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Estimating the Romanian Economic Sentiment Indicator Using Artificial Intelligence Techniques

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Abstract

The subject of the present paper represents the result of a research that uses artificial intelligence,

through the artificial
neural networks, in order
to simulate the Romanian
Economic Sentiment
Indicator (ESI-mentioned
by The Economist and

provided by the European Commission – Economic and Financial Affairs website). The reason for the research is to determine a better method

to forecast the Romania ESI considering its nonlinear behavior. For the simulation, a feed forward artificial neural network (ANN) was used. For this

type of ANN, the best training algorithm is the back propagation algorithm. Training condition were set to a smaller than 5% error

between the real data and the simulated data. The research is then extended to new input data (not available at the time of ANN training) used for

comparison and forecasting of the real trends with the simulated ones. Even with new data, the use of the ANN determined forecasting

results smaller than 5% (between -4.92; 5.16%). Also the ANN simulation offers an image about how indicators influence the ESI. In conclusion, the use

of the ANN is considered a success and the authors determine the possibility that ANN research application be extended to

other countries ESI or even
to the European zone

Keywords: Artificial intelligence, Artificial Neural Network (ANN), Economic Sentiment Indicator.

Introduction

The confidence in
Romanian economy can be
a very exciting subject
considering the way

Romanians see the economic development and also from a foreign point of view. Also it is necessary to have a forecast of several indicators in order to

invest in certain economic fields and Economic Sentiment Indicator (ESI) is one of them. But what is the way to do it if the calculated ESI is different

from the real sentiment about the country economy? As presented in chapter 3, the ESI is calculated using five sector-specific confidence

indicators. But is this calculus representative of the real sentiments about countries' economies? The researchers think that the real confidences in

economies are more nonlinear which can be determined with calculus. This is why Artificial Neural Networks are used to see if these types of

methods can provide a better forecast than the simple calculus. The artificial neural networks have proved their effectiveness in simulating

the nonlinear processes
and phenomenon;
moreover, they offer in
almost all researches
superiority over the other
simulating methods.

The researchers knew that ANN can learn from the past ESI values, considering the five sector-specific confidence indicators, and they

thought that the ANN will forecast accurate values of the ESI.

The data used for the all the trainings and

simulations were taken
from European
Commission – Joint
Research Centre website:
[http://composite-
indicators.jrc.ec.europa.eu/](http://composite-indicators.jrc.ec.europa.eu/)

CI_Econ0001.htm in
January 2011.

The objectives of the
research are as follows:

1. Building, training and validating a specific ANN for the simulating of the Economic Sentiment Indicator considering five sector-

specific confidence indicators and the imposed conditions;

2. Testing the trained ANN in order to check that

the difference between
the real data and the
simulated is smaller
than 5%;

3. Determining the trend of Economic Sentiment Indicator with the trained ANN;

4. Establishing the sustainability of future ANN use for the forecast of the ESI.

Artificial Neural Network (ANN)

Today, Artificial Neural Network (ANN) can be found in the majority of the

human life activity, their potential being considered immense. Starting with the human brain and continuing with the actual common application of the

ANN, their use effectiveness is demonstrated as can be seen in Akira Hirose's book "Complex-valued neural networks: theories and

applications" [World Science Publishing Co Pte. Ltd, Singapore, 2003].

Regardless of the type, ANN has a few certain

common unchallengeable
elements mentioned by
Zenon WASZCZYSZYN in
his book: "Fundamentals of
Artificial Neuronal
Networks" [Institute of

Computer Methods in Civil Engineering, 2000]:

- micro-structural components: processing

elements – neurons or nodes

- input connections of the processing elements

- output connections of the processing elements
- the processing elements can have optional local memory transfer

(activation) function,
which characterizes the
processing elements.

Figure 1. Schematic Representation of a Multilayer ANN

**Please see Figure 1 in Full
PDF Version**

The schematic graphic representation of a multilayer ANN is presented in figure 1, where x_i ($i = \overline{1, N}$) is the input ANN values, H_1 and H_2 are the

numbers of neurons from the first and second hidden layer, M is the number of neurons from the output ANN layer and y_j ($j = \overline{1, M}$) is

the values of the output
data.

The Economic Sentiment Indicator (ESI)

The Economic Sentiment Indicator is used in order to combine business

tendency surveys into a single cyclical composite or confidence indicator with a view to reduce the risk of false signals and provide a cyclical indicator with

better forecasting and tracking qualities than any of its individual components, as defined by The European Commission

[http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.htm].

Economic Sentiment Indicator purpose is to track GDP growth at Member State, EU and euro-area level. The ESI can be viewed as a

summary of the five sector-specific confidence indicators

[http://ec.europa.eu/economy_finance/db_indicators]

/surveys/documents/user
guide_en.pdf].

1. Industrial confidence indicator (INDU). The industrial confidence

indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on

production
expectations, order
books and stocks of
finished products (the
last with inverted sign).
Balances are seasonally

adjusted

[http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/userguide_en.pdf].

2. Services confidence indicator (SERV). The services confidence indicator is the arithmetic average of the balances (in

percentage points) of the answers to the questions on business climate and on recent and expected evolution

of demand. Balances are seasonally adjusted.

3. Consumer confidence indicator (CONS). The consumer confidence

indicator is the arithmetic average of the balances (in percentage points) of the answers to the questions on the

financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and

savings, all over the
next 12 months.

Balances are seasonally
adjusted

[http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/userguide_en.pdf].

4. Retail trade confidence indicator (RETA). The retail trade confidence indicator is the arithmetic average of the balances (in

percentage points) of the answers to the questions on the present and future business situation and on stocks (the last with

inverted sign). Balances
are seasonally adjusted

[http://ec.europa.eu/economy_finance/db_indi

cators/surveys/documents/userguide_en.pdf].

5. Construction confidence indicator (BUIL). The

construction confidence indicator is the arithmetic average of the balances (in percentage points) of the answers to the

questions on order
book and employment
expectations. Balances
are seasonally adjusted

[http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/userguide_en.pdf].

6. Economic Sentiment Indicator purpose is to track GDP growth at Member State, EU and euro-area level. The ESI can be viewed as a

summary of the five
sector-specific
confidence indicators.

The exact calculation of the ESI on the basis of its component series can be summarized by the following three simple steps

[http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/user_guide_en.pdf]:

1. For each component
 $n=1, \dots, 15$

$$B_{n,t} = \frac{A_{n,t} - \bar{A}_n}{S_n} \quad \text{where}$$

$$\bar{A}_n = \frac{1}{T'} \sum_{t=1}^{T'} A_{n,t} \quad \text{and}$$

$$S_n = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (X_{n,t} - \bar{X}_n)^2}$$

$$2. \quad C_n = \frac{\sum w_n \cdot B_{n,t}}{\left(\sum_n w_n \right)_t}$$

where $\left(\sum_n w_n \right)_t$ is the
sum of the weights of the
available series at time t

$$3. \quad SEI_t = \frac{C_t - \bar{C}}{S_C} \cdot 10 + 100$$

where $\bar{C} = \frac{1}{T'} \sum_{t=1}^{T'} C_t$ and

$$S_C = \sqrt{\frac{1}{T' - 1} \sum_{t=1}^{T'} (C_t - \bar{C})^2}$$

The X_n variables represent the 15 components of the

confidence indicators for industry (3 components), services (3), consumers (4), construction (2) and retail trade (3).

Since the confidence indicators described above are made up of the same, but non-standardized component series, the ESI cannot precisely be derived

from applying the given sector weights to the five confidence indicators. In fact, it can occasionally happen that, due to the influence of some more

volatile component series,
the sum of the (weighted)
confidence indicators
shows movements that are
not reflected in the ESI,
summarizing the properly

standardized components.
In the same way, impulses
from rather damped
components that are not
visible in the confidence

indicators may actually
show up in the ESI.

Simulating the ESI Using ANN

Regardless of the ANN
used the processed data or
the simulated problem and

the phases in the implementation of ANN are the same, as shown by the authors in authors articles.

[Ilie C., Ilie M., Moldova
Republic's Gross Domestic
Product Prevision Using
Artificial Neural Network
Techniques, OVIDIUS
University Annals,

Economic Sciences Series,
Volume X, Issue 1, Year
2010, OVISIUS University
Press, p. 667-672, ISSN
1582-9383]. Considering
this, the following

simulation follows those
phases.

Phase 1 - Initial Data Analysis

Data analysis consists in dividing data into separate columns, defining types of

these columns, filling out missing number values, defining the number of categories for categorical columns, etc.

Data analysis revealed the following results:

- 6 columns and 79 rows were analyzed;

- Data partition method: random;
- Data partition results: 57 records to Training set (72.15%); 11 records to

Validation set (13.92%)
and 11 records to Test set
(13.92%).

As can be seen, the
database is divided in three

sets. While the training sets are used only for training, the validation and testing sets are used also for testing. Presented in table 1 are the maximal and

minimal value limits of the
input and output data.

Table 1: The Database

**Please see Table 1 in Full
PDF Version**

Phase 2 - Data Pre-Processing

This is the phase in which the above defined data are prepared and reshaped for

an easier use and for obtaining best results, according to the requirements and the imposed results.

Pre-processing means the modification of the data before it is fed to a neural network. Pre-processing transforms the data to make it suitable for neural

network (for example, scaling and encoding categories into numeric values, "one-of-n" or binary) and improves the data quality (for example,

filtering outliers and approximating missing values), as different software uses different methods [see Alyuda NeuroIntelligence -

<http://www.alyuda.com/neural-networks-software.htm>].

“One-of-N” encoding is
Method of encoding

categorical columns into numeric ones. Each new numeric column will represent one category from the categorical column data. For example,

categorical column

Capacity that has High,
Medium and Low as its
values will be encoded into
3 numeric columns and
value High will be

represented as $\{1, 0, 0\}$,
Medium as $\{0, 1, 0\}$ and
Low as $\{0, 0, 1\}$.

Considering the past
research and experiences,

the database was
reorganized as random
series replacing the initial
time series.

The reasons for this change came from the need to avoid the obstruction of the training and also the probability of the ANN to consider the trend of the

time series database as universal trend. The second problem can be determined by the impossibility for future estimates. So the data on

which the ANN was trained were fed to it as non-time series; and for the present database, the encoding chosen was numeric encoding. Numeric

encoding means that a column with N distinct categories (values) is encoded into one numeric column, with one integer value assigned for each

category. For example, for the Capacity column with values "Low", "Medium" and "High", "Low" will be represented as {1}, Medium as {2} and High as

{3} [Alyuda
NeuroIntelligence -
[http://www.alyuda.com/neural-networks-
software.htm](http://www.alyuda.com/neural-networks-software.htm)]. In table 2,

the characteristics of pre-processed data are shown.

The results of completed pre-processing process are:

- Columns before preprocessing: 6;
- Columns after preprocessing: 6;

- Input columns scaling
range: $[-1..1]$;
- Output column(s) scaling
range: $[0..1]$;

- Numeric columns scaling parameters: INDU: 0.06993; SERV: 0.027586; CONS: 0.05102; RETA:

0.042283; BUIL:

0.040404; ESI: 0.025381.

Table 2: The Pre- Processed Database

**Please see Table 2 in Full
PDF Version**

Phase 3 – Artificial Neural Network Structure

Considering the characteristics of the simulated process, many

ANN structure can be determined and compared through the specificity of the process and the data that are being used for simulations. Thus, the feed

forward artificial neural network is considered the best choice for present simulation [Lucica Barbe , Corneliu Neagu, Lucia Melnic, Constantin Ilie,

Mirela Velicu, The Use of Artificial Neural Network (ANN) for Prediction of Some Airborne Pollutants Concentration in Urban Areas, Revista de chimie,

Martie 2009, 60, nr. 3,
Bucharest, p. 301-307,
ISSN 0034-7752].

After building and testing
several ANN with feed

forward structures, having in mind the comparison of the errors between the real data and ANN output data, the best ANN network was defined. This has the

following structure (figure 2): 5 neurons in the input layer, 11 neurons in the hidden layer and 1 neuron in the output layer.

Figure 2. Simplified Graphic Representation of ANN with Structure

**Please see Figure 2 in Full
PDF Version**

Also, the activation function for different layer neurons are chosen: Hidden layers activation function is hyperbolic tangent (ratio between the hyperbolic

sine and the cosine functions (or expanded, as the ratio of the half-difference and half-sum of two exponential functions in the points z and $-z$) and

Output layer activation function is logistic (sigmoid curve) [Dumitru Iulian N stac, Re ele Neuronale Artificiale. Procesarea avansat a datelor

(Artificial Neural Network.
Advance Data Processing.)
Printech Pub., Bucharest,
2000].

Phase 4 - Training

Being an essential phase in the use of ANN, the training must use certain training algorithms which

essentially modifies the structural elements of ANN (weights) modified through several iterations. Those modifications establish the future ANN accuracy. For

the selected ANN, the most common training algorithm is Back propagation algorithm.

Back propagation algorithm. Back propagation is the best-known training algorithm for multi-layer neural networks. It defines rules of

propagating the network error back from network output to network input units and adjusting network weights along with this back propagation. It

requires lower memory resources than most learning algorithms and usually gets an acceptable result, although it can be too slow to reach the error

minimum and sometimes
does not find the best
solution [Alyuda
NeuroIntelligence–
[http://www.alyuda.com/n
eural-networks-](http://www.alyuda.com/neural-networks-)

software.htm]. For a quicker training process, a modification of the back propagation algorithm, called quick propagation, was made.

Quick propagation is a heuristic modification of the back propagation algorithm invented by Scott Fahlman. This training algorithm treats the

weights as if they were quasi-independent and attempts to use a simple quadratic model to approximate the error surface. In spite of the fact

that the algorithm has no theoretical foundation, it is proved to be much faster than standard back propagation for many problems. Sometimes the

quick propagation
algorithm may be unstable
and inclined to block in
local minima [Alyuda
NeuroIntelligence –
<http://www.allyuda.com/n>

eural-networks-
software.htm].

The training conditions
were established in order
to achieve the best results

using the quick propagation training algorithm. Thus, the quick propagation coefficient (used to control magnitude of weights increase) was 0.5 and the

learning rate (affects the changing of weights – bigger learning rates cause bigger weight changes during each iteration) was 0.3. The small values of

these two, especially of the learning rate, are explained by the necessity of avoiding the local minima blockage.

The results of training details are presented in table 3.

Table 3: The Training Details

**Please see Table 3 in Full
PDF Version**

- AIC is Akaike Information criterion (AIC) is used to compare different networks with different weights (hidden units).
With AIC used as fitness

criteria during
architecture search,
simple models are
preferred to complex
networks if the increased
cost of the additional

weights (hidden units) in the complex networks do not decrease the network error. Determine the optimal number of weights in neural

network [Alyuda
NeuroIntelligence -
[http://www.allyuda.com/
neural-networks-
software.htm](http://www.allyuda.com/neural-networks-software.htm)];

- Iters. are the iterations
[Alyuda
NeuroIntelligence -
<http://www.alyuda.com/neural-networks-software.htm>];

- R-squared is the statistical ratio that compares model forecasting accuracy with accuracy of the simplest model that just use mean

of all target values as the forecast for all records. The closer this ratio to 1 the better the model is. Small positive values near zero indicate poor

model. Negative values indicate models that are worse than the simple mean-based model. Do not confuse R-squared with r-squared that is

only a squared
correlation [Alyuda
NeuroIntelligence -
[http://www.allyuda.com/
neural-networks-
software.htm](http://www.allyuda.com/neural-networks-software.htm)];

The stop training conditions were: maximum of 500000 iterations or a maximum absolute training error value of 0.25%. The results of

training are Number of iterations: 500001 (Time passed: 00:09:35 min.). The training stop reason was: All iterations done.

Training Results

After the training, the ANN evaluated the importance that every input data has over the output data. The

result of the evaluation is presented in table 4 and figure 3.

Table 4: Input Data over Output Data Importance

**Please see Table 4 in Full
PDF Version**

Figure 3. Input Data over Output Data Importance

**Please see Figure 3 in Full
PDF Version**

Figure 4. Evolution of the Network Errors

Please see Figure 4 in Full PDF Version

**Figure 5. Comparison
between Training Set
Dataset Errors and
Validation Dataset Error**

**Please see Figure 5 in Full
PDF Version**

Figure 6. Training Errors Distribution

**Please see Figure 6 in Full
PDF Version**

Figure 7. Network Weight Distribution

Please see Figure 7 in Full PDF Version

Phase 5 - Validation and Testing

The last phases of ANN simulation indicate the level of ANN preparedness

regarding the expected results.

Testing is a process of estimating quality of the trained neural network.

During this process, a part of data that was not used during training is presented to the trained network case by case. Then forecasting error is

measured in each case and is used as the estimation of network quality.

For the present research, three different sets of data

were used for the testing and validation of the ANN training. The first set is the one already used in the training process, but never fed to the ANN: 11 records

to Test set (13.92%) (see phase 1). The results of this testing is presented in table 5. Also the difference between the real values (target) and the simulated

values (output) of the output data are presented in figure 8.

**Table 5: Test No. 1.
Automat Testing Results
– Actual Vs. Output**

**Please see Table 5 No. 1.
in Full PDF Version**

- AE is the absolute error as the difference between the actual value of the target column and the corresponding network output, in absolute values

[Alyuda NeuroIntelligence

-

<http://www.alyuda.com/neural-networks-software.htm>];

- ARE is the absolute relative error as the difference between the actual value of the target column and the corresponding network

output, in percentage terms [Alyuda NeuroIntelligence - <http://www.alyuda.com/neural-networks-software.htm>].

The second set is formed from data that was never fed to the ANN in order to train it. So this set was new to the trained ANN. The results of the comparison

between the real data and the simulated data are presented in table 6.

**Table 6: Test no. 2.
Testing Results - Actual
vs. Output**

**Please see Table 6 No. 2.
in Full PDF Version**

**Figure 8. Actual vs.
Output Values. Automat
Testing**

**Please see Figure 8 in Full
PDF Version**

The third set was a new set and when the ANN was trained, this set was not yet revealed on European Commission – Economic and Financial Affairs

website

[http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.htm]. The result of this set on the ESI simulation is

presented in table 7. The importance of this test came from the economic Romanian situation at that time, which was slightly different from the ESI point

of view. So it was necessary to determine how the trained ANN behave in somehow illogical (the non-linear conditions that we refer to) conditions, such as

higher than expected
confidence in country's
capabilities.

**Table 7: Test no. 3.
Testing Results - Actual
vs. Output**

**Please see Table 7 No. 3.
in Full PDF Version**

The absolute values and relative difference for the third testing process, between the third real set of values and the simulated ones are shown in figure 9.

**Figure 9. Actual vs.
Output Values. Test no. 3**

**Please see Figure 9 in Full
PDF Version**

From the previous results, the following conclusions are drawn:

- The training phase was successful, the maximum

absolute error was 1.866
and the maximum
absolute relative error
was 0.016;

- Testing the training with the new data set resulted in a smaller than 3.3% difference between the real data and simulated output.

Simulating the Trend ESI Using the ANN

The researchers did not only evaluate the success of ANN training by

comparing the real input data with the ANN simulated data, but they also observed the trend that ANN simulates,

considering new data for each of the input.

In order to see the way the ANN behaves after the training, we fed the ANN

with the new data, as consecutive values in arithmetic progression, for each and every input, while the other four inputs remained the same as in

training session. Then we considered the trend of the new used data in comparison with the real trend. We used the trend of the simulated data

because, as expected, the simulated data were affected by the simulation errors and thus the trends will be easier to compare.

The trends were determined using a simple program from the Mathcad 2001 software, for the calculation of the equation that approximates the

trend. The results of ESI simulations for the new data were considered (with consecutive values in arithmetic progression and all other inputs remaining

as in original database). An example of the program which determined that trend for the INDU input data is presented here in figure 10.

Also, the researchers must explain the interval values chosen for the new simulations. For example, the real values for the INDU data were between [-

16.7; 11.9], but we want to verify and test even more the ANN trained with a different values interval. So a new interval for INDU was considered as [2; 10],

this interval showed that the trained ANN can simulate using new data that were never fed to it. In addition, the trained ANN simulation can be

appreciated considering that all values are only positive and can be found in a smaller cluster than the real data (that were used for training).

In the following figures the simulated ESI (ESI_simul) is shown for each of the new sets of values for the input data: INDU_simul, SERV_simul, CONS_simul,

RETA_simul and
BUIL_simul (noted with a)
in the following figures)
and the trend determined
from the simulated ESI
(noted with b) in the

following figures). Also in order to evaluate the ANN, the difference between the real ESI (ESI_real) and the simulated ESI (ESI_simul) is presented as percentage

(noted with a) in the following figures) and also as absolute values graphics (noted with b) in the following figures).

Trend Simulation with New INDU Values

The values for the INDU input data was chosen between [2; 10], the other

input data values remained as shown in table 1. The results of the simulation are presented in figure 11.a and the calculated trend in figure 11.b.

**Figure 10. The Program
for the Calculus of the
INDU's Trend Equation**

**Please see Figure 10 in
Full PDF Version**

**Figure 11. a) ESI
Simulated for the New
INDU Values; b) Trend of
the ESI Simulated for the
New INDU Values**

**Please see Figure 11 in
Full PDF Version**

Figure 12. a) The Difference between Simulated ESI and Real ESI for the New INDU Values (%); b) ESI_real vs. ESI_simul for the New INDU Values

**Please see Figure 12 in
Full PDF Version**

Trend Simulation with New Serv Values

**Figure 13. a) ESI
Simulated for the New
SERV Values; b) Trend of
the ESI Simulated for the
New SERV Values**

**Please see Figure 13 in
Full PDF Version**

Figure 14. a) The Difference between Simulated ESI and Real ESI for the New SERV Values (%); b) ESI_real vs. ESI_simul for the New SERV Values

**Please see Figure 14 in
Full PDF Version**

Trend Simulation with New CONS Values

**Figure 15. a) ESI
Simulated for the New
CONS Values; b) Trend of
the ESI for the New CONS
Values**

**Please see Figure 15 in
Full PDF Vrsion**

Figure 16. a) The Difference between Simulated ESI and Real ESI for the New CONS Values (%); B) ESI_Real vs. ESI_Simul for the New CONS Values
Trend simulation with new RETA Values

**Please see Figure 16 in
Full PDF Version**

**Figure 17. a) ESI
Simulated for the New
RETA values; b) Trend of
the ESI Simulated for the
New RETA Values**

**Please see Figure 17 in
Full PDF Version**

Figure 18. a) The Difference between Simulated ESI and Real ESI for the New RETA Values (%); b) ESI_real vs. ESI_simul for the New RETA Values

**Please see Figure 18 in
Full PDF Version**

Trend Simulation with New BUIL Values

**Figure 19. a) ESI
Simulated for the New
BUIL Values; B) Trend of
the ESI Simulated for the
New BUIL Values**

**Please see Figure 19 in
Full PDF Version**

Figure 20. a) The Difference between Simulated ESI and Real ESI for the New BUIL Values (%); B) ESI_Real Vs. ESI_Simul For The New BUIL Values

**Please see Figure 20 in
Full PDF Version**

Table 8: The New Values of the Input Data Used for the Simulations and the Results of Simulation

**Please see Table 8 in Full
PDF Version**

As we can see, the results of simulation of the new values, even with the imposed value restrictions, correspond to the conditions established at

the beginning of the
research.

Acknowledgment and Conclusions

The research established the necessary theoretical characteristics for the pre-

processing, training,
validating and testing the
used ANN for the
simulation of the
Romanian ESI. Considering
the validating and testing

results, the ANN training is considered a success and all the initial conditions are respected.

In the beginning of the paper, it is shown how the ANN was trained and tested. The results for the ANN training before the testing were:

- The training error was 0.254;
- The automat testing deviation of the training was [0.000944;

1.866115] as absolute
value and [0.000009;
0.016087] as relative
value;

- The second testing (with data never feed to the ANN) results produced a relative deviation between $[-0.8474; 1.0690]$;

- The third test (with fresh new data) showed relative deviation between [1.276444; 3.276444].

All the tests confirm good results of the training process as the relative difference between the real ESI and the simulated ESI are smaller than the initial

conditions (smaller than 5%).

In the second part of the paper, the comparison between the real trends

and the simulated trend show the effectiveness of ANN built and trained. The small difference between those two trends, even in harder conditions for the

ANN, validates all the choices that the researchers made for the ANN structure and training methods and also for the

conditions defined for the use of ANN.

Overall the ANN training and use is considered a success and the future use

of the ANN can be implemented for the forecasting of ESI from different Member State countries and even for the entire euro-area. But also

the researchers consider that the studies must be extended over a larger period of time and also over a bigger database. This can create a more

prepared ANN, and thus a more accurate result.

Another direction of research is considered. Starting with the intern

and foreign investments,
another type of ESI can be
used to train the ANN in
order to forecast the future
investment or the way that

certain economies are
viewed and evaluated.

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