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Article

Using GMDH Neural Networks to Model the Power and Torque of a Stirling Engine

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Abstract: Different variables affect the performance of the Stirling engine and are considered in optimization and designing activities. Among these factors, torque and power have the greatest effect on the robustness of the Stirling engine, so they need to be determined with low uncertainty and high precision. In this article, the distribution of torque and power are determined using experimental data. Specifically, a novel polynomial approach is proposed to specify torque and power, on the basis of previous experimental work. This research addresses the question of whether GMDH (group method of data handling)-type neural networks can be utilized to predict the torque and power based on determined parameters.

Keywords: GMDH; neural network; Stirling engine; torque; power

1. Introduction

Reducing use of fossil fuels is a significant energy quest of the world today, and many researchers are seeking ways to harness alternative energy resources and developing enhanced energy conversion systems.

The Stirling engine can be very efficient, having the same theoretical energy efficiency as the Carnot engine for transforming heat to work. It is environmentally advantageous and can mitigate CO_2 emissions from combustion.

An important energy conversion system that can contribute to these goals is the Stirling engine, which can generate electrical power with high thermal efficiency. It is an external combustion engine that works within an extensive temperature interval and provides opportunity of enhanced combustion control. Stirling engines works utilize expansion and compression processes of a working fluid (e.g., gases such as hydrogen, helium and air) [1,2]. The efficiency of a Stirling engine varies with charge pressure, mechanical connections, temperature difference between the cold and hot reservoirs, regenerator efficiency, heat transfer coefficient, impermeability ratio and physical and thermal properties of the working fluid (e.g., thermal conductivity, viscosity, heat capacity) [3].

Many efforts at manufacturing and enlarging of Stirling engine have been put forth by companies and research organizations. The period of new Stirling engine improvement began in 1937 by the Philips Company, which developed Stirling engine sizes up to 336 kW [4]. More recently, Prodesser [5] built a Stirling engine that is fueled with biomass to produce electric power, and that can generate an electric power of 3.2 kW while achieving a pressure of 33 bars. Sripakagorn and Srikam [6] built a beta-type Stirling engine that operated at a medium temperature range and generated 95.4 W of electric power with internal conditions of 773 K and 7 bar. Karabulut *et al.* [7] built a Stirling engine capable of generating 183 W of electric power using a working fluid of helium that attains a pressure of 4 bar. Cheng and Yu [8] investigated numerically a beta-type Stirling engine to identify the effects of various parameters, including non-isothermal effects and the performance of the regenerative channel. Chen *et al.* [9] developed a numerical approach for assessing a c-type Stirling engine so as to permit prediction of various geometrical and process characteristics, and showed that regeneration effectiveness influences efficiency and engine speed influences engine power the most. Formosa and Despesse [10] developed a model to investigate heat exchanger efficiency and regenerator flaws for a Stirling engine, and examined the effects of regeneration on thermal efficiency and output power. Also, a smart model to predict Stirling heat engine power output using an evolutionary approach was developed by Ahmadi *et al.* [11–17].

System identification methods are able to demonstrate and estimate the behaviors of unidentified and/or very complicated systems on the basis of specified input–output data, for various fields of engineering [18]. Calculation approaches for these methods [19], which involve specification in an uncertain environment, have attracted considerable attention from researchers. The most common calculation approaches include neural networks, fuzzy logic and evolutionary algorithms, and these have contributed significantly to improving understanding of recognition and control issues for complicated, non-linear systems.

Various investigations have been performed on methods for utilizing evolutionary algorithms for system recognition [20–24]. Amongst these, the group method of data handling (GMDH) is a self-organizing technique that creates a progressively more complex approach on the basis of the assessment of its effectiveness for an assortment of multi-input, single-output data couples (Xi,yi)

(i = 1,2,…,M). GMDH was introduced by Ivakhnenko [25] as a multivariate analysis approach for complicated systems modeling and recognition. GMDH can be utilized to avoid the complexity of obtaining former information with the algebraic approach of the progression. Thus, GMDH can be utilized to demonstrate complicated systems without having particular information of the systems.

GMDH operates by creating an analytical function in a feed forward network on the basis of a quadratic node transfer function [26], in which constants are obtained by a regression procedure. The actual GMDH approach, where method factors are approximated via a least squares approach, can be categorized based on comprehensive initiation and partial initiation to illustrate the combinatorial (COMBI) and multi-layered iterative algorithms (MIA), correspondingly [27].

Presently, the employment of self-organizing networks has increased the effectiveness of the GMDH approach for a wide variety of fields and applications [25–31]. There have been many attempts in the past to assemble population-based stochastic search methods such as evolutionary approaches like ANNs (artificial neural network), particularly since such evolutionary methods are helpful for complicated problems having large search spaces with many local optimums [32]. A review of evolutionary approaches within ANNs is presented in [33]. Genetic algorithms have been utilized in feed-forward GMDH style NNs, in which a neuron explores its optimum assortment of connections with the previous layer [34].

In the present work, a model is developed incorporating GMDH and Stirling engine experimental [35,36] outcomes for the first time. The results are verified against experimental values. In the study, 112 configuration numbers, obtained from prior experimental works [35,36], are utilized for both training the polynomial NN and estimation. Inputs for the NN model are temperature of the hot working fluid, pressure and fuel, while the outputs are torque and power. The GMDH-style NN is developed to determine the input–output relationship in the form of polynomials. Such NN recognition progression requires some optimization approaches to specify the best network topology. In this regard, the Genetic Algorithms (GAs) are organized in a novel model to specify the complete topology of the GMDH-style NNs, *i.e.*, the neurons' number throughout every hidden layer and their connection conformation. Singular Value Decomposition (SVD) is employed to identify the optimum constants of quadratic formulations for predicting of torque and power.

2. Principles of Modeling Using GMDH Types of Artificial Neural Networks

An approach can be expressed as an assortment of neurons where various pairs throughout every layer are associated via a quadratic polynomial through the GMDH algorithm and, consequently, generate fresh neurons throughout the further layer. Such information can be used in modeling to link outputs to inputs. The accepted definition of the recognition issue is to determine a function $\hat{f}$ that can be roughly utilized in place of real one, f, with the intention of estimating output $\hat{y}$ for a specified input vector $X = (x_1, x_2, x_3, \ldots, x_n)$ that is close to its real output y. For specified M observations of multi-input–single-output data couples the real target can be expressed as follows:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \qquad (i = 1, 2, 3, \ldots M) \tag{1}$$

Now, a GMDH style NN is trained to estimate the target values $\hat{f}_i$ for any specified input vector $X = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})$ as follows:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \qquad (i = 1,\ 2,\ 3,\ \ldots M) \tag{2}$$

In this step, the issue is to specify a GMDH style NN in order to minimize the square of the difference between the real target and the estimated one, as follows:

$$\sum_{i=1}^{M} \left[\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - \hat{y}_i \right]^2 \rightarrow min \tag{3}$$

The overall relation between input and output parameters can be formulated by a complex discrete form of the Volterra functional series as follows:

$$y = a_\circ + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \ldots \tag{4}$$

which is recognized as the Kolmogorov–Gabor polynomial [25,27–29]. This full algebraic arrangement can be represented by a system of partial quadratic polynomials containing only two parameters (neurons) as follows:

$$\hat{y} = G(x_i, x_j) = a_\circ + a_1 x_i + a_2 x_j + a_3 x_i^2 + a_4 x_j^2 + a_5 x_i x_j \tag{5}$$

In this regard, such partial quadratic sketch is utilized reversely throughout a network of linked neurons to form the universal arithmetic correlation of input and output parameters specified in Equation (4). The coefficients a_i in Equation (5) are specified by regression approaches in order to minimize the difference between real output y and the determined one $\hat{y}$ for each pair of input parameters x_i, x_j.

In actuality, it can be observed that a hierarchy of polynomials is built utilizing the quadratic form provided in Equation (5) whose constants are acquired via least-squares logic. Then, the constants of every quadratic function G_i are obtained to optimally fit the output throughout the entire set of output–input data pairs, as follows:

$$E = \frac{\sum_{i}^{M} (y_i - G_i)^2}{M} \rightarrow min$$

In simple terms, in the GMDH approach the probabilities are provided of two autonomous parameters out of the entire n input parameters being chosen. This is done with to create the regression polynomial in Equation (5) that best fits the dependent observations $(y_i, i = 1,2,\ldots M)$ through least-squares logic.

Accordingly, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons are assembled throughout the prime hidden layer of the feed forward NN from the observations $\{(y_i, x_{ip}, x_{iq}); (i = 1,2,\ldots M)\}$ for various $p, q \in \{1, 2, \ldots, n\}$. That is, it is now promising to build M data trebles $\{(y_i, x_{ip}, x_{iq}); (i = 1, 2, \ldots, M\}$ from observations utilizing such $p, q \in \{1, 2, \ldots, n\}$ sets as follows:

$$\begin{bmatrix} x_{1p} & x_{1q} & y_1 \\ x_{2p} & x_{2q} & y_2 \\ x_{3p} & x_{3q} & y_M \end{bmatrix}$$

Utilizing the quadratic sub-formulation type of Equation (5) for every row of M data trebles, the subsequent matrix formula can be straightaway gained as

$$Aa = Y \tag{6}$$

$$a = \{a_\circ,\, a_1,\, a_2,\, a_3,\, a_4,\, a_5\} \tag{7}$$

$$Y = \{y_1, y_2, y_3, \ldots y_M\}^T \tag{8}$$

Here, a denotes for the vector of unidentified constants for the quadratic polynomial in Equation (5), and Y denotes the vector of output values from observations. Thus, the following expression can be formulated:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \hdashline 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix} \tag{9}$$

The least-squares approach from the analysis of the multiple-regression effect leads to the following standard expression:

$$a = (A^T A)^{-1} A^T \tag{10}$$

This equation specifies the vector of the best constants of Equation (5) for the entire array of M data trebles. Note that this technique is iterated for every neuron of the further hidden layer accompanied by the connectivity structure of the NN. Such an answer from standard equations is more exactly vulnerable to improve deviations and, more outstandingly, to boost the individuality of the aforementioned formulas [37–42].

There are two central concepts included in a GMDH type of artificial neural network scheme, *i.e.*, topology identification and the parametric [37–42] utilization of the GA for designing the structure for GMDH type of NNs. Stochastic techniques are generally utilized throughout the process of training of NNs in terms of connected coefficients or weights, and have been effectively implemented and demonstrated to be superior to conventional gradient-based approaches.

In the most GMDH types of NNs, neurons throughout any layer are linked to a neuron in a neighboring layer, as indicated earlier for techniques I and II that report in references [30–35]. With this improvement, a straightforward programming pattern can be used for the genotype of any individual throughout the population, as previously suggested [33,37,38]. The programming scheme is presented in Figure 1.

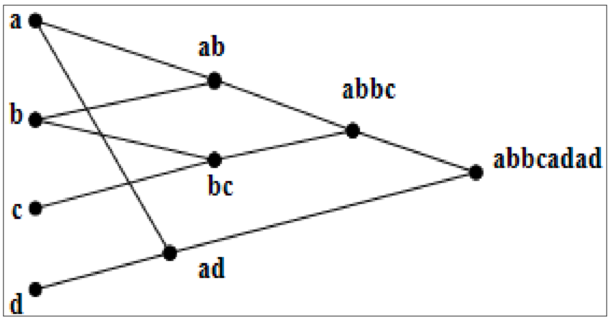

Figure 1. A generalized GMDH network structure of chromosome.

GMDH NNs (GS-GMDH) should be capable of demonstrating various lengths and sizes of such NNs. throughout a GS-GMDH NN, as demonstrated in Figure 1, neuron ad inside the principal hidden layer is attached to the output layer by straightforwardly extending the further hidden layer. Thus, it is relatively simple to perceive that the designation of the network's output includes ad double as abbcadad. That is, a cybernetic neuron named adad is assembled throughout the further hidden layer and utilized within the same layer to create the output neuron, as illustrated in the Figure 1.

This procedure occurs when a neuron is delivered to particular neighboring hidden layers and links to an alternative neuron in the succeeding hidden layer (2nd, or 3rd, or 4th, *etc.*). Throughout this programming pattern, the number of replications is determined as $2^{\tilde{n}}$ in which neuron is subject to the number of approved hidden layers, $\tilde{n}$. Note that a chromosome such as ababbcbc, is different from chromosome ababacbc, and thus it is not a usable individual in the GS-GMDH networks and has to be re-written straightforwardly as abbc.

Now it is possible to generate two offsprings from two parents by implementing the GA operatives of mutation and crossover. The process of selection is performed on the basis of a natural roulette wheel selection approach for selecting two parents generating two offsprings [33,37,38].

The combination of a GA into the scheme of GMDH style NNs commences by demonstrating each network as a string of consecutive sub-strings of sequential numbers. The fitness, φ, of each whole string of representative numbers which characterizes a GMDH style NN approach is assessed as follows:

$$\phi = \frac{1}{E} \tag{11}$$

where E denotes the mean square of error (MSE) in Equation (10), which is minimalized inside the evolutionary progression by exploiting the magnitude of fitness, φ.

The evolutionary progression is initiated by arbitrarily producing an initial population of representative series, as a proposed solution. Then, genetic operations such as mutation, crossover and roulette wheel selection are performed on the overall population of representative series to improve the solution progressively. In this regard, GMDH style NN approaches with increasingly rising fitness, φ, are created until no additional substantial progress is possible.

To determine the integrity and reliability of the proposed polynomial models for modeling torque and output power of the Stirling engine, the correlation of determination (R^2), as a mean absolute percentage of error (MAPE), and root mean square error (RMSE) which are used, expressed as follows [43–45]:

$$R^2 = 1 - \left[\frac{\sum_{i=0}^{M} \left(Y_{i(\mathrm{model})} - Y_{i(Actual)} \right)^2}{\sum_{i=1}^{M} \left(Y_{i(Actual)} \right)^2} \right] \tag{12}$$

$$RMSE = \left[\frac{\sum_{i=0}^{M} \left(Y_{i(\mathrm{model})} - Y_{i(Actual)} \right)^2}{M} \right]^{1/2} \tag{13}$$

$$MAPE = \left[\frac{\sum_{i=0}^{M} \left| Y_{i(\mathrm{model})} - Y_{i(Actual)} \right|}{M \sum_{i=1}^{M} \left(Y_{i(Actual)} \right)} \right] \tag{14}$$

3. Results and Discussion

In the present work, a model is developed with respect to GMDH and Stirling engine (Philips M102C engine) experimental outcomes for the first time [35,36]. The results are verified against experimental values. Also, statistical properties of data set are shown in Table 1.

Table 1. Statistical properties of the data set used in this study.

	T_h **(°C)**	P **(bar)**	F **($\frac{gr}{min}$)**	**Output Power (W)**	**Torque (N.m)**	**Ref.**
Input	(600–900)	(4.14–12.41)	(2.5–7.8)	-	-	[35,36]
Output	-	-	-	(36–500)	(0.19–3.7)	[35,36]

Based on the approach described in the preceding section, the polynomial generated for the Stirling engine for torque is formulated as follows:

$$\begin{aligned} Torque &= 4.19018 - 0.013268T_h - 0.00270926AT_h + 0.00000990598T_h^2 + 2.8801A + 0.155272A^2 \\ A &= -0.189686 + 2.02653B - 0.930981BC + 0.381378B^2 - 0.480105C + 0.305945C^2 \\ B &= -3.45598 + 0.00754163T_h + 0.000582712T_h p - 0.00000502679T_h^2 - 0.0170738p^2 \\ C &= -1.45881 + 0.253347p + 0.0575211pF - 0.0282376p^2 + 0.441726F - 0.0596564F^2 \end{aligned} \tag{15}$$

and for output power is formulated as follows:

$$\begin{aligned} Output\quad power &= 373.951 - 1.12004T_h - 0.00564667A'T_h + 0.000785436T_h^2 + 1.50314A' \\ A' &= 20.687 + 1.51768B' + 0.00209829B'C' - 0.0018406B'^2 - 0.660555C' \\ B' &= -638.237 + 1.30715T_h + 0.0842743T_h p - 0.000835089T_h^2 + 12.9758p - 3.19127p^2 \\ C' &= -162.822 + 47.9507p + 5.65611pF - 4.19637p^2 + 16.5671F \end{aligned} \tag{16}$$

Here, p denotes pressure, T_h denotes temperature of the hot working fluid, and F stands for consumption fuel. Statistical indices for the results obtained with the aforementioned polynomial approaches are summarized in Tables 2 and 3 for torque and power, respectively.

Table 2. Values of absolute fraction of variance, root-mean squared error and mean absolute percentage, respectively, for torque model.

Statistical Parameter	Value
R^2	0.9518
MAPE	0.0007
RMSE	0.1718

Table 3. Values of absolute fraction of variance, root-mean squared error and mean absolute percentage, respectively, for power model.

Statistical Parameter	Value
R^2	0.9737
MAPE	0.0005
RMSE	0.1838

As illustrated in Figure 2, the deviations (ARD = Average Relative Deviation) for torque values predicted with the model are not considerable when the torque is between 0.1 and 1.5 N.m, are low when the torque is between 1.5 and 2.5 N.m and approach zero when the torque is between 2.5 and 3.7 N.m. The relative error of the developed ANN model for torque determination *versus* relevant actual torque values are also shown in Figure 2, where the maximum relative error is seen to be 32% for the low torque boundary and to decrease as torque rises, reaching a value of 11% for high torques.

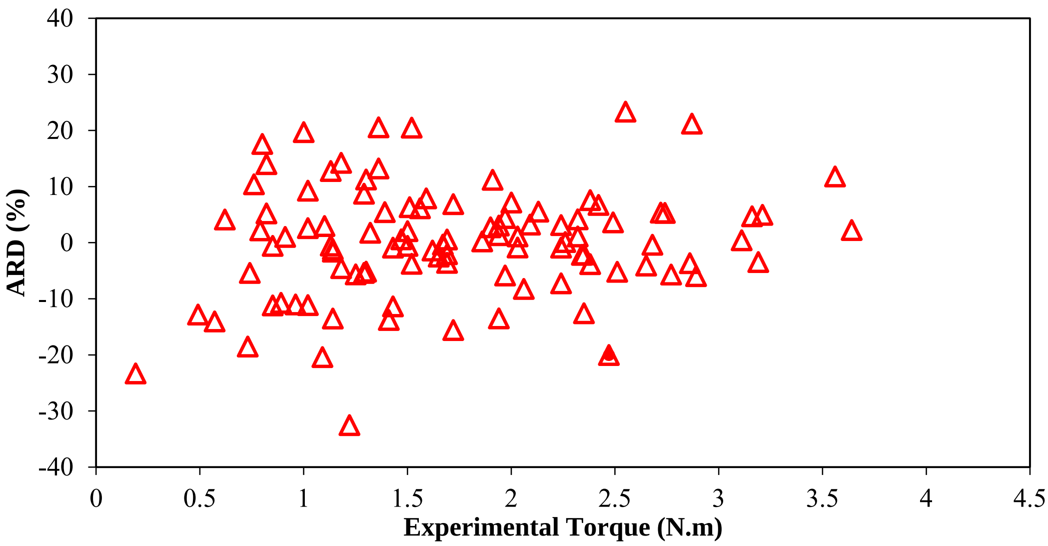

Figure 2. Variation of relative error with corresponding experimental torque values.

It can be seen in Figure 3 that there is a good agreement between the model outputs and the experimental torque based on the data index simulated in this work.

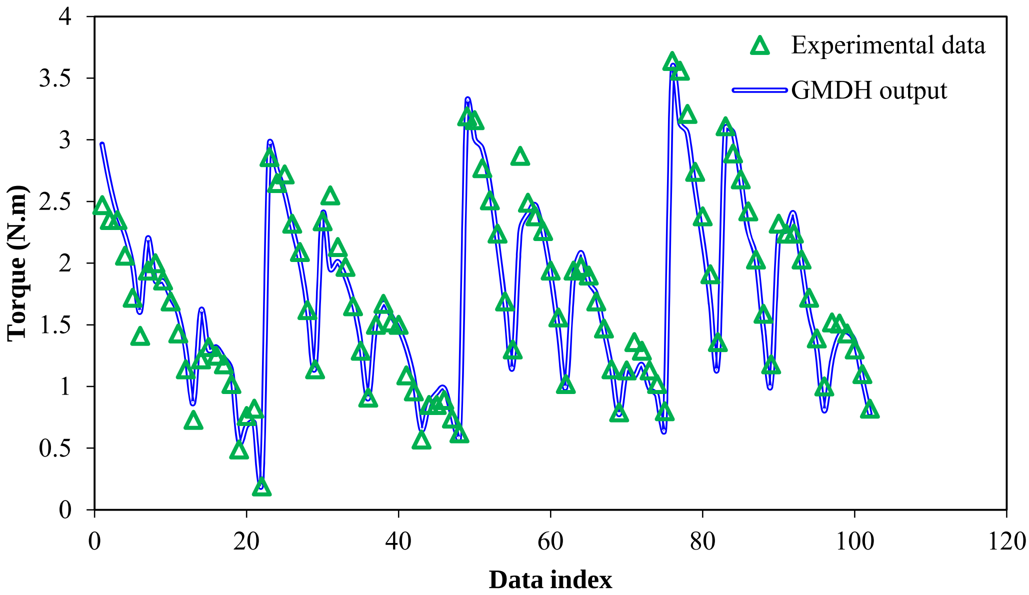

Figure 3. Comparison of experimental torque and outcomes of the GMDH approach.

The output results of GMDH model in Figure 4 for experimental power outputs of 50 W through 500 W are compressed around zero deviation line, which means that the deviation of the addressed model in this interval is very low. Nonetheless, about five noisy points experimental power outputs lower than 150 W are observed in the figure.

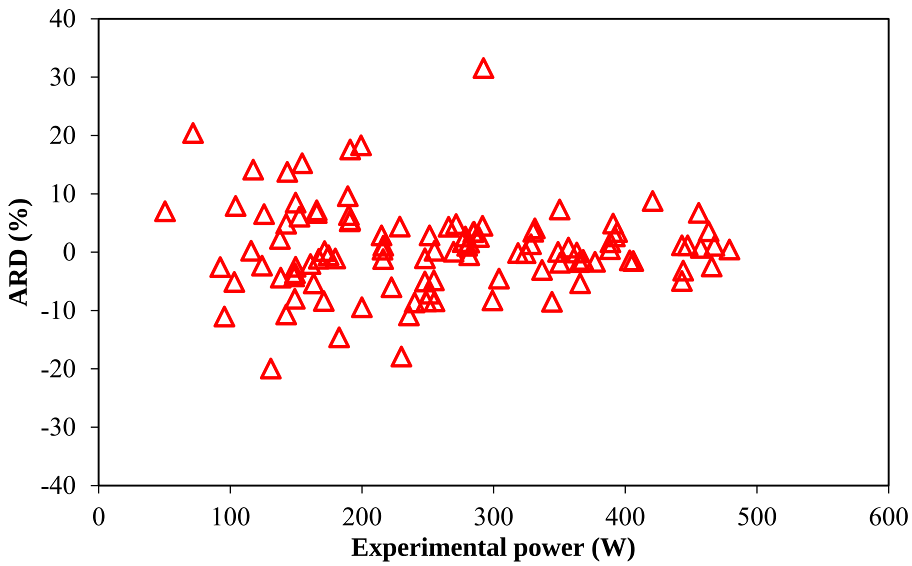

Figure 4. Variation of relative error with experimental power output values.

The outcomes of the evolved GMDH model are seen in Figure 5 to follow the actual trend of the output power of the Stirling engine based on the corresponding data index simulated in this study.

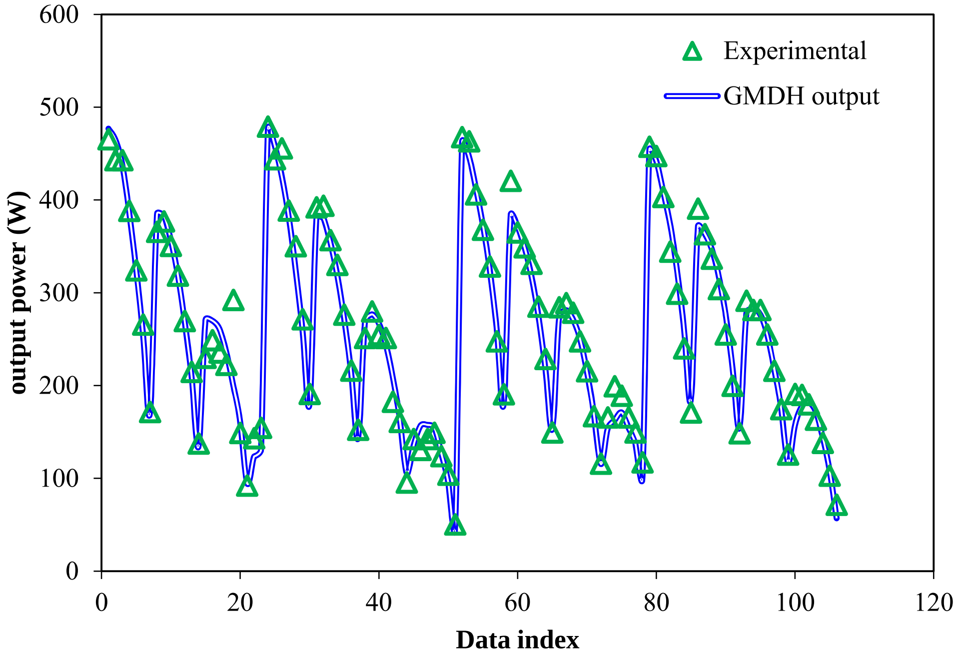

Figure 5. Comparison of experimental power output and outcomes of the GMDH approach.

4. Conclusions

An intelligent approach to determine the output power and torque of a Stirling heat engine is proposed and developed. The approach employs the GMDH method to develop an accurate predictive tool for determining output power and torque of a Stirling heat engine in manner that is inexpensive, fast and precise. Accurate actual data banks employed for testing and optimizing of the predictive tool. The statistical criteria regarding the output results of the developed GMDH model suggest that the suggested method has a high level of robustness and integrity for determination of output power and torque. Consequently, based on the output results, the GMDH approach can help energy experts to design Stirling heat engines with high levels of performance, reliability and robustness and with a low degree of uncertainty.

Author Contributions

All authors have contributed equally to this draft. All have authors read and approved this draft.

Conflicts of Interest

The authors declare no conflict of interest.

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