Development of a Hyper-Intelligent System with New Combustion Analysis Concepts

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ABSTRACT

This paper presents new concepts for combustion analysis of engines together with Hyper-Intelligent System developed for the analysis. The analysis involves the following three elements: (1) Constructing a database of relationships among experimental conditions and combustion characteristics to predict combustion performance for a given condition; (2) Extracting the physical relationships among the combustion factors; (3) Using the ability of the Hyper-Intelligent System to cover deficiencies in measurements and numerical simulations by adjusting empirical parameters in the simulation to fit calculated results to measurements. These above three elements are independent, but common in establishing relationships among a number of non-linear parameters; e.i. learning the spatial distribution of experimental data in a multi-dimensional space. The experiments found that a conventional neural network is insufficient for these applications, and the present study developed an inference method which enables the analysis of nonlinear-multi-variable relationships. A feasibility study with this new Hyper-Intelligent System showed good learning and inference performance within the proposed framework.

INTRODUCTION

Extensive research has been made into combustion analysis, but the complexity of phenomena limits the analysis to specific aspects, and there has been no attempt to analyze total phenomena from accumulated data. Engine manufactures generate vast amount of data from experiments, but the data are used only for specific comparisons and objectives before they are discarded. By accumulating the vast amounts of data, an intelligent system which is able to learn the data should be able to predict results for given conditions based on the accumulated data, recent information technology may be able to realize such an analysis. The objective of this research is to use accumulated data to propose new basic concepts of combustion analysis for engines, and to develop an intelligent system to enable learning and prediction of multi-dimensional relationships.

The analysis involves the three elements listed above. First an attempt was made to apply conventional Fuzzy Neural Network AI to the concepts [1]. The result was quite poor, probably because this kind of AI is basically linear and requires much data to express non-linear functions by fitting a series of linear sections. The limiting element is the inadequate amounts of data available for this kind of application. Thus a new system, termed a Hyper-Intelligent System, was developed to overcome the drawbacks. The system draws on non-linear grids in a multi-dimensional space for the learning process. As the amount of data increases, the grid becomes more complex and accurate. The new system was applied to learning actual engine data and to predicting engine performance at non-learned conditions. The agreement between prediction and experiment was quite good with the limited number of learned data.

The analysis detailed here may be applied, for example, to the development of engines, evaluation of sub-systems, validation of hypotheses, and improvement of numerical simulations. It has not been possible to locate other research similar to that in this paper.

CONCEPTS OF THE NEW COMBUSTION ANALYSIS METHODS

The analysis involves three elements as illustrated in Fig. 1, and the major concepts involved are explained in the following.

Establishing Database of Experimental Results and Predicting Performance.

In engine design and development, experiments are conducted to elucidate specific points of interest, and similar experiments are repeated under slightly different conditions when new engines are developed. Thus experimental data accumulates but is not efficiently used to predict new conditions. The main reason for this is that combustion phenomena are very complex and it has been impossible to establish physical relationships among the large number of parameters.

The method of analysis presented here proposes to construct a database of relationships among experimental conditions and combustion characteristics to predict combustion performance for a given condition through learning and inference. The circle in the upper center of Fig. 1 corresponds to the learn-

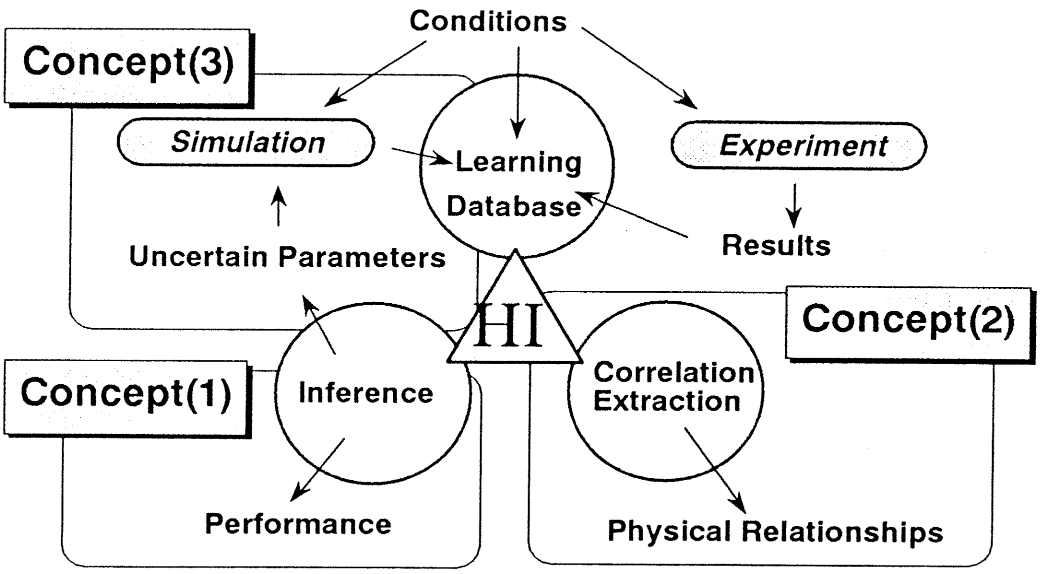

Fig.1 Schematic presentation of the three elements of the conceptual framework.

ing part of the intelligent system, where the relationships between experimental conditions and results, input and output, are learned and a database of learned results is created. Then based on this established database, performance is inferred for new conditions as indicated in the lower left part of the figure.

Extracting Physical Relationships Among Combustion Parameters

The main objective of combustion research is to identify physical relationships among the parameters related to combustion, and to quantify these. This is to enable an analysis of the relationships using the ability of the Hyper-Intelligent System. As the Hyper-Intelligent System learns the input and output relationships, it becomes possible to extract physical relationships from the learned database. This is shown at the lower right in Fig. 1. This may be used, for example, in distinguishing major parameters from insignificant parameters in the phenomena and in evaluating hypotheses.

Making up for Deficiencies in Measurements and Numerical Simulations

Photographic observations provides information of the range of view, but it is difficult to obtain quantitative information from pictures. Numerical simulation yields quantitative information easily with poor reliability however. This is because the simulations involve many empirical and model constants and because of the complexity of combustion phenomena. Here the aim was to make up for deficiencies in measurements and numerical simulations by adjusting empirical parameters in the simulation to fit the calculated results to measurements. The upper left part of Fig. 1 illustrates this aspect.

This may be achieved by knowing the relationship between the empirical parameters in the simulation and the characteristics in the calculated results. As the Hyper-Intelligent System establishes a database of relationships, it can infer the optimum setting of the empirical parameters which agree best. As the database increases the inferences become more reliable.

In this manner, the simulated results become increasingly reliable and quantitative information corresponding to the observed phenomena may be obtained. By analyzing fluctuations in the empirical parameters, it becomes possible to evaluate the simulation program and identify limits to the simulation. In this manner the simulation can be simplified by compounding the complexity into a few empirical parameters and determine these. This would be possible both for photographic observation and other kinds of measurements.

APPLICATION OF CONVENTIONAL AI AND ITS LIMITATIONS

The critical function for this system is the ability to learn relationships among non-linear and multiple variables from a limited set of data. In most experiments there are about five values of data for one variable and the data-sets are generally one part of the matrix in a full combination of all parameters.

Conventional artificial intelligence (AI) systems comprise Neural Networks, Fussy, and Expert systems, and Fussy-Neural-Networks [2]. Here Fussy Neural Networks were investigated because this kind of system requires a smaller number of data for learning than Neural-Networks. The Fuzzy-Neural-Network consists of one network layer and the weight function is determined by fussy logic. Inferences with this system are made from the relative likelihood of a condition to belong to a category region, established in multi-dimensional space.

To evaluate the ability of this kind of AI, input and output data-sets for a given function are studied by the AI, and inferences for given conditions are compared with the correct answers to the functions. In the experiments here the number of input parameters was varied from one to three, and the effect of repetitions was examined.

Figure 2 shows the result for a simple linear function, and Fig. 3 for a non-linear function. The abscissa presents the

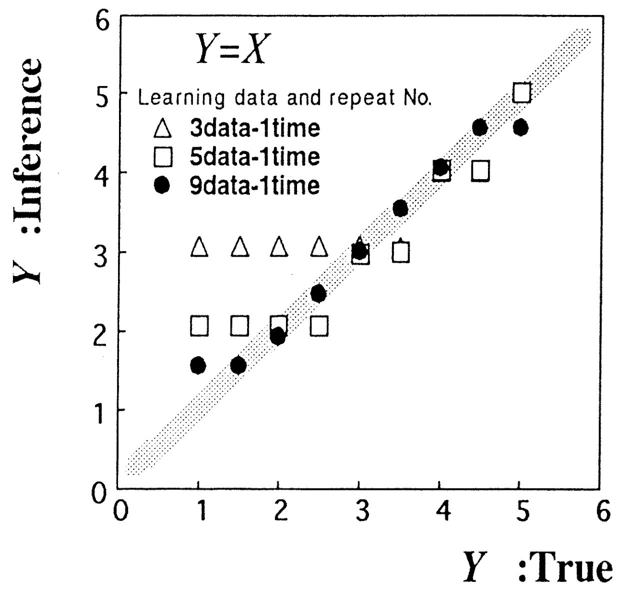

Fig.2 Results of learning and inference with function data using a Fuzzy-Neural-Network (Linear function)

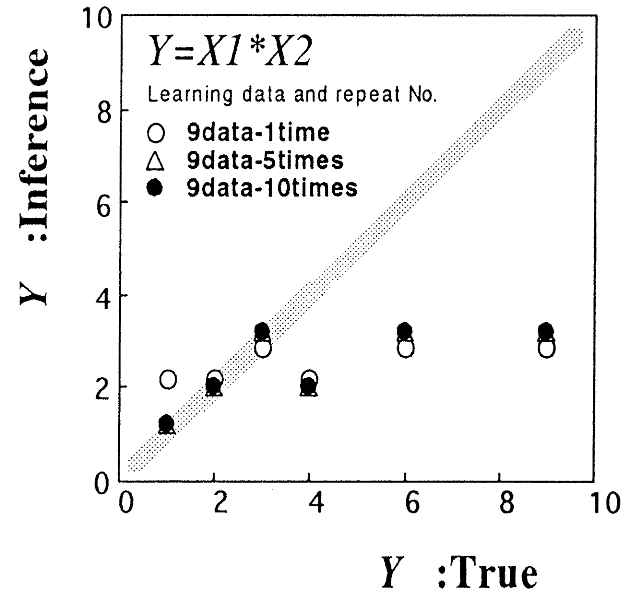

Fig.3 Results of learning and inference with function data using a Fuzzy-Neural-Network (Non-linear function)

true (right) answer and the ordinate is the inference of the AI system. The parameters in the figures are the number of data-sets and the number of times learning was repeated. The learned data-sets in the figure distribute so that inference can be made to interpolate the region involved. It is seen from the figures that the learning ability of conventional AI is poor, particularly when the number of data-sets is limited. When the function is non-linear, the result is quite poor and outside acceptable limits.

An application of the ideas presented here to predict engine performance for the conditions in Table 1 were made. Some of the data measured in few different engines were evaluated by Fuzzy-Neural-Network AI, and predictions were made for the rest of the measured data. An example of the results is

Table 1 Input and output parameters

INPUT PARAMETERES
Combustion Chamber Configuration
Swirl Ratio
Number of Nozzle Holes
Injection Timing
Engine Speed
Mean Effective Pressure
OUTPUT PARAMETERS
Specific Fuel Consumption
NOx
Smoke
Maximum Rate of Heat Release

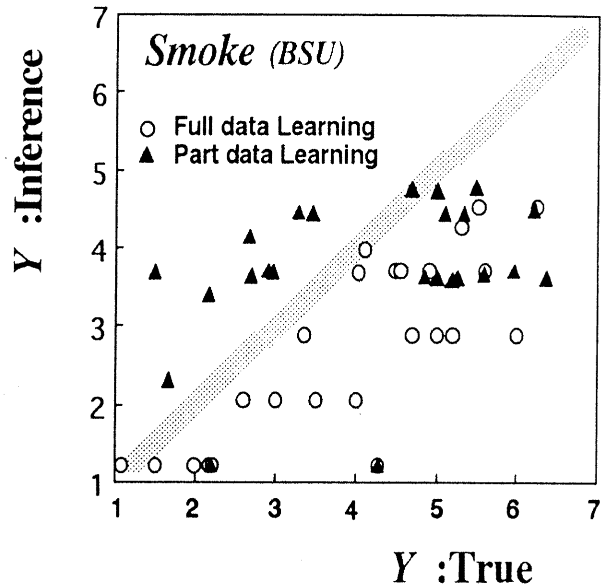

Fig. 4 Learning and inference of smoke emissions using a Fuzzy-Neural-Network

shown in Fig. 4, where "full data learning" is where the AI learns all the measured data and makes predictions for a part of the learned conditions. The inferences of this conventional AI are extremely poor.

This makes it apparent that conventional artificial intelligence is not adequate for the proposed application. The reason may be that conventional AI is essentially linear. For example, the logic of neural networks is a simple addition of weighting functions in the network synapse. To realize the proposed concepts it is necessary to develop a different intelligent system which achieve prediction of non-linear relationships from a limited volume of data. There is multivariate analysis theory [3], but this is also limited to linear relationships.

CONCEPT AND ALGORITHM OF THE HYPER-INTELLIGENT SYSTEM

Major Elements of the Hyper-Intelligent System

The experimental conditions and results create a multidimensional space of coordinates of condition parameters and results. With physical problems a result, solution, is generally unique for one condition, and a set of the experimental results

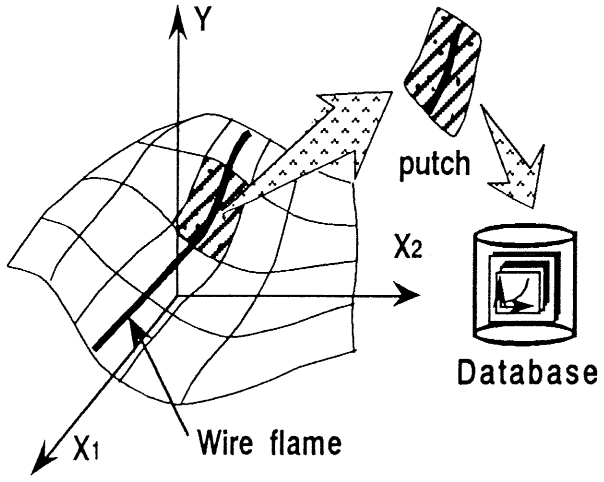

Fig.5 Hyper-Intelligent System

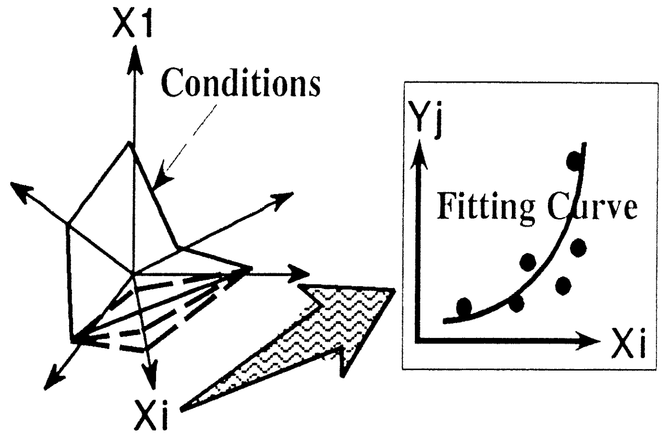

Fig.6 Multi-dimensional coordinates and grid generation in a multi-dimensional space

forms a curved surface in multi-dimensional space, which can be treated as a geometrical figure.

Figure 5 is an example of a three dimensional surface, X1 and X2 are the conditions and Y is the result parameter. Here it is possible to impose a grid on the surface, and a major concern of the Hyper-Intelligent System is to create grid lines and store grid information. In the intelligent system this is extended to multi-dimensional coordinates. With three points in space, one may form a three dimensional plane. As implied by this, the Hyper-Intelligent System infers space from a limited amount of data, and as the number of the data-sets increases the accuracy of the inference improves.

Algorithm of the Learning in the Hyper-Intelligent System

It is not feasible to draw multi-dimensional space but it may be imaged as in Fig. 6, where radiating coordinates are conditions and a result exists for each set of coordinate values. The grid line in the Xi direction is where all coordinate values other than Xi have the same value and the Xi value varies as shown by the dotted lines in Fig. 6. This yields a curve in the Yj-Xi plane as shown in the figure, stored as grid information. Thus the projection of experimental results on to the Xi plane is equivalent to project points which, except for the Xi coordinate, have the same coordinate values.

In the first approximation of the projection, space is divided into small sections termed patches as shown in Fig. 5, and the points in a patch are projected linearly on to the Xi plane. Figure 7 illustrates the process of projection: First all the points in the patch are projected to have one variable of the same value, Xk, different from Xi. The projection of point A on to the Xk plane is determined as the point C, where the line between A and B crosses the plane, and B is the point on the other side of the plane closest to A. The vector of C is then

$$(1-\alpha) * A\{Yj, X1, \ldots Xk, \ldots\} + \alpha * B\{Yj, X1, \ldots Xk, \ldots\} = C\{(1-\alpha)Yj_A + \alpha Yj_B,\ (1-\alpha)X1_A + \alpha X1_B, \ldots\ldots,\ (1-\alpha)Xk_A + \alpha Xk_B, \ldots\}$$

where the α is determined to give

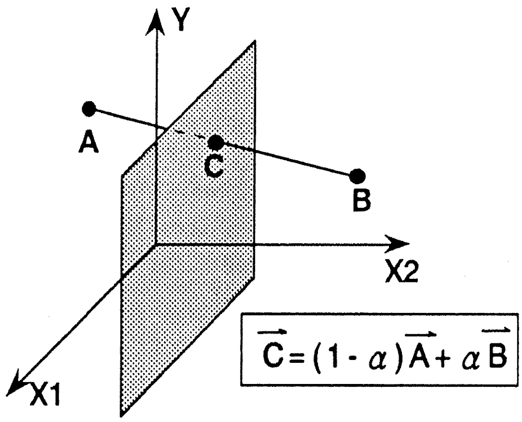

Fig.7 Schetch showing the establishment of point C on the Xk plane

$$Xk = (1-\alpha)Xk_A + \alpha Xk_B$$

In this way all points in a patch can be projected on to the Xk plane, and one dimension , e.i. Xk, can be ignored in the further process. Repeating this for the other coordinates (other than Xi) finally yields the projection on the Xi plane as in Fig. 6. Then the grid function can be obtained by simply fitting a curve to the projections. This function is stored as the result. In the present study a second order polynomial function was used for the fitting.

In this manner grid lines are created for any point and direction, and the knowledge of the system improves. As the number of points in a patch increases, the patch size can be reduced, or non-linear projection may be possible using the already established functions. For a region where points distribute in a plane, patches may be consolidated into larger ones to make the space simpler. With optimization of patches the time for analysis and the size of the memory required becomes the minimum, and details of the space become clearer.

Algorithm of Inference in the Hyper-Intelligent System

Inference can be made from the established grid lines. First a patch with the condition of inference is identified. This was performed with a fuzzy algorithm in the present system. Then by substituting the condition values into a few grid functions close to the inferred condition, points are created in the vicinity of the condition involved. As most of the grid lines do not involve the condition, the calculated points locate over a range in the space. Similarly in the learning process, a projection of the points is made to the point of the condition. The inference is finally achieved by averaging the projected values.

APPLYING THE HYPER-INTELLIGENT SYSTEM TO COMBUSTION ANALYSIS

Learning and Inference of Functions

To evaluate the usefulness of the Hyper-Intelligent System, an examination was made for a variety of functions. The results are shown in Fig. 8 to Fig. 11, where the number of patches dividing the space was varied. The inference is significantly better than with conventional AI as shown in Figs. 2 to 4. In Figs. 9 and 10, for example, the fit is good even for nonlinear functions. The accuracy of the inference increases as the patch number increases, particularly with non-linear functions. The number of data necessary is much smaller than with conventional AI, indicating that the Hyper-Intelligent System is suitable for the proposed application, where usually only a limited number of data is available. Even with three variables as in Fig. 11, the fit is still good, although it requires more leaning

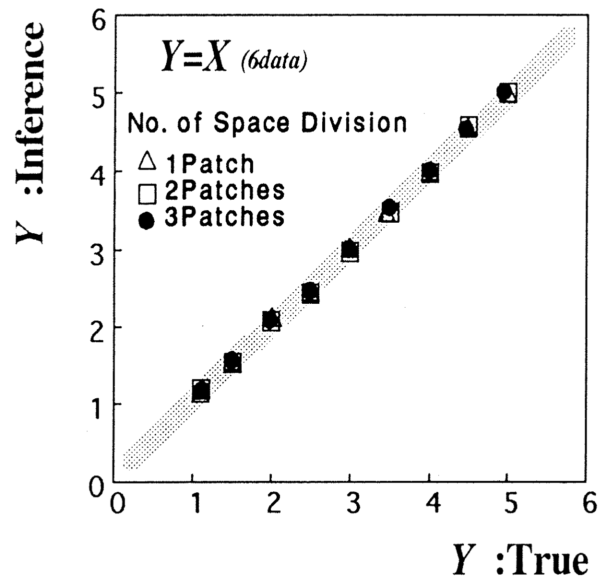

Fig. 8 Results of tests using the Hyper-Intelligent System (Linear function)

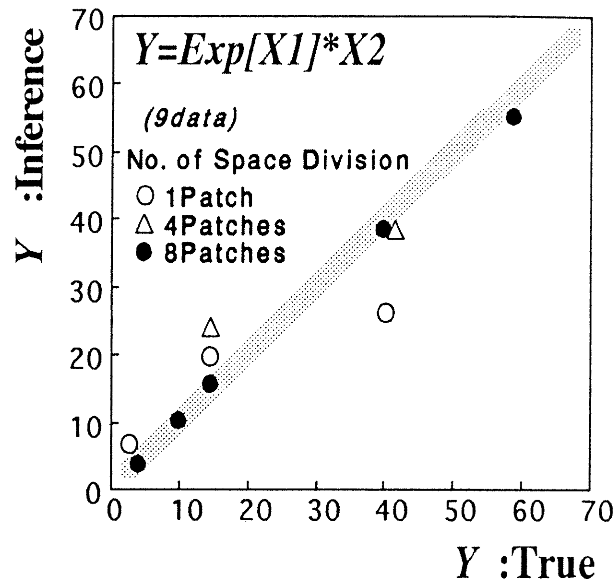

Fig. 10 Results of tests using the Hyper-Intelligent System (Non-linear function)

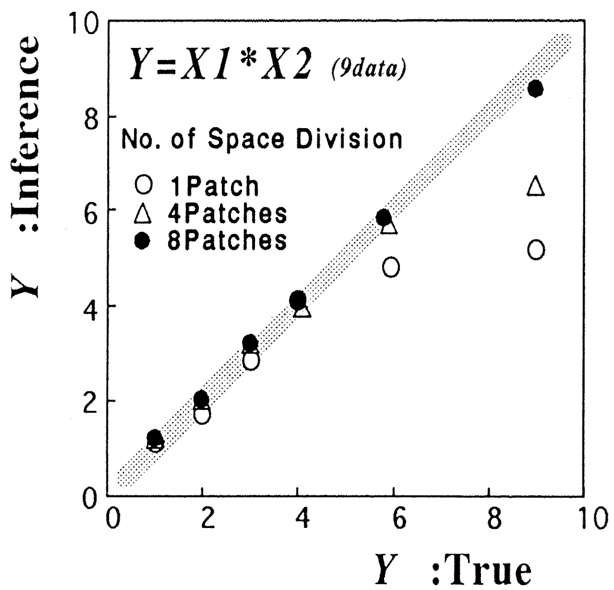

Fig. 9 Results of tests using the Hyper-Intelligent System (Non-linear function)

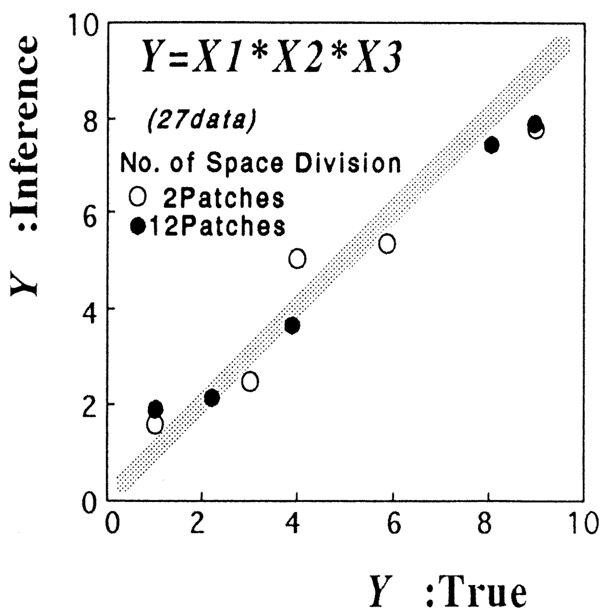

Fig. 11 Results of tests using the Hyper-Intelligent System (Non-linear function with three variables)

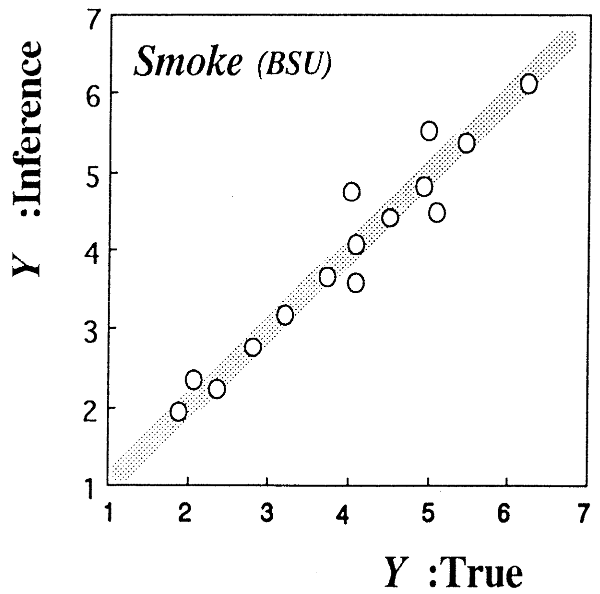

Fig. 12 Results of engine data tests using the Hyper-Intelligent System (Smoke emission)

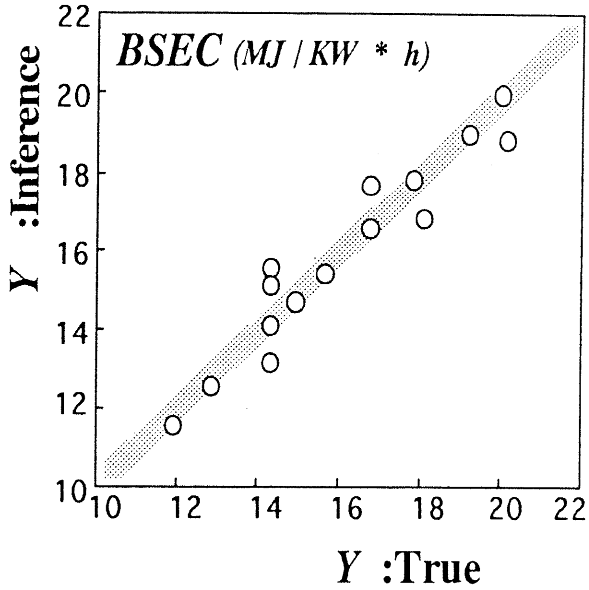

Fig. 13 Results of engine data tests using the Hyper-Intelligent System (Fuel consumption)

data and patches than with two variables.

As the characteristics of physical problems are usually simple, the Hyper-Intelligent System appears to be a good learning and inferring tool necessary for the proposed application.

Engine Performance Prediction

The same set of engine data used in the previous section for the Fuzzy-Neural-Network was used with the Hyper-Intelligent System, and the performance was compared with the measured values. The results for smoke and specific fuel consumption are shown in Figs. 12 and 13. The abscissa is the measured true value and the ordinate is the inferred value predicted by the Hyper-Intelligent System. Compared with Fig. 4 for the Fuzzy-Neural-Network, the prediction ability is significantly better. There is some scattering in the figures, due to errors in the inference and scatter in the experimental data.

The treatment of errors in the learned data is one of the problems to be addressed in the next stage of the development of the intelligent system. Investigation must also be made of the sensitivity of the intelligent system to the number of variables, the size of the data-sets for learning, and the limits to the complexity of the phenomena.

CONCLUSIONS

1. The study proposed the following combustion analysis framework to enable learning and inference:
• Establishing a data-base of experimental results for performance prediction.
• Extracting physical relationships among combustion factors.
• Adjusting for deficiencies in measurements and numerical simulations.

2. Conventional artificial intelligence, Fuzzy-Neural-Network AI, was used with the framework to learn and predict engine performance. The result was quite poor and it was found to require a large number of data sets for learning. This is partially due to the essentially linear summation of the weight functions in the network.

3. A prototype of a new intelligent system, termed Hyper-Intelligent System, was developed for the concepts. This system enables an analysis of non-linear, multi-variable relationships with a limited number of data sets.

4. The performance of the Hyper-Intelligent System was examined by predicting a variety of function and engine data. The results with the intelligent system were good with a limited number of learning data. The intelligent system has good potential as a powerful tool to realize the proposed ideas. Further investigation is necessary to handle errors in the learning data, establishing limitations of the intelligent system, the validity of the concepts proposed, and speed of the algorithm.

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