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# DEVELOPMENT OF A METHOD FOR FINDING THE OPTIMAL SOLUTION WHEN UPGRADING A MOTORCYCLE ENGINE

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Abstract

This paper describes a method for finding the optimal parameters of a spark-ignition engine gas exchange system for a motorcycle. The vectors of the initial data for filling the parameter space, in which the search for the optimal solution has been made, have been formed through methods of experiment planning and technique nonlinear programming quadratic line search. As the quality criteria, the engine power has been used at selected points of the external speed characteristic. The results of the work have shown how using the proposed optimization method allows modernization of a gas exchange systems in order to increase the engine power.

## Introduction

All stages of the life cycle of an engine, from design to the recycling process, require optimization methods that improve the processes included in its production and exploitation. Bearing in mind the subject of studies – a four-stroke spark-ignition engine of a sport motorcycle, the following specific character must be taken into consideration. Almost every motorcycle of that class

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is exclusive. In that case, the quality indicators differ from the indicators assumed for consumer products (BRANNEN et al. 2012). Primarily, what is taken into account includes power, torque, visual and acoustic effects of the machine. On rare occasions, we pay attention to fuel consumption, oil consumption, or a set of environmental standards.

For the first time, such engines were presented before a larger audience in the last century and, from that time, they have been constantly improved and optimized. The traditional approach towards optimization of engines employs a sequential change of individual parameters (factors). The univariate approach appeared to be expensive and inefficient, especially when the requirements concerning modernization become more numerous and contradictory to each other.

Many of the exploited motorcycles are equipped with an engine with natural suction. An increase of the power of such engines during modernization is possible thanks to application of inertia supercharging of engine cylinders (HARRISON, DUNKLEY 2004). It is possible to implement all the advantages of such boost, which involves all wave phenomena during the flow of air and exhaust in the discharge and inlet ducts of the engine, provided that the geometrical dimensions and regulation of systems responsible for the gas exchange have been selected in an optimum manner. The application of the boost, thanks to an improved method of filling the cylinder with a fresh feed and of cleaning the combustion by-products also leads to a certain decrease in fuel consumption.

Thus, it is important to elaborate optimization methods for processes of gas exchange in high-speed motorcycle engines. In order to achieve this goal, it is necessary to develop an algorithm that will cover the verified optimization techniques as well as methods for planning and processing the experimental results.

Apart from the traditional univariate approach, in the recent years, new optimization methods have been proposed which have been successfully applied in the industry (SHIH et. al. 2012, DESHMUKH et. al. 2004, MACKEY et. al. 2002, YONGFAN et. al. 2017, SYAHRULLAH, SINAGA 2016, STELIOS et. al. 2014, WANG et. al. 2016). The possibility of quick data processing becomes complicated due to the statistical methods applied in the case of optimization, as well as due to modeling and computing methods used to model cycles of an engine (HEYWOOD 1988). When it comes to the analysis of engine performance, engine processes can be described in detail by using laws of mechanics, hydrostatic and gas dynamics, and laws of thermodynamics. Advanced process models of an engine can be integrated in a simulation of a complete cycle of a particular subject, in order to predict its capacities, provided that relevant data are provided, as well as more general aspects of the cycle operation. Opportunities to create integrated models of vehicles and power sources are being established.

The problems that arise during the optimization of an internal combustion engine are explained by the need to consider a large number of factors affecting the process being optimized. These factors usually have a weakly pronounced correlation. The engine of the vehicle operates in a wide range of changes in load, equipment, and, as a consequence, changes in fuel consumption, environmental indicators. This leads to problems when choosing the quality criteria of the investigated thermodynamic, hydro-gas-dynamic, mechanical processes.

Currently, researchers and engine developers have at their disposal software systems that simulate these processes with high accuracy. Simulation techniques can take into account almost all the factors affecting the processes. When forming the engine design model, hundreds of input design and adjustment parameters are used, as well as fitting coefficients. The use of such a "virtual engine" shortens the product design period. And also allows you to upgrade existing engines in operation.

Computer models of engines can be used to analyze a high number of construction and operational variables. The analysis of results of the simulation will show the possibility of improving the required quality of the subject, for instance its power in particular load points, which will help in choosing an optimum combination of construction factors and adjusting elements. Consequently, of course, the demand for experimental devices, the time to develop a product, and costs of testing equipment become significantly lower.

The task of optimization can be now performed by applying one or a combination of the following strategies:

1. Design of Experiments (DoE) Methods (ROSS 1998). Usually, the application of those methods allows choosing an optimum solution. However, the outcome of application of those methods can be unsatisfactory, especially in the case of choosing a complete or partial factor. If robust screening methods are selected such as the use of orthogonal arrays, then result testing is more efficient, and the method becomes viable.

2. Methods of optimization. There are many such methods available on the market. However, the choice of the optimization algorithm that must be used is a very important element, since some optimization methods are permitted in the case of some application, depending on the spatial parameter (spatial modality, continuity, linearity, etc.).

The efficiency of those methods increases, when they are used together. At the initial stage, for instance, one method can be used for experiment planning in order to test the space determined by limit values of factors being the subject of interest and to find the intended best option. After construction of the surface, it is possible to use a relevant optimization method in order to find the ultimately optimum construction point. The search for an optimum solution, in this case, does not start from scratch nor at random in any area of design. Results of DoE used to have a deliberate choice of the initial searching conditions. In practice, the optimization method will work when DoE had been stopped. It leads to a significant decrease in number of optimization iterations for convergence.

The optimum solution is an ultimately optimum solution since the approximation of the answer surface is mathematically set before the commencement of optimization (the optimizer already knows the surface topology of the answer – peaks, gradients, bottoms from DoE coefficients). It should ensure that the local optimum will not be selected as the global optimum.

## Objective and scope of the optimization

The optimization work covered in this paper is pertinent to the performance of a S+S 113 CID (Fig. 1) spark-ignition engine used mainly in automotive applications such as motorcycles. The said engine, as any power plant, has to meet some requirements, such as power output, fuel consumption, emissions levels, and noise limits. The optimization work at hand covers exclusively the optimization of power output, using the finite volume modeling scheme to solve the thermodynamic equations for all the control volumes in the engine simulation (valves, manifolds, exhaust components, etc. (Fig. 2). Detailed geometry and engine operating conditions are defined as input data.

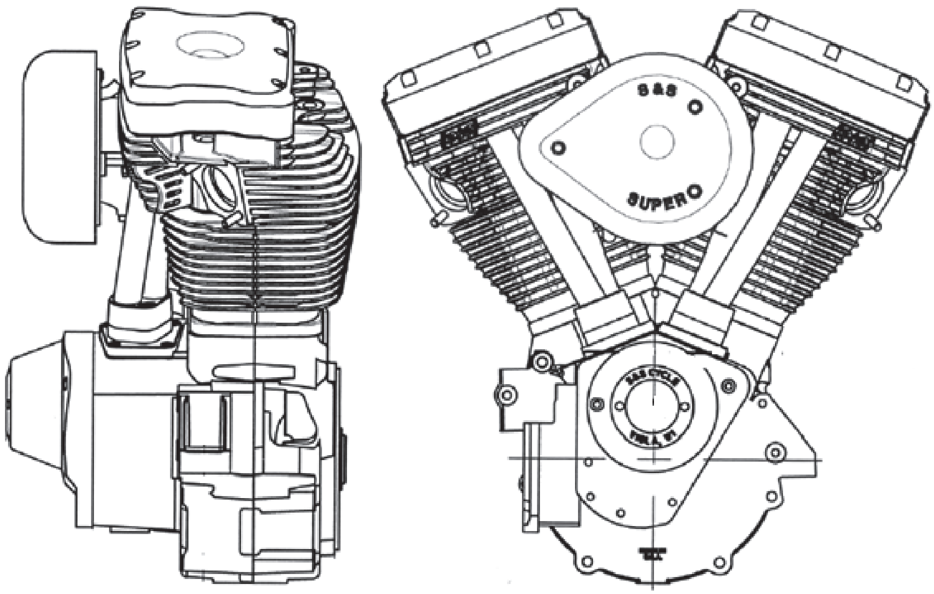



Fig. 1. Motorcycle engine HD S+S 113 CID (HD Manual 2015)

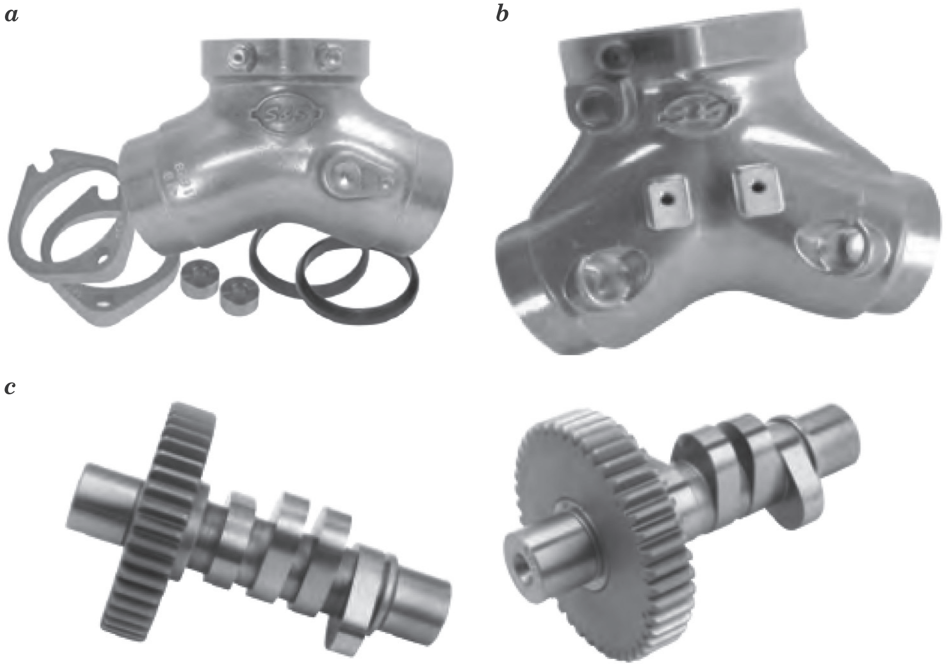



Fig. 2. Optimized elements of an engine: *a* – intake manifold of an engine with a carburettor, *b* – intake manifold of an engine with a dispersed injection system, *c* – camshaft

## Selection of controllable factors

Selection of factors based on operational and modernization experiments of such a motorcycle class has been presented in Table 1 as well as in the set of tests presented in works (JAWAD et. al. 2001, BLAIR et. al. 2003, ZHAO 2011, ALESSANDRO, MARCO 2014). However, authors also applied methods of modeling of the physical and mathematical model. Such parameters influence the engine power. Thus, their optimum combination allows increasing the engine power in characteristic points. So far, little attention has been devoted to the interaction between selected factors (Tab. 1), starting from such interaction, including a high number of factors that are not too obvious, prior to the commencement of testing of the planned experiment.

In this investigation, the applied answer function is the criterion of «myObjective» synthesis quality, which allows searching for an optimum criterion through a value the goal of which is "0". As it has been mentioned, the quality criterion constitutes a condition to achieve the maximum power in the tested charging mode. As an example of application of the proposed

Table 1

List factors and Output parameter

| Factor | Name | Units | Default value | Lower bound | Upper bound |
|---|---|---|---|---|---|
| Intake valve diameter | IVD | mm | 50 | 45 | 55 |
| Intake Valve Opening timing (cad BTDC) | IVO | degree | 5 | 0 | 10 |
| Intake plenum pipe length | len | mm | 125 | 110 | 140 |
| Exhaust valve diameter | EVD | mm | 42 | 38 | 46 |
| Exhaust Valve Closure timing (cad ATDC) | EVC | degree | 10 | 0 | 20 |
| Pipe exhaust diameter | diameter | mm | 50 | 45 | 55 |
| Exhaust plenum pipe length | Lex | mm | 500 | 250 | 750 |
| Exhaust orifice area | pole | $mm^2$ | 1,500 | 1,000 | 2,000 |
| Output parameter | | | | | |
| myObjective | | | | | |

optimization record, this article considers the possibility of achieving 75 kW at 4,000 rpm. In that case, the criterion «myObjective» = 75-Pi, where Pi is the engine power in that calculation.

Based on the selected eight controlling factors, the minimum number of projects implemented with the method of a full-scope experiment is 256. Usually, there is a need for an additional flow in order to verify the proposed optimum for the project. Of course, after DoE, there will be more launches necessary to complete the third part of the optimization of the study. However, the number of flows required to optimize to convergence is significantly lower, since optimization starts near the intended optimum solution. Again, the NLPQL surface approximation ensures that the optimum solution is a global (ultimate) one.

## Selection of the optimization technique

Different design problems require different optimization techniques. As such, the selection of an optimization technique is a big challenge, and oftentimes, a combination of two or more techniques should be used to get a specific optimization task done. Generally, optimization techniques can be divided into three broad categories:

1. Numerical optimization techniques assume the parameter space is unimodal, convex, and continuous. Popular techniques in this category are sequential linear or quadratic programming, methods of feasible directions, etc.

2. Exploratory techniques evaluate designs throughout the parameter space in search of the global optimum. Like most search problems, the techniques in

this category typically, but not necessarily, require a larger number of iterations than the numerical techniques.

3. Expert system techniques follow user defined directions on what to change, how to change it, and when to change it.

Due to the large number of control factors considered in the study at hand and the lack of in-advance information about the response surface, the optimization techniques in the third category above are not considered. Also, since a DoE method is used prior to the optimization part of the study, the second category may not be the best choice in terms of optimization convergence time. Therefore, the designer is left with choosing a numerical technique.

The most appropriate numerical technique for the study in this paper is the NLPQLP method, a newer version of NLPQL, solves smooth nonlinear programming problems by a Sequential Quadratic Programming (SQP) algorithm. The new version is specifically tuned to run under distributed systems. In case of computational errors, caused for example by inaccurate function or gradient evaluations, a non-monotone line search is activated. The code is easily transformed to C by f2c and is widely used in academia and industry.

NLPQL is a sequential quadratic programming (SQP) method which solves problems with smooth continuously differentiable objective function and constraints. The algorithm uses a quadratic approximation of the Lagrangian function and a linearization of the constraints. To generate a search direction a quadratic subproblem is formulated and solved. The line search can be performed with respect to two alternative merit functions, and the Hessian approximation is updated by a modified BFGS formula (SCHITTKOWSKI 2011, 1986).

The aim of an optimization process is to find the best design (parameter settings) that matches a given objective (minimize a value), and does not violate the constraints.

$$x \in \Re^n \qquad \begin{array}{l} \min f(x) \\ g_j(x) \geq 0 \quad j = 1, \ldots, m \\ x_l \leq x \leq x_u \end{array}$$

$f$ is the objective function, and the $g_j$ ($j = 1, \ldots, m$) functions represent the constraints. Constraints are different from bounds. Indeed, bounds are known a priori and are never violated, whereas constraints are known a posteriori and are something the algorithm tries not to violate (then they may be violated).

## Set up of the doe study and software integration

Figure 3 presents the basic engine model used in the study that has been described in this article. Constructive solutions for that scheme involve installing an inlet distributor (submodel "Intake") to the point fuel injector (Fig. 2*b*), separated from every piston of the exhaust system (submodel "Exhaust").

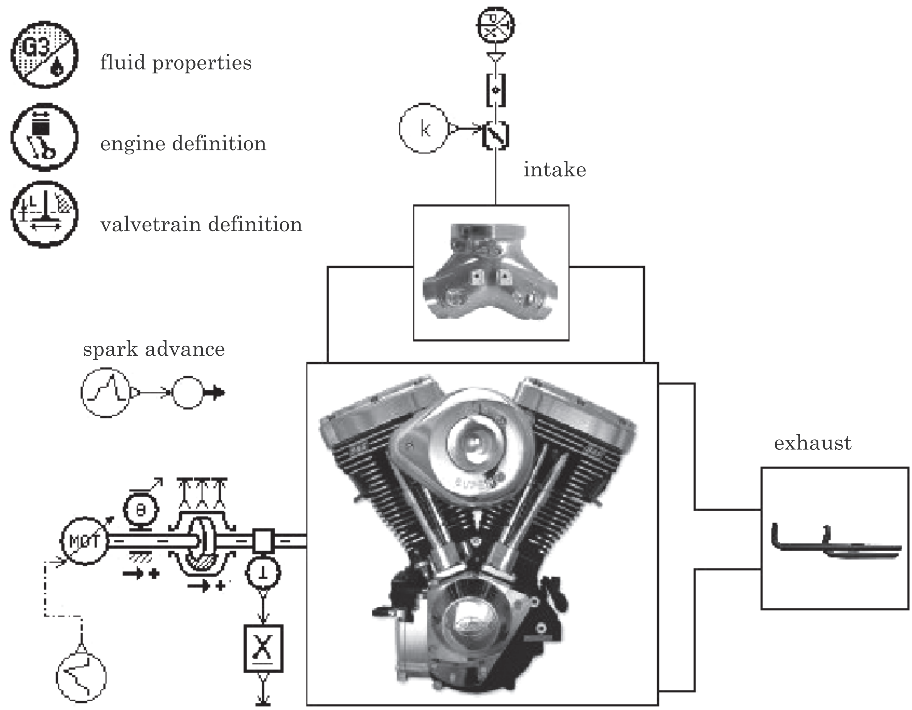



Fig. 3. Baseline Engine Model

They also involve choosing one of two methods for fuel supply (to the carburetor or the injectors) without changing the design scheme. The study of opportunities for application and optimization of such a system is the subject of further research. Calculations concerning one variant are made in a way that allows giving access for the program to the input file containing eight factors, while the output file contains quality criteria, in this case: «myObjective». Our goal is to reach a power value of 75 kW, we have to set the parameter «myObjective» as the objective function. Thus, the NLPQL process will try to decrease this quantity down to zero. The NLPQL algorithm is based on the use of gradients and is an iterative process. It tries to decrease the objective function to zero. For this, it computes the gradients of the objective function and constraints in all directions available in the design space (each input parameter involved in the optimization process is a direction).

In our physical example, the problem is to find an appropriate set of parameters to reach a specified injected quantity, and to keep the constraints not violated.

Program automatically parses input and output files, as specified by the designer. Parsing input file for the input parameters, and substituting values from the DoE matrix (Tab. 2) for eight factors for those parameters in input files for each run case, saves the designer a considerable amount of time.

Table 2

DoE matrix of full factorial

| Point | Diameter | len | IVD | EVD | Lex | Pole | IVO | EVC |
|---|---|---|---|---|---|---|---|---|
| 1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 2 | 1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 3 | -1 | 1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 4 | 1 | 1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 5 | -1 | -1 | 1 | -1 | -1 | -1 | -1 | -1 |
| … | … | … | … | … | … | … | … | … |
| 255 | -1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 256 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Accordingly, such automation of tasks would help the designers spend less time on routine tasks, and focus their attention on more creative engineering work. The time difference between using a traditional routine engineering approach and an automation engineering approach is called the cycle time reduction.

Selecting a DoE and/or an Optimization technique is straightforward and is done using the graphical menus to select the method or technique of interest. Optimization solution constraints are also provided at this time. In the current study, the intake and exhaust valve diameters were constrained using a special relation with the cylinder bore. This was done to ensure that the area of all valves did not exceed a specified fraction of the cylinder bore area, based on packaging, stress analysis results, and other practical considerations.

Simulation Runs The average time for running one experiment is 30 seconds. The combined number of runs to convergence for both the DoE and Optimization was found to be 279. Knowing that the DoE is comprised of 256 runs would indicate that the optimization convergence, from the DoE estimated optimal, occurred over 23 runs (or 12.5 minutes of CPU run-time.) Using the same simple calculation, the DoE run-time was 128.5 minutes.

Post-processing and Analysis of Results keeps track of the input parameters and output response for each run case in a database. The program also has the capability of displaying dynamically the output results on a graphical scope. Figure 4 shows a sample graph of the «myObjective» response, as the DoE and then the optimization progressed, against the run (trial) counter. Please note that following the DoE part of the study (after run counter = 23), the optimization technique is automatically started and one can easily see how the optimization drives the response to convergence.

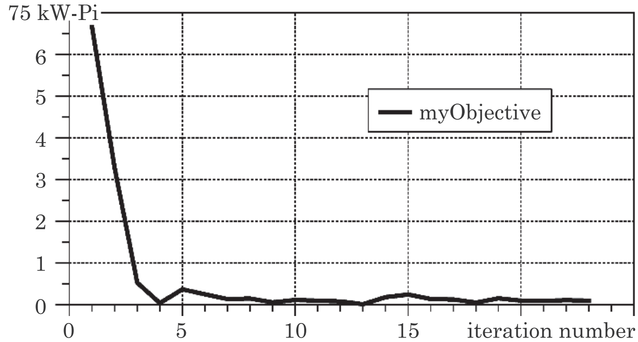



Fig. 4. Optimization Graphical Scope

One of the useful post-processing tools that provides the designer with is the Pareto graphs. These are ordered bar charts showing the average effects of the input factors on the selected response. Using such graphs helps the designer identify the top factors that significantly contributed to the response under study. Figure 5 shows an example Pareto graph from the study covered in this paper. Red bars are used to indicate positive values since the absolute values of the effects are plotted. Green bars indicate a negative relationship between a factor and its average effect on the response. For example, let's consider the two factors at the top in Figure 5*a*. These are labeled "diameter" and EVD, which represent, for the engine covered in this paper, the exhaust valve and pipe diameters respectively. These were the two top contributing factors to the change in the response of the study. The Pareto graph (CZYZAK, JASZKIEWICZ 1998) shows a direct relationship between the aforementioned factors and the response (red bar color). What is more, the reliance of quality on "diameter" in the accepted conditions of the 3$^{rd}$ factor experiment is 43%, while EVD has influence on quality of 36%. On the other hand, the fourth factor diameter/IVD (grey bars) in Figure 5*a* show an inverse relationship with the response. The designer can benefit from the Pareto graph by identifying fewer factors than had resulted from the brainstorming session. Now instead of considering all 8 factors (parameters),

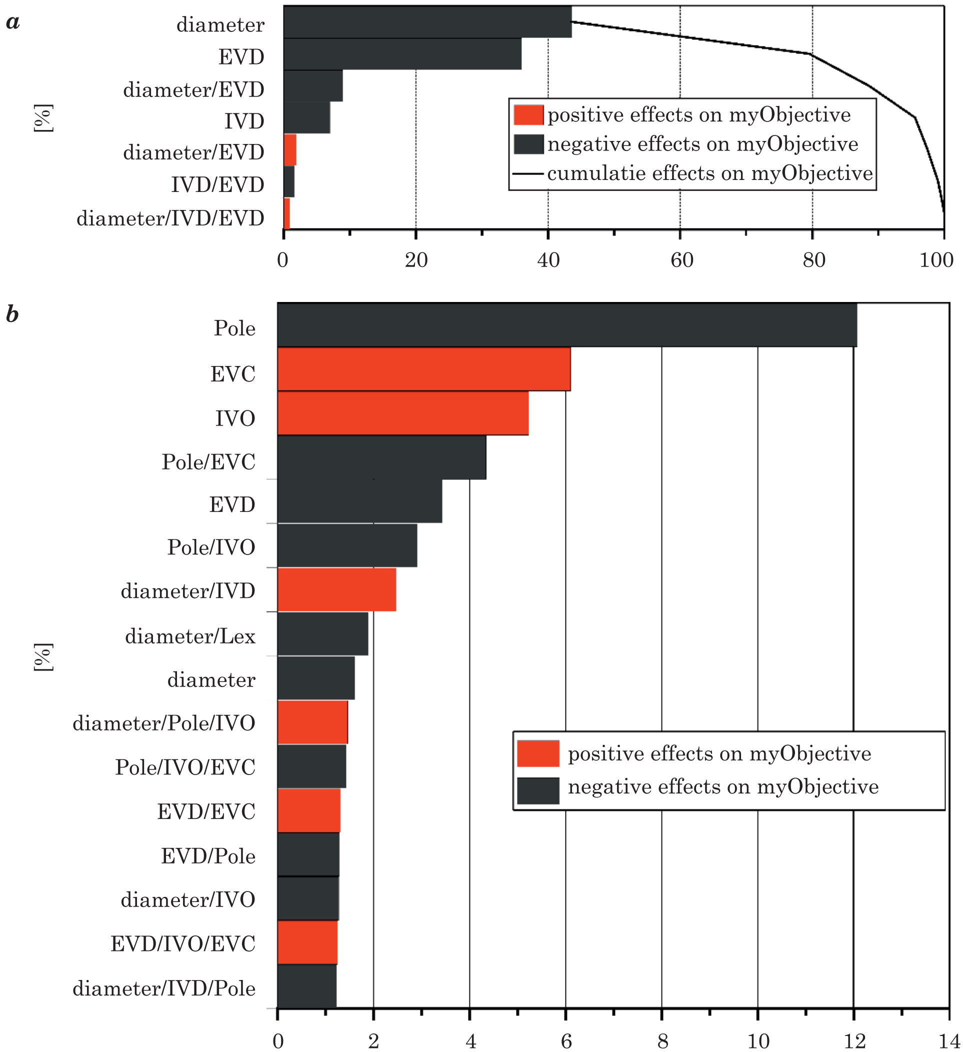



Fig. 5. Pareto diagram for results: *a* – 3 factors DoE (Fig. 4), *b* – 8 factors DoE (Tab. 1)

the designer may choose to focus only on the top 3 or more (Fig. 5*b*) factors that affected the response most significantly.

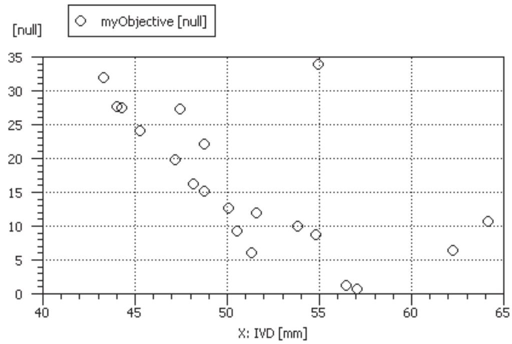
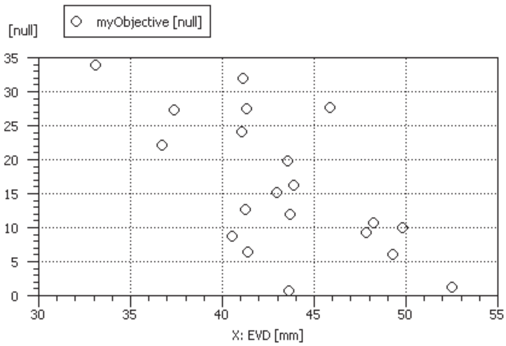
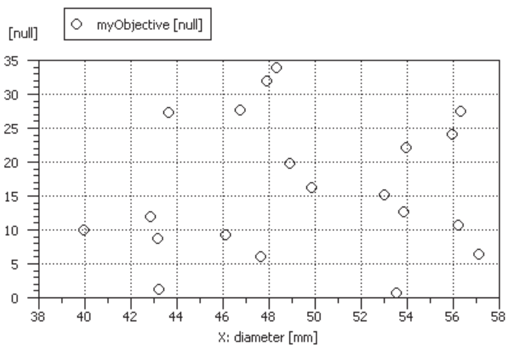
Under the conditions of the $8^{th}$ factor experiment, the impact of "pole" the highest it amounts 12.1%. The reliance of "myObjective" on "diameter" is reduced to 1.65%, while the EVD level of 3.5%. The results reveal the difficulties encountered during the analysis of the results obtained with the use of DoE. Thus, the next reasonable step in formalization of the task to find optimum parameters of the engine intake system and the exhaust system is to apply one of the optimization methods.

## The results of using the method NLPQL

In the second stage of the solution process regarding optimization, with the use of the NLPQL method, the value of global optimum was achieved in accordance with the set criterion of «myObjective». The limits for changes in

Table 3

The dependence of the quality criterion «myObjective» on changes in selected factors

| Factor | Distribution of calculated points |
|---|---|
| Intake valve diameter (IVD) |  |
| Exhaust valve diameter (EVD) |  |
| Pipe exhaust diameter (diameter) |  |

factors, presented in Table 1, as well as the parameter vector for the initial point of the optimum search were selected on the basis of an analysis of DoE results and a test of parameter space by using the Monte Carlo method (RUBINSTEIN, KROESE 2008, SHLOMO, SHAUL 2011). Partial results for scans of the parameter space with the Monte Carlo method have been presented in Table 3.

The results in Table 3 imply that it is possible to have an unambiguous determination of the reliance of correlation for the diameter of the inlet pipe; the change effect for the diameter of the outlet pipe is harder to predict. In the case of the diameter of the exhaust pipe, the reliance is also obvious, but it has a vivid stochastic character.

The application process of the NLPQL method that covered the search for an optimum value of 8 factors in accordance with the «myObjective» criterion consisted of 23 iterations (Fig. 6). What is more, the last 4 iterations were conducted with the accuracy of search for optimum set to 0.01. Consequently, the search for an optimum process was complete when the obtained value of «myObjective» = 9.7214789533E-02.

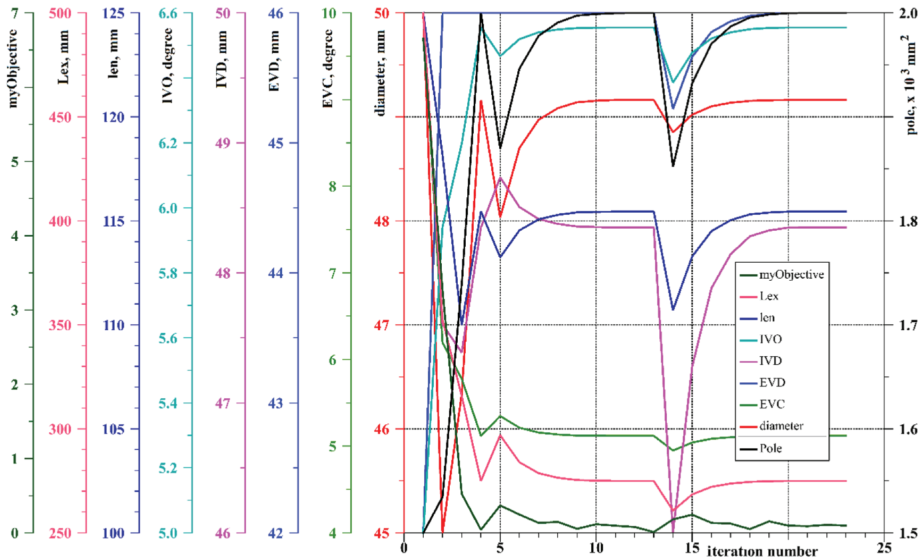



Fig. 6. Optimization Graphical Scope 8 factors

The last entry in the database file is the most feasible, and also the global optimal, design. The final results of the optimization study showed a brake power improvement of about 5.4% at rated power compared with the baseline value. Improvement on the power response was also observed at low and high RPMs of the engine operation range.

## Conclusions

The application of the known methods of studying spatial parameters allows optimizing the design and tunable parameters of the engine and thereby improving its operating parameters at selected points of the external velocity characteristic. As an example, the elements of the engine intake and exhaust system are considered, which determine the quality of gas exchange. The chosen optimization strategy makes it possible to use the concept of inertia supercharging of engine cylinders, in the conditions of modernization. The consideration involved 8 design parameters of systems and one quality criterion – engine power. The proposed optimization method can be used to upgrade motorcycle engines in operation.

To find the optimal solution, the initial parameter vectors are formed using the full-factor experiment planning methods.

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