Artificial Neural Networks for Combustion Interferometry and other Optical Methods of Combustion Diagnostics and Control

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Key words: artificial neural networks, combustion, optical diagnostics, control systems.

Introduction

Interferometry has the wide possibilities in combustion research [1-3]. It allows to determine simultaneously the integral characteristics of combustion flows as well as local characteristics.

We have the special computer programs [2] for the semi-automatic calculation of the integral and local characteristics of flame. At usage our program, the operator should fulfils about ten clicks by the computer mouse only. However the involvement of the operator is obligatory. Therefore the work of computer program cannot be completely automated. It does not allows to use our program in control systems of such combustion processes, where the instant response to change of the characteristics of system is required.

Basic Problem. Possibilities of ANN Usage for Combustion Interferometry

The goal of this paper is to show perspectives and efficiency of usage ANN for diagnostics and control of combustion processes.

Nowadays the ANN are using for solution the different tasks. Main advantage of ANN is that they can be used at solution of problems, which ones have no algorithmic solution or have considerable difficulties. They are applicable when the task is multifactor and the straight lines links between the factors are unknown. The ANN allow to reveal legitimacies of the system behavior on a basis "of inexact data" about the characteristics of the system. In some cases, the ANN is capable to induce the analytical relations between inputs and outputs of real systems directly from experimental data.

The basic problem set in our work was a problem of studying the possibilities of ANN usage for combustion interferometry, in particular for determination of the integral and local characteristics of flame based on incomplete parameters of interferometric images. It is very important for solving of the problems of full automation of measurement and especially for usage of interferometry as well as other optical methods in control systems.

The ANN Determination of Integral Characteristics

The integral characteristics that we consider here were mass of flame (m), the Archimedean lifting force (F_a) acting on flame and quantity of heat (H) in flame. A flame forming during ignition of propellant by laser radiation was considered.

The following geometrical parameters of the interferometric images of flame: maximal height (h) and width (w) of the image, its square (s) and perimeter (e) were used as incomplete parameters of the interferometric images. Their determination is simple and can be completely automated.

The Neural Network Wizard 1.7 (NNW) of BaseGroup Laboratory (www.basegroup.ru) was used in our work. While training the NNW, the various combinations of the above-stated

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geometrical parameters of the interferometric image were used. They were as input parameters of NNW. The values of above-stated integral characteristics that we have determined beforehand were installed on the output of the NNW. It was necessary to find what combinations of input values yield more exact results and to obtain the NNW, which would allows to determine the integral characteristics of flame on basis of incomplete (geometrical) parameters of the interferometric image.

The six sets of values of integral characteristics (output parameters) and geometrical parameters of the six interferometric images (input parameters) are presented in the Table 1.

Table 1. The sets of values of integral characteristics *m, F_a, H* (output parameters) and geometrical parameters *w, h, S, e* of the interferometric images (input parameters).

№	w, cm,10^{-2}	h, cm,10^{-2}	S, cm^2	e, cm	m, g	F_a, dynes	H, J
1	65	65	0,325	1,991	0,00008	0,080	0,024
2	88	85	0,624	2,774	0,00022	0,226	0,070
3	108	147	1,264	4,088	0,00052	0,566	0,175
4	130	222	2,252	5,619	0,00125	1,065	0,324
5	142	274	2,989	6,688	0,00190	1,422	0,430
6	151	341	3,914	8,114	0,00267	1,904	0,575

The five sets were used while training the NNW. The set N4 was used for testing the NNW. Twelve various combinations of each set of values of the geometrical parameters were used as input data while training and testing of the NNW. One of the results of testing of the NNW is shown in Fig. 1. The horizontal line on the Fig.1 gives the “exact” value. The vertical columns correspond to the values obtained with the help of the NNW. Various columns correspond to various input data combinations. For example, the sign (*hse*) shows that the height (*h*), the square (*s*) as well as the perimeter of the image (*e*) were used as the input data.

The results show that the NNW can calculate the integral characteristics of flame successfully enough. But the analysis of results shows also, that the exactness of the result depends on the combination of input data. For example, if we use combinations of values, which include width and square of the image, we have more high error. On the other hand, we receive low error while use combinations of values that include height and perimeter of the image.

We have trained the NNW on the basis of five interferograms only (the sixth interferogram and it’s data were applied to check up the trained NNW). If we will increase the number of interferograms, it is possible to obtain a very good NNW for calculation of integral characteristics of the flame formed at ignition of propellant by laser radiation.

As we have marked above, the ANN is capable to induce the analytical relations between inputs and outputs of real systems directly from experimental data. Below, one of the obtained analytical models of flame mass calculations is shown.

$$m = 0.0534 + 1.5017x_1 + 2.3405x_2 - 2.5898x_3 - 0.3031x_4 \quad (1)$$

Here x_1, …, x_4 are normalized width, height, square and perimeter of flame image, respectively, $x_i = z_i/max(z_i)$, and z_i is current value, $\max(z_i)$ is maximum rating of a variable.

It is important to note that coefficients at x_i show their significance from the point of view of influence on m. The Eq. (1) can serve as simple example of analytical interferometric diagnostics model for propellant ignition by laser radiation.

The obtaining (training) of ANN for calculation of flame integral characteristics by means of having experimental data is considered above. Another and much more interesting way of forming (creation) of database for training NNW is numerical solution of basic equation of interferometry on the basis of a set of tested function. Example of this way used for solving of inverse problem of optics presented below. Another example of usage of this approach in the field of hydrodynamics (the task of hard wall shock about a layer of fluid and the task of wave propagation on a free surface of a fluid) is presented in [4].

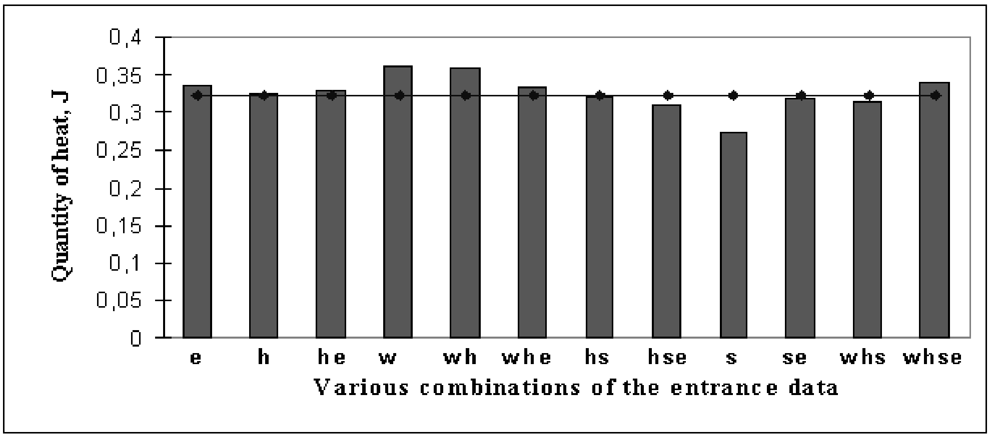

Fig. 1. The results of NNW calculation of quantity of heat at various combinations of input (entrance) data.

The ANN Determination of Local Characteristics.
ANN Solution of Inverse Problem of Optics.

In the section, the possibility of usage of ANN for solving of inverse problem of optics is presented on the example of a task of determination of refractive index distribution in flame. The task of determination of integrand meanings on basis of integral meanings was considered. Abel integral equation (the case of cylindrical symmetry) was examined.

The main feature of the work is solving of inverse problem on the basis of incomplete data of the phase difference distribution function (incomplete data of integral meanings) in an interferogram plane. The only meaning of integral allows restore the all meanings of the integrand (refractive index distribution and then temperature distribution in flame).

The NNW was used for fulfilling of the task. The solving was carried out as follows. The dimensionless Abel's equation was obtained:

$$S(p) = 2\int_{0}^{\sqrt{1-p^2}} (n_0 - n(r))dz\ ,$$

where $z^2+p^2=r^2$, z – ray's path in object, p - aiming distance ($p=0\ ...1$), r - variable radius (see Fig. 2).

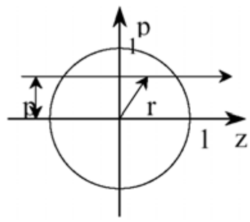

Fig. 2.

Then we have obtained the integrals $S(p)$ from different integrands of form $n_0–n(r) =1+ar–br^2$, where a and b – various coefficients.

In total, we have used 7 different integrands mirroring a real-life distribution of refractive index distribution in flames. The NNW training database was made as follows. For above-mentioned 7 integrands, values $n_0–n(r)$ for various r were calculated. Then, the integrals from each of 7 integrands were calculated. For example, for the function $n_0–n(r) =1+4r–5r^2$, was received the following expression

$$S(p) = \sqrt{1-p^2}\cdot\left(\frac{8}{3}-\frac{10}{3}p^2\right)+2p^2\cdot\ln\frac{1+\sqrt{1-p^2}}{1-\sqrt{1-p^2}}\ .$$

Then $S(p)$ values are calculated for different p.

The input data, at the stage of NNW training, were the following: $S(p)$ values, p values and values of r. Values of integrand corresponding to each radius were getting on the output of NNW. In total there were used about 700 sets of the above-mentioned parameters: $S(p)$, p, r and $n_0–n(r)$.

The results of testing NNW for an integrand n_0–$n(r)=1+0.5r-1.5r^2$ that has not used during the training are represented on Fig. 3.

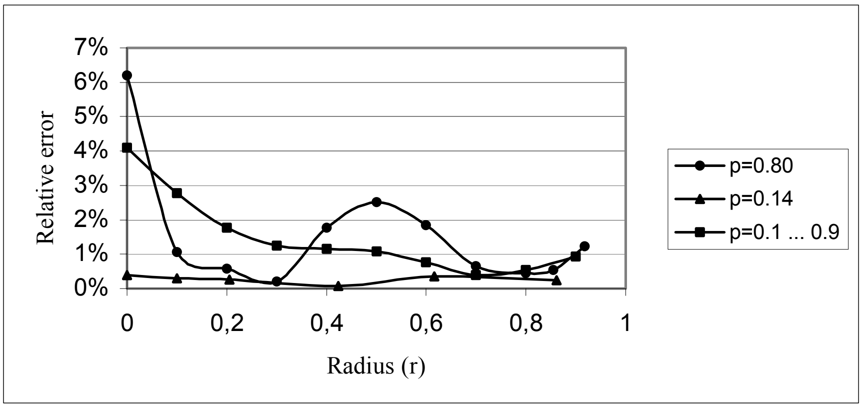

Fig. 3. The relative errors of NNW integrand calculation for two values of aiming distance p and the errors of NNW integrand calculation that have averaged by all aiming distances within the aiming distance interval from 0.1 up to 0.9.

The investigation of stability of NNW calculation to mistakes of input data has been also conducted. One gets the output error less than 3 % for 2% errors artificially involved to the input data. It speaks about quite a good stability of the NNW calculation.

In total the results show that NNW can solve the inverse problems quite exactly in a case of cylindrical symmetry. The definition of one integral value (and also it changes during time in case of non-stationary objects) can be completely automated. Therefore it is possible to use the NNW-like chip (microprocessor) in automated control systems, especially, taking into account it's considerably greater fast action in comparison with usual computer programs. The further perspectives of the work are concerned with the realization of ANN's opportunities for solving the inverse problems for other optical methods as well as with ANN usage for solving the practical problems of combustion control.

Conclusions

Among our future research direction one can mark the following:

1. In the field of diagnostics, we are planning to investigate the ANN opportunities for the analysis of optical images of the pulse detonation engine exhaust from the point of view of calculation of integral characteristics of engine (for example, thrust).

2. We are planning the ANN usage for solution of inverse problem (determination of local parameters of the combustion and detonation wave in engine on the basis of data that can be received by various diagnostic techniques, for example, by laser-diode technique).

The solution of these problems will allow to expand essentially the scientific opportunities of optical diagnostic techniques as well as its possibilities for creation of fast control systems of engine.

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