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Fertigation Scheduling in Hydroponics System for Cucumber (*Cucumis sativus* L.) Using Artificial Neural Network and Genetic Algorithms

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ABSTRACT

A computer program for fertigation scheduling in a hydroponics system has been developed using Artificial Neural Network (ANN) and Genetic Algorithms (GA). The ANN model was used to establish the relationship between the environmental factors and outflow volume of fertigation in a hydroponics system for cucumber. The result showed that the predicted outflow volume agreed well with those of the measured values. The correlation coefficients (R^2) between the predicted and measured values were 0.9673, 0.9432, and 0.8248 for vegetative, flowering and maturation stages, respectively. Optimum schedules for vegetative, flowering, and maturation stages were in a good coincidence at R^2 of 0.8808 with the amount of fertigation required by the plants as calculated using the empirical method.

Key words : System identification, optimization, plant water consumption, fertigation, hydroponics

INTRODUCTION

Hydroponics system has received more attention because it promises more controllable crop management under greenhouse. Generally in Indonesia, fertigation in hydroponics system with drip irrigation is applied manually according to the weather and condition of the plants. This technique is less accurate and can cause significant losses of fertigation. Therefore, it is necessary to develop an accurate method in fertigation scheduling for the plants grown under hydroponics system. Water requirement of plant in a greenhouse has been calculated through evapotranspiration rate and crop coefficients (Harmanto *et al*., 2005; Orgaz *et al*., 2005).

Agricultural systems, such as an environment-plant system, are quite complex systems. They can be considered as ill-defined systems. It is, therefore, difficult to quantify the complex relationships between the input and the output of a system based on analytical methods (Hashimoto, 1997). This paper has focused on the application of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) on fertigation scheduling in a hydroponics system. ANN has the capability to identify an unknown complex dynamic plant system (Purwar *et al*., 2007). The benefit of ANN model is the ability to learn and generalize the system (Nugroho, 2003). Genetic algorithms (GA) is the search algorithm based on the mechanism of natural selection and genetics to search through decision space for optimal solutions. It can solve a complex objective function, with a multi-point search procedure, by simulating the biological evolutionary process based on crossover and mutation in genetics (Goldberg, 1989).

The objectives of this research were: 1) to establish the relationship between the environmental factors and outflow volume of fertigation using ANN; 2) to determine the optimum schedule of fertigation using GA; 3) to compare total volume of plant water consumption obtained through ANN and GA with that of empirical method. With this method, it is expected to gain a new effective and efficient method in fertigation scheduling in hydroponics system. Cucumber plants were selected in this research because economically it is one of the most high-valued crops usually grown in a hydroponics farm.

MATERIALS AND METHODS

Experimental Set-up and Measurements

Experiments were conducted in a hydroponics system in greenhouse at Bogor Agricultural University field laboratory, Darmaga, Bogor, Indonesia (6°30' south latitude and 106°45' east longitude). The greenhouse is a standard peak type greenhouse with steel frame structure. It has 12 m length and 6 m width with polycarbonate sheets cover. It is a naturally ventilated greenhouse with wall and ridge openings.

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The nutrient solution (Joro AB mix formula) was supplied into the growing media through emitter of drip irrigation system. Charred rice hulls were filled into the polyethylene bags (10 x 8.6 litres) and used as the growing media. Twenty cucumber plants (*Cucumis sativus* L) were grown in these polyethylene bags. Each polyethylene bag consisted of two cucumber plants.

Measured variables were emitter discharge (ml/s), duration of fertigation (s), interval of fertigation (h), air temperature (^{o}C), solar radiation (W/m^2), relative humidity (%), wind speed (m/s), and plant height (cm). A set of portable weather station (***R.M.-Young***) was used to record environment parameters that are solar radiation, air temperature, relative humidity, and wind speed. Plant height, discharge emitter, duration and interval of fertigation data were recorded manually everyday. Plant height included all of the two plants in each polyethylene bag and noted as height of plant I and II.

Artificial Neural Network Model for Identification of Outflow Volume

ANN was used to establish a black-box model for identification of the outflow volume of fertigation which is flowing out from the polyethylene bags. The ANN model consisted of three layers, i.e. input layer, hidden layer and output layer (Figure 1). Learning method used in this model was back-propagation. The back-propagation algorithm trained a given feed-forward multilayer neural network for a given set of input patterns with known classifications. When each entry of the sample set was presented to the network, the network examined its output response to the sample input pattern. The output response was then compared to the known and desired output and the error value was calculated. Based on the error value, the connection weights were adjusted.

In this study, outflow volume of fertigation was used as the output of the ANN model. The input data were discharge emitter (ml/s), duration of fertigation (s), interval of fertigation (h), air temperature (^{o}C), solar radiation (W/m^2), relative humidity (%), wind speed (m/s), age of plant (day), height of both plants (cm).

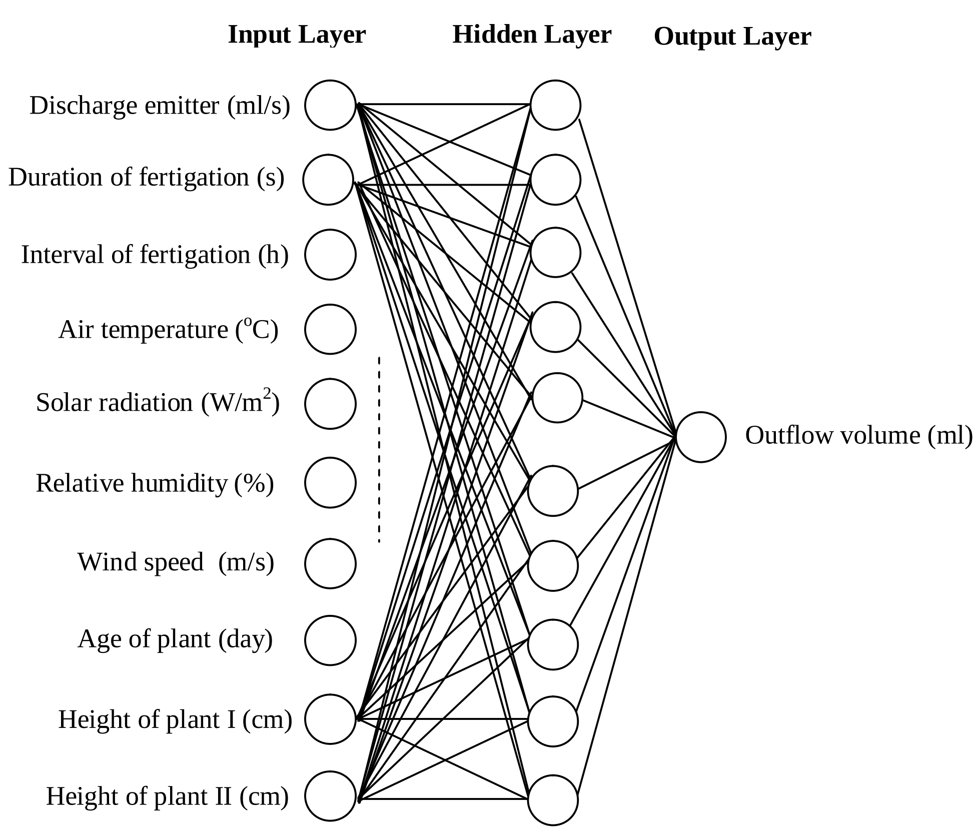

Figure 1. The Artificial Neural Network model for predicting the outflow volume of fertigation.

Optimization of Fertigation by Using Genetic Algorithms

Genetic algorithm (GA) was used to optimize the schedule of fertigation through minimization of outflow volume of fertigation. The schedule of fertigation was represented by duration and interval of fertigation. The objective function was given by ANN model which can be described as follows:

$$y = f(E, D, I, T, RAD, RH, v, A, H_1, H_2) \quad \text{.......} (1)$$

minimize y

Subject to $240 \le D \le 900$; $1 \le I \le 8$

where y is function of outflow volume (ml) given by ANN model, E is discharge emitter (ml/s), D is duration of fertigation (s), I is interval of fertigation (h), T is air temperature (°C), RAD is solar radiation (W/m^2), RH is relative humidity (%), v is wind speed (m/s), A is age of plant (day), H_1 is height (*cm*) height of plant I (cm) and height of plant II (cm). Flow chart of optimization by using GA is presented in Figure 2. The flow chart describes the mechanism to optimize schedule of fertigation.

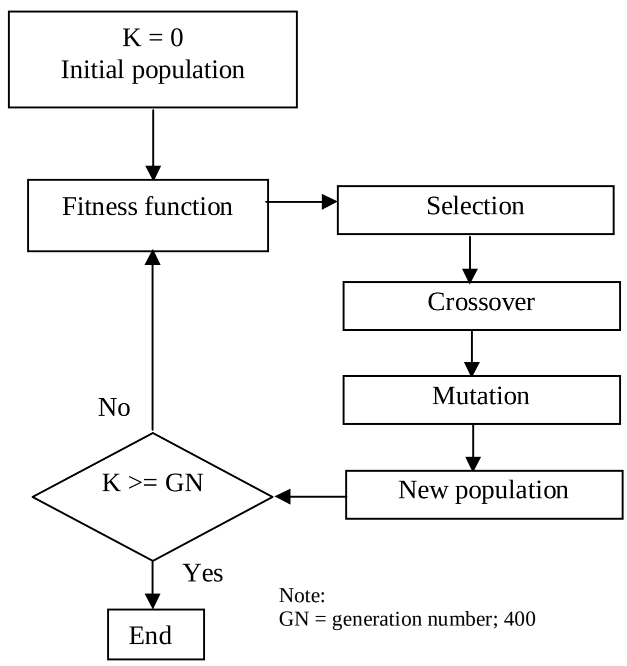

Figure 2. Flow chart for optimization using Genetic Algorithms.

The procedure of GA according to the flowchart was given by following steps: a) in the initial population process, individuals in one population were created randomly; b) the fitness function of all individuals was calculated according to the objective function in Equation 1 as given by ANN model; c) the selection process based on elitist strategy was used to select individuals who have better fitness value; d) crossover was applied to the selected individuals; e) mutation was applied for chromosomes; f) the new population was created; g) steps (b) to (f) were repeated until the required generation number achieved. Finally, an optimal value was given as an individual reached the highest fitness.

During crossover, the best individual was crossed with the second one, and the third one was crossed with the fourth one. The mutation process was initially conducted by creating one randomized value for each chromosome. If this value was smaller than or equal with probability of mutation, then the chromosome would be changed. And if the value was greater than probability of mutation, then the chromosome would be remained constant;

Probably in the process of evolution, local convergences happened. It may be caused by the loss of diversity within the population. To avoid this condition, a higher level of diversity in the population could be maintained by adding a number of individual to the population, randomly (Morimoto *et al.*, 1997b).

RESULTS AND DISCUSSION

Identification Process of Outflow Volume by Artificial Neural Network Model

In identification process using ANN model, data samples are divided into two data sets, i.e. training data set and testing data set. The training data set is used for training the neural network, while the testing data set is used for evaluating the accuracy of the identified model. The testing data set has to be independent from the training data set. This type of model validation is called "cross-validation" (Morimoto and Hashimoto, 2000).

The total training data set was about 65% of all data, while the testing data set was about 35% of all data. All variables were normalized between 0 and 1 using fixed minimum and maximum values both in training and testing processes. These values can be seen on Table 1.

Table 1. Ranges of value for parameters used in this Artificial Neural Network modelling

Layer	Parameter	Range	Unit
Input	Discharge	0.44 – 0.67	ml/s
	Duration of fertigation	240 - 900	second
	Interval of fertigation	1 - 8	hour
	Air temperature	29 -34	^oC
	Solar radiation	17.52 - 677.83	W/m^2
	Relative humidity	52 - 78	%
	Wind speed	0.1 – 0.7	m/s
	Age of plant	12 - 37	day
	Height of plant I	23 - 276	cm
	Height of plant II	24 - 278	cm
Output	Outflow volume	0 - 140	ml

The training process was carried out using the following learning parameters: learning rate (η) = 0.6, momentum (α) = 0.6, and gain = 1. This process was conducted repeatedly in 25000, 29000, and 30000 iterations for vegetative, flowering and maturation stages, respectively. The total numbers of data for these three stages were 30, 75, and 80, respectively.

The testing results showed the performance of ANN-based computers program to explain the relationship between input and output variables. The correlation coefficient (R^2) was used to evaluate the model performance. R^2 is defined as ratio of variation of data explained by model to the total variation. The bigger the value of R^2 or closer to 1, the better is the performance of the model. The correlation coefficients (R^2) of the relationship for each growing stage are shown in Figure 3. The correlation coefficients between the predicted and measured values were 0.9673, 0.9432, and 0.8248 for vegetative, flowering and maturation stages with total number of data were 20, 35 and 50, respectively. These mean that the predicted outflow volume agreed well with that of the measured value. Thus, a reliable computational model could be obtained for predicting outflow volume of nutrient solutions from the polyethylene bag.

Optimization Process for Fertigation

Fertigation scheduling was done through optimization process using GA. Some inputs were needed to run the optimization of fertigation scheduling. Table 2 shows the examples of values for input parameter of each growing stage which was used in the optimization process. The GA operators which influence the accuracy of the process cover the member of population, crossover rate, probability of mutation, and the number of generation. In this study, number of population was 20, crossover rate was 40%, probability of mutation was 1% and number of generation was 400. Mutation tends to make the population heterogeneous while crossover tends to make it homogeneous. The GA with high mutation and crossover rates allows an optimal value to be quickly sought (Morimoto *et al.*, 1997a).

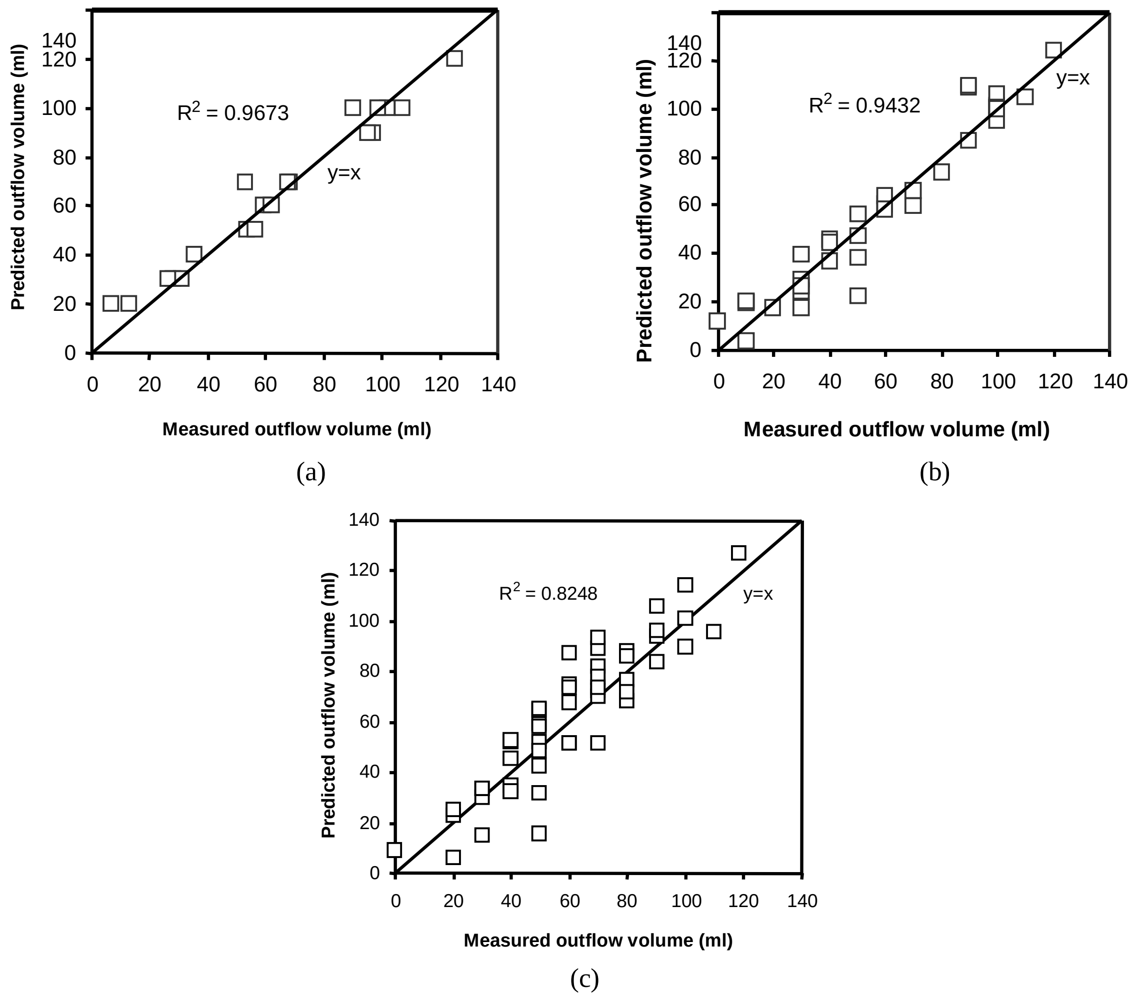

Figure 3. The predicted outflow volume as compared to that of the measured value for vegetative stage (a), flowering stage (b), and maturation stage (c).

Table 2. Examples of input parameter values used in the optimization of fertigation

Parameter	Growing stage								
	Vegetative			Flowering			Maturation		
Discharge emitter (ml/s)	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
Air temperature (^oC)	31	31	32	33	32	31	31	32	33
Relative humidity (%)	65	68	62	59	60	61	58	50	54
Solar radiation (W/m^2)	255	280	79	366	303	292	285	347	436
Wind speed (m/s)	0.4	0.3	0.3	0.4	0.3	0.4	0.3	0.4	0.4
Age of plant (day)	12	13	14	24	26	27	35	36	37
Height of plant I (cm)	26	28	32	104	123	134	222	229	241
Height of plant II (cm)	27	30	33	113	134	143	240	247	259

Table 3 shows the result of optimization. It can be seen that the duration of fertigation in the maturation stage was the longest as compared to that of other growing stages. It means that the total volume of fertigation given to the plants during the maturation stage was the largest. On the contrary, the duration of fertigation in the vegetative stage was the shortest. It means that the total volume of fertigation given to the plants during vegetative stage was the least, as compared to that of other growing stages. The differences in growing stages represented the differences in dry matter of the plants.

Table 3. Optimum schedule of fertigation based on Genetic Algorithms

Growth stage	Age of plant (day)	Duration of fertigation (s)	Interval of fertigation (h)	Outflow volume (ml)	Total volume (ml/day)
Vegetative	12	240.0	3.00	66.08	403.2
	13	240.0	5.46	32.50	268.8
	14	240.0	3.00	61.36	403.2
Flowering	24	300.0	4.00	7.47	504.0
	26	360.0	4.00	0.46	604.8
	27	306.6	3.01	0.04	515.2
Maturation	35	300.0	1.00	22.88	1344
	36	900.0	2.11	70.86	2016
	37	900.0	3.38	70.65	1512

Optimization using GA resulted in different duration and interval of fertigation for each growing stage as presented in Table 3. It was caused by the differences in input parameters and plant factor for each growing stage although the GA operators used were the same. A convergence value reached during optimization process shows that the GA program gave a good result. This result shows that the GA operators used for the current optimization were reasonably accurate in fertigation scheduling in the hydroponics system.

Plant Water Consumption

Plant water consumption shows the total water that is needed by plant. The empirical method to calculate plant water consumption is evapotranspiration. To evaluate the performance of optimization by GA, it is essential to compare it with the empirical method.

Plant evapotranspiration (ETc) was obtained from the difference in inflow and outflow volume of fertigation, while reference evapotranspiration was calculated using Hagreaves method based on temperature and solar radiation data (Wu, 1997). This method is the most effective along with Turc and Jense-Haise methods (Suprayogi, 2003). Species and growing stage of plant influence crop factor (Kc). The crop factor was estimated by dividing the plant evapotranspiration (ETc) with reference evapotranspiration (ETr). The values of plant evapotranspiration are presented in Table 4.

Table 4. Evapotranspiration of cucumber plant based on empirical method

Growing stage	Age of plant (day)	*ETc* (ml/day)	*ETr* (ml/day)	*Kc*	Area (cm^2)	Plant water consumption (ml/day)
Vegetative	12	4.27	3.89	1.10	490.62	209.3
	13	3.91	3.38	1.16	490.62	191.7
	14	4.79	4.52	1.06	490.62	235.0
Flowering	24	11.12	4.75	2.34	490.62	545.7
	26	12.75	4.52	2.82	490.62	625.5
	27	18.14	4.65	3.90	490.62	890.1
Maturation	35	26.47	4.62	5.73	490.62	1298.5
	36	33.38	4.91	6.80	490.62	1637.7

Plant water consumption increased during plant growth (Table 4). The averages of plant water consumption for vegetative, flowering and maturation stages were 212, 687.1, and 1468.1 ml/day respectively. It was caused by increasing of ETc and Kc values. The ETc value increased by the growth of cucumber plant and this demonstrates a reasonable relationship. The highest ETc and Kc were found in the maturation stage, as the more developed plant requires a larger amount of water. In maturation stage, fertigation is used for growing the plant and forming the fruit.

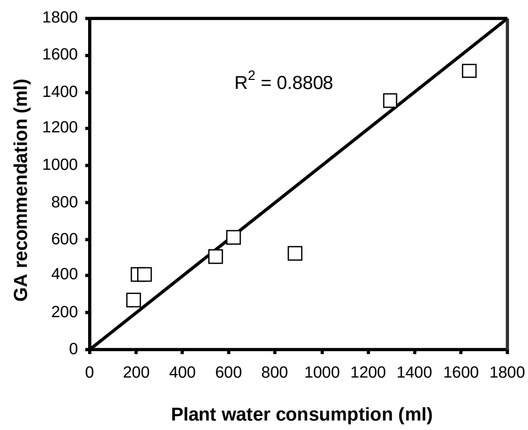

Figure 4. Comparison of daily total volume of fertigation resulted from optimization using Genetic Algorithms and that of empirical method.

Figure 4 shows the comparison between the optimum total volume of fertigation by GA and by empirical method. As can be seen in Figure 4, optimum schedules of fertigation by using GA for vegetative, flowering, and maturation stages of the cucumber plant were in good agreement with the amount of fertigation required by the plants from the empirical method with R^2 of 0.8808. It means that ANN model and optimization using GA achieved a good performance in fertigation scheduling in a hydroponics system.

CONCLUSIONS

Artificial Neural Network (ANN) and Genetic Algorithms (GA) were applied to the optimization of fertigation scheduling in a hydroponics system. The ANN model predicted outflow volume successfully with the correlation coefficients (R^2) between the predicted and measured values were 0.9673, 0.9432, and 0.8248 for vegetative, flowering and maturation stages, respectively. The GA searched the optimum schedule of fertigation in each growth stage. Optimum schedules of fertigation for vegetative, flowering, and maturation stages were in a good coincidence at R^2 of 0.8808 with the amount of fertigation required by the plants, as calculated using the empirical method.

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