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IMPROVED PREDICTIONS OF ONSET TEMPERATURE IN TWIN THERMOACOUSTIC HEAT ENGINE BY NEURAL NETWORK BASED CALIBRATED THERMOACOUSTIC MODEL

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ABSTRACT

Thermoacoustic heat engines are promising devices converting thermal power into acoustic power with the distinct merits of simplicity, and possibility for utilizing low-grade heat sources. As well known, design parameters are usually determined based on weakly non-linear thermoacoustics theory which of course produces significant deviations due to non-capturing of nonlinear phenomena. In order to improve inaccurate predictions of onset temperature obtained by DeltaEC linear thermoacoustic model, artificial neural network is first proposed to be hybridized with DeltaEC model to provide a new synergistic approach. This synergistic approach was applied to a twin thermoacoustic heat engine for improving the computational efficiency of DeltaEC model itself through considering some nonlinearities existing in the whole thermoacoustic system. The onset temperature was predicted as the responses to both resonator length and charging pressure and the obtained results had been proven to be desirable in their accuracy compared to experimental ones and better than literature DeltaEC results under same given conditions.

Keywords: Thermoacoustics, Artificial neural network-DeltaEC hybrid model, Twin thermoacoustic heat engine, Onset temperature, Resonator length, Charging pressure

NONMENCLATURE

Abbreviations	
ANN	Artificial Neural Network
DeltaEC	*Design Environment for Low-Amplitude Thermoacoustic Energy Conversion*
Symbols	
t	target (Actual output)
o	Network output (predicted output)

1. INTRODUCTION

Thermoacoustic heat engines (TAHEs) are considered as promising thermodynamic machinery converting thermal power into acoustic power based on the so called "thermoacoustic effect". They provide many significant advantages including using fewer or no moving parts, environmentally friendly working substances as well as possibility to utilize low-grade heat sources [1]. The most potential applications of thermoacoustic heat engines are either to drive refrigerators or electrodynamic linear alternators [2, 3]. Recently, thermoacoustic heat engines have made rapid advancements in theoretical and practical research scope [4]. In this regard, it is imperative to focus on some design parameters influencing onset temperature as one of the most important performance indicators for thermoacoustic heat engines. Hence, suitable selection of design parameters to achieve appropriate onset temperature is required.

Generally, in practical development of thermoacoustic heat engines, appropriate selection of design parameters is still a hard task to achieve desirable performances including either onset temperature (corresponding to heating temperature), acoustic wave parameters (i.e. oscillating frequency or acoustic pressure amplitude), acoustic power or the efficiency.

These performances depend primarily on various design parameters either operational such as charging pressure, geometrical such as resonator length and stack/regenerator dimensions besides thermo-physical properties of gas and solid media [5, 6]. Regarding onset temperature as our major of concern in this present study, it is considered one of the most important performance indices for thermoacoustic heat engines where lower onset temperature is always desirable as the limiting condition for TAHEs operation. Meanwhile, onset temperature should overcome thermal and viscous dissipations to excite oscillations. In this regard, Swift [1] had conducted a quantitative study on the building of thermoacoustic oscillations and proposed the "critical temperature gradient" which represents the limit between prime mover and refrigerator functions of thermoacoustic engines. Furthermore, Atchley et al. [7] had conducted many studies on the onset behavior describing the transition to onset in thermoacoustic heat engines. Later, Zhou and Matsubara [6] had experimentally studied the onset process in thermoacoustic heat engines and found that onset and damping temperatures are not the same. Also, Chen and Jin [8] had studied the onset and damping behavior in thermoacoustic prime movers based on the hysteresis phenomenon and found that the damping temperature lags the onset temperature. In addition, low and high-frequency modes in the onset process were observed by Yu et al. [9] in one thermoacoustic Stirling prime mover to investigate the stability of oscillation modes namely, stability mode and transition mode. In their work [9], it was found that once the low-frequency mode oscillation is excited at the existence of high-frequency mode oscillation, the latter mode will be gradually slaved and suppressed by the former one. Also noticed that mean pressure is considered an important control parameter influencing the stability mode in the tested thermoacoustic system. On the other hand, Qiu et al. [10] had experimentally applied pressure disturbance in thermoacoustic heat engines to significantly minimize the onset temperature.

Furthermore, recently, Wang et al. [11] had visualized the onset mechanism characteristics in traveling wave thermoacoustic heat engines using infrared imaging. It was noticed that Gedeon streaming has a significant effect on the axial temperature distribution of the onset and damping processes. Thereafter, He et al. [12] had experimentally and analytically interpreted the onset and damping behaviors in a standing-wave thermoacoustic heat engine considering the convective heat transfer between gas and stack. It was found that both efficiency and acoustic power output increase with increasing the gas-stack heat transfer coefficient, the gas displacement amplitude and the heating temperature difference across the stack. Also, it was found that decreasing the tilted angle leads to increasing the gas-stack heat transfer coefficient of the natural convection which consequently decreases the onset and damping temperature differences. Besides, theoretically (or analytically), de Waele et al. [13] had obtained analytical expressions for the onset temperature, the damping coefficient and the oscillation frequency, that allows stable oscillations, based on a fourth-order differential equation which determines damping, growth, or stability of oscillations and describe the dynamics of the individual thermoacoustic components.

On the other hand, Guedra et al. [14] had focused on predicting the onset conditions of thermoacoustic instability for various thermoacoustic engines either with standing-wave or traveling-wave modes using a semi-empirical way and treating thermoacoustic core as a black box. Specifically, in their work [14], an experimental apparatus was successfully presented to deduce transfer matrix coefficients of thermoacoustic core under various heating conditions by means of a four-microphone through applying a "two-load" method for acoustic measurements, then developing an analytical model to predict onset conditions (i.e., onset heating power supplied and onset frequency). Moreover, Sun et al. [15] had developed a simplified physical model for calculating the onset temperature ratio and the frequency of a standing wave thermoacoustic engine in the time domain based on thermodynamic analysis. The effects of stack spacing, charge pressure, and resonator length on the onset temperature ratio and the frequency were calculated. Relatively good agreement between the computational and experimental results has been achieved, which validated the model for calculating the onset characteristics of thermoacoustic heat engines. Additionally, based on numerical investigations, Qiu et al. [16] had numerically simulated the onset process in a standing-wave thermoacoustic heat engine based on thermodynamic analysis. Transient pressure drop and heat transfer data were first calculated based on weakly non-linear thermoacoustics theory. Thereafter, the effects of stack spacing, charge pressure, and resonator length on onset temperature were numerically investigated and compared with experimental results to demonstrate a good agreement. More recently, Boroujerdi et al. [17] had analytically investigated the influences of stack and thermoacoustic heat engine dimensions as well as charging pressure on both onset temperature and oscillating frequency under different working gases. Furthermore, Meir et al. [18] had experimentally and analytically demonstrated that mass transfer can significantly lower the temperature gradient required to achieve acoustic onset in phase-change thermoacoustic heat engines.

Undoubtedly, all aforementioned attempts had presented quite-well predictions to some extent for the onset temperature compared with experiments. However, accurate numerical predictions of onset temperature is still lacking. Therefore, to explore an accurate predictive approach is quite useful and still needed. From here, artificial neural network (ANN) as an intelligent approach was first proposed to improve the computational efficiency of one thermoacoustic numerical model called DeltaEC model in order to reduce the deviations arising from the latter model. It is noteworthy that DeltaEC model is only convenient for the applicability within linear (or weakly non-linear) thermoacoustic regime where such a limitation makes it ineffective in capturing intrinsic nonlinear phenomena [1]. Therefore, to make DeltaEC platform more powerful to deal with nonlinear problems such as temperature non-uniformity as in our case study, ANN is introduced as a synergistic (or calibrating) approach to be coupled with DeltaEC model and form a hybrid model. Generally, hybrid systems combine more than one machine learning technology where each system represents a part of these integrated systems for performing a specific task by one technique that will be followed by another task from the other technique to completely solve the considered problem.

Regarding ANN technique, it is a data-driven model where its characteristics are pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance as well as learning and generalization ability. Also, ANN does not need any prior assumptions concerning data distribution or lengthy iterative calculations, which makes it more attractive alternative to both statistical and numerical methods [19]. A. Rahman et al. [20] had initiated the application of ANN to different thermoacoustic heat engine and refrigeration systems in a series of research work for data prediction. On the other hand, DeltaEC is considered a powerful simulation platform used to design thermoacoustic devices [1]. Many research work have used DeltaEC for design and modeling of thermoacoustic systems [21]. To authors' knowledge, very few literature work had focused on improving the computational efficiency of numerical models by using ANN technique, mainly for improving environmental, oceanic and hydrological numerical models [22-26]. Recently, related to engineering applications, Wani et al. [27] had used the same concept of our hybridization technique. In their work [27], the performance indices of a two stroke spark ignition engine including power and break specific fuel consumption, were predicted as responses to three inputs namely speed, throttle position (or load) and air-to-fuel ratio. Their hybrid model had presented more accurate results than those obtained from the conventional numerical model itself. More recently, Lü et al. [28] had used ANN as a calibrating model for one building numerical model to simulate the indoor temperature or/and humidity for unheated and uncooled buildings which can be extended to other building simulations. It was found that the calibrated numerical model by ANN model can provide more accurate results compared to the numerical model alone. Moreover, the developed calibration model needs only few measurements as necessary inputs which significantly simplifies the calibration (synergism) process for modeling the building performances. In this present study, a hybrid model combining artificial neural network (ANN) and DeltaEC models, would be developed for one typical twin standing wave thermoacoustic heat engine as considered the computational example from published literature [29]. Herein, the onset temperature would be predicted as a response to both resonator length and charging pressure as the considered geometrical and operational parameters, respectively. Thereafter, the significance of proposed hybrid model would be verified where our objective here is to introduce a novel effective and practical approach for more accurate thermoacustic predictions by ANN-DeltaEC hybrid model.

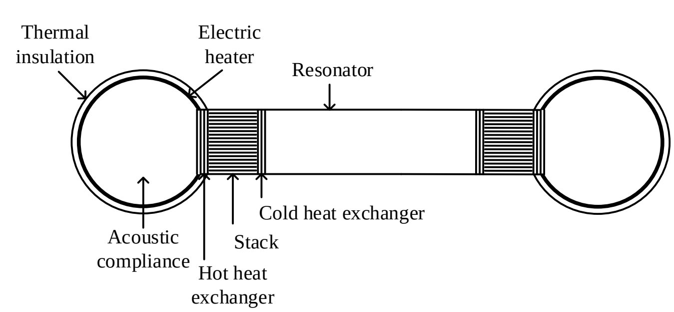

Fig 1 Schematic diagram for twin standing-wave thermoacoustic heat engine

2. NEURAL NETWORK-DELTAEC HYBRID MODEL FOR IMPROVED PREDICTION OF ONSET TEMPERATURE

2.1 Physical Model

For convenience of comparison, the experimental set up of a twin thermoacoustic prime mover (twin TAPM) in [29] was used here as the physical model as shown in Fig.1. This twin TAPM can produce acoustic waves of desired frequency with enhanced pressure amplitude. Compared to single TAPM, this twin TAPM generates the acoustic waves with high pressure amplitude and acoustic power which can be utilized to effectively drive refrigerators and pulse tube cryocoolers [29]. As shown in Fig.1, stack, hot and cold heat exchangers were assembled perpendicular to each other to prevent blockage of heat and fluid flow. The diameter of resonator, stack and heat exchangers is 0.038 m. Nitrogen was used here as the working fluid with charging pressure varying from 0.1 to 1 MPa with a gradual step of 0.1 MPa. Also, resonator length was varied to be either 0.5m, 0.6m, 0.8m, 1.1m or 1.4 m. The stack has a length of 0.05 m, a spacing of 0.5 mm and a thickness of 0.5 mm while hot and cold heat exchangers have lengths of 0.02 m and 0.01 m, respectively.

2.2 Determination of samples, structure and training algorithm

For the sake of convenience of comparison, 50 experimental data from [29] would be used as the data samples. Resonator length and charging pressure were considered as the variables of interest influencing onset temperature. Initially, experimental data samples were divided into two groups, one for building our ANN model while the other for verifying the ANN prediction ability. More specifically, the first group data samples were divided into two distributed modules each with 20 input data samples. Each 20 data samples were split into three data sets: 70% for training to learn, 15% for validation to minimize over-fitting and 15% for testing to assess the generalization performance [20]. These three data sets were normalized according to Eq. (1), then randomized and finally introduced sequentially to the ANN model. On the other hand, the remaining 10 data samples would be introduced as new unseen input data to the established neural network model.

$$x_i = 0.8\left(\frac{k_i - k_{\min}}{k_{\max} - k_{\min}}\right) + 0.1, \tag{1}$$

where x_i represents the normalized value of k_i.

ANN models are often characterized by structure, neuron characteristics, learning parameters, training algorithm and training function, which represent the constraints for optimizing the network performance. Structurally, a typical feed-forward neural network with one hidden layer is commonly adopted in majority of applications. Besides, the number of input and output neurons is determined according to the considered modelling problem while number of hidden neurons needs to be accurately optimized. In this regard, it was recommended that the number of hidden neurons can be a function of the number of input neurons (*n*) as follows: "*n*/2", "*n*", "2*n*" and"2*n* + 1" [20]. Moreover, back-propagation algorithm as shown in Fig. 2 with Levenberg-Marquardt training function was adopted here for low- and moderate-sized networks.

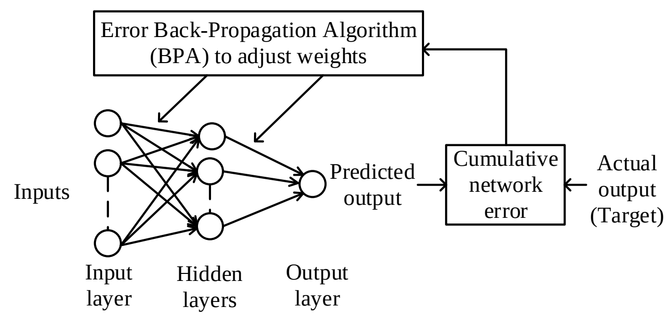

Fig 2 A schematic diagram for multi-layer feed-forward ANN model with an error back-propagation training algorithm

Regarding ANN performance evaluation, the least mean square error (*MSE*) during the validation phase has the priority to be selected as the generalization criterion to show how close or far the network outputs are with respect to the actual ones according to Eq. (2). In addition, the other criterion is to analyze the regression between the network responses and corresponding targets (actual outputs) from the correlation coefficient (R^2) as illustrated in Eq. (3) and hence confirm the optimum number of hidden neurons. In general, R^2 value varies between 0 and +1, where R^2 value close to +1 indicate a robust positive linear correlation between the network outputs and targets, while the values near to 0 indicate a very weak correlation [20].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - o_i)^2 \,, \tag{2}$$

$$R^2 = 1 - \left(\frac{\sum_i^n (o_i - t_i)^2}{\sum_i^n (t_i)^2}\right). \tag{3}$$

2.3 Neural network – DeltaEC hybrid model

Herein, ANN-DeltaEC hybrid model comprises of two major parts, conventional DeltaEC model and distributed synergistic multi-structure ANN model as shown in Fig. 3. Regarding synergistic ANN model, it consists of specific number of modules, each of which comprises of multi-structure units of neural networks with different neuron characteristics (i.e. different transfer functions) as shown in Fig. 4.

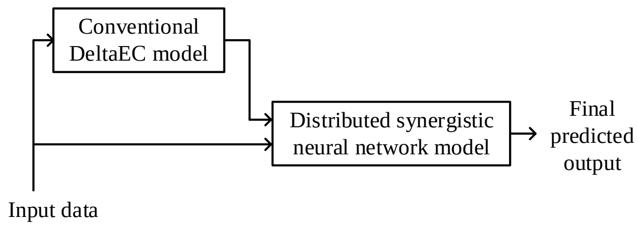

Fig 3 ANN-DeltaEC hybrid model

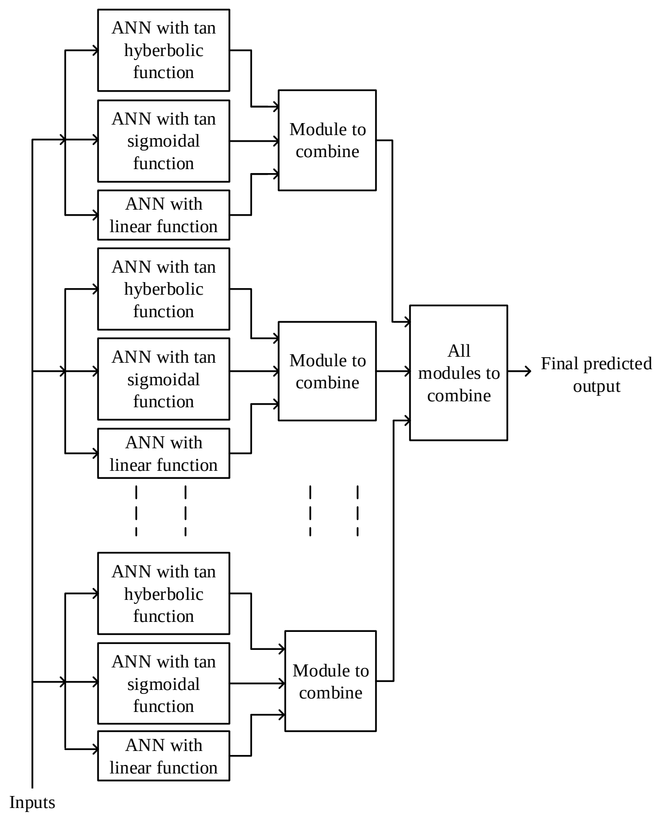

Fig 4 Distributed synergistic multi-structure ANN

The characteristics of the data set are trained in parts on various unit structures where the unit structure in a single module is responsible for identifying only a part of the data set characteristics. Moreover, this hybrid model regards the DeltaEC model output as an additional input for the sake of synergism as shown in Fig. 3. Therefore, the word "synergistic" would be given to DeltaEC model outputs which need to be improved. Furthermore, the output of each module was obtained by averaging the outputs from its three unit-structure neural networks. Then, the final predicted output will be determined as the highest averaged output obtained among these individual modules [27]. This work was implemented using Neural Network Toolbox of MATLAB platform.

3. Results and Discussions

Based on sensitivity analysis, it was found that the hybrid network structure with the configuration of 3-7-1 was adopted here with least *MSE* (i.e. best validation performance) as well as highest correlation coefficient, R^2 satisfying the two aforementioned performance evaluation criteria as shown in bold in Table 1. On the other hand, regression plots for the network outputs were presented in Fig.5 with respect to the targets (actual outputs) during training, validation and testing phases (i.e. overall regression plots). Here, the final overall regression value represents the average from all groups of data samples at different hidden transfer functions. These plots indicate a very good fit between the network outputs and actual ones due to higher values of regression.

Table 1 Sensitivity analysis for proposed synergistic neural networks concerning onset temperature

Network structure	*MSE*	R^2
3-2-1	0.000798	98.54
3-3-1	0.003585	95.45
3-6-1	0.000645	99.46
3-7-1	**0.000547**	**99.51**

Moreover, the 10 new unseen data samples were used for verification as shown in Fig. 6 from which the average prediction error was minimized at 7 hidden neurons. Furthermore, compared to experimental results under same conditions, predicted onset temperature by hybrid model had shown a very good agreement with average prediction error percentage of 4.54%. These predicted results demonstrated the ability of our hybrid model to predict the onset temperature inside the covered range with a high degree of accuracy as shown in Fig. 7. On contrary, DeltaEC results had shown some deviation from experimental ones with average prediction error percentage of 8.3%.

The deviations of DeltaEC model results can be interpreted from (i) Not taking thermal losses associated with the experimental setup into consideration; (ii) Ignoring the effect of thermoacoustic core inside thermoacoustic system; (iii) Non-uniformity in average gas temperature arising from non-uniformity of stack

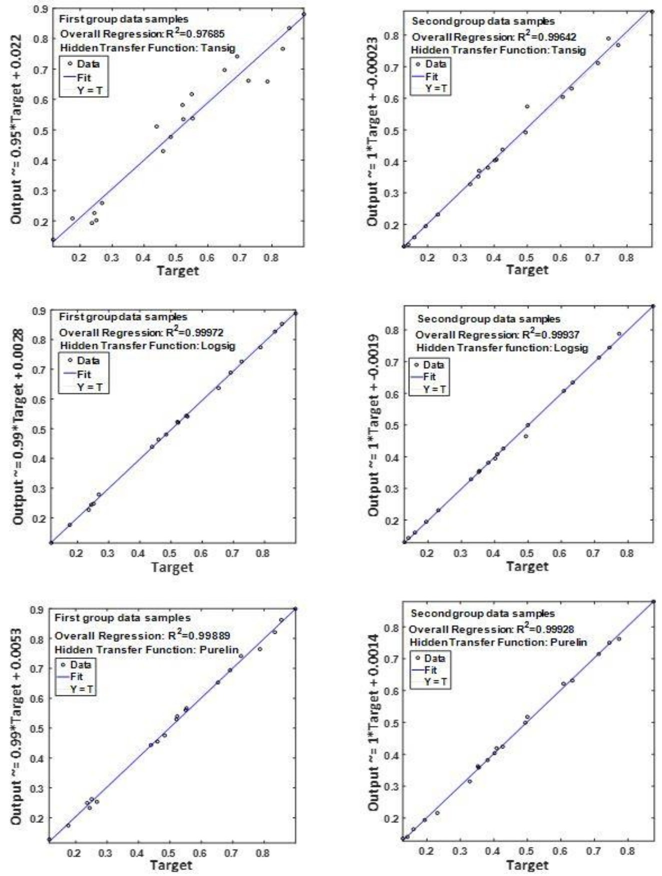

Fig 5 Overall regression plots for both first and second groups of data samples at different hidden transfer functions

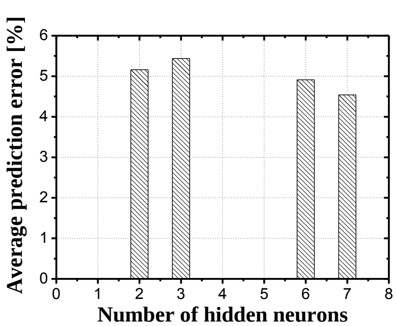

Fig 6 Average prediction error of onset temperature [%] *vs.* number of hidden neurons

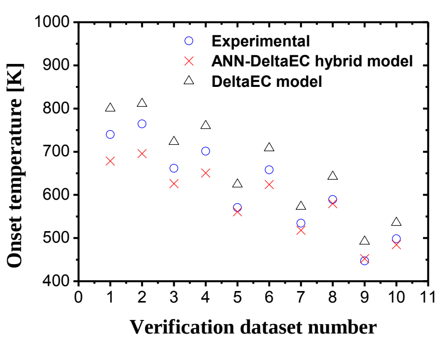

Fig 7 Experimental and predicted onset temperature by both DeltaEC and hybrid models *vs.* verification dataset numbers

plate spacing, which consequently affects the gas temperature distribution, as well as (iv) entropy generation by irreversibilities resulting from fluid friction and heat transfer to surroundings. From here, one can see the degrees to which linear (or weakly non-linear) thermoacoustics theory cannot describe these influences of nonlinear dissipations. On contrary, the good agreement of ANN-DeltaEC hybrid model results with experimental ones had demonstrated the capability of handling complex nonlinear phenomena, and describing more real world physical matters by learning from experimental data.

4. Conclusions

The present work provides a novel practical and effective modeling approach for thermoacoustics based on a distributed and synergistic ANN-DeltaEC hybrid model to accurately predict the onset temperature of a twin thermoacoustic heat engine. The results from conventional DeltaEC model itself had been significantly improved to be close to experimental results, which implies the strong ability of ANN in capturing the nonlinearities existing in the considered thermoacoustic system through effectively combining ANN model and DeltaEC model to perform complementary tasks. The present work presented a more significant and flexible approach for obtaining more accurate thermoacustic predictions by ANN-DeltaEC hybrid model. On the other hand, for future research work, more applied research will be devoted to more complex mappings, system identification as well as optimization for nonlinear thermoacoustic problems through using ANN technique either alone or hybridized with other conventional numerical models to improve their computational efficiencies.

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