure 1: Map showing KWDS and Antalya WDS with monitoring stations, reservoirs and pumping station.

The established monitoring stations can collect on-line water quality data sets for FRC, temperature (T), electrical conductivity (EC), pH and turbidity (Turb). Pressure (P) and water flow rates (Q) are also being recorded on-line and continuously for the monitoring stations: Bogacay Pumping Station and Reservoir, ON 67, ON 68, ON 70, ON 71, ON 72, ON 73 , ON 74 and Hurma Balancing Reservoir (Figure 1). These parameters are expected to influence FRC levels and its decay kinetics in WDS. Data sets from the analyzers were recorded and stored at five-minute intervals at SCADA center. For this study, these data sets were converted into quarterly averaged values. We have utilized the water quality and operational data provided by ASAT for the months September 2009 and October 2009 for the above mentioned monitoring stations. There was some missing data within time series for some of the parameters due to short time power failures and due to unavoidable operational problems. Missing data points were generated synthetically by averaging the earlier and following values. The number of missing information was relatively few.

2.2 Selection of Input Variables

The purpose of ANN modeling in WDS field of water resources engineering is in general to obtain a mathematical tool to calculate the necessary input levels at control points to satisfy the desired levels of chlorine in future at the critical points of WDS. In this study, the control point is Bogacay Pumping Station and Reservoir and the critical points are the other monitoring stations namely ON 67, ON 68, ON 70, ON 71, ON 72, ON 73, ON 74 and Hurma Balancing Reservoir (Figure 1). An earlier study (TUBITAK, 2009) has suggested that in cases where supplied water quality is high and where the chlorine decay rates are very low, tools other than classical ANN methodology with multiple inputs should be investigated and adopted for more simplified modeling. Because of this observation, in this research only single controllable input, namely Free Residual Chlorine at Bogacay Pumping Station and Reservoir ($FRC_{Bogacay}$), has been utilized. Further, the collection of data for model building has been realized in such a way that the specifically created FRC perturbations within control point has created FRC time series at monitoring points that are suitable to develop SISO-TS-ANN models for control purposes as consistent with (TUBITAK, 2009).

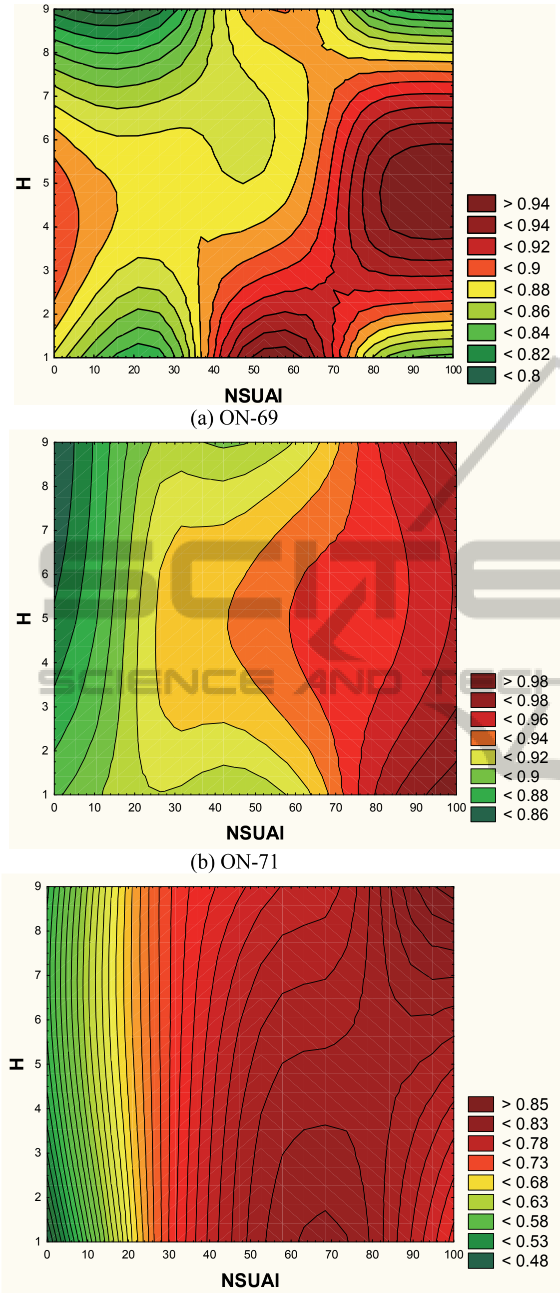
2.3 Model Building

Through this research we wanted to investigate the applicability of SISO-TS-ANN models developed as a FRC control tool and as a forecaster for a fairly complex WDS with high quality raw water input. The selected single input was $FRC_{Bogacay}$. In order to initiate ANN modeling one has to decide about selecting NSUAI and H. In order to establish criteria to select the best combinations of NSUAI and H for different monitoring stations, we have adopted response surface methodology for R^2 and MAE. The creation of response surfaces required selection of experimental matrix that covers reasonable and practical combinations of (NSUAI,H), including (8,2), (8,4), (8,8), (12,2), (12,4), (12,8), (24,2), (24,4), (24,8), (48,2), (48,4), (48,8), (72,2), (72,4), (72,8), (96,2), (96,4), (96,8). The tested NSUAI values were 8, 12, 24, 48, 72 and 96. The tested H values were 2, 4 and 8. The R^2 and MAE values have been estimated for each combination of NSUAI and H; then the contour plots were prepared by using STATISTICA (SANN, 2008). SISO-TS-ANN models for forecasting FRC levels at monitoring stations have been developed utilizing the software SANN ANS (Statistica Automated Neural Network-Automated Network Search) package (SANN, 2008). Modeling constraints were as follows: 1) Minimum and maximum numbers of hidden neurons were 3 and 11 respectively, 2) 20 candidate structures have been tested for each data set and only the one with best performance and precision was requested to be retained. MLP approach has been instructed to be utilized.

The best SISO-TS- ANN for each monitoring station has been found by examining the response surfaces developed for that station. Several different combinations of types of hidden and output activation functions, number of neurons, number of steps used as inputs (NSUAI) and number of steps ahead to predict (H) have been tested and the one that minimizes MAE and maximizes R^2 has been selected and listed in Table 1.

3 RESULTS AND DISCUSSIONS

The developed response surfaces as contour plots for R^2 and MAE are given in Figures 2 and 3 respectively. These figures cover response surfaces for monitoring stations ON69, ON71 and Hurma balancing reservoir only. Similar response surfaces are obtained for other monitoring stations as well. In order to save space, only the response surfaces of

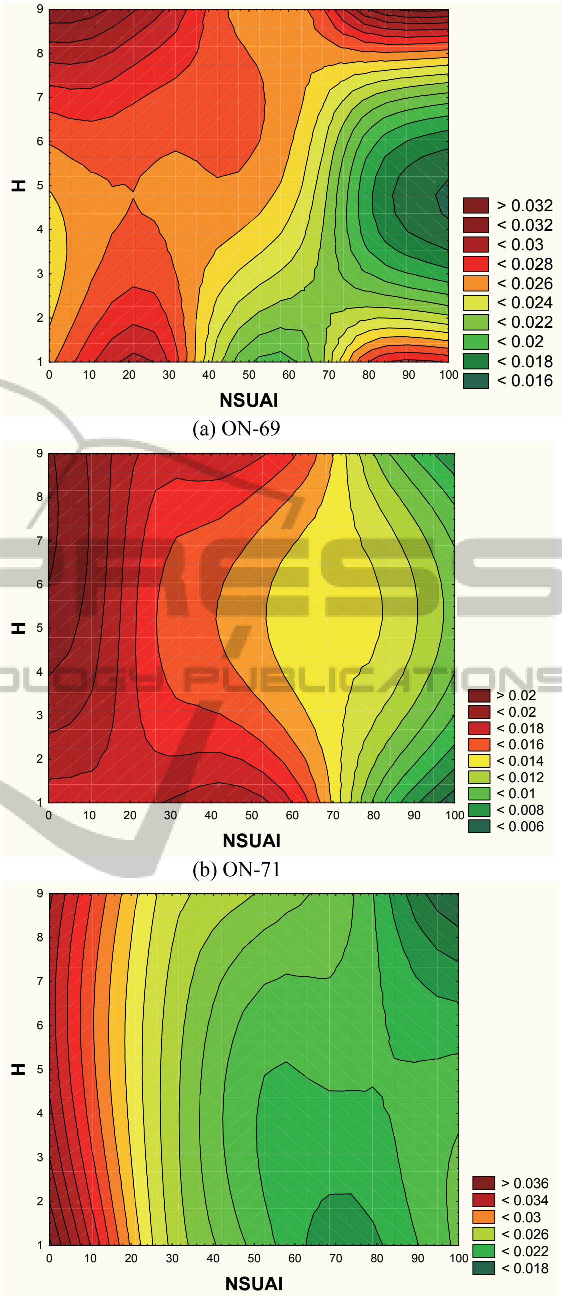


(a) ON-69

(b) ON-71

(c) Hurma Balancing Reservoir

Figure 2: Contour plots for R^2 against number of steps used as inputs (NSUAI) and number of steps ahead to predict (horizons).



(a) ON-69

(b) ON-71

(c) Hurma Balancing Reservoir

Figure 3: Contour plots for MAE against number of steps used as inputs (NSUAI) and number of steps ahead to predict H (horizons).

three stations are presented here. If we examine the response surfaces for different stations, the following strategies for selecting NSUAI and H combinations can be reached:

1) *The suggested NSUAI and H levels for monitoring station ON69:* The dynamics of KWDS dictate to utilize as much past data as possible for this station; however the forecasting horizon should be kept about 4 to 6 (1 to 1.5 hours) so that maximum R2 and minimum MAE values can be attained (Please refer Figures 2-a and 3-a).
2) *The suggested NSUAI and H levels for monitoring station ON71*: The general trend is to

utilize as many past data as possible for this station since Figure 2-b indicates that as NSUAI reaches to 96 (= 1 day) , R^2 values is about 96 %. The same trend is also obvious from Figure 3-b that indicates the reduction and minimization of MAE as NSUAI increases. Both Figures 2-b and 3-b indicate to keep forecasting horizon either lowest or highest for the studied range.

3) *The suggested NSUAI and H levels for monitoring station Hurma Balancing Reservoir:* The general trend suggests the utilization of as many past data as possible for this station since Figure 2-c indicates that as NSUAI reaches to 96 (= 1 day) , R^2 values is more than 85 %. Figure 3-c indicates the reduction and minimization of MAE as NSUAI increases. Figure 3-c further suggests keeping forecasting horizon as large as possible to minimize MAE.

The best SISO-TS-ANN models for these monitoring stations as suggested by response surfaces are summarized in Table 1. For ON 69, maximum attainable R^2 was very high (0.946) and MAE value was less than 0.02 ppm (0.0163 ppm). For ON 71, maximum attainable R^2 was even higher (0.972) and the corresponding minimum MAE was 0.008 ppm. For Hurma balancing reservoir, the attainable performance and precision levels were also satisfactory with 0.839 and 0.0193 ppm values of R^2 and MAE levels respectively.

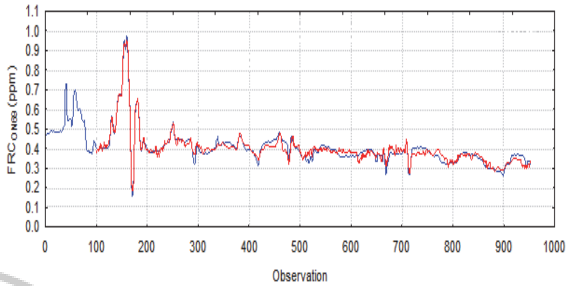
Table 1: The performance levels of SISO-TS-ANN model structures as suggested by R^2 and MAE response surfaces.

Monitoring station	Selected H utilizng response surface criteria	Selected NSAUI utilizing response surface criteria	Best model structure by statistica	Overall R^2	Overall MAE	Hidden activation	Output activation
ON68	2	96	96-9-1	0.872	0.0236	Tanh	Identity
ON69	4	96	96-10-1	0.946	0.0163	Logistic	Logistic
ON70	2	96	96-5-1	0.964	0.0084	Logistic	Tanh
ON71	2	96	96-10-1	0.972	0.0080	Logistic	Exponential
ON73	8	96	96-8-1	0.656	0.0284	Exponential	Tanh
ON74	2	96	96-9-1	0.915	0.0090	Logistic	Identity
Hurma Balancing Reservoir	8	96	96-2-1	0.839	0.0193	Logistic	Exponential

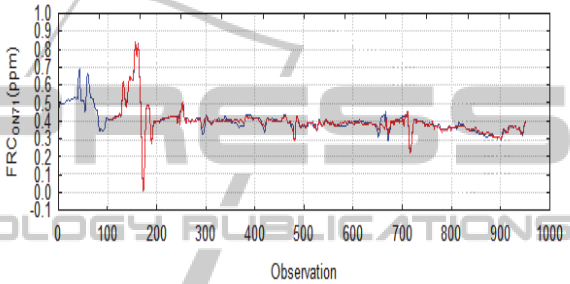
Figure 4 summarizes the model predictions and measurements as comparative time series.

Note that one may not still observe the impact of traveling time from the figured out results because of dynamically changing complex nature of the network under study. However, we can at least say that as the distance from major source of chlorine water supply increases, R^2 values decrease in a nonlinear fashion and MAE values increase again in non-linear fashion.

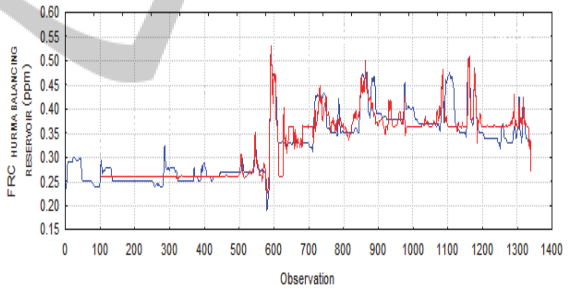
One of the major concerns was to establish trends for precision and performance levels as a function of distance from major source of chlorine.



(a) Measured FRC (Blue) and MLP 96-10-1 Model (Red) results for ON-69.



(b) Measured FRC (Blue) and MLP 96-10-1 Model (Red) results for ON-71.



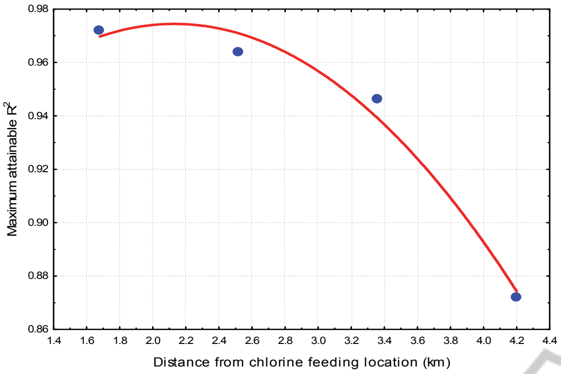
(c) Measured FRC (Blue) and MLP 96-10-1 Model (Red) results for Hurma Balancing Reservoir.

Figure 4: SISO-TS-ANN model predictions and measurements for ON69, ON71 and Hurma Balancing Reservoir monitoring stations.

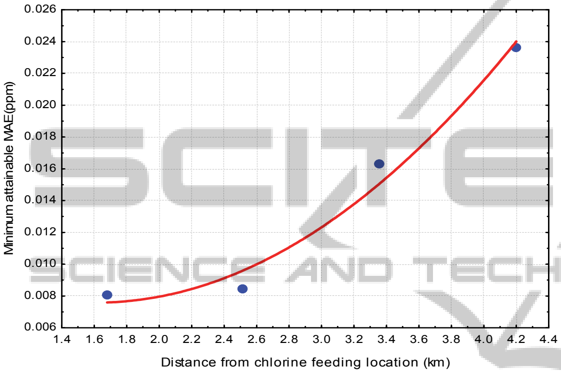
This was achieved by preparing non-linear plots of maximum attainable R^2 and MAE as a function of distance from chlorine feeding station, Bogacay Pumping Station and Reservoir, see Figure 5.

4 CONCLUSIONS

Modelers prefer simple structures that give highest precision and performance. This study has shown that SISO-TSS-ANN models that have only single input and single output can be efficiently utilized as FRC forecasting tools in complex WDSs that are



(a)



(b)

Figure 5: Maximum attainable R^2 and minimum attainable MAE as a function of distance from source of chlorine supply.

supplied with raw waters of low FRC decay rates. This may bring the possibility of reduction of monitored variables in future that will create the minimization of cost of monitoring. One of the major conclusions is: irrespective of the locations of the monitoring stations, utilization of maximum past information for the single input has yielded best results. We could not create *any generalized rule* for the number of forecasting horizons that will yield the best results. The number of forecasting horizons should be specifically determined for each station by examining its response surfaces. Therefore, preparation of response surfaces for R^2 and MAE is very useful in selecting best combinations of NSUAI and H for developing forecasting tools.

REFERENCES

Bowden, G. J., Nixon, J. B., Dandy, G. C., Maier, H. R., Holmes, M., 2006. Forecasting chlorine residuals in a water distribution system using a general regression neural network. *Mathematical and Computer Modelling,* 44, 469-484.

EPANET 2, 2000. *Users' Manual*. Lewis A. Rossman, Cincinnati, OH, USA.

Gibbs, M. S., Morgan, N., Maier, H. R., Dandy, G. C., Holmes, M., Nixon, J.B., 2003. Use of artificial neural networks for modelling chlorine residuals in water distribution systems. *Modsim 2003 - International Congress on Modelling and Simulation*, Townsville., Australia, Part 2, 789-794.

May, R. J., Maier, H. R., Dandy, G. C., Nixon, J. B., 2004. Control-oriented water quality modelling using artificial neural networks. *Proceedings on CD-ROM,* Enviro '04, Sydney, Australia.

May, R. J., Dandy, G. C., Maier, H. R., Nixon, J. B., 2008. Application of partial mutual information variable selection to ANN forecasting of water quality in water distribution systems, *Environmental Modelling and Software* 23, 1289–1299.

May, R. J., Maier, H. R., Dandy, G. C., Fernando, T.M.K.G., 2008b. Non-linear variable selection for artificial neural networks using partial mutual information. *Environmental Modelling and Software,* 23, 1312-1326.

Polycarpou, M. M., Uber, J. G., Wang, Z., Shang, F., Brdys, M. A., 2002. Feed-back control of water quality. *In: IEEE Control Systems Magazine*, pp. 68–84.

Rodriguez, M. J., Sérodes, J. B., 1999. Assessing empirical linear and non-linear modelling of residual chlorine in urban drinking water systems. *Environmental Modelling and Software,* 14, 93-102.

SANN (*Statistica Automated Neural Network Software*), Stat Com, 2008.

Sharma, A., 2000. Seasonal to inter-annual rainfall probabilistic forecasts for improved water supply management: Part 1 – a strategy for system predictor identification. *Journal of Hydrology*, 239 (1-4), 232 – 239.

Sérodes, J. B., Rodriguez, M. J., Ponton, A., 2001. Chlorcast(c): a methodology for developing decision-making tools for chlorine disinfection control. *Environmental Modelling and Software* 16, 53-62.

Statsoft, 2012, Statistica Electronic Statistics Text book.

TUBITAK Proje Gelişme Raporu, 2009. İçme suyu dağıtım sebekelerinde optimum klorlama uygulamalarının matematiksel modeller kullanılarak gerçekleştirilmesi ve dezenfeksiyon sistemlerinin Yönetimi, *Proje No:107G088, Antalya (Turkey) (In Turkish).*