Technology Collaboration Programme
by iea

Heat Pumping Technologies
MAGAZINE
Smart Controls and AI for Next-Generation Heat Pump Efficiency
Vol.43 No.2/2025
A HEAT PUMP CENTER PRODUCT

Topical Article

Applying Artificial Neural Networks for Predicting the COP of a Stirling-Based High-Temperature Heat Pump

DOI: 10.23697/et2f-zc06

José Daniel Marcos (Spain), Iman Golpour (Spain), Rubén Barbero (Spain), Alex Butean (Romania), Arne Høeg (Norway), Antonio Rovira (Spain)

This study employs a Multilayer Perceptron Feedforward Artificial Neural Network (MLP FFANN) trained with the Levenberg–Marquardt Backpropagation algorithm to predict the coefficient of performance (COP) of a Stirling cycle High-Temperature Heat Pump (HTHP). The ANN model, tested with various neuron numbers, used sigmoid and Purelin activation functions. Inputs included temperature ratios, sink/source temperatures, and hot water inlet temperatures. The 4-6-1 topology showed strong predictive performance, with correlation coefficients up to 0.995 and low MSE. Results confirm the ANN's accuracy and reliability in predicting COP for HTHP systems.

Introduction

The industrial sector is a leading source of global greenhouse gas (GHG) emissions [1] and presents a major challenge in the transition to a low-carbon society [2]. Heating accounts for roughly 50% of global energy consumption, with the industrial sector responsible for approximately 44% of that demand [3]. Heat pumps (HPs), a renewable energy source, can

upgrade low-quality waste heat into high-temperature heat, offering significantly higher energy efficiency than conventional methods, such as fossil fuel boilers. The advancement of High-Temperature Heat Pumps (HTHPs) capable of achieving sink temperatures above 150°C has become a prominent area of research and development. Due to the high cost and time demands of experimental studies, artificial intelligence offers an efficient alternative for predicting values from existing data. Among these methods, Artificial Neural Networks (ANNs) are widely used across various fields, including manufacturing, optimization, signal processing, and energy systems [4]. A literature review shows no prior development of an ANN model for estimating the COP of a Stirling Cycle-based HTHP. This study fills that gap by applying an ANN to predict the COP of a Stirling Cycle HTHP using helium as the working fluid in a heating system.

HoegTemp HTHP system

This study applies ANN to predict the performance of the 400 kW HoegTemp High-Temperature Heat Pump, developed by Enerin (see Figure 1). Using helium (R-704) and operating on the Stirling cycle, the unit is installed at IVAR's biogas plant in Stavanger, Norway, for steam supply and waste heat recovery in a CO_2 capture process [5]. The HoegTemp heat pump is engineered to deliver a thermal capacity of 400 kW. Heat output is measured via a pressurized water circuit linked to a steam generator. Data covers sink temperatures of 139–199°C and source temperatures of 21–22°C. Water temperature is measured via in-flow Pt-100 sensors. Flow rates are recorded using an in-line vortex meter (sink side) and an in-line electromagnetic meter (source side). The heat pump operated for 30–90 minutes per test. Mean temperature and flow values over a stable 30-minute period were used for calculations and reporting [5]. The COP of the Stirling cycle HTHP is calculated using the following equation:

$$COP = \frac{Q_h}{W_E} \qquad \textbf{Eq. (1)}$$

Where COP denotes the performance coefficient, Q_h is the thermal energy delivered, and W_E represents the electrical energy consumption.

Figure 1: HoegTemp HTHP at IVAR biogas facility [5]

ANN Approach

This study used MATLAB R2023a Neural Network Toolbox to develop an MLP Feed-Forward Back-Propagation (FFBP) ANN. Various single hidden-layer configurations with different neuron counts were tested. The network was trained using the Levenberg-Marquardt (LM) algorithm [6]. Figure 2 shows the FFANN structure used to predict COP, including input, output, and hidden layer neurons. The ANN model's input layer included the temperature ratio (1.4–1.6 K/K), average sink temperature (139–199°C), average source temperature (21–22°C), and hot water inlet temperature (137–197°C). The output layer predicted the COP, ranging from 1.4 to 1.7. The input and output dataset used in the developed BPFF ANN model is randomly divided into 60%, 20%, and 20% for training, validation, and testing, respectively. the Tansig transfer function was applied to the hidden layer, while the Purelin transfer function was used for the output layer of the ANN, to determine the most suitable transfer functions for predicting the COP of the HTHP. To evaluate performance, error analysis was performed. In this study, the Mean Squared Error (MSE) and Correlation Coefficient (R) were used to assess the accuracy of the ANN. Training of the Neural Network (NN) was stopped when the target error dropped below 0.01. It is important to note that the sampling iteration for the trained ANN was set to 1000 by default.

Figure 2: Schematic diagram of an MLP-FFNN with one hidden layer

ANN Results

Experimental data and related parameters were used to train the ANN, testing various neuron counts in a single hidden layer. Based on Table 1, the optimal configuration was a 4-6-1 FFBP network with Tansig-Purelin functions and LM training (1 epoch), yielding the lowest MSE and highest R-value for accurate COP prediction.

Table 1: R and MSE of the trained ANN

	Observation	R	MSE
Training	7	0.9799	0.0016
Validation	3	0.9942	0.0002
Test	3	0.9951	0.0004

Table 2 presents the MSE and R for the training, validation, and testing datasets from the trained neural network. The low MSE values, approaching 0, and the high R values, nearing 1, confirm the high accuracy of the model's prediction (COP) across all dataset partitions. The MSE values for Training, Validation, and Test are 0.0016, 0.0002, and 0.0004, respectively (see Table 2).

Table 2: The optimal topology for COP prediction

Network	Training algorithm	Transfer function	Topology	Epoch
FFBP	LM	Tansig-Purelin	4-6-1	1

The performance of the initial prediction model is assessed using the coefficient of correlation and mean square error. The regression R values quantify the strength of the correlation between the model's outputs and the target values. As shown in Figure 3, the x-axis represents the empirical data, serving as the reference, while the y-axis displays the approximations generated by the ANN. Upon analysis, it is clear that the data points are almost aligned with the zero-error line. Training samples were used to train the network, with adjustments made based on the error during the process. Validation samples were used to assess the network's generalization ability and to determine when training should be stopped, as generalization ceased to improve. Testing samples, on the other hand, remained independent of the training process and provided an unbiased evaluation of the network's performance both during and after training. Figure 3 shows the ANN regression plot using the LM algorithm for COP prediction. The model achieved R-values of 0.97989 (training), 0.99421 (validation), 0.99509 (testing), and 0.96592 overall, indicating strong accuracy (R > 0.965). Compared to Thango et al. [7], who reported 96.38% accuracy, the proposed ANN model demonstrates high reliability for COP prediction.

Figure 3: Correlation coefficient for predicting COP: training, validation, and testing

The first step in assessing the predictive capability of the ANN architecture is to confirm the successful completion of its training and learning phases. During the training phase of the MLP networks, information flows from the input layer to the output layer and is then fed back

to the input layer to reduce errors. This iterative cycle is referred to as an "epoch." By the end of each epoch, the gap between the target and predicted data is expected to narrow, resulting in a reduction in MSEs. Figure 4 shows MSE variation during training. Initially, MSE was high but gradually decreased, reaching an optimal value of 0.00022234 at epoch one after five iterations. Further training reduced accuracy, triggering early stopping. Figure 5 displays the state transition outcomes of ANN, which describe gradient values, epoch numbers, and mu and validation checks. In an ANN, the gradient is used to assess how much the output of a function changes when there are modifications to the inputs. The gradient represents the backpropagation gradient for each epoch, displayed on a logarithmic scale. During the neural network training, the parameter “mu” was used to regulate the weights of neurons during training of the backpropagation process, specifically the weights. If training stops, it indicates that the maximum value of mu has been reached. According to the obtained results, the network achieved high validation accuracy, with training halted at the point of maximum failure to prevent overfitting.

Figure 4: MSE variation for the trained ANN for the prediction of COP

Figure 5 shows the training gradient (3.83e-11) and maximum mu value (1e-8), both at epoch 5. The low gradient and near-zero mu reflect the LM algorithm’s efficiency in COP prediction. Training stopped at epoch five due to four consecutive validation failures, indicating the onset of overfitting as validation MSE began to rise.

Figure 5: Gradient curve, momentum coefficient (mu), and best validation performance of the used ANN

Conclusions

This study used an MLP BPFF with the LM algorithm to predict the COP of a Stirling cycle high-temperature heat pump. Inputs included temperature ratio, sink/source temperatures, and hot water inlet temperature. Model performance was evaluated using the correlation coefficient and MSE during training, testing, and validation, achieving an overall R of 0.96592. The optimal 4-6-1 network used Tansig (hidden) and Purelin (output) functions with one epoch. The high R-value confirms the model's accurate prediction capability. COP predictions using FFNN are highly promising. The study demonstrates that neural networks are effective tools for identifying and optimizing HTHP performance. Trained models can be integrated into control systems for continuous prediction and adjustment.

Author contact information

Name	Dr. José Daniel Marcos
Affiliation	Department of Energy Engineering, National University of Distance Education, UNED, Madrid, Spain
E-mail address	jdmarcos@ind.uned.es

References

[1]. Ritchie, H., Rosado, P., and Roser, M. 2023. "CO2 and Greenhouse Gas Emissions" OurWorldInData.org, accessed Jan. 3, 2024, https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.2020.

[2]. United Nations, Paris Agreement to the United Nations Framework Convention on Climate Change," United Nations, San Francisco, CA, T.I.A.S, 2015. No. 16-1104.

[3]. IRENA., Global Energy Transformation: A Roadmap to 2050, IRENA, Abu Dhabi. 2019.

[4]. Keçebaş, A., Yabanova, İ., and Yumurtacı, M., 2012. "Artificial neural network modeling of geothermal district heating system through exergy analysis". Energy Conversion Management. 64: p. 206–12.

[5]. Høeg, A., Løver, K., and Vartdal, G. 2024. "Performance of a high-temperature industrial heat pump, using helium as refrigerant. In High-Temperature Heat Pump Symposium", Copenhagen.

[6]. Golpour, I., Amiri Chayjan, R., Amiri Parian, J., & Khazaei, J. 2015. "Prediction of Paddy Moisture Content during Thin Layer Drying Using Machine Vision and Artificial Neural Networks". Journal of Agricultural Science and Technology. 17: p. 287-298.

[7]. Thango, S. G., Drosopoulos, G. A., Motsa, S. M., and Stavroulakis, G. E. 2023. "Prediction of the response of masonry walls under blast loading using Artificial Neural Networks". Infrastructures. 2023. 9(1): p 5.