Forecasting neural networks, such as forecasting sale the plastic injection machine market.

Hind Khalid

Al- Naharin University
E-mail: hind.1969@yahoo.com

Abstract.

The aim of this research is to show what benefits the use of neural networks in forecasting processes can bring, among its development throughout the years considering different kinds of mathematical methods. The software applications that have been developed recently for forecasting processes are neural and AI-based. Data entries from previous months are used in mathematical methods to calculate and predict sales in a company. By the use of these neural and AI-based processes, predictions of whether company sales will go up or down the next month can be made. This research will help to better understand the process behind these predictions and how the developments of neural networks come into place.

Keywords: neural networks, forecasting processes, Artificial Neural Networks (ANN), Alyuda

1. Introduction

The first thing we have to consider in order to fully understand the subject is demand forecasting. This can be defined as: “The process of finding values for demand in future time periods” (Douglas, 1992). The reason why demand forecasting is so important is because it has a crucial role in inventory management. Without it, we cannot optimize and determine the rate of profit within a business. The supply chain (SC) management is affected by all of this in return. The SC is a dynamic system with a continuous flow of data, product, and funds between stages (Chopra & Meindl, 2001). Accurate market forecasts will assist with profit maximization, improved revenue, and effective production planning, among other things. In both the micro and macro stages, it is essential to the strategy and activity of retail companies (Doganis, 2006). If there’s even a small error made while calculating a forecast of demand, it can be crucial for the organization and cause financial loss.

When a market grows, the products presented on that market become more diverse and the factors that affect that market become more dynamic. However, mapping the demands for a product becomes more complicated because of the different factors affecting it. Using neural networks in cases like this has the advantage of mapping the dependence of each factor or variable involved, with accuracy. We don't have to care about any of the nuances of what's going on inside these systems as long as our artificial neural network knows as much as possible. However, fitting the problem well and mathematically modeling it is one of the most critical challenges in adapting neural network models to functional problems. As a consequence, any aspect that might have an effect on the issue must be considered and translated into a numerical physical quantity. Otherwise, our neural network would obtain redundant inputs if these variables are not independent of one another. These variables may also be selected at random. Climate change is an example. This can impact sales volume on a given day, and since we can't reliably forecast the weather over time, we can't predict sales volume on that single day. If the weather...
maintains a consistent trend over a longer time span (such as a year), we will estimate revenue for the week. We must presume that the weather would not be predictable just during the week.

We take advantage of the fact that random errors have a Gaussian curve pattern, which is advantageous to us. Another thing to consider is the location. We are unable to achieve the physical and numerical quantities that refer to a given region and can be used to forecast commodity demand in that area. However, estimating the impact of the region on demand is not completely impossible. It can be modeled very effectively by the use of NN networks.

Since forecasting is so critical in business, the theoretical workload is very significant. It is a rapidly changing market, and as a result, a lot has changed in the last ten years. Since commodity demand was steady and few new products were introduced in the 1950s and 1960s, it was much easier to forecast market share and overall market growth.

1.1 Research objectives
1. Establish an accurate model;
2. Understand the impact of external economic variables on forecasting models
3. Establish a practical and feasible sales forecast framework for the plastic injection machine market to provide assistance for business management decisions.

1.2 Research problems
In the past ten years, many changes have occurred considering forecasting processes and techniques. This is a branch that keeps evolving since the demand and variety in sectors keep changing. Some of the challenges that may occur are knowing the uncertainty and the need for probabilistic forecasts, recognizing and identifying what the basic elements are of a useful forecast, measuring what the limits are considering forecast ability and forecast accuracy, establish appropriate forecast accuracy benchmarks, and precisely defining the importance of demand when making requirements. As we read, many problems have been solved by using Neural Networks in forecasting programs, however, NN requires a lot of time and information and it is difficult to measure something that is in a short period of time.

2. Literature review
In the past, Artificial Neural Networks (ANN) have been successfully used to forecast demand and stations in a variety of situations. An ANN model was suggested by Ali, Paul, Ahsan, and Azeem (2011) for estimating the raw material inventory optimum level as a commodity demand function, manufacturing lead time, material retention costs, supply reliability, and input costs (Ali, Paul, Ahsan, and Azeem, 2011). ANN was used as one of the predictive models of estimating how much water was consumed in urban environments in order to plan a well-functioning water resource management with a priority to maintain a daily supply of clean water with the amount that the user wants (Herrera, Torgo, Uzquierdo, & Perez-Garcia, 2010). In terms of predicting international tourism demand, (Coshall & Charlesworth, 2011) distinguished exponential smoothing, uncertainty, regression, and naive models and then were considered in conjunction using strictly statistical parameters. (Mandal & Prabaharan, 2006) defined an ANN with a recurrent neural network that was used for wave prediction and used the riprap update algorithm. By integrating linear and non-linear static models, (Chen, 2011) investigated the estimation accuracy of combination models. Using real-time data sets of outbound tourism demand, he forecasts time series with potential non-linear characteristics. (Carbonneau, Kersten, & Vahidov, 2006) examined the applicability of sophisticated machine learning approaches such as vector supporting machines, neural networks that were repeated and neural networks for the forecasting of interrupted demand at a supply chain’s end (bullwhip effect). Other more conventional approaches such as linear regression, moving average, naive forecasting, and trend were compared to this method. (Synetos, Babai, Davies, & Stephenson, 2010) looked at the problem of judiciously changing predictive forecasting for ‘fast’ demand products, as well as the effects of interventions as such in terms of inventory management and forecasting accuracy, of which the
inventory management is calculated by volumes of inventory and the levels of service that entered the pharmaceutical industry dataset. By comparing various forecasting approaches, (Weatherford & Kimes, 2003) discovered a reliable approach for estimating arrivals, which is critical for a competitive hotel revenue management scheme. (Yelland & Dong, 2014) introduced a Bayesian mathematical model that was created for the sole purpose of forecasting demand for parts for a major supplier of business computing devices. (Pedregal & Trapero, 2010) developed a standard approach that included several speeds for forecasting load demand that is sampled hourly for the medium term. It was proposed by Diamantopoulos & Winklhofer (2001) and validated a course model for forecasting export sales activity and efficiency, which took into account both organizational and export-specific factors.

2.2 Significance of ANN model

Biological neural networks’s structure and/or function inspires a mathematical model or learning algorithm known as an artificial neural network (NN). An artificial neural network is made up of interconnected artificial neurons that process data using connectivity theory. Most of the time, an ANN is an adaptive mechanism that is capable of changing its structure thanks to information that is either external or internal. The data moves through the network as the learning process takes place. Non-linear simulation tools are Non-linear neural networks (NNs). Their use is for modeling dynamic relationships between outputs and inputs, and also finding data patterns. If there isn't enough information to represent the majority of the working environments, or if there is a lot of rhetoric, NN technology might not be the right choice. However, NN technology is a good alternative where there is a lot of data and it is difficult to grasp the issue in order to arrive at an estimated model.

Our experiment falls into the second group. Although sales statistics may be used, the relationship between input and output is much too nuanced to comprehend. This is the reason for using NN for the modeling of input and output’s dynamic relationship or for searching patterns in data. The artificial neural network (ANN) is a non-linear is a system that is adaptive, and usually non-linear that is capable of learning to function performance (input/output graphs) from data. Adaptive refers to the method of modifying device parameters during service, which is generally referred to as the training period.

2.3 Artificial Neural Network:

Artificial neural networks are a dynamic mathematical construct based on the human brain’s configuration. A single neuron or node acts as the central part, and is connected to other neurons. All of these neurons, when connected, form a network with varying degrees of complexity and topology. This machine can benefit from its surroundings and enhance its efficiency as a result. Haykin et al., 1998

NNs have various shapes and sizes, each of which has its own set of characteristics. They are divided into three groups based on topological structure: the first one is Single-layer Feedforward Networks, the second is Multilayer Feedforward Networks, and the third one Recurrent Networks. We can distinguish Recurrent Networks from Feedforward Networks by seeing if there is a Feedwards loop. Recurrent Networks have a big effect on the general results and the learning abilities (Haykin, 1998). Since they are able to capture today’s challenges’ dynamic interactions, prediction fields is where artificial neural networks are usually used in. They are non-parametric data-driven approaches. The mechanism’s essence is no longer of importance to be considered, which is expected to be a result of this. In comparison with parametric models, it’s more user-friendly, because in paramedic models can have inaccurate model methods and create great issues. Zhang, G. P. (2004) Remus and O'Connor (2001) point out that Artificial neural networks are better than conventional models in the process of forecasting the monthly results as well as the quarterly results as well. However, the same cannot be said for the annual data because the artificial neural network is in need of a great measurements number during the learning process. The most beneficial thing
about artificial neural networks over approaches that are conventional is the fact that they are able to create models of the nonlinear interactions between the variables and take the role of a general approximator (Remus & O’Connor, 2001).

In some areas, for example finance (Bodyanskiy & Popov, 2006), power demand forecasting, and wind energy forecasting (More & Deo, 2003), ANN has been a well-known forecasting technology (Hippert, Pedreira, & Souza, 2001). There have been researches as such in the port throughput forecasting field. They’re put to two separate uses. The first is that they can be used as a single forecasting tool (Nuo, 2003). The second is as part of a mixed model, as stated in the subsection Hybrid Approaches. Artificial neural networks have been around for a long time, and there are several different forms. Nonetheless, the backpropagation neural network is the most common among the papers discovered (BP NN). According to (Nuo, 2003), it is defined by its basic structure and mathematical computation’s limited amount, that can overcome its flaws, like the collapsing to a sluggish convergence speed and local minimum. There also are Radial Basis Function Neural Networks (RBF NN) and Elman Neural Networks, in addition to these two forms of ANN (ENN).

3. Methodology

3.1 Data collecting method
The methods and data collection used in this study are secondary data based on European economic sentiment as an example to illustrate how modern stimulating artificial intelligence can be used to help forecast forecasts.

3.2 Data Analysis
The effect of the production volume index, internal company R&D budget, contraction turnover rate, and job and operation index on economic sentiment evolution indicators is simulated in this paper using artificial neural network technology. The below are the simulation parameters:
Volume index production (abbreviation: sts_inpr_a) (which includes mining and quarrying, natural gas, manufacturing and electricity, air conditioning supply and steam.
Instead of seasonally adjusted data, Calendar-based data used (Index, 2015 = 100).
According to Eurostat, The industrial production index (IPI, also either called the industrial output index or the industrial volume index) is a market cycle indicator that is responsible for tracking the monthly changes in the industry’s price-adjusted output. The Industrial Production Index, which excludes the building sector, calculates the progression of industrial production using data that has been calibrated for calendar and seasonal factors. By combining seasonally adjusted country data, the seasonally adjusted Eurozone and EU series data are generated. Countries who have not changed their data for seasonal effects are liable to seasonal modifications by Eurostat. 4. The intra-city R&D budget rd_e_gerdtot is seen below, broken down by performance department and all departments [per capita euro] as mentioned by (Manual, 2002). Intra-wall expenditure refers to R&D spending in a statistical unit or financial department over a given time span, regardless of funding source. 5. Tightening Turnover Index (hereinafter referred to as sts_trtu_a), Car and motorcycle maintenance, wholesale and retail trade, calendar-based data, not seasonally adjusted data [Index, 2010 = 100].
The turnover index’s aim is to demonstrate the evolution of the demand for goods and services. Turnover is a "preferred tool" that converts overall turnover using relevant market metrics (Benoid & Eun-Pyo, 2006). Jobs and behaviors by gender and age (hereinafter referred to as lfsi_emp_a, annual data from 15 to 64 years old, totaled in thousands) The index is made up of five departmental trust indexes of varying weights:
- Index of Industrial Confidence (40%)
- index of Construction confidence (5%)
- Index of Service Confidence (30%)
- index of Consumer confidence (20%)
- index of Retail trade confidence (5%)

Eurostat codes are used for each metric, as seen above, to make monitoring and checking the value simpler. The authors used data from the Eurozone in their study (EA19). This zone was chosen because it has the most leverage in the European economy in terms of manufacturing, construction, retail, and services, hence generating the data. The data listed is more accurate and easier to locate as compared to data from young European countries. This information was gathered between 1999 and 2016. Eurostat is the primary source. The European Union’s statistical office. As a whole, the author assumes that these results are trustworthy. One of the benefits of using Alyuda NeuroIntelligence for data analysis is "feature filtering," which can detect whether the information is useful and greatly improve the neural network's performance. After analyzing using various methods (such as genetic algorithms), the user may choose whether to keep all of the columns that were originally identified for simulation or to exclude columns that are no longer relevant for ANN processing. Although using feature collection can expose inefficiency of columns as such, (indicators are considered columns by ANN), like the contraction turnover index, it was decided for the data that ANN issued to be retained by the writers. The explanation for this decision is that decreasing the data column numbers would result in the research targets being more difficult to accomplish and accurate, and one of the research goals is to determine the organizational structure of the metrics. When considering the grouping of data values for each index, it should be noticed that the value of the performance data (economic confidence indicator) column was one year overdue. As a result, the artificial neural network self-trained based on the effect of the four input metrics from one year on the performance of the next year. This is because the author wanted to quantify the effect of this year’s economic prosperity index on the value of the index for the second year, while bearing in mind that in order to assess the degree of trust in the economy this year, one must first consider the economic condition.

Table 1 shows the farthest year in comparison with the nearest year where every value was written down and also used by the authors during the start of 2018, which was the time of which the research was conducted.

| Features        | sts_impr_a | rd_e_gerdtot | sts_trtu_a | lfsi_emp_a | ci_lbsi_m_r2_real |
|-----------------|------------|--------------|------------|------------|------------------|
| Min. values     | 89.8       | 372.3        | 94.8       | 127,756.00 | 78.8666667       |
| Max. values     | 107.3      | 674.8        | 116.3      | 144,645.00 | 115.9833333      |
| Farthest year   | 1999       | 1999         | 1999       | 1997       | 1999             |
| Nearest year    | 2017       | 2016         | 2016       | 2016       | 2017             |

The number of record sets (17) is determined by the number of available records for all data used in the research. In terms of in-wall R&D expenditure (rd_e_gerdtot), the only value recorded is between 1999 and 2017, so the number of sets (18 sets, 17 sets for ANN training and one set for query) correspond to these years. The author also wanted to understand how ANN’s training handles a small number of data sets and assumes the possibility of failure. Another argument when choosing the number of data sets is to train ANNs with data that contains inconsistent developments, such as the changes caused by the 2009-2012 financial crisis.
3.3 Pre-processing

Preprocessing refers to the modifications made prior to entering data values into the neural network. It transforms data into neural network-coordinated data (via scaling and numerical coding) and increases data consistency (via filtering out-of-proportion values and approximating values that are missing). The zoomed number column will be monitored, along with the coded segment column, and the date/time column, as well as the detailed statistical details for each column, depending on the program. One justification for using preprocessing is to make it easy for the ANN to use the data values during the training phase. For instance, it can be suggested to use visual analysis, in which it is hard to model two data sets at the same time, one data set has a value between [-10; 10], and the other data set has a value between [-10; 10], and again, another one has a value of [700,000; 1,200,000]. Even if logarithmic representation can be used, the seeing, reading, analyzing, and the processing of the 1st data evolution is nearly impossible. To get a clearer representation, divide the value of the second data set by 100,000, resulting in the current interval to which the value belongs: [7; 12]. The evolution of the two data sets will now be easier to read and analyze. This example is comparable to the necessity of preprocessing using ANN, observed in Figure 1.

![Figure 1. The importance of preprocessing: (A) raw data values; and (B) simple mathematical division used for processed values. Source: Authors’ graphic representation using Office Excel.](image)

The following data values are important for preprocessing: (A) raw data values; and (B) data values that have been processed using basic mathematical division. The Alyuda NeuroIntelligence program has a number of preprocessing algorithms for classification columns that can be automatically encoded during data preprocessing (Alyuda, 2002).

- One-of-N coding is a method of transforming a classification column to a numerical column. In the categorical column results, each new numeric column will denote a segment. For example, if the classification column potential is set to High, the values Medium and Low will be encoded as three numerical columns, while the value High will be expressed as {1, 0, 0}, Medium will be represented as {0, 1, 0}, and Low will be represented as {0, 0, 1}.
- Encoding a column of N different categories (values) into a series of M binary columns, where M is equal to the length of a binary number needed to represent N different values, is referred to as binary encoding. The "color" column, for example, with values "red," "yellow," "green," "blue," and "white," will be encoded as three binary columns, with red described as {0,0,0}, yellow Will be expressed as {0,0,1}, green is {0,1,0}, blue is {0,1,1}, and white is {1,0,0}.
Encoding a column of N distinct categories (values) into a numeric column and assigning an integer value to each category is what numerical coding is all about. For example, in the "Capacity" column, where the values are "low," "medium," and "high," "low" will be expressed as {1}, "medium" will be represented as {2}, and "high" will be represented as {3}. Scaling formula provided by (Basheer & Hajmeer, 2001) 

\[ y_i = z_a + (z_b - z_a)(x_i - x_{max})/(x_{max} - x_{min}) \]  

\( y_i \) is the normalized value of \( x_i \); \( x_{max} \) and \( x_{min} \) are the maximum and minimum values of \( x_i \); and \( z_b \) and \( z_a \) are the intervals in \( [z_b; z_a] \) that correspond to the transfer function's range, which in our case is \([-1; 1]\).

### 3.4 Input Importance

This parameter is used to assist us in calculating using sensitivity analysis techniques.

![Input Importance after training process](source)

Figure 2. Input importance after training process. Source: Authors’ graphic representation using Alyuda.

Table 2. Input importance. Source: Authors’ data representation using Alyuda and Microsoft Office.

| Input Column Name | Importance, % |
|-------------------|---------------|
| stts_inpr_a       | 14.60583      |
| rd_e_gerd/tot     | 18.848676     |
| stts_trtu_a       | 14.005347     |
| lfsi_emp_a        | 52.540147     |

The significance of this input will be used in another analysis and the subject of another article, which will be studied to assess the hierarchical structure of indicators based on their effect on economic sentiment indicators. In their future analysis, the authors will validate the ANN-generated hierarchy and present alternative theories to clarify the hierarchy, show in figure 2.

### 3.5 Results

#### 3.5.1 Data Analysis Results

A brief overview of the data analysis conducted by ANN is given below:

- There were 6 columns and 17 rows of works examined.
- There were 5 columns and 17 rows among the works approved for NN preparation.
- there were the 5 numeric columns: stts_inpr_a, rd_e_gerd/tot, stts_trtu_a, lfsi_emp_a, and ei_bssi_m_r2.
- The output column's name was ei_bssi_m_r2.
- The data partitioning approach was ad hoc.
3.5.2 Pre-Processing results

The data for this study were only numerical, and the effects of their pre-processing seen as table 2, were as follows:

- The number of columns that had not been pre-processed: 5;
- The number of columns that existed after they had been pre-processed: 5;
- The input columns' scaling range: [−1..1];
- The output columns' scaling spectrum: [0..1];
- Scaling meters for numerical columns: 
sts_inpr_a: 0.114286, rd_e_gerdtot: 0.006612, sts_trtu_a: 0.093023, lfsi_emp_a: 0.000118, and ei_bssi_m_r2: 0.026942.

| Features    | sts_inpr_a | rd_e_gerdtot | sts_trtu_a | lfsi_emp_a | ei_bssi_m_r2 |
|-------------|------------|--------------|------------|------------|--------------|
| Parameter   | Value      | Value        | Value      | Value      | Value        |
| Format      | numerical  | numerical    | numerical  | numerical  | numerical    |
| Scaling range | [−1;1]    | [−1;1]     | [−1;1]    | [−1;1]    | [0;1]        |
| Encoded into | 1 column   | 1 column    | 1 column   | 1 column   | 1 column     |
| Min.        | 89.8       | 372.3       | 94.8       | 127756     | 78.86667    |
| Max.        | 107.3      | 674.8       | 116.3      | 144645     | 115.98333   |
| Mean        | 98.105852  | 528.476471  | 103.6      | 138,057,823,529 | 100.498039 |
| Std. deviation | 4.50718  | 96.18759    | 5.118134  | 4538.426654 | 8.432465    |
| Scaling factor | 0.114286 | 0.006612    | 0.093023  | 0.000118   | 0.026942    |

Table 3: Result of pre-processing. Source: Authors’ data representation using Alyuda and Microsoft Office.

Tracking preparation and trial outcomes to determine the right structure that would satisfy the study objectives. Below is what was concluded in the architecture quest report of the ANN:

- It was chosen by hand.
- 4-9-6-1 Figure 3 portrays the architecture chosen for preparation.
- Hyperbolic tangent is the activation mechanism for hidden layers.
- Output parameters: ei_bssi_m_r2;
- Error function: Sum-of-squares;
- Activation function: Logistic.

Figure 3: ANN design. Source: Authors’ graphic representation using Alyuda and Paint software
4. Discussion
We consider using ANN prediction metrics for all EU member states in the Eurozone when predicting economic sentiment for future studies. Research can also be done over a longer span of time and on a wider database, using more powerful metrics. This will lead to improved artificial neural networks that have more reliable and significant outcomes for training and prediction. Finally, based on the evolution of chosen effect markers, a complex artificial neural network can be generated to automatically train and determine continuous predictions.

5. Conclusions
The study's key aim was to achieve high precision in training the whole artificial neural network. The importance of sentiment indicators in 2004 can be estimated by taking the following four indicators into account: output volume index, barriers to R&D spending, and tightening turnover. The following targets were placed to validate the results: the neural network training error must be less than 5% and the prediction verification error must be less than 10%. Given AI's revolutionary capabilities in all economic and social fields, it must be used as a new technology for simulating and/or forecasting different metrics as a medium for sustainable growth.

The following are the research findings discussed in this paper:
• Attempts to model the progression of economic sentiment based on economic variables from the previous year.
• The following criteria are developed for an artificial neural network: 4-9-6-1, or five layers, with five neurons in the input layer (number of input indicators) and fifteen neurons throughout the two hidden layers. Factor (nine neurons in the first layer, six in the second layer, and one in the output layer) (neuron of economic sentiment indicator).
• ANN is feedforward, and the training algorithm is Fahlman's quick propagation (back propagation), with certain artificial neurons changed, such as the hyperbolic tangent feature used to mask the hidden layer and the escape layer's logic function.
• The training findings are acceptable in terms of the research's specified intent: training error = 0.099; verification error = 3.035102; test error = 9.9675.
• In addition, the other four metrics from 2003 were checked, as were the economic prosperity indicators from 2004. This measure has an absolute difference of -1.94 and a relative difference of 2.02 percent.

The below are some of the benefits of the suggested solution:
• The ability to forecast the impact of various indicators on human decision-making based on artificial intelligence will mimic biological knowledge, making it more reliable than decisions taken using abstract mathematical methods.
• Time for simulation, checking, and verification is held to a minimum.
• The method's characteristics
• Useful for a variety of fields

The below are the drawbacks of the suggested solution:
• the description of ANN's black box
• ANN modeling can take longer than conventional methods.
• A certain number of training-based databases are required.
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