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Prediction of the Premium Production of Some Insurance Companies Operating in Turkey with Artificial Neural Networks

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R E S E A R C H A R T I C L E

A B S T R A C T

The insurance sector can be seen as a sector that directly affects the country's economy and development with its ability to fund financial markets and meet risks. In this respect, estimating the premium size, which is the main factor that constitutes the volume of the insurance sector, as accurately and reliably as possible, indirectly means predicting the risks that may arise in terms of the economy and development of the country and taking precautions. necessary measures. In this study, premium productions of some insurance companies operating in Turkey were estimated with different artificial neural networks and their results were evaluated comparatively. In this context, two different artificial neural networks (ANNs), feed forward and feedback, were used as the estimation tools for insurance premium production. Two training algorithms and two different activation functions were run in the structure of the ANNs used. Thus, eight different estimation tools were created for insurance companies' premium production. The estimation performances of ANNs were evaluated on test sets by using error criteria such as Root Mean Square Error, Mean Absolute Percentage Error, and Median Absolute Percentage Error (MdAPE). In terms of the MdAPE criterion in our best-performing algorithms, in the analysis of a total of 36 data sets, 18 quarters of 18 months in total, the predictions for only 6 data sets were estimated with an error of more than 10%, and 5 of them were around 10% or just above, which is still acceptable. have an acceptable level of error.

1. Introduction

In addition to social, economic and political issues, the insurance sector is of great importance in carrying out profitable activities, especially in countries that are growing resilient and decisively. The insurance sector is accepted as an important indicator in determining the development and welfare levels of countries. Within the scope of this study, estimating the premium volumes/sizes of some insurance companies operating in Turkey with different artificial neural networks is the subject of the study. Although artificial neural networks are widely used and an important resource in the prediction of financial time series in the literature, a limited number of studies have been carried out especially in this field. In this respect, the thesis study reveals the prediction of premium production of some insurance companies with artificial neural networks with a comparative approach in order to fill this gap in the literature. With this study we have prepared, it will help insurance companies to estimate premiums and make

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strategic decisions and will help to determine the actions that can be taken in advance. In this context, forward and feedback, which are basically two different artificial neural networks, were used as the estimation tool for insurance premium production. In addition to training the two artificial neural networks with different training algorithms, eight different artificial neural network structures with different activation functions used in the output layer units and thus eight different estimation tools for insurance companies' premium production were created. These algorithms we used helped us get better output results and produce useful outputs. Therefore, we used our choices in favour of these algorithms.

For the insurance industry, Hawley, Johnson and Raina [1] and Wilson and Wilson [2] presented studies using ANNs to predict bankruptcy in the insurance industry. Huang, Dorsey, and Boose [3] proposed using an ANN model to predict life insurance financial distress. Kitchens [4] preferred to use ANN to estimate losses in auto insurance and suggested the related methodology. Bayır [5] made an application on forecasting modelling using ANN in his study, and multiple linear regression analysis and forecasting models were established with artificial neural networks and compared for Turkey's manufacturing industry export values. Doğan [6] made a portfolio evaluation of a private insurance company operating in Turkey using ANNs. Uslu [7] presented a study comparing classical time series methods and ANN predictions and comparing the prediction successes of time series methods "Box-Jenkins" and "Artificial Neural Networks" methods in Turkey's long-term forecasting. The method that provides the highest success in electrical energy consumption has been tried to be determined. Bahia [8], on the other hand, used artificial neural networks to reveal the income forecast of the Iraqi national insurance agency. Sakthivel and Rajitha [9] used ANNs to estimate the frequency of future losses in non-life insurance. Çetinkaya [10], on the other hand, estimated the three-month life insurance premium production in Turkey between the years 2006-2019 using classical time series analysis approaches and ANNs and evaluated the obtained results comparatively. Hoysater and Larsplass [11] used different forecasting tools, including ANNs, for predictive modelling of customer claims across multiple insurance policies and compared the results.

The remainder of this work is organized as follows: The second section presents the basic information about feed forward and feedback Elman ANNs. In the third chapter, the main features and results of the applications are given. Finally, conclusions and recommendations are presented in the fourth section.

2. Artificial Neural Networks

2.1. Feedforward artificial neural networks

The feedforward artificial neural network (FFANN) is a multilayer perceptron introduced to the literature by Werbos [12] and Rumelhart et al. [13]. Feedforward ANN consists of layers and these layers are artificial nerve cells, which are the most basic units of the network. FFANNs consist of three layers, the input layer, the hidden layer(s), and the output layer. There is no connection between neurons in the same layer. In feedforward neural networks, the communication between neurons works forward in a one-way direction. A prototype of FFNN with this structure is given in Figure 1. In the input layer, the inputs (X) are transferred to the hidden layer without any processing. net values of each hidden layer unit are created by adding (Σ) bias values (θ_h) to the values obtained by multiplying each input by weights ($W_h = w_{ij} \quad, i = \overline{1,m};\ j = \overline{1,k}$).

$$net_j = \theta_{h_j} + \sum_{i=1}^{m} w_{ij}\, x_i \quad , \quad j = \overline{1,k} \tag{1}$$

These net values, then, are converted to the output of the relevant hidden layer unit by passing through an activation function (f_1).

$$o_j = f_1(net_j) \tag{2}$$

These outputs form the inputs for the output layer unit and similarly, the net value of the output layer unit is obtained by means of the respective weights ($W_o = w_{o_j} \quad, j = \overline{1,k}$) and bias values ($\theta_o$).

$$net_o = \theta_o + \sum_{j=1}^{k} w_{o_j}\, o_j \tag{3}$$

The final output ($\hat{Y}$) of the ANN is obtained by passing this value through an activation function (f_2).

$$o_{Final} = \hat{Y} = f_2(net_o) \tag{4}$$

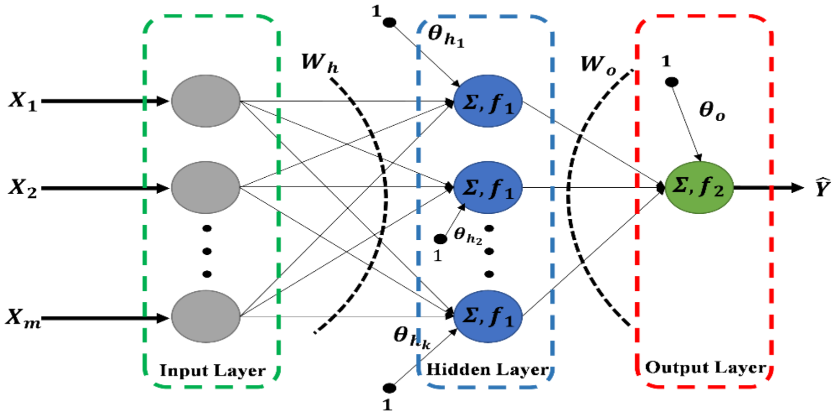

Figure 1. Feed forward ANN structure

2.2. Elman-feedback artificial neural networks (E-FBANN)

Feedback artificial neural networks, just like feed forward networks, were introduced to the literature by Werbos [12] and Rumelhart et al. [13] It is a type of multilayer perceptron developed by [13]. In these artificial neural networks, the last output or the outputs produced in the hidden layer are fed again as input or as input to the previous hidden layer units. Thus, they transmit information in neurons or layers both forward and backward. Feedback can occur within neurons as well as within neurons between layers. Thanks to this ability, non-linear processes also yield successful results. The feedback networks proposed by Elman [14], on the other hand, include the three layers in its structure, as well as the context layer, which displays the hidden layer outputs as input to the network. The network thus operates a feedback mechanism. An E-FBANN architecture is given in Figure 2.

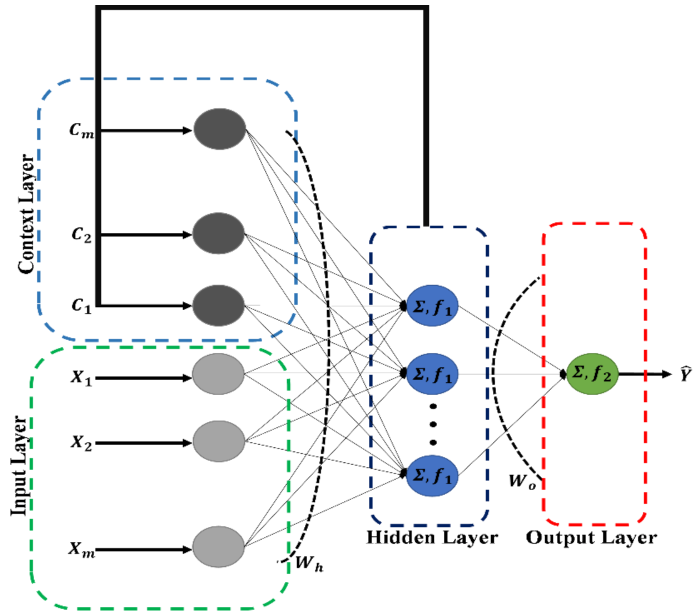

Figure 2. Elman-feedback ANN structure

3. Application

The insurance sector can be seen as a sector that directly affects the country's economy and development with its ability to fund financial markets and meet risks. In this respect, predicting the premium sizes, which is the main factor that constitutes the volume of the insurance sector, as accurately and reliably as possible, indirectly means foreseeing the risks that may arise in terms of the economy and development of the country and taking the necessary measures. One of the main aims of this study is to provide as accurate and reliable forecasts as possible, albeit to some extent, to the insurance sector and users in different fields. In this direction, between 2015 and 2021, the premium productions of 6 companies selected among the top 10 companies operating in Turkey have been predicted using different ANNs on a monthly and quarterly basis. For this purpose, two main ANN structures, FFANN and E-FBANN, have been used. Using Levenberg-Marquardt (LM) and Bayesian Regularization Backpropagation (BR) training algorithms, Both of the ANNs have been trained. Two different activation functions, sigmoid and linear, in the output layers of the networks, have been used. Eight different prediction models, thus, have been established to predict monthly and quarterly premium productions in 3 branches of 6 companies. These models can be listed as follows:

Model 1: FFANN - LM Training Algorithm - Linear Activation Function

Model 2: FFANN - LM Training Algorithm - Sigmoid Activation Function

Model 3: FFANN - BR Training Algorithm - Linear Activation Function

Model 4: FFANN - BR Training Algorithm - Sigmoid Activation Function

Model 5: E-FBANN - LM Training Algorithm - Linear Activation Function

Model 6: E-FBANN - LM Training Algorithm - Sigmoid Activation Function

Model 7: E-FBANN - BR Training Algorithm - Linear Activation Function

Model 8: E-FBANN - BR Training Algorithm - Sigmoid Activation Function

In practice, the number of ANN input layer units ($NoILU$), which we can call the model degree, or in short, the model input number is taken by changing it between 1 and 12. Similarly, the ANN hidden layer unit number ($NoHLU$) is taken by changing between 1 and 12. Thus, $12 \times 12 = 144$ different analyses have been performed for each ANN prediction model. During the applications, the time series is divided into two parts, the *training set*, and the *test set*. The training set has been used to train artificial neural networks. The test set has been used to evaluate the forecasting performance of ANNs and to reveal the reliability of the predictions. For monthly data sets with 84 data points, the test set size has been determined as 12 with a one-year prediction period. For monthly data sets with 28 data points, the test set size has been taken as 4 with a one-year prediction period again.

3.1. General application results

The obtained best results from 144 different analyses have been given in Table 1. The results have been summarized in terms of three error metrics for each branch of each insurance company. These error criteria are Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Median Absolute Percentage Error (MdAPE), which are given in equations (5)-(7).

$$RMSE = mean\left(\sqrt{Target_t - Predictied_t}\right) \ , t = \overline{1,T} \tag{5}$$

$$MAPE = mean\left(\left|\frac{Target_t - Predictied_t}{Target_t}\right|\right) \ , t = \overline{1,T} \tag{6}$$

$$MdAPE = median\left(\left|\frac{Target_t - Predictied_t}{Target_t}\right|\right) \ , t = \overline{1,T} \tag{7}$$

Here, T represents the # of predicted data points. Table 1 also includes the ANN models with the best prediction results and the architectural structure of these models.

When Table 1 is examined, considering that the primary expectation from a good prediction tool is to produce predictions with an error of around 10% or less, it is seen that errors above this error level are observed for some data sets in terms of the MAPE. However, this does not mean that the relevant foresight tools do not produce satisfactory results. Especially in terms of the MdAPE metric, which gives a median value of absolute percentage errors, it is seen that almost all data sets produce predictions with error levels at the sought level and below. This fundamental disadvantage of using the MAPE is that, although the prediction models produce predictions with very low error levels for many months within the 12-month period, especially in monthly data, the high prediction errors for one or a few months misleadingly raise the MAPE. The main reason for this is the mean-based formulation of MAPE, and the mean is known to be very sensitive to extreme values. On the other hand, since MdAPE is a median-based metric, it is not affected by high errors that do not reflect the overall error level. This feature makes the MdAPE more useful than the MAPE for the overall performance of the predictor. Although the results obtained in this respect are also given in terms of the MAPE criterion, the general evaluations were made over MdAPE. In this regard, in terms of MdAPE error criteria, in the analysis of 36 data sets, 18 quarterly of 18 monthly in total, the predictions for only 6 data sets were estimated with an error of more than 10%. In addition, 5 of them have been observed around 10% or slightly above, and these error levels are still acceptable. As can be seen in Figure 3, it can be said that for 55% of all analyses, predictions were produced with a median percentage error of less than 5%. It should be emphasized here that the error level is below the acceptable level for almost all months, except for a few, for the predictions obtained with an error of more than 10% on a monthly basis.

Table 1. The prediction results

Company	Period	Branch	Error Metric			The Best		
			RMSE	MAPE	MdAPE	Model	Architecture	
							$NoILU$	$NoHLU$
A	Monthly	Health	54587	31.47%	17.87%	Model 7	2	9
		Auto Insurance	16341	11.83%	4.79%	Model 6	11	10
		Traffic Insurance	69123	17.92%	9.49%	Model 5	4	6
	Quarterly	Health	53781	40.22%	4.13%	Model 3	4	4
		Auto Insurance	49842	10.04%	2.60%	Model 5	1	3
		Traffic Insurance	85987	9.45%	1.66%	Model 3	4	4
B	Monthly	Health	80866	11.93%	6.41%	Model 3	6	2
		Auto Insurance	10224	6.83%	4.34%	Model 8	11	11
		Traffic Insurance	33682	12.55%	6.99%	Model 3	7	2
	Quarterly	Health	49862	3.71%	1.94%	Model 3	4	3
		Auto Insurance	25721	4.78%	2.91%	Model 5	4	4
		Traffic Insurance	30251	5.81%	4.98%	Model 4	1	4
C	Monthly	Health	11014	8.46%	7.01%	Model 2	11	2
		Auto Insurance	25723	10.78%	8.41%	Model 3	12	4
		Traffic Insurance	27018	9.99%	3.46%	Model 4	5	2
	Quarterly	Health	32656	5.67%	1.25%	Model 2	3	2
		Auto Insurance	22029	3.60%	2.01%	Model 6	4	4
		Traffic Insurance	13798	1.99%	1.42%	Model 4	3	4
D	Monthly	Health	22824	17.94%	7.90%	Model 8	9	2
		Auto Insurance	20327	14.95%	10.02%	Model 1	12	8
		Traffic Insurance	27949	10.34%	6.13%	Model 4	4	3
	Quarterly	Health	7697	4.99%	3.67%	Model 4	3	3
		Auto Insurance	28559	5.18%	0.74%	Model 4	2	3
		Traffic Insurance	11320	1.85%	1.00%	Model 2	3	4
E	Monthly	Health	11833	14.42%	9.38%	Model 4	12	10
		Auto Insurance	17191	9.45%	6.50%	Model 2	12	3
		Traffic Insurance	18846	14.47%	12.88%	Model 2	6	5
	Quarterly	Health	20613	6.72%	2.78%	Model 4	4	3
		Auto Insurance	13637	4.31%	4.54%	Model 5	4	4
		Traffic Insurance	19624	7.48%	5.79%	Model 2	4	4
F	Monthly	Health	4652	17.69%	11.82%	Model 4	11	4
		Auto Insurance	19360	9.63%	4.34%	Model 2	4	4
		Traffic Insurance	45085	14.22%	12.89%	Model 3	6	2
	Quarterly	Health	41447	2.36%	2.81%	Model 2	3	3
		Auto Insurance	4670	0.81%	0.86%	Model 4	4	3
		Traffic Insurance	27138	10.75%	11.02%	Model 3	3	4

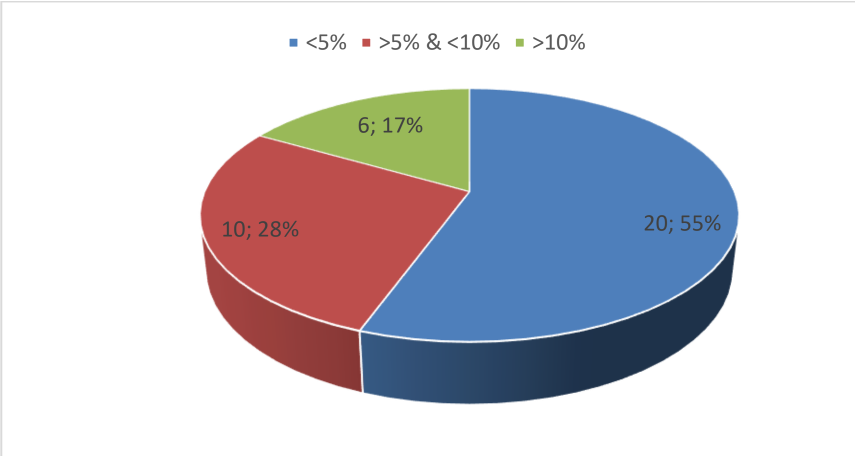

Figure 3. Artificial neural network results

3.2. Company and branch-based evaluation of results

Within the scope of this study, the premium productions of 6 companies selected among the top 10 companies operating in Turkey in terms of premium volume, on the basis of 3 different branches, were analysed with different ANN models in monthly and quarterly periods. Under this subsection, for a chosen company among six companies, a detailed performance evaluation has been carried out by presenting actual observations and forecast values together with graphs (Figure 4-9) regarding the situations in which the best forecast performances.

When the predictions of the health branch against the observations are analysed on a monthly basis, as given in Figure 4, it is observed that the actual premium productions and the predictions are generally in line except for the 1st, 5th, 10th, and 12th months. Although the observations and predictions for the months with the said observations are relatively far, it is seen that directional accuracy has been achieved.

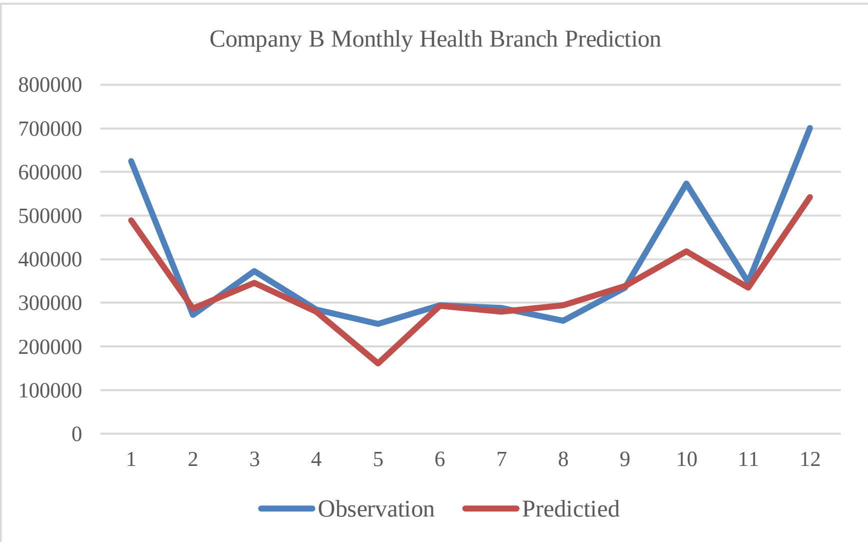

Figure 4. Company B monthly health branch prediction

When the predictions of the auto insurance branch against the observations are investigated on a monthly basis, as given in Figure 5, it is observed that the actual premium productions and the predictions are generally quite compatible with each other except for the 3rd and 8th months. While the observations and predictions for the months with the said observations are relatively far, it is seen that directional accuracy has been achieved.

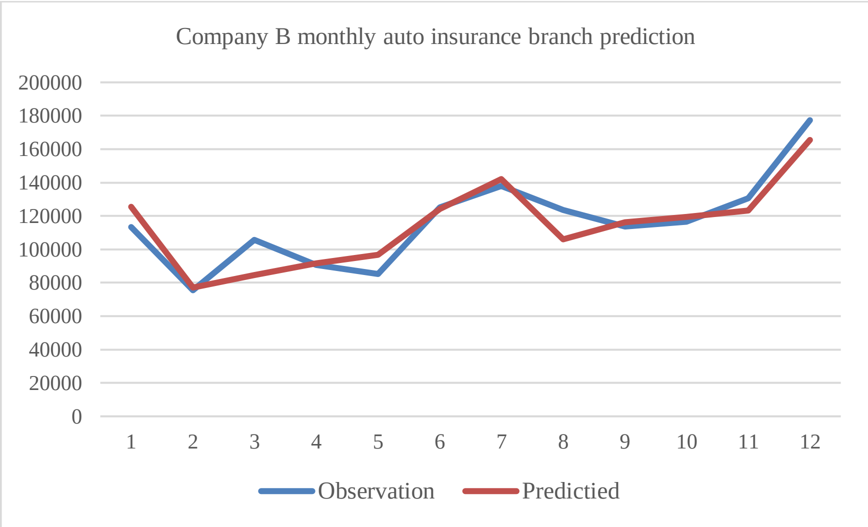

Figure 5. Company B monthly auto insurance branch prediction

When the predictions of the auto insurance branch against the observations are analysed on a monthly basis, as given in Figure 6, it is observed that the actual premium productions and the predictions are generally quite compatible with each other except for the 6th and 11th months. Although the observations and predictions for these two months with the said observations seem relatively far, it is also seen that directional accuracy has been provided again.

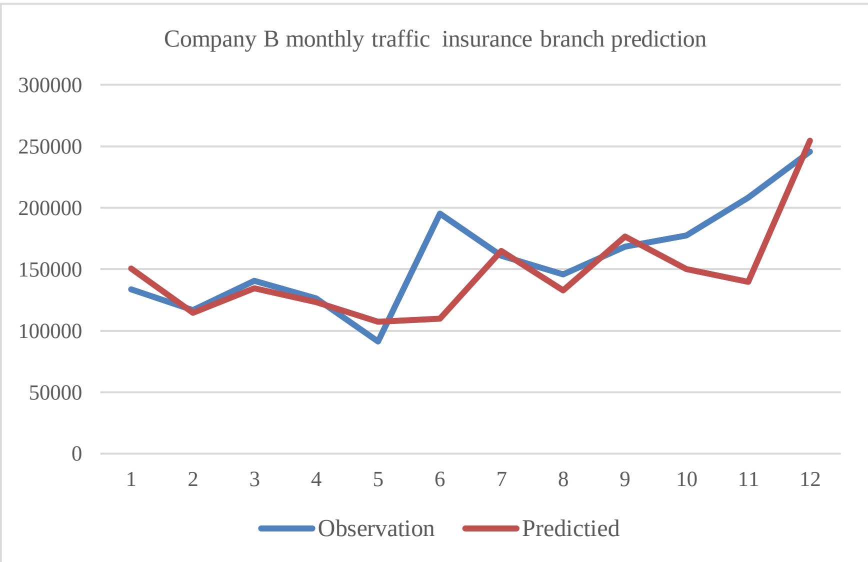

Figure 6. Company B monthly traffic insurance branch prediction

When the predictions of Company B in Figure 7 regarding the health branch are considered on a quarterly basis against observations, it is seen that the predictions obtained are in almost perfect harmony with the actual premium production. Obtaining this outstanding harmony can be seen as another indication that highly superior prediction results have been achieved.

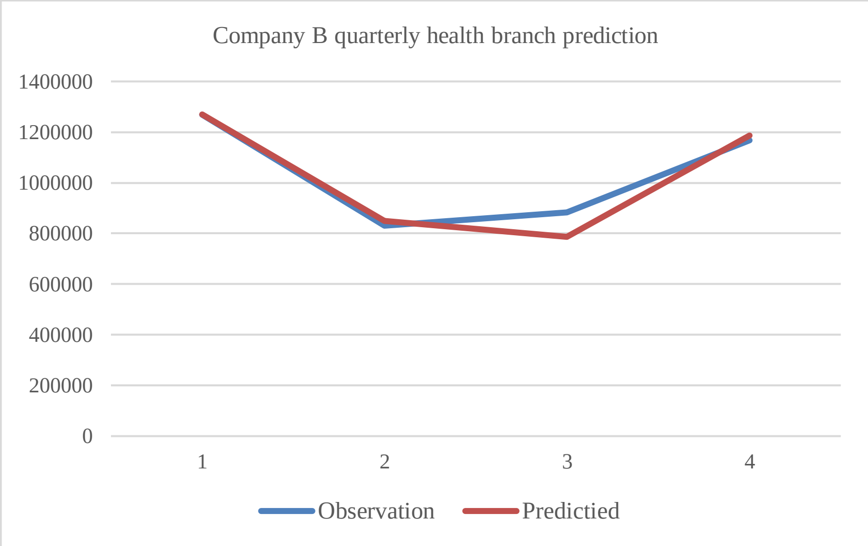

Figure 7. Company B quarterly health branch prediction

When the predictions of the B Company auto insurance branch, given in Figure 8, are evaluated on a quarterly basis against the observations, it is observed that the forecasts for the 1st and 4th quarters are in perfect harmony with the actual premium values. And also, very satisfactory prediction results have been obtained for the 2nd quarter.

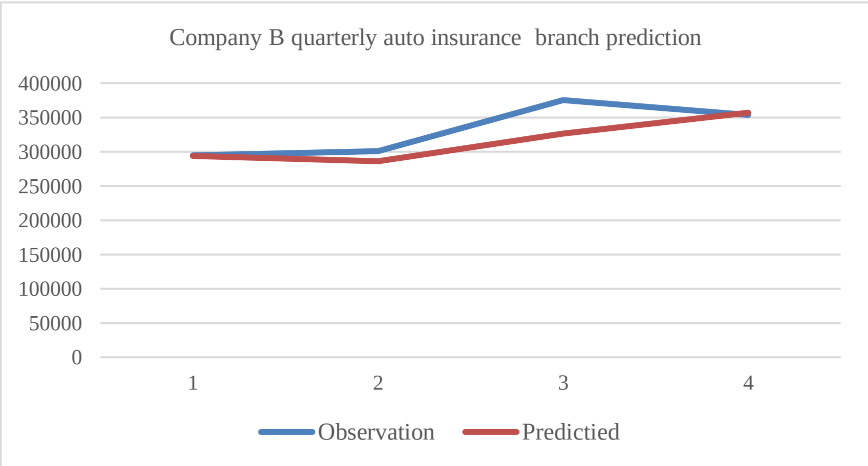

Figure 8. Company B quarterly auto insurance branch prediction

When obtained predictions for B Company in the traffic branch, given in Figure 9, are investigated on a quarterly basis against the observations, it is seen that the predictions for all periods are quite consistent with the actual observations.

4. Conclusion and Suggestions

It can be said that the data on the insurance sector can be used as an indicator of the development and welfare levels of the countries. In this respect, accurate and reliable prediction of data on the insurance sector becomes an important element in taking realistic and effective decisions for the future, both in terms of the sectoral and national economy and sociology. From this point of view, this study is aimed to predict the premium production sizes in 3 different areas of 6 companies that are selected among the top 10 companies actively operating in Turkey and considering the premium volume. For this purpose, data sets with 84 observations on a monthly basis and 28 observations on a quarterly basis have been recorded between the years 2015-2021, and premium production sizes for the last year were predicted. Two basic ANN structures, FFANN and E-FBANN, have been used as estimation tools. A total of 8 different models based on artificial neural networks were created by training these neural networks with LM and BD training algorithms and using linear and sigmoid activation functions in the output layer units.

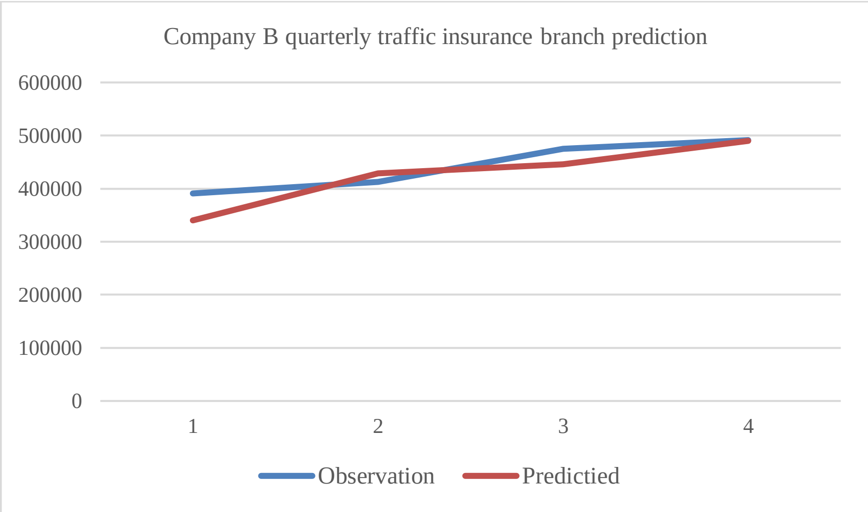

Figure 9. Company B quarterly traffic insurance branch prediction

If the data sets produced in the insurance sector are considered as a financial time series, when the relevant literature is examined, although ANNs are widely used in the estimation of financial time series, no study has been found that deals with the size of premium products on the basis of companies and branches in the insurance sector of our country. In this respect, this study also aimed to fill this gap, which is thought to exist in the literature.

As a result of the analyses carried out in order to foresee three different branches of six different insurance companies on a monthly and quarterly basis among the insurance companies active in Turkey with high premium production:

➢ On a monthly basis;

- While the prediction results of the health branch can be obtained with an error in the 6-10% band in terms of MdAPE criteria, it can be said that these error levels are at an acceptable level. However, especially the health branch belonging to a company (Company A) could be estimated with a median error of approximately 17%. So, it should be said that this prediction performance seems to need improvement.
- While predictions for the auto insurance branch can generally be obtained with an error in the range of 4-10%, considering that these error levels are at an acceptable level, especially for three companies (Companies A, B, and F), this level is approximately 4%. It can be said that successful prediction performances have been exhibited for this branch.
- While the prediction results obtained for the traffic insurance branch can be produced with an error of approximately 3-9% in terms of MdAPE criteria, it can be said that these error levels are at an acceptable level and indicate a successful prediction performance, except for two companies. However, the traffic insurance branch of the two companies (Companies E and F) can be estimated with a median error of approximately 12%. Thus, it should be said that these forecasting performances need improvement.

➢ On a quarterly basis;

- While the prediction results of the health branch can be obtained with an error in the 2-4% band in terms of MdAPE criteria, it can be said that these error levels are at a very low level and prediction performances with these error levels are quite successful. Especially for companies B and C, the median percent error level dropped below 2%, indicating a near-perfect forecasting performance.
- Predictions for the auto insurance branch can generally be obtained with an error in the 2-4% band. Considering that these error levels are very low for this branch and even below 1% for two companies (firms D and F), it can be said that near-perfect forecast performances are displayed.
- While the prediction results of the traffic insurance branch can be produced with approximately 1-5% error in terms of MdAPE criteria, it can be said that these error levels are at a very low level and indicate a successful estimation performance. In addition, the traffic branch premium production volumes of especially three companies (Companies A, C, and D) are predicted with a median error of approximately 1%, which indicates an extraordinary prediction performance. However, the premium production size of a

company's (Company F) traffic insurance branch could be estimated with a median error of approximately 11%, and this prediction performance needs to be improved.

In general, the prediction results obtained reveal that the premium production volume in 3 different areas of 6 companies actively operating in Turkey can be successfully estimated with the estimation models based on ANNs established in this study. In this way, meaningful and useful results can be obtained by using ANNs in foresight studies in the insurance sector, and thus, it will be possible to have an idea beforehand in cases where actions that may positively affect the profitability of the company should be taken.

However, it can be concluded that forecasting tools used to estimate premium sizes, which are formed by the effect of the pandemic process and current economic fluctuations and differ from general premium production trends, should be developed. In future studies, different methods can be tried in this area. Among these, the use of artificial neural networks with robust (robust) training algorithms or durable architectural features can be preferred. In addition, using neural networks having deeper architectures can be seen as a potential alternative that can improve prediction accuracy.

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