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Anas A. Rahman
Future University in Egypt (FUE), anas.mohamed@fue.edu.eg

Xiaoqing Zhang
Huazhong University of Science and Technology, zhangxq@mail.hust.edu.cn

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Prediction of Temperature Difference across Thermoacoustic Stack through Artificial Neural Network Technique

Anas A. Rahman[a]*, Xiaoqing Zhang[b]

[a] *Department of Mechnical Engineering, Future University in Egypt, End of 90th st., Fifth settlement, New Cairo, Cario, 11835, Egypt.*

[b] *Department of Refrigeration and Cryogenics, Huazhong University of Science and Technolgy, Luoyu Road, Hong shan District, Wuhan 430074, China.*

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ABSTRACT

This study involved the application of an artificial neural network (ANN) as a new approach for thermoacoustic refrigerators to predict the temperature difference across the stack under some operating conditions. One ANN model for a standing wave thermoacoustic refrigerator had been developed based on the experimental data from other literature. The temperature difference across the stack was chosen as a response to the input parameters, mean pressure, and frequency in the proposed ANN model. A multi-layer feed-forward neural network with a backpropagation algorithm had been proposed for predicting the temperature difference across the stack of the thermoacoustic refrigerator. This proposed ANN model has three layers with configuration 2-12-1, namely, the input layer with two neurons representing the two operating parameters, one hidden layer with an optimal 12 hidden neurons, and the output layer with one neuron representing the temperature difference across the stack, as a response. The high ability of ANN for data prediction was proven in this study by achieving an average prediction error of 0.2% and a regression coefficient (R) of 0.99979 during the testing phase. This research work provides a new approach based on the ANN technique to solve complex thermoacoustic problems with linear or nonlinear nature through either modeling, optimization, or system identification.

1. Introduction

Thermoacoustic refrigerators are considered potential alternative technologies to vapor-compression refrigerators. This kind of device developed new concepts for the operation based on the thermoacoustic effect where there is an energy transfer between a compressible fluid and a solid boundary in the presence of an acoustic wave. Several practical thermoacoustic refrigerators, both standing- and traveling-wave, have already been demonstrated (Swift, 1988, Swift 2003, Wang, Xu, Wu & Luo, 2022). This new technology offers many significant advantages in certain areas of application where it uses environmental- friendly working substances such as air or inert gases, fewer or no moving parts in addition to utilizing low-grade heat input which provides new opportunities for energy conservation (Devkota, Babu, Gupta, Kant, & Vidya, 2022 & Zhang, Chang, Cai, & Hu, 2016 & Shen, He, Li, Ke, Zhang, & Liu, 2009 & Gardner & Howard, 2009). The performance parameters for a thermoacoustic refrigerating system, are commonly defined in terms of the temperature difference across the stack (Nsofor, & Ali, 2009 & Allesina, 2014 & Marx, & Blanc-Benon, 2005 & Jensen, Raspet, & Slaton, 2006) or the lowest temperature obtained (Tijani, Zeegers, & De Waele, 2002 & Wetzel, & Herman, 2000) where both of them affect the cooling power produced directly

* *Corresponding author.* Tel.: +202-010-6235-4239; fax: +202-2618-6111.

E-mail address: anas.mohamed@fue.edu.eg

and hence control the coefficient of performance (COP) (Wetzel & Herman, 1997 & Reid & Swift, 2000 & Tijani, Zeegers, & De Waele, 2002). Till now, these devices suffer from a lack of performance despite their advantageous features. Therefore, the performance of these devices is considered a crucial issue compared with conventional vapor compression refrigerators. These performance measures mentioned above depend on the parameters of this system concerning operating conditions, structure geometry of stack/regenerator and refrigerator, thermo-physical properties of the working fluid and solid of stack/regenerator, as well as (Thermo) acoustic driver (Ghorbanian, Hosseini & Jafargholi, 2008). For the desired performance, these parameters of the system are commonly determined based on linear thermoacoustic design theory (Swift, 2003, Ghorbanian, Hosseini, & Jafargholi, 2008 & Tijani, Zeegers, & De Waele, 2002) or partly based on the experience of designers, which make these traditional computational methods generally difficult and time-consuming with unacceptable uncertainties. To solve this complex problem, an artificial neural network would be introduced as an intelligent technique to map the relationship between the apparatus parameters and their responses. In this work, a mapping between operating parameters namely mean pressure and driving frequency, and their response represented in the temperature difference across the stack had been achieved through ANN as a prediction task.

ANN is considered a purely data-driven model where it can learn from examples. This learning ability makes it highly efficient problem-solving paradigms with obvious advantageous features including that, (i) it does not require detailed knowledge of the physical phenomena of the underlying relations between inputs and outputs, (ii) it maps the relationship between parameters regardless of the problem dimensionality and system nonlinearity and (iii) it has a high tolerance to data containing noise and measurement errors due to distributed processing within the network [Stuart & Peter, 2010 & Basheer, & Hajmeer, 2000). Therefore, ANN has been a powerful tool that is commonly used in different science and engineering fields. Recently, ANN has been applied to solve complex problems related to refrigerators, air conditioning systems, heat pumps, and heat exchangers. These applications mainly include thermal load analysis, prediction of performance, thermophysical properties, and heat transfer parameters for heat exchangers, in addition to optimization for energy utilization (Ewim, Okwu, Onyiriuka, Abiodun, Abolarin, & Kaood, 2022 & Hosoz, & Ertunc, 2006 & Ali, & Chakraborty, 2015 & Cortés, Urquiza, & Hernández, 2009 & Şencan, Köse, & Selbaş, 2011 & Li, Shao & Zhang, 2016 & Mohanraj, Jayaraj, & Muraleedharan, 2015 & Kusiak, Xu, & Zhang, 2014). More recently, ANN is used to the field of energy and power engineering, such as internal combustion engine and Stirling engine (Ghobadian, Rahimi, Nikbakht, Najafi, & Yusaf, 2009 & Özgören, Çetinkaya, Sarıdemir, Çiçek, & Kara, 2013). However, to the authors' knowledge, there is only a fewer publications about the application of ANN in the thermoacoustic field. Fatih S. etc. (Selimefendigil, & Öztop, 2014) presented simulation results based on a combination of black-box approaches with both dynamic fuzzy identification methods and dynamic neural networks for the prediction of thermoacoustic instability. These results had been compared with the results of another combination between a soft computational tool (Comsol) and a traditional numerical method (Galerkin solver). The results had shown a satisfactory agreement for these combinations. Xing J. etc. (Xing & Chen, 2015) designed a thermoacoustic sensor for low-intensity ultrasound measurements based on an artificial neural network, to map the relationship between the temperature rise of sample part subjected to the ultrasound intensity and ambient temperature, and compensate for temperature drifts and increase the reliability of the thermoacoustic measurements. These researches have demonstrated that proposed ANN models are capable of modeling the nonlinear mapping between the input and output parameters successfully and predicting the performance of systems in consideration with good accuracy.

To the best of the authors' knowledge, so far, there is a fewer research work involving the application of ANN for thermoacoustic refrigerators and thermoacoustic engines (Machesa, Tartibu, Okwu, 2021 & Alamir, 2021, Rahman & Zhang, 2019, Rahman & Zhang, 2018). The motivation of this study is to first predict the temperature difference across the stack under the effect of two operating parameters namely, mean pressure and driving frequency without the need for carrying out extra complex experiments hence high computational costs and consumed time can be saved. The ability of the proposed ANN had been demonstrated and proven for mapping a good relationship between the aforementioned operating parameters as inputs and the temperature difference across the stack as the response, with a high degree of accuracy.

2 Artificial Neural Network for prediction of temperature difference across the stack for a standing wave thermoacoustic refrigerator

2.1 Theoretical background

When a plate is placed in a standing acoustic wave, one end of the stack plate heats up whilst the other end cools down due to the thermoacoustic effect (Swift, 1988). The temperature difference between the two ends are often calculated using linear thermoacoustic theory which assumes that the thermoacoustic heat flux carried along the plate is balanced by conductive return heat fluxes in both the plate and fluid (Wheatley, Hofler, Swift, & Migliori, 1983). This temperature difference is considered a major concern as it is directly proportional and varies linearly with the cooling load (Nsofor, & Ali, 2009 & Tijani, Zeegers, & De Waele, 2002). The temperature difference across the stack, is generally affected by many operating conditions such as mean pressure, driving frequency (Nsofor, & Ali, 2009), drive ratio (Tijani, Zeegers, & De Waele, 2002 & Marx, & Blanc-Benon, 2005) and stack position (Marx, & Blanc-Benon, 2005). Several authors conducted studies for evaluating this temperature difference either experimentally or numerically and made comparisons with the linear theory predictions, but all studies do not reach the same conclusions due to the effect of some phenomena such as non-linear effects, thermal effects and temperature non-linearities (Marx, & Blanc-Benon, 2005). Hence, ANN model would be introduced as a new approach to deal with these critical issues related with the accuracy for calculating the temperature difference across the stack.

2.2 Related work

For comparison, the experimental setup system in (Marx, & Blanc-Benon, 2005) was used as the physical model in the present research. It is a standing wave thermoacoustic refrigerator with a one-quarter wavelength ($\lambda/4$) resonator tube, driven by an acoustic driver at one end, and closed rigidly with a sphere-like part at the other end. Helium was used as the working medium. Nsofor et al. (Nsofor & Ali, 2009) conducted experimental work on the performance of such a thermoacoustic refrigerator mentioned above by studying the relationship between operating parameters (mean pressure and frequency) and temperature difference across the stack which in turn affects the cooling load. In our research work, the temperature difference across the stack would be focused on as a primary indication of the performance of the thermoacoustic refrigerator. The experimental values of the temperature difference across the stack at different mean pressures and driving frequencies were extracted from the figures (Nsofor & Ali, 2009). It is noticed that 39 experiments had been conducted as a whole for studying the influence of mean pressure and driving frequency individually on the temperature difference across the stack as shown in Fig. 1. The data sample values of mean pressure (Pm) range from 3 bar to 6 bar with a step of 0.25 bar while the values of frequency (f) range from 250 Hz to 500 Hz with a step of 10 Hz. It is also noticed that there would be optimum values for either mean pressure or driving frequency for generating the highest temperature difference across the stack (ΔT stack) as shown in Fig.1. Therefore, both the mean pressure and frequency are important parameters influencing the temperature difference across the stack and were chosen for our study.

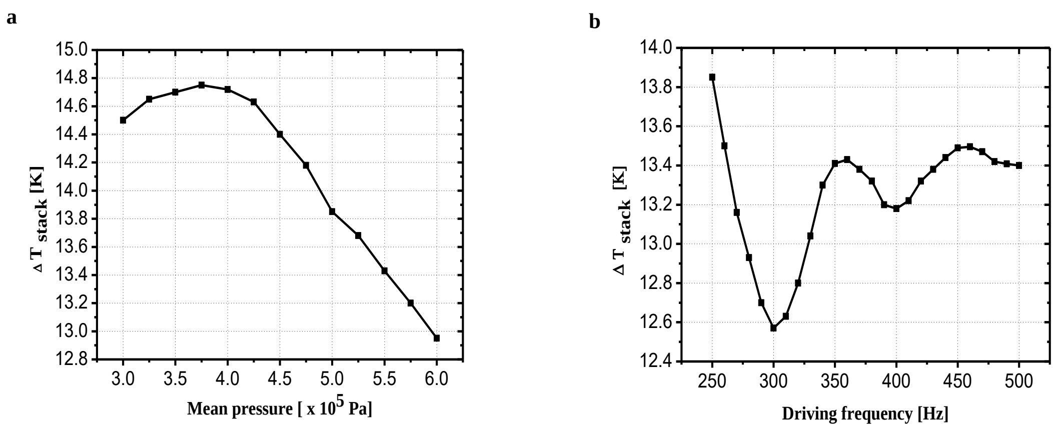

Fig.1 - (a) Temperature difference across the stack versus mean pressure; (b) Temperature difference across the stack versus driving frequency (here, data is extracted from Nsofor & Ali, 2009).

2.3 Determination of samples, structure and training algorithm for ANN model

The quality and quantity of experimental data are a major concern where they are considered the first and most important step for the design of the ANN model. The quality means a good representation of the training sample for the environment of interest whilst the quantity means that a sufficient training sample size is required for the success of the proposed model to learn well from these known data and predict unknown data accurately. Therefore, for the sake of convenience of comparison, 39 experimental datasets were used here and divided into two subsets; 30 experimental data out of the whole experimental data mentioned above, were used as sample data introduced to the proposed model for learning and readiness for data prediction whilst the remaining 9 experimental data were used only to verify the prediction ability for this model. In the proposed ANN model, the mean pressure and frequency were selected as input parameters and were also the same parameters as that in (Nsofor & Ali, 2009), whilst the output parameter was temperature difference across the stack, as a response which needs to be predicted using ANN model. For our ANN model, the 30 experimental data set mentioned above, were split into three data sets, namely the training data set, validation data set, and test data set. The training data set is used only for learning (i.e., to fit the weights of the network) whilst the validation data set is used to minimize the over-fitting problem that may occur in the training process and the test data set is used only to assess the generalization performance of the trained neural network. These three data sets were randomized and then introduced sequentially to the proposed model after the determination of the network structure and suitable training algorithm.

A typical multi-layer feed-forward neural network structure was adopted in the present study as shown in Fig. 2. This structure of a network consists of many layers, namely an input layer, one or more hidden layers, and an output layer with a specific number of neurons. The neurons in each layer are linked to other neurons of subsequent layers by weights where these neurons perform two functions, summation and activation functions respectively to sum the weighted inputs and then squash this summation to produce the output. Many parameters related to the network structure and training algorithm, need to be accurately selected. These parameters include several hidden layers, the number of neurons in the hidden layers, learning rate, momentum factor, weights, and variants. The weights are adjusted via a training algorithm. The back-propagation algorithm is commonly used as a training algorithm for feed-forward neural networks on MATLAB Software Package (Stuart & Peter, 2010 & Basheer & Hajmeer, 2000). In this training algorithm, the cumulative network error between predicted outputs and actual ones is calculated internally based on the information flowing between neurons in the forward direction and then backpropagated to adjust the values of the weights in the whole network mechanism as shown in Fig. 3(a). One hidden layer was found to be enough in this study and thus the architecture of ANN was a three-layer structure as shown in Fig. 3(b). The parameters for the input layer and output layer had been selected as mentioned previously, while the number of neurons in the hidden layer needs to be optimized. To find the optimum number of neurons in the hidden layer, their number was changed iteratively where predicted and experimental outputs at a different number of neurons in the hidden layer were compared. The prediction error and average prediction error were calculated, respectively

$$\text{Prediction error \%} = \left|\frac{\text{Predicted result} - \text{Experimental result}}{\text{Experiment result}}\right| \tag{1}$$

$$\text{Average prediction error } \% = \frac{\sum_{i=1}^{n} \text{Prediction error } \%}{n} \tag{2}$$

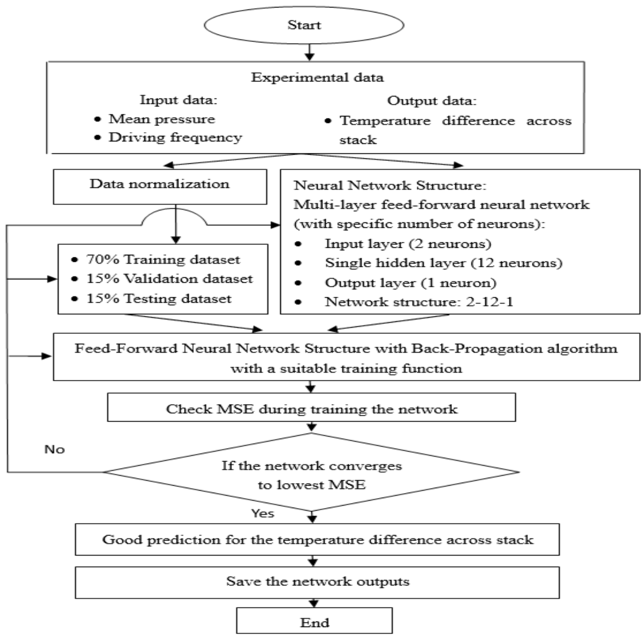

Fig. 2 - A flowchart for the proposed ANN model (Rahman & Zhang, 2018)

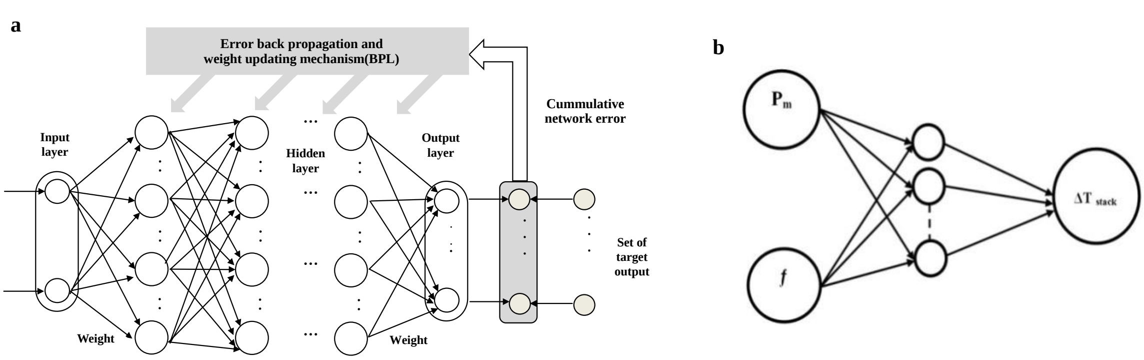

Fig. 3 - (a) A multi-layer ANN with back-propagation algorithm; (b) A three-layer ANN model for the thermoacoustic stack.

3. Results and Discussions

Temperature difference across the stack in one thermoacoustic refrigerator, was predicted by the ANN model under the effect of mean pressure and driving frequency. The proposed model had been trained several times until the error between predicted and actual output was minimized. In addition, the average prediction error between predicted and experimental outputs was calculated and plotted against the number of hidden neurons as shown in Fig. 4 and the average prediction error was found to be minimized at 12 hidden neurons. Moreover, it was noticed that the performance of the proposed ANN model in predicting the temperature difference across the stack of thermoacoustic refrigerator, was satisfactory due to higher values of regression (R) between the predicted and target (actual) outputs during training, testing and validation phases as shown in Fig. 5. These regression plots indicate the higher performance of the proposed neural network in predicting responses for any new input data within the covered range of the present study.

In order to check the prediction ability of our ANN model, the aforementioned unseen nine experimental data, had been used for the purpose of verification. The predicted results from ANN model were compared with corresponding experimental results under the same operating conditions. The error percentage of predicted temperature difference across the stack in each verification experiment, was calculated as individual for the single hidden layer with 12 neurons. Furthermore, it was observed that the predicted results were in a good agreement with the experimental results as shown in Fig. 6. And the average prediction error was calculated as shown in Table 1. The average prediction error between the predicted and experimental results was found to be 0.2 % which demonstrated the ability of ANN model to predict the temperature difference across the stack for any input values in the covered range with a high degree of accuracy.

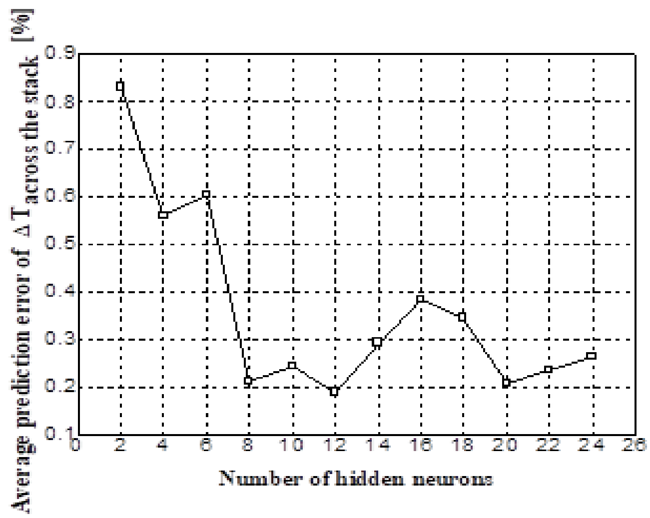

Fig. 4 - Average prediction error of temperature difference across the stack vs. number of hidden neurons.

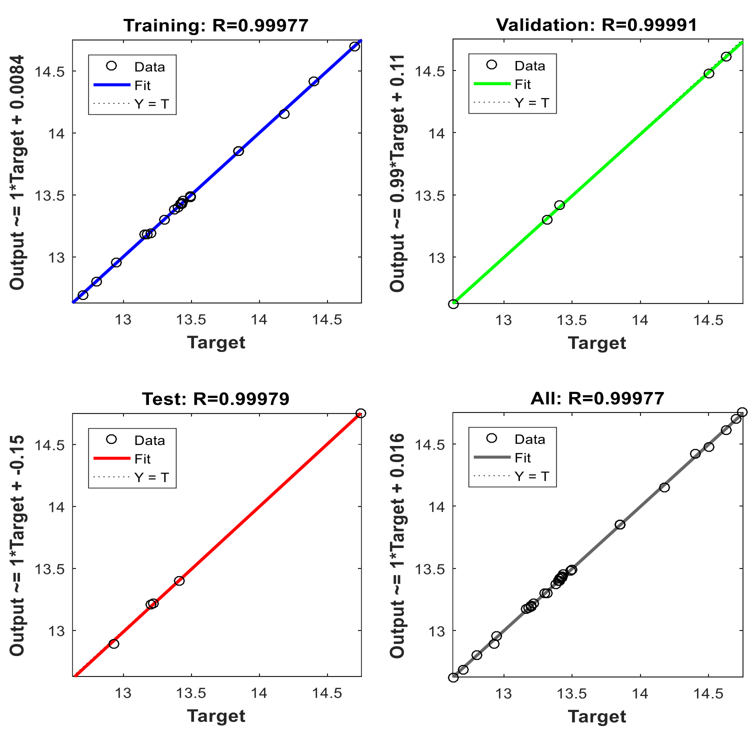

Fig. 5 - Regression plots for training, testing and validation phases.

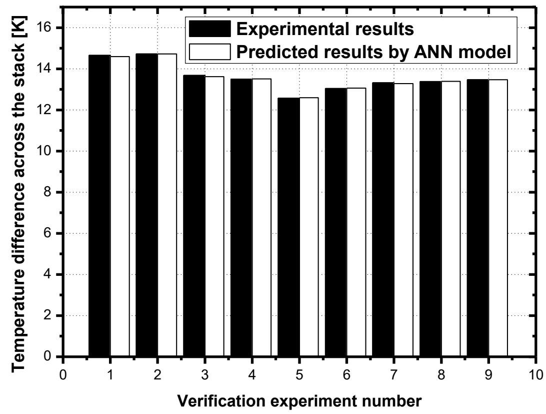

Fig. 6 - A comparison between predicted and actual values of temperature difference across stack at different verification experiments

Table 1 Comparison of predicted results by ANN model with experimental results for temperature difference across the stack (Note: experimental data were extracted from Nsofor & Ali, 2009).

Verification experiment number	Experimental results ΔT_{stack} [K]	Predicted results by ANN model ΔT_{stack} [K]	Prediction error of temperature difference across the stack [%]	Average prediction error of temperature difference across the stack [%]
1	14.65	14.59	0.41	
2	14.72	14.73	0.07	
3	13.68	13.61	0.51	
4	13.50	13.51	0.07	
5	12.57	12.59	0.16	0.20
6	13.04	13.06	0.15	
7	13.32	13.28	0.30	
8	13.38	13.39	0.07	
9	13.47	13.46	0.07	

4. Conclusions

A novel modeling method for thermoacoustic refrigerators based on an artificial neural network technique had been presented in this paper. A multi-layer feed-forward network with a back-propagation algorithm was adopted for this work. It was found that one hidden layer with 12 neurons can provide a better prediction performance. The average percentage of error for predicted temperature difference across the stack, compared to experimental values was 0.2 % which indicates the high accuracy of the proposed model and proves that well-trained neural network models can provide fast, accurate, and consistent results. The present work is considered the first attempt in the application of an artificial neural network to model a thermoacoustic refrigerator stack. For further development, this model can be improved by its integration with any other intelligent techniques such as a genetic algorithm to optimize its structure and hence minimizes the average prediction error. It can be also extended to include many input parameters affecting the temperature difference across the stack and map their complex relationship. Finally, ANN was found to be a new flexible modeling tool with a high degree of accuracy for linear and nonlinear thermoacoustic problems.

REFERENCES

Alamir, M. A. (2021). An artificial neural network model for predicting the performance of thermoacoustic refrigerators. International Journal of Heat and Mass Transfer, 164, 120551.

Ali, S. M., & Chakraborty, A. (2015). Thermodynamic modelling and performance study of an engine waste heat driven adsorption cooling for automotive air-conditioning. Applied Thermal Engineering, 90, 54-63.

Allesina, G. (2014). An experimental analysis of a stand-alone standing-wave thermoacoustic refrigerator. International Journal of Energy and Environmental Engineering, 5, 1-9.

Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks: fundamentals, computing, design, and application. Journal of microbiological methods, 43(1), 3-31.

Cortés, O., Urquiza, G., & Hernández, J. A. (2009). Optimization of operating conditions for compressor performance by means of neural network inverse. Applied Energy, 86(11), 2487-2493.

Devkota, R., Babu, A., Gupta, P., Kant, K., & Vidya, S. (2022). Application of Thermoacoustics for Cooling: A Review. Innovations in Mechanical Engineering, 421-427.

Ewim, D. R. E., Okwu, M. O., Onyiriuka, E. J., Abiodun, A. S., Abolarin, S. M., & Kaood, A. (2022). A quick review of the applications of artificial neural networks (ANN) in the modelling of thermal systems. Engineering and Applied Science Research, 49(3), 444-458.

Gardner, D. L., & Howard, C. Q. (2009). Waste-heat-driven thermoacoustic engine and refrigerator. In Proceedings of ACOUSTICS: 23-25.

Ghobadian, B., Rahimi, H., Nikbakht, A. M., Najafi, G., & Yusaf, T. F. (2009). Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. Renewable energy, 34, 976-982.

Ghorbanian, K., Hosseini, H., & Jafargholi, M. (2008). Design road-map for thermoacoustic refrigerators. The Journal of the Acoustical Society of America, 123(5), 3546-3546.

Hosoz, M. U. R. A. T., & Ertunc, H. M. (2006). Modelling of a cascade refrigeration system using artificial neural network. International Journal of Energy Research, 30(14), 1200-1215.

Jensen, C., Raspet, R., & Slaton, W. (2006). Temperature gradient integration in thermoacoustic stacks. Applied acoustics, 67, 689-699.

Kusiak, A., Xu, G., & Zhang, Z. (2014). Minimization of energy consumption in HVAC systems with data-driven models and an interior-point method. Energy Conversion and Management, 85, 146-153.

Li, Z. Y., Shao, L. L., & Zhang, C. L. (2016). Modeling of finned-tube evaporator using neural network and response surface methodology. Journal of Heat Transfer, 138(5).

Machesa, M., Tartibu, L., & Okwu, M. (2021). Prediction of the Oscillatory Heat Transfer Coefficient in Thermoacoustic Refrigerators. Sustainability, 13(17), 9509.

Marx, D., & Blanc-Benon, P. (2005). Numerical calculation of the temperature difference between the extremities of a thermoacoustic stack plate. Cryogenics, 45, 163-172.

Marx, D., & Blanc-Benon, P. (2005). Numerical calculation of the temperature difference between the extremities of a thermoacoustic stack plate. Cryogenics, 45, 163-172.

Mohanraj, M., Jayaraj, S., & Muraleedharan, C. (2015). Applications of artificial neural networks for thermal analysis of heat exchangers–a review. International Journal of Thermal Sciences, 90, 150-172.

Nsofor, E. C., & Ali, A. (2009). Experimental study on the performance of the thermoacoustic refrigerating system. Applied Thermal Engineering, 29, 2672-2679.

Özgören, Y. Ö., Çetinkaya, S., Sarıdemir, S., Çiçek, A., & Kara, F. (2013). Predictive modeling of performance of a helium charged Stirling engine using an artificial neural network. Energy conversion and Management, 67, 357-368.

Rahman, A. A., & Zhang, X. (2019). Improved predictions of onset temperature in twin thermoacoustic heat engine by neural network based calibrated thermoacoustic model. In Proceedings of 11th international conference on applied energy, 12-15.

Rahman, A. A., & Zhang, X. (2018). Prediction of acoustic wave parameters of thermoacoustic prime mover through artificial neural network technique: Practical approach for thermoacoustics. Thermal Science and Engineering Progress, 8, 257-268.

Rahman, A. A., & Zhang, X. (2018). Prediction of oscillatory heat transfer coefficient for a thermoacoustic heat exchanger through artificial neural network technique. International Journal of Heat and Mass Transfer, 124, 1088-1096.

Reid, R. S., & Swift, G. W. (2000). Experiments with a flow-through thermoacoustic refrigerator. The Journal of the Acoustical Society of America, 108(6), 2835-2842.

Selimefendigil, F., & Öztop, H. F. (2014). Soft computing methods for thermo-acoustic simulation. Numerical Heat Transfer, Part A: Applications, 66, 271-288.

Şencan, A., Köse, İ. İ., & Selbaş, R. (2011). Prediction of thermophysical properties of mixed refrigerants using artificial neural network. Energy conversion and management, 52(2), 958-974.

Shen, C., He, Y., Li, Y., Ke, H., Zhang, D., & Liu, Y. (2009). Performance of solar powered thermoacoustic engine at different tilted angles. Applied Thermal Engineering, 29(13), 2745-2756.

Stuart J. R. & Peter N. (2010). Artificial intelligence : a modern approach, (3rd ed.) New Jersy: Prentice-Hall.

Swift, Gregory W. (1988). Thermoacoustic engines. the Journal of the Acoustical Society of America, 84, 1145-1180.

Swift, Gregory W. (2003) Thermoacoustics: A unifying perspective for some engines and refrigerators, 2379-2381.

Tijani, M. E. H., Zeegers, J. C. H., & De Waele, A. T. A. M. (2002). Construction and performance of a thermoacoustic refrigerator. Cryogenics, 42, 59-66.

Tijani, M. E. H., Zeegers, J. C. H., & De Waele, A. T. A. M. (2002). Prandtl number and thermoacoustic refrigerators. The Journal of the Acoustical Society of America, 112(1), 134-143.

Tijani, M. E. H., Zeegers, J. C. H., & De Waele, A. T. A. M. (2002). Design of thermoacoustic refrigerators. Cryogenics, 42(1), 49-57.

Wang, X., Xu, J., Wu, Z., & Luo, E. (2022). A thermoacoustic refrigerator with multiple-bypass expansion cooling configuration for natural gas liquefaction. Applied Energy, 313, 118780.

Wetzel, M., & Herman, C. (1997). Design optimization of thermoacoustic refrigerators. International journal of refrigeration, 20, 3-21.

Wetzel, M., & Herman, C. (2000). Experimental study of thermoacoustic effects on a single plate Part I: Temperature fields. Heat and Mass Transfer, 36, 7-20.

Wheatley, J., Hofler, T., Swift, G. W., & Migliori, A. (1983). An intrinsically irreversible thermoacoustic heat engine. The Journal of the Acoustical Society of America, 74, 153-170.

Xing, J., & Chen, J. (2015). Design of a Thermoacoustic sensor for low intensity ultrasound measurements based on an artificial neural network. Sensors, 15, 14788-14808.

Zhang, X., Chang, J., Cai, S., & Hu, J. (2016). A multi-stage travelling wave thermoacoustic engine driven refrigerator and operation features for utilizing low grade energy. Energy Conversion and Management, 114, 224-233.