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Effect of MDF-Cover for Water Reservoir Evaporation Reduction, Experimental, and Soft Computing Approaches

H. Ghazvinian[1*], H. Karami [2], S. Farzin [2], S.F. Mousavi[3]

1. Ph.D. Student, Faculty of Civil Engineering, Semnan University, Semnan, Iran
2. Assistant Professor, Faculty of Civil Engineering, Semnan University, Semnan, Iran
3. Professor, Faculty of Civil Engineering, Semnan University, Semnan, Iran

Corresponding author: *hamidrezaghazvinian@semnan.ac.ir*

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ABSTRACT

In the civil engineering designs and water resources management projects, various methods have been proposed to prevent the evaporation of water storage tanks and pools, including the use of physical materials. The use of MDF sheets is an evaporation reduction method using physical elements, which can be useful in controlling evaporation. The present study investigates water evaporation reduction from a standard Colorado Sunken evaporation pan using 50 mm-thick MDF sheets covering 100% of the evaporation pan. The least-square support vector machine (LSSVM) and an artificial neural network (ANN) were used to estimate evaporation reduction. The efficiency of the intelligent methods was evaluated by the root mean square error (RMSE), coefficient of determination (R2), and mean absolute error (MAE). The R^2, RMSE, and MAE values were attained for the LSSVM method in the test stage 0.8755, 1.6517, and 2.2042, and for the ANN model 0.7714, 2.112 and 1.6732 respectively which shows the LSSVM model has better performance than ANN model. The evaporation correlation, according to the Pearson test for sheet cover, MDF with minimum temperature, maximum temperature, sunny hours, is positive. It has 0.442, 0.362, and 0.387 values, respectively, and with minimum damp, maximum damp, pressure is negative and has -0.313, -0.350, and -0.319 values, respectively. The results reveal that MDF had satisfactory performance in controlling evaporation and lead to higher water resource storage. Performing tests for three months indicate that MDF sheets can result in an approximately 91% reduction in evaporation on average.

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1. Introduction

Considering that designing a dam, channel, and other water structures is in the branch of civil engineering science, dissipations such as evaporation and presenting an approach to control and reduce these dissipations can be useful in designing the water structures. In dry areas, much amount of water from the surface level of the dam reservoirs and channels is lost by evaporation; however, this dissipation cannot often be seen due to not being seen the water vapor. The amount of water which is lost by evaporation from water tanks with a partly large surface (compared with the stored volume of water), is sometimes more than that which is used for making the product.

Assessment of water resources potential plays a crucial role in effective water resources management [1].Water is among the essential factors in the development of agriculture and industry in arid and semiarid climates [2]. The abnormal use and loss of water resources in various ways have imposed very intensive water challenges and tension [3]. Currently, the ever-increasing growth of population and reduction of natural resources on earth force humans to consider different methods to save such resources for the future. Water is among the essential requirements of humans. Temporal and local limitations, on the one hand, and the very limited amount of fresh and usable water, on the other hand, have led to more requirements in water programs. Dam- and pool-stored water is one of the most critical water resources supplying agriculture, drinking water, and the industry in Iran, particularly in arid and semiarid climates [4]. The dam-stored water also encounters the evaporation problem. Given Iran's climate, the evaporation of water tanks is inevitable. Thus, it seems to be practical to employ methods to reduce evaporation. Different covers have been used to decrease water evaporation.

Khan and Issac [5] studied the use of polyethylene layers floating on the water. The examination took nineteen months and covered approximately 75% of the water. A 66% reduction was observed in evaporation. Martinez-Alvarez et al. [6] investigated the use of aluminum and polyethylene shadow covers on the water to reduce daily evaporation. The aluminum and polyethylene cover decreased evaporation by 50% and 80%, respectively. Alam and AlShaikh [7] reduced evaporation by single- and double-layered palm tree stem covers on a Class A evaporation pan and compared the covers. The 1.9 mm-thick single-layer covers reduced evaporation by 47%, while the 3.8 mm-thick double-layer covers decreased evaporation by 57%. Santafe et al. [8] proposed a floating solar cell cover to reduce evaporation. Their proposed method not only reduced evaporation but also supplied the power of irrigation systems, which is increasingly growing today. Their research was conducted on Valencia tanks. They described their proposed double-purpose method as a relatively simple and cost-effective method.

Aghvamipanah [9] studied the effect of applying perlite, leca, and straw covers to standard Colorado evaporation pan on evaporation reduction. The results demonstrated that perlite, leca, and straw reduced evaporation by 35%, 22%, and 20%, respectively.

Regarding the estimation of evaporation via intelligent methods, Guven et al. [10] investigated the ability of linear genetic programming (LGP) to model pan evaporation. They compared the results to the radial basis neural network, extended neural network regression, and the Stephens-Stewart model. It was found that the LGP method had higher performance.

Kisi [11] explored the accuracy of the least square support vector machine (LSSVM), multivariate regression spinning (MARS), and the tree model (M5) in modeling evaporation. They employed Mersin and Antalya stations, Turkey. It was observed that the LSSVM model outperformed the MARS and M5Tree models in estimating the parameters of Mersin and Antalya stations with local input and output data.

Tezel and Buyukyildiz [12] evaluated the monthly evaporation of the Beysehir weather station, Turkey using LSSVM and artificial neural network (ANN) approaches. The statistical period included 1972- and the data of temperature, relative humidity, wind speed, and precipitation were used. The results indicated that the perceptron neural network model had excellent performance.

Kisi and Heddam [13] estimated pan evaporation via the only input data of minimum and maximum monthly temperatures at three weather stations in Turkey with the two approaches of MARS and M5. Also, the models were compared to the calibrated Hargeeves-Samani (HS), Stephens-Stewart, and multiple linear regression methods. It was observed that the MARS model was more accurate than other models.

The review of previous studies indicates that studies have been conducted on evaporation control. However, only a few studies investigated tank evaporation reduction in Iran. Serious and scientific measures must be taken in implementing evaporation methods, particularly in arid and semiarid climates, considering the limited water resource of Iran on the one hand and factors such as climate change, which can negatively affect water resources, on the other side. The present study primarily aims to investigate the use of MDF sheets on water tanks to reduce evaporation in a period of three months. Then, the observed data are simulated using ANN and LSSVM models to introduce the best model.

2. The study location

The study was conducted in the north part of the Faculty of Civil Engineering, Semnan University, Semnan, Iran, 53.26° E, 35.36° N, with an elevation of 1149 m. The temperature, humidity, sunny hours, wind, and precipitation data were provided by the central synoptic station of Semnan, which was the closest station to the study location at a distance of 2.39 km.

3. Stages

The ground of the area was flatted. Then, the hold locations were identified by mapping and colors, followed by an excavator digging the holes. Four standard Colorado evaporation pans were placed in the pits. Three of the pans were employed as observation pans containing water, while the remaining pan was used as the test pan containing water with MDF sheets of 100×100 cm size and 50 mm thickness placed on the pan. The MDF sheets covered 100% of the water within the pan. The standard Colorado evaporation pans were galvanized. The water's height was 40 cm from the bottom. Table 1 provides the dimensions of a standard Colorado evaporation pan.

Table 1
The specifications of a standard Colorado evaporation pan [14].

Length (cm)	Width (cm)	Height (cm)	Thickness (mm)	Total Volume (cm^3)
92	92	46	3	389344

Fig. 1. The MDF sheet.

MDF can serve as a thermal and humidity insulator, MDF products are manufactured in different thicknesses with different applications. The Colorado evaporation pan was placed entirely in shadow as the MDF sheets employed in this study were of a thickness of 500 mm, which is a relatively large thickness. Moreover, the MDF sheets did not become wet as they were placed on the pan with no contact with the water. Fig. 1 illustrates the MDF sheet.

The tests and data collection were performed from 23 May to 22 August 2018. The evaporation loss specifications were directly measured by rulers installed in the pans every day, and the mean value of three attempts was recorded as the daily evaporation value of the uncovered pans. Figs. 2, 3, and 4 show the pan locations, uncovered pans, and the MDF-covered pan, respectively. The Class A evaporation pan data were provided by the Semnan synoptic station and compared to those of the Colorado evaporation pan. The SAS Software Pack v9.1 analyzed the results.

Fig. 2. The standard Colorado evaporation pan locations.

Fig. 3. The uncovered pan.

Fig. 4. The MDF-covered pan.

4. Intelligent methods for estimating evaporation reduction

The statistical data provided by the main synoptic weather station of Semnan, along with the observed evaporation of the covers, were investigated for artificial intelligence simulation. Also, the ANN and LSSVM methods were employed to predict evaporation reduction by using artificial intelligence. The mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination was used to evaluate the evaporation reduction results.

4.1. Least square support vector machine (LSSVM)

The least-square support vector machine (LSSVM) was introduced by Suykens [15]. It is less complicated and more affordable than the standard support vector machine as it applies least-square optimization rather than a second-order method. LSSVM transforms the nonlinear relation between inputs and outputs into a linear relation by mapping inputs from a small space to a large space. Eq. (1), expresses the linear regression coherence between the inputs and outputs in the least-squares support vector machine algorithm.

$$\hat{y} = W^{T}\phi(x) + b \tag{1}$$

where w is the weight of inputs, b is the bias or model error, ϕ is a nonlinear function to map inputs from the main space to a larger space, x is the input, and y is the output. The objective is to reduce the error between inputs and outputs while keeping the model simple. Thus, the objective function represented in Eq. (2) must be minimized [16].

$$Min : \psi(W, e) = \frac{1}{2} W * W^{T} + \frac{1}{2} C \sum_{i=1}^{N} e_i$$
$$Subject\ to : e_i = y_i - \hat{y}_i \tag{2}$$

In Eq. (2) C is a constant positive real number as the penalty coefficient. The smaller the first term in Eq. (2), denoting weights is, the less complicated the model will be. The second term represents the penalty function of the difference between real outputs and the model outputs. The lower the C, the less complicated the model will be [15,17]. In Eq. (3) K is the kernel function., kernel functions are the inner products of x and larger linear spatial x_i, employed in nonlinear problems.

$$\hat{y} = \sum_{i=1}^{n} \alpha_i - \alpha_i^{*} \;\; K(x, x_i) + b \tag{3}$$

Different kernel functions have been introduced, including the linear, polynomial, sigmoid, and radial kernels. The linear kernel is a specific type of the radial kernel. Also, the sigmoid kernel serves as the radial kernel for some parameters at specific values [18]. According to [18], the radial kernel has better performance. Thus, the present study employed the radial kernel. Eq. (4) presents the Radial Kernel Function formula. A schematic diagram of the least-squares supports vector machine algorithm is shown in Fig. 5.

$$K(x, x_i) = \exp\left(\frac{-\left\| x - x_i \right\|^2}{2\sigma^2}\right) \tag{4}$$

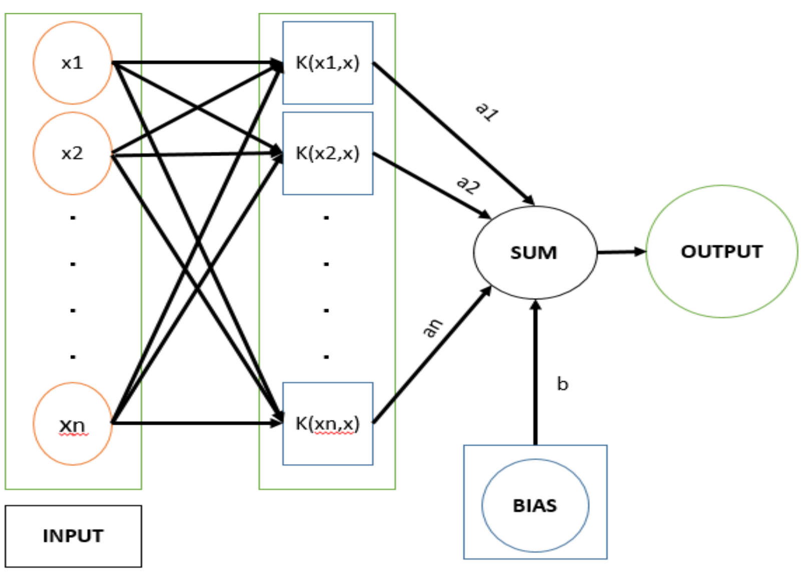
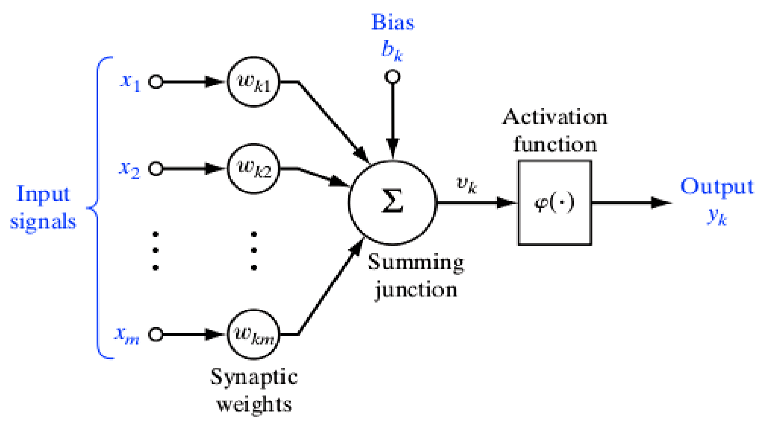


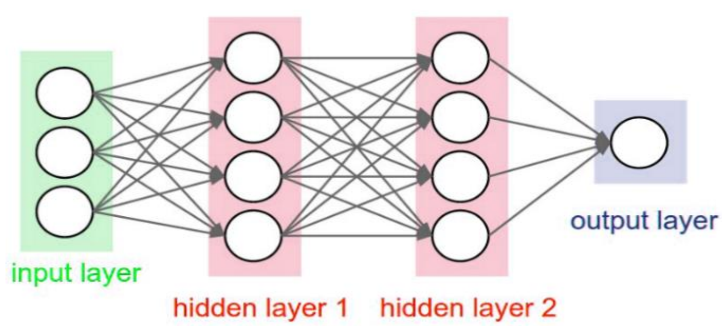
Fig. 5. A schematic of the LSSVM architecture.

4.2. Artificial neural networks (ANNs)

An artificial neural network (ANN) consists of an input layer, one or more hidden layers, and an output layer. Each layer is composed of several neurons. In the ANN algorithm, each communication link between neurons has a weight [19]. A neuron produces an output by summing up the products of inputs and their weights and passing them through a transfer function. Then, the output is used as the input of the next neuron. The closest output to the observed output is determined by adjusting the communication links [20]. The present study adopted the multilayer perceptron network as the ANN [21]. Also, the Levenberg-Marquardt algorithm was used as the training algorithm. The result examination shows that there is no difference between the educational methods and the excitation functions, but the Levenberg-Marquardt method presents more accurate results. Fig. 6 demonstrates the flowchart of an ANN.



a)



b)

Fig. 6. The flowchart of an ANN, a) the structure of an artificial neuron, and b) the structure of ANNs.

4.3. Criteria for model accuracy evaluation

Prediction models must be tested with several indexes to evaluate their performance [22]. R^2, RMSE, and MAE are calculated to evaluate the simulation results as The values of mentioned indexes calculate in Eq. (5) to (7).

$$R^2 = \left(\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) / \sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}\right)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{N}} \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|(y_i - x_i)\right| \tag{7}$$

In Eq. (5) to (7), x_i is the measured evaporation reduction on a day, y_i is the evaporation reduction predicted for the same day, $\bar{x}$ is the mean measured evaporation reduction, and $\bar{y}$ is the mean predicted evaporation reduction.

5. Experimental results

This section analyzes the experimental results and the relationships of the evaporation of the Class A pan, Colorado pan, and MDF-covered pans with the minimum temperature, maximum temperature, minimum humidity, maximum humidity, wind, sunny hours, and pressure.
Fig. 7 compares the MDF-covered pan's evaporation to that of the observation pan. According to Fig. 7, the observation pan's evaporation initially increases but then begins to reduce. This was also the case for the MDF-covered pan. Besides, a significant difference is seen between the MDF-covered pan and the observation pan in evaporation. Fig. 8 indicates the MDF-covered pan's evaporation during the experiment. According to Fig. 8, the MDF cover has an excellent performance in controlling evaporation and reduces 96% of evaporation on average.

It should be noted that MDF covers cannot be employed on a large scale and would prevent light and rain. To solve this problem, thinner MDF covers that can be applied to water may be manufactured. Such caps would reduce costs. Moreover, the present study's objective is to use MDF sheets on small-scale storage tanks and pools. Fig. 9 shows the cumulative evaporation values of the covered and non-covered pans. The area under the curve represents the water lost by evaporation. The space between the two curves represents the water saved by the MDF cover. The area of the Colorado pan is 0.82 m^2. The evaporated water was calculated by multiplying the evaporation pan surface by the cumulative evaporation height. The evaporated water volume of the MDF-covered observation pan was obtained to be 0.1 m^3.

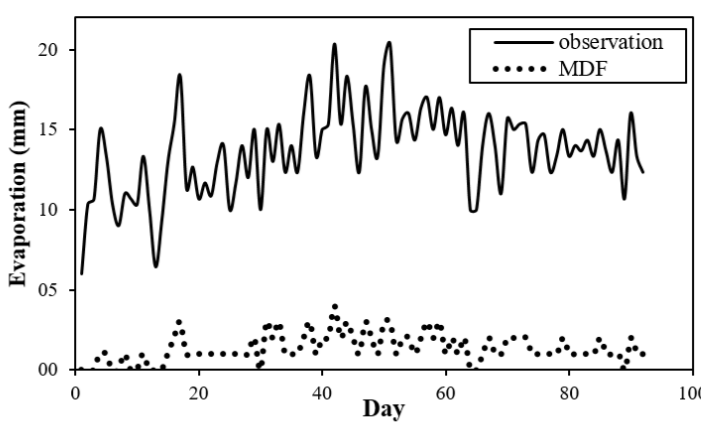


Fig. 7. Comparing the MDF-covered pan to the observation pan.

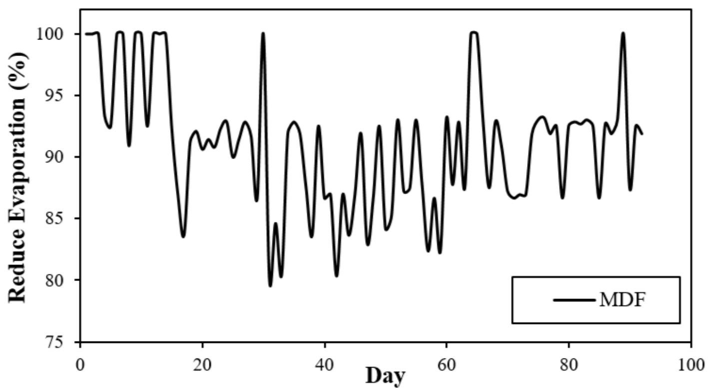


Fig. 8. The MDF-covered pan's evaporation reduction.

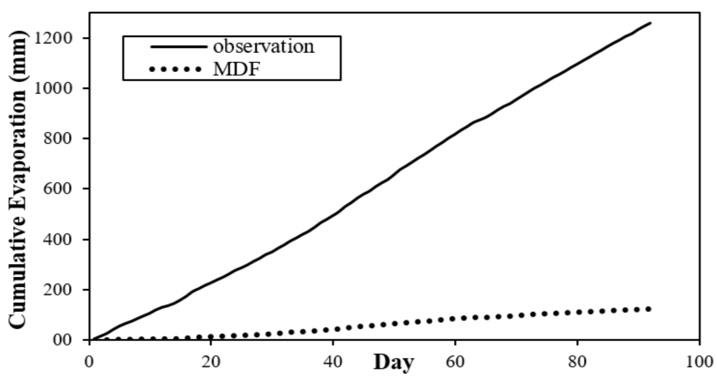


Fig. 9. Comparing the cumulative evaporation values of the observation and MDF-covered pans.

The results from the MDF-covered pan can be compared to the results of Khan and Issac [5], which could reduce evaporation by nearly 75% via placing polyethylene layers on the water. Martinez-Alvarez et al. decreased evaporation by 50% and 80% using aluminum and polyethylene covers, respectively. A comparison of the proposed material to the method of Martinez-Alvarez et al. [6] indicates the higher performance of MDF covers than aluminum covers. Table 2 provides Pearson's correlation and significance results for MDF sheets and station data. According to Table 2, MDF cover evaporation is positively correlated to the minimum temperature, maximum temperature, and sunny hours. In other words, a rise in temperature or sunny hours enhances evaporation. Moreover, MDF cover evaporation is negatively correlated to the minimum humidity, maximum humidity, and pressure, which suggests an increase in the humidity or pressure decreases MDF cover evaporation. Besides, the significant levels of the entire parameters are below 5%, except for the wind.

Table 2
Pearson's correlation and significance results for MDF cover evaporation and station data.

MDF evaporation	Minimum Temperature	Maximum Temperature	Minimum Humidity	Maximum Humidity	Wind Speed	Sunny hours	Pressure
Pearson's correlation	0.442	0.362	-0.313	-0.350	-0.043	0.387	-0.319
Mutual Sig.	0.000	0.000	0.002	0.001	0.687	0.000	0.036
Number	92	92	92	92	92	92	92

Table 3 investigates the feasibility of MDF covers for small and large tanks with different coverage. According to Table 3, MDF covers can be applied to small and large containers with coverage of approximately 60%. MDF coverage of above 60% can be used only to small tanks.

Table 3
The feasibility of MDF covers.

	Feasibility	
Coverage (%)	**Large Tanks**	**Small Tanks**
0-60	✓	✓
60-100	x	✓

6. Intelligent simulation results

The intelligent LSSVM and ANN models were employed to achieve a model to simulate the application of MDF covers to the Colorado Sunken evaporation pan and the measurement of evaporation reduction. The parameters of the minimum and maximum temperature, the minimum and maximum relative humidity, the wind speed and direction, the sunny hours, and the air pressure have been considered as input data. The mentioned parameters are the most important and practical factors on the evaporation amount in the Guven et al. [10], Kisi [11], Tezel, and Buyukyildiz [12] and Kisi and Heddam [13] researches the input parameters of the present study have been used. Eight inputs were included in each of the three models. 70% of data were used for training, while the remaining 30% were employed for the tests. The ANN model included one hidden layer. The tansig transfer function was employed in the hidden layer, while the linear pureline transfer function was used in the output layer. The hidden layer contained three neurons. Also, the Levenberg-Marquardt learning technique was adopted. After searching the network with a size of 1 for the LLSVM, the optimal C and σ were obtained to be 991 and 31, respectively. Table 4 represents the statistical fitting indexes of the observed results and those of the three models. The data were evaluated in the training and test stages. Fig10 for the cover of MDF plates, the graph of the percentage of observed and estimated evaporation reduction for the two models used in this study is shown at the training and testing step. Also, the distribution diagram of the predicted values compared with the observed values is shown at the training and testing step. The coefficients of determination for MDF in the models, LLSVM and ANN, are 0.9404 and 0.8052, respectively. These values indicate that both models are highly efficient for this material, and the LLSVM model performs better function than the ANN model for covering.

Table 4
Comparing the statistical indexes of the models.

	R^2		RMSE		MAE	
	Training	**Test**	**Training**	**Test**	**Training**	**Test**
LSSVM	0.9525	0.8755	1.4331	1.6517	1.1960	2.2042
ANN	08335	0.7714	2.0201	2.112	1.3264	1.6732

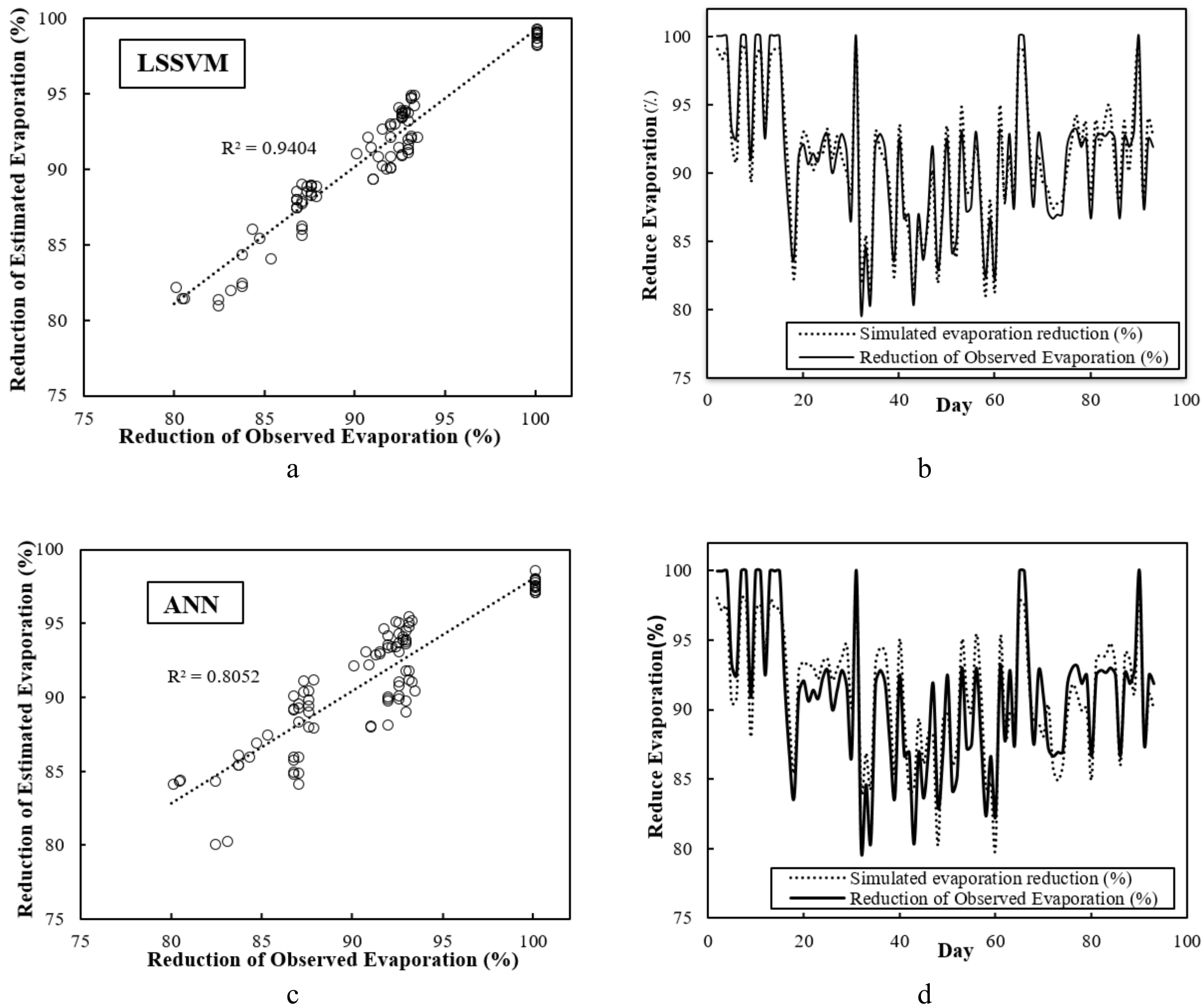


Fig. 10. Comparing the experimental and simulation results of MDF evaporation reduction obtain from a), b) LSSVM model, c), and d) ANN model.

The statistical results in Table 4 suggest that both models had a good performance. This could be seen in the training stage. The LSSVM and ANN were more accurate in the test stage.

The statistical results imply that all three models had a good performance. In the test stage, the LSSVM and ANN were more accurate. Aghvamipanah [9] employed the LASSVM, M5 decision tree, and ANN methods to model evaporation reduction via perlite, leca, and straw. They concluded that the M5 decision tree had the highest performance, with a determination coefficient of 91% in the test stage.

The medial of the daily minimum temperature had the highest effect on the evaporation modeling that corresponds with the results coming from Nourani and Sayyah Fard [23], and Traore et al. [24].

7. Conclusion

The minimum and maximum temperatures and sunny hours were positively and significantly correlated with the MDF-covered pan's evaporation. The minimum and maximum humidity and pressure, on the other hand, were negatively associated with the MDF-covered pan's evaporation. Moreover, wind speed showed no significant correlation with the evaporation of the MDF-covered pan. The highest correlation coefficients were obtained to be 0.442 and -0.219 between the minimum and maximum temperatures and the pressure on the one hand and the MDF-covered pan's evaporation on the other side. The mean evaporation reduction of the MDF-covered pan was derived approximately 91%. Considering the relationship between the experimental data and those from the LSSVM and ANN models, evaporation reduction using the proposed material can be predicted by including meteorology data as inputs to the models. For the LSSVM model, R^2, RMSE, and MAE were calculated to be 0.94%, 1.26%, and 1.19%, respectively, suggesting that the LSSVM model outperformed the two other models.

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