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# An Improved Extreme Learning Machine Based on Gravitational Search Algorithm for Groundwater Modeling in Lowland Reclamation Areas

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***Abstract*—This research was conducted to improve Extreme Learning Machine (ELM) with Gravitational Search Algorithm (GSA) which applied to create groundwater height level model of tidal lowland reclamation areas in Indonesia. The availability of groundwater height fluctuation information is essential in managing tidal lowland reclamation areas mainly related to the use of the areas as agricultural areas (cultivating crops). The improvement on ELM based on GSA is applied to adjust input weights and hidden biases so that the performance of ELM can also be improved. Groundwater flow in this research is categorized as one-dimensional flow. Data used in this research consist of groundwater height in secondary canal, rainfall, evapo-transpiration, hydraulic conductivity, and distance between two secondary canals. The prediction performed by improved ELM based on GSA is better than ELM. Based on this result, improved ELM based on GSA could be applied to predict groundwater height level. Thus, this improvement could help decision makers to determine perfect water management strategy and suitable cultivation pattern for tidal lowland reclamation areas.**

***Keywords—Extreme Learning Machine; Gravitational Search Algorithm; Tidal Lowland; Ground Water***

## I. INTRODUCTION

Indonesia has about 33.4 million Ha lowland areas, consisting of 20 million Ha tidal lowland areas, 12 million Ha non-tidal lowland areas, and 1.4 million Ha lebak lowland areas spread across Kalimantan, Sumatera, and Papua (Ngudiantoro 2009). Since 1968, Indonesian government has done reclamation efforts on lowland areas in order to increase agricultural products and improve the areas.

Water management is the key of tidal lowland improvement as agricultural field, especially in cultivating crops. Tidal lowland improvement as agricultural field must be supported by information regarding groundwater height fluctuation. Groundwater fluctuation can be used as indicator of water availability which determines cultivation pattern (Susanto 2003). Groundwater fluctuation can be identified by predicting groundwater height fluctuation. Therefore, a model which is able to predict groundwater height fluctuation accurately is needed in order to obtain information regarding groundwater height in tidal lowland area.

In this research, the model used in predicting groundwater height level is Extreme Learning Machine (ELM). The ELM is improved to upgrade its performance.

The improvement is based on Gravitational Search Algorithm (GSA). GSA is applied to adjust input weight rate and hidden biases. Therefore, it will improve ELM method. This improvement is relatively new, since the implementation of this method as tidal lowland groundwater flow model has not ever been done before.

Data used in this research consist of groundwater height in secondary canal, rainfall, evapo-transpiration, hydraulic conductivity, and distance between two secondary canals and groundwater height level in tidal lowland area.

The result of this research is expected to be able to predict tidal lowland area groundwater height level as a reference in deciding strategies regarding water and land management, especially for agricultural uses (i.e. cultivating crops).

## II. EXTREME LEARNING MACHINE

### A. *Extreme Learning Machine*

ELM is a new learning method for artificial neural network. This method was introduced by Huang in 2004. ELM is feedforward artificial neural network with single layer which is commonly known as Single Layer Feedforward Neural Network (SLFNs) (Huang et al. 2004; Huang et al. 2005; Huang et al. 2006; Huang et al. 2008; Sun et al. 2008; Widodo et al. 2013; Nurhayati et al. 2013).

Standard mathematical model for SLFNs with N hidden biases and g(x) activation function with N different samples $(x_i, t_i)$ are expressed by:

$$x_i = [x_{i1}, x_{i2}..., x_{in}]^T \in \mathrm{R}^n \text{; and}$$

$t_i = [t_{i1}, t_{i2} ..., t_{im}]^T \in R^m$ is:

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

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

$w_i = [w_{i1}, w_{i2}, ..., w_{in}]^T$ : the weight vector which connects i-th hidden nodes and input nodes

$\beta_i = [\beta_{i1}, \beta_{i2}, ..., \beta_{im}]^T$ : the weight vector which connects i-th hidden nodes and output nodes

$b_i$ : i-th 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: $\sum_{j=1}^{\tilde{N}} \| o_j - t_j \| = 0$

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

This formula can be simply expressed as:

$$H\beta = T \qquad (3)$$

where:

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

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{N \, x \, \tilde{N}} \quad \text{dan} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \, x \, m} \qquad (5)$$

H in expression (4) indicates hidden layer output matrix of the neural network. $g(w_1 . x_1 + b_1)$ indicates hidden neuron output which is closely related to the inputs. $\beta$ indicates output weight matrix and T indicates target (output) matrix.

In ELM, input weight and hidden biases are determined randomly, thus hidden layer output weight is determined by expression (3).

$$\hat{\beta} = H^T T \qquad (6)$$

*B. Gravitational Search Algorithm*

Gravitational search algorithm is a new metaheuristic optimation algorithm which is influenced by Newton Law regarding gravitation and movement. GSA was introduced by Esmat Rashedi in 2009. Based on GSA, agent is considered as object, and performance is measured by mass. Every object attracts other objects due to gravitational force.Procedures for implementing the GSA method to the problem of hourly groundwater modeling are shown below:

1. Determining the parameters of GSA.
2. Initializing a population with random positions.
3. Evaluating the fitness function.
4. Updating the gravity constant (G).
5. Calculating the inertial mass (M) for each agent.
6. Calculating the acceleration (a).
7. Updating the velocity (v).
8. Updating the position of agent.
9. Repeating again starting from step 1 to 8 and stop until the maximum number of iterations has been met.

The flowchart of the GSA, as shown in Figure 1.

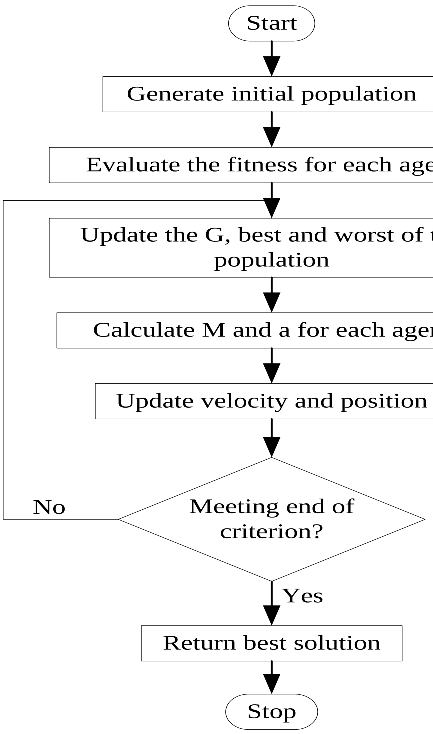


Fig.1. Flowchart of the GSA (Rashedi et al. 2009; Purwoharjono et al. 2013)

## III. METHODOLOGY OF RESEARCH

*Step 1*: 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.

$$x_i = (x_i^1, \cdots, x_i^d, \cdots, x_i^n), i = 1, \cdots, N \qquad (7)$$

Where:

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

*Step 2*: Extreme learning machine

Training and testing process are essential in the prediction process using ELM. Training process was intended to develop a model of the ELM while testing was used to evaluate the validity of ELM as prediction model. Therefore the data were categorized into two, namely training data and

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testing data. Data were proportioned by the ratio of 60:40, (i.e. 60% for training and 40% for testing).

*Step 3*: Fitness Measurement

Objective function of ELM based GSA is mean square error (MSE).

$$MSE = \sum_{i=1}^{n} e_i^{\,2} / n \qquad (8)$$

Where: $e_i = X_i - F_i$

To evaluate the object function, the best and the worst fitness were measured on each iteration by:

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

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

where:

$fit_j(t)$ : fitness of j-th agent on t-th time

$best(t)$ and $worst(t)$ : the best fitness (minimum rate) and the worst fitness (maximum rate)

*Step 4*: Gravitational Constant Measurement

Updating gravitational constant (G) are done based on the best fitness population (minimum) and the worst fitness population (maximum). Gravitational constant on the t-th time (G(t)) is measured by:

$$G(t) = G_0 \exp\left(-\alpha \frac{t}{T}\right) \qquad (11)$$

Where:

$G_0$ : gravitational constant input (random)

$\alpha$ : constant

$t$ : number of iteration

$T$ : total iteration

*Step 5*: Inert Mass and Gravitation Measurement

Measuring inert mass (M) for each agent are done based on expression (12) and (13).

$$mg_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \qquad (12)$$

Where:

$fit_i(t)$ : fitness of i-th agent on t-th time

$$Mg_i(t) = \frac{mg_i(t)}{\sum_{j=1}^{N} mg_j(t)} \qquad (13)$$

Where:

$Mg_i(t)$ : mass of i-th agent on t-th time

*Step 6*: Total Force Measurement

On this step, total force operated on i-th agent $\left(F_i^d(t)\right)$ is measured by:

$$F_i^d(t) = \sum_{j\in kbest j\neq i} rand_j\, F_{ij}^d(t) \qquad (14)$$

Where:

$rand_j$ : random number on the interval [0,1]

$kbest$ : unit of k agent with the highest fitness

The force operated on i-th mass $(M_i(t))$ and j-th mass $(M_j(t))$ on the specified t-th time is described by gravitational theory as follow:

$$F_{ij}^d(t) = G(t)\frac{M_i(t)\times M_j(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \qquad (15)$$

Where:

$R_{ij}(t)$ : Euclidian range between i-th agent and j-th agent $\left(\left\|X_i(t), X_j(t)\right\|_2\right)$

ε : Small constant

*Step 7*: Acceleration Measurement

On this step, the acceleration of i-th agent on t-th time and d-th dimension $\left(a_i^d(t)\right)$ is measured by the gravitation law and the law of motion below:

$$a_i^d(t) = \frac{F_i^d(t)}{Mg_i^d(t)} \qquad (16)$$

*Step 8*: Velocity Measurement

On this step, n velocity of i-th agent on t-th time and d-th dimension $\left(v_i^d(t)\right)$ is measured by the gravitation law and the law of motion below:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \qquad (17)$$

Where:

$rand_i$ : random number on the interval [0,1]

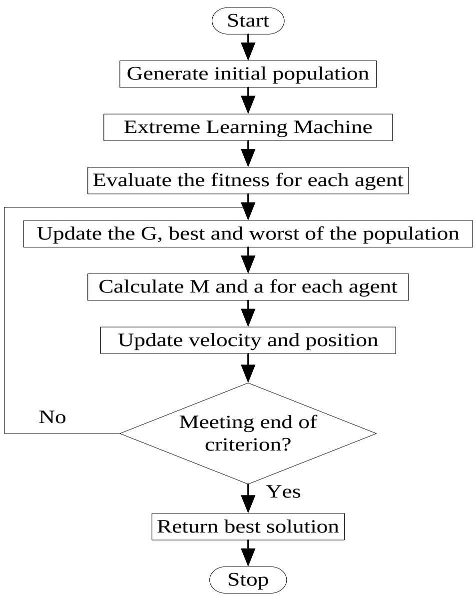


Fig 2. ELM-based GSA improvement flowchart

*Step 9*: Agent Position Update

On this step, the next position of i-th agent on d-th dimension $\left(x_i^d(t+1)\right)$ is updated based on:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{18}$$

*Step 10*: Repetition

On this phase, the previous steps (the 3 step up to the 9) are repeated until the iteration reaches the criteria. At the end of the iteration, the algorithm will return position rate of each agents into the specified dimension. This rate also serves as global solution. An improved ELM based on GSA algorithm applied to predict groundwater level is shown by Figure 2.

## IV. RESULT AND DISCUSSION

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The convergence results using improved ELM based on are as follows:

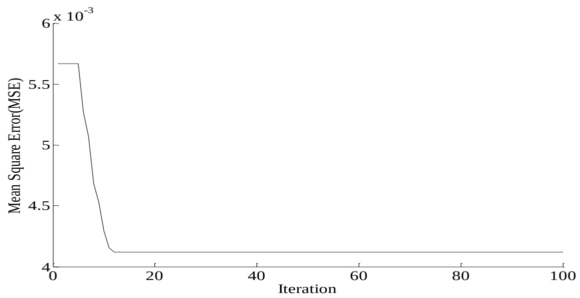


Fig 3. Convergence of improved ELM based on GSA

Convergence curve of improved ELM based on GSA in MSE arrangement is shown on Figure 3. Convergence characteristics indicates that MSE arrangement of improved ELM based on GSA is able to result lower MSE rate compared to standard ELM.

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

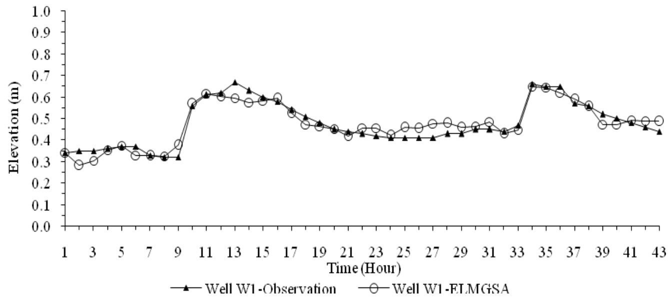


Fig 4. Groundwater level well-W1 as a result from the training using improved ELM based on GSA

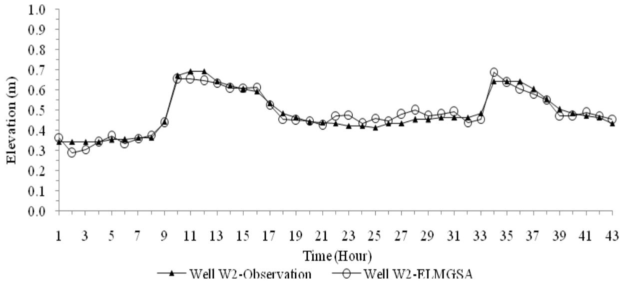


Fig 5. Groundwater level well-W2 as a result from the training using improved ELM based on GSA

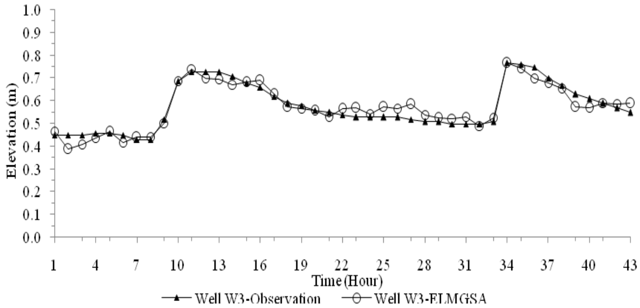


Fig 6. Groundwater level well-W3 as a result from the training using improved ELM based on GSA.

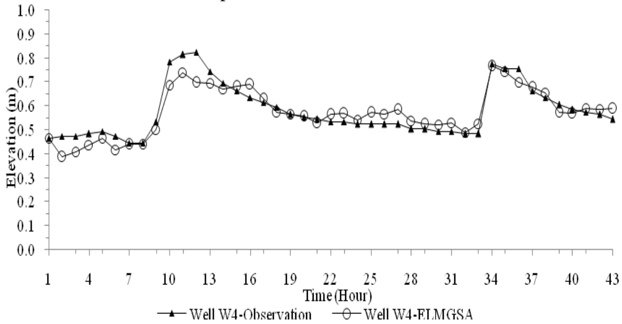


Fig 7. Groundwater level well-W4 as a result from the training using improved ELM based on GSA

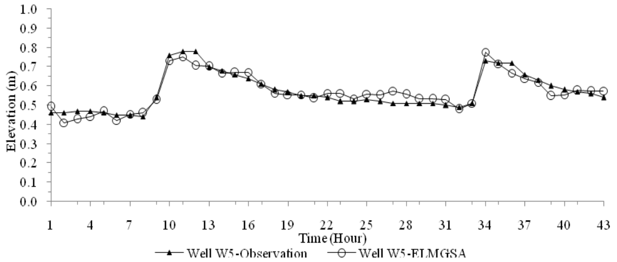


Fig 8. Groundwater level well-W5 as a result from the training using improved ELM based on GSA

Figure 4, figure 5, figure 6, figure 7 and figure 8 shows that the groundwater level on well W-1, well W-2, well W-3, well W-4 and well-W5 as a result from training using ELM has a relatively small error rate value. It meant that the result of the groundwater level of the training was the same as the groundwater level of the result of the observation. Therefore, it can be concluded that the training on groundwater level was successful. The values of the error rate as a result of the training were as follows: RMSE well-W1 = 0.0333, RMSE well-W2 = 0.0272, RMSE well-W3 = 0.0291, RMSE well-W4 = 0.0365, and RMSE well-W5 = 0.0303.

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The result of the groundwater level prediction using ELM was as follows:

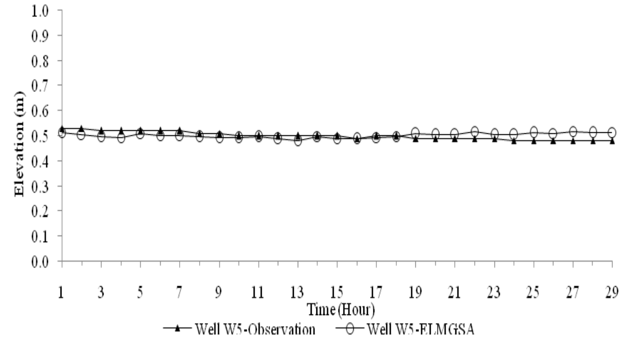


Fig 9. Groundwater level well-W1as a result from the prediction using improved ELM based on GSA.

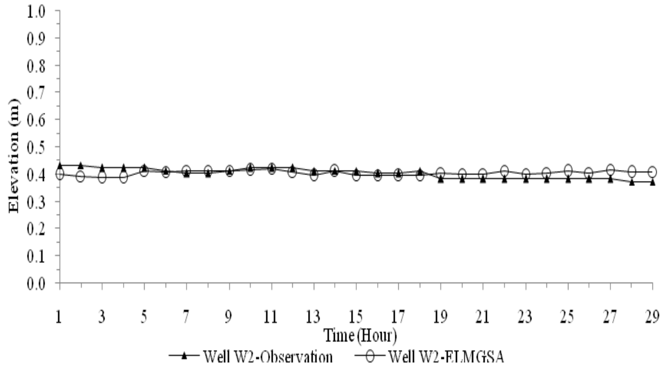


Fig 10. Groundwater level well-W2 as a result from the prediction using improved ELM based on GSA.

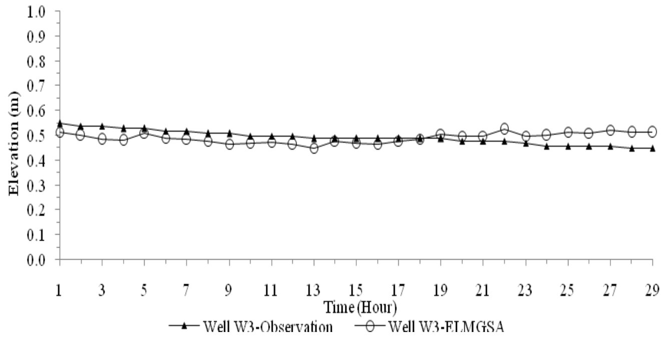


Fig 11. Groundwater level well-W3 as a result from the prediction using improved ELM based on GSA.

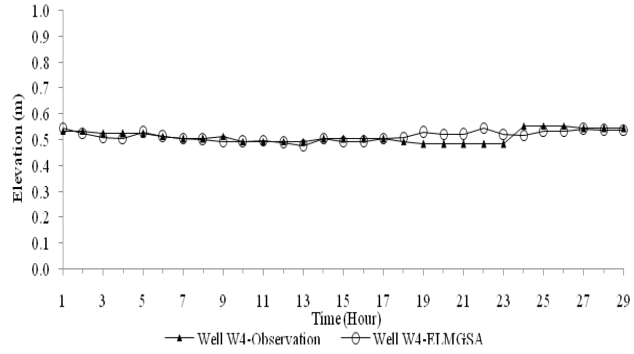


Fig 12. Groundwater level well-W4 as a Result from the prediction using improved ELM based on GSA.

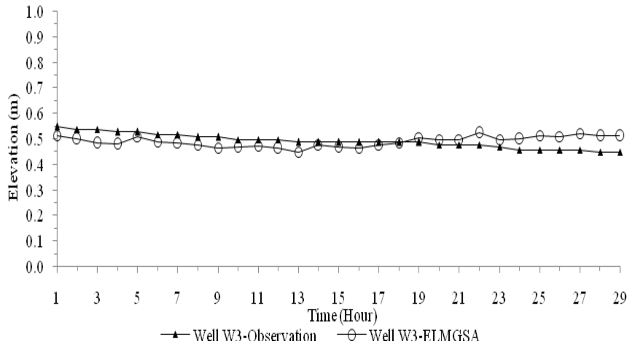


Fig 13. Groundwater level well-W5 as a result from the prediction using improved ELM based on GSA.

Figure 9, figure 10, figure 11, figure 12 and figure 13 shows that the ground water level as a result from prediction on well W-1, well W-2, well W-3, well W-4 and well-W5 using ELM has a relatively small error rate value. It meant that the result of the groundwater level of the training was the same as the groundwater level of the result of the 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: RMSE well-W1 = 0.0297, well-W2 RMSE = 0.0224, RMSE well-W3 = 0.0383, well-W4 RMSE= 0.0223.RMSE well-W5 = 0.0205.

Comparison of the results of the ground water level prediction using improved ELM based on GSA and ELM can be seen in Table 1.

TABLE I. Comparison of the Results of the Groundwater Level Using Improved Elm based on Gsa and Elm

| Simulation | MSE Training | MSE Testing |
|---|---|---|
| ELM | 0.0357 | 0.0306 |
| ELM-GSA | 0.0315 | 0.0275 |

Table 1 show that the result of training and prediction using ELM-GSA and ELM is able to work well in recognizing input data given to the system because the error rate is relatively small. The result of training and prediction using ELM-GSA is better than those using ELM.

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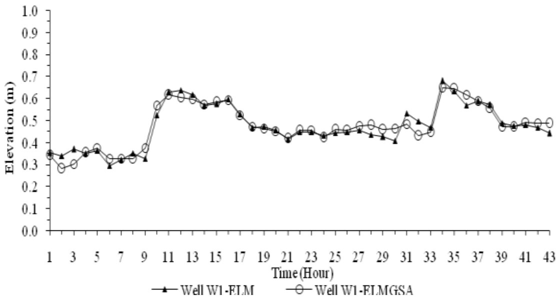


Fig 14. Comparison of the results of the ground water level training using the ELM and ELM-GSA on well-w1

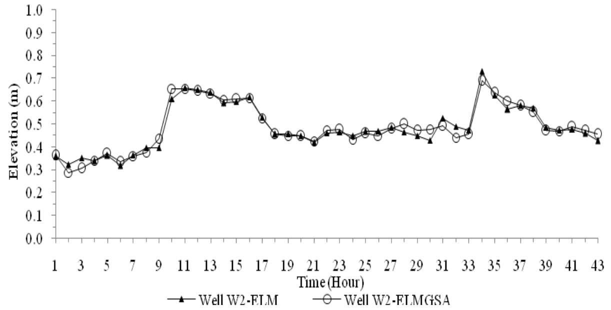


Fig 15**.** Comparison of the results of the ground water level training using the ELM and ELM-GSA on welL-W2.

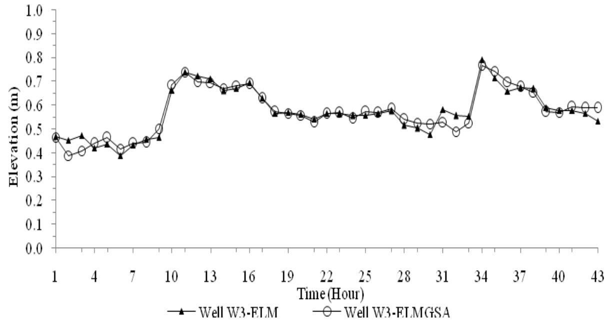


Fig 16. Comparison of the results of the ground water level training using the ELM and ELM-GSA on well-W3

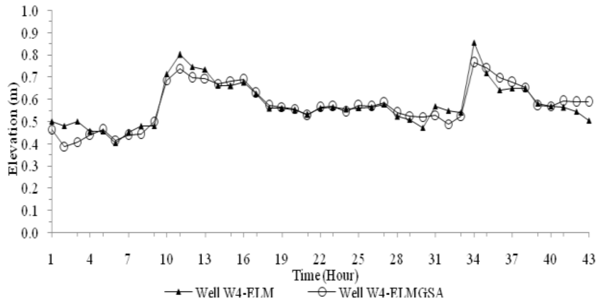


Fig 17. Comparison of the results of the ground water level training using the ELM and ELM-GSA on well-W4.

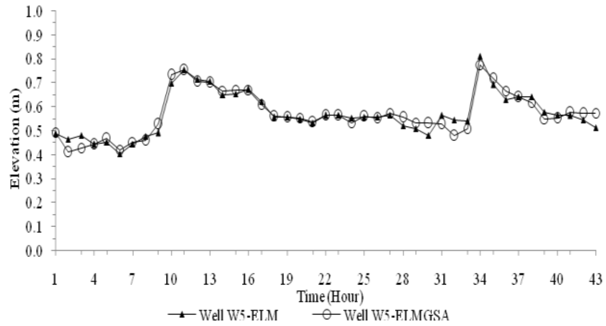


Fig 18. Comparison of the results of the ground water level training using the ELM and ELM-GSA on well-W5.

Figure 14, 15, 16, 17 and 18 describes groundwater level training on each well (well-W1, well-W2, well-W3, well-W4 and well-W5) using improved ELM based on GSA. It indicates that improved ELM-GSA has better MSE rate than standard ELM.

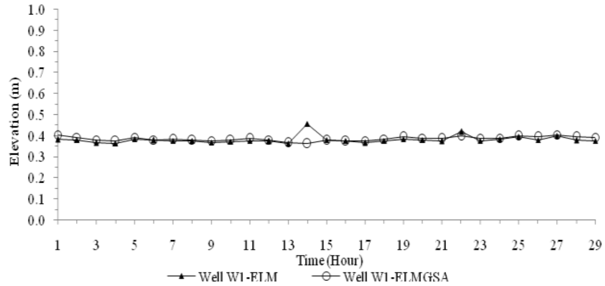


Fig 19. Comparison of the results of the ground water level prediction using the ELM and ELM-GSA on well-W1.

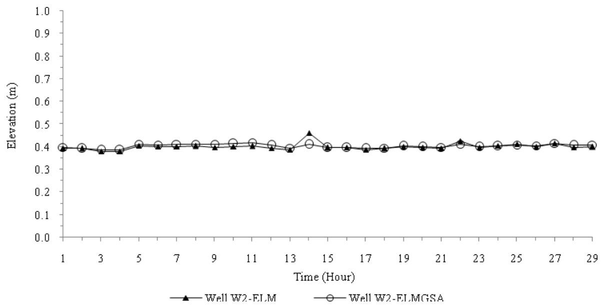


Fig 20. Comparison of the results of the ground water level prediction using the ELM and ELM-GSA on well-W2.

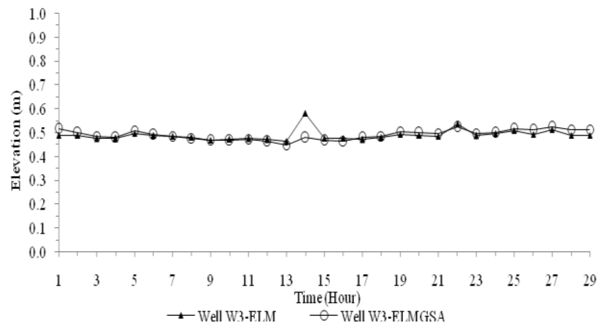


Fig 21. Comparison of the results of the ground water level prediction using the ELM and ELM-GSA on well-W3.

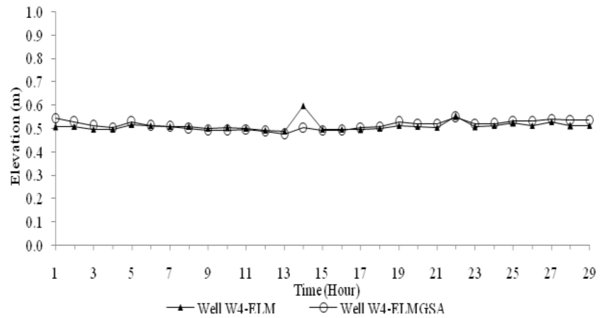


Fig 22. Comparison of the results of the ground water level prediction using the ELM and ELM-GSA on well-W4.

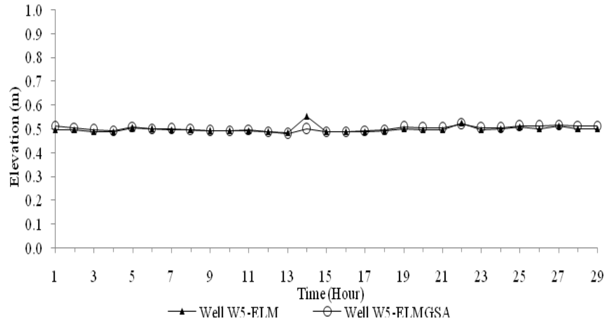


Fig 23. Comparison of the results of the ground water level prediction using the ELM and ELM-GSA on well W-5.

Figure 19, 20, 21, 22 and 23 describes groundwater level predictions on each well (well-W1, well-W2, well-W3, well-W4 and well-W5) using improved ELM based on GSA. It indicates that improved ELM-GSA has better MSE rate than standard ELM.

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