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Hourly Groundwater Modelling In Tidal Lowlands Areas Using Extreme Learning Machine-Particle Swarm Optimization

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ABSTRACT:- The Information groundwater levels are very important in the management of tidal lowland, especially for food crop farming. This study aims to perform modelling groundwater levels using Extreme Learning Machine (ELM) paralleled with the Particle Swarm Optimization (PSO). PSO is used to set the value of the input weights and hidden biases on ELM methods in order to improve the performance of the method ELM. Groundwater levels are modelled is hourly groundwater level at tertiary block. Data input for modelling is the water level in the channel, rainfall and temperature. Results of ground water level predictions using ELM-PSO is better than predictions of groundwater levels using ELM. Based on these results, the ELM-PSO can be used in predicting groundwater levels, so as to assist decision makers in determining water management strategies and the determination of appropriate cropping pattern in tidal lowland.

Keywords:- extreme learning machine, particle swarm optimization, tidal lowland, groundwater.

I. INTRODUCTION

West Kalimantan, Indonesia has an area of lowland approximately 2.94 million hectares, consists of tidal lowlands and non-tidal lowlands. Lowland areas mainly located in coastal areas, in Kubu Raya district, Pontianak district, Bengkayang district, Sambas district, Ketapang district and Singkawang district. Back swamp contained in Kapuas Hulu. Approximately 70% of lowlands in West Kalimantan potential to be developed for food crops, plantations, farms and settlements. Tidal lowland management for food crop farming activities should be supported by the ground water level information. The success of farming in tidal wetlands, especially food crops, should be supported by the management of water [1]. Groundwater levels can be used as indicators of the availability of water for planting pattern [2]. Groundwater levels can be determined by predicting groundwater levels, therefore, necessary modelling can predict groundwater levels are accurate to obtain information on the ground water level tidal lowland land.

Modelling for predicting groundwater levels, in research using hybrid between Extreme Learning Machine (ELM) and Particle Swarm Optimization (PSO). ELM used in modelling will be improved to increase the performance of ELM using PSO. PSO is used to set the value of the input weights and hidden biases in the methods ELM, in order to improve the performance of the method ELM. PSO based repair ELM is relatively new, since the implementation of the modelling of groundwater flow in tidal lowland land use methods for modelling like this has never been done.The data used in this study is the water level in the channel, rainfall, and air temperature, while the outcome of this study is the height of ground water level in tidal lowland land.

The end result of this research can be used to predict the groundwater level in tidal lowland land as the basis for determining water management strategies and the use of farm land, particularly for food crops.

II. EXTREME LEARNING MACHINE (ELM)

ELM learning method is applied to minimize the disadvantages of artificial neural networks specifically in case of learning speed. Input weight and hidden bias of ELM are determined randomly, therefore ELM could perform higher learning speed and good generalization performance [3].

According to Huang [4], standard mathematical model for SLFNs with N hidden nodes and g(x) activation functions for N different samples (x_i, t_i), where $x_i = [x_{i1}, x_{i2} \ldots, x_{in}]^T \in \mathrm{R}^n$ and $t_i = [t_{i1}, t_{i2} \ldots, t_{im}]^T \in \mathrm{R}^m$ is expressed by:

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_i . x_j + b_i) = o_j \quad (1)$$

where:
j =1,2,..., N

$w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$: weight vector which connects i_{th} hidden nodes and input nodes

$\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$: weight vector which connects ith hidden nodes and output nodes

b_i : ith hidden nodes threshold

$w_i x_j$: w_i and x_j inner products

SLFNs with $\tilde{N}$ hidden nodes and activation function $g(x)$ are assumed to be able to predict as many as N samples with zero error. Thus, it can be notated as:

$$\sum_{j=1}^{\tilde{N}} \left\| o_j - t_j \right\| = 0$$

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i . x_j + b_i) = t_j, \text{where } j = 1, \ldots, N \tag{2}$$

This formula can be simply expressed as:

$$\mathbf{H}\beta = \mathbf{T} \tag{3}$$

where:

$$\mathbf{H}(w_1, \ldots, w_{\tilde{N}}, b_1, \ldots b_{\tilde{N}}, x_1, \ldots, x_N) = \begin{bmatrix} g(w_1.x_1 + b_1) & \ldots & g(w_{\tilde{N}}.x_N + b_{\tilde{N}}) \\ \vdots & \ldots & \vdots \\ g(w_1.x_N + b_1) & \ldots & g(w_{\tilde{N}}.x_N + b_{\tilde{N}}) \end{bmatrix}_{N\,x\,\tilde{N}} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{N\,x\,\tilde{N}} \quad \text{and} \quad \mathrm{T} = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N\,x\,m} \tag{5}$$

Where **H** in this expression (4) refers to hidden layer output matrix of neural network. Meanwhile, $g(w_1 x_1 + b_1)$ indicates hidden nodes output which are related to input. β is the output weight matrix and T matrix of the target or output.

Input weight and hidden bias in ELM are determined randomly. Thus, output weight related to hidden layer can be determined by expression (3).

$$\hat{\beta} = \mathbf{H}^T \mathbf{T} \tag{6}$$

III. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a stochastic optimization technique based on population, developed by Dr. Eberhart and Dr. Kennedy in 1995 [5]-[13]. PSO method or pattern inspired by the activities of a group of birds when searching for food. When the birds will find food, then it will move in a group of birds in large numbers. When it finds large amounts of food and then the birds will mutually inform each other with regard to the presence of food. So that all parts of the group would obtain food. These properties were subsequently became the inspiration to develop methods of optimization PSO.

Some common terms used in Particle Swarm Optimization (PSO) can be defined as follows: 1). Swarm: a population of an algorithm, 2). Particle: members (people) in a swarm. Each particle represents a potential solution to the problems solved. The position of a particle is determined by the representation of the current solution, 3). Pbest (personal best): the best position of each particle indicates the particle positions are prepared to get a best solution, 4). Gbest (Global best): the best position of all particles in the swarm, 5). Velocity: vectors that drive optimization process that determines the direction in which a particle is needed to move to correct the original position, 6). Inertia weight: inertia weight w symbolized, this parameter is used to control the impact of the velocity that is given by a particle [13].

In recent years, PSO applied to several research and other applications successfully. This shows that the PSO method, the result is a better and faster and cheaper than other methods. Another reason why PSO is more interesting is the use of few parameters. PSO can work well on a wide application with one simple version

IV. STUDY AREA

The data used in this study are primary data, covering the water level in the secondary channel, water level in the channel, rainfall, and temperature. Observations made at tertiary TR7-TR9 secondary block Bintang Mas II lowland area RasauJaya, West Kalimantan Province. Observations made during 72 hours.

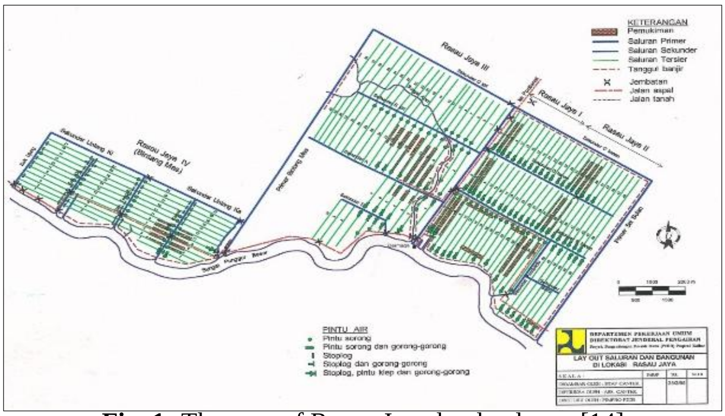

Fig. 1: The map of Rasau Jaya lowland area [14]

Data input and output in the PSO-ELM network should be normalized so as to have a value with a specific range. This is necessary because the activation function used will produce the output data range [-1,1]. Training data in this study are normalized, so it has a value range [-1,1].

V. METHODS

A. Initialization of Population

If one assumes that there is a system with N (dimension of the search space) mass, the mass of the ith position is explained as follows. At first, the position of the mass is fixed randomly.

$$x_i = \left(x_i^1, \cdots, x_i^d, \cdots, x_i^n\right), i = 1, \cdots, N \tag{7}$$

Where:

x_i^d = Position of the i_{th} mass in d_{th} dimension.

B. Extreme learning machine

Several stages to go through in the ground water level prediction using ELM are as follows:

1) *Data Distribution*

Training and testing process are absolutely necessary in the prediction process using ELM. Training process was used to develop a model of the ELM while testing was used to evaluate the ability of ELM as forecasting tool. Therefore the data were divided into two, namely the training data and the testing data. Data were shared with the ratio of 60:40, ie 60% for training and 40% for testing.

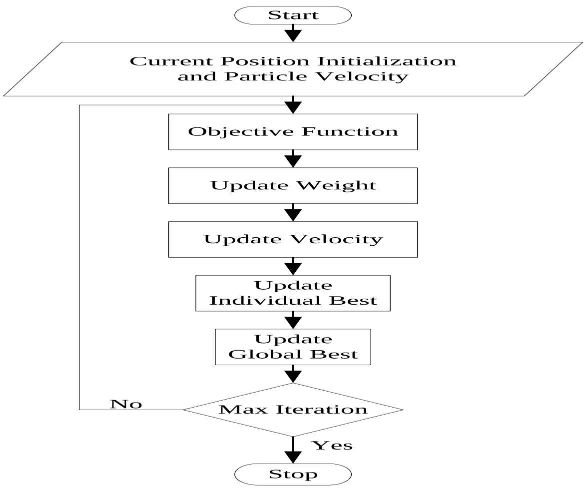

Fig. 2: Flowchart of ELM-PSO

2) Calculation of Fitness

The objective function for the ELM-PSO is the mean square error (RMSE),

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_1^2} \tag{8}$$

Where: $e_i = X_i - F_i$

Best and worst fitness is calculated on each iteration of this objective function evaluation:

$$best(t) = \min_{j\in(1,\dots N)} fit_j(t) \tag{9}$$

$$worst(t) = \max_{j\in(1,\dots N)} fit_j(t) \tag{10}$$

Where:

$fit_j(t)$ =*fitness* of agent j at time t.

$best(t)$ and $worst(t)$ =the whole of best agent *fitness* (minimal) and worst (maximum).

VI. RESULTS AND DISCUSSIONS

The convergence results (predictions) using improved ELM based on PSO are as follows:

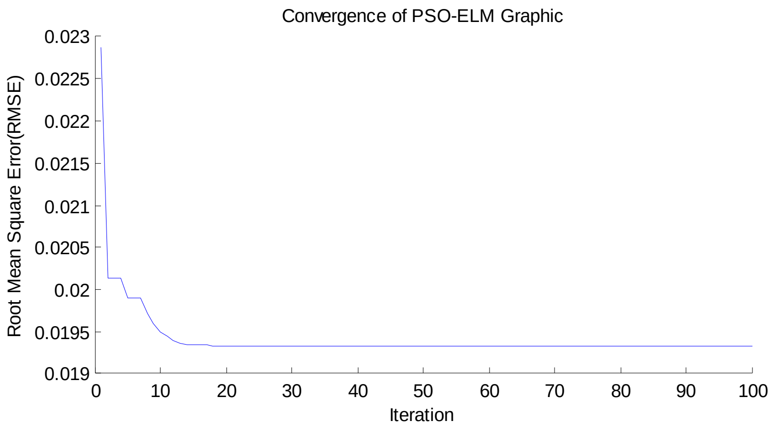

Fig. 3: Convergence of improved ELM based on PSO

ELM improved convergence curve based on PSO in RMSE settings is shown in Figure 3. Characteristics of convergence suggests that the RMSE through improved ELM settings based on PSO is able to produce a lower RMSE value compared to using standard ELM.

The testing results (predictions) using improved ELM based on PSO are as follows:

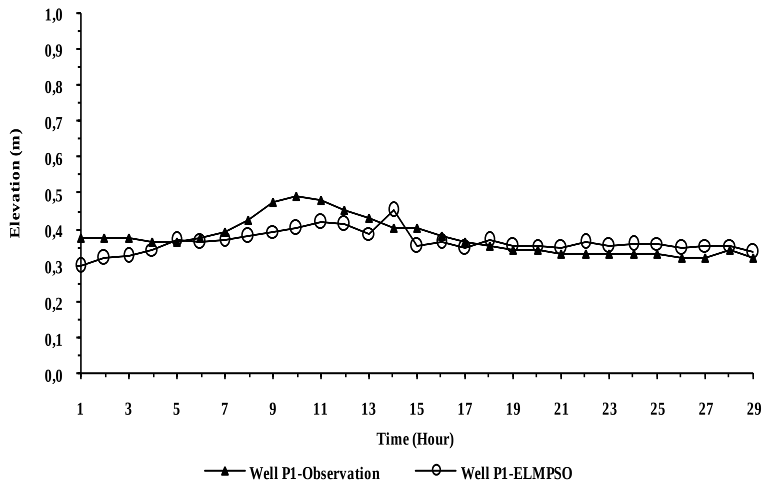

Fig. 4: Groundwater level P1 as a result from the Testing using ELM-PSO

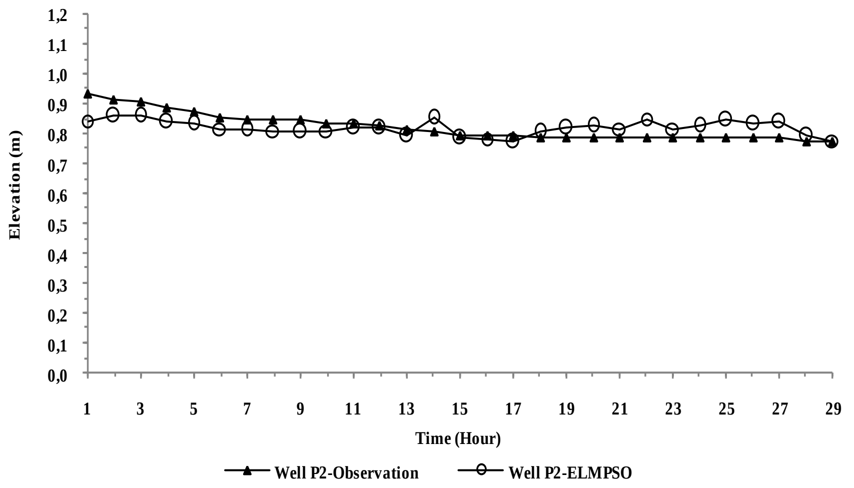

Fig. 5: Groundwater level P2 as a result from the Testing using ELM-PSO

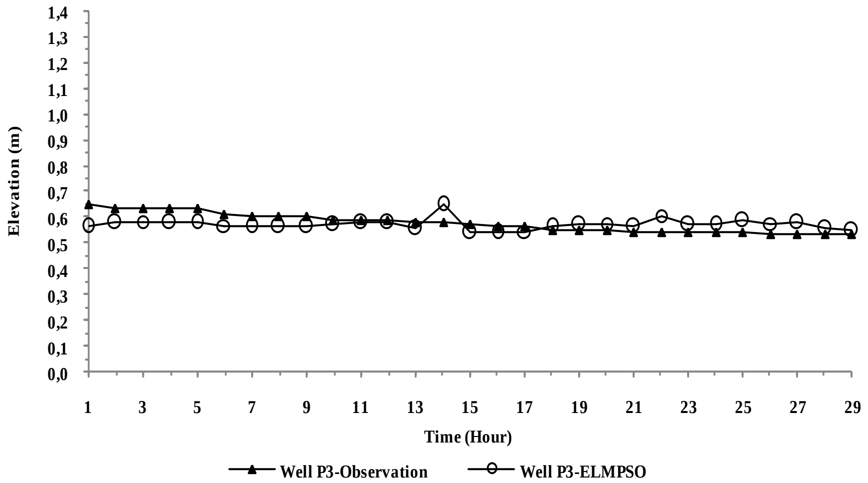

Fig. 6: Groundwater level P3 as a result from the Testing using ELM-PSO

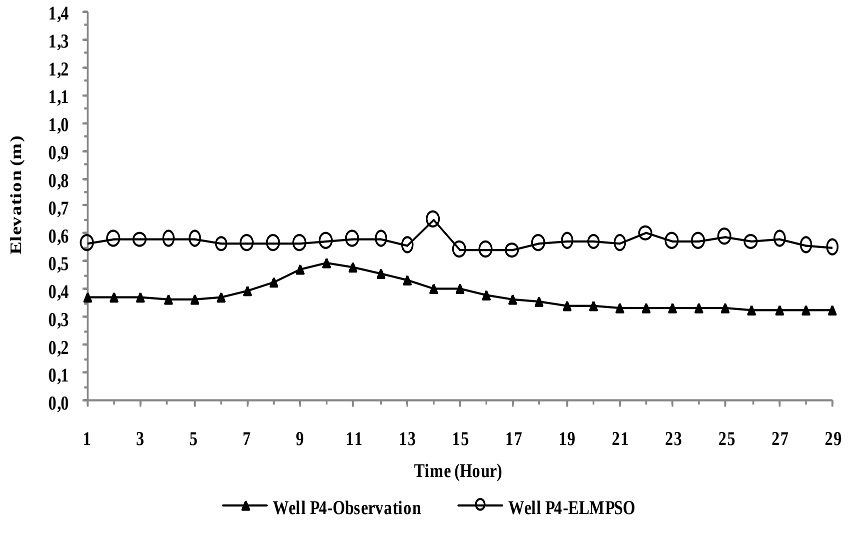

Fig. 7: Groundwater level P4 as a result from the Testing using ELM-PSO

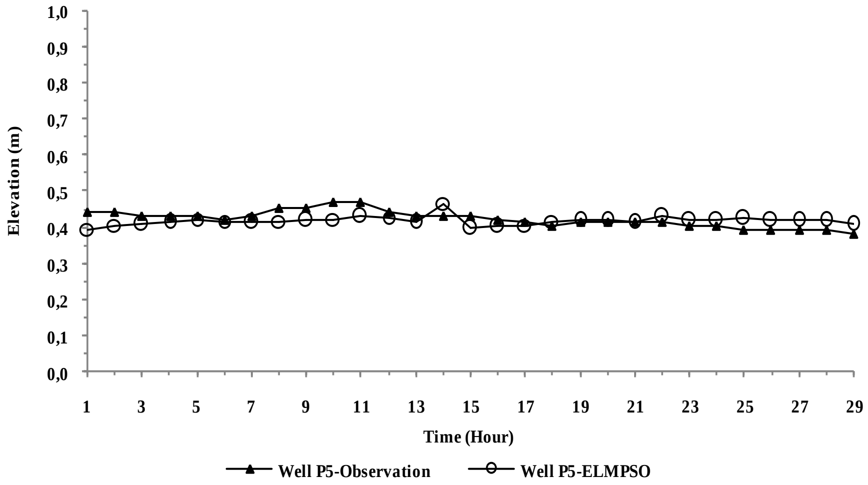

Fig. 8: Groundwater level P5 as a result from the Testing using ELM-PSO

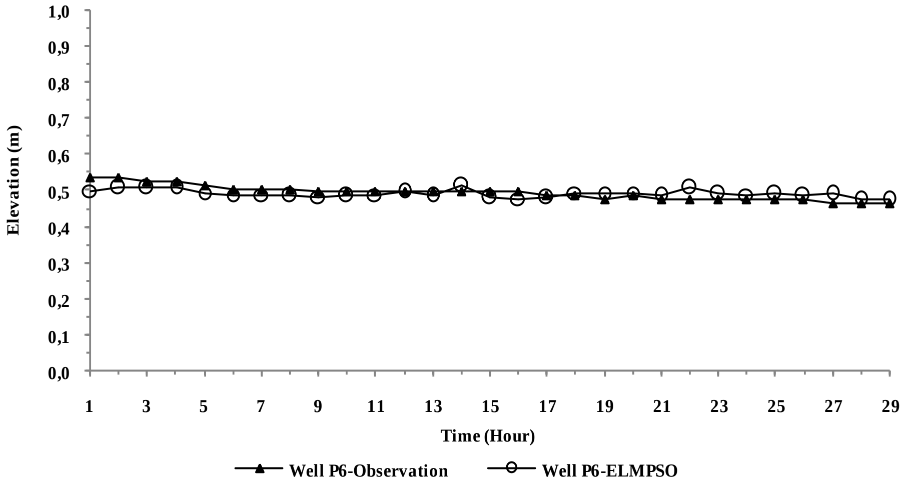

Fig. 9: Groundwater level P6 as a result from the Testing using ELM-PSO

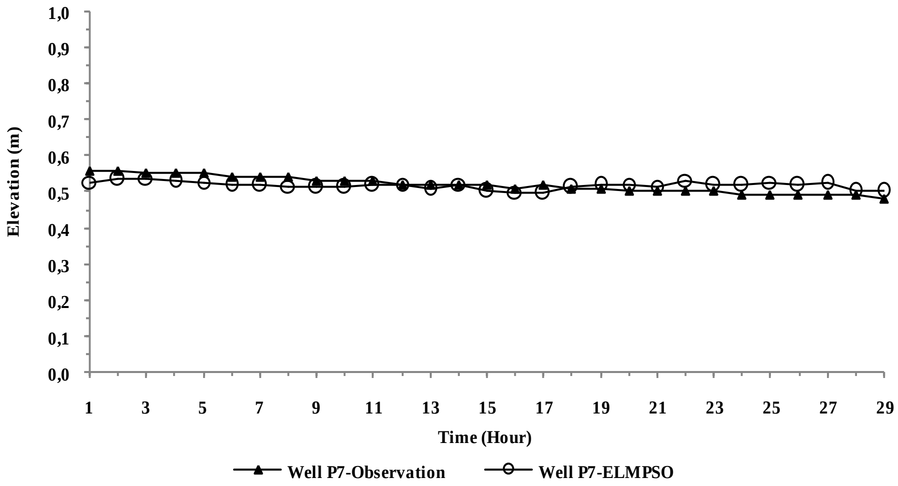

Fig. 10: Groundwater level P7 as a result from the Testing using ELM-PSO

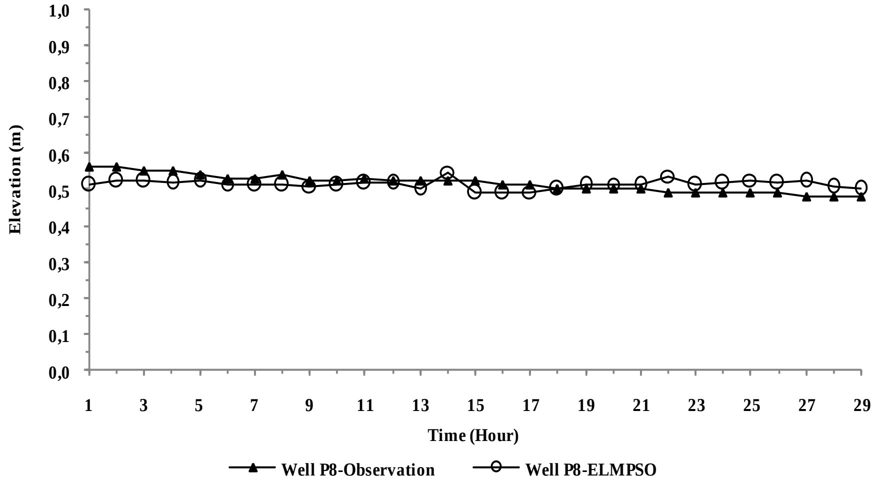

Fig. 11: Groundwater level P8 as a result from the Testing using ELM-PSO

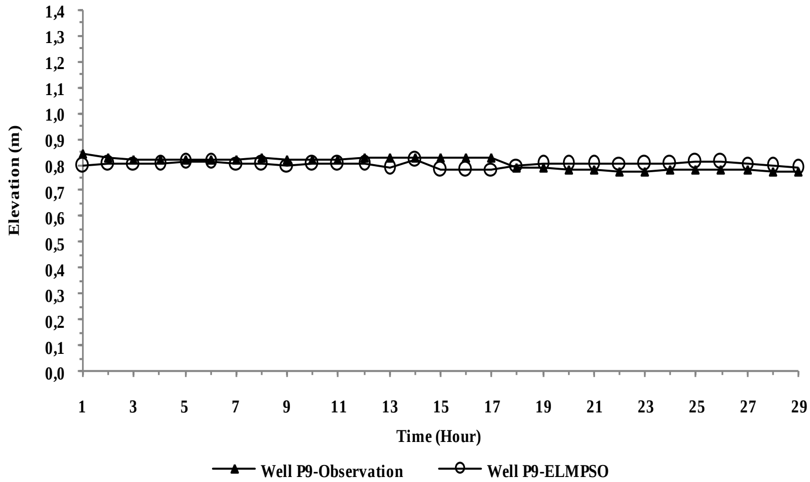

Fig. 12: Groundwater level P9 as a result from the Testing using ELM-PSO

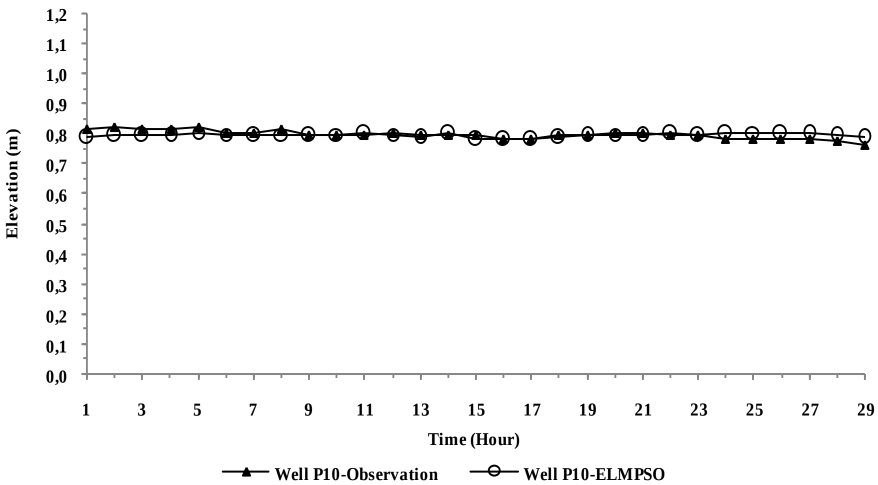

Fig. 13: Groundwater level P10 as a result from the Testing using ELM-PSO

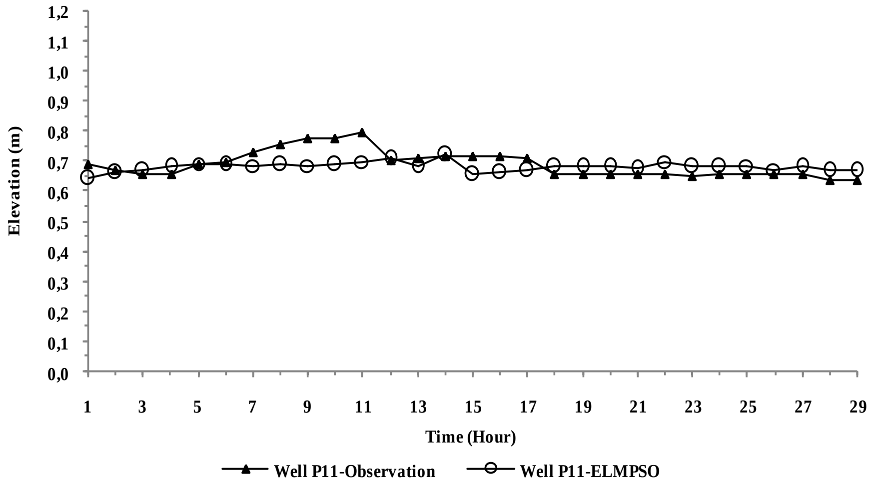

Fig. 14: Groundwater level P11 as a result from the Testing using ELM-PSO

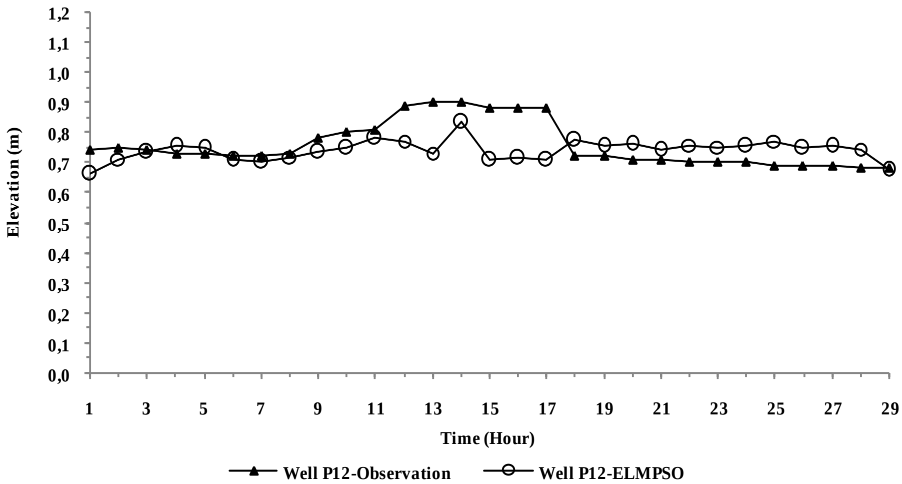

Fig. 15: Groundwater level P12 as a result from the Testing using ELM-PSO

Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, Figure 11, Figure 12, Figure 13, Figure 14, and Figure 15 shows that the ground water level as a result from prediction on well-P1, well-P2, well-P3, well-P4, well-P5, well-P6, well-P7, well-P8, well-P9, well-P10, well-P11, and well-P12 using ELM-PSO has a relatively small error rate value. It meant that the result of the prediction was the same as the result of observation. Therefore, it can be concluded that the prediction on groundwater level was successful. The values of the error rate as a result of the prediction were as follows: RRMSE well-P1 = 0.0400, RRMSE well-P2= 0.0407, RRMSE well-P3= 0.0401, RRMSE well-P4= 0.0407, RRMSE well-P5= 0.0263, RRMSE well-P6= 0.0173, RRMSE well-P7= 0.0214, RRMSE well-P8= 0.0257, RRMSE well-P9= 0.0276, RRMSE well-P10= 0.0146, RRMSE well-P11= 0.0428, and RRMSE well-P12= 0.0793.

VII. CONCLUSIONS

This research use improvement based ELM ELM-called PSO and PSO for modelling of the groundwater level. The results showed that the use of simulation-based ELM improved PSO result RRMSE value which is smaller than using ELM.

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