Proceedings of Global Power and Propulsion Society
ISSN-Nr: 2504-4400
GPPS Xi'an21
18th – 20th October, 2021
www.gpps.global

GPPS-TC-2021-0035

CALCULATING THE PARAMETERS OF A GAS TURBINE ENGINE TAKING INTO ACCOUNT THE UNCERTAINTY OF THE INITIAL DATA

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ABSTRACT

The paper describes a method developed by the authors that allows the stochastic distribution of output parameters to be determined from known probability distributions of uncertain initial data by means of a mathematical model of the engine. It was found that the number of calls to the mathematical model is such that the calculation taking 7-8 uncertain variables into account, even with simple mathematical models, takes a huge amount of time. For this reason, a method was developed to obtain reliable stochastic results with a reduced number of uncertain initial data taken into account, based on sensitivity analysis. The calculated stochastic results were compared with experimental data. It was shown that the difference between the stochastic results of the calculation and the experiment represents a scattering bell (bivariate distribution) and can be described by 4 numerical criteria.

INTRODUCTION

The design methods used today for heat engines have led to the creation of highly efficient products. For further significant improvements in engine characteristics, it is necessary to look for unconventional solutions both in the design of the engines and units themselves and in the methods of their design. In particular, a number of scientists note the fact that the computational models used today require to set unambiguous (deterministic) values of the initial data to obtain solutions [1, 2, 3]. As a result of calculations, the mathematical model gives an unambiguous answer, which is equal to the value of the parameter of interest for the accepted initial data.

In fact, the researchers often do not know the exact value of the input parameters. Thus, the researcher knows not a discrete value as the initial data, but the limiting values of the quantity and the probability of its distribution between the limits. With such initial data, the real result of a calculation using a mathematical model is the probability distribution of the output parameter of interest. In other words, instead of a point describing the parameter of interest on the graph, we have a “spot” which is a region of possible values.

Awareness of the uncertain nature of the initial calculation data will allow the researcher to take a fresh look at the process of computational research, validation of mathematical models and design.The field associated with carrying out calculations considering the uncertainty of the initial data is called uncertainty quantification [1] (abbreviated as UQ).

To calculate the parameters considering the uncertainty of the initial data, several approaches are used: sensitivity analysis [4], conjugate gradient method [5], post-processing using statistical methods, and sampling on a Monte Carlo lattice (MCM) [6], generalized polynomial chaos [7].

The conducted review of the available literary sources showed that today a generally accepted method of UQ calculation has not been formed. Many researchers [1, 4, 5, 6, 7] note the fact that a lot of iterations with the computational model are required to obtain a result. Moreover, if a "heavy" model is used requiring large computational resources and computation time, the time to obtain a stochastic solution, especially with many initial data, turns out to be unacceptable. This circumstance significantly complicates the development of UQ methods.

The authors consider the main purpose of this work to be the development and testing of a method for determining the probability distribution of the output parameters of the engine mathematical model taking into account the uncertainty of the initial data.

It was decided to base the developed methods and algorithms on a simple mathematical model - the thermodynamic model of the engine [8]. It is based on the simplest conservation laws, easily subject to algorithmizing, and well developed. Its application promises to carry out tens and hundreds of thousands of iterations in a reasonable time, which will provide a large amount of information for statistical processing. For this reason, such a choice looks promising for UQ analysis.

TEST OBJECT AND EXPERIMENTAL RESULTS

The two-shaft turbojet engine AI-25 was chosen as an object for testing UQ calculation technologies. The engine was developed in 1966 at the Zaporozhye Machine-Building Design Bureau "Progress" (former USSR, now Ukraine) [10]. Main parameters are listed in Table 1 [10, 11].

Table 1 Basic technical data of the AI-25 turbojet engine at takeoff mode (at H = 0, Mfl = 0)

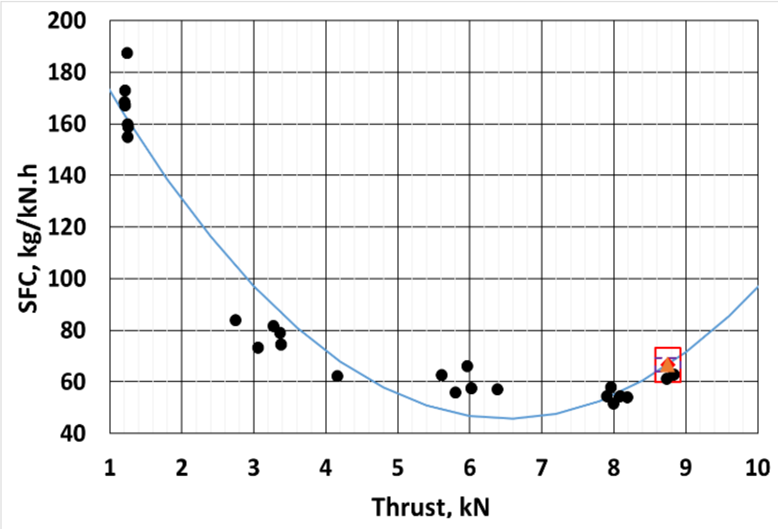
P, kN	14.7	G_{Σ}, kg/s	44.25
SFC, kg/kN hour	56.8	Turbine inlet temperature T_{405}*,K	1185
Overall pressure ratio (π_{Σ})	8	Weight, kg	350
Fan PR (π_{fII})	1.71	Length/Diameter, mm	3358/985
Bypass ratio	2.27	Life cycle, hours	3000

One such engine is installed at the test bench of the Samara University and has been used for many years in educational laboratory works at the courses "Tests of Gas Turbine Engines " and "Theory of Gas Turbine Engines"[9]. During the existence of the laboratory, a large archive of test results of one engine in various conditions was accumulated. These results were reduced to standard atmospheric conditions (p_h = 101325 Pa T_h = 288 K) [8]. The obtained data were plotted on the graphs of changes in the main parameters of the engine from its thrust as points. Fig. 1 shows a graph of changes in specific fuel consumption from engine thrust as an example. Other graphs have a similar form.

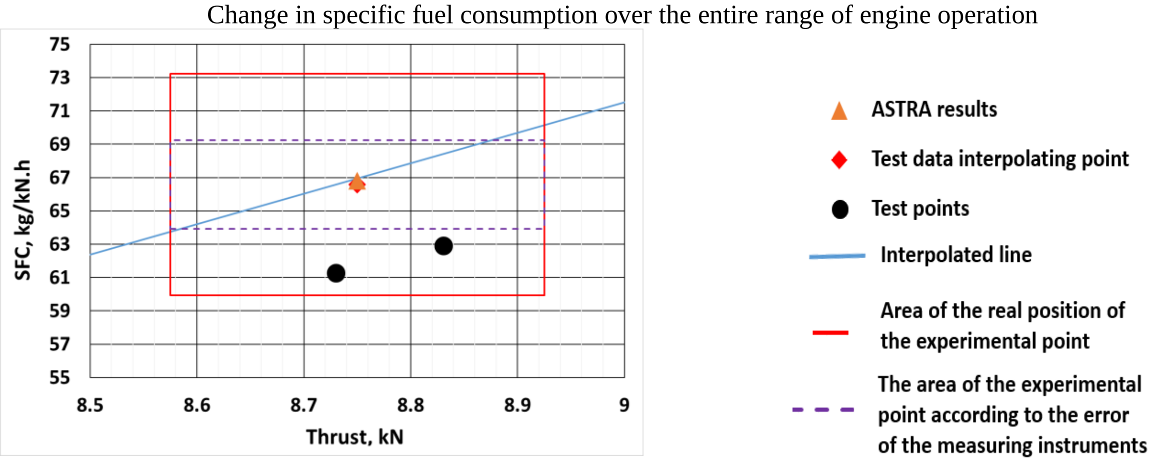
Based on the available experimental data, interpolation curves were found that describe the change in engine parameters when changing its operating mode in the experiment. With their help, the expected values of the main parameters of the GTE were determined at the maximum engine thrust, which was achieved in the tests (P = 8.75kN) (Fig.1).

As noted earlier, the researcher does not know the exact value of the experimental value in the real case, but only knows the estimated range of its variation, which is mainly determined by the measurement error. The boundaries of such a range are plotted in Fig. 1 as purple dotted lines. Analyzing the position of the experimental points on the graph (Fig. 1), one can conclude that the actual error in determining the flow parameters in the flow path of the AI-25 at the Samara University stand is significantly greater than claimed in the certificate. The reason for the mismatch is a significant non-uniformity of the flow in the gas-turbine engine flow path, the operation of the engine at modes different from the real operating conditions (maximum engine operation mode achieved on the test bench is P=8.75, while the actual engine takeoff mode is P=14.7 kN), which leads to an off-design unsteady nature of the gas flow, as well as the error accumulated during the reduction and interpolation of the results.

As a result of the analysis of the available data, a refined error in determining the main parameters of the engine corresponding to the selected operating mode (P = 8.75 kN) was found on the experimental characteristics. They are marked with red lines in Fig. 1. These lines were defined by analyzing the scatter of experimental points on the engine characteristic. Considering that the probability of finding a real point in the specified range obeys the normal distribution law, it is possible to quantify the stochastic parameters measured in the experiment (Table 2).



Change in specific fuel consumption over the entire range of engine operation



Change in specific fuel consumption near the considered operating mode (P = 8.75 kN)

Figure 1 Example of experimental characteristics of the AI-25 engine obtained at the test bench of Samara university with the results of the calculation by the thermodynamic model

Table 2 Parameters characterizing the experimental data near the mode P = 8.75 kN

Parameter	Min. value, $\mu - \Delta \cdot \mu$	Mean Value, μ	Max. value, $\mu + \Delta \cdot \mu$	Relative absolute error Δ, %	pdf, σ
π^*_{LPC}	1.57	1.755	1.93	10	0.17
π^*_{Σ}	5.30	5.58	5.85	5	0.279
G_{Σ}, kg/s	37.93	39.93	41.92	5	1.99
G_f, kg/s	462.31	486.64	510.97	5	24.33
T^*_{LPC}, K	325.59	332.24	338.885	2	6.64
T^*_{HPC}, K	488.50	493.44	498.37	1	4.93
T_n, K	745.69	768.76	791.82	3	23.06
SFC, kg/kNh	59.922	66.58	73.238	10	6.65

APPLIED MATHEMATICAL MODEL

Based on the experimental data, a thermodynamic model of the working process of the AI-25 engine at the operating mode P = 8.75 kN was created. It was created in the ASTRA software, developed at the Department of Aircraft Engine Theory of Samara University by Associate Professor A.Yu. Tkachenko [12]. The thermodynamic model is based on the law of conservation of energy and mass and contains simple mathematical expressions. It does not require significant computer resources for calculations. The computation time for one combination of (deterministic) initial parameters on an ordinary office computer is 0.2 sec.

Some of the initial data required to create the model were taken from the experimental data (pressure ratio of the compressors, air flow rate, thrust, etc.). Other unknown parameters (efficiency and loss coefficients) were selected in the course of a series of iterative calculations in such a way that all the obtained results were as close as possible to the average values of the GTE parameters obtained in the experiment at the indicated mode. The difference between the experimental and calculated data does not exceed 1%. A larger error was obtained only for the air flow through the engine and the mass fuel consumption. The difference in the estimation of the air flow rate can be associated with the choice of the line for interpolation of experimental data. The difference in the estimation of fuel consumption is apparently due to the imperfection of the calculation model. The obtained results are shown as orange triangles in Fig. 1.

A feature of the GTE thermodynamic model is that the areas of its main flow sections (throats of turbine nozzle guide vanes and nozzles) are determined during the calculation and change with a change in the initial data. It is obvious that the flow areas of the engine installed on the test bench do not change significantly during the test. For this reason, the created and validated thermodynamic model of the AI-25 engine was transformed into a model for calculating the characteristics of a GTE (off-design model) in the ASTRA software. This model uses the same equations as the initial one, but the calculation is based on the laws of joint work of the nodes of the existing GTE. These laws are derived on the basis of the balance of capacity and flow rates, as well as the equality of rotation speeds of turbomachinery in the existing engine. They clearly define the parameters of the working process of the existing engine at a given mode of operation [8]. This model uses the same equations as the original one.

To estimate the scatter of the output parameters of the engine mathematical model (GTE parameters), it is necessary to set undefined initial data, the lack of knowledge about which leads to a computational error. In the mathematical model used for the calculation, the engine workflow is determined by only one independent variable (operating mode parameter: thrust, speed, fuel consumption, etc.). In this case, other parameters of the engine working process are uniquely determined by the selected operating mode of the engine and the conditions of joint operation of the components [8]. However, it is necessary to know the characteristics of the main components to carry out such a calculation, which are unknown. Therefore, it is the lack of information associated with them (primarily efficiency) that will make the main contribution to the error (uncertainty) of the calculation results. The most probable values of efficiency and loss factors were taken based on the results of the thermodynamic model validation. They, as well as the expected values of the error in finding the efficiency of engine components and loss factors, are given in Table 3. It also shows the calculated values of the engine flow areas and the expected error in their determination.

Table 3 - The values of the variables of the engine mathematical model found when creating the thermodynamic model and their errors

	Parameter	Value (μ)	Uncertainty (abs)	σ
1	$TPR_{int.}$	0.99	±0.005	0.522827
2	η_{LPC}	0.85	±0.01	0.452469
3	η_{fII}	0.85	±0.01	0.449818
4	η_{HPC}	0.86	±0.01	0.455110
5	η_{cc}	0.97	±0.01	0.513322
6	TPR_{cc}	0.95	±0.01	0.502738
7	η_{HPT}	0.87	±0.01	0.460402
8	η_{LPT}	0.86	±0.01	0.4551107
9	TPR_{bypass}	0.97	±0.01	0.512260
10	F_{405}	0.01695	2.0%	0.008935
11	F_{455}	0.03153	2.0%	0.166210
12	F_9	0.19265	2.0%	0.101555
13	F_{19}	0.06776	2.0%	0.035719
14	P	8.75	2.0%	4.612577

CALCULATION OF THE COMPUTATIONAL DATA

At the next stage, the authors developed an algorithm that allows transforming the created (deterministic) mathematical model of the working process of the AI-25 engine at the operating mode of interest into a stochastic one, i.e. such a model that can be used to determine the spread of the values of the output parameter knowing the spread of several input parameters. Its flow diagram is shown in Fig. 2.

The initial data for the calculations is the probability scatter of each input parameter (one or several (k variables) from those given in Table 3), described by a continuous function, given by the value of the mathematical expectation μ_i and the standard deviation σ_i. The range of possible values of each initial variable is divided into n_i sections. The numbers of sections may be the same or different. For each section, the mean value of the variable x_{ij} and the probability of its occurrence $P(x_{ij})$ are found. Thus, the continuous probability distribution of the initial data is replaced by a discrete two-dimensional array in which each range of the variable is assigned 2 values: the mean value of the variable and the probability of its occurrence $\{x_{ij}, P(x_{ij})\}$. The number of such arrays corresponds to the number of considered independent variables - k. Then all possible combinations of initial data $\{x_{1i}, x_{2j}, x_{3l}, \dots x_{kp}\}$ are taken and for it, using the mathematical model of the engine described earlier, the value of the required output parameters $y_{ijl\dots p}$ is calculated. In parallel for the chosen values of the variables the probability of its occurrence is calculated as multiplication of the probabilities of initial data $P_{ijl..p}=P(x_{1i})$ $P(x_{2j})$ $P(x_{3l})\cdot \dots \cdot P(x_{kp})$ (since the occurrence of particular values of the initial data is an independent event). Thus for all possible combinations of initial data the values of output parameters $y_{ijl\dots p}$ and probabilities of its occurrence $P_{ijl..p}$ are calculated. The obtained array is converted into a probability distribution of the output parameter of interest. On the basis of data analysis, the numerical values characterizing it are found mathematical expectation μ_y and standard deviation σ_y.

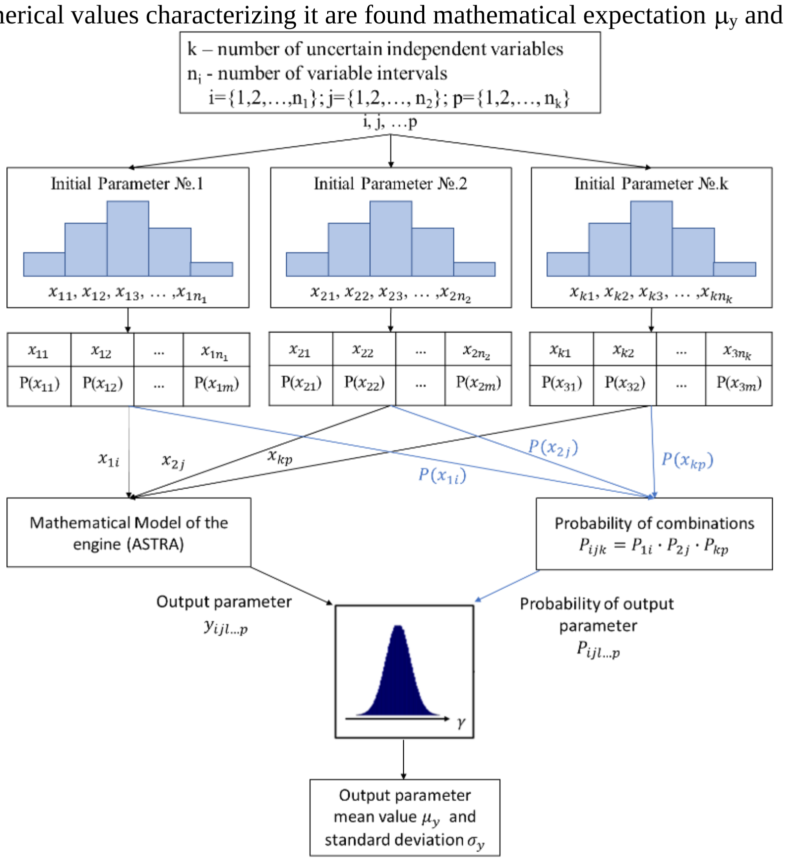


Figure 2 Flow diagram of stochastic model for calculation of the AI-25 engine process at the set operation mode

TIME OF CALCULATION

The calculation time for one combination of initial data using the ASTRA software is 0.2 sec. A simple calculation shows that if each range of variation of the undefined initial variable is divided into n segments, then the number of iterations with the computational model will be n^m (m is the number of unique variables). The calculation time with an increase in the number of unique initial data also grows exponentially and with 8 variables approaches a day. It will take 38.7 years to calculate all the combinations of 14 initial variables in the problem under consideration. In practice, the calculation with 7 unique variables led to an overflow of the computer RAM and the impossibility of recording the result.

Thus, even though the study is based on a simple model that requires insignificant computer resources and computation time, it is not possible to find the scatter of the GTE parameters when varying all 14 uncertain initial parameters (in order to obtain the most accurate result) using the developed algorithm. The real number of undefined variables that can be considered using the created mathematical model within a reasonable time does not exceed 8. Reducing the calculation time to reasonable limits can be achieved in two ways: by reducing the number of calculated variables and by reducing the number of iterations with the calculation model.

INFLUENCE OF THE CHOICE OF VARIABLES TO BE CONSIDERED

At the next stage of the work, a study was carried out aimed at finding the minimum number of variables to obtain a result as close as possible to the "ideal" (with varying all possible uncertain variables).

To investigate the effect of the choice of uncertain initial data and their number on the spread of the quantity of interest, a study was carried out, during which, from the parameters indicated in Table 3, 3 random sequences (Table 4) were formed of 6 variables.

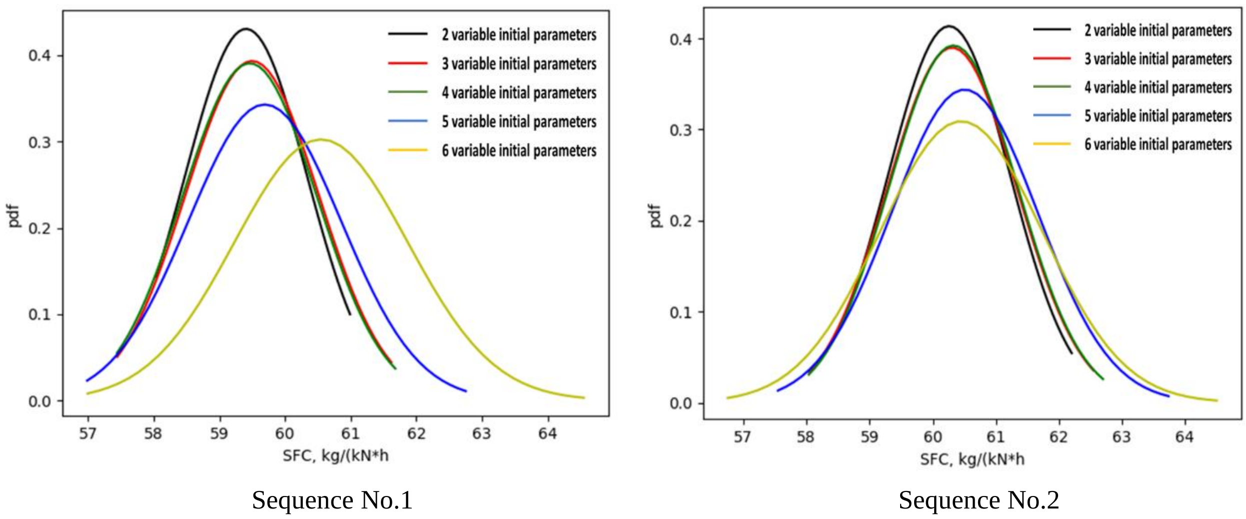
Table 4 - Random sequences of uncertain initial data selected for calculation

Serial number	1	2	3	4	5	6
Sequence No.1	η_{HPC}	F_{405}	η_b	F_{19}	η_{fII}	TPR_{int}
Sequence No.2	TPR_{int}	η_b	TPR_{bypass}	F_{405}	TPR_b	η_{LPT}
Sequence No.3	F_9	TPR_b	η_{HPT}	F_{19}	TPR_{int}	η_b
Number of iterations with mathematic model	5	25	125	625	3125	15625
Calculation time, s.	6	6	21	91	344	3780

Then, for each of the sequences, the scatter of specific fuel consumption was calculated using the created stochastic model of the engine working process, taking into account the first 2, 3, 4, 5, and 6 variables from the sequence. The results obtained for sequences 1 and 2 are shown in Fig. 3. In a similar way, the probability distribution of any other calculated engine parameter with any sequence of initial data can be obtained.

It can be seen from the obtained results that adding an additional variable to the calculation changes both the expected value of the calculated parameter and its standard deviation σ.

It can be seen, that the choice of variables and their place in the sequence has a significant impact on the results of determining the parameters of the probability distribution of the quantity of interest. This is an important conclusion since the created mathematical model cannot consider all the variables. As the number of considered variables increases, the difference between the results obtained using different sequences decreases. The reason, obviously, is that the changes in the uncertain input data affect the result to varying degrees. Changing some parameters has a significant effect on the output parameters while varying others have almost no effect on the result. Considering this fact, it was suggested that if only those parameters that most affect the parameter of interest are taken as the initial data under consideration, then the final distribution will be as close as possible to that which would be obtained taking into account all variables.



Sequence No.1 Sequence No.2

Figure 3 Influence of the number of variables and the order of their choice on the results of stochastic calculation of specific fuel consumption

SELECTION OF THE SEQUENCE OF ACCOUNTING VARIABLES USING SENSITIVITY ANALYSIS

Based on the gained experience, an algorithm for UQ calculation was developed, which includes a sensitivity analysis to select the initial data most influencing the output parameter of interest.

During sensitivity analysis, 7 values of the initial parameter were taken from its range of variation (Table 3). The rest of the variables did not change and were taken equal to their expected value $\boldsymbol{\mu}$. As a result, the change in the value of the output parameters of interest (maximum and minimum deviation) was determined. This study was conducted for all variables listed in Table 3. The obtained results were sorted by the degree of change in the output parameters and presented in the form of a tornado diagram. Similar plots can be obtained for any other output parameter (Fig. 4).

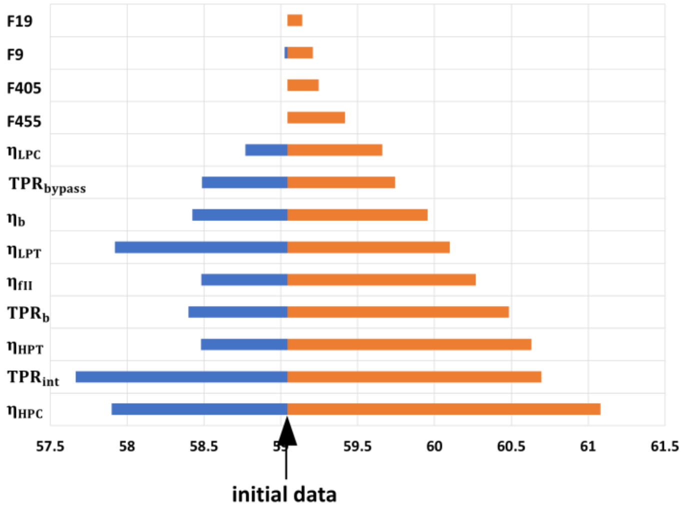


Figure 4 Tornado diagram of sensitivity analysis results for specific fuel consumption

As a result, a sequence of initial data was found by the degree of influence on the result. It was built based on an averaged sensitivity analysis of the three output parameters. The following parameters have the greatest effect on the output parameters (in decreasing order of significance): $\boldsymbol{\eta_{HPC}}$, $\boldsymbol{TPR_{int}}$, $\boldsymbol{\eta_{LPT}}$, $\boldsymbol{\eta_{HPT}}$, $\boldsymbol{TPR_b}$, $\boldsymbol{\eta_{fII}}$. For this sequence, a study was carried out in which the scatter of specific fuel consumption was sequentially calculated using the created stochastic model of the engine workflow for the first 2, 3, 4, 5, and 6 variables of the series. The results are shown in Fig. 5.

As can be seen from the results, the spread of SFC values changes little after considering more than 5 most influencing variables, and then the degree of change in the result becomes less and less. Obviously, considering the last variables, due to their small influence on the result, does not significantly change the result.

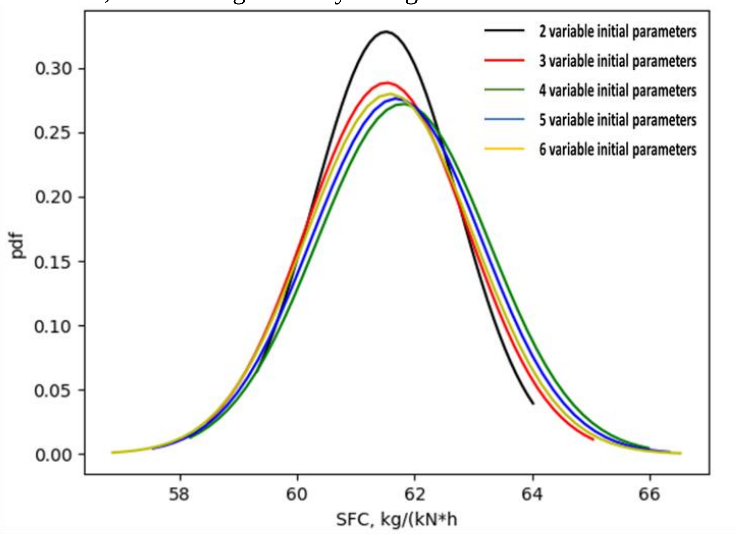


Figure 5 Influence of the number of considered variables ordered by the importance of the initial data sequence on the results of calculating the stochastic value of SFC

COMPARISON OF STOCHASTIC RESULTS OF EXPERIMENT AND CALCULATION

As a result of the carried out stochastic calculation with the sorting of uncertain data according to the degree of influence, a probabilistic spread of the value of specific fuel consumption and other important output parameters was obtained at the engine operating mode with the thrust P = 8.75 kN. These data were transformed into a bell of bivariant distribution on the graph of the dependence of the parameter of interest on the operating parameter (total air mass flow rate) (Fig. 6). The same graph shows a similar bell obtained from experimental data.

In the traditional deterministic approach, the results of the calculation and experiment on the graphs are given by points. Their discrepancy is in the form of two differences which are deviations along two coordinate axes. Considering that the errors in the determination of the compared points are not considered, the found discrepancy has an error, the value of which is not known. The stochastic approach provides an accurate description of the possible dispersion of the mismatch.

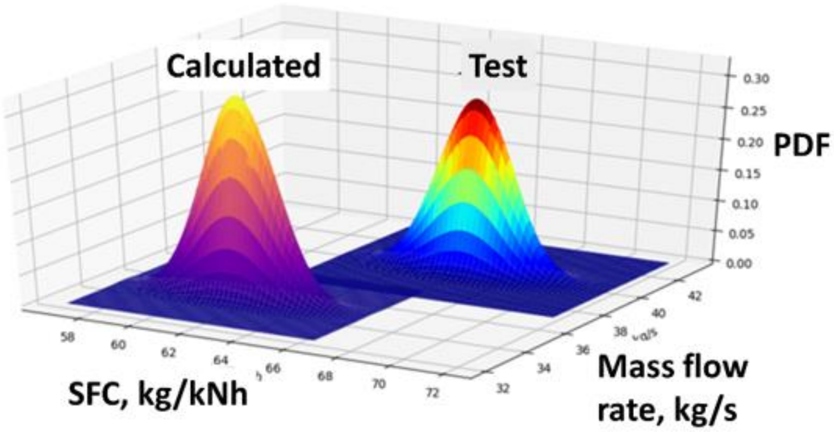


Figure 6 Comparison of bivariant distributions for the SFC from the total mass floe rate through the engine at P=8.75 kN obtained in calculation and experiment

As seen from Fig. 6, the calculated and experimental data are described as a probability distribution bell with the stochastic approach. To find the discrepancy with the stochastic approach, it is necessary to find the difference between all points, considering the probability of the event. As a result, the discrepancy between the calculation and experiment data is a bell of the bivariant distribution, which is described by two parameters: the expected value of the difference and the standard deviation for the two coordinate axes.

The result of comparing the calculated and experimental points for the mode P = 8.75 kN, obtained using the created stochastic model, is shown in Fig. 7.

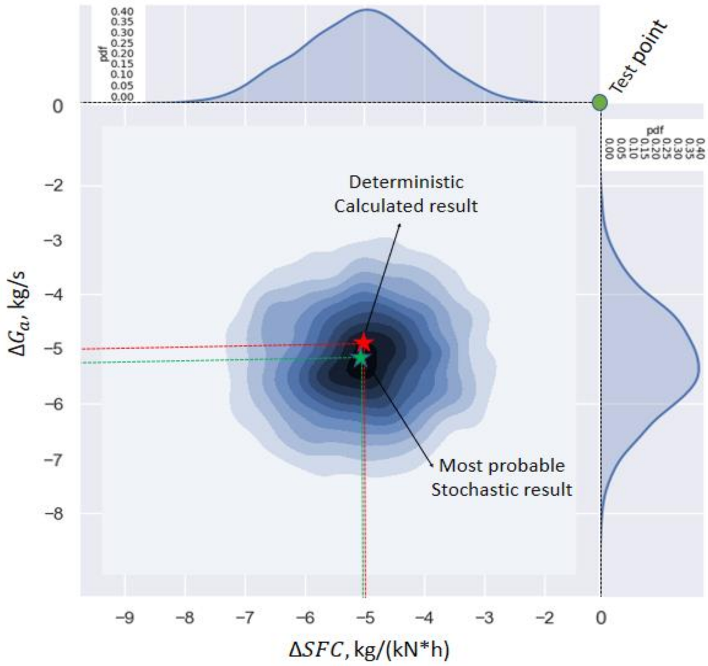


Figure 7 Bivariant distribution of the difference of the experimental and calculated SFC values for the AI-25 engine when operating at P=8.75 kN mode

This distribution is characterized by the following numerical values:

- expected value of the difference in air flow rates $\sigma_{SFC} = -5.02825$ kg/sec;
- expected value of the difference in specific fuel consumption expected value - rates $\mu_{SFC} = -5.1907$kg/kNh;
- standard deviation of the difference in air flow rates $\sigma_G = 0.2365$;
- the standard deviation of the difference in specific fuel consumption $\sigma_{SFC} = 0.220061$.

It should be remembered that the real value of the difference can be located anywhere on the bell. The resulting numbers show the likelihood of gaining a difference. It is obvious that the closer the calculation results to the experimental one, the closer the expected value and sigma to 0.

CONCLUSION

During the study, the following results were obtained.

A stochastic method was developed and tested for determining the probability distribution of the output parameters of the engine mathematical model considering the uncertainty of the initial data.

It was found that a feature of the stochastic model is a huge number of iterations with the computational model. For this reason, at the current level of development of computer technology and using the created mathematical model, it is not possible to study the influence of more than 7...8 parameters on the probabilistic distribution of output parameters even using simple mathematical models.

It was shown that the difference between the stochastic results of calculation and experiment can be displayed as a scattering bell and described by 4 numerical criteria characterizing the bivariant probability distribution.

Numerical criteria for comparing experimental and calculated data were found, considering the uncertainty of the initial data and the experimental error.

A method was developed to reduce the number of iterations with the computational model in the stochastic method for determining the probability distribution of output parameters by excluding the least influencing input data from consideration.

It should be noted that the obtained results, are universal in nature and can be applied with other mathematical models in various industries although they were developed on the example of a mathematical model of a gas turbine engine.

NOMENCLATURE

F	flow area;
G	mass flow rate;
H	flight altitude;
m	bypass ratio;
M_{fl}	flight Mach number;
p	pressure;
P	thrust;
P(x)	probability;
T	temperature;
TPR	total pressure recovery coefficient;
SFC	specific fuel consumption;
σ	standard deviation;
μ	expected value of a variable;
π	pressure ratio;
Δ	relative deviation of the value from the mean;
η	efficiency
f	fuel-related;
LPC	low pressure compressor;
HPC	high pressure compressor;
HPT	high pressure turbine;
LPT	low pressure turbine;
UQ	uncertainty quantification;
Σ	total;
h	atmospheric;
fII	related to the fan;
int	related to the input device;
n	related to the nozzle;
cc	related to the combustion chamber;
405	section in the HPT throat;
455	section in the LPT throat;
9	section at the outlet of the main duct nozzle;
19	section at the outlet of the secondary duct nozzle;
GTE	gas turbine engine;
MCM	Monte Carlo method.

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