Implementation of Bayesian Regulation Algorithm for Estimation of Production Index Level Micro and Small Industry

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Abstract. Small Industry is an industrial company whose workforce consists of 5-19 people. While the Micro Industry is an industrial company whose workforce consists of 1-4 people. The purpose of this study is to estimate the Production Index of Micro and Small Industries according to KBLI for years to come. KBLI is a reference classification used to classify Indonesian economic activities into several business fields that are distinguished based on the type of economic activity that produces products in the form of goods and services. In this study, the estimation method used is the Bayesian Regulation Algorithm. This algorithm is one of the Artificial Neural Networks algorithms that can solve many estimation problems by building a trained model and showing good performance. The data to be estimated in this study are data of Micro and Small Industry Production Index according to KBLI processed from the Central Board Statistics of Indonesia. This study uses 3 architectural models, namely: 5-10-20-1, 5-15-30-1 and 5-20-40-1. The best architectural model is 5-10-20-1, resulting in 83% accuracy, MSE 0.0031434897 with a minimum error of 0.001 - 0.05.

1. Introducing

A company or industrial business is a business unit that conducts economic activities, aims to produce goods or services, is located in a particular building or location, and has a separate administrative record regarding production and cost structure, and there are one or more persons responsible for the business that. One type of industrial activity is small and micro industries. Small Industry is an industrial company whose workforce is between 5-19 people. While the Micro Industry is an industrial company whose workforce is between 1-4 people. The classification of the manufacturing industry is solely based on the large number of workers who work, regardless of whether the company uses a power machine or not, and regardless of the size of the company's capital. Micro and Small Industries are a strategic force to accelerate regional development. Therefore the growth index of the production index of micro and small industries have a vital role and can be used as an early indicator of the development of production from sectors, especially micro and small-scale...
manufacturing because the resulting index number can describe the development of the manufacturing sector.

In this study, the production index of micro and small industries that will be discussed is according to 2-digit KBLI. KBLI is a reference classification used to classify Indonesian economic activities/activities into several business fields/business fields that are distinguished based on the type of economic activity that produces products/outputs in the form of goods and services. There are 23 components (descriptions) of micro and small industrial production indices according to KBLI (Table 1). Based on data from the Central Statistics Agency (Table 1), the production index of micro and small industries in Indonesia in 2011-2017 experienced ups and downs. There are ± 26% of the micro and low industrial production index of 23 descriptions according to KBLI which experienced a decline while 74% experienced an increase. Although the decrease in the micro and small industrial production index is not too significant, the government needs to be aware of all the possibilities that occur in the coming years. Therefore, it is essential to estimate the growth rate of micro and small industrial production indices. Because the production index of micro and small industries is an early indicator of the development of production from enterprises, especially micro and small-scale manufacturing [1].

The technique used in this study to estimate is the Bayesian Regulation neural network. This algorithm can remember and make generalizations based on previously available data (times series data) [2]. Similar to other artificial neural network algorithms, this algorithm also has a three-layer structure: the input layer, hidden layer, and output layer [3]–[5]. The way the Bayesian Regulation algorithm works is to use a linear combination of mean squared errors and weights for the network performance evaluation function. The weight of the model will be optimized by Bayesian regulation, and hidden layer nodes play a significant role and determine the network structure. There have been many previous studies using Bayesian regulation algorithms to solve computational problems, especially for forecasting and optimization [6]–[11]. It is expected that with the application of this algorithm, it will get the predicted results of the micro and small industrial production index for the years to come. So that the government and the private sector have references and considerations in determining policies related to micro and low industrial production indices.

2. Methodology

2.1. Data Collection

The data on micro and small industrial production indexes in Indonesia according to KBLI (Table 1). Data is taken from the Indonesian Central Bureau of Statistics and Statistics Publications. Explanation from table 1 that the micro and small industrial production index according to KBLI consists of 23 descriptions. Of the 23 specifications, there is a number instability in each year. In 2017 there was a decline in the production index in several parts, including tobacco processing, pharmaceuticals, chemical, medicinal products, and traditional medicines, rubber, articles of rubber and plastics, metal goods, not machinery and equipment, machinery and equipment and motorized vehicles, trailers and semi-trailers.

| No | KBLI (Description) | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|----|--------------------|------|------|------|------|------|------|------|
| 1  | Food               | 105.39 | 109.52 | 128.77 | 138.62 | 148.09 | 159.23 | 173.87 |
| 2  | Drink              | 99.45 | 100.44 | 112.28 | 117.56 | 131.10 | 146.37 | 154.38 |
| 3  | Tobacco Processing | 98.14 | 99.31 | 95.05 | 70.87 | 76.30 | 80.36 | 63.93 |
| 4  | Textile            | 103.95 | 107.02 | 115.79 | 120.88 | 130.09 | 142.72 | 145.56 |
| 5  | Apparel            | 105.61 | 110.00 | 119.37 | 124.14 | 132.44 | 141.70 | 149.88 |
| 6  | Leather, Leather Goods and Footwear | 104.50 | 113.79 | 124.88 | 128.72 | 133.75 | 143.73 | 145.55 |
| 7  | Wood, Gabus (Not Including Furniture) and Woven from Bamboo, Rattan, etc. | 100.88 | 101.52 | 104.75 | 103.43 | 99.57 | 103.14 | 104.96 |
| 8  | Paper and Paper Products | 100.19 | 106.31 | 108.30 | 112.59 | 131.01 | 153.06 | 180.47 |
| 9  | Recording Media Printing and Reproduction | 103.63 | 109.91 | 112.21 | 125.01 | 135.31 | 164.80 | 183.63 |
| 10 | Chemicals and Goods from Chemicals | 100.55 | 102.12 | 109.08 | 107.40 | 122.76 | 141.24 | 167.59 |
| 11 | Pharmacy, products of chemical drugs & traditional medicines | 110.21 | 105.19 | 110.70 | 100.14 | 104.67 | 116.24 | 108.64 |
2.2. Stages of Research
The stages of this study are as follows:

Start
Collecting Data
Literature Review
Identifying Problems
Preprocessing
Determine Pattern
Test Data Processing Results
Predict
Final Evaluation
Finished

Figure 1. Stages of Research

From the framework of Figure 1, it can be explained that collecting data in a study is the first thing to do. The second stage was carried out a literature study to complement the basic knowledge and theories used in this study. The third stage identifies the problem to process the conversion phase of the data obtained in accordance with the specified weight. The fourth stage preprocesses with the aim to facilitate understanding of the contents of the record. The fifth stage determines the pattern and determination of the network architecture model that is adapted to the research problem faced. The sixth stage examines the results of data processing using the Matlab application. The seventh stage predicts that is to see comparisons of several architectural models used in the study in order to obtain the best architectural models and the most accurate level of accuracy. The eighth stage evaluates the end to find out whether the results of data processing are as desired.

2.3. Data Normalization
The formula used is [12]–[16]:

\[ x' = \frac{0.8(x - a)}{b - a} + 0.1 \]  \hspace{1cm} (1)

Explanation:

\( x' \): Data transformation, \( x \): Data to be normalized, \( a \): The lowest value data, \( b \): Data with the highest value

The production data index of Indonesian micro and small industries according to KBLI is divided into 2 parts, the first is training data for 2011-2015 with the target in 2016, then the
testing data for 2012-2016 with the target for 2017. The following are Table normalization of training data and testing data:

Table 2. Normalization of Data Training

| Data | 2011 | 2012 | 2013 | 2014 | 2015 | Target |
|------|------|------|------|------|------|--------|
| 1    | 0,394006 | 0,429181 | 0,593133 | 0,677025 | 0,757681 | 0,852560 |
| 2    | 0,343415 | 0,351847 | 0,452688 | 0,497658 | 0,612978 | 0,743032 |
| 3    | 0,332258 | 0,342223 | 0,305941 | 0,100000 | 0,146247 | 0,180826 |
...   |      |      |      |      |      |        |
| 21   | 0,426541 | 0,456010 | 0,466315 | 0,527467 | 0,594837 | 0,662857 |
| 22   | 0,396646 | 0,392558 | 0,425945 | 0,489226 | 0,514266 | 0,507623 |
| 23   | 0,352614 | 0,380975 | 0,439828 | 0,509071 | 0,542031 | 0,435228 |

Table 3. Normalization of Data Testing

| Data | 2012 | 2013 | 2014 | 2015 | 2016 | Target |
|------|------|------|------|------|------|--------|
| 1    | 0,333406 | 0,431960 | 0,482388 | 0,530872 | 0,587905 | 0,662857 |
| 2    | 0,286919 | 0,347536 | 0,374568 | 0,443888 | 0,522066 | 0,563074 |
| 3    | 0,281134 | 0,259324 | 0,135531 | 0,163330 | 0,184116 | 0,100000 |
...   |      |      |      |      |      |        |
| 21   | 0,349533 | 0,355728 | 0,392487 | 0,432983 | 0,444349 | 0,471791 |
| 22   | 0,311391 | 0,331460 | 0,369500 | 0,384551 | 0,380558 | 0,436772 |
| 23   | 0,304429 | 0,339805 | 0,381428 | 0,401242 | 0,337041 | 0,351427 |

3. Results and Discussion

There are 3 architectural models used in this study, including: 5-10-20-1 (5 input layers, 2 hidden layers with 10 neurons and 1 output), 5-15-30-1 (5 input layers, 2 hidden layers with 15 neurons and 30 neurons and 1 output), and 5-20-40-1 (5 input layers, 2 hidden layers with 20 neurons and 40 neurons and 1 output). The parameters used are as follows:

- Epochs (Maximum number of epochs to train) = 1000; goal (Performance goal) = 0; mu (Marquardt adjustment parameter) = 0.005; mu_dec (Decrease factor for mu) = 0.1; mu_inc = Increase factor for mu = 10; mu_max (Maximum value for mu) = 1e10; max_fail (Maximum validation failures) = 5; mem_reduc (Factor to use for memory/speed tradeoff) = 1; min_grad (Minimum performance gradient) = 1e-10; show (Epochs between displays (NaN for no displays)) = 25; showCommandLine (Generate command-line output) = 0; showWindow (Show training GUI) = 1; time (Maximum time to train in seconds) = inf;

Based on Table 4 can be seen the comparison of each architectural model. Level iteration and time speed of 3 architectural models viewed using the Matlab application. The level of accuracy and value of MSE (Mean Squared Error) from the five architectural models is obtained using Microsoft Excel. All architectural models both produce 83% accuracy, it's just that the epoch 5-10-20-1 architectural models are lower and training times are faster than other architectural models, although the MSE is slightly higher than other models.

Table 4. Comparative Results of Architectural Models Used with Bayesian Regulations

| Bayesian Regulation | Architecture | Epoch | Time | MSE | Accuracy |
|---------------------|--------------|-------|------|-----|----------|
| 5-10-20-1           | 898          | 00.31 | 0.0031434897 | 83% |
| 5-15-30-1           | 1000         | 02.41 | 0.0030497874 | 83% |
| 5-20-40-1           | 1000         | 09.25 | 0.0030497874 | 83% |
Based on Figure 2 it can be explained that from the training process using the 5-10-20-1 model produces an epoch of 898 iterations with a time of 31 seconds.

Table 5 shows the results of the micro and small industrial production index according to KBLI for the next three years, namely 2018-2020. The results are obtained from calculations with the best 5-10-20-1 architectural models using Matlab and Microsoft Excel applications. Based on the comparison of the previous data with the results of the prediction it can be seen that the micro and small industrial production index according to KBLI tends to decrease, although the decline is not too significant.

| No | KBLI (Description)                              | Previous data | Prediction Results |
|----|------------------------------------------------|---------------|--------------------|
|    |                                               | 2015         | 2016       | 2017       | 2018   | 2019   | 2020       |
| 1  | Food                                          | 148.09       | 159.23     | 173.87     | 172.77 | 172.19 | 170.09     |
| 2  | Drink                                         | 131.10       | 146.37     | 154.38     | 159.46 | 154.66 | 152.85     |
| 3  | Tobacco Processing                            | 76.30        | 80.56      | 63.93      | 63.91  | 63.54  | 63.54      |
| 4  | Textile                                       | 130.09       | 142.72     | 145.56     | 147.98 | 147.34 | 145.86     |
| 5  | Apparel                                       | 132.44       | 141.70     | 149.88     | 146.81 | 148.93 | 147.11     |
| 6  | Leather, Leather Goods and Footwear           | 133.75       | 140.73     | 145.53     | 147.61 | 145.73 | 144.17     |
| 7  | Wood, Gabus (Not Including Furniture) and Woven from Bamboo, Rattan, etc. | 99.57        | 103.14     | 104.96     | 106.92 | 104.70 | 103.96     |
| 8  | Paper and Paper Products                     | 131.01       | 153.06     | 180.47     | 178.40 | 176.20 | 176.20     |
| 9  | Recording Media Printing and Reproduction    | 135.31       | 164.80     | 183.63     | 184.74 | 184.99 | 182.63     |
| 10 | Chemicals and Goods from Chemicals           | 122.76       | 141.24     | 167.59     | 162.04 | 163.19 | 161.26     |
| 11 | Pharmacy, products of chemical drugs & traditional medicines | 104.67       | 116.24     | 108.64     | 108.41 | 111.73 | 110.76     |
| 12 | Rubber, Goods from Rubber and Plastics       | 93.90        | 91.07      | 85.86      | 86.02  | 85.77  | 85.32      |
| 13 | Non-Metallic Excavation Items                | 102.57       | 103.74     | 104.29     | 103.33 | 103.46 | 102.77     |
| 14 | Base Metal                                   | 122.30       | 125.65     | 140.32     | 134.15 | 133.00 | 133.74     |
| 15 | Metal Goods, Not Machinery and Equipment     | 97.04        | 85.42      | 84.19      | 84.03  | 85.21  | 84.78      |
| 16 | Computers, Electronic and Optical Goods      | 124.11       | 162.80     | 220.19     | 219.10 | 217.16 | 214.18     |
| 17 | Electrical equipment                         | 130.00       | 139.71     | 148.59     | 144.50 | 147.15 | 145.53     |
| 18 | Machinery and Equipment ytdl                 | 98.89        | 117.96     | 115.31     | 116.84 | 115.80 | 114.81     |
| 19 | Motorized Vehicles, Trailers and Semi Trailers | 118.80      | 128.99     | 126.11     | 133.58 | 130.70 | 129.31     |
| 20 | Other Transport Equipment                    | 92.08        | 103.37     | 108.12     | 106.26 | 105.25 | 104.38     |
| 21 | Furniture                                   | 128.97       | 131.19     | 136.55     | 137.68 | 136.09 | 134.76     |
| 22 | Other Processing                             | 119.51       | 118.73     | 129.71     | 127.10 | 126.49 | 125.12     |
| 23 | Machine and Equipment Repair and Installation Services | 122.77      | 110.23     | 113.04     | 115.79 | 114.44 | 113.47     |
4. Conclusion

Based on the results of research regarding micro and small industrial production indices that will be discussed according to 2-digit KBLI, it can be concluded that with 5-10-20-1 architectural models, can predict with 83% accuracy with a fairly fast time, although the MSE level not too small. Based on the comparison of the previous data with the results of the prediction it can be seen that the micro and small industrial production index according to KBLI tends to decrease, although the decline is not too significant.

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