Fuzzy Logic and Neuro-fuzzy Modelling of Diesel Spray Penetration

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Abstract. This paper describes a comparative evaluation of two fuzzy-derived techniques for modelling fuel spray penetration in the cylinders of a diesel internal combustion engine. The first model is implemented using conventional fuzzy-based paradigm, where human expertise and operator knowledge were used to select the parameters for the system. The second model used an adaptive neuro-fuzzy inference system (ANFIS), where automatic adjustment of the system parameters is effected by a neural networks based on prior knowledge. Two engine operating parameters were used as inputs to the model, namely in-cylinder pressure and air density. Spray penetration length was modelled on the basis of these two inputs. The models derived using the two techniques were validated using test data that had not been used during training. The ANFIS model was shown to achieve an improved accuracy compared to a pure fuzzy model, based on conveniently selected parameters.

1 Introduction

In a diesel engine, the combustion and emission characteristics are influenced by fuel atomisation, nozzle geometry, injection pressure, shape of inlet port, and other factors. In order to improve air-fuel mixing, it is important to understand the fuel atomisation and spray formation processes. Researchers have investigated the characteristics of the spray behaviour, formation and structure for the high-pressure injector by experimental and theoretical approaches in order to improve the combustion performance and reduce exhaust emissions. However, further detailed studies of the atomisation characteristics and spray development processes of high-pressure diesel sprays are still relevant.

Intelligent systems, software systems incorporating artificial intelligence, have shown many advantages in engineering system control and modelling. They have the ability to rapidly model and learn characteristics of multi-variant complex systems, exhibiting advantages in performance over more conventional mathematical techniques. This has led to them being applied in diverse applications in power systems, manufacturing, optimisation, medicine, signal processing, control, robotics, and social/psychological sciences [1, 2]. Fuzzy logic is a problem-solving technique that derives its power from its ability to draw conclusions and generate responses based on vague, ambiguous, incomplete and imprecise information. To simulate this process of human reasoning it applies the mathematical theory of fuzzy sets first defined by Zadeh, in 1965 [3]. Fuzzy inference is the process of formulating a mapping from a given input value to an output value using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. It has been proved that the system can effectively express highly non-linear functional relationships [4]. Fuzzy inference systems (FIS) have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems and computer vision.

The Adaptive Neuro-Fuzzy Inference System (ANFIS), developed in the early 90s by Jang [5], combines the concepts of fuzzy logic and neural networks to form a hybrid intelligent system that enhances the ability to automatically learn and adapt. Hybrid systems have been used by researchers for modelling and predictions in various engineering systems. The basic idea behind these neuro-adaptive learning techniques is to provide a method for the fuzzy modelling procedure to learn information about a data set, in order to automatically compute the membership function parameters that best allow the associated FIS to track the given input/output data. The membership function parameters are tuned using a combination of least squares estimation and backpropagation algorithm for membership function parameter estimation. These parameters associated with the membership functions will change through the learning process similar to that of a neural network. Their adjustment is facilitated by a gradient vector, which provides a measure of how well the FIS is modelling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimisation routines could be applied in order to adjust the parameters so as to reduce error between the actual and desired outputs. This allows the fuzzy system to learn from the data it is modelling. The approach has the advantage over the pure fuzzy paradigm that the need for the human operator to tune the system by adjusting the bounds of the membership functions is removed.

Many of the combustion problems are exactly the types of problems and issues for which an AI approach appears to be most applicable and has the potential for making better, quicker and more accurate predictions than traditional methods. The increasing availability of advanced computer equipment and sensory systems, frequently results in the production of large amounts of information-rich data, and there are often inadequate means of analysing it so as to extract meaning. The aim of this investigation was to apply intelligent systems tools and techniques to achieve an improved ability to analyse large complex data sets generated during engine research in a semi-automated way. An intelligent paradigm was created based on a fuzzy logic inference system combined with conventional techniques.

2 Methods

2.1 Pure Fuzzy Logic Model

Fuzzy logic provides a practicable way to understand and manually influence the mapping behaviour. In general, fuzzy logic uses simple rules to describe the system of interest rather than analytical equations, making it easy to implement. An advantage, such as robustness and speed, fuzzy logic method is one of the best solutions for system modelling and control. A FIS contains three main components, the fuzzification stage, the rule base and the defuzzification stage. The fuzzification stage is used to transform the so-called crisp values of the input variables into fuzzy membership values. Then, these membership values are processed within the rule-base using conditional 'if-then' statements. The outputs of the rules are summed and defuzzified into a crisp analogue output value. The effects of variations in the parameters of a FIS can be readily understood and this facilitates calibration of the model.

The system inputs, which in this case are the cylinder pressure and the air density, are called linguistic variables, whereas 'high and 'very high' are linguistic values which are characterised by the membership function. Following the evaluation of the rules, the defuzzification transforms the fuzzy membership values into a crisp output value, for example, the penetration depth. The complexity of a fuzzy logic system with a fixed input-output structure is determined by the number of membership functions used for the fuzzification and defuzzification and by the number of inference levels. A fuzzy system of this kind requires that knowledgeable human operate initialise the system parameters e.g. the membership function bounds. The operator must then optimise these parameters to achieve a required level of accuracy of mapping of the physical system by the fuzzy system. While the visual nature of a fuzzy system facilitates the optimisation of the parameters, the need for it to be accomplished manually is a disadvantage.

2.2 ANFIS Model

ANFIS largely removes the requirement for manual optimisation of the fuzzy system parameters. A neural network is used to automatically tune the system parameters, for example the membership function bounds, leading to improved performance without operator invention. In addition to a purely fuzzy approach, an ANFIS was also developed for the estimation of spray penetration because the combination of neural network and fuzzy logic enables the system to learn and improve its performance based on past data. The neuro-fuzzy system with the learning capability of neural network and with the advantages of the rule-base fuzzy system can improve the performance significantly and can provide a mechanism to incorporate past observations into the classification process. In a neural network the training essentially builds the system. However using a neuro-fuzzy scheme, the system is built by fuzzy logic definitions and then it is refined using neural network training algorithms.

3 Experimental Work

A large collection of spray data are generated using the Ricardo Proteus test engine. These data comprised images depicting the spray patterns of diesel injection processes, under selected conditions of relative pressure, nozzle size and type and in-cylinder air temperature. The images representing time-varying spray under each relative pressure condition were examined and processed using a thresholding technique whereby each image representing the instant of maximum penetration length was then determined, yielding a maximum penetration value which could be linked with its corresponding relative pressure across the injector. The collected maximum spray penetration values and corresponding relative pressures then formed a labelled data to be modelled by the FIS as shown schematically in Figure 1.

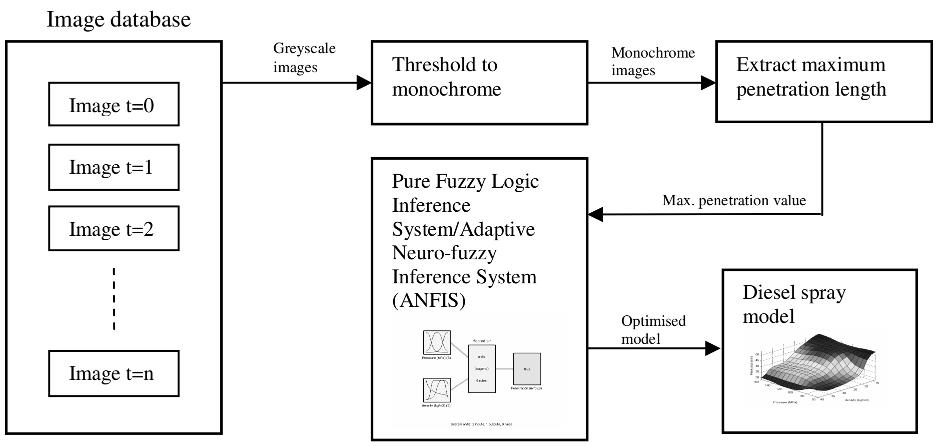

Fig. 1. Schematic diagram of FIS modelling

3.1 Pre-processing

Raw penetration lengths were plotted against time under each relative pressure and density condition. Polynomial fitting was employed to produce best fitted curves where maximum penetration values can be depicted. These were combined into a vector with which to train the ANFIS as shown in Table 1.

Table 1: Training data sets and results

Data set	Parameters		Measured penetration (mm)
	Relative pressure (MPa)	*Density (kg/m^3)*	
1	60	14	53
2	60	35	32
3	100	14	52
4	100	35	38
5	160	14	54
6	160	35	36

3.2 Pure Fuzzy Inference Model

Figure 2 illustrates the fuzzy sets which were used in the pure fuzzy logic inference system. There were two stages in the inference model, the in-cylinder pressure and the air density; both stages are described in detail. The pressure and density range from 60MPa - 160MPa and 14kg/m^3 - 42kg/m^3 respectively. Both in-cylinder pressure and air density fuzzy sets used generalised bell-shaped membership functions for classes low, medium and high. It was empirically selected based on the features of all data under consideration although in many cases membership functions are fixed and somewhat arbitrarily chosen. The process was carried out by examining the ranges of all data sets to determine where the majority of points were located. The functions were also created to have an approximately equal amount of overlap between each membership curve. Experimental adjustment of the limits of the membership classes enabled the response of the model to be tailored to the experimental output from the experimental data.

The rule structure is essentially predetermined by the user's interpretation of the characteristics of the input parameters in the model. The contents of these rule-base and membership functions undertake many modifications as part of the process of heuristic optimisation and in many cases it is a continuing process. Examples of the rules initially contained in the rule-base for the pure fuzzy model are shown in Table 2.

Table 2. Fuzzy rule-base

IF Pressure = Low AND Density = Low THEN Penetration = Large
IF Pressure = Low AND Density = Med THEN Penetration = Small
IF Pressure = Low AND Density = High THEN Penetration = Small
IF Pressure = Med AND Density = Low THEN Penetration = Medium
IF Pressure = Med AND Density = Med THEN Penetration = Very Large
IF Pressure = Med AND Density = High THEN Penetration = Very Small
IF Pressure = High AND Density = Low THEN Penetration = Large
IF Pressure = High AND Density = Med THEN Penetration = Medium
IF Pressure = High AND Density = High THEN Penetration = Very Small

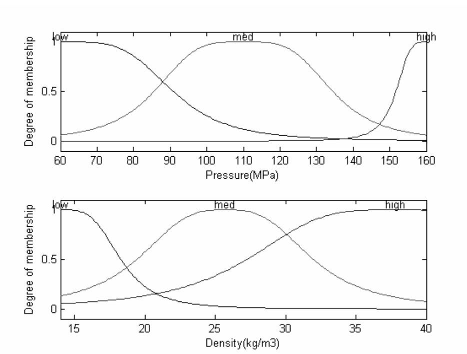

Fig. 2. Fuzzy sets

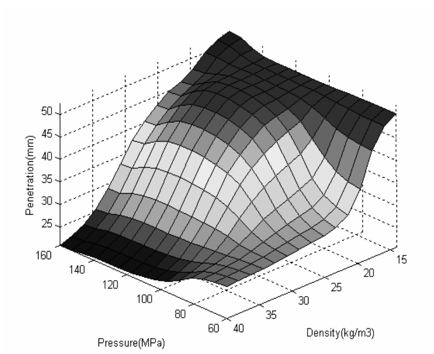

Fig. 3. Pure fuzzy logic model – surface plot

The fuzzifed values for the outputs of the rules were classified into membership sets similarly to the input values. While the output membership functions may be trapezoidal or triangular, in this case, an output singletons were used which has a compact form and computationally efficient representation. The fuzzy output singletons were defuzzified to a crisp value of penetration depth by means of the widely-used centre of gravity method.

The control surface in Figure 3 shows the crisp value of penetration depth at different combinations of in-cylinder pressure and air density using a pure fuzzy logic model. Each of these intersection points indicates the differing predicted value of spray penetration depth, which is determined by the design of fuzzy sets, rule-base and membership functions. The surface plot acts as a practical means of determining the output needed for each combination of input parameters.

3.3 Neuro-fuzzy Model

A FIS was devised using Matlab® based application, ANFIS. A neuro-adaptive learning technique facilitated the learning of information about a data set by the fuzzy modelling procedure, in order to compute the membership function parameters that best allow the associated FIS to track the given input/output data rather than choosing the parameters associated with a given membership function arbitrarily.

A Matlab programme was generated and compiled; The pre-processed input/output spray vector matrix which contained all the necessary representative features was used to train the FIS. Figure 4 shows the structure of the ANFIS; a Sugeno FIS was used in this investigation. Figure 5 shows the fuzzy rule architecture of the FIS which consisted of 9 fuzzy rules. During training in ANFIS, 6 sets of pre-processed data were used to conduct 180 cycles of learning. Figure 6 shows the final membership functions under two different air input conditions derived by training the generalised bell-shaped membership function.

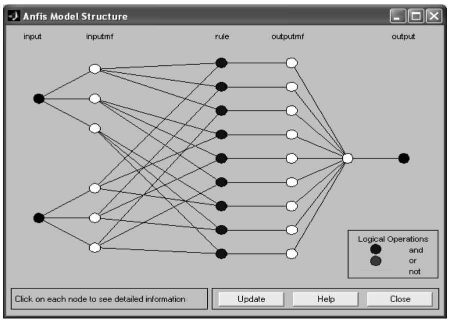

Fig. 4. The ANFIS model structure

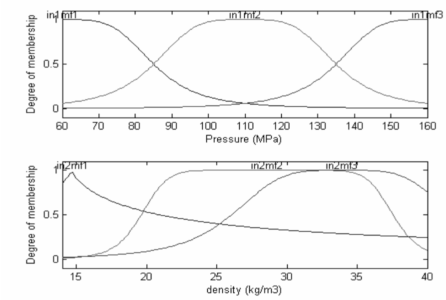

Fig. 6. Fuzzy sets

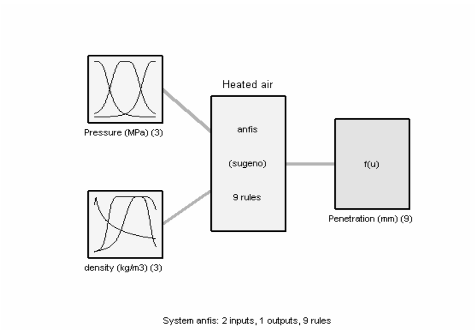

Fig. 5. Fuzzy rule architecture of the generalised bell-shaped membership function

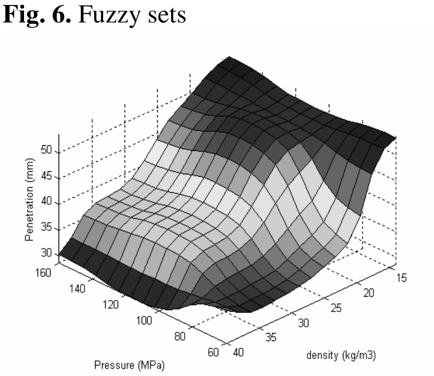

Fig. 7. Surface plot showing relationship between input and output parameters

4 Results and Discussion

Table 3 shows the predicted penetration length obtained from the ANFIS. Figure 7 depicts a three-dimensional plot that represents the mapping from relative pressure and air density to spray penetration length. As the relative pressure and air density increases, the predicted penetration length increases in a non-linear piecewise manner, this being largely due to non-linearity of the characteristic of the input vector matrix derived from the raw image data. This assumes that these raw image data are fully representative of the features of the data that the trained FIS is intended to model. However the data are inherently noisy and training data may not always faithfully represent all the features of the data that should be presented to the model. Therefore, the accuracy of the model will be adversely affected under such circumstances.

4.1 Model Validation

The data in Table 3 was used to determine how well the FIS model could predict the penetration length corresponding to various values of pressure and density. Figure 8 shows scatter plot of the measured and FIS modelled penetration length utilising six sets of testing data. These two diagrams demonstrate that the predicted values are close to the experimentally-measured values, as many of the data points fall very close to the diagonal (dotted) line, indicating good correlation. Figure 9 shows similar comparisons between the FIS-modelled and measured values of the penetration length using the same testing data. Clearly the model created by ANFIS has a better agreement than the pure fuzzy logic model. The correlation coefficient also suggested identical findings.

Table 3. Testing data and results

Data set	**Parameters**		Penetration (mm)		
	Relative pressure (MPa)	*Density (kg/m^3)*	*Measured*	*Pure Fuzzy Paradigm*	*ANFIS*
1	60	28	33	30	33
2	60	40	35	28	35
3	100	28	40	40	41
4	100	40	29	23	29
5	160	28	40	39	40
6	160	40	30	21	30
		Correlation coefficient		0.971	0.997

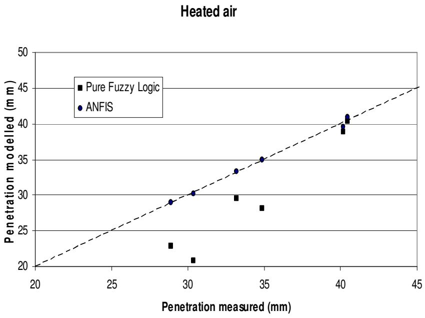

Fig. 8. Scatter plot of measured penetration and predicted penetration

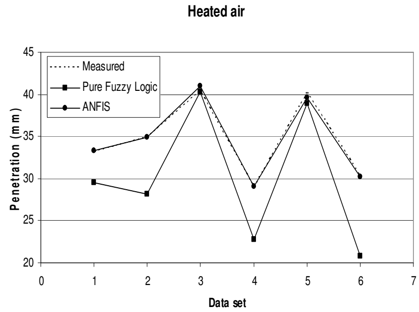

Fig. 9. Comparisons between predicted and measured penetration

4.2 Discussion

The ANFIS is a non-linear computational method that has potential for modelling complex systems with unclear input to output relationships due to its ability to combine fuzzy logic and system identification techniques in a hybrid manner. This type of system has several advantages when assigned to applications in which only partial knowledge of the system characteristics are known, as is typically the case with engineering systems. Additionally, the ANFIS can rapidly identify important characteristics of the data, which is an important and useful feature of models used for estimation purposes in IC engines research. In the experiment, we have used an ANFIS to predict changes in diesel spray penetration depth as a potential means to monitor impending changes in combustion chamber and fuel injector design. As an initial step toward modelling and prediction with an ANFIS for this particular application, it has proven very useful for short-term prediction of penetration depth using engine operating parameters as the input.

The correlation coefficient reflects a model's ability to predict the output based on the input used. While both models performed fairly well and approximated the output function to a reasonable extent, the ANFIS model exhibited improved performance in this respect. Pure fuzzy logic models were conveniently constructed whilst the ANFIS performed well in cases where the input to output relationships become more complex.

5 Conclusions

This paper demonstrated that fuzzy and neuro-fuzzy techniques can be used to model diesel fuel spray penetration for an internal combustion engine, leading to convenient and quick investigation on the effect of penetration length under different operating parameters, including in-cylinder pressure, density, air temperature, etc. The pure fuzzy logic and neuro-fuzzy system, ANFIS employed in this work are quick and robust. It has been applied to sets of pre-processed raw diesel engine spray data and successfully compared. The pure fuzzy logic model employed simple calibrated membership functions and nine optimised rules to represent a diesel spray input/output mapping whilst the neuro-fuzzy model has based on a total of six sets of experimental image data which were used for training the FIS. Both devised models were validated by comparing the predicted results against the experimental data. The correlation coefficient of the penetration length estimated by ANFIS is 0.997. The pure fuzzy logic model has a smaller figure of 0.971 which suggested a poorer correlation with this model.

These fuzzy models set an example of how intelligent technique can be used in diesel spray modelling. The system is very conductive to improvement and adjustment and it can be fine-tuned and improved over time when more engine operating parameters become available. Moreover, these techniques and idea can conveniently be extended to, and be invaluable for, other combustion systems such as modelling and emission predictions in: boilers, furnaces and incinerators. Also, for internal combustion engines, potential applications include modelling and control of: spark ignition engines and gas engines.

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