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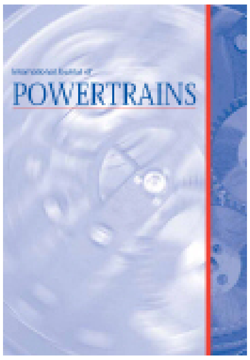


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# Thermal efficiency predictive modelling of dedicated hybrid engines based on an optimal multi-network structure

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**Abstract:** This paper presents an evolutionary data-driven modelling approach for dedicated hybrid engine thermal efficiency (TE) prediction, in which a multi-network structure is developed to further improve the prediction accuracy. This structure enables adaptively segmenting input channels in order to reduce the nonlinearity of data representation in each channel so that the sub-networks can be trained efficiently. In the context, the grey wolf optimisation (GWO) algorithm is applied to find the breakpoints of segmentation for building an optimal multi-network structure. The multilayer perceptron (MLP) is introduced as the basic network due to its simple structure with only two hidden layers. Validated by the experimental data, the accuracy of the multi-network prediction model incorporating GWO improves from 82% to 89%. Also, GWO converges to the optimal solution with 21 iterations compared to 26 for particle swarm optimisation and 31 for the gravitational search algorithm, which demonstrates that GWO has a better performance in this study.

**Keywords:** optimal network structure; engine thermal efficiency; grey wolf optimisation algorithm; data-driven modelling.

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## 1 Introduction

At present, air pollution from vehicle exhaust emissions is a major problem of global environmental issue. Hybridisation technology is a promising solution to improve fuel economy and reduce vehicle exhaust emissions (Lijewski et al., 2020). Dedicated hybrid engines can provide up to over 40% thermal efficiency (TE) and further reduce energy consumption (Lu et al., 2021). Meanwhile, innovative technologies in the field of combustion and integration with alternative fuels can also improve emissions and fuel economy (Dimitrakopoulos et al., 2017). A comprehensive assessment of the main advantages and disadvantages of using alcohols as primary fuels or additives in diesel fuel is presented in Shamun et al. (2020). New injector nozzle configurations and nozzle configurations proposed in Sequino et al. (2018) further help to improve combustion efficiency and engine emissions. Additionally, injection strategies can have a significant impact on engine efficiency (Svensson et al., 2019). The success of hybrid engines relies on the internet of things (Li et al., 2021a, 2021b) and is paired with multiple sets of electronic control components to enhance engine performance, such as direct gasoline injection (Li et al., 2019) and variable valve timing (VVT) (Di et al., 2010). While these auxiliary systems improve the TE of hybrid engines, the hybrid engine systems become more complex. Consequently, the development of hybrid engines becomes costly and time-consuming. In order to quickly commercialise this technology for dedicated hybrid engines, a modelling approach with a short development cycle and low cost is urgently needed.

Modelling approaches for engine parameter prediction can be generally divided into three categories: white-box, grey-box and black-box modelling (Yusri et al., 2018). White-box modelling is the interpretable modelling approach based on physical and mathematical relationships. Computational fluid dynamics (CFD) as a typical white-box approach is often used to model the combustion of diesel engines (Martinez et al., 2013). The grey box model is a model that combines theory and data (Sohlberg and Jacobsen, 2008). A grey-box model is designed for optimising the combustion system of medium-sized direct-injection diesel engines (Benajes et al., 2016). Different from the white-box and grey-box modelling approaches, black-box modelling is based on the functional relationship between system inputs and system outputs. Since this approach does not require full consideration of the complex relationships within the system, it requires less time cost and expertise (Fu et al., 2022). Consequently, black-box modelling is a promising approach for building engine prediction models. Also, transfer learning is an alternative solution to reduce the development workload which provides transferable representation modelling routines for knowledge transfer of biofuel combustion (Li et al., 2022a), energy management controller (Zhou et al., 2021a; Li et al., 2021c), and batteries (Zhou et al., 2021b).

In industry, errors beyond the tolerance range may cause the problems such as equipment damage, which means it is significant to aim for high accuracy when building the model. Modern hybrid engine systems are complex and nonlinear, while conventional black-box models are difficult to model highly nonlinear systems with high accuracy, so some studies are proposed to solve this problem. Such as feature selections (Kavzoglu and Mather, 2002), integrating the actual physical model (Ou and Achenie, 2005), and new structural design (Sainath et al., 2013; Ma et al., 2021). In structural design, the dataset is segmented based on special features to change into multiple sub-datasets with poor nonlinearity. For data-driven modelling approaches, the linearity of the data can greatly affect the predictive accuracy of the model and reducing the nonlinearity of the data is a promising way to increase the accuracy of the model. Therefore, segmentation of dataset is a promising solution to improve accuracy of black-box models. Optimisation algorithms are promising to help find the optimal structure based on data segmentation solutions like particle swarm optimisation (PSO) (Clerc, 2010), gravitational search algorithm (GSA) (Rashedi e al., 2009), and grey wolf optimisation (GWO) (Mirjalili et al., 2014). This paper applies and compares these three algorithms to finding optimal breakpoints to improve accuracy of TE prediction model of the dedicated hybrid engine.

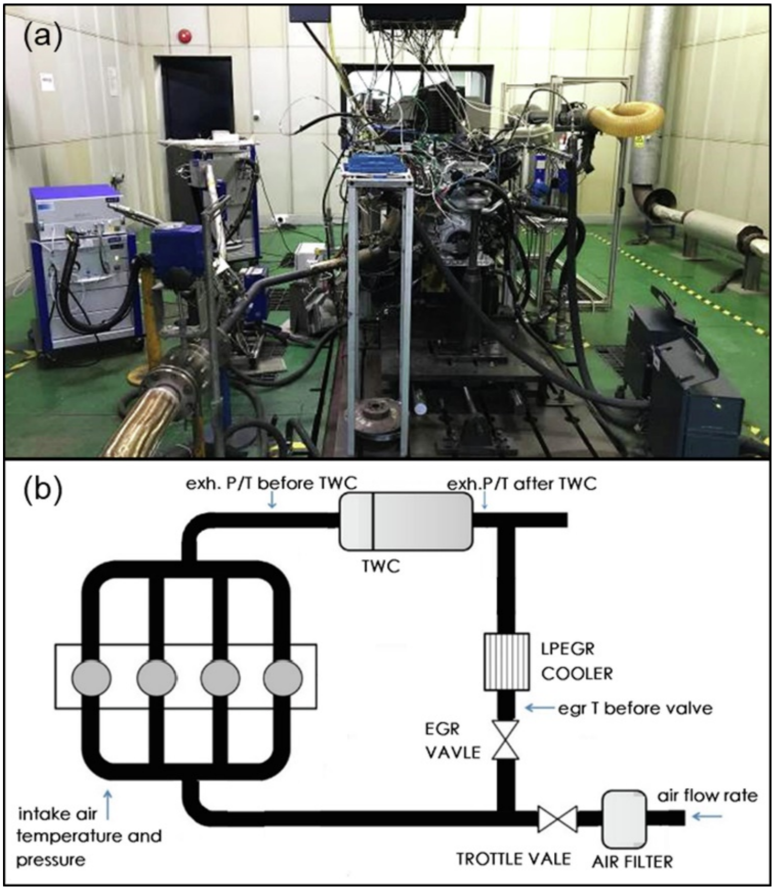
To further improve the accuracy of the dedicated hybrid engine TE prediction model, this paper presents an evolutionary data-driven modelling approach with a multi-network structure based on MLP networks. Unlike the single network structure, this multi-network structure enables adaptively segmenting input channels and feeding data with different features into different channels, so that the sub-networks can be trained efficiently. Different multilayer perceptron (MLP) networks are used to train and predict different groups of data. The manner of data segmentation will directly affect the accuracy of the final multi-network model, so optimisation algorithms are introduced to find the most reasonable segmentation solution. Because GWO is promising to quickly search for the global optimal solution, it is selected in this case to find the optimal segmentation solution. Finally, the effectiveness of the proposed modelling approach in building TE prediction models is experimentally verified.

The paper outline is as follows. In Section 2, the data sources and testing environment are presented. Section 3 describes the proposed methodology scheme of data-driven structural optimisation for TE prediction model of dedicated hybrid engines, which includes: problem formulation for TE prediction model; GWO algorithm implementation; Establishing multilayer perceptual (MLP) network. In Section 4, a comparative study is carried out: the effect of segmentation strategy on model accuracy; the comparison in three studies of algorithms; the analysis of error distribution; the analysis of network performance. The conclusions are summarised in Section 5.

## 2 Experimental setup

The experiments were conducted with an in-line 4-cylinder, 1.5 L gasoline engine. The data source for this experiment is the measurement of steady-state conditions on this engine covering the entire torque and speed range. The engine layout is shown in Figure 1, and the relevant variables required to implement the TE prediction model are recorded.

**Figure 1** Dedicated hybrid engine, (a) testing bench (b) principal diagram (see online version for colours)




*Source:* Li et al. (2022b)

The range of collected data is as follows: speed in [1,000, 6,000] rpm, engine torque in [1.5, 135] N·m. The features of the engine are shown in Table 1 (Li et al., 2022b).

**Table 1** Engine specifications

| *Parameter* | *Value* | *Unit* |
|---|---|---|
| Cylinder number | 4 | - |
| Bore × stroke | 72*92 | mm |
| Displacement | 1,498 | $cm^3$ |
| Compression ratio | 15.5 | - |
| Injection system | PFI | - |
| Maximum power | 81/6,000 | kW/rpm |
| Maximum torque | 135/4,500 | N·m /rpm |

Sampling data at 10 Hz frequency at steady state, a total of 2,732 samples were collected under the condition that EGR is on.

Experimental studies often have various errors, which can generally be classified as random and systematic errors. Among them, random errors are unpredictable during experiments, e.g., mechanical variations, electrical disturbances, and temperature variations. Systematic errors, on the other hand, are non-random and can be defined as the difference between the actual value and the mean value. The accuracy of the experimental study can be demonstrated by uncertainty analysis. In this project, experimental errors and uncertainties are calculated by the statistical tolerance analysis method root sum of square (RSS), which can be defined as the following equation (Li et al., 2022b).

$$RSS = \sqrt{(\varepsilon s)^2 + (2\varepsilon r)^2} \tag{1}$$

where $\varepsilon s$ is a system error, and $\varepsilon r$ is a random error. The relative percentage uncertainties of each parameter are calculated as shown in Table 2.

**Table 2** Signal measurement and testing facilities

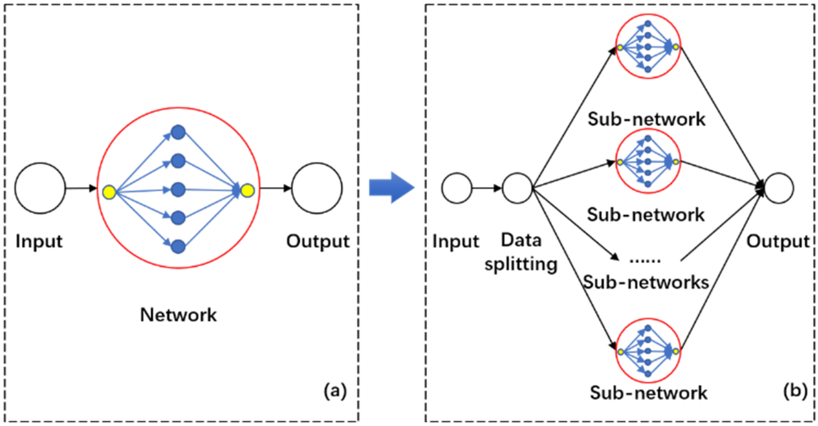
| *Signal parameters* | *Uncertainties* | *Signal parameters* | *Uncertainties* |
|---|---|---|---|
| Speed | ±1 rpm | Intake pressure | ±0.25% |
| Torque | 0.1 N·m | Fuel consumption | ±1% |
| In-cylinder pressure | 0.2% | Fuel pressure | ±0.25% |
| Exhaust temp | ±15°C | EGR | ±2° |
| Intake temp | ±2°C | Exhaust pressure | ±0.25% |

The target of this study is building a IMEP prediction model to evaluate indicated thermal efficacy. The indicated mean effective pressure (IMEP) can be influenced by engine speed and ignition angle (Zhang et al., 2013). Jaliliantabar et al. (2020) investigated shows that EGR will strongly affect the value of IMEP. The studies of He et al. (2014) showed the correlation between IMEP and fresh gas relative intake, I_VVT. Liu et al. found that with the increase of lambda, IMEP gradually increases first and then decreases (Bin Liu et al., 2015). From the study by Kuboyama et al. it is known that IMEP is strongly correlated with intake air temperature, which is influenced by the cooling water temperature on the intake side, but not significantly (Kuboyama et al., 2013). To increase the generalisation capability of the data-driven model, all measurable parameters are chosen.

## 3 Methodology

In order to reduce the maximum errors in TE prediction model with low reliance on expertise and development cycle, this paper proposed a new structure with multiple networks (multi-network structure) designed by the optimisation algorithm.

**Figure 2** Structure diagrams of (a) single network structure and (b) multi-network structure (see online version for colours)




The multi-network structure combines four parts:

1 input: entry the original dataset

2 data splitting: distinguishing data by measuring the value of speed

3 sub-networks: trained by different input intervals after the segmentation

4 output: output the prediction results.

Data splitting module enables data to be split according to the speed of the data set. After gaining the optimal grouping node, the speed of the input data set is compared with the speed of each point in the splitting sequence sorted from smallest to largest, and when the speed of the input data set lies between the speed values of the two splitting points, the data set is fed into the corresponding sub-network for training. The multi-network structure has the ability to use different sub-networks to train different segment data. Using the optimisation algorithm can find the optimal segmentation solution to improve the prediction accuracy.

## *3.1 Problem formulation*

To reduce the maximum errors caused by the specificity of the data, adaptively segmenting the original dataset by optimisation algorithms into several groups with specificity requires low significant expertise and short development time. To enable the optimisation algorithm to solve the problem of optimising the data segmentation solution, the optimisation parameters need to be well defined.

In order to use the data splitting in the multi-network structure to distinguish the segmented data for training using sub-networks, the first step is sorting original data by speed from small to large, which is function *Sort*

$$D_s = Sort(D_0) \tag{1}$$

where $D_0$ is original data collected from the testing bench and $D_s$ is the sorted data. Function *Sort* has following steps: compare two neighbouring data from back to front, placing the smaller one in front after every comparison. Repeat this process until all data is compared.

After initialising the parameters of the optimisation algorithm, 20 random numbers are generated to initialise the search agents in the optimisation algorithm, then the initialised values are mapped to the range [0, 2,732] and rounded upward to obtain a vector $P_i$ representing the segmentation solution

$$P_i = \lceil N \times [b_1, b_2, \ldots, b_{20}] \rceil \tag{2}$$

where $\lceil \cdot \rceil$ means rounding upward data, $[b_1, b_2, \ldots, b_{20}]$ are random numbers uniformly distributed on [0, 1] and $N$ is total amount of data 2,732.

Then, merging the elements by

$$P_m = Merge(P_i) \tag{3}$$

where *Merge* returns the same data as in vector $P_i$, but with no repetitions. Function *Merge* can perform the sorting of the series and the merging of the same number of values in the series. The sorting algorithm is the same as the *Sort* function. After sorting is completed, the neighbouring numbers in the series are compared from front to back, if they have the same value, the former is deleted. Repeat this step until the last two numbers have been compared.

Next, $P_s$ is the vector sorting data in $P_m$ from small to large by using function *Sort*:

$$P_s = Sort(P_m) \tag{4}$$

Using the data in $P_s$ as the breakpoints of $D_s$ to segment $D_s$ into multiple data sets, sending them into different sub-networks for training and testing. So far, the optimisation variables of the optimisation algorithm are transformed into the position of breakpoints for adaptively segmenting the TE prediction model by equations (3) to (4).

Next, input all the data into the trained network. In this study, the output of the prediction model is IMEP, which is the effective work emitted per unit of cylinder working volume. Cause 0.2 bar is a common tolerance range for prediction IMEP in the industry (Bidarvatan and Shahbakhti, 2013), the output of the prediction model is considered correct if the absolute error between the predicted and experimental values is within 0.2 bar. Therefore, the network prediction accuracy $Ac$ is defined as the percentage in which the absolute error between the predicted and experimental values is within the 0.2 bar, which can be described as:

$$Ac = \max\left(\frac{E_{\leq 0.2 \text{ bar}}}{N}\right) \tag{5}$$

where $E_{\leq 0.2 \text{ bar}}$ is the amount of data with absolute errors exceeded 0.2 bar.

## *3.2 Network structural design*

To apply GWO to find the optimal segmentation solution, the methodology contains the following three main parts:

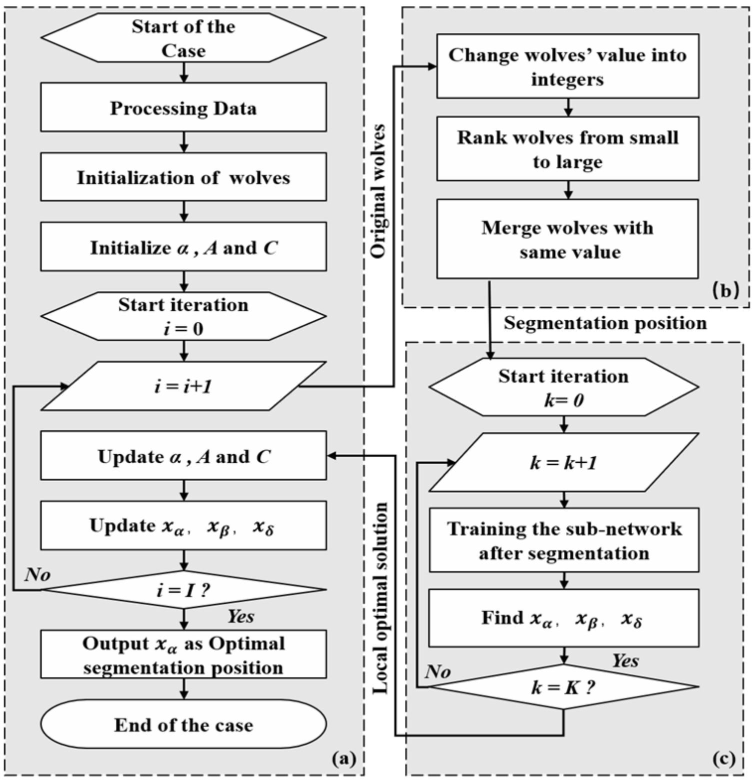
1 problem formulation for optimisation of the multi-network structure of TE prediction model

2 GWO for finding the optimised segmentation solution

3 parameters for MLP network settings.

The flowchart of the entire data-driven structural optimisation methodology is shown in Figure 3.

**Figure 3** Flowchart of GWO for finding the optimal segmentation solution, (a) the main loop of GWO (b) processing of wolf values (c) network training and testing




In Figure 3,

a This part is the main loop to find the best solution for TE prediction model. This part needs to define the number of search agents and wolves. Then send original wolves to (b). $I$ is the maximum number of iterations to find the global optimum by GWO. Output the optimal solution and end the case when $i$ equal to $I$.

b Transforming part is developed for turning wolves' value into integers and sorting them to meet the requirements of the segmentation solution and send the solution to next part.

c Network training part, segmenting the data into multiple parts according to the solution passed in the previous part, training and testing the segmented data using different sub-networks respectively, obtaining the prediction accuracy (the value of wolf's cost function) of the network under this segmentation solution and finding the top three best solutions.

Compared to classic optimisation algorithms, GWO algorithm considers first three agents in each iteration as a reference to update the velocities in rest of them (Mirjalili et al., 2014). Considering more different search agents together makes it difficult for the GWO algorithm to get the local optima. And GWO algorithm can find the global optimum more easily under the same number of search agents.

Generally, GWO divides the segmentation solution into four levels. The solution is a vector within breakpoints of original dataset. Using these levels to make the wolves move toward the goal and find the optimal solution. The most suitable solution is $\alpha$, the second solution is $\beta$, the third best solution is $\delta$, and the others are denoted as $\omega$. Throughout the process of finding the optimal solution, $\alpha$, $\beta$ and $\delta$ are guides, and the remaining values move to these three solutions.

Equation for calculating the distance moved of the wolf is

$$D = \left| Cx_p(t) - x(t) \right| \tag{6}$$

in which

$$X = 2 \cdot r_c \tag{7}$$

And $t$ is the current iterative algebra, $r_c$ is the number of vectors whose modulus is between [0, 1]. $x_p$ and $x$ are the position vector of the prey and the position vector of the grey wolf, which is the segmentation solution in this case.

Equation for updating position of the grey wolf is

$$x(t+1) = x_P(t) - A \cdot D \tag{8}$$

In which

$$A = 2ar_A - a \tag{9}$$

$a$ is the convergence factor, and its value decreases from 2 to 0 with the number of iterations. $r_A$ is the number of vectors whose modulus is between [0, 1].

When the grey wolf recognises the location of the prey, $\beta$ and $\delta$ will guide the wolf pack to surround the prey under the leadership of $\alpha$. The mathematical model of individual grey wolf tracking the position of the prey is described as follows

$$D_m = \left| Cx_m - x \right| \tag{10}$$

$m$ is $\alpha$, $\beta$ and $\delta$. $D_i$ represents the distances from other individuals; $x_i$ represents the current positions, $C$ is random vectors, $x$ is the position of the grey wolf whose position needs to be updated at this time. Finally, the grey wolf finds the optimal solution.

### *3.3 Multi-layer perceptron network*

MLP is a popular network commonly used in prediction models. It consists of an input layer, hidden layers and an output layer, and this simple structure leads to building it very easily (Slišković et al., 2004). Its layers are connected to each other using a fully connected method, and the nodes in each implicit layer carry an activation function, and the introduction of nonlinear effects allows the network to fit any linear or nonlinear function (Seiffert, 2001). These features have promising potential in the development of fast modelling methods, this paper tries to use this promising structure to establish the TE prediction model. The network parameters as considered in the work of Feng and Lu (2019) are summarised in Table 3. In this study, as we proposed a multi-network structure to predict the IMEP, the network parameters here are applied for every sub-network. The training data set for each sub-network was randomly selected from its corresponding data set by 70%, and the rest of the data was used as the validation set (15%) and test set (15%) of the network. Random selection of data ensures that the data in the training set is disordered, which can effectively prevent the network from overfitting.

**Table 3** Parameters of MLP network for TE prediction model

| *Network parameters* | *Value* |
|---|---|
| Network layers | 2 |
| Network activation function | tanh |
| Number of neurons | 10 per layer |
| Ratio of data in the training set | 70% |
| Ratio of data in the testing set | 15% |
| Ratio of data in the validation set | 15% |

## 4 Result and dissection

From here on, a comprehensive comparative study is carried out from four aspects of:

1 effect of dataset segmentation strategy

2 comparison of segmentation strategy under different optimisation algorithms

3 relative error distribution for studied algorithms

4 network performance analysis.

It is necessary to define the parameter to evaluate the proposed approach. Firstly, the accuracy of prediction model needs to be clearly defined. In this case, the accuracy is defined as the percentage of data with the absolute error between prediction value and real value less than 0.2 bar, which is wildly used in IMEP prediction (Bidarvatan and Shahbakhti, 2013). Then, convergence is usually defined as the process by which a curve becomes flat and no longer increases, and the convergence speed is defined as the number of iterations from start to convergence (Yiyang et al., 2021; Collotta et al., 2017). In this case, there are two cases of stopping the optimisation algorithm and ending the loop:

1 the value of the accuracy curve based on the optimisation algorithm does not change within five iterations, then the loop is end and the accuracy is no longer updated

2 the loop is stopped when the maximum number of iterations is reached.

In Dewangan et al. (2019), the target is to find the optimal path planning solution, and they experimentally verify that the GWO algorithm produces near-optimal results in fewer iterations, and the final result is less likely to change even if the number of iterations increases. Based on their study the max number of iterations can be set between

[25, 50]. In this case, the optimisation problem in this study only requires finding the appropriate segmentation position among 2,732 sets of data, thus the max number of iterations is set as 50.

## *4.1 Segmentation strategies in multi-network structure*

This section investigates the effect of segmentation strategies on the accuracy of TE prediction model. Two segmentation strategies are compared: the optimal segmentation strategy found under the uniform segmentation condition; and the optimal segmentation strategy found under the non-uniform segmentation condition.

**Figure 4** Comparison of TE prediction model accuracy and number of segmentation groups under different segmentation strategies (see online version for colours)

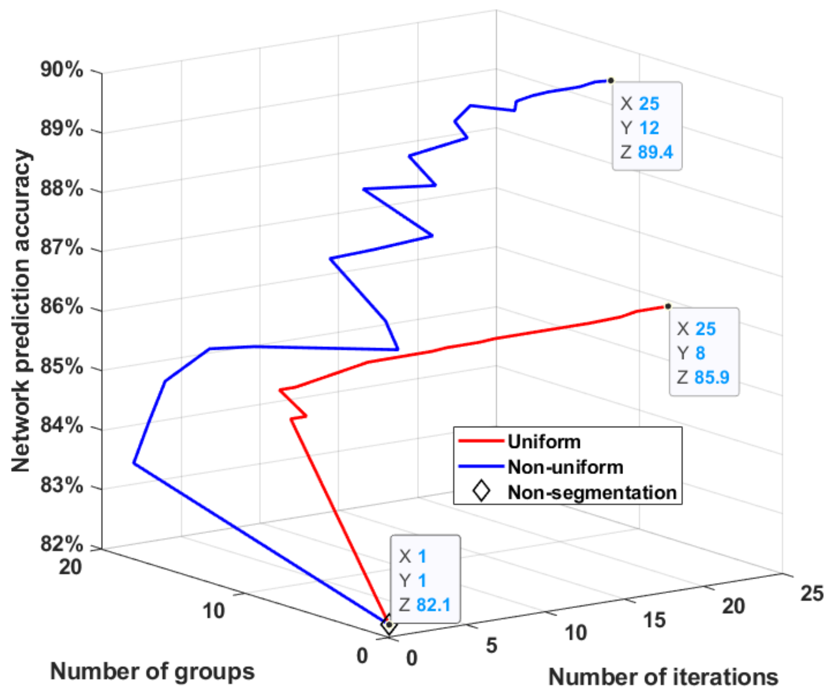



Figure 4 shows the process of GWO algorithm to find the optimal accuracy of the model under different segmentation strategies. Obviously, as the number of iterations rises, the model accuracy gradually improves until it converges to the optimal accuracy (six iterations under the uniform segmentation strategy: 18 iterations under the non-uniform segmentation strategy). The point in the black diamond is the accuracy of the original model without optimisation, which is the lowest point in figure. That means these two segmentation strategies can significantly improve the accuracy of TE prediction model. Furthermore, the optimal accuracy under uniform segmentation converges in six iterations is still low. This may be caused by the inability of this strategy to effectively segment the original data specifically by features, resulting in an insufficient reduction of data nonlinearity for the multi-network structure in this case, which ultimately affects the accuracy of the TE prediction model.

**Table 4** Comparison of model accuracy and RMSE under different segmentation strategies

| *Segmentation strategy* | *No segmentation* | *Uniform* | *Non-uniform* |
|---|---|---|---|
| Optimisation algorithm | None | GWO | GWO |
| Accuracy | 82% | 86% | 89% |
| RMSE | 3.0 | 2.0 | 0.31 |

From Table 4, the RMSE value of the multi-network structure TE prediction model decreases 2.7 compared to 3.0 of the single structured model and decreases 1.7 compared to 2.0 of the multi-network structure model in uniform segmentation. The multi-network structure model after using GWO to non-uniformly segment the data has a prediction accuracy of 89%, which is higher than the single network structure model by 7%, and 3% higher than the accuracy of the multi-network structure model under uniform segmentation strategy.

Clearly, the proposed methodology does help the improvement of TE prediction model, and optimisation under a non-uniform strategy can maximally help improve the model accuracy.

## *4.2 Comparison of the segmentation algorithm*

To evaluate optimisation performance of GWO algorithm, two representative optimisation algorithms, PSO and GSA, are introduced as baselines to make a comparison. Every result point is an average value after 30 repetitive experiments. For a fair comparison, set the same population size 30 for all algorithms.

**Figure 5** GWO, PSO and GSA find the optimal segmentation solution after five repetitive experiments for TE prediction model (see online version for colours)

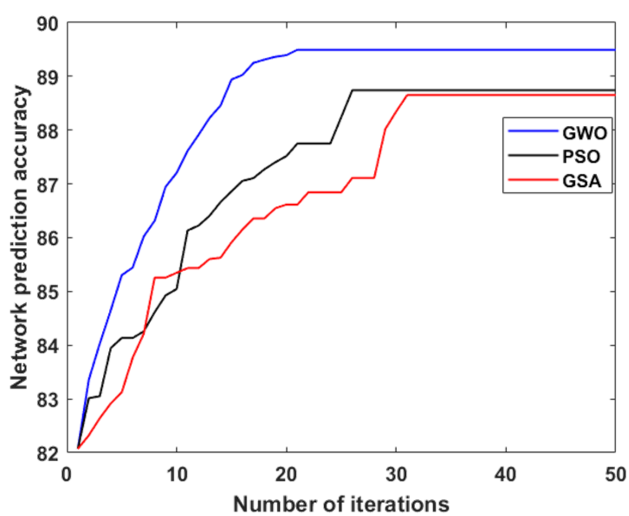


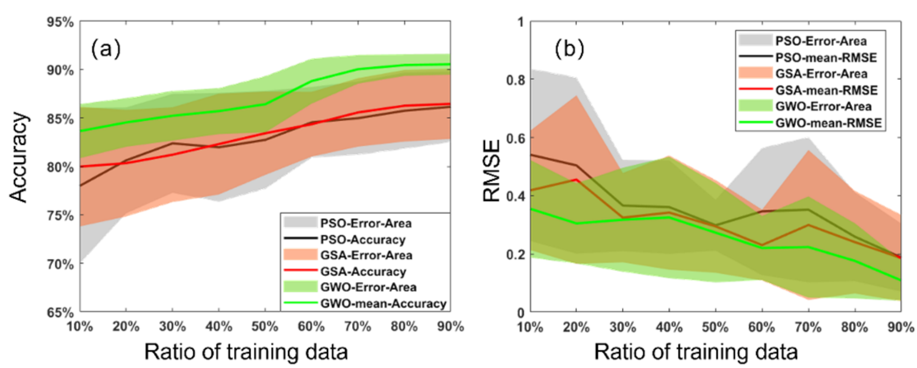
**Table 5** Comparison of model accuracy, and RMSE under different optimisation algorithms

| *Optimisation algorithm* | *GSA* | *PSO* | *GWO* |
|---|---|---|---|
| Convergence speed | 31 | 26 | 21 |
| Segmentation number | 9 | 12 | 12 |
| Accuracy | 88% | 88% | 89% |
| RMSE | 0.41 | 0.31 | 0.31 |

Figure 5 shows that GWO finds the optimal global solution with 89% of TE prediction accuracy after 21 iterations, while PSO and GSA find solutions with 88% after 26 and 31 iterations. PSO always has a simplified updating policy of randomness, which makes it easy to fall into local minimum (Li et al., 2020). GSA is good at global searching, but it has a slower search process cause the population information is not shared with agents (Hu et al., 2017). On the contrary, the updating policy of GWO is based on the position information shared from three guides, which are the best three solutions in every iteration (Mirjalili et al., 2014). It can be seen from Figure 5 that GWO has high accuracy in every iteration, which may be explained why the best solution in each iteration helps to update other agents to move to an optimal area and the second and third solutions are used to avoid GWO falling into a local optimum.

To investigate the effect of the network training set ratio on the prediction model accuracy, a comparison of the evolution of the model accuracy and RMSE when the network training set ratio is increased from 10% to 90% is presented here. Both the validation set and the test set have the same percentage of data, which is half of the data left after the training set data is removed. This experiment is all based on the optimal segmentation solutions found by the three optimisation algorithms. Since the training set data are randomly grabbed each time, to ensure the reliability of the conclusions, the experiments are repeated 50 times to show error bands of accuracy and RMSE. The result is shown in Figure 6.

**Figure 6** (a) Accuracy of GWO, PSO, and GSA change vs. the ratio of training data (b) RMSE of three algorithms vs. the ratio of training data (see online version for colours)




It is clear from Figure 6 that the accuracy error band of GWO is at the top and its RMSE error band is at the bottom. Furthermore, the mean value shows that GWO is more effective than PSO and GSA. Meanwhile, after reaching 70% of the training set, the accuracy of the model remains largely unchanged and the decrease in RMSE becomes slower. From this, it can be suggested that a 70% training set ratio is reasonable, cause increasing the ratio does not lead to a significant increase in accuracy but may lead to overfitting of the network.

## *4.3 Analysis of error distribution*

This section investigates the relative error distribution of the TE prediction model based on optimisation algorithms, which includes two parts:

1 the impact of GWO, PSO, and GSA on the accuracy of the TE prediction model is further investigated

2 the error analysis of the network structure based on the GWO algorithm is investigated by speed and torque.

Firstly, the distribution of the relative error between the predicted and target values under the optimal segmentation solution found by the three optimisation algorithms is studied, where the width of each bar is set as 0.05 bar.

**Figure 7** Relative error distribution of using studied algorithms for TE prediction model (see online version for colours)

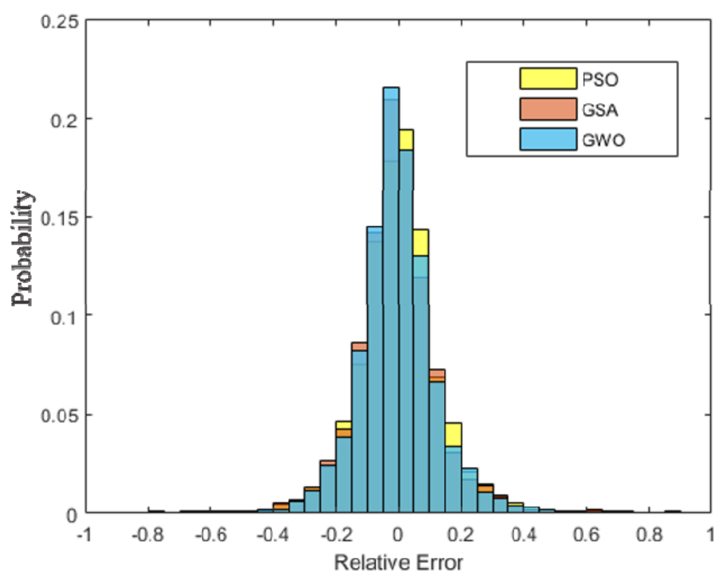



Figure 7 shows that the errors of TE prediction model identified by using the three studied optimisation algorithms are all mainly concentrated in the interval [–0.4, 0.4] bar. The value of error less than 0.2 bar is the judgment indicator of TE prediction model, and it can be seen that TE prediction models based on these three algorithms have less amount of data where the error falls outside the interval [–0.2, 0.2] bar, which indicates that these TE prediction models have ability to ensure that the predicted target parameter values can meet the industry standards under most circumstances. Meanwhile, out of the tolerance error interval ([–0.2, 0.2] bar), the bar region of GWO is significantly less than the remaining two, which indicates that the TE prediction model under GWO algorithm possesses higher accuracy.

Then, the error distribution of TE prediction model optimised by GWO is investigated. This prediction model is analysed by observing the relative errors for different speed and torque conditions. The data in Table 6 are the mean values of the relative errors of all points in this interval, and here 'overall' represents the weighted average of the relative error values. The result is shown as follows.

**Table 6** Relative error based on speed and torque

| *Speed(rpm)* | *Torque(N·m)* | | | | |
|---|---|---|---|---|---|
| | *0–50* | *50–75* | *75–100* | *100–135* | *Overall* |
| 0–2,000 | 3.1% | 1.8% | 1.4% | 0.82% | 2.0% |
| 2,000–3,000 | 2.8% | 1.3% | 1.1% | 0.60% | 1.6% |
| 3,000–4,000 | 2.0% | 1.3% | 1.1% | 0.61% | 1.2% |
| 4,000–5,000 | 2.1% | 1.5% | 1.2% | 0.86% | 1.4% |
| 5,000–6,000 | 2.5% | 2.4% | 1.7% | 1.6% | 2.0% |
| Overall | 2.5% | 1.6% | 1.3% | 0.84% | 1.6% |

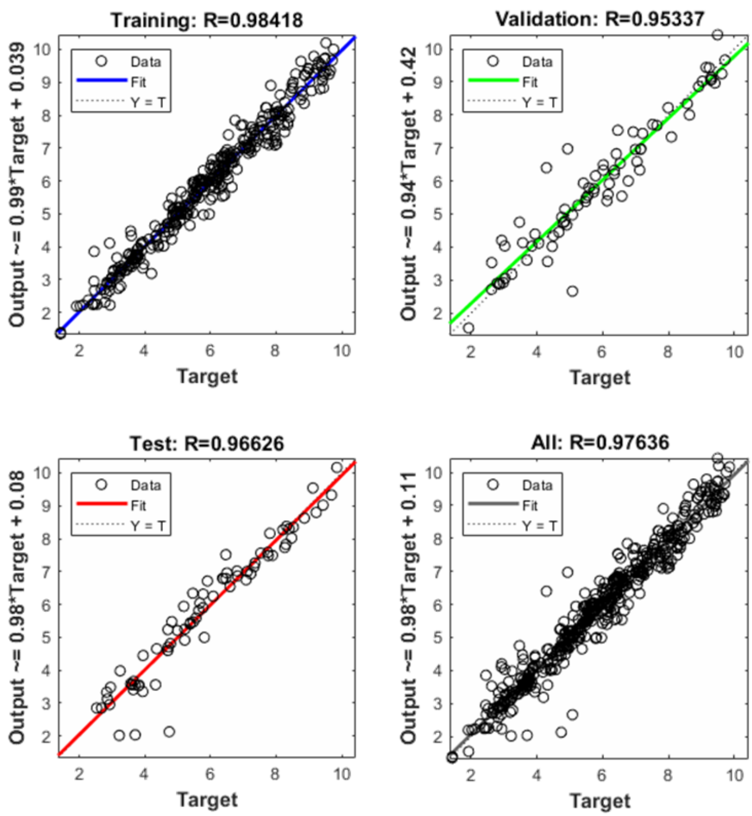
Through the comparison of speed, it is obvious that the relative error is the smallest in the interval [3,000, 4,000] rpm, 1.2%, which means that the TE prediction model is more accurate in predicting the data in this interval. On the contrary, the relative error is the largest in the [5,000, 6,000] rpm interval, 2.0%, which means that the prediction model cannot achieve high accuracy for the data in this interval. And the relative error in the [0–2,000] rpm interval is also high, 2.0%, which may be caused by the insufficient training of the network due to the low amount of data in this interval. Meanwhile, the comparison by torque shows that the relative error is the smallest in the interval of [100–135] N·m, 0.84%, and the largest in the interval of [0–50] N m, 2.5%. It means that TE prediction model is more accurate in intervals [100,135] N·m, and the predictive ability of the model is poor in intervals [0, 50] N·m. Combining the above two characteristic values, the relative error of TE prediction model decreases as the torque of the engine grows, and the relative error decreases as the speed approach [3,000, 4,000] rpm. The reason for these cases may be due to the high amount of data in these regions, which leads to the network being adequately trained on these kinds of data, which leads to low relative errors within these regions.

## *4.4 Network performance analysis*

In this section, regression analysis is performed to evaluate the prediction accuracy of the MLP network. The regression analysis of a randomly selected MLP network is illustrated in Figure 8.

The regression graph of the test set shows that the data in it are closer to the fit line than in the validation set, which can be explained by that the MLP network is trained on both the training and validation data sets, and the test dataset is used to evaluate the network performs. And in the regression graph of all datasets, most of the data falls on the regression line, which indicates that the MLP network performs effectively after training.

**Figure 8** MLP network performance analysis (see online version for colours)




Through the above experiments as well as discussions, the proposed evolutionary data-driven modelling approach for dedicated hybrid engine TE prediction based on a multi-network structure can effectively improve the accuracy of the prediction model. Meanwhile, the effectiveness of GWO and PSO and GSA in this study is verified by experimental comparison, and the accuracy of the multi-network structure constructed based on these three algorithms is close to the accuracy limit of the MLP network with two hidden layers, thus the accuracy difference between them is not significant. However, it is evident that the GWO algorithm finds the optimal solution with the least number of iterations, and for data-driven modelling methods which require a large number of computational resources, reducing the number of iterations can significantly reduce the development time.

## 5 Conclusions

This paper investigates an evolutionary data-driven modelling approach to obtain an optimal multi-network structure used for the TE prediction model of the dedicated hybrid engine. The proposed approach has been comprehensively evaluated from four aspects of:

1. effect of dataset segmentation strategy
2. comparison of segmentation strategy under different optimisation algorithms
3. relative error distribution for studied algorithms
4. network performance analysis.

The result proves that the multi-network structure designed by GWO can help improve the accuracy of the TE prediction model. In this case, indicates mean effective pressure (IMEP) is defined as the output of prediction model to evaluate indicated thermal efficacy. The conclusion under the investigation is drawn as follows.

1. By using the proposed evolutionary data-driven modelling approach, the TE prediction model with the multi-network structure shows 7% of higher accuracy than that with a single network structure.
2. In comparison with segmentation strategies in multi-network structure, the developed non-uniform partitioning strategy helps improve 3% of accuracy compared to using the uniform partitioning strategy (86%).
3. In this case study, GWO illustrates superior optimisation performance with fast convergence (21st interaction reach the maximum accuracy 89%) rather than particle swarm optimisation (26th interaction reach the maximum accuracy 88%) and GSA (31st interaction reach the maximum accuracy 88%).

This paper proposed an optimisation algorithm-based methodology to quickly build a data-driven prediction model for engine parameters. The multi-network structure modelling approach proposed in this paper needs to be tested with new engine parameters to improve its generalisation capability. On the other hand, it is also worthwhile to experiment with new combinations of structures for predictive modelling of different hybrid engines, for example in combination with deep learning structures. Finally, further consideration needs to be given to the real-time performance of the predictive models for real-world vehicle applications. Based on the above discussion, the future work will be two parts:

1. testing with new engine parameters and continuing research to improve the generalisation capabilities of the proposed algorithms
2. trying to model based on different structures, such as recurrent neural networks (RNN), and testing new network structures as well as comparing them.

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