CALIBRATION OF MICROPROCESSOR CONTROL SYSTEMS FOR SPECIFIED LEVELS OF ENGINE EXHAUST TOXICITY

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Abstract

A fast experimental procedure for the calibration of internal combustion engines microprocessor control systems is proposed. This procedure is based on using a new approach to the solution of many-parametric optimization problems with constraints. The main benefit of this approach is that it requires a minimum number of experimental measurements where the measurements can have a high level of noise stability to the inaccuracy of measurements and adjustments. The efficiency of the suggested procedure is demonstrated by the search for air-fuel ratio, ignition timing and exhaust recirculation optimum bounded control that provide for the minimum fuel consumption for each speed-load regime at a given emission level. The optimization problem was defined by three variables and three constraints. The optimization criterion extremum value was found in 14 direct calls to the mathematical model computing the objective function. Ten tasks with different initial points of search have confirmed these results. The comparative analysis of the method efficiency with other well-known non-linear programming methods (the methods of Powell and Nelder-Mead) has shown the advantage of the proposed procedure that required only one-third of the experiments needed by these algorithms.

Key Words: automatic control, evolutionary optimization, engine exhaust toxicity, engine fuel efficiency

Introduction

Achieving high efficiency of automotive engines at a specified level of exhaust gases' emissions poses a problem of many conflicting demands. Satisfying such demands could be achieved by using a microprocessor control system (MS). The optimum control of the elements regulating the engine is mainly realized through an appropriate selection of all control contours calibration. The toxicity and efficiency of an engine are evaluated according to their integral indexes for the sum of regimes of the working cycle. Therefore, calibration of the MS requires the solution of complex multi-parametric and multi-objective problems of optimization. A practical approach to calibrating the MS often employs decomposition [1]. The purpose of decomposition is the substitution of integral limits for local ones and the substitution of a common problem for a set of local problems with a relatively small dimensionality. This approach permits the development of the optimum calibration by taking into account real features of the automotive engines.

When using the experimental data for the calibration of MS, it is necessary to use fast optimization methods that allow us to make a decision based on a small number of experiments. It is known that the efficiency of the classic methods of non-linear programming (MNP) depends on topology of the objective function and constraints. The experience accumulated during the solution of a number of real MS calibrating problems confirmed that the topology of the objective and the constraint functions are not only complex, but could be different according to their classifications - even, uni-modal, multi-extremal, raven, etc. In case of the absence of *a priori* information about the objective function and constraints topology, it is difficult to choose the proper method of the non-linear programming. Our experience in some practical optimization and control problems allows us to state that the highest effectiveness can be achieved with a help of structured parametric optimization methods that are practically invariant to the topology of the functions to be optimized and that allow for the automatic adaptation of the search parameters during the process of the extremum searching.

The Indirect Optimization method based on Self-Organization (IOSO) is the algorithm that was developed by the lead author [2] and has been used for the solution of these types of problems [3-8]. IOSO is a novel evolutionary optimization algorithm for the robust solution of complex practical problems characterized by the following features.

1 Ability to deal with complex and not *a prori* known topology of the objective function space and constraints.
2 Ability to find a global minimum with a minimum number of numerical or experimental evaluations of the objective functions.
3 Ability to deal efficiently with the large dimensionality of the problem to be solved (up to 100 variables and more);
4 Ability to deal with non-differentiable objective functions.

Summary of IOSO Algorithm

The *multi*-objective optimization problem maximizes a vector of n objective functions

$$\max\ F_i(\bar{x}) \qquad \text{for } i = 1, \dots n \tag{1}$$

subject to a vector of inequality constraints

$$g_j(\bar{x}) \leq 0 \qquad \text{for } j = 1, \dots m \tag{2}$$

and a vector of equality constraints

$$h_q(\bar{x}) = 0 \qquad \text{for } q = 1, \dots k \tag{3}$$

In general, the solution of this problem is not unique. Classical gradient-based optimization algorithms are capable, under strict continuity and derivability hypotheses, of finding the optimal value only in the case of a single objective. For these algorithms, the problem of finding the group of non-dominated solutions (the Pareto front) is reduced to several single objective optimizations where the objective becomes a weighted combination of the objectives called utility function. Multi-objective optimization algorithms based on a genetic algorithm have been successfully applied in a number of engineering disciplines. However, for a large number of design variables and objective functions that need to be extremized simultaneously, this approach becomes progressively too time consuming and unreliable for practical applications in industry.

With the introduction of the Pareto dominance concept the possible solutions are divided in two subgroups: the *dominated* and the *non-dominated*. The solutions belonging to the second group are the "efficient" solutions, that is, the ones for which it is not possible to improve any individual objective without deteriorating the values of at least some of the remaining objectives. At the present time methodologies are being intensively developed for the multi-disciplinary analysis and optimization of entire systems.

Our approach is based on the widespread application of response surface technique, based upon the original approximation concept, within the frameworks of which we adaptively use global and middle-range multi-point approximation. One of the advantages of the proposed approach is the possibility of ensuring good approximating capabilities using a minimum amount of available information. This possibility is based on self-organization and evolutionary modeling concepts [3]. During the approximation, the approximation function structure is being evolutionarily changed, so that it allows successful approximation of the optimized functions and constraints having sufficiently complicated topology. The obtained approximation functions can be used by multi-level procedures with the adaptive change of simulation level within both a single and multiple disciplines of object analysis, and also for the solution of their interaction problems.

Every iteration of IOSO consists of two steps. The first step is the creation of an analytical approximation of the objective function(s). Every iteration in this step represents a decomposition of the initial approximation function into a set of simple approximation functions so that the final response function is a multi-level graph. The second step is the optimization of this approximation function. This approach allows for corrective updates of the structure and the parameters of the response surface approximation. The distinctive feature of this approach is an extremely low number of trial points to initialize the algorithm.

The obtained response functions are used in the multi-level optimization while adaptively utilizing various single and multiple discipline analysis tools that differ in their level of sophistication. During each iteration of IOSO, the optimization of the response function is performed only within the current search area.

This step is followed by a direct call to the mathematical analysis model or an actual experimental evaluation for the obtained point. During the IOSO operation, the information concerning the behavior of the objective function in the vicinity of the extremum is stored, and the response function is made more accurate only for this search area. While proceeding from one iteration to the next, the following steps are carried out: modification of the experiment plan; adaptive selection of current extremum search area; choice of the response function type (global or middle-range); transformation of the response function; modification of both parameters and structure of the optimization algorithms; and, if necessary, selection of new promising points within the researched area. Thus, during each iteration, a series of approximation functions for a particular objective of optimization is built. These functions differ from each other according to both structure and definition range. The subsequent optimization of these approximation functions allows us to determine a set of vectors of optimized variables.

Examples With *a Priori* Known Exact Solutions

Following is an example of using this procedure and IOSO software for solution of real-life emission control problems in Russian car companies such as AvtoVAZ, ZMZ, UMZ and others [2]. Specifically, effectiveness of the method of quick search for optimum adjustments of the automotive engine control system by utilizing IOSO algorithm was demonstrated on a mathematical model for VAZ-2110 car engine. It allowed us to determine the solution of the optimization problem that enabled the search of air-fuel ratio, ignition timing and exhaust recirculation optimum bounded control. For each speed-load regime it was necessary to find the appropriate values of these three control parameters (air-fuel ratio, ignition timing and exhaust recirculation) that provide minimum fuel consumption (the optimization objective) at the limited (specified or constrained) emission levels of CO, NO and CH.

At the initial stage, the optimization is performed in a deterministic setting that supposes the existence of a feasible constrained part of the objective function space. It also assumes that the evaluations of the optimization objective function and the constraints are performed without errors. During the optimization process it was assumed that the *a priori* information about the topology of the objective function and the constraints is unavailable. Consequently, the initial accumulation of information was performed by random generation of a certain set of variable parameter vectors in the area of search. Figure 1 shows the examples of the solution of an optimization problem with 10 different sets of initial points. It is evident that IOSO algorithm is capable of finding the unique global extremum solution after only 14 calls to the evaluation of the objective functions despite the fact that there were 10 widely different initial guesses. Comparison of IOSO algorithm with typical well-known nonlinear programming methods (the methods of Powell and Nelder-Mead) demonstrates the advantage of the suggested method that is more than three times faster (Fig. 2). However, in practice, the presence of errors is inevitable when determining the optimization objectives and constraints and when applying the preset values to the engine variable parameters. It is important to understand that in our case the matter is not about the systematic measuring errors, but about random deviations of actual values of regime parameters from preset ones and about random deviations of measured values from their real values. The existence of such random errors requires a method for optimization of a stochastic objective function with stochastic constraints.

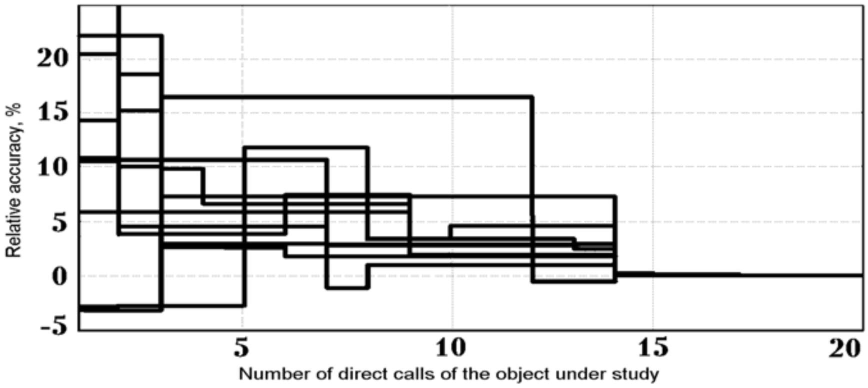

Fig. 1 Dynamic of extremum search under different initial conditions

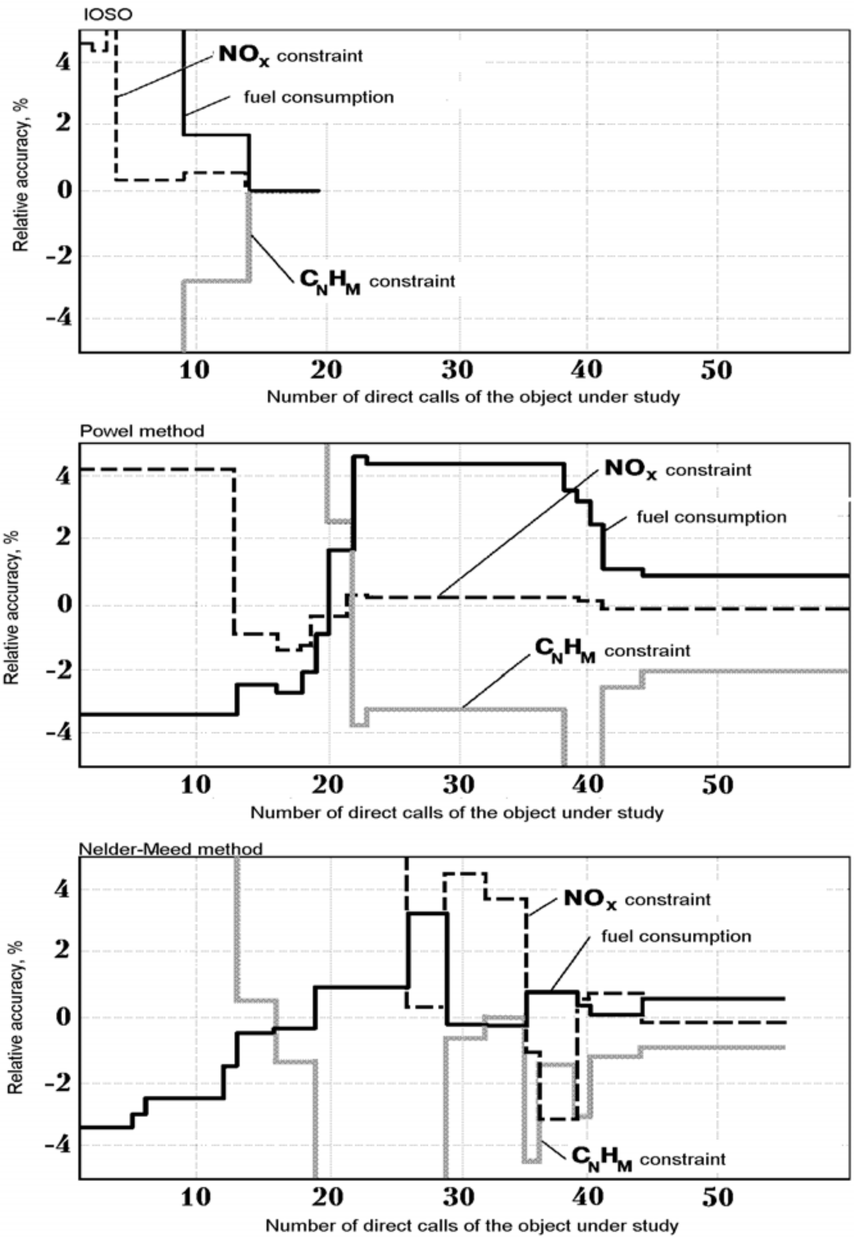

Fig. 2 Comparison of the various methods efficiency

Following is a methodical investigation of the influence of an average-level of random errors on the efficiency of the optimization process based on the accuracy of the solution of the problem and the number of calls to the object function evaluation under study. For simplicity of analysis, deviations of all considered random values (crankshaft rotation frequency, power output, fuel consumption, exhaust emission levels) were assumed to have normal Gaussian distribution law with zero shift and the given level of the standard deviation "σ". The investigations were performed for the values of "σ" = 0.1%; 0.3%; 0.5%; and 1.0%, which approximately corresponded to the capabilities of the available experimental apparatus.

For each value of "σ" the solution of 10 optimization problems with different initial data was performed with IOSO, Powell method and Nelder-Mead simplex method. The optimization process was terminated when a solution with the required accuracy was achieved. Then, evaluation of the mathematical expectations of the needed numbers of the direct calls to the object function evaluation, fuel consumption and the limited parameters in the point obtained was performed. Some results of this investigation are shown in Fig. 3. One can see that for all considered optimization methods the increase of the disturbance level leads to the increase in the number of calls to the object function evaluation and to decrease of the solution's accuracy. In particular, the increase of the average fuel consumption appears to cause violation of the specified average values of the exhaust toxicity levels. The analysis of the results demonstrates (Fig. 3) that IOSO optimization algorithm provides essential advantages in comparison with two other optimization methods both in terms of a lower number of calls to the objective function evaluation and in terms of lower fuel consumption and a lower level of exhaust toxicity deviation from their specified values.

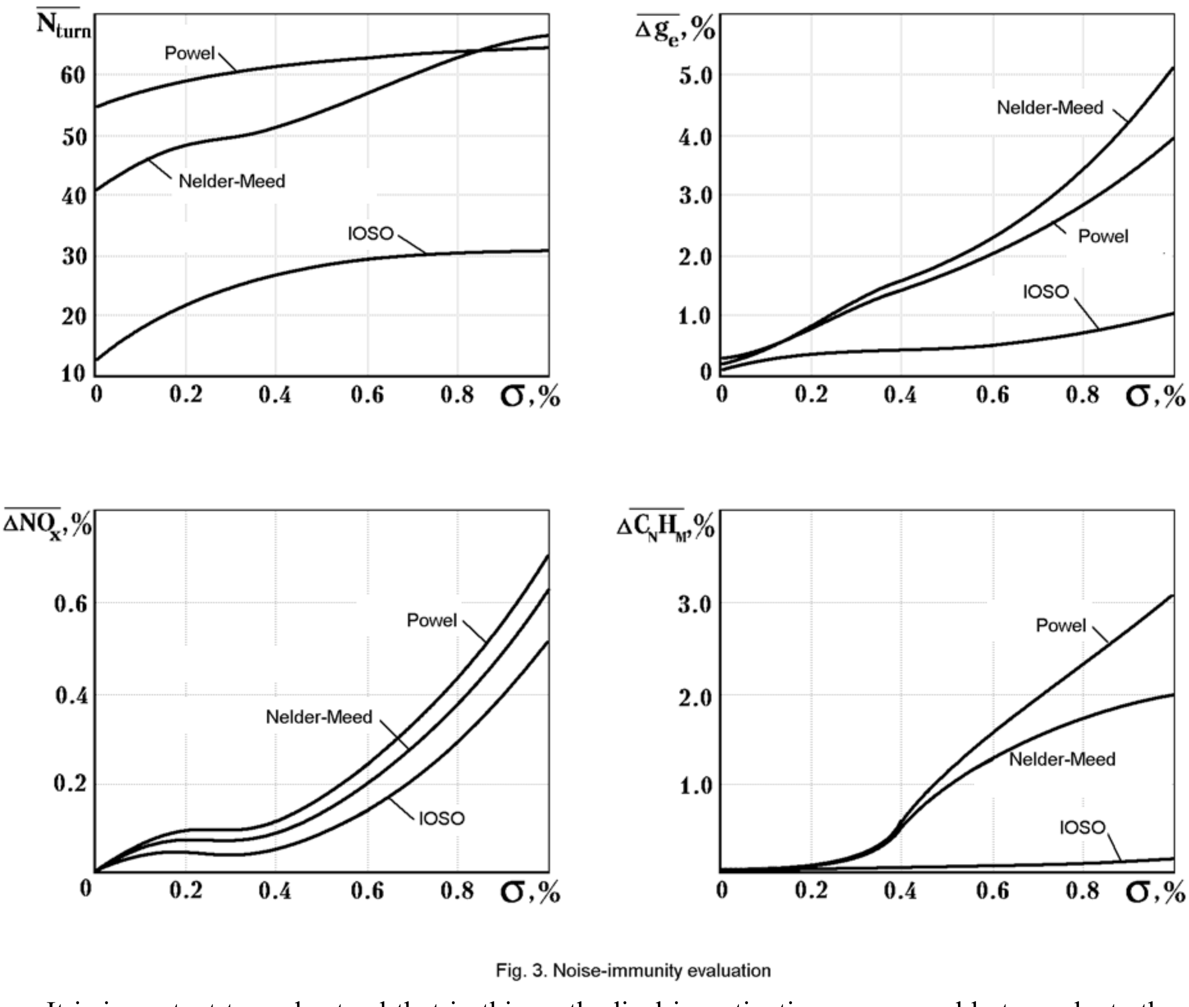

Fig. 3. Noise-immunity evaluation

It is important to understand that in this methodical investigation we were able to evaluate the solution quality, because the accurate solution was known *a priori*. In realistic situations the accurate solution is unknown. As a consequence, the low disturbance immunity of the optimization method can result not only in the considerable increase of the control system microprocessor optimum calibration time, but also degrades the engine characteristics obtained. Thus, the performed investigation shows that

1. IOSO allows an effective solution to the problem of the MS calibration,
2. Small number of direct evaluations of the object under study is needed,
3. IOSO efficiency is practically independent of the starting-procedure, and
4. IOSO method is capable of obtaining the solution even when the random errors exist in the process of the experimental calibration.

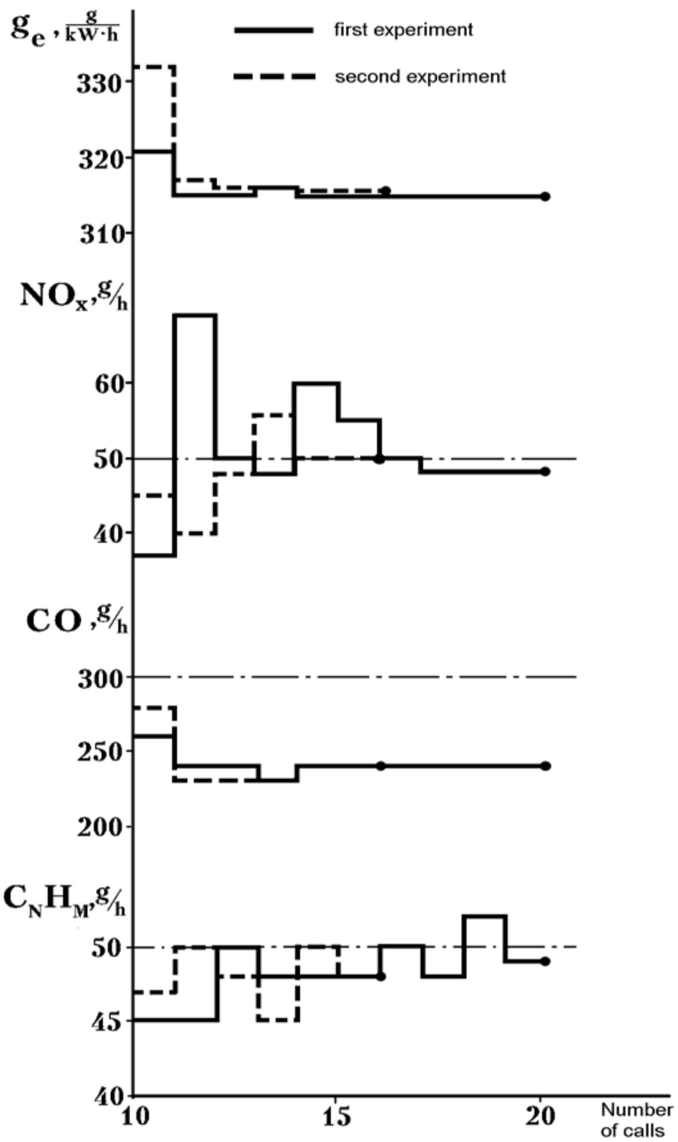

Fig. 4. Dynamic of experimental search

(constraints : NO_x-50 g/h , CO-300 g/h , C_NH_M-50 g/h).

A Real-Life Example

As a real-life demonstration of its capabilities, the efficiency of the suggested optimum control method was experimentally checked on a 16-valve engine with V = 1500 cm^3. The engine was equipped with the MS which included the electronic system of the fuel supply with the feedback on the λ-probe, ignition timing control system, turbulent flow intensity control system (tampers in the inlet collector are dosing the quantity of the gang air through one of the two inlet dampers for each cylinder) and the system of the exhaust recirculation optimum control.

As an illustrative example we chose the regime from the driving cycle area that has the essential timing "weight" in the matrix of the equivalent regimes corresponding to $n=2500\ min^{-1}$ and torque $M_e = 40\ Nm$. For the evaluation of the search algorithm the number of the controlled parameters was limited to three variables: ignition timing, exhaust recirculation and the intensity of turbulence in the flow. Such a set of independent variables corresponds to the concept of engine with a 3- components neutralizer ($\alpha = 1.0$) and a system of the exhaust recirculation optimum control for the purpose of increasing fuel economy and decreasing toxic characteristics of the engine. In order to exclude the possibility the detonation combustion, each time when the detonation occurs the objective function was penalized with the "jump" -like penalty.

Two experiments using IOSO were performed. The allowable ranges of the permissible values were limited as follows. Turbulent flow intensity was limited by the location of the turbulence flow dampers control from 0^o to 60^o (maximum turbulence flow). Exhaust recirculation (ER) was allowed to vary from 0% to 25% and the ignition timing (IT) from 10^o to 60^o. The optimization program chose the initial 10 points by utilizing a random number generator.

Figure 4 shows the optimization history of the optimum control search in the laboratory. Following values of accuracy "σ" of the preset and measured parameters were realized: n – 0.1%; Me –0.5%; turbulence flow – 1.5%; ER – 3.0%; IT – 1.5% Ge –0.4%; CO – 2.0%; CH – 2.0%; NO_x – 2.0%. The archived data demonstrate that even when rather high levels of random errors exist during the process of calibration, IOSO algorithm can be used with success for the fast experimental calibration of the automotive engine microprocessor control system with only 25-30 calls to the object function evaluation.

Figure 5 and Figure 6 show the dynamic process of optimization of a real-life car engines VAZ-2112 and UMZ. Note that for optimization of the modern UMZ engine there were two stages of minimization:

1. For acceleration when $\Delta\alpha$ of throttling is being constrained, and
2. For throttling when $\Delta\alpha$ of acceleration is being constrained.

For solution of the second optimization problem we used a database that we obtained when we solved the first optimization problem. In this case, we needed only two new steps of experimental research. This shows that this procedure can use an existing database. In this case we can minimize the number of experimental data that are needed for solution of the optimization problems. Note that both experimental stands (in AutoVAZ and UMZ Company) allow up to 5.0 percent error of experimental measurements. This means that we are solving the optimization problem in a stochastic formulation and that this problem represents a robust design optimization. Figure 7 shows the experimental stand that we used for the solution of this practical optimization problem in the automotive industry.

Multi-level Optimization Approach

The typical situation when solving the problem of a car engine optimization is that a researcher has several tools for analysis of engine effectiveness indices that are distinguished according to their levels of complexity and accuracy. The high-fidelity tools can be the detailed nonlinear mathematical models and the pertinent software for the numerical implementation of these models. Or, the high-fidelity tool could be even the experimental testing rig for the engine or its components. However, the implementation of the optimization research using such tools is associated with the significant time expenditures.

On the other hand, the low-fidelity analytical models and the software for their implementation allow us to carry out the optimization search efficiently, but the validity of the obtained results can be rather low. Therefore, the optimization methods based on a combination of various levels of fidelity of the analysis tools should be used for optimization of the car engine's parameters and control laws.

The given paper introduces the multi-objective optimization procedure for car engines and their components. The procedure is based upon the adaptive use of different fidelity analysis tools. This approach is intended to minimize the number of the most complicated and costly analysis tools applications or the number of experimental data evaluations. It uses the method of indirect optimization on the base of self-organization, which permits to find numerically the Pareto-optimal set of solutions, uniformly distributed in the criteria space.

The effectiveness of the proposed optimization procedure is demonstrated by a real-life AvtoVAZ car engine.

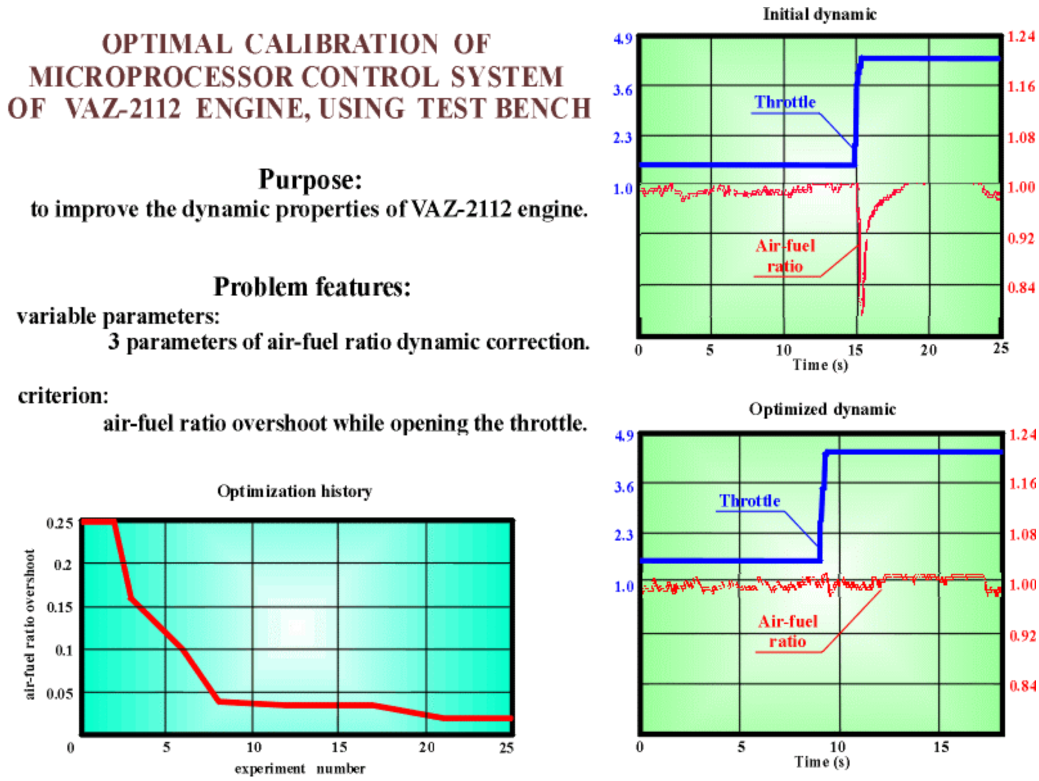

Figure 5. Optimal calibration of a multiprocessor control system of VAZ-2112 car engine to insure minimum undershoot of air-fuel ratio while opening the throttle.

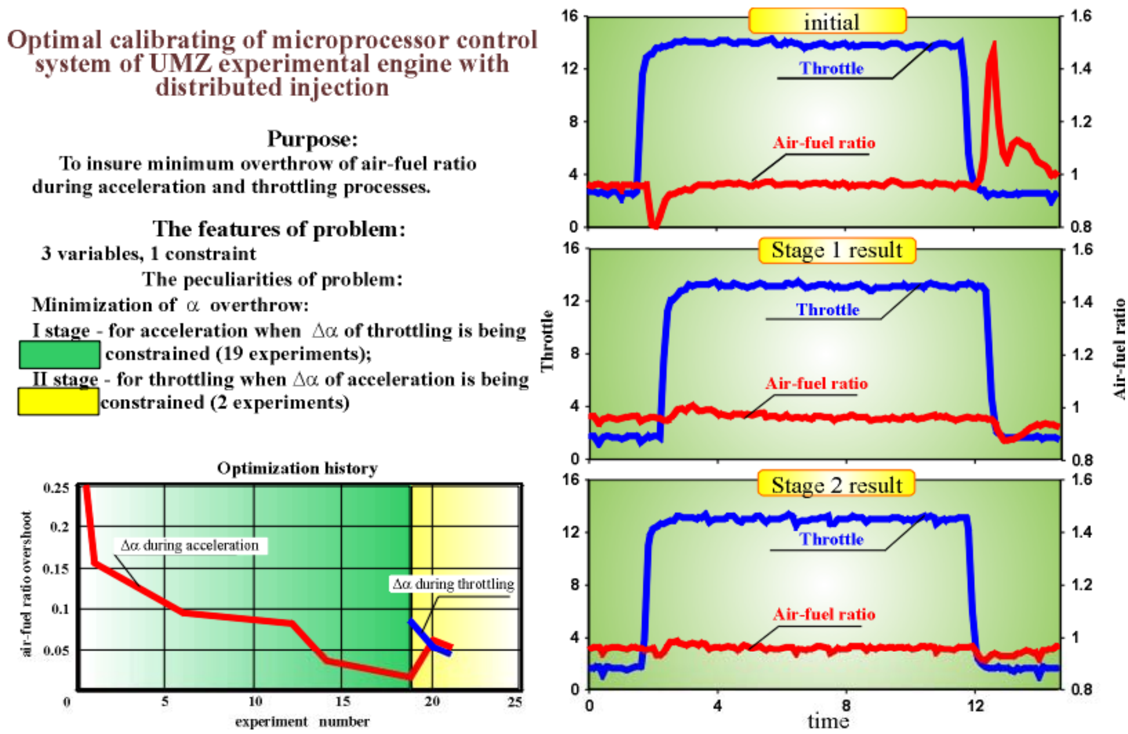

Figure 6. Optimal calibration of a multiprocessor control system of UMZ experimental car engine to insure minimum over/undershoot of air-fuel ratio during acceleration and throttling.

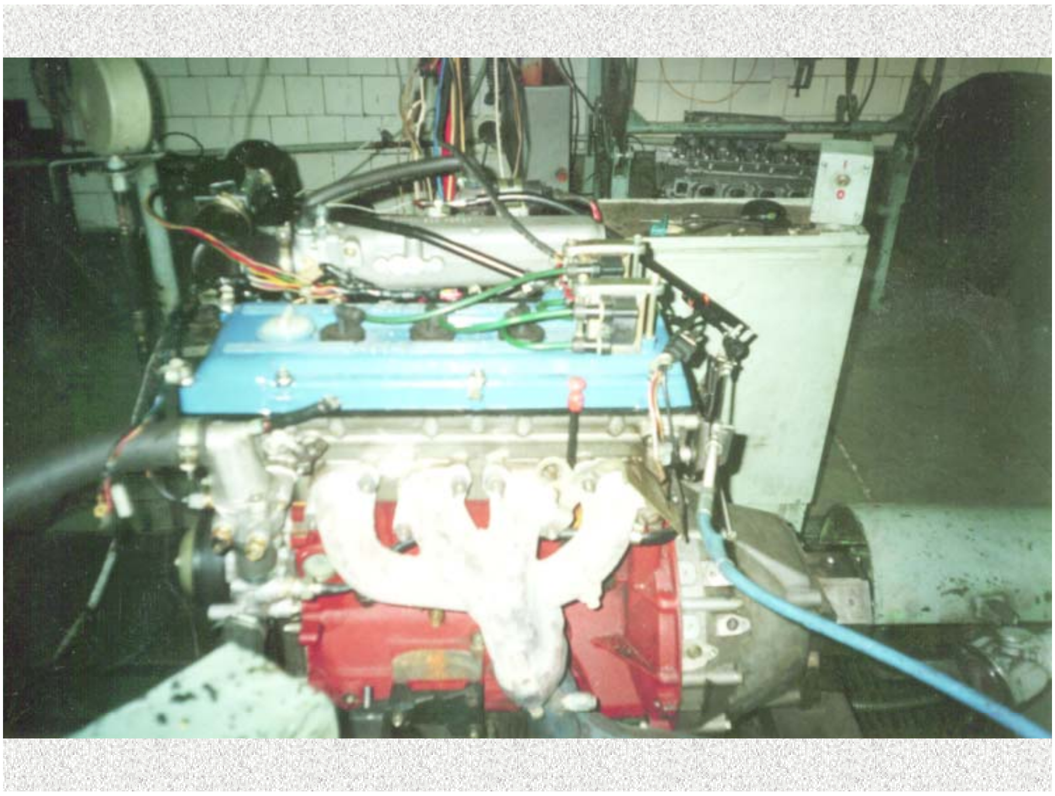

Figure 7. Experimental test stand for the AvtoVAZ car engine.

The Basic Scheme of Multi-level Optimization

The simplified scheme for the multilevel optimization procedure can be represented as follows (Fig. 8).

I) Solve the multi-objective optimization problem based upon a simplified mathematical model for the analysis. For this purpose, the method of indirect optimization based on the self-organization (IOSO) is used. This method allows finding the Pareto-optimal set of solutions numerically. The found Pareto-optimal set is uniformly distributed in the design space with respect to optimization objectives. IOSO can solve the problems of large dimensionality (tens and hundreds of variables and up to 10 simultaneous objectives). The number of solutions (degree of discritization of the Pareto set) is specified by the user and can be purposefully varied during search.

II) For the obtained Pareto set the indicators of effectiveness are updated using the high-fidelity analysis tools.

III) The identification of the simplified mathematical model is performed. Depending upon the peculiarities of the applied mathematical simulation, the identification procedure can be performed using various approaches. One such approach involves non-linear corrective dependencies construction that includes evaluation of the results deviation approximation functions obtained with different fidelity analysis tools. The other possible approach is application of internal parameters nonlinear estimation.

IV) Replacement of the simplified mathematical model by the identified one and the return to step I).

The particular features of the actual multi-objective optimization problem define the number of iterations for such a multilevel procedure. The number of applications of high fidelity analysis tools is limited to the product of the number of iterations and the number of Pareto-optimal solutions [9].

While solving the problem of optimization of complicated engineering systems the accuracy difference between high fidelity and low fidelity tools can be rather large. For such cases the series of intermediate middle-fidelity tools can be applied. The scheduling of their application during the problem solution process must be adaptively changed to minimize the temporal expenditures. This is true in multi-objective optimization as well, where the accuracy and execution speed levels of the available analysis tools for various disciplines can be substantially different.

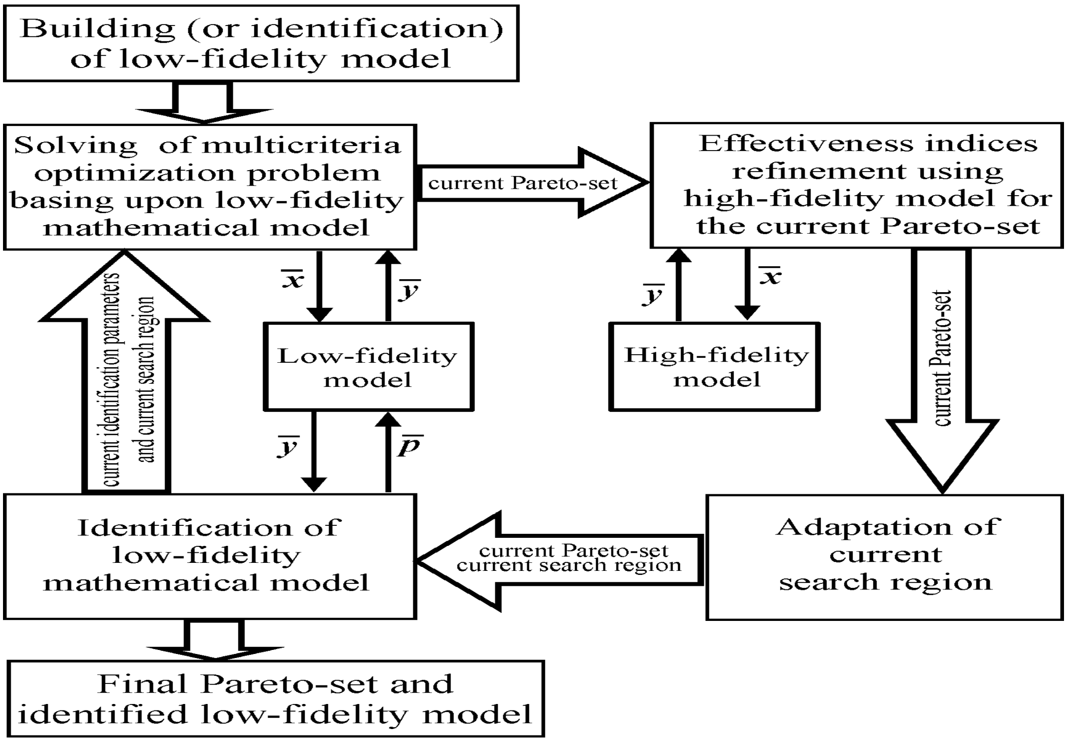

Figure 8. The scheme of multilevel optimization procedure

The information stored during the search is used to improve the simplified models. After the given analysis procedure termination, one can construct the researched object response functions. However, both identification and approximation are correct, not for the entire initial search area, but only for certain neighborhoods of the obtained Pareto set. This ensures purposeful improvement of approximating properties only in the area of optimal solutions that noticeably reduce the computing effort to construct these functions.

The developed methodical approaches considerably increase the effectiveness of complicated multiobjective optimization problems solution. The stored information for identification of the simplified analysis tools and for approximation allows expanding hierarchically the thoroughness of the problem review. It also allows for the incorporation of new disciplines in the object analysis.

A Real Life Example of IOSO for Multi-level Optimization of a Car Engine Exhaust Toxicity

In this example of the proposed multi-objective optimization, the problem is in finding the optimal control by controllable elements of an automobile internal combustion engine in order to insure minimum fuel consumption and to satisfy the legislative constraints upon the exhaust gas toxicity. The main difficulty of this problem is that the toxicity constraint is established for the entire drive cycle, that is, for some totality of load-velocity operating modes. One way to solve this problem is to decompose it, that is, to treat it as a number of auxiliary multi-objective optimization problems for each operating mode. The auxiliary problem is in search of the Pareto-optimal solutions set, while the toxicity constraints are considered as additional objectives. Let us demonstrate the specific example.

The variable parameters were air-fuel ratio, ignition timing, and exhaust recirculation coefficient for the exhausted gases. The multiple objectives were fuel consumption and toxicity indices (CO; C_nH_m; NO_x). The high-fidelity analysis tool was the actual engine on the experimental bench. The low-fidelity model was a full-square regression model.

At the initial stage of the problem solving (iteration 0) within the search region there were 16 vectors of quasi-random parameter variables generated using Sobol's generator [10]. For this set, the true (experimental) values of objectives were obtained after which a low-fidelity model was built. Then, two iterations of the developed multi-level optimization procedure were performed. The required number of Pareto-optimal solutions was specified as 16 for this problem.

The total number of actual experiments performed in the solution of this multi-objective optimization problem was 48. At the final stage, the finishing identification of a low-fidelity model was performed (model

2 was obtained). Figure 9 shows the distribution of experimentally obtained points in the parameters' space and the change of search region. Figure 10 presents the changing of average precision of the low-fidelity model. Figure 11 depicts the improvements in the prediction accuracy of the low-fidelity model during the problem solving process.

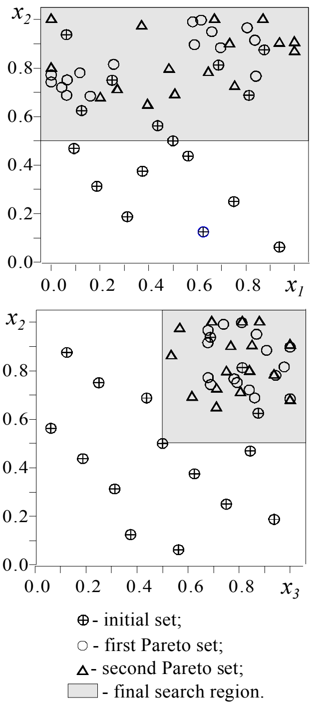

Figure 9. The search domain adaptation.

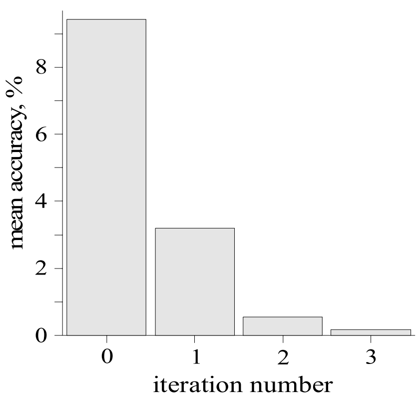

Figure 10. The low fidelity model inaccuracy reduction dynamics.

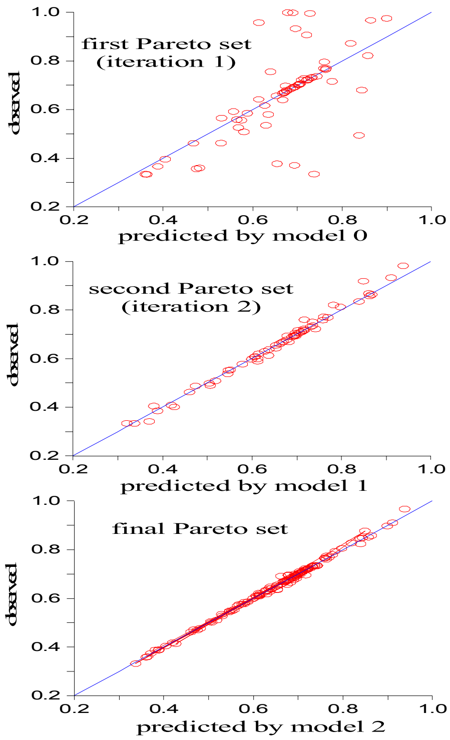

Figure 11. The low-fidelity model accuracy improving dynamics.

Conclusions

A new robust optimization algorithm (IOSO) was shown to be highly efficient and reliable tool for calibration of microprocessor control systems in internal combustion engines when toxicity levels of the constituents in the exhaust gases are specified. IOSO was demonstrated to require significantly smaller number of experimental measurements when compared to other well-known optimization algorithms used for the same purpose. A multi-level optimization approach employing low-fidelity algorithms and a high-fidelity experimental evaluation of the objective functions of complex system like car engines has been demonstrated to work remarkably efficiently in case of real car engines during transient operating regimes.

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