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PLANTING CALENDAR FORECASTING SYSTEM USING EVOLVING NEURAL NETWORK

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Abstract

Weather forecast information, where the rainfall is crucial factor, is extremely needed in agriculture sector so the farmer can predict the beginning of growing season in the planting calendar. The planting calendar is required by Department of Agriculture to maximize the agricultural production. In this research, it has been conducted using evolving neural network (ENN) algorithm on forecasting system. The forecasting system is used by Department of Agriculture of Bandung Regency (Indonesia) to recommend the beginning of growing season for the farmers. The data used in the research is gained from Department of Agriculture and Indonesian Agency for Meteorology Climatology and Geophysics (BMKG) including monthly rainfall forecasting data from 2003-2012 in Soreang (Bandung Regency). The research can be successfully conducted because of rainfall forecasting application system remains best accuracy of 70%.

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1. Introduction

Weather forecast information is highly needed in most aspects in life especially for agriculture sector. In this sector, the information is used to determine the beginning of growing season of the plant. The information is required to minimize the risk of planting, so the farmers do not lose their capital. Moreover, Department of Agriculture of Bandung Regency (Indonesia) may also make the planting target and production target for their area. The plant growth is influenced by the weather [11] involving the rainfall which has the important role in agriculture. Therefore, weather forecast information is firstly needed to make planting calendar based on the plant characteristics. Soft computing (SC) is one of the methods in artificial intelligence that can be used to doing weather forecasting. SC consists of three basic algorithms, namely fuzzy systems, artificial neural network (ANN), and evolutionary algorithms (EAs). ANN algorithm is very widely used for prediction problems. In [3], ANN models are used for river flow forecasting gives better accuracy than the auto-regression time series models. Meanwhile, feedforward neural network successfully doing forecasting of groundwater levels in Venice Lagoon, Italy [12]. Next, Adiwijaya et al. present a weather data forecasting by using ANN algorithm [1, 2]. It had raised analysis some parameters of ANN such as determining input numbers, hidden layer numbers and hidden neuron numbers. However, it has not provided an optimum result. One algorithm that can be used to overcome the problems of ANN is by doing optimization using evolutionary algorithms. This algorithm is often called the *evolving neural network* (*ENN*) *algorithm*.

Genetic algorithm can optimize fuzzy algorithm studied on soft computing [4]. Hence, this research has done the optimization of neural network algorithm using genetic algorithm to obtain optimal ANN architecture and weight to be the model of rainfall forecasting for the next 12 month, then the result will be used as the planting calendar for the plants involving rice, potato, and corn. The rainfall forecasting data has been gained from Indonesian agency for meteorology climatology and geophysics (BMKG) and Department of Agriculture of Bandung Regency from 2003 to

2012. The planting calendar is used as the information for Department of Agriculture of Bandung Regency to forecast proper growing season functioned to minimize crop failure. It is also made for 3 types of plant including rice, potato, and corn since they are the primary plant produced by Department of Agriculture of Bandung Regency. In addition, its potato has contributed a 20% national production.

The difference between this research to the previous research [2, 4, 5, 9] is the type of data and algorithms used. In previous research, forecasting rainfall conducted based on the data of rainfall, temperature, humidity, duration of solar radiation and wind speed in the area of Kemayoran, Jakarta. In these studies, forecasting conducted to the using some variation of the algorithm on the SC as evolving fuzzy algorithm [4], neural network optimized using the line search technique [2], evolving neural network and architectural modifications [5, 9]. Meanwhile, in this research, rainfall forecasting conducted based on rainfall data earlier in Bandung Regency using ENN. Before the implementation of ANN, the preprocessing conducted to the using the moving average algorithm. In addition, the contents of which are optimized GA chromosome is different to the publication [5], because in this study the optimization of the number of input rainfall data. Furthermore, the results of rainfall forecasting is used to create a planting calendar for the next twelve months in correspond to the characteristics of the plants.

2. Research Method

2.1. Evolving neural network

The primary issues on artificial neural network (ANN) are determining the architecture of node input, hidden layer numbers, hidden neuron numbers, and optimal weight. It can be solved, one of the ways, by hybrid process between ANN algorithm and evolutionary algorithm’s (EAs) which is best known by evolving neural network (ENN) [5-7, 8-10]. One of EAs commonly used is genetic algorithm (GA). There are various architectures on ANN algorithm [9], one of them is multilayer perceptron (MLP) where there is the interconnection of each neuron.

In evolving neural network (ENN), ANN will be optimized by GA in order to find out the connection and optimal weight represented by chromosome or individual in GA. This general scheme is started by chromosome representation then will be executed as the code of the architecture and weight for ANN. Those chromosomes are conducting evolution process using GA operators. Thus, in ENN, there will be only architectural optimization, weight optimization, or both of them.

The best chromosome has been gained from the evaluation process in its generation using fitness score where the solution can be accepted or not (individual). Its score will be the parameter in reaching the optimal score of evolving neural network. Fitness score calculation uses feedforward propagation of ANN architecture gained from genetic algorithm. In this type of propagation the score will be calculated using mean absolute percentage error (MAPE) as follows [8]. Besides MAPE, the fitness value can also be calculated using the mean absolute error (MAE) or mean squared error (MSE) [10].

$$Fitness = \frac{1}{MAPE},$$

where

$$MAPE = \left(\frac{1}{n}\sum \frac{|\,actual\ data - prediction\ data\,|}{|\,actual\ data\,|}\right) * 100\%,$$

and n is the number of data.

2.2. Moving average algorithm

One important part of the preprocessing phase is data smoothing. There are several algorithms that can be used for smoothing process, such as local regression smoothing and exponential smoothing [10]. In the proposed scheme, the data smoothing process is provided by using the moving average. Moving average algorithm is used to have data smoothing process using the equation as follows [8]:

- Moving average 1 (MA 1):

$$S_t = \frac{A_{t-2} + (2 * A_{t-1}) + (4 * A_t) + (2 * A_{t+1}) + A_{t+2}}{10}.$$

- Moving average 2 (MA 2):

$$S_t = \frac{(2 * A_{t-1}) + (6 * A_t) + (2 * A_{t+1})}{10},$$

where t = the period; S_t = smoothing result; A_t = actual value.

2.3. Plants and rainfall relationship

Plant growth is closely related to weather. The factors of weather influencing the plant are temperature, water, sun radiation, and wind [5]. Every plant needs the different supply of water especially for those which require lots of water so it is assisted by the rain. For instance, rice involves high level of rainfall intensity amounts for its irrigation system. The table below shows the harvesting seasons of rice, potato and corn and their rainfall requirements.

Table 1. Rainfall requirements of plants [5]

Plants	Harvesting seasons	Rainfall Requirements
Rice	around 110-115 days after growing season	200 mm/ month
Corn	around 86-96 days after growing season	85-200 mm/month and must be smooth
Potato	around 90-180 days, it depends on its varieties	Potato's growing season is around 3-6 months depending on its varieties represented by the details of rainfall requirements as follows: • 1st Month: 130-200 mm per month • 2nd Month: 100-120 mm per month • 3rd Month: 60-70 mm per month • Last month before harvesting it does not need rain

2.4. Description of forecasting system

The issue raised in this research is how to forecast the rainfall considering to the previous data of rainfall. Forecasting system built in this research is the system in which the rainfall can be forecasted further. Figure 1 presents block diagram of forecasting system.

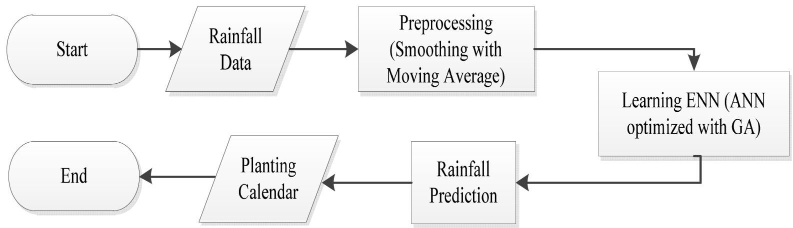

Figure 1. Block diagram of system.

From Figure 1, the data of rainfall is firstly processed using moving average algorithm. Furthermore, it goes to learning process by ENN algorithm. Then Figure 2 serves the learning process of ENN.

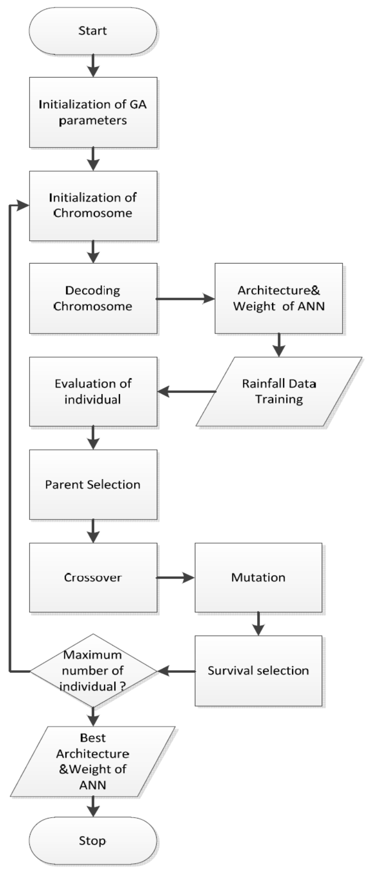

Figure 2. ENN learning process.

The best individual is the chromosome which contains ANN architecture and optimal weight. This chromosome design will be crucial since it will be the ENN solution. The following is chromosome design of GA to optimize ANN architecture and weight:

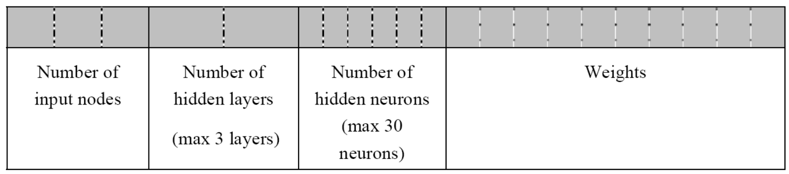

Figure 3. GA chromosome design in ENN.

Learning process results in the best chromosome that will be the model to forecast further monthly rainfall.

2.5. The data used and moving average implementation

The data used in this research is the monthly rainfall data from BMKG from 2003 to 2012 and Department of Agriculture of Bandung Regency from 2003 to 2012. The following is the data samples of monthly rainfall used.

Table 2. Data samples of BMKG's monthly rainfall (in millimeter)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2003	113,7	292,0	291,8	209,8	113,0	33,8	7,8	58,2	80,3	329,6	156,6	218,2
2004	291,2	136,5	222,8	242,3	158,7	49,0	10,0	1,0	143,1	43,5	217,9	264,4
2005	346,4	316,6	229,0	115,2	105,4	212,6	46,5	60,9	78,8	217,8	181,4	121,0

Based on the system design on Figure 1, there will be the preprocessing of rainfall data using moving average. Table 3 shows the data samples of rainfall data used and the comparison of actual data pattern with the data of moving average.

The data processed by moving average will step learning process by observation parameter which can be seen in Table 4.

Table 3. Sample of preprocessing data result

Year	Month	Actual Data (mm)	MA1 (mm)	MA2 (mm)
2003	Jan	113,7	-	-
2003	Feb	292,0	-	256,3
2003	Mar	291,8	239,75	275,4
2003	Apr	209,8	197,46	206,8
2003	May	113,0	123,88	116,5
2003	Jun	33,8	64,48	44,4
2003	Jul	7,8	40,85	23,1
2003	Aus	58,2	77,24	52,5
2003	Sep	80,3	126,12	125,7
2003	Oct	329,6	206,86	245,1
2003	Nov	156,6	209,35	203,5
2003	Dec	218,2	223,45	220,5
2004	Jan	291,2	225,36	245,7
2004	Feb	136,5	203,45	184,7

Table 4. GA parameters

Parameters	Value
Numbers of individual	5000
Numbers of population	[5 50 100]
Probability of crossover	[0.1 0.3 0.5 0.7 0.9]
Probability of mutation	[0.05 0.1 0.2 0.3 0.4]

3. Results and Analysis

3.1. Planting calendar forecasting system

To forecast the rainfall of the next 12 months, the model remains the best chromosome gained from the result of ENN learning process. Then, the result will be used as the planting calendar. Initially, the forecasting system is designed based on rainfall data in the range of 2003-2012 in order to be compared with the data of BMKG is available only up to 2012. Furthermore, the system that has been built can be used for modeling forecasting in the following years.

According to the discussion result with the member of Department of Agriculture, rainfall forecasting is extremely needed for the rainfed irrigation system. In this system, the beginning of growing season of rice is held from October to March while other plants are from April to September. Due to that, the planting patterns involve potato/corn, then rice.

Based on the GA parameter experiments in Table 4, MAPE and accuracy has been obtained and they can be seen in Table 5 below.

Table 5. Experiment results

Data	MAPE	Accuracy
Data from BMKG	26,90%	73,10%
Data from Department of Agriculture	24,36%	75,64%

On the basis of Table 5, it can be inferred that learning process results involving the data from BMKG compared to the data from Department of Agriculture has the difference accuracy around 2,54% which remains a low gap. Therefore, the designing future forecasting model can be created by Department of Agriculture using its own rainfall data as the input for the system. Table 6 presents the best chromosome, gained when GA parameter lies in the size of 200 chromosome population that is equal to the data of BMKG and of Department of Agriculture. It remains also for the best model in mutation opportunities which gain 0.05.

Table 6. GA parameters from the best chromosome

Parameters	Data from BMKG	Data from Department of Agriculture
Number of Population	200	200
Number of Gen per Variable	90	50
Crossover Probability	0.1	0.3
Mutation Probability	0.05	0.05
Number of input nodes	4	4
Number of hidden layer	1	1
Number of hidden neurons	1	1

The best chromosome showed in Table 6 has 4 nodes as the input where the forecasting process for month + 1 $(M+1)$ requires data from 4 months ago (M-3, M-2, M-1, and M). The learning process data of Department of Agriculture and BMKG serve the similar node numbers, hidden layer numbers, and neuron numbers. One of the outputs of the calendar for the beginning of growing season involving rice, potato, and corn made from rainfall forecasting is presented in Figure 4 as follows:

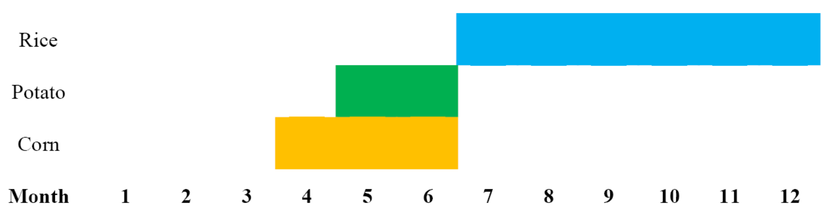

Figure 4. Sample of planting calendar.

Furthermore, complexity analysis of ENN algorithm in Table 7 can be used for the further system development.

Table 7 shows the highest result of asymptotic complexity which lies in Agobservation module. There will be module calling process to rank the linear fitness, selection of parents, recombination or crossovers, and binary mutation for each chromosome. The process can be accelerated by dividing the subprocess into several computers to be parallel executed such as using embarrassingly parallel.

Table 7. Complexity analysis

Function	Algorithms Complexity	Values of Complexity
MutationBiner	T(n) = JumGen	T(n) $\in$ O(n)
CrossoverBiner	T(n) = TotGen	T(n) $\in$ O(n)
RouletteWheel	T(n) = LinearFitness + UkPop	T(n) $\in$ O(n)
Parent Selection	T(n) = length(x) * T(n)RouletteWheel + length(x)	T(n) $\in$ O(n^2)
Agobservation	T(n) = length(ObUkPop) * length(ObGenPerVar) * length(ObProbCrossover) * length(ObPmutation) * JumObs * MaxG * (UkPop+length(MatingPool)+UkPop)	T(n) $\in$ O(n^7)
AGstandar2D	T(n) = MaxG * (UkPop+length(MatingPool)+UkPop)	T(n) $\in$ O(n^2)
DecodingChromosome	T(n) = GenPerVar + (nVar*GenPerVar) + 3*nNeuron	T(n) $\in$ O(n^2)
EvaluateIndividual	T(n) = DataSetRainfallInput * (3*nNeuron + Joneuron + length(Error))	T(n) $\in$ O(n^2)
InisializationPopulation	T(n) = 1	T(n) $\in$ O(1)
LinearFitnessRanking	T(n) = UkPop	T(n) $\in$ O(n)
MovingAverage	T(n) = length(data)	T(n) $\in$ O(n)

4. Conclusion

Rainfall forecasting system using ENN can result more than 75% accuracy represented by the data from Department of Agriculture of Bandung Regency which shows the different accuracy about 2,54% compared to the data from BMKG. The forecasting is used for the calendar of the beginning of growing season involving rice, potato, and corn based on the rainfall requirements of each plant.

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