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To cite this article: Predrag Mrdja *et al* 2022 *IOP Conf. Ser.: Mater. Sci. Eng.* **1271** 012005

IOP Conf. Series: Materials Science and Engineering 1271 (2022) 012005 doi:10.1088/1757-899X/1271/1/012005

Internal combustion engine test plan execution order optimization using Travelling Salesman Problem heuristics approach

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Abstract. For a given internal combustion (IC) engine stationary test plan, significant time savings during its realization could be achieved if the sequence of test points execution is adequately determined. The criterion for stabilizing the engine operating point is determined by the magnitude of the change in the most inert parameter, and in the general case, it is the temperature of the engine exhaust gases. A certain level of prior knowledge about the examined object is necessary to conduct such an analysis. If there are no results from previous tests, simulation models, or experiences, the Slow Dynamic Slope (SDS) tests are a great way to quickly gather the necessary information. The task of finding the optimal sequence for a stationary engine testing plan can be set as Travelling Salesman Problem (TSP). This paper will present the application of one of the heuristic methods for solving the TSP on the example of testing the IC engine, which is a very complex dynamic system. Following this model, it is possible to optimize the stationary test plan for any other dynamic system. The basic idea is to find such a sequence of stationary operating points, during the realization of which a minor deviation of the engine exhaust gas temperature is obtained, resulting in the operating point's shortest stabilization time.

1. Introduction

The tightening of legal regulations and increasingly strict market requirements in terms of performance and comfort demand lead to a continuous increase in the complexity of the vehicle's drive system. Although the powertrain may consist of various subsystems, the central point where all information intersects is the engine control unit (ECU). Modern vehicles are equipped with numerous additional systems that can be managed by separate control units, but a certain level of communication and information exchange between the peripherals and the central ECU must exist, so that the functionality and the possibility of conducting service diagnostics are satisfied. For this reason, modern ECU counts several thousand parameters based on which the management of the drive system and other vehicle systems will be formed.

To optimally adjust the control parameters based on which the ECU will form proper system control, the so-called process of calibration of the parameters of the control unit is carried out. As a result of the increased complexity, nonlinearity, and multidimensionality of the object, the calibration of the control parameters of the ECU has become a process that requires the most significant financial and time resources during internal combustion (IC) engine and drivetrain development. The algorithm of the control unit consists of numerous functions [1] and corresponding models that can be of different complexity. Mathematical models used for these purposes are divided into complex submodels of the physical process of a given subsystem and simplified submodels in the form of control maps or curves.

The calibration and verification of mathematical models and parameters that will later be used on the ECU cannot be successfully realized without data gathered from in-laboratory engine testing. Considering the complexity of the object, the efficiency of the testing process is of crucial importance, and one of the methods that can be used for testing efficiency improvement is the Slow Dynamic Slope (SDS) method [2,3], which was the subject of earlier research [4,5].

The methods of dynamic engine testing can contribute to stationary test plan improvement in terms of determining the operating points in which the tests make the most sense [6]. However, this paper will focus on the further use of this information and determining the most efficient experiment plan execution sequence. The method that will be explained in detail consists of configuring an efficient genetic algorithm (GA) that solves this problem extremely well and reduces the time needed for engine test bench operation.

2. Dynamic Engine testing using Slow Dynamic Slope Method

The idea of the SDS test is based on a slow continuous change of the control parameter. The continuous change of control parameters over time results in deviation (offset) of the measured output of the system concerning the stationary values that will occur if the test was carried out as a quasi-stationary. The values and position of the offsets will depend on the system's characteristics (system gain, time constants) and the slope of the input. In the ideal case, when increasing the value of the control parameter during a test, we expect this offset to have some constant value, and when decreasing this parameter by the same intensity in the opposite direction, we expect the offset to be symmetrical. By determining the mean value of the response during the ascending and descending control slopes, an approximation is obtained that adequately corresponds to the results of the quasi-stationary test.

During dynamic test sequences, the engine load parameter (represented as Effective Torque M_e) was varied while the Engine Speed (n) was kept at a constant level. After the test was completed, the Engine Speed was successively changed until the entire global operation field of the engine was covered.

Two concepts of this type of examination were carried out:

- Tests with stationary preparation (Figure 1) during which the dynamic sequence begins with the stationary engine operation (curve index S),
- Tests with dynamic preparation (Figure 2) during which no parts with a stationary operation are applied (curve index D).

Also, each dynamic engine load pass is configured with a different total ramp time, i.e., a different gradient of the ascending and descending slope function. To see the effect of the speed of change of the control parameter on the final results (thus system response), the duration of the experiment was varied from 120 s to 600 s for each examined Engine Speed. The revolutions were kept constant in the range of 1500 to 3000 min^{-1}.

Each of these tests has certain specific advantages and disadvantages [6], but at this point, it should be noted that the SDS data were used to quickly collect information and generate approximate stationary results on a wide engine operation domain, and later that results will serve to optimize the detailed stationary test plan.

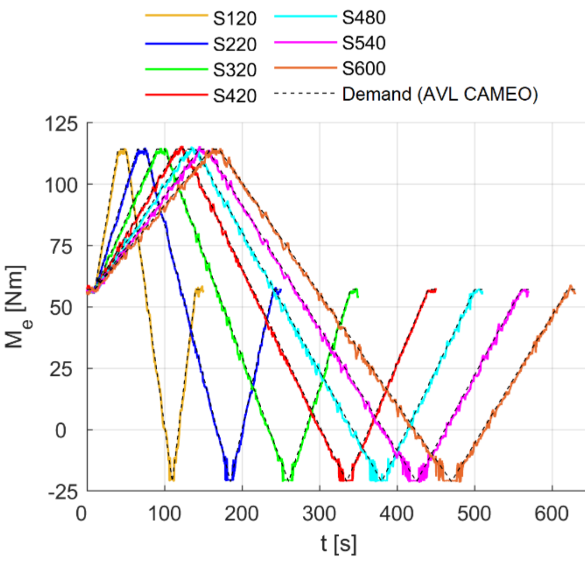

Figure 1. Engine load change for SDS tests with stationary system preparation at 1500 min^{-1}.

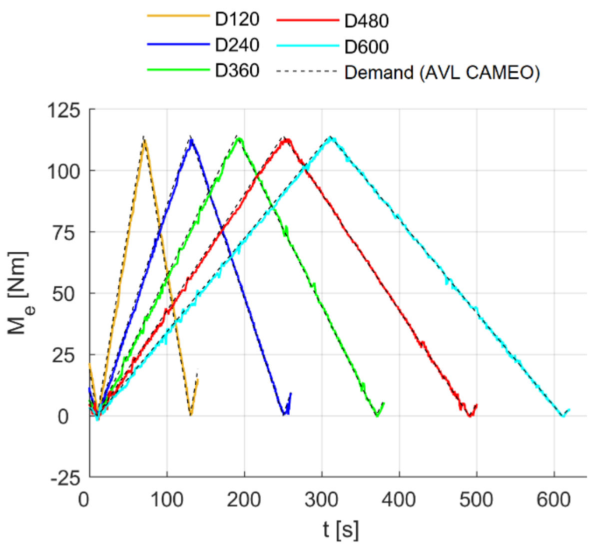

Figure 2. Engine load change for SDS tests with dynamic system preparation at 1500 min^{-1}.

3. Experimental Setup

The highest level of the engine test bench automation implies centralized supervision and control of all subsystems. The commercially available platform AVL PUMA Open [7] incorporates dyno control, control of other measuring devices, including a system for determining the composition of exhaust gases and analysis of the combustion process by engine indication, implementation of automated test plans with the possibility of calibrating the control parameters of the control unit. The use and maintenance of such a platform require exceptional financial and engineering resources and are justified in the companies of the global automotive industry. Automated engine test plans are implemented using commercially available software to define them; in this particular case, the AVL CAMEO software was used [8]. The AVL PUMA Open software's basic functionality in communication between the AVL CAMEO software and the Rotronics [9] brake controller, which does not support an interface for AVL CAMEO, is implemented within the NI LabVIEW programming environment. The AVL CAMEO software is an engineering tool that enables complete management of the test bench for engine testing, calibration of control parameters, and formation of simple mathematical models of parameters that characterize the engine working process. This software is primarily intended for testing the IC engines, but newer versions also provide support for testing hybrid powertrains and engines with a gearbox assembly. For this research purpose, the software module Test & Measure [8,10] was used and could be characterized by the following capabilities:

- Formation and execution of the IC engine test plan based on the factorial design concept and other Design of Experiment (DoE) methods;
- The possibility of optimizing the test plan by iterative means (direct model-based calibration);
- Connecting to application systems of engine control units (ECUs) through standardized interfaces, with the most significant support for the ETAS INCA software environment [11];
- Possibility of integration with the AVL PUMA Open system. By automating the test table, it is possible to send centralized commands for acquisition control and collect information about the statistical measurement values at the currently tested engine operation point;
- If the engine test plan is too extensive, there is support for networking test benches.

Thanks to the automated engine test bench and the SDS test method, Figure 3 shows the approximate results of exhaust gas temperature (T_31) measurements at the inlet section of the turbine for a wide operation field of the IC engine obtained in only 20 minutes of testing. Figure 4 shows the relative deviations compared to reference stationary tests of the same parameter (T_31). It is noted that the deviation is in the range of ±15%, but the trend of the change of T_31 has been obtained, and it will serve for further analysis and determination of the "almost" optimal sequence of execution of the stationary test plan. The engine under test was automotive PSA 1.4 HDI (40 kW at 4000 min^{-1}).

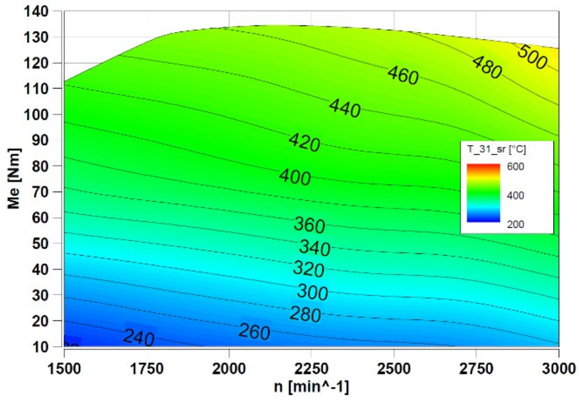

Figure 3. The exhaust gas temperature (T_31) during SDS with stationary preparation and 120 s sweep duration (S120).

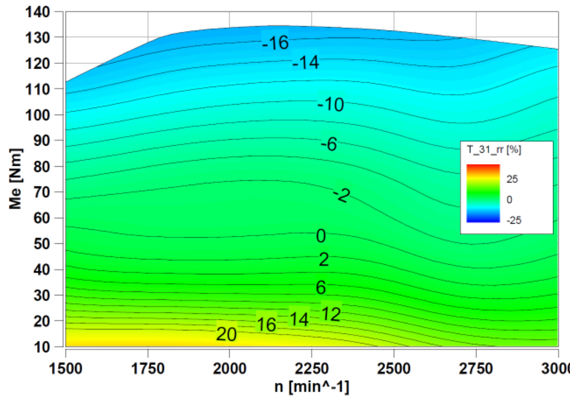

Figure 4. Relative change of T_31 gathered by SDS S120 test compared with stationary testing results.

4. Determining the optimal execution sequence for a stationary test plan

Assuming that a sufficiently good test plan exists, further time savings in its execution can be achieved if a favorable sequence of execution of the operating points is determined. As was emphasized, the criterion of stabilization of the operating point is determined by the magnitude of the change of the most inert parameter, and in the general case, it is the temperature of the engine exhaust gases. The basic idea is to find such a sequence of stationary operating modes, during the implementation of which a minor deviation of the engine exhaust gas temperature is obtained. This will result in the shortest stabilization time for a given series of operating points.

According to some predefined criteria, determining the favorable sequence of execution of operating points belongs to the category of optimization problems called "Traveling Salesman Problem" (TSP). The basic wording reads:

- For a given list of cities and their mutual distances, what would be the shortest possible route, such that each city is visited only once and after completing the tour of all cities, the merchant returns to the city from which he started?

The TSP mathematical formulation represents one of the most frequently considered numerical optimisation problems [12]. Algorithms were developed to determine possible solutions, and it was concluded that there is no way to solve this problem correctly except for an exhaustive search. The problem is that it is impossible to define a rule that would reduce the number of attempts to find a solution to a number smaller than the total number of solutions, that is, the total number of path combinations.

There are several different mathematical formulations of TSP, and the basic formulation is Dantzig-Fulkerson-Johnson [13] of the following form:

$$\min \sum_{i=1}^{p} \sum_{j=1}^{p} d_{ij} x_{ij} \tag{4.1}$$

$$\sum_{i=1}^{p} x_{ij} = 1, \qquad i = 1,2, \dots, p \tag{4.2}$$

$$\sum_{j=1}^{p} x_{ij} = 1, \qquad j = 1,2, \dots, p \tag{4.3}$$

$$\sum_{i \in S, j \in S}^{p} x_{ij} \leq |S| - 1, \qquad S \subset \{1,2, \dots, p\} \tag{4.4}$$

$$x_{ij} = 0 \vee 1, \qquad \forall i, j \tag{4.5}$$

for nodes i and j , mutual distances $d(i,j)$ and for coefficient x_{ij} which takes the values $x_{ij} = 0 \vee 1$ depending on whether the route between nodes i and j belongs to the final optimal path. The first equation defines that it is necessary to minimize the total distance. The following two equations limit the number of branches of each node to one incoming and one outgoing branch. Equation 4.4 prevents the creation of sub-routes, i.e., routes that contain a smaller number of nodes (cities) than a total of p nodes.

TSP has numerous applications in designing logistics and optimizing production processes. Just as the number of points (cities) is one of the parameters in defining the problem, the values that quantify the relationships between them (distance) can be expressed through money, time, or some other parameter. In the case considered here, there are p engine operating points that need to be tested, and the relation between them is represented by the approximate value of exhaust gas temperature T_31. Given that during the stationary engine testing, there is no need to repeat the operating point by returning to the initial one, the case of an open TSP will be considered. Also, the repetition of one or more operating points is not of interest (nodes or branching), so the total number of potential sequences for executing the test plan can be described by the equation:

$$N = \frac{p!}{2} \tag{4.6}$$

where p is the number of points of the considered test plan, and dividing by 2 is the consequence of the formation of identical paths, only in the opposite order. For an examination plan of $p = 45$ points, an approximate $N \cong 6 \cdot 10^{55}$ potential combinations of execution order. Solving TSP by exhaustive numerical search belongs to the category of algorithms of factorial dependence of execution duration as a function of the number of parameters. Due to many such combinations, it is impossible to realize (execute) a program that will find the optimal solution through an exhaustive search on an ordinary computer.

The simplest algorithms are based on local path optimization. For this very reason, they are not able to globally optimize the problem [14], and the well-known among them are the Nearest Neighbor Algorithm, Cheapest Insertion Algorithm, Nearest Insertion Algorithm, Christofides Algorithm, and Replacement of pairs of routes (2-OPT, 3-OPT, 4 -OPT, k-OPT).

5. Genetic Algorithm configuration for stationary engine testing optimization

Genetic algorithms are based on the principles of natural processes of selection and evolution [15, 16]. Unlike simpler algorithms for solving TSP, where only the current solution and its quality are considered in the observed iteration, genetic algorithms (GA) perform a simultaneous search of a larger population of potential solutions. For this reason, GAs belong to the category of heuristic search algorithms. Such algorithms are often called metaheuristic because they are not based on an exclusively random search for the best solution, but rather the following series of steps are carried out:

- Upon initialization, a certain number of random sequences (vectors) are generated. Vector elements represent the indices of the operating points for which the minimum is to be determined by the criteria. One such array represents a potential solution to the TSP and is called a path vector;
- After forming a given number of such vectors, the value of the criterion function is determined, i.e., the total path length for each path vector is determined. This identifies better solutions that will be considered in the further steps of the algorithm, while worse solutions are rejected;
- A reduced number of path vectors that have undergone selection (parents) are subjected to so-called mutations, i.e., random changes, which form new path vectors (offspring). In addition to the changed path vectors, the previous path vectors (parents) are also passed into the next iteration because it can happen that the mutation had a negative effect even though the initial vector (parent) has potential, i.e., a quality genetic code in the sense of having parts of the route that are an integral part of the optimal solution (or are close to the optimal solution);
- In the iterative process, the selection is performed according to the value of the criterion function and certain mutations, which ensures the transfer of the best genetic material, i.e. parts of the path within the TSP, to the next iteration. The condition for stopping the GA can be the control of the change of the final solution or the total number of iterations. If the algorithm is well-adjusted, a sufficiently accurate solution (almost optimal) should be obtained after a certain number of iterations.

Genetic algorithms enable a high level of flexibility in defining the way of changing the path vector, i.e., the previously mentioned mutations. Within the used genetic algorithm [17], mutations of the selected path vector are based on two of the randomly selected indices (points in the path) on which GA:

- Performs full rotation of path vector elements between specified indices (points);
- Replaces the value of the path vector at the given indices;
- Performs a phase shift of part of the path vector with an adequate displacement of one element.

In this way, for every parent path, three modified paths are formed, for which the criterion function is determined, and the process of further selection is carried out. All mentioned random choices are characterized by a uniform distribution of the probability function.

6. Optimal execution sequence based on GA and SDS results

In the following chapter, the DoE test plan of 45 operating points will be analyzed. Figure 5 shows the sequence of execution according to the DoE, and an analogy with the random selection of the sequence can be observed, i.e. it is impossible to establish any rule on which the given sequence was formed. If the condition of minimizing the total Euclidean distance between the points is set for the same set of points, and the approximately optimal solution is determined using GA, the results shown in Figure 6 will be obtained. To get appropriate results, the total span in terms of engine speed and engine load would be at the same absolute level.

Determining the shortest path within the n-Me domain is justified if there is demand for the smallest possible deviations of the control parameters during the experiment, but from the aspect of the necessary stabilization time, it is not possible to determine which is closer, a change in engine speed or a change in the engine load. To identify the impact of execution order, feedback on system performance is required. The approximate models of exhaust gas temperature T_31 for stationary and tests with SDS will be discussed in this sense. The criterion function, i.e., the matrix of cross distances, can be formed based on the value of the absolute deviation of the exhaust gas temperature between the modes of the given test plan according to:

$$\boldsymbol{M}_{D(T\_31)}(i,j) = \left|\hat{y}_{T\_31}\big(DoE(i)\big) - \hat{y}_{T\_31}\big(DoE(j)\big)\right|, \qquad i,j = [1,p] \tag{6.1}$$

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where DoE indicates the operation points contained in the test plan, and $\hat{y}$ represents certain mathematical models formed over different groups of data. Given that GA successfully finds (almost) optimal execution sequences for a given $\boldsymbol{M}_D$, it is necessary to compare the results obtained based on SDS approximations and the ideal case of execution sequences, thus for stationary test results. In this sense, Figure 7 shows the cumulative exhaust temperature growth formed based on optimal execution sequences and different models $\hat{y}_{T\_31}$ according to:

$$\sum |\Delta T\_31| = \sum_{i=1}^{p-1} \boldsymbol{M}_{D(T\_31)}\,(i, i+1) \tag{6.2}$$

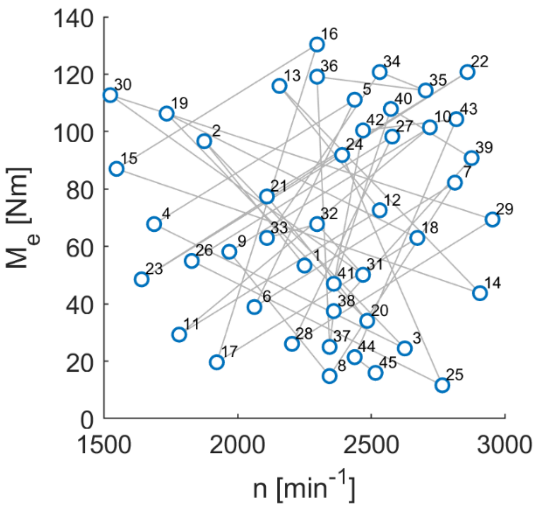

Figure 5. Initial sequence of execution DoE operating points for stationary engine testing.

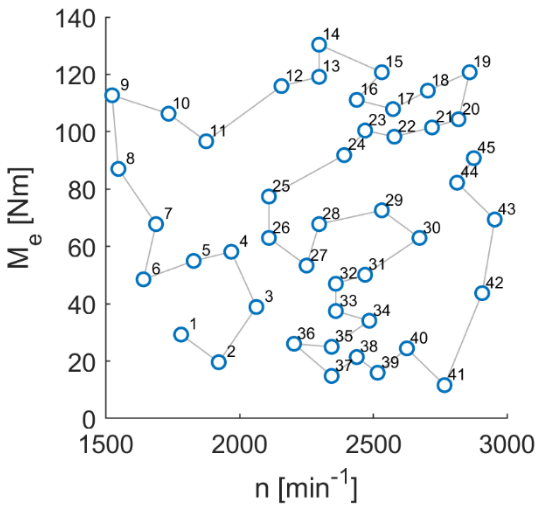

Figure 6. The shortest execution path within n-Me operation domain.

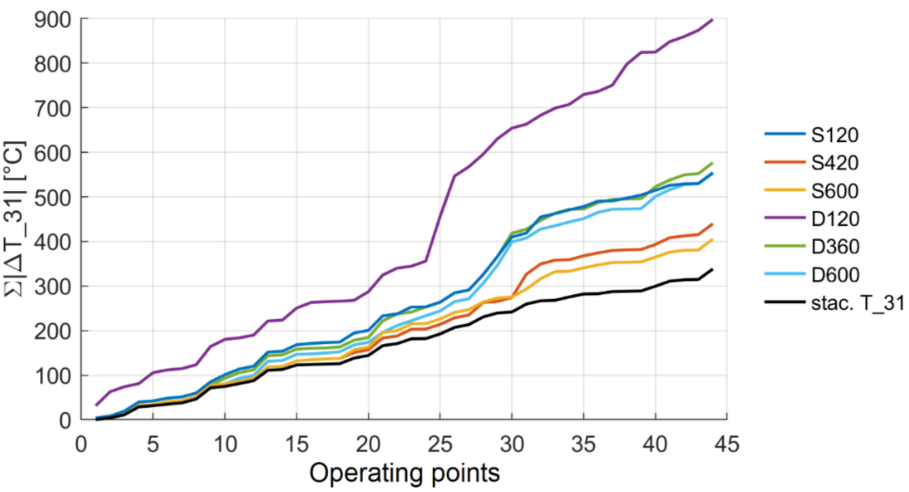

Figure 7. Cumulative deviation of exhaust gas temperature T_31 for optimal execution sequences based on different stationary approximation models.

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In the worst case, if the sequence of execution were random (Figure 5), the average deviation of the exhaust gas temperature would be about 140 °C. If the optimized execution order is determined based on the minimum distance criteria in the n-Me space (Figure 6), the mean temperature deviation of T_31 would be 34 °C.

In the ideal case, for the known stationary test results, the mean value of the exhaust gas temperature deviation is 7.7 °C per operating point. If the models obtained from SDS testing were used to determine the optimal sequence, the mean values of the deviations per operating point would range from 20.5 °C to 9.2 °C, depending on the type and duration of the SDS experiment, which is very close to the ideal case.

Figure 8 and 9 shows the sequences obtained based on the minimization of the total distance of the operating points in terms of the absolute temperature curves T_31. The approximately optimal execution sequences for the $\boldsymbol{M_D}$ based on the approximate reference stationary model and the stationary approximation of the exhaust gas temperature determined by the dynamic test S120, are shown. Given that the principal trend of exhaust gas temperature values is very similar in both models, the results of GA application in the execution sequence are also very similar.

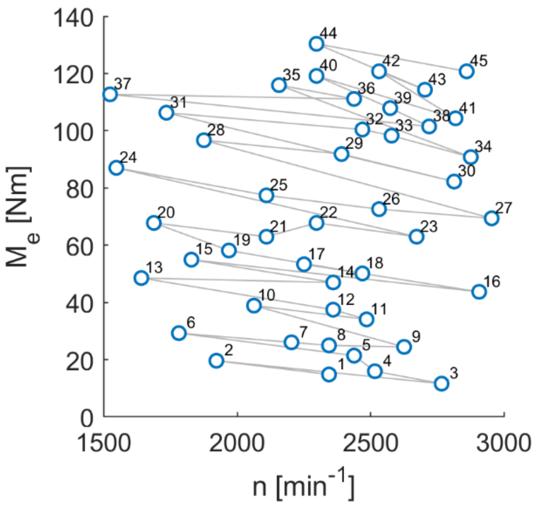

Figure 8. The execution sequence of the operating regimes determined by GA for the reference stationary model T_31.

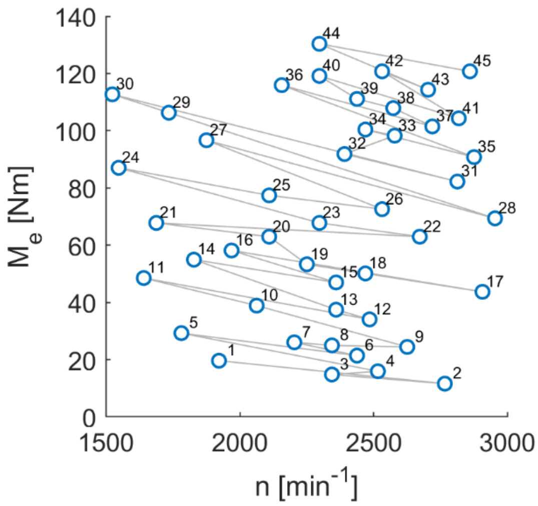

Figure 9. The execution sequence of the operating regimes determined by GA for the model is based on SDS (S120).

The initial matrix of the mutual distances of the test plan points in terms of temperature deviation T_31, for the model, formed based on the SDS test S120, is given in Figure 10. After determining the approximately optimal path according to the criterion of minimizing the deviation of the exhaust gas temperature, a matrix of cross distances is shown in Figure 11. If the execution sequence is optimal, this diagram should indicate monotonically increasing (or decreasing) differences in exhaust gas temperature according to the execution sequence of operating points. Given that GA cannot provide a correct execution sequence of operating points based on the minimization of the criterion function, a slight irregularity is observed in the central part of the diagram in Figure 11. Considering the principle flow of the temperature difference shown in this diagram and the speed of execution of GA, of only 6 seconds, the presented results are more than satisfactory. For the execution sequence shown in Figure 9, the mean deviation of the temperature of the exhaust gases according to the operating point during the stationary test of the engine would be about 12.5 °C.

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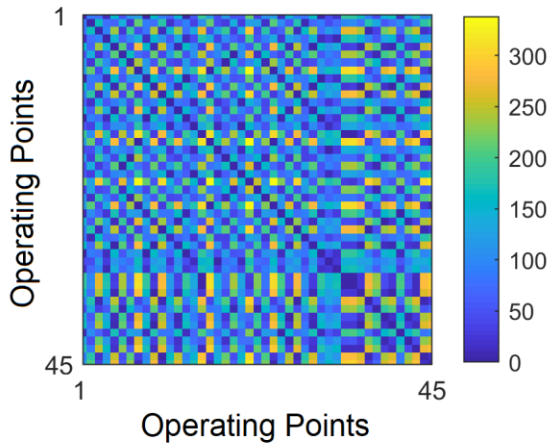

Figure 10. Initial matrix of distances $\boldsymbol{M}_D$ for DoE 45 test plan and SDS S120 T_31 model.

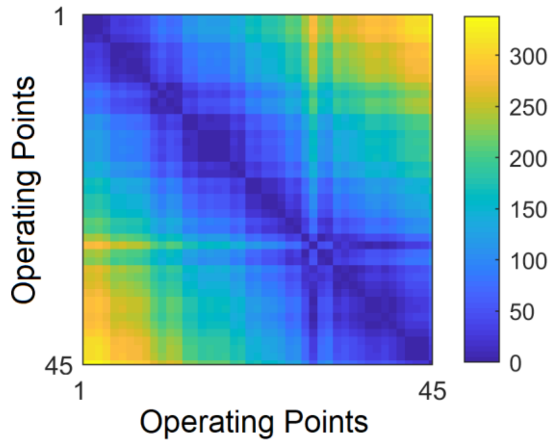

Figure 11. GA resulting matrix of distances $\boldsymbol{M}_D$ for DoE 45 test plan and SDS S120 T_31 model.

7. Conclusions

Forming the IC engine test plan requires prior knowledge about the tested object. For example, prior knowledge is needed to define the system's boundaries in terms of allowed combinations of control parameters, or prior knowledge is necessary for choosing the appropriate architecture of mathematical models to be used in the formation of the mentioned approximations. Dynamic testing is a very effective way to collect information about the investigated object. During dynamic engine testing, the time needed for stationary operating point stabilization is saved, but it is necessary to define an appropriate dynamic test plan and develop a method for interpreting the results of such a test. In this paper, the dynamic method is presented on IC engine tests during which one control parameter changes relatively slowly - the SDS method.

The IC engine exhaust gas temperature belongs to the category of parameters characterized by longer stabilization time. With approximate exhaust gas temperature characteristics obtained based on SDS testing, an approximately optimal test plan execution sequence is formed to obtain the shortest possible stabilization time between operating points of the given test plan. The analysis was carried out by setting the problem as the open path TSP and forming the corresponding genetic algorithm for solving it.

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