Performances of Solar Vapor Compression Refrigeration Systems: Comparison of Simulations between an Auto-Regressive with eXogeneous Variables (ARX) and an Artificial Neural Network (ANN)

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Abstract

In this study, a solar vapor compression refrigeration system was modeled by using the two machine learning approaches, Auto-Regressive with eXogeneous Variables (ARX) and an Artificial Neural Network (ANN). The performances of these two approaches were compared. The system being modeled was composed of a vapor compression refrigerator unit, two 300 W solar modules, two 12 V batteries with a capacity of 200 Ah (each) and a charge controller. Ten experiments were carried out using this system. Bottles of water were used as cooling loads. Data collected from the experiments that used loads of 10, 30, 50, 70 and 100 liters of water were used to build the models, and the experiments with the loads of 20, 40, 60, 80 and 90 liters of water were used to test the performance of the models. The differences between the experimental load temperatures and the predicted load temperatures for these models, were used as indicators of the performance of the models, which were stated as the percentage of the root mean square difference relative to the mean measured values (RMSD) and the percentage of mean bias difference relative to a mean measured values (MBD). The RMSD of the ARX model was 4.3% and the MBD was 0.6%. The RMSD of the ANN model was 66.1% and the MBD was 20.1%. These results show that the ARX learning approach performed better than the ANN learning approach for this system.

Keywords: Solar energy, solar vapor compression refrigeration system, ARX, ANN

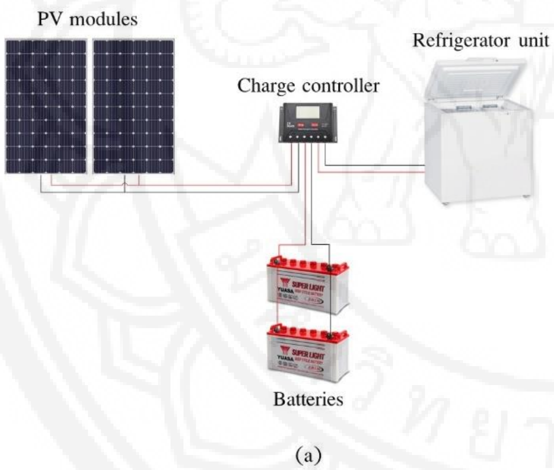
Introduction

Tropical and subtropical areas have plenty of solar radiation available for running solar-powered refrigeration systems and there are considerable demands for refrigeration for the preservation of perishable food as well as chilled and frozen foods in households and shops, and, of great importance, the maintenance of stored vaccines and lifesaving drugs in hospitals and medical clinics. The use of a solar-powered refrigeration system is a good economic and environmental option in these areas where the electricity supply is often non-existent, or erratic. Particularly, solar-powered refrigeration systems are very useful for rural and remote areas where electricity from grids is not available. Thus, there is a research need for solar-powered refrigeration systems.

Several studies have been reported on modeling and simulation of solar vapor compression refrigeration systems (Gao, Ji, Han, & Zhang, 2021; Majid, Saleh, & Jaber, 2021; Mba, Chukwuneke, Achebe, & Okolie, 2012; Su, Ji, Cai, Gao, & Han, 2020). Sharma, Singh, Sharma, and Gupta (2016) reported that, in a comparative performance analysis between solar photovoltaic (SPV) operated vapor compression refrigeration system and vapor absorption refrigeration system, the vapor absorption refrigerator takes longer to decrease the temperature of the refrigeration cabinet than the vapor compression refrigerator yet it consumes less power. Pattarapanitchai, Janjai, Sirikaew, and Bala (2022) reported ARX modeling and simulation of vapor compression solar refrigeration systems. Reddy, Panitapu, and Govindarajulu (2016) reported an ANN modeling of vapor compression refrigeration system. However, no comparative study of ARX and ANN modeling and simulation of vapor compression solar refrigeration systems have been reported. Therefore, the objectives for this study were to investigate ANN performance of a vapor compression solar refrigeration system and also to make a comparative study of ARX and ANN modeling of vapor compression solar refrigeration system.

Methods and Materials

A solar vapor compression refrigeration system was designed and constructed in the Department of Physics, Silpakorn University (13.82°N, 100.04°E), Nakhon Pathom, Thailand to study the performance of the system. The system being investigated comprised a vapor compression unit with two 300 W solar modules, two 12 V batteries with a capacity of 200 Ah (each) and a charge controller. The cooling chamber of the refrigerator unit had a volume of 169 liters and a power requirement of 120 W. Fig. 1 shows the schematic diagram of the vapor compression solar refrigeration system. The system operates as follows: if electricity from the modules is greater than the requirement for the refrigerator unit, this electricity will be used directly to supply the refrigerator unit and the excess will be stored in the batteries. In the case where the electricity from the modules is not sufficient, the electricity from the batteries will be supplied to the refrigerator unit. The use of electricity is controlled by the charge controller. This charge controller helps maintain the power supply within the current and voltage range tolerated by the refrigerator unit and prevents the overcharge of the batteries. The batteries have the capacity to run the refrigerator for two days without solar radiation.



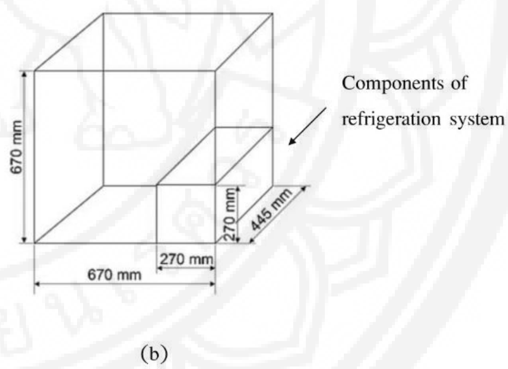


Figure 1 Vapor compression solar refrigeration system: (a) Diagram of the system and (b) Diagram of the cooling chamber of the refrigerator unit

Water contained in plastic bottles was used as cooling loads and ten experiments were carried out. The solar radiation was measured by a pyranometer (Kipp&Zonen, medel CMP6). The indoor temperature, outdoor temperature and load temperature were measured by thermocouples (K-type). The outputs from these sensors were recorded using a multichannel data logger (Yokogawa, model DC100) every 1 minute. Testing over a 10-minute period is sufficient to detect the change of input variables of solar radiation, indoor temperature and outdoor temperature. Each experiment started at 6 a.m. and continued until the set temperature is reached.

ARX approach

For the ARX (Auto-Regressive with eXogeneous variables) approach, let $y(k\Delta t)=y_k$ be the sequence "y" of the output variable at a constant time interval Δt, $u(t)=u_k$ is the corresponding input u(k=1, 2, 3, …). The input variables were solar radiation (u_1), indoor temperature (u_2), outdoor temperature (u_3) and volume of load (u_4). The cooling water temperature inside the cooling chamber of the refrigeration unit is the output variable, y(t) which depends on the previous time series data and the exogenous variables of solar radiation (u_1), indoor temperature (u_2), outdoor temperature (u_3) and volume of load (u_4). The input variables of ARX are u_1, u_2, u_3 and u_4 and the relation between input and output can be written in general form as

$$A(z)y(t)=B(z)u(t)+e(t) \tag{1}$$

where A(z) is the coefficient of y(t), B(z) is the coefficient of u(t), z is delay operator, and e(t) is a model error. The details of the ARX modeling are given in Pattarapanitchai et al. (2022). In this study, the modeling was built from the experimental data for loads of 10, 30, 50, 70 and 100 liters of water. The experiments employing loads of 20, 40, 60, 80 and 90 liters of water were used to test the performance of the model. The amount of data for modeling depends on the volume of the load. For example, for the load of 10 liters, the input data includes a solar radiation period of 10 minutes, and indoor temperature and outdoor temperature.

ANN approach

The ANN (Artificial Neural Network) emulates biological neural functions and structures. In such a modeling approach, there is no need to formulate an analytical description of the process. Instead, a black box process model is constructed by interacting the ANN with a representative sample of the input and output of the system. In this study, a multilayer ANN was constructed for simulating the refrigeration system. The ANN has four input layers: solar radiation, indoor temperature, outdoor temperature and volume of load, two hidden layers and one output layer. The output layer has only one variable, the temperature of the load. Fig. 2 shows the ANN model of the vapor compression solar refrigeration system with four inputs, two hidden layers and one output layer. The activation function is in the form of a sigmoid and the ANN was trained by the backpropagation algorithm. The experimental data with loads of 10, 30, 50, 70 and 100 liters of water were used to train the model and the experimental data with loads of 20, 40, 60, 80 and 90 liters of water were used to test the performance of the model. This process is performed using the WEKA program.

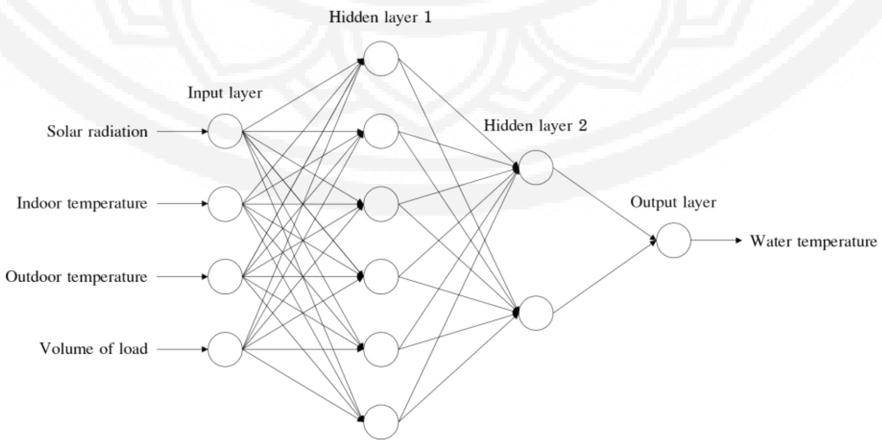


Figure 2 ANN model of the vapor compression solar refrigeration system with four inputs, two hidden layers and one output

Uncertainty Analysis

Uncertainty analysis refers to the uncertainty or error in experimental data. In general, there are two types of error, systematic error and random error. Normally, systematic error in the experimental data is a repeated error of constant value and the random error is due to imprecision. Systematic error can be removed by calibration but random error cannot be removed. The imprecision due to random error can be numerically defined. The measured data on solar radiation, indoor temperatures, outdoor temperatures and the temperature of the load were recorded during calibration. The mean value of the measurements and standard deviation of the random errors of the data on the temperatures and solar radiation were determined.

The variable x_i that has an uncertainty dx_i is expressed as (Holman, 2012; Schenck, 1979).

$$x_i = x_{mean} \pm dx_i \qquad (2)$$

where x_i is the actual value, x_{mean} is the measured value (mean value of the measurements) and dx_i is the uncertainty in the measurement.

There is an uncertainty in x_i that may be as large as dx_i. The value of dx_i is the precision index that is usually taken as 2 times the standard deviation and it encloses approximately 95% of the population for a single sample analysis.

Indicators of the performance of the models

Statistical analysis was performed to estimate the percentage of root mean square difference relative to the mean measured value (RMSD) and the percentage of mean bias difference relative to the mean measured value (MBD) between the cooling temperature predicted in the model and the experimentally determined values, and the square of the correlation coefficient (R^2). To measure the performance of the models, RMSD, MBD and R^2 were used. They were calculated using the following equations:

$$RMSD = \frac{\sqrt{\frac{\sum_{i=1}^{N}(T_{i,model} - T_{i,measure})^2}{N}}}{\frac{\sum_{i=1}^{N} T_{i,measure}}{N}} \times 100 \qquad (3)$$

$$MBD = \frac{\frac{\sum_{i=1}^{N}(T_{i,model} - T_{i,measure})}{N}}{\frac{\sum_{i=1}^{N} T_{i,measure}}{N}} \times 100 \qquad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(T_{i,measure} - T_{i,model})^2}{\sum_{i=1}^{N}(T_{i,measure} - \bar{T}_{i,measure})^2} \qquad (5)$$

where $T_{i,model}$ is the cooling temperature from the model, $T_{i,measure}$ is the cooling temperature from the measurements, $\bar{T}_{i,measure}$ is the average cooling temperature from the measurements, and N is the number of data points.

Results and Discussion

Experimental studies on the cooling effect of a vapor compression solar refrigeration system were conducted at the solar energy field laboratory on the premises of the Faculty of Science at Silpakorn University in Nakhon

Pathom, Thailand to demonstrate the performance of the system and to assess the prediction capability of the cooling effect by the ARX model and ANN model.

The ARX model was simulated to predict water temperature inside the cooling chamber. The input data of the ARX model were time series of solar radiation, indoor temperature, outdoor temperature and the volume of the water (loads), and the predicted temperature of the water inside the cooling chamber was the output. To validate the ARX model for the prediction of the cooling effect of the vapor compression solar refrigeration system, the predicted water temperatures inside the vapor compression solar refrigeration system were compared with the experimental data of water temperature inside the vapor compression solar refrigeration unit itself. Fig. 3 shows a typical comparison between the cooling temperatures predicted by the ARX and the experimental data. The model predictions based on RMSD, MBD and R^2 were evaluated (Fig. 4). To plot Fig. 4, the value of the load temperature obtained from the ARX prediction was plotted against the corresponding value obtained from the physical measurement. Fig. 3 and Fig. 4 illustrate similar information on the accuracy of the predictions from the ARX modeling. The RMSD of the prediction of the cooling temperatures inside the vapor compression solar refrigeration system from the ARX was 4.3%, the MBD was 0.6% and the R^2 was 0.9961. Thus, these evaluation results demonstrate that the ARX model predictions of the cooling temperatures are excellent. Furthermore, the model predicted RMSD is 4.3% which is within the acceptable limits of 15% (O'callaghan, Menzies, & Bailey, 1971).

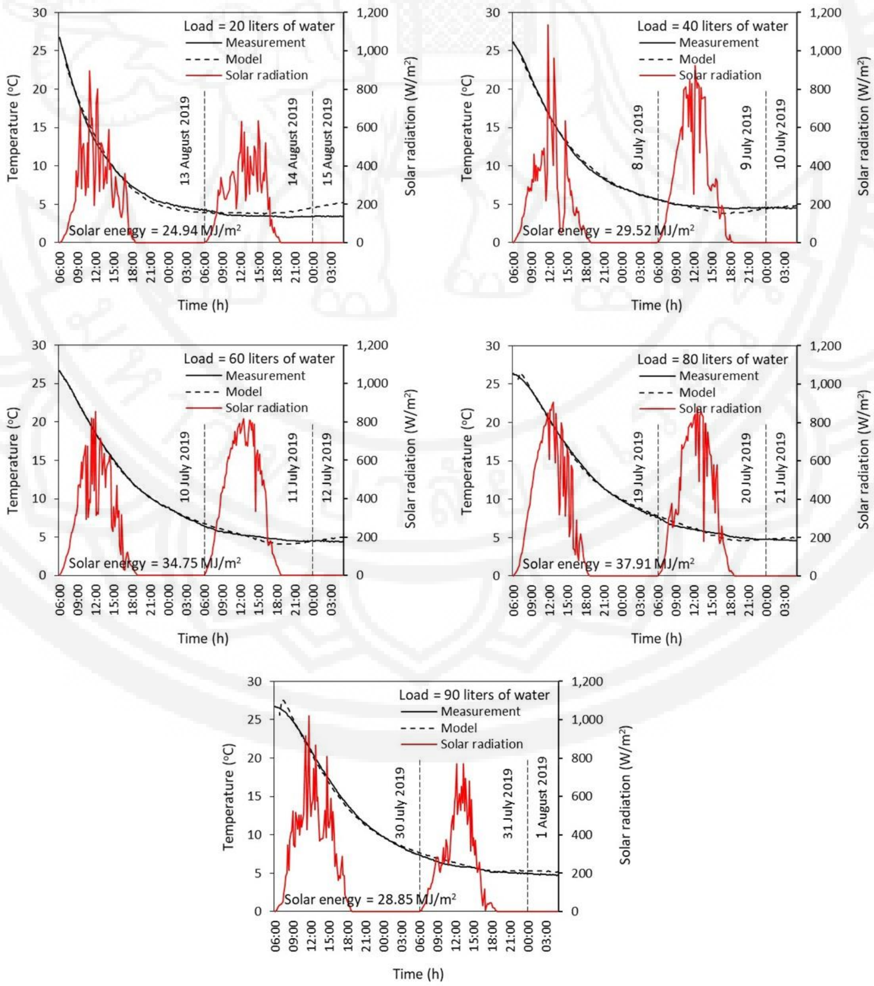


Figure 3 Time series of water temperatures predicted from the ARX model and physically measured

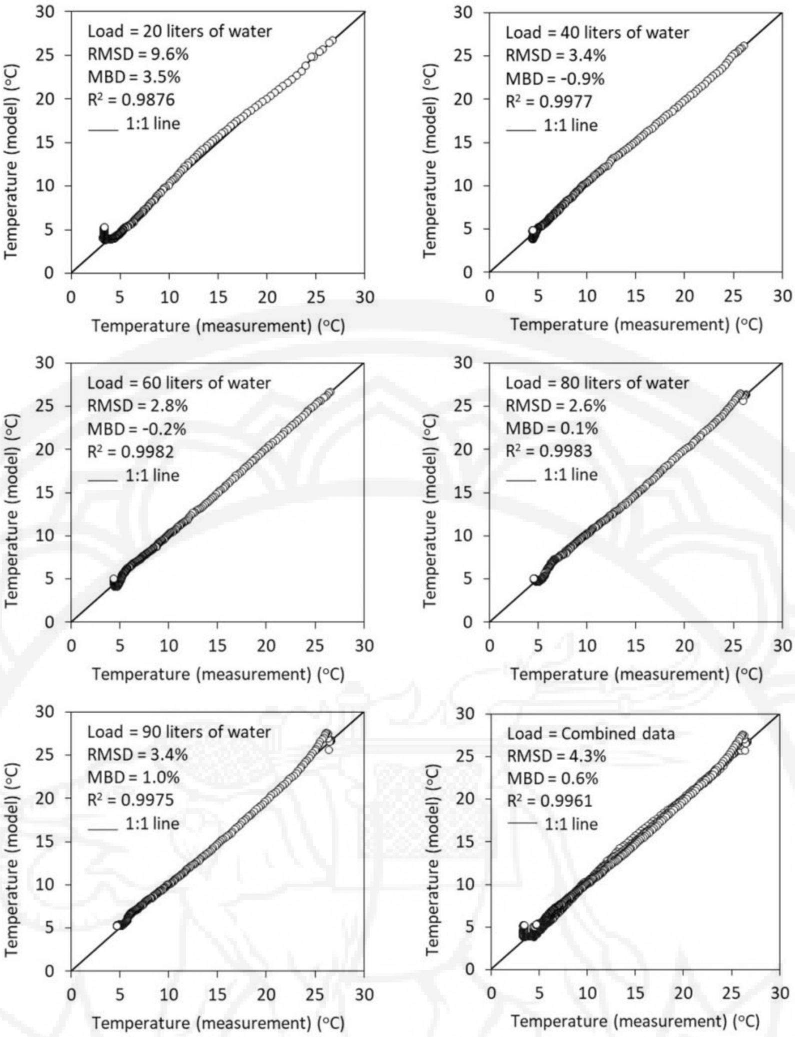


Figure 4 Comparison of the ARX model predictions with the measured values of the cooling temperature of the water

Although the load temperatures from the ARX prediction agree well with the physical measurements, there are still discrepancies which may be due to the low performance of the measuring instruments. It is recommended that higher- performance instruments should be used to improve the measurements and better prove the comparisons.

The ANN model also simulated predictions of the water temperatures inside the cooling chamber. The input data of the ANN model was the same as the ARX model. These were the time series of solar radiation, outdoor temperature, indoor temperature and the volume of the water (loads). The predicted temperature of the water inside the cooling chamber was the output. To validate the ANN model for the prediction of the cooling effect of the vapor compression solar refrigeration system, the predicted water temperatures were compared with the experimental data inside the vapor compression solar refrigeration unit. Fig. 5 shows a typical comparison between the cooling temperatures predicted by the ANN model and the physical experimental data. The model predictions of the RMSD, MBD and R^2 were evaluated (Fig. 6). The RMSD of the prediction of the cooling temperatures inside the vapor compression solar refrigeration system was 66.05%, the MBD was -20.14% and the R^2 was 0.1632. The discrepancies between the load temperature obtained from the ANN predictions and those obtained from the physical measurements are quite high. As the accuracy of the ANN prediction depends on the amount of data used to train the model, it is necessary to increase the number of data points to train the ANN and to improve the performance of the model.

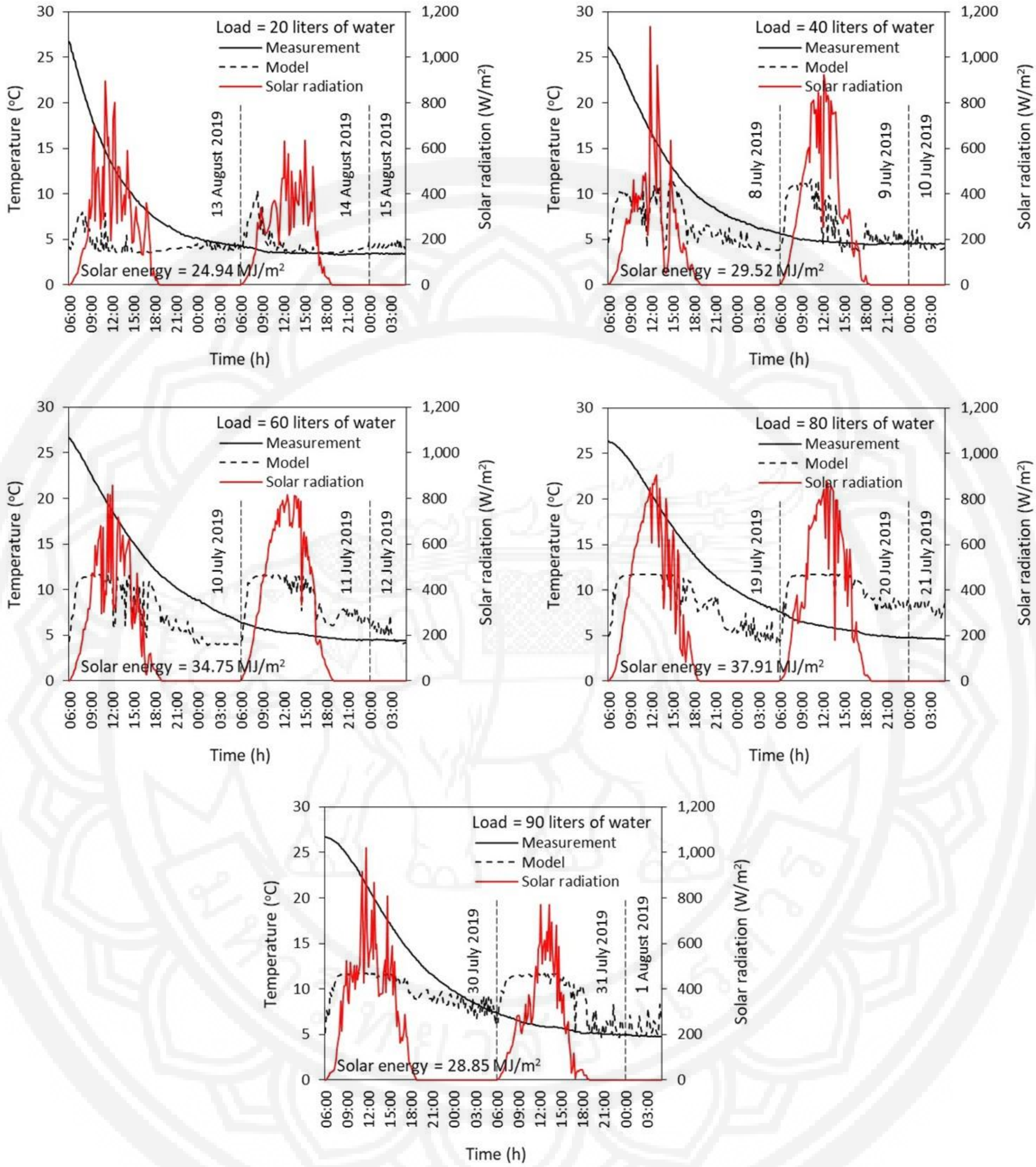


Figure 5 Time series of water temperatures predicted from the ANN model and those from measurement

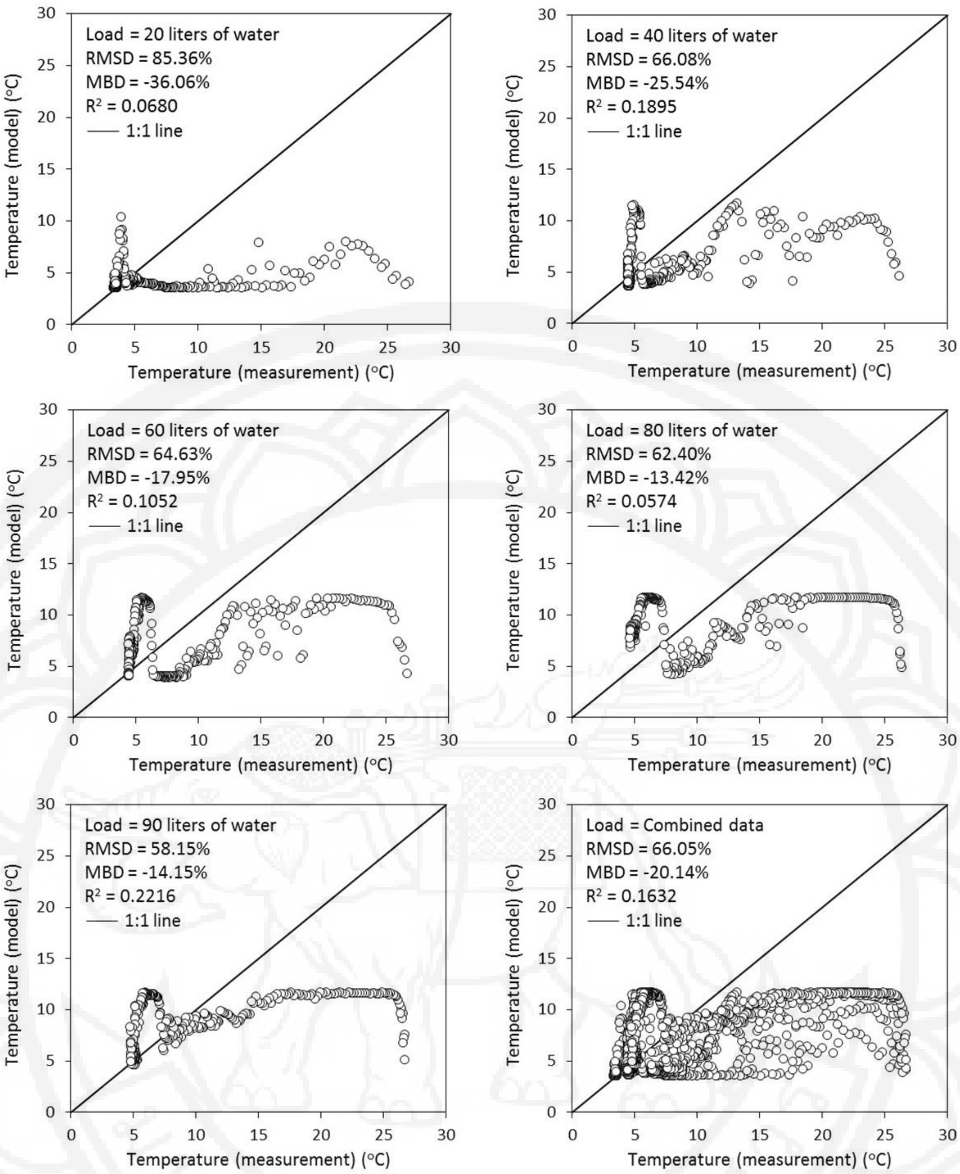


Figure 6 Comparison of the ANN model predictions with the measured values of the cooling temperature of the water

Fig. 7 shows the comparison of the predictions of the ARX model and ANN model for the combined data. In this study, we compared only the performance of ARX and ANN. The ARX model gives RMSD of 4.3%, MBD of 0.6% and R^2 of 0.9961 while the ANN model gives RMSD of 66.05%, MBD of -20.14% and R^2 of 0.1632. Although ARX and ANN approaches are both machine learning techniques, the ARX model performed better than the ANN model, for the refrigeration system. This is because ANN requires all the main inputs to be included for both training and testing as well as requiring more data, while ARX requires less experimental data. In this system, the ANN model was built using only one experimental dataset for each load. Our findings suggested that ARX could be used to predict the load temperature which was useful for the development of the refrigeration system.

ANN gave a lot of errors which may be due to the small number of experiments. To improve the performance of ANN, it is necessary to increase experiment data for training the ANN.

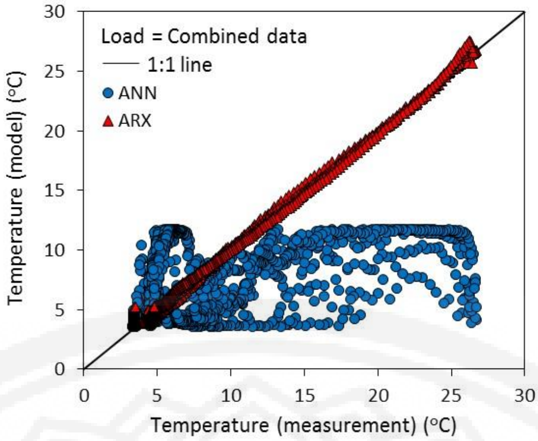


Figure 7 Comparison of the ARX and ANN model predictions with the measured values of the cooling temperature of water for the combined data

ARX modeling also provides a simple and quick method of its simulation to assess the performance of the vapor compression solar refrigeration system, and to show its useability for cooling household products where electricity is unreliable or the electrical grid system is non-existent (Amratwar & Hambire, 2021).

Conclusion

In this work, the performances of the ARX and ANN models for simulating a solar-powered compression refrigeration system have been compared. It was found that the ARX model could predict cooling temperature more accurately than the ANN model. In addition, the ARX model proved to be a simple and quick method for assessing the performance of the vapor compression solar refrigeration system.

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