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Araştırma Makalesi / Research Article

5-YEAR FORECAST OF ANNUAL NUMBER OF FIXED TELEPHONY SUBSCRIBERS FOR TURKEY USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

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Abstract: *It is estimated that Fixed Telephony Service will have an important share in a near future, just like in the past. This paper discusses the "artificial neural networks", which can correctly model non-linear multi-input dynamic systems, and forecasts the number of the subscribers of this service, comprising a period of future 5 years by using a solution searching technique used in simulation applications called "genetic algorithms".*
Keywords : *Artificial neural networks, genetic algorithms, number of fixed telephony subscriber, forecast model*

Türkiye için Yapay Sinir Ağları ve Genetik Algoritmalar ile 5 Yıllık Sabit Telefon Abone Sayısı Tahmini

Özet: *Sabit telefon hizmetinin elektronik haberleşme pazarında geçmişte olduğu gibi yakın gelecekte de önemli bir paya sahip olacağı düşünülmektedir. Bu çalışma ile doğrusal olmayan çok girdili dinamik sistemleri doğru şekilde modelleyebilen "yapay sinir ağları" ve simülasyon uygulamalarında kullanılan bir çözüm arama tekniği olan "genetik algoritmalar" birlikte kullanılmak suretiyle, bu hizmet için gelecek 5 yıla dair abone sayısı tahmini yapılmıştır.*
Anahtar Kelimeler: *Yapay Sinir Ağları, Genetik Algoritmalar, Sabit Telefon Abone Sayısı, Tahmin Modeli*

Introduction

Forecasting, which is a statistically important concept, can be defined as predicting the approximate value of a variable under certain assumptions for future periods (Kayım, 1985).

Forecasting is mostly done by extending the event to the future both by depending on its past values, and by using a number of techniques (Çevik, 1999). At this point, the "time series" methods are most worth mentioning. If the data obtained from observations changes in accordance with the changes of a variable during a given time, these data are called time series (Arıcı, 1993).

An event, of which the future situation is to be forecasted, may be under the influence of various factors. It becomes harder for them, however, to be analyzed and anticipated, since it is likely that the influencing factors come in various combinations. Thus, a perfect forecasting technique is not possible (Bowerman ve O'Connell, 1993). It is also impossible to eliminate uncertainty, since all of the influencing factors could not be taken into consideration in forecasting (Mendelhall vd., 1989).

Various factors like economic, sociological, psychological, etc. influence the event represented by a time series and may show some fluctuation and instability. These influences may be in different directions and severities (Gurtan, 1977). Due to the difficulties of understanding the definitions of simultaneously interacting factors that pave way for such influences, a need for gathering numerous influences under several groups emerges (Ekeblad, 1962). which can be classified as "trend, seasonal, cyclical, and coincidental (irregular, random) fluctuations"

The trend, or the "general tendency", is the long term behavior of the event, indicating how it will continue to behave in the future. It may be associated with population growths, technological developments, and massive changes in consumer behavior (Hamburg, 1970). The trend, which is a long term movement, is shaped by factors like technological developments, consumer preferences, individual earnings, population, market size, and price levels.

Seasonal fluctuations are the variations in the event over time with the influence of natural and social causes depending on the season. They all happen in one year, and vary almost during the same times and reiterate nearly in the same levels of severity, i.e., cyclic (Cillov, 1975) (Arkın vd., 1968). Being so, makes them easy to predict. Variations depending on season in volumes of manufacturing, sale, consummation, price, etc. of a commodity are examples of this kind of fluctuations.

Cyclical fluctuations provide a view of the general situation of economy. In other words, economic fluctuations in forms of stagnation, ascension, prosperity and regression are called cyclical fluctuations. These fluctuations reiterate periodically (Turanlı, 1994). Cyclical movements observed in forms of cycles gradually reach to a certain level and then begin to descend, then ascend again. These ups and downs take place around a certain trend. The completion of a cycle can take place after 1, 5 or 10 years. The sizes of the changes around the trend may also differ for each period (Hatiboğlu, 1994). The most outstanding difference between cyclical and seasonal fluctuations is that each cyclical fluctuation encompasses longer periods. Furthermore, it is believed that cyclical fluctuations generally depend on causes other than causes like the climate, which can be associated with seasons.

It is quite difficult, even impossible to predict the duration of any cyclical fluctuation, kinds and severities of sequential changes.

Coincidental (irregular, random) fluctuations are the ones that happen by means of natural, economic or political causes. It is absolutely uncertain and cannot be kept under control when and in which form they will occur (Çömlekçi, 1982). Fluctuations due to factors like wars, natural disasters and strikes are the examples of these fluctuations. It is assumed that coincidental fluctuations equilibrate each other in the long run.

Scope of the Research

Regarding the forecasting model for the number of fixed telephony subscribers, this paper takes into consideration factors such as population, number of households, GNP per person, and the number of mobile telephony subscribers to estimate the number of fixed telephony subscribers for 2007-2011. The trend is shaped by factors like technological developments, consumer preferences, individual earnings, population, market size, and price levels, while the GNP is a cyclical of fluctuation. These factors are determined by referring to the indicators of the International Telecommunication Union (ITU) (World Telecommunication Indicators, 2001), (Saygı, 2002). These indicators are used to define telecommunication services and shown in **Table 1.**

Table 1. ITU telecommunication indicators

Population and economic structure	Population, number of households, GDP, import and export of telecommunication devices
Fixed telephony network	Number of telephone lines, fixed telephony penetration per person and household, digitalization rate, number of public pay phones, waiting list for subscription
Mobile services	Number of mobile telephony subscribers and penetration of mobile telephony

Political, technological and factors such as laws and regulations, which have influence on telecommunication industry, but cannot be measured on a numerical basis, are coincidental (irregular, random) fluctuations. It is necessary to assign a certain time limit for the forecast of the number of subscribers and other predictions in an industry like telecommunication. These factors equilibrate each other in the long run and are irregular. They also cannot be kept under control. From this point of view, a perspective of 5 years has been designated for the forecast. Therefore, the influences of the factors can be maintained under a certain level.

In this model, the factors that are believed to have influences on the value to be forecasted in the past are assumed to hold the interaction in the same manner in the future, and the value of the factors should be numerically predicted. This is another mean in determining the already mentioned factors. It is possible to add other factors as inputs in this developed model, necessarily requiring however, the predictions of the future values of these newly added factors, which ultimately will make the model more and more complex due to the increase in the number of parameters and uncertainty. It is hardly possible to eliminate uncertainty in forecasting the future for all the influencing factors , since they cannot be taken into consideration Therefore, the values that the number of fixed telephony subscribers will take in 5 years is forecasted based on population, household, GNP and the number of mobile telephony subscribers.

In modeling the forecast, "artificial neural networks" has been used in conjunction with a solution search technique called "genetic algorithms" used in simulation applications. Artificial neural networks can correctly model multi-input dynamic systems. It is, in this context, described in many sources as "the state of the art technology" for forecasting (Zhang vd., 1998). The superiority of artificial neural networks over conventional methods (such as regression analysis) has been proven by their observed performance in forecasting studies as far as goodness of fit test results are concerned (Baker, 1998),(Shi vd., 1999).

On the other hand, the application of genetic algorithms in our research can be summarized as follows:

Initialization; initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Selection; during each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming.

Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.

Reproduction; the next step is to generate a second generation population of solutions from those selected through genetic operators: crossover (also called recombination), and/or mutation.

For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each child, and the process continues until a new population of solutions of appropriate size is generated.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions, for reasons already mentioned above.

Termination; this generational process is repeated until a termination condition has been reached. Common terminating conditions are;

- A solution is found that satisfies minimum criteria
- Fixed number of generations reached
- Allocated budget (computation time/money) reached
- The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
- Manual inspection
- Combinations of the above.

In our research, the highest ranking solution has been used.

The structure of artificial neural networks is based on the imitation (modeling) of the functioning of the human nervous system by neglecting a number of biologically known details of it. An artificial neural network is a system composed of layers (formed fundamentally of an input, an hidden and an output layer) in parallel with each other with sufficient numbers of cells (processors) within each of the layers (Şen, 2004). It may also be considered as a network of adaptive incomplex components (Kohonen,1988), (Kung,1993). There is a quite complex communication between these layers according to the nature of the event studied. Like in the nature, the communication between cells (processors) is executed through a network. The efficiencies of the connections between the cells in such a network are represented by weights, and their training and contributions to outputs in accordance with input and output data and are calculated separately.

The factors that characterize an artificial neural network model are the topology of connected processors, the summation and activation functions of the processors and the learning rule used. Which artifical neural network to use is an issue depending on type of the problem. "Elman Artificial Neural Network" has been used in conjunction with genetic algorithms for the forecast model discussed in this paper. It is important for the network to perceive time delays that recurrences shall exist in modeling dynamic systems like time series. To ensure this, the output of the network is accounted for by depending on both previous and actual status of the network, which enables recurrent networks to perform dynamic modeling[1] by recalling previous status (temporal memory). Having the simplest structure and being the easiest to train among recurrent networks, the "Elman Network" has been preferred for forecast modeling (Elman, 1990).

To enhance the performance of artificial neural networks, genetic algorithms are benefited from mainly in selecting the inputs to be used for the training of the artificial neural networks, and to optimize the number of both parameters based on the type of the artificial neural network and the learning rule, the number of hidden layers and processors. "Genetic search" is executed in the training by use of genetic algorithms, based on the selected training stop criteria (falling of the error values related to the training set below the determined threshold values or rising of the error values related to the data set reserved for cross validation), and on the error values that artificial neural networks of a combination of various "numbers of hiden layers and processors and learning rule parameter values" generate. In other words, the "goodness of fit" is the generated error values as far as application steps of genetic algorithms are concerned, while the mutated genes are the number of hidden layers and processors and the learning rule parameter values. It is also likely to perform genetic search into the influences of inputs to the solution of the problem.

When using genetic algorithms, random initial solutions are detected first. Then, these solutions are matched to generate better solutions. New solutions are searched by exactly the same way, by continuously matching solutions (genetic search) "until no better solutions more can be obtained". It is assumed in this approach that features, which will generate the almost optimum result, will be passed on inheritably from initial solutions to latter solutions. Because the initial solutions are selected randomly, algorithms never promise to reach to an optimum result (Banks vd., 2000). This feature of it, however, brings along practicability in applications, for the trial of all the solutions in the solution space (which is impossible for some problems) would take too much time, and thus, cash. This needed time can only be shortened by randomly selected solutions (Goldberg, 1999), (Koza, 1992).

Forecast Model

The values for population, the number of households, the GNP per person and the number of mobile telephony subscribers and the values for the number of fixed telephony subscribers over the past 17 years (1990-2006), which are considered to be the factors that will have influences on the future 5 year forecast, are used to train the established Elman Artificial Neural Network. The values for the factors have been taken on a monthly basis for the much data is needed for the training of artificial neural networks. Therefore, the annual values have been turned into monthly values by fitting a curve valuing higher than the determination coefficient (r2) 0,99. By doing so, 5 time series of 204 months each have been obtained corresponding to 17 years. While working with artificial neural networks, no analysis has been made to define the correlation ratios between the inputs and the number of fixed telephony subscribers since no pre-analysis is needed for data added into the model as inputs.

Table 2. shows the annual values of model inputs and penetration rates for 1990-2006.

Table 2. Inputs of the forecast model for the number of fixed subscribers (1990-2006)

	Forecast Model Inputs					**Penetration Rates for**	
Year	**Number of Fixed Telephony Subscribers**	**Population**	**Number of households**	**GNP* ($/person)**	**Number of Mobile Telephony Subscribers**	**Population**	**Household**
1990	6.893.267	56.154.000	11.188.636	2.599	-	12,3 %	61,6 %
1991	8.199.568	57.262.000	11.737.227	2.557	-	14,3 %	69,9 %
1992	9.410.486	58.374.000	12.285.818	2.669	-	16,1 %	76,6 %
1993	11.019.710	59.491.000	12.834.409	2.832	-	18,5 %	85,9 %
1994	12.305.760	60.612.000	13.383.000	2.611	81.276	20,3 %	92,0 %
1995	13.331.537	61.737.000	13.664.183	2.767	332.716	21,6 %	97,6 %
1996	14.286.478	62.873.000	13.945.365	2.911	692.779	22,7 %	102,4 %
1997	15.744.020	64.015.000	14.226.547	3.096	1.483.149	24,6 %	110,7 %
1998	16.959.500	65.157.000	14.507.729	3.159	3.262.302	26,0 %	116,9 %
1999	18.054.047	66.293.000	14.788.911	2.916	7.232.917	27,2 %	122,1 %
2000	18.391.171	67.420.000	15.070.093	3.049	13.421.130	27,3 %	122,0 %
2001	18.904.486	68.529.000	15.758.547	2.718	18.178.199	27,6 %	120,0 %
2002	18.914.857	69.626.000	16.447.000	2.892	23.525.089	27,2 %	115,0 %
2003	18.916.721	70.712.000	16.684.844	3.020	28.754.382	26,8 %	113,4 %
2004	19.125.163	71.789.000	16.973.605	3.276	34.707.549	26,6 %	112,7 %
2005	18.978.223	72.844.000	17.256.958	3.325	43.608.965	26,1 %	110 %
2006	18.803.505	73.905.000	17.515.738	3.376	51.219.673	25,4 %	107,4 %
* Prices valid for the year 1998.							

[1] In the static case, the weigths of the network are adjusted in consideration of the current status only .

20% of the data for 17 years (204 months) is classified as "cross validation", 20% as "test", and the remaining 60% as "training". The data that "cross validation" classification contains have been selected randomly in order to avoid bias.

In training the established Elman Artificial Neural Network, the criteria to stop the training has been determined as the increase in the value of the calculated Mean Square Error (MSE) for the cross validation in order for the model not to lose its ability to generalize. Genetic algorithms have been used to specify parameters used for emitting errors in reverse, and the number of processors within the hidden layer. At the end of the training,

MSE values generated by the model for the training and the cross validation sets have been 0,00053 ve 0,0061 respectively. These values indicate that the deviation from the actual values is minor, and therefore, that the trained network is very highly able to model. After the training of the network, the data in the test set (randomly selected subscriber number for 40 months) have been entered into the network. Figure 1 compares the data in the test set (expected values) with the output generated (forecasted) by the trained artificial neural network.

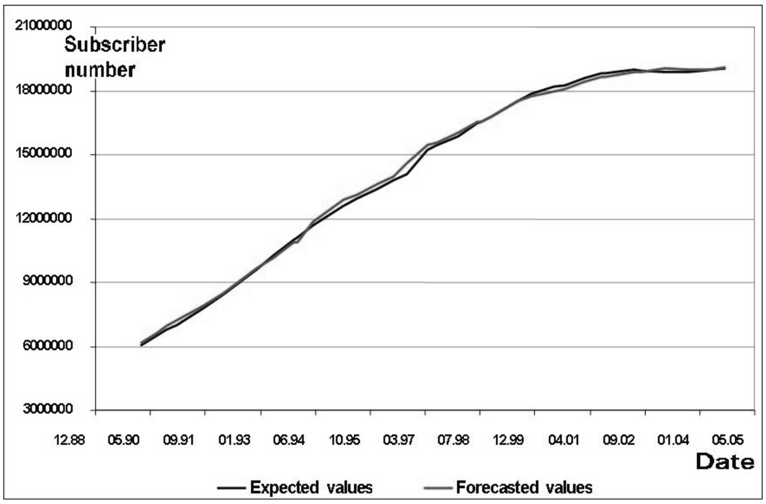

Figure 1. Comparison of the expected values and the forecasted values of trained artificial neural network

The Mean Absolute Percentage Error (MAPE) value based on the values forecasted by the trained network over expected values has been calculated as 2,11 %. This value's being low obviously expresses the modeling ability of the network. In another way, the Elman Artificial Neural Network established by means of genetic algorithms can, within the framework of the factors of population, household, GNP per person and number of mobile telephony subscribers, model the number of fixed telephony subscribers between 1990-2006 at a ratio of 97,89% . Alternative models have been tried with Multilayer Perceptron, some other Recurrent and CANFIS – Coactive Neuro-Fuzzy Inference System artificial neural networks prior to the usage of the Elman Artificial Neural Network. Under given data and with regard to the below-mentioned parameters, however, the best possible results have been achieved with Elman Artificial Neural Network.

The forecast has been made by entering the estimated values for the specified inputs of population, number of households, GNP per person and number of mobile telephony subscribers between 2007-2011 into the instructed network. Among these factors, population values encompassing the period between 2007-2011 are the values forecasted by the Turkish Statistical Institution, and are in linear corelation. The forecast for the number of households for the same period has been made by taking into consideration the decrease trend in the average number of persons per household since the 1980's. The average number of persons per household in the 1980's was more than 5. Then it fell down to an average of 4,5 by the 1990's. The indications of the census in the year 2000 for population and the number of households are 67.804.000 and 15.070.093 respectively, which leads us to 4,5 as the average number of persons per household (Türkiye İstatistik Yıllığı, 2001). The forecast showed in Table 3 has been made with the assumption that the number of households will fall down even to 3,9 during the period covering 2010-2020. The 2007-2011 forecast for GNP contains three scenarios in which GNP grows at the percentages of 3%, 5% and 7% during this period alongside with calculations of the values for GNP per person for each case. The values for the estimated number of mobile telephony subscribers for the same period are yields of another forecast study (Turgut, 2005). It is, in a sense, worth mentioning that this whole forecast study constitutes a sensitivity analysis of the future values for the number of fixed telephony subscribers to the individual earnings and the number of mobile telephony subscribers.

It is assessed that the most probable of the growth percentage assumed for GNP for the next 5 years will be an average of 5% since it was predicted in the "Pre-Accession Economic Programme for the Year 2004", which was presented to the EU Commission as of December 23, 2004 after being adopted by the decree (dated November 29, 2004 no: 2004/89) of the Supreme Planning Council. The agreement upon this value was based on the annual growth rate for the period between 1980-2000 (Türkiye Cumhuriyeti 2004 Yılı Katılım Öncesi Ekonomik Programı, 2004). The forecast covers a period of 3 years, and the forecast of 5% that is based on an average growth for a duration of 20 years is believed to be generalized for the next 5 years especially bearing in mind the economic stability achieved during the last years.

The reason why different scenarios in forecasting the factors of population and household other than GNP and the number of mobile telephony subscribers were designed is that, these two factors tend to perform their past statistical trends also in the long run, and do not deviate much. In this context, Table 3. shows the forecasted values for 2007-2011 regarding to the inputs used in the forecast.

Table 3. Forecasted values for the number of fixed telephony subscribers forecast model inputs (2007-2011)

Year	Population	Number of households	GNP* *($/personi)* and Number of Mobile Telephony Subscribers *(million)*					
			GNP (3%)	Mobile	GNP (5%)	Mobile	GNP (7%)	Mobile
2007	74.944.000	17.769.153	3.429	53,72	3.633	54,34	3.844	55,12
2008	75.961.000	18.480.379	3.485	58,47	3.763	58,77	4.058	60,17
2009	76.956.000	18.729.129	3.543	61,56	3.900	62,24	4.286	64,92
2010	77.918.000	18.969.629	3.604	63,64	4.045	64,86	4.530	68,76
2011	79.021.000	19.718.847	3.660	65,50	4.188	66,77	4.779	70,81
* Prices valid for the year 1998								

Forecasted values for the number of fixed telephony subscribers has been obtained by entering the input values in Table 3. into the trained network. The forecasted values obtained for the input set based on an annual growth of 5% in GNP, are shown in Figure 2. and Figure 3.

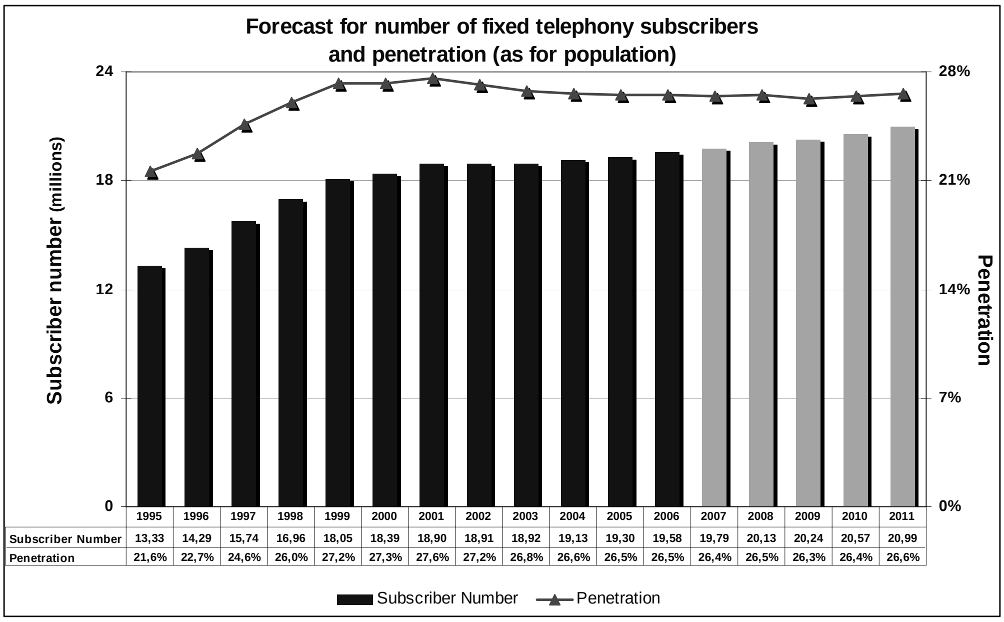

Figure 2. Forecast for the number of fixed telephony subscribers and penetration (as for population)

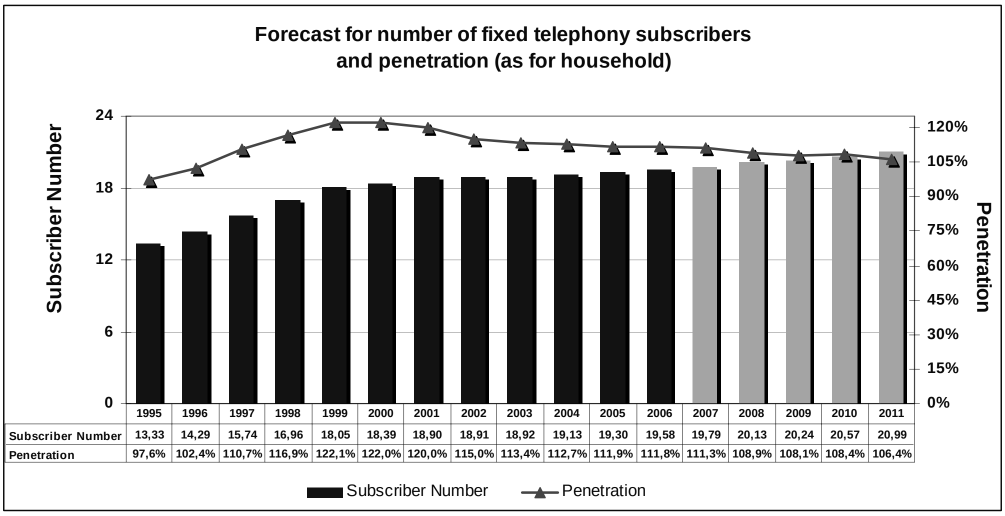

Figure 3. Forecast for the number of fixed telephony subscribers and penetration (as for household)

Conclusion

To conclude, this paper discusses the "artificial neural networks", which can correctly model non-linear multi-input dynamic systems, and forecasts the number of the subscribers of fixed telephony service, which is estimated to have an important share in the electronic communication market in a near future, just like in the past, comprising a period of future 5 years by using a solution searching technique used in simulation applications called "genetic algorithms".

Three scenarios in which GNP grows at the percentages of 3%, 5% and 7%, and for each case, the values forecasted by the trained artificial neural network for the number of fixed telephony subscribers have turned out to be very much similar to each other. Thus, the forecasted values obtained for the input set based on an annual growth of 5 % in GNP, are shown in Table 2 and Table 3. This situation can be perceived as the reflection of the stagnancy of the fixed telephony subscriber numbers and penetration values in Turkey for the last 4 years to the future, just like in many countries.

These forecasted values could also be interpreted as the future reflections of the corelation between past consummation of voice transmission service via fixed network and the factors of population, household, individual earnings and the number of mobile telephony subscribers of the past years. Factors, which will have influence on the number of fixed telephony subscribers but not actually predicted or predicted without an expression of future state through a numeric model should be taken into consideration in other predictions based on this work.

One forecast of the Deutsche Bank in 2001 stated that the population penetration of the fixed telephony service in Turkey would remain stable at 28% by the year 2010 [15]. This forecast supports the forecasted values shown in Table 2. It is also forecasted that the yearly population penetration value will be around 26%.

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