

Salt Fields Productivity Forecasting Based On Sunlight Duration, Wind Speed and Temperature Data

Indra Cahyadi¹, Heri Awalul Ilhamsah¹ and Ika Deefi Anna¹

Abstract—Once a major salt producer, Indonesia has imported million tons of salt in recent years to meet domestic demands of chemical industries. Indonesia's salt-producing potential has been hindered by lack of competitiveness and unsynchronized production data. The salt supply chain process is typically finished on a monthly basis, yet the uncertainty of weather conditions often leads to erratic production yields. Since heavy reliance on the weather can bring negative consequences for salt farmers around the country, accurate salt field productivity forecasting is of great importance. This study aims at examining sunlight duration, wind speed and temperature data to predict salt field productivity in Kalianget Sumenep Madura. The predictive model is developed using Artificial Neural Network (ANN) method because it has a low risk of fault to solve nonlinear relationships. The effects of different learning rate and momentum values are analyzed by full factorial design of experiment and evaluated based on the lowest root mean square error (RMSE). Then, the optimal model is used to test and compare the forecasting performance based on ANN and Holt-Winters predictors. The result demonstrates that the proposed model is accurate and efficient to represent a good solution to predict salt field productivity in the region.

Keywords—Artificial Neural Network, Forecasting, Predictive Modeling, Salt fields, Supply Chain Management.

I. INTRODUCTION

Data from the Ministry of Industry of Indonesia shows that national salt consumption, driven by industrial raw material and household consumers needs, is growing. In 2018, demand for industrial salt has reached 3.7 million tons or increased 76.19% compared to 2017. However, domestic salt production cannot meet the national demands, especially the needs of industrial grade salt. Therefore, almost 100% of national industrial salt demands are fulfilled from the international market. Indonesia's great dependence on imported salt reflects the inability of domestic salt production to offset the increasing demand for domestic industrial salt[1].

In general, salt production in Indonesia is produced by salt farmers by utilizing salt fields[2]. The production of salt in Indonesia comes from the evaporation of sea water

contained in salt ponds. Salt production with such methods is highly dependent on natural conditions, climate and weather.

As a result, national salt production is heavily influenced by unpredictable climate and weather anomaly phenomena. According to [3], salt supply chain and distribution channels in Indonesia are less efficient than any other countries, as shown in Figure 1 below.

This is due to too many players involved in the supply chain of salt resulting in a lengthy distribution process that hinders national industry production continuity. Based on the above description, the salt industry in Indonesia is a strategic industry that must be properly developed and managed. The development of salt industry can be done by effectively and efficiently managing all supply chain agents so that they can be optimally utilized[4]. Some ways to achieve this objective are to maximize production and determine the right time to produce which requires accurate forecasting results[5].

To set accurate salt field productivity forecasting results, it is important to collect data of various factors that influence the salt production process. Experience has proven that the level of salt field productivity is difficult to forecast because it is affected by a number of variables, such as amount of temperature, area of salt fields and the number of salt farmers among others[3], [6], [7]. Acknowledging how complex is the problem, this research proposes an Artificial Neural Network (ANN) model for forecasting salt field productivity. The ANN method is chosen because it has advantages in the aspects of adaptive system learning and a low risk of fault to solve forecasting problem, especially in approximating nonlinear relationships[8]. This study employed secondary data obtained from the Trade and Industrial Agency of Sumenep Madura, Central Bureau of Statistics Indonesia (BPSS) and Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG). Based on the historical data and the performance of each ANN models, the optimal forecasting model for salt field productivity can be selected through the least Root Mean Squared Error (RMSE).

II. METHOD

ANN method acts as a data processing system which mimics the human nervous system. A neural network is an

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interrelated network of processing layers where independent computations typically start from the first layer (input layer) and passes on to next layers that pass the results to another layer (hidden layers). This process will continue to progress into the last layer (output layer) which determines the output from the neural network. The processing signal between these layers enables the network to solve complex nonlinear and linear systems[9], [10].

In this study, the objective of the forecasting model is the amount of production from salt fields in month t . The data for ANN method consist of four variables: data of area of salt fields and monthly production yields collected from the Trade and Industrial Agency of Sumenep Madura, BPS, and data of amount of sunlight duration, wind speed and temperature in Sumenep Madura collected from BMKG.

The next step is to determine the best model based on parameters set in the data training. After the modeling process in the previous step, then performance test using testing data on the selected model is conducted. In the last step, the optimal model is used to test and compare the forecasting performance based on ANN and Holt- Winters predictors using the time-series data set as the input.

The input data for ANN method consist of three variables: monthly data of average sunlight duration, wind speed and temperature in Sumenep from 2010 until 2018. The output is salt field productivity rate calculated from average salt fields area and monthly production yields in Kalianget Sumenep. These four data sets are plotted against year in figure 3. Those data sets of time series are used to generate data training and testing. Each of these data sets

then is divided into training and testing data by ratio of 70:30.

In order to achieve optimal training algorithm and activation functions, forecasting parameters used in this study are adjusted and fine-tuned, as follows:

- Learning Rate - It defines the duration of the learning process model for any iteration. The scale value of the learning rate parameter ranges from 0 to 1.
- Epoch - The epoch parameter is the value of the number of iterations used.
- Momentum - This parameter determines the maximum permissible fault limit that the model allows. The value of the momentum scale is determined between 0 and 1.
- Desired Error (Mean Squared Error): This value desired mean squared error of the network. This study set MSE parameter to 0.0001

The ANN models in this study are developed using Fast Artificial Neural Network (FANN) programming library which has some features to construct optimal training algorithm and activation functions[11]. FANN determines whether resilient propagation or back-propagation is the optimal training algorithm for data training. The objective of back-propagation training is to adjust the weights in order to minimize the error function. In this algorithm, the weights are updated after each training pattern that means weights are updated many times during a single epoch. On each iteration, the new weights are given by

$$w_{st}^{new} = w_{st}^{old} + \Delta w_{st} = w_{st}^{old} + \eta \frac{\partial E}{\partial w_{st}} \quad (1)$$

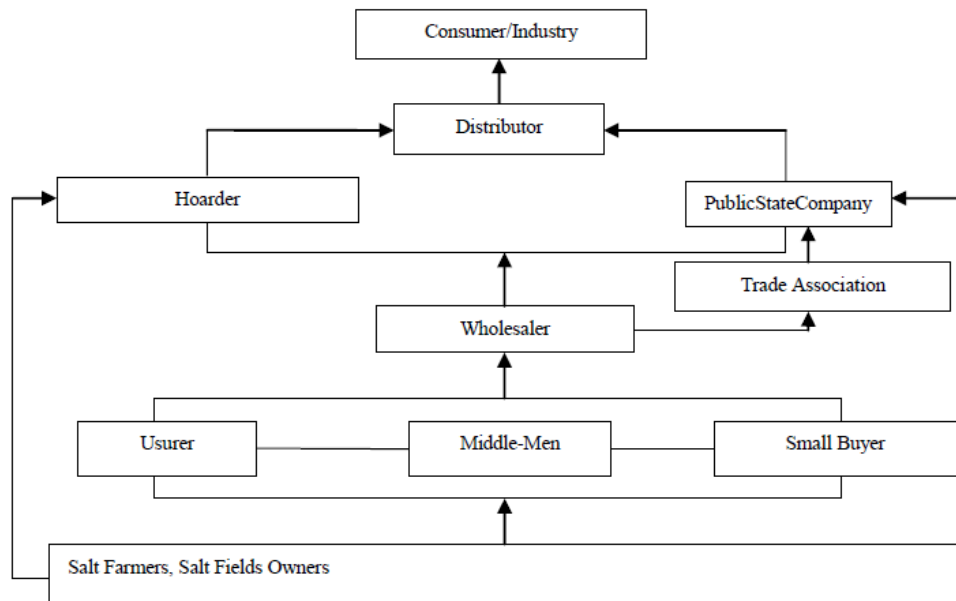


Figure 1. Typical Salt Supply Chain in Indonesia[3].

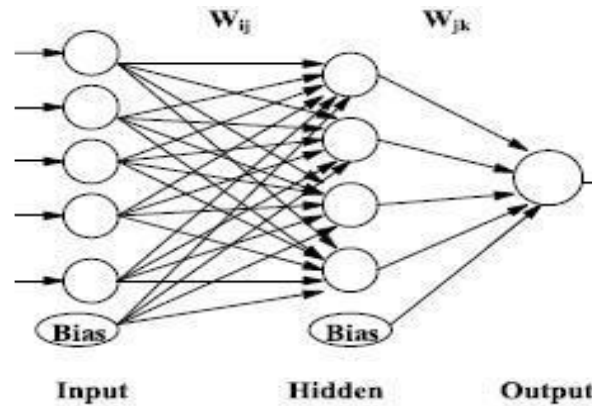


Figure 2. Topology of the three-layer feed forward neural network[10].

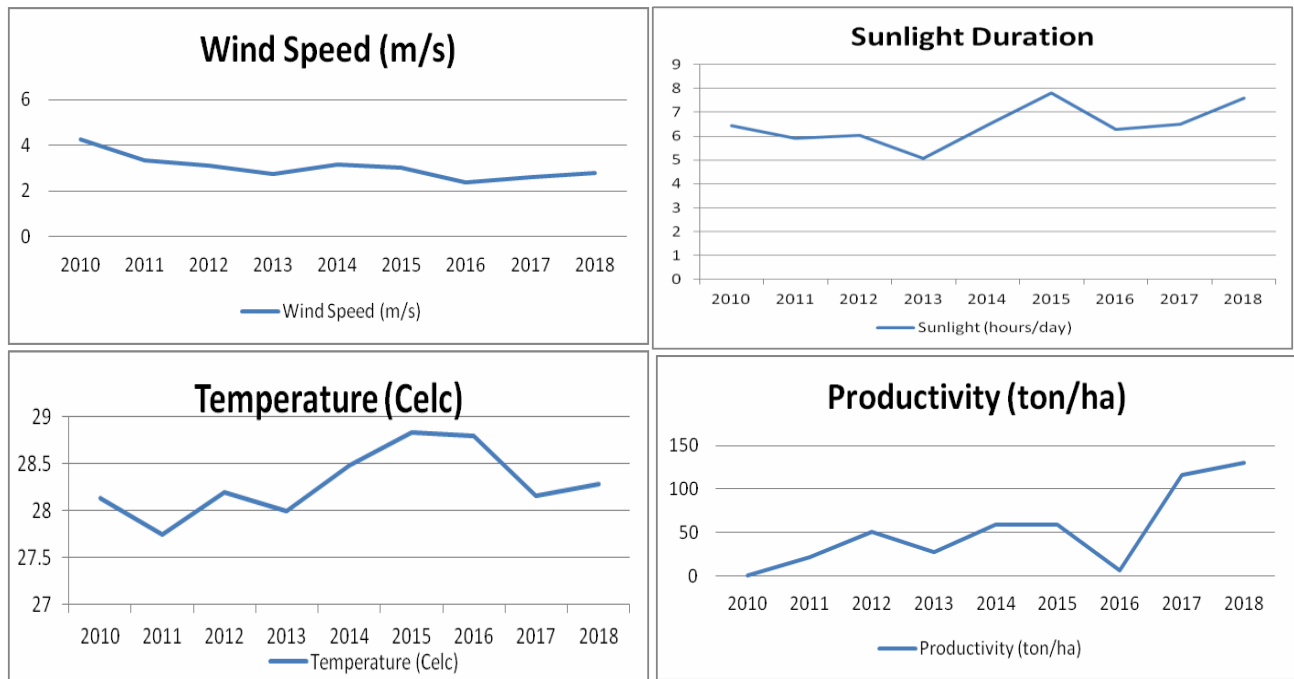


Figure 3. Time series plots for the data sets.

Where w_{st} is the weight change between neuron s to neuron t in the next layer and η is the learning rate[9], [12].

The objective of resilient-propagation training algorithm is to adjust weights of the network according to signal error propagation. In this algorithm, the weight updates are controlled for each connection during the training process. On each iteration, the new weights are given by

$$w_{ij}^{(t+1)} := w_{ij}^{(t)} + \Delta w_{ij}^{(t)} \tag{2}$$

and the step-sizes are computed as

$$\Delta w_{ij}^{(t)} := -sign\left(\frac{\partial E^{(t)}}{\partial w_{ij}}\right) \Delta_{ij}^{(t)} \tag{3}$$

where the "sign" operator returns +1 if its argument is positive, - 1 if the argument is negative, and 0 otherwise[13].

FANN also includes a feature to select the optimal activation functions based on the given parameters. The activation functions can either be defined for a group of neurons by hidden activation function, output function or a single neuron by input to activation function and the steepness of an activation function.

III. RESULTS AND DISCUSSION

Seven models are initially proposed as the foundation of salt field productivity forecast model development, each of which is described as follows:

- (1) Model 1: This model uses 1 input variable with input neuron (x)
- (2) Model 2: This model uses 1 input variable with input neuron (y)
- (3) Model 3: This model uses 1 input variable with input neuron (z)

(4) Model 4: This model uses 2 input variables with input neurons (x) and (y)

(5) Model 5: This model uses 2 input variables with input neurons (x) and (z)

(6) Model 6: This model uses 2 input variables with input neurons (y) and (z)

(7) Model 4: This model uses 3 input variable with input neurons (x), (y) and (z)

where,

x = average sunlight duration in month t

y = average wind speed in month t

z = average temperature in month t

In order to obtain the optimal model, training process are conducted for the proposed models using these parameters; number of hidden layer equals to 1, number of neurons in that layer equals to 2, the learning rate of 0.7, the momentum of 0.1 and the maximum epoch of 50,000 epoch. All models are trained and tested with 1 hidden layer and 2 neurons in its hidden layer. According to[14], one hidden layer is sufficient to resolve most of neural network problems. Two neurons in that layer is considered to give decent performance, since it lays between mean of the neurons in the input and output layers and the upper bound on the number of hidden neurons that shall not result in over-fitting[15]. The comparison of training results from each model is summarized in table 1.

Based on the FANN programming library execution result, Model 4 is selected because it is more optimized compared to the other proposed models. The selected ANN methods for Model 4 are summarized as follows[11];

- Quick propagation: This algorithm adjusts weights of the network according to signal error propagation. The objective is to maximize the parameters to achieve good results for many problems.
- Sigmoid symmetric activation function: The sigmoid produces a "S" shaped curve to recognize nonlinearity in the model. The output range is between zero and one.

$$y = \frac{1}{1+e^{-2xs}} \quad (4)$$

span: $0 < y < 1$

- Cos symmetric activation function: this periodical cosinus activation function is required over the activation range for smoother control. The output range is between -1 and 1.

$$y = \cos(x * s) \quad (5)$$

The obtained MSE value from training procedure is convincing, since any model with MSE value which is significantly less than 0.001 will be able to predict the value in a given period[16].

One of the most important parameters of an artificial neuron network is the value of learning rate. Training result is more reliable when the learning rate is low, but optimization will take a lot of time because the required steps to achieve minimum value of the loss function are

tiny. If the learning rate is high, then training may not be satisfying because the optimizer will overshoot the minimum and make worse error rate. Another important parameter which needs to be set is the learning momentum. Learning momentum enables the estimation of a certain weight and the search of the global minimum at a given time[14], [15]. In order to get satisfying results, a model must go through training process in ANN method which is usually tedious and based on trial and error. This study employs design of experiments training, to determine a reliable learning rate. The learning rate parameter in this design of experiments is set between 0.3 and 0.9[16], [17].

In general, the bigger the data sets, the neural network model will be more accurate. However, data collection process requires some time, and the model development process will be inefficient if too much time is wasted on building the database. Therefore, the idea in this study was to develop a model capable of learning from the available amount of training data. Design of experiments are prepared to obtain learning momentum value that can accelerate the training process of the ANN model. In this study, this momentum parameter is set between 0.5 and 0.9[16]–[18].

In order to determine the size of the Model 4, training and test process have been conducted to determine the numbers of learning rate and learning momentum that give the satisfactory results. The results considered as satisfactory when those gave the least RMSE. During the determination of network Model 4, it was considered that squared error (RMSE) of validation data was obtained when the learning rate on level one, i.e., 0.3 and momentum constant on level two, i.e., 0.9. This setting is presumed will give better accuracy and reliable computation time.

The forecasting results with Model 4 are then compared with the Holt-Winters method. The Holt- Winters method is a classic method that is well known for predicting time series results that have seasonal factors and elements of trends or trends. Total 108 time- series data on productivity of salt fields in Kalianget Sumenep are used as input data and the resulting RMSE value was 0.0395.

Comparison of RMSE values shows that both Holt-Winters and ANN methods have a value below 10%, so both methods are feasible to use. However, the ANN method still has advantages over the Holt-Winter employing different combinations on testing and training data would be more efficient.

Since this study aims to investigate the impacts of learning rate and momentum values on ANN model and performance, full factorial parameter design was implemented. Each one of the parameters has low and high levels for different neural networks to created and tested. Table 2 summarizes the parameter designs used in this study.

Moreover, this study applies a mid point in the low and high experiment levels to explore whether the relation

between low and high levels consists of a non-linear reaction. By adding a mid point between the low and high level, the existence of curvature between the two points can be inspected. Therefore, this study has added 2 central points to inspect the low and high levels in the experiment. The effect of learning rate and momentum parameter values variations is described in Table 3.

As seen in Table 3, the use of learning rate and momentum variations is considered influential to the final result of forecasting. The minimum root mean method because the RMSE value is smaller than the Holt-Winters method.

TABLE 1.
COMPARISON OF OPTIMUM ANN METHODS FOR EACH MODEL

Model	Train Method	Hidden	Output	MSE
1	RPROP	SIGMOID	ELLIOT_SYMMETRIC	0.000265
2	SARPROP	SIGMOID_SYMMETRIC	ELLIOT_SYMMETRIC	0.000262
3	RPROP	SIN_SYMMETRIC	GAUSSIAN_SYMMETRIC	0.000264
4	RPROP	SIGMOID_SYMMETRIC	COS_SYMMETRIC	0.000261
5	SARPROP	SIN_SYMMETRIC	COS_SYMMETRIC	0.000264
6	RPROP	LINEAR	GAUSSIAN_SYMMETRIC	0.000264
7	BATCH	COS_SYMMETRIC	GAUSSIAN_SYMMETRIC	0.0012

TABLE 2.
NEURAL NETWORK PARAMETER DESIGN

Item	Neural Network Parameters	Levels	
		1 (Low)	2 (High)
A	Learning Rate	0.3	0.9
B	Momentum	0.5	0.9

TABLE 3.
DESIGN OF EXPERIMENTS RESULTS OF MODEL 4.

Learning Rate	Momentum	Training MSE	Test MSE	Average MSE	Root MSE
0.3	0.9	0.00026	0.000614	0.0004	0.020964
0.6	0.9	0.00026	0.000614	0.0004	0.020963
0.9	0.9	0.00026	0.000614	0.0004	0.020962
0.3	0.7	0.00026	0.000614	0.0004	0.020967
0.6	0.7	0.00026	0.000614	0.0004	0.020962
0.9	0.7	0.00026	0.000614	0.0004	0.020963
0.3	0.5	0.00026	0.000614	0.0004	0.020966
0.6	0.5	0.00026	0.000614	0.0004	0.02096
0.9	0.5	0.00026	0.000614	0.0004	0.020966

IV. CONCLUSION

This study shows that the proposed model can work well in predicting salt field productivity by considering weather factors and determining the optimum parameter values. This study also illustrates how ANN methods can be applied to improve the accuracy of estimates of salt field productivity in supporting supply chain management innovations. The most efficient neural network examined, Model 4 with sunlight duration and wind speed as input neurons, 1 hidden layer and 2 neurons in the hidden layer, has a RMSE value of 0.0209.

The problem of salt fields productivity forecasting has been compared by calculation results of the Holt-Winters method.

The RMSE values of both ANN and Holt-Winters methods show that achieved forecasting results are good and satisfactory. However, the selected model ANN-based forecast results are still better than their corresponding forecast results calculated via the Holt-Winters method because the ANN method produces lower RMSE value.

The application of ANN method in this study are justified because, in many cases, the salt industry stakeholders want to know various factors, such as the influence of weather, seawater quality, humidity, rainfall, and salt production technology. In addition, stakeholders also want to see the integration between forecast results and production planning strategies to better manage their supply chains. Therefore, further research needs to explore how to include these additional factors and implement the

results of this study in an integrated enterprise resource planning application system.

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