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Comparison Of Modeling Techniques To Be Used As An Objective Function In Optimization Techniques

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Abstract: In recent years, the stringent environmental regulations from the government have made the automotive industry to find alternative ways to decrease the emission level in the internal combustion engines. Compressed natural gas (CNG) is a promising alternative fuel, which decreases emissions, in dual fuel mode; the thermal efficiency is slightly less than that of a diesel engine. Optimizing the input parameters like load, CNG flow rate, and compression ratio, such that the output parameters like efficiency are high and emissions are lower, is very important. Optimization techniques are being widely used in this efforts. In this paper, an attempt has been made to compare different modeling techniques like Adaptive neuro fuzzy inference system (ANFIS), radial basis function extreme learning machine (RBF-ELM), and response surface methodology (RSM), to evaluate them and to identify the best possible alternative as an objective function for use in optimization techniques.

1. Introduction:

The dual fuel engine is a diesel engine that operates on two fuels; they are gaseous fuels, which is passed into the combustion chamber along with air and liquid diesel fuel that is injected into the cylinder, which acts as a source for ignition. The replacement of diesel with various gaseous fuel in a diesel engine, while maintaining satisfactory engine performance but decreasing diesel consumption has been demonstrated by Saidur [1]. The dual fuel diesel engine has several advantages including fuel adaptability, working with a cleaner and less expensive gaseous fuel when accessible and on diesel alone when necessary. The potential advantages of using gaseous fuel in diesel engines are both cost-effective and nature-friendly. The high auto-ignition temperature of gaseous fuels like compressed natural gas (CNG), Liquefied Petroleum Gas (LPG), Hydrogen is an advantage since the compression ratio of diesel engines can be maintained. These gaseous fuels are highly knock-resistant when used as a fuel in internal combustion (IC) engines. The emissions in dual fuel diesel engines are less due to complete combustion of gaseous fuels [2,3].

Engine tests done by researchers and automotive companies for determining engine performance, are time-consuming, expensive and has a harmful effect on human health and causes environmental pollution. Thermodynamic models are complicated, since thorough knowledge of thermodynamic conditions, occurring inside the engine is required. Artificial Neural Network (ANN) systems are established as a technology that offers a way to tackle such non-linear problems that cannot be modeled using mathematics. ANN techniques have been used efficiently in modeling and prediction of the performance and emission characteristics of diesel engines. By using ANN models, controlling and modeling of various parameters of IC engines such as air-fuel ratio, ignition timing, emissions, have been carried out. When these systems are compared with traditional thermodynamic models, it has been found that ANN models are superior in terms of efficiency, robustness, reliability [4]. However,
traditional ANNs have numerous shortcomings for its learning process, user burden on the choice of optimal network structure, slow learning speed, substantial training data size and reduced generalization performance [5]. Recent approaches like extreme learning machine (ELM) has helped in overcoming most of the problems mentioned above. Unlike conventional ANNs where the output weights are found iteratively, ELM analytically determines the output weights using a Moore Penrose generalized inverse [7]. Hence, it has the advantages of rapid learning and better generalization capability. A few latest studies have shown that ELM can be used for IC engines under scarce and exponential dataset [8].

Adaptive neuro-fuzzy inference system (ANFIS) is a combination of ANN and fuzzy logic, in this technique ANN is used to tune a fuzzy logic model. In recent years, ANFIS has been used in modeling of IC engines. Ghanbari et al [8], used ANFIS model for predicting the performance, and exhaust emissions of a diesel engine operating on nano diesel blended fuel. Kasthurirangan Gopalakrishnan et al [9], used ANFIS and Dynamic Evolving Neuro-Fuzzy Inference System to predict emissions of a biodiesel fuelled transit buses.

Engineering applications require the optimal utilization of resources, time and money. This requires the application of optimization techniques. Nature inspired optimization algorithms have become very popular due to its versatile nature and have less computational costs [10]. For any optimization problem, the objective function is a critical component used. The objective function can be calculated using ANN models, RSM model or simple mathematical equation. The output value obtained by the objective function is a single parameter that needs to be optimised using different optimization techniques[11]. In this context, this work aims to make a comparative study of different modeling techniques like ANN, ANFIS and RSM about its use as an objective function in optimization studies. PSO, a widely used nature-inspired, metaheuristic optimization algorithm has been used for the study and comparison

2. Optimization Techniques:

For many engineering problems, it is hard to find out the best solution directly, but it is comparatively easy to set up a function that measures in what way a solution is worthy and then minimizes or maximizes the parameters of that function to find the optimal solution. In recent years, nature-inspired optimization technique has received considerable interest among researchers. The computational power of current computers has made it an effective tool for solving simulation and optimization problems. Nature inspired optimization algorithms like cuckoo search, ant colony optimization, particle swarm optimization, etc. and evolutionary optimization technique like genetic algorithm, gravitational search optimization are being used. An optimization algorithm is an iterative technique, starting from an initial guess. After a certain (sufficiently large) number of iterations, it may converge toward to a stable solution, ideally the optimal solution to a problem of interest [10]. This is necessarily a self-organizing method with results as states and the converged results as attractors. Such an iterative, self-organizing system can evolve according to a set of guidelines or mathematical equations.

2.1. Particle Swarm Optimization (PSO)

Particle swarm optimization is nature influenced optimization technique, which simulates the behavior of fish or birds in nature. It is most widely used algorithm in engineering problems since there is no encoding or decoding of the parameters into binary as with those in genetic algorithms and it has simple mathematical equations and faster computational speed when compared to the genetic algorithm. It is a computational algorithm that optimizes the objective function by adjusting the flights of a single bird, called as particles, in a space spanned by the decision variables called the search space [12].

PSO is loaded with random particles and then search for an optimal solution takes place by updating every generation. For each iteration, each particle is updated by following two "best" values. The former one is the best solution (fitness) it has attained so far. This value is known as pbest. Additional "best" value that is tracked by the particle swarm optimizer is the best value, achieved so far by any particle in the population. This best value is a global best and called gbest [13,14]. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest. The velocity and the position of the particle is calculated using equation 1 and 2.
\[ v_{id}^{new} = w \times v_{id}^{old} + c_1 \times \text{rand} \times (pbest - x_{id}^{old}) + c_2 \times \text{rand} \times (gbest - x_{id}^{old}) \]  (1)
\[ x_{id}^{new} = x_{id}^{old} + v_{id}^{new} \]  (2)

Where \( v_{id}^{new} \) and \( v_{id}^{old} \) are the updated and initial particle velocities, \( x_{id}^{new} \) and \( x_{id}^{old} \) are the updated and initial particle position, \( w \) is the inertia, \( C_1 \) and \( C_2 \) are learning factors, which control the local and global behavior of the particle. \( R_1 \) and \( R_2 \) are uniformly distributed random numbers in the range of \{0, 1\}. In this work, \( C_1 \) and \( C_2 \) are taken 1 and 3 respectively, by trial and error to attain the best possible performance. The number of particles is fixed as 10 and a maximum number of iterations as 100.

3. Development of objective function

In any optimization study, objective function plays a vital role in a proper convergence to take place. In this work, two significant parameters namely performance (brake thermal efficiency) and emissions, which are opposite need to be optimized. Performance is to be increased, and emissions should be decreased. In this work, the authors use a single objective function representing a simple mathematical equation, which is given in equation 3
\[ OF(x) = (1 - \text{BTE}(x)) + \sum_{i=1}^{N} K_i \times \exp \left( \frac{E(x)_{MAX_i}}{MAX_i} \right) \]  (3)

where \( E(x)_i \) describes the amount of emission at the instance of \( i \) for the single value \( x \), \( MAX_i \) maximum amount for emission parameter in the data set and \( K_i \) is a penalty factor and it is taken as small as possible. To overcome the opposite nature of the output characteristics, the authors have defined a new term that is unused heat energy, which is given as (1-BTE), which should decrease along with emissions [15].

In this work, the values of the input parameters of the objective function is obtained using following three techniques

Technique 1: ELM-RBF based ANN model
Technique 2: ANFIS model
Technique 3: RSM based model

3.1. ELM-RBF based ANN model

The emissions developed in IC engines are dependent on several factors like temperature, air-fuel mixture, etc. thus making it difficult to develop a simple mathematical equation describing the same. Radial basis function (RBF) is chosen because its shape is similar to a gaussian transfer function and non-linear data readily fits in this form and is given in equation 4.
\[ \phi(\mu) = \exp \left( \frac{|x-\mu|^2}{2\sigma^2} \right) \]  (4)

where \( x \) and \( \sigma \) are input vector and width of each node. \( \mu_i \) are the centers of the RBF units (hidden neurons) in the input vector space.

ELM has a significant advantage over conventional ANN, namely faster learning rate and better generalization capability. Its capability to find the output solution using equation 5 has made it a more popular learning algorithm for ANN [16, 17].
\[ \beta = H^\dagger T \]  (5)

where output weight matrix \( \beta \) i.e. weight between the hidden layer and output layer neurons, \( H^\dagger \) is the Moore- Penrose generalized inverse of matrix \( H \), \( H \) is the hidden matrix and \( T \) is the output vector.

In this work, 85% of data has been used for training the model out of a total of 100 datasets. The input parameters for this model are CNG flow rate (kg/h.), load (kg), compression ratio.

3.2. Adaptive Neuro-Fuzzy Interference System (ANFIS) based model
ANFIS is a combination of fuzzy logic and ANN. Fuzzy logic can change the qualitative aspects of human intelligence and insights into the process of accurate quantitative analysis. Nevertheless, it does not have a particular technique that can be used as a guide in the process of conversion of human thought into rule base fuzzy inference system (FIS), and it also takes significantly long time to fine-tune the membership functions (MFs). Unlike ANN, it has a higher capability in the learning process to adapt to its environment. Therefore, the MFs are altered automatically using ANN, and hence the rate of errors in the determination of rules in fuzzy logic is decreased. ANFIS uses hybrid-learning algorithm, which can accelerate the convergence and reduce the possibility of trapping in local minima [8, 18].

In this work, ANFIS toolbox provided in Matlab 2016 is used, which has two ways to create initial FIS namely GRID partitioning method and sub-clustering method. In Grid partitioning, the rules are generated that enumerate all possible combination of membership functions for all inputs, leading to a situation called as the curse of dimensionality, which refers to an exponential increase in number of fuzzy rules for moderately large input variables. In sub-clustering partitioning method, the curse of dimensionality is overcome by using fuzzy rules which is equal to the number of the input variables. The shape of the input membership functions has been chosen as Gauss MF, since it can solve most of the ill-treated data and number of membership functions is taken as three which is the default value [9, 11].

3.3. Response Surface Method (RSM) based Model

RSM is an approximation technique that is easy to estimate and apply, even when there is little knowledge about the process. It is most widely used in problems in which a response is influenced by several parameters and objective is to optimise the response [16].

In this work, RSM has been used for modeling and analyzing the output parameters of IC engine namely performance and emission parameters. The relationship between the independent input variables and their dependent output variables have been achieved by using the second order model as shown in equation 6

\[ Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \sum_{i} \sum_{j} \beta_{ij} X_i X_j + \epsilon \]  

where \( Y \) is the predicted response, \( \beta_0, \beta_j, \beta_{ij} \) are regression coefficients for intercept, linear and interaction respectively, while \( X_i, X_j \) are independent variables and \( \epsilon \) is the error. The toolbox stepwiselm, which is available in Matlab 2016 is used for model development [19].

4. Experimental data

The data is obtained by conducting experiments on a naturally aspirated, single cylinder, water cooled, direct injection diesel engine computerized test rig. The engine has been linked to an eddy current dynamometer for loading the engine, and it is made to run at a constant speed of 1500 rpm.

The experiments have been conducted for different loads of 0.3, 0.6, 0.9 and 12 kg, at different compression ratios of 14, 16, 17 and 18, along with different flow rates of CNG gas (0.0, 0.2, 0.4, 0.6 and 0.8 kg/h), resulting in 100 sets of experimental data which is used for modeling purpose.

5. Results and Discussion

In any IC engine, the performance has to be improved, and emissions are to be reduced. However, the primary problem is that both the performance and emission parameters show opposite behavior. Hence, it is highly challenging to obtain a combination of input variables for which there are minimal emissions and maximum performance. It is incredibly challenging to obtain the optimal parameters either by experimenting or through thermodynamic analysis. Hence the modeling techniques such as ANN, ANFIS, and RSM are used which are popular modeling tools. The input parameters are CNG flow rate, compression ratio, load and among the output parameters, the performance of the engine can be calculated analytically, but emission parameters like oxides of Nitrogen (NOx), Hydrocarbon (HC), carbon monoxide (CO) and smoke cannot be calculated using simple mathematical equation since it is dependent on several environmental factors. In this work, particle swarm optimization is used to find the optimal input parameters for which higher brake thermal efficiency and lower emissions are obtained. In any IC engine, the maximum performance is obtained at 3/40 of the full load, higher
compression ratio and for pure diesel. However, in pure diesel, the emissions are higher. Hence, use of alternative fuels which gives slightly lesser efficiency than that of the pure diesel but decreases the emissions are being used these days. The 15% of the data has been used for testing the developed models. The errors obtained from the different models are compared using root mean square error (RMSE) as shown in table 1. The RMS error is calculated using equation 7.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_p - X_a)^2}
\]  

(7)

where \(X_p\) and \(X_a\) are predicted and experimental values respectively and \(n\) is the total number of data. It is seen that ELM-RBF model gives the lowest RMSE for test data.

Table 1: RMSE obtained by different models on test data

| Models               | RMSE on Test data |
|----------------------|-------------------|
| ELM-RBF              | 0.0079            |
| ANFIS (GRID)         | 0.089             |
| ANFIS (Sub-clustering)| 0.0844           |
| RSM                  | 0.08              |

5.1. ELM-RBF based modeling
The overall time taken to model using this method and to find the optimal input parameters is 0.944692 seconds. Figure 1 shows the number of iterations vs objective function for ELM-RBF model using PSO as the optimization algorithm. It can be seen that there is sudden convergence taking place at 190 iterations and further fine-tuning takes place and reaches to the optimal value within 310 iterations.

![Figure 1. Number of iterations vs objective function for ELM-RBF model using PSO algorithm.](image)

5.2. ANFIS (GRID) based model
In case of ANFIS, the total time for modeling is very large (average time 12 minutes), when compared to ELM-RBF or RSM. The time taken to find the optimal input parameters is 45.074613 seconds. Figure 2 shows the number of iterations vs objective function for ANFIS (GRID) model using PSO as optimization algorithm. It can be seen that ANFIS GRID based model helps PSO to converge faster than ELM-RBF based model. However, optimal solution found by ANFIS GRID is not acceptable, which may be due to overfitting of the model.
5.3. ANFIS (Sub-Clustering) based Model

In this case, the total time for training is large (average time is 16 minutes) when compared to ELM-RBF or RSM. The time taken find the optimal input parameters is 45.074613 seconds. Figure 3 shows the number of iterations vs objective function for ANFIS (Sub-clustering) model using PSO as optimization algorithm. It can be seen from the figure that this model helps PSO to converge faster than ELM-RBF, but slower than ANFIS (GRID). However, optimal solution found by ANFIS (Sub clustering) is not acceptable, which may be due to overfitting of the model.

5.4. RSM based Model

The overall time taken to model and find the optimal input parameters is 19.941752 seconds, which is significantly less than ANFIS models, but significantly higher than ELM-RBF model. Figure 4 shows the number of iterations vs objective function for RSM based model using PSO as optimization algorithm.
6. Comparison of modelling techniques
In this work, comparison of different models done for its use as an objective function in optimization algorithms. Table 2 shows the comparison of techniques. The time taken by ANFIS (sub clustering and GRID) is very high when compared to ELM-RBF and RSM modelling and prediction values are not within the acceptable limits. ELM-RBF model has a total execution time of 0.944692 sec which is the lowest among all the models and the predicted optimal parameters are very close to the experimental values as shown in Table 3. Also it is clear that the optimized input parameters predicted by ELM-RBF Model is as per the requirements of the need to go for CNG as an alternative fuel, which is good BTE and low emissions.

Table 2: Comparison of Optimization Techniques

| Modelling Technique  | Total Execution Time (Training + Testing) | Optimal Parameter Prediction is Near to Experimental Value |
|----------------------|------------------------------------------|----------------------------------------------------------|
| ELM-RBF              | 0.944692 sec                             | Yes                                                      |
| ANFIS (GRID)         | 12 minutes                               | No                                                       |
| ANFIS (Sub clustering)| 16 minutes                               | No                                                       |
| RSM                  | 19.941752 sec                            | No                                                       |
Table 3: Comparison of optimized values with the Experimental values

| INPUT PARAMETERS | ELM-RBF | ANFIS (GRID) | ANFIS (Sub Clustering) | RSM | Experimental |
|------------------|---------|--------------|------------------------|-----|---------------|
| Load (kg)        | 11.6929 | 11.9984      | 11.9269                | 11.9659 | 12            |
| Compression Ratio| 16.0265 | 16.2539      | 16.5936                | 17.9886 | 17            |
| CNG Flow Rate (kg/h) | 0.1954 | 0.0181       | 0.0041                 | 0.0174 | 0.2           |
| OUTPUT PARAMETERS | BTE (%) | 26.6         | 18.49                  | 38.87 | 38.73         |
|                  | Nox (ppm) | 355           | 410                    | 360   | 329           |
|                  | HC (ppm)  | 111           | 178                    | 138  | 1.039         |
|                  | CO (%)    | 0.03          | 0.000487               | 0.000862 | 0.0669 | 0.009         |
|                  | Smoke (HSU) | 37.88 | 31.44                    | 39.06 | 21.39 | 12            |

7. Conclusion
In the current work, CNG diesel dual fuel engine experimental data has been used for finding the optimal parameters of the engine, which gives good performance and minimum emissions. For any optimization technique, the objective function plays a vital role. In this work, modelling techniques like ELM-RBF, ANFIS (GRID and Sub clustering) and RSM have been used to develop the objective function used in the optimization techniques. The comparison between the models is made. ELM-RBF neural network model can be effectively used to develop the objective function for optimization techniques. It gives high prediction accuracy and takes least time for convergence and gives optimal input parameter values which are close to those obtained from experiments.

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