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Analyse the Most Significant Components for Forecasting the Herfindahl-Hirschman Index Using an Adaptive Neuro-Fuzzy Technique

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Abstract
It is important to note that the link between investment in company and competitiveness in the product market is rather complicated. It is possible that the connection is favourable on the one hand, but it is also possible that it is bad on the other side. For the goal of designing measures to reduce or remove market power, a number of different procedures have been presented as potential approaches to evaluate market power. Indices, such as the Hirschman-Herfindahl Index (HHI), are employed in the majority of the methodologies that are often used. Given that the Herfindahl-Hirschman Index (HHI) is a very sensitive indicator, the primary objective of this research was to investigate the ways in which various economic and business factors influence projections of the HHI. In order to examine the data and identify the most important parameters for predicting HHI, an adaptive neuro fuzzy inference system, also known as an ANFIS, was used. According to the findings of the study, the variable that has the most significant impact on HHI projections is the number of workers.

Keywords: ANFIS forecasting, Herfindahl-Hirschman Business

Introduction

A diversity in the size of firms within an industry or the economy as a whole is one phrase that is occasionally used to explain the phenomenon of economic power concentration. For the purpose of evaluating market efficiency and the policy implications of anti-monopoly laws (AMLs), it is essential to conduct research on the concentration of economic power and its development over time. The topic of monopoly is one that is both basic and necessary. For empirical research on market efficiency evaluation and the repercussions for anti-money laundering legislation, its trajectory is of the utmost importance. Within the context of dealing with limited survey data, it is of the utmost importance to correctly determine the real trend. Because of their flawed accounting system and the growing number of bigger businesses over time, this is very important for countries that are rapidly industrialising and developing.

While assessing the level of rivalry in the product market, we only utilise one statistic. In order to assess competitiveness at the industry level, the Herfindahl-Hirschman index (HHI) is used. This index is computed by adding up the squared market shares of businesses that are competing in each industry for each country-year combination. As a result of the fact that every company operating within a given industry has the same HHI value, this measure demonstrates the disparities in competitiveness that exist across industries and unveils the market power that is possessed by every company operating within that sector. When the Herfindahl-Hirschman Index (HHI) is greater, it suggests that there is less rivalry in the market and better control over the market.

In the conclusion of article, it was determined that more concentration in the system, as evaluated by the HHI, results in enhanced financial stability for banks. Increasing market power in circumstances of low concentration does not inevitably result in a reduction in competitiveness, according to research, which revealed that this phenomenon occurs [1, 2]. In the work, an improved version of the Herfindahl-Hirschman Index (HHI) was developed in order to consider candidates that are close options. This modified index was shown to have a higher performance than the standard indicator, according to the results. For the purpose of determining the real movements that have occurred in China's industrial market monopoly, an alternative measure of HHI was developed. In this research, the relevance of firm-level, industry-level, and country-level factors in predicting the ownership concentration of enterprises was studied. According to the findings of an econometric analysis conducted on a panel data set consisting of seven European countries, there seems to be a connection between nonlinear pricing and the growing monopolistic dominance in European banking. Companies that have a strong market position and a high level of industrial concentration have a greater capacity to estimate their profitability and have less uncertainty about the information they have access to. In the meanwhile, governmental institutions that encourage competition effectively constrain the power of the market. The influence of leverage on performance is amplified when there is competition in the product market [3-8]. There is a non-linear relationship between leverage and product market competition, which may be either parabolic or cubic in nature. This relationship changes depending on the industry, the size of the business, and the growth possibilities of the firm.

It is normal practice to make use of the HHI, and it is often the target of criticism. One of the most significant limitations of the HHI is that it is susceptible to the proper representation of the market, which includes geographical limitations and product similarities. Concerning the resilience in relation to the market definition, there are two basic types of criticisms: those that dispute the relationship between concentration and market power, and those that attack the market definition itself.

In spite of the fact that various new mathematical functions have been developed specifically for this purpose, the primary objective of this research is to overcome the large nonlinearity that is present in HHI analysis via the use of soft computing approaches. It is possible to employ artificial neural networks (ANN) as an alternative to analytical approaches because they provide a number of benefits, including the fact that they do not need knowledge of the features of the system that is being analysed and that they provide succinct solutions to difficult issues that include several variables. An artificial neural network known as the Adaptive Neuro-Fuzzy Inference System (ANFIS) was used in the research project in order to determine the most important factors that should be considered when forecasting the Herfindahl-Hirschman Index (HHI) by using data from a variety of nations. ANFIS is a strong tool that may be used to handle uncertainties in any system since it exhibits great learning and forecasting skills. In a number of different engineering systems, researchers made use of ANFIS, which is a hybrid intelligence system that is well-known for its ability to learn and change on its own [12-15]. There have been a number of studies that have been carried out on the use of ANFIS for the purpose of estimating and recognising different systems in real time.

Methodology

Statistical Data

When it comes to economics, the Herfindahl index, which is also widely referred to as the Herfindahl–Hirschman Index or HHI, is used to quantify the concentration of industries. It may be approximated by utilising the equation (1), which states that it is defined as the sum of the squares of all of the market shares that are held by enterprises operating within a certain industry. The Herfindahl index ranges from 1/N, which suggests that there is perfect competition, to 1, which indicates that there is complete monopoly. Here, N is the number of businesses that are present in the market. Higher values imply a stronger market concentration, a lower level of market competition, and a greater degree of market dominance by certain businesses, while lower values indicate the opposite of these characteristics.

$$H = \sum_{i=0}^{N-1} s_i^2 \quad (1)$$

where is the market share of the ith firm and N is the number of firms in the market?

The Herfindahl index considers the quantity and market share of all market participants and provides a thorough measurement of industry concentration. To determine the concentration of the spectrum, a comparable definition is constructed, as shown in Eq (2).

$$H(N) = \sum_{i=0}^{N-1} s_k^2 \qquad (2)$$

where $s_i = \frac{|X[k]|^2}{\sum_{i=0}^{N-1}|X[i]|^2}$ is the percentage of total energy at the kth frequency, and N is the number of points to be converted.

If HHI is 0 it means the perfect market concentration. If HHI is 10000 it means total market monopoly. Table 1 shows the HHI and different business performances in period of 2017-2021 for several countries in Europe. Three inputs are identified which are analyzed for the HHI forecasting. The following groups can be noted according to the HHI:

- HHI < 1.000 – competitive market,
- 1.000 < HHI < 1.800 – small market concentration and
- HHI > 1.800 – high market concentration [23].

Table 1: Business performances in period of 2017-2021 [23-25]

		Output	Input 1	Input 2	Input 3
Country	Year	HHI index	Number of companies	Number of workers	Bonus per capita
Serbia	2017	1.23	26	11,142	79
	2018	1.12	28	11,289	73
	2019	1.12	28	11,283	77
	2020	1.13	28	11,408	76
	2021	1.09	28	11,480	78

Croatia	2017	1.13	27	11,184	88
	2018	1.02	26	11,085	96
	2019	1.12	26	11,259	90
	2020	1.10	27	11,652	81
	2021	1.00	26	11,533	80
Slovenia	2017	0.74	18	6,269	1,019
	2018	0.75	19	6,091	1,023
	2019	0.79	19	6,056	987
	2020	0.84	25	6,062	983
	2021	0.87	24	5,970	984
Bulgaria	2017	0.72	325	8,600	114
	2018	0.66	367	8,782	111
	2019	0.81	417	8,711	110
	2020	0.91	468	8,624	110
	2021	1.01	498	8,612	110
Romania	2017	1.25	45	15,083	88
	2018	1.20	43	9,220	96
	2019	1.10	43	8,230	90
	2020	1.05	41	11,837	81
	2021	0.99	38	12,299	81
Greece	2017	1.10	82	9,000	480
	2018	1.03	73	9,000	468
	2019	0.79	69	8,000	439
	2020	0.81	69	8,000	388
	2021	0.85	66	8,000	388
Hungary	2017	1.14	82	23,914	306
	2018	1.14	73	25,003	303
	2019	1.09	69	24,493	261
	2020	1.00	69	21,113	264
	2021	0.87	66	20,361	263
Austria	2017	0.63	72	26,732	1,965
	2018	0.75	72	26,538	1,999
	2019	0.76	72	25,794	1,958
	2020	0.78	70	26,094	1,937
	2021	0.80	69	26,124	1,935

ANFIS Methodology

MATLAB's fuzzy inference technology is used throughout the whole ANFIS training and assessment procedure. Figure 1 illustrates an ANFIS network with two input variables.

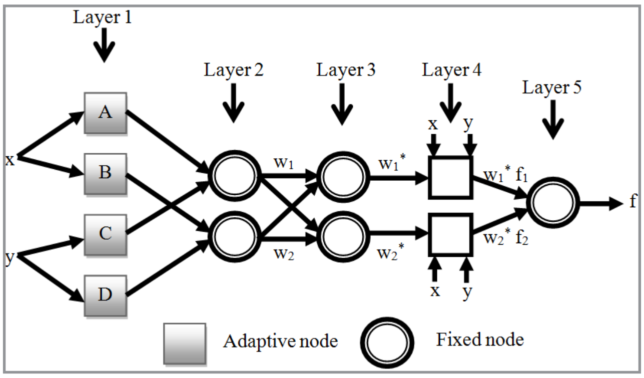


Figure 1. ANFIS structure

For the objectives of this research, the fuzzy IF-THEN rules of Takagi and Sugeno's class and two inputs for the first-order Sugeno are applied:

$$if\ x\ is\ A\ and\ y\ is\ C\ then\ f_1 = p_1x + q_1y + r_1 \quad (3)$$

The first layer consists of input parameters MFs, which supply input values to the subsequent layer. Each node in this network is an adaptive node with a node function and where and are functions associated with membership. The membership functions chosen have a bell shape and have a maximum value of (1.0) and a minimum value of 0.0. Some examples of these functions include,

$$\mu(x) = bell(x; a_i, b_i, c_i, d_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (4)$$

where is the list of parameters. As the name suggests, the parameters of this layer are known as the premise parameters. In this case, x and y serve as inputs to the nodes.

The second layer is the membership layer. It attempts to determine the weights of each membership function. This layer receives the receiving signals from the previous layer and then functions as the membership function for the fuzzy set representations of each input variable. Nodes in the second layer are not adaptable. The layer functions as a multiplier for the received signals and transmits the resulting signal in $w_i = \mu_{AB}(x) * \mu_{CD}(y)$ form. The firing strength of a rule is shown by each and every output node.

The third layer, which comes next, is referred to as the rule layer. Every neuron in this layer performs the function of a precondition in order to meet the fuzzy rules; specifically, the activation level of each rule is determined, and the number of fuzzy rules is proportional to the number of layers. Each node is responsible for computing the normalized weights. Additionally, the nodes that make up the third layer are deemed to be non-adaptive. Each of the nodes does the computation necessary to determine the value of the rule's firing strength relative to the total firing strengths of all rules using the form of $w_i^* = \frac{w_i}{w_1+w_2}, i = 1,2.$ The outcomes are refered to as the normalized firing strengths.

The provision of output values as a direct consequence of the derivation of rules falls within the purview of the fourth layer. In certain contexts, this layer may also be referred to as the defuzzification layer. Each and every node on the fourth layer is an adaptive node that has the node function $O_i^4 = w_i^* xf = w_i^*(p_ix + q_iy + r_i)$. In this layer, the $\{p_i, q_i, r\}$ is the variable set. The variable set is designated as the consequent parameters.

The fifth and last layer is called the output layer. It totals all inputs received from the previous layer. The system then turns the fuzzy categorization results into a binary value (crisp). The solitary node of the fifth layer is non-adaptive. This node computes the output total as the sum of all received signals,

$$O_i^5 = \sum_i w_i^* xf = \frac{\sum_i w_i f}{\sum_i w_i} \quad (5)$$

The identification of variables included within the ANFIS designs was accomplished via the use of hybrid learning approaches. The functional signals continue to progress until they reach the fourth layer, which is the point at which the hybrid learning process is finally effective. Furthermore, the estimate of least squares is used in order to ascertain the variables that are subsequently derived. While performing the backward pass, the error rates are iterated in the opposite direction, and the premise variables are sychornized in the order of the gradient drop.

Results

Evaluating Accuracy Indices

The forecasting capabilities of the suggested model were provided as root mean square error, Coefficient of determination, and Pearson coefficient (r). These numbers are described as follows:

1) root-mean-square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \quad (6)$$

2) Pearson correlation coefficient (r)

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \quad (7)$$

3) coefficient of determination (R2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \quad (8)$$

where Pi and Oi are experimental and forecast values of, respectively, and n is the total number of test data.

ANFIS Results

The ideal combination of inputs (Table 1) that has the greatest significant influence on the output parameters (HHI) was determined by an exhaustive search that was carried out. A single session of training is followed by the construction of an ANFIS model, which is effectively constructed by the functions for each combination. After then, the actual performance is detailed in the documentation. As can be seen in Figure 2, the most significant input that was considered for anticipating the output was recognised and established at the beginning of the process. The input variable that displays the least amount of training error has the most influence on the result that is ultimately achieved. There are the fewest faults in the input variables that are located on the left, and they have the biggest influence on the output (HHI). As can be seen in Figure 2, the input parameter "number of employees" has the least amount of root mean square error (RMSE) and the most significant impact on the HHI prediction. Input 1 has the biggest root mean square error (RMSE), which means that it has the least impact on HHI predictions.

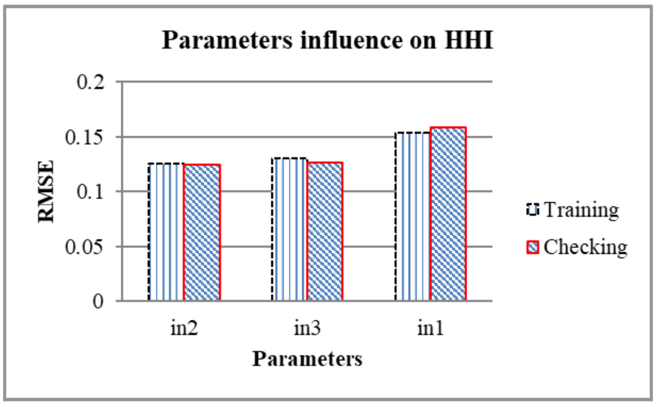


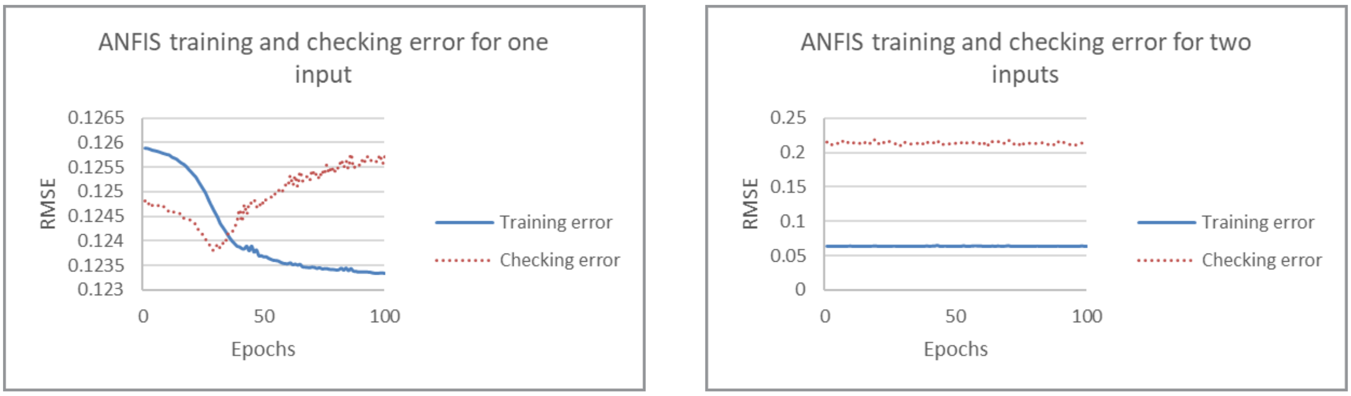
Figure 2: Every input parameter's influence on HHI

Table 2 displays the numerical findings for the effect of all single factors on the HHI as well as the influence of the two inputs combinations on the HHI predictions. According to the data, the ideal combination for HHI forecasting is the number of employees and bonus per capita. The chosen combinations with one and two parameters are retrieved for further study.

Table 2: Input parameters influence on forecasting of the HHI

One input	Two inputs
ANFIS model 1: in1 --> trn=0.1535, chk=0.1588	ANFIS model 1: in1 in2 --> trn=0.0725, chk=2.6702
ANFIS model 2: in2 --> trn=0.1259, chk=0.1248	ANFIS model 2: in1 in3 --> trn=0.0637, chk=0.2155
ANFIS model 3: in3 --> trn=0.1303, chk=0.1262	ANFIS model 3: in2 in3 --> trn=0.0890, chk=0.7220

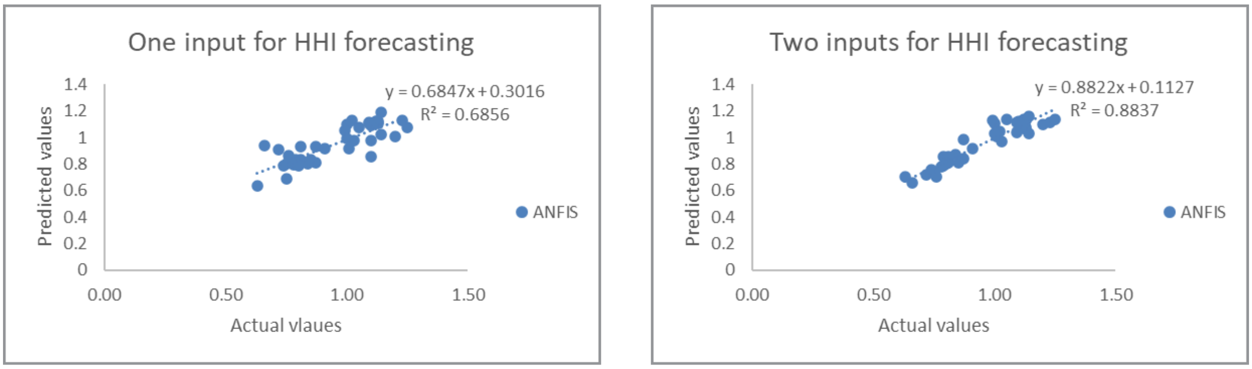
For the purpose of facilitating the rapid identification of the appropriate inputs, the training function for each variable in ANFIS is limited to a single epoch inside the system. Following the selection and extraction of the input combinations, the ANFIS model is trained for a total of one hundred epochs using the inputs that have been provided in order to evaluate the degree of overfitting that exists between the training data and the validation data. The error curves for the three extracted input pairs are shown in Figure 3, which depicts the results of one hundred training and testing rounds. Both the solid and dotted curves are representations of mistakes that occurred during training and validation, respectively. Figure 3 depicts a strong connection between training data and testing data for a particular input combination. This association is especially evident when the validation error becomes closer and closer to the training error. Considering that the checking error is greater than the training error for the two input combinations shown in Figure 3(b), this suggests that there is an overfitting between the training data and the checking data.



(a) (b)

Figure 3: Training and checking errors of ANFIS for two extracted combinations for (a) one and (b) two inputs

The scatter plots of the ANFIS forecasting for the ideal combinations of the input parameters that were supplied for the HHI are shown in Figure 4. Having a coefficient of determination that is very high may provide evidence that this observation is accurate. There are very few instances in which the values that are created are either improperly computed or undervalued. Consequently, it should not come as a surprise that the numbers that were forecasted were quite accurate. When compared to other possible combinations, the coefficient of determination indicates that combining two inputs may lead to more accurate predictions than any other possible combination.



(a) (b)

Figure 4: ANFIS scatter plots for forecasting of HHI for (a) one input and (b) two inputs

A comparison of the prediction accuracy of the three models was carried out in order to provide a more lucid illustration of the advantages offered by the suggested models. For the purpose of comparison, the values of RMSE, r, and R2 were employed as statistical markers of standard error. The results of the forecasting to determine the accuracy of the inputs that were used to anticipate the HHI are shown in Table 3.

Table 3: Statistical results for forecasting of the HHI for the two selected combinations

HHI forecasting for one input	r	0.828017
	R2	0.6856
	RMSE	0.095838
HHI forecasting for two inputs	r	0.940027
	R2	0.8837
	RMSE	0.058303

Figure 5 depicts the graph of the model for the ANFIS input-output (decision) surface for predicting the HHI. Figure following also depicts the ANFIS model's reaction to different input parameters.

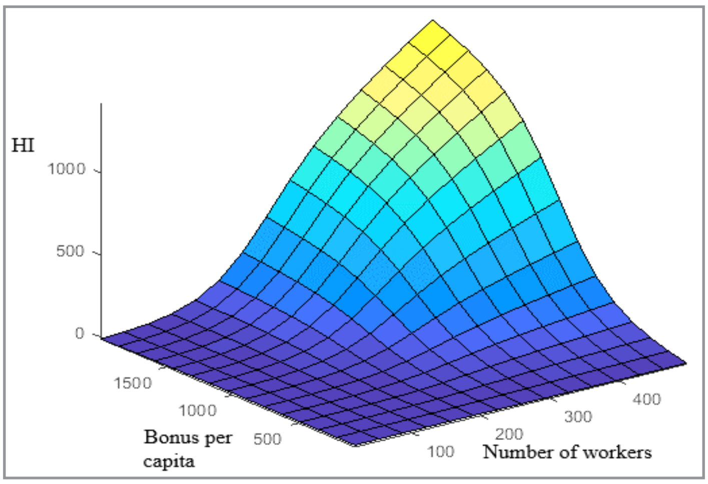


Figure 5: ANFIS forecasted relationship for HHI forecasting according to the two selected inputs

Conclusion

There is a significant level of rivalry in product marketplaces, which is an essential component of the industry that adds to the informational and financial instability that commercial firms suffer. It has been shown via both theoretical and empirical study that competition in the product market has an effect on the disclosure practices of private companies. When it comes to making forecasts, financial analysts use on inputs such as earnings attributes and corporate disclosures. The amount of competition in product marketplaces may have an effect on these assumptions. There is a growing recognition among economists working in finance and industry that there is a connection between the competitiveness of product markets and the choices that corporations make about financing. The Herfindahl-Hirschman index (HHI) was taken into consideration in this article in order to evaluate the degree of competition that exists within the industry.

There are a variety of indications and factors that have an impact on the Herfindahl-Hirschman Index (HHI), which makes it difficult to make accurate predictions about its future movement. In this research, a novel approach was proposed as a means of handling the difficulties associated with forecasting the HHI. By using this approach, it is necessary to eliminate some input variables that are not essential.

By using the ANFIS method in a methodical manner, the identification of the components that have the most significant impact on the HHI projection was carried out. The use of ANFIS leads to ideal forecasting circumstances and decreases the amount of uncertainty that is present in the HHI. The complicated array of performance characteristics is transformed into a unified multi-response performance index via the use of the ANFIS model. The approach for predicting economic growth analysis that was established in this study is helpful for improving a variety of economic growth indicators. Based on the findings of the study, it has been determined that the HHI projections are most significantly impacted by the number of persons who are actively executing the task.

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