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THE IDEA OF THE OPTIMIZATION STRATEGY FOR INDUSTRIAL PROCESSES

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Abstract

The paper is devoted to strategies used in the optimization of processes. The strategy for optimization of a process incorporates modelling with the use of design parameters, metamodelling, global sensitivity analysis and optimization algorithms. The strategy for selecting a proper organization algorithm is also discussed. The paper provides an example of a computer implementation of a simple expert system, designed to help the end user follow the strategies. The presented strategy contains also some information on modelling with the use of the finite element method. The strategy is included as an expert system in the ManuOpti optimization of the industrial processes system.

Key words: strategy, optimization, optimization algorithms, modelling

1. INTRODUCTION

The optimization plays an important role in the optimization of industrial processes (Bonte et al., 2010; Kuś & Burczyński, 2008; Kuś & Burczyński, 2009). In many cases, the numerical models of processes are optimized to lower the production costs or obtain the desired properties of a product. There are many optimization techniques that can be used to find the design variables values for the optimal solution of the problem. The goal of the optimization strategy, presented in this paper, is to obtain good results in a reasonable computational time.

The paper emphasizes the importance of reducing the number of the model design variables as well as the application of metamodels. The presented approach is an extended version of the optimization strategies that were described in papers (Bonte et al., 2008; Venugopal et al., 2004). The strategy for problems identification can be found in (Szeliga, 2013). Chapter 2 of this paper discusses the overall strategy for optimization, the starting point of which is to formulate the optimization problem. Chapter 3 is devoted to the selection of the optimization algorithms - a separate strategy. It then presents some chosen optimization algorithms, including the classic and the bioinspired algorithm. Finally, the implementation of the presented strategy as an expert system is described in chapter 4. The numerical example solved on the basis of described strategies are shown in chapter 5.

2. PROCESS OPTIMIZATION STRATEGY

The optimization problem can be defined with the use of objective functions and constraints. The goal of the optimization is to obtain the design parameters values which gave the optimum of the objective function. For minimization problems, the optimization task is formulated as follows:

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$$\min F_i(\mathbf{x}) \\ g_j(\mathbf{x}) \le 0 \qquad (1) \\ h_k(\mathbf{x}) = 0$$

where:

$F_i(\mathbf{x})$ - are objective functions,

$\mathbf{x}$ - is vector with design variables

$g_j(\mathbf{x})$ - are inequality constraints,

$h_k(\mathbf{x})$ - are equality constrains.

The design variables determine the process parameters, shape and topology of the optimized tool or structure. The number of design variables constitutes one of the most important parameters in optimization problems.

The strategy is presented in figure 1. The starting point is a formulated optimization problem with objective functions, constraints and a set of design variables. Many optimization problems are analyzed with support of the finite element method (FEM) (Zienkiewicz et al., 2005). The first step in optimization strategy is to reduce (if possible) of the number of design variables. In some cases, it is possible to reduce them with the use of parametric curves, e.g. NURBS (Piegl & Tiller, 1997). The operation should lead to the simplification of the optimization problem, reduction dimensionality of the search space and at the same time allow for flexibility and the spectrum of possible results to remain at the acceptable level. The sample reduction of the number of the design variables in shape optimization of tool - anvil is shown in figure 2. The NURBS curve is used instead of coordinates of nodes in the finite element model.

In the majority of instances, the objective functions evaluation is the most time consuming stage of the optimization process. Before the decision on reduction of the model complexity can be made, the estimation of computational times has to be carefully considered. It is because the analysis of 3D models of real processes like stamping, forging, crash simulations can take a couple of hours. In some cases, it is impossible to perform optimization with such complicated and time consuming analyses. Thus, metamodels (Wang & Shan, 2006) can help overcome these difficulties. The artificial neural networks, Kriging methods, and response surface methods, take the role of metamodels. Such metamodels can be used in optimization because objective functions evaluations are very fast. The optimization with metamodels application calls for verification of the results with the use of models.

The next step is to check the sensitivity of objectives to the change of design variables values. The global sensitivity methods (Szeliga, 2013; Sandoval et al., 2012) allow for further reduction of the design variables. The parameters which do not significantly affect the objective functions can be fixed to a constant value and removed from the design parameters vector.

In case of optimization strategy, the choice of an optimization algorithm is crucial and it depends on the information about objective function changes in design space, smoothness and continuity. The behavior of constraints in the design space is of equal importance. The strategy for choosing an optimization algorithm is presented in chapter 3. The optimization algorithms employs an iterative approach, that is operate on a single design variables vector or on a set of vectors, improving the optimal solution which was found in each iteration. Each step of optimization allows for the metamodel to be verified, e.g. for the best possible solution. Some of the metamodels can be also updated during optimization which in result leads to better fit metamodels and helps in finding an optimum.

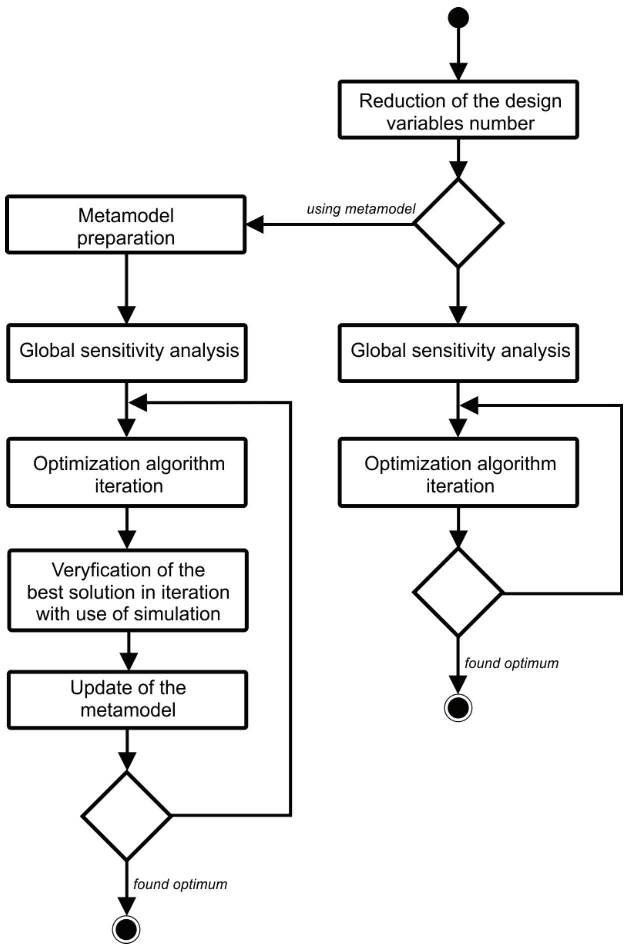

Fig. 1. *The strategy for optimization of process*

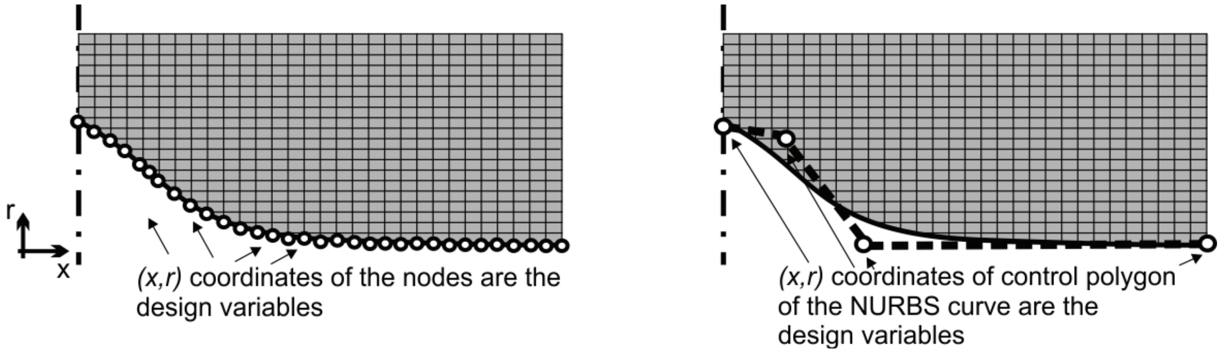

Fig. 2. *The number of design variables reduction: a) the original formulation with coordinates of finite element nodes, b) the NURBS curve with design variables - coordinates of polygon nodes*

3. THE OPTIMIZATION METHOD CHOICE STRATEGY

Here, the classic and bioinspired optimization methods are discussed, together with a few arbitrarily chosen methods (Kuś et al., 2011). Some of the methods are available in the ManuOpti system (ManuOpti, 2013). The proper optimization method can be selected on the basis of prior comprehension of optimized objective functions. The strategy for choosing an optimization method is presented in figure 3. The choice between a single or a multi-objective optimization algorithm depends on the number of objective functions. The application of the multiobjective optimization algorithms will result in a set of solutions. The set of solutions, in case of the majority of algorithms, is given as an optimal in Pareto sense. The choice of one of the solutions from the front is made in accordance with the opinion of an expert, decision maker and takes into account his experience from previous projects or technological constraints which are not included in the optimization problem, etc.

The optimization problem can be solved with the use of optimization algorithms, based on the information about the gradient of objective function (computed directly or with the use of finite differences) or the non gradient algorithms. The gradient based algorithms are generally converged faster than the non gradient ones. Unfortunately, for most optimization problems, the information about the gradient of objective function is not available. The numerical evaluation of the gradient function value is time consuming and the overall optimization time may be longer than in the case of the non gradient algorithms. The next choice depends on the objective function smoothness and multimodality. The problem with many local optima should be optimized with a global algorithm or a local algorithm with multistart (run many times with different starting points). The bioinspired algorithms (Kuś & Burczyński, 2008) are global optimization algorithms which can be used with nonsmooth, noncontinous, multimodal objective functions. The bioinspiered algorithms mimic nature, e.g. evolutionary algorithms (Michalewicz, 1996) work in a way similar to the evolution of the species, artificial immune system (de Castro & Timmis, 2003) takes some mechanisms present in mammal immune system, particle swarm optimization (Kennedy et al., 2001) acts similar to swarms of birds or fishes. The bioinspired algorithm can be used both for single and multi-objective problems. The multi objective problems with the number of objectives higher than three should be treated with caution and specialized multiobjective algorithms should be used (Jarosz & Burczyński, 2010). The weakness of the bioinspired algorithms is that it might identify the surrounding area of the global optima in search space, but not the exact location of the global optimum. The problem with finding the exact optimum location can be solved with the help of the hybrid algorithms which incorporate e.g. the gradient base algorithm with the bioinspired algorithm (Orantek, 2004). It is possible to make use of the optimization results having decided whether the optimization when deciding if the optimization method should be changed and repeated. The results from a series of local algorithms, each with different results, imply many local optima objective function. Changing the optimization algorithm to bioinspired one allows to find the area near the global optimum. The bioinspired algorithm's results can also be used as a starting point for gradient based algorithm and pointing to the exact global optimum.

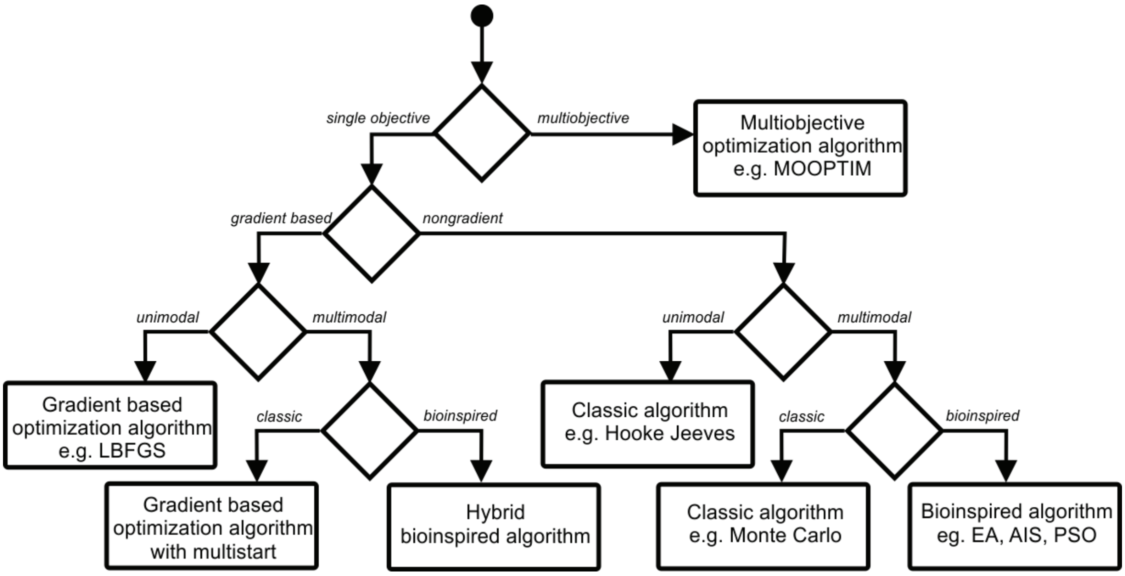

Fig. 3. The optimization algorithm choice strategy

4. EXAMPLE OF IMPLEMENTATION OF EXPERT SYSTEM TO OPTIMIZATION SYSTEM

The strategies can be presented as an expert system to the users of optimization system. Thorough insight into each step, but also into parameters of algorithms, can be coded into decision trees. In such approach, the expert systems have two main functions. They help choose the proper steps in the optimization or the algorithm and the algorithm parameters in the first runs. Their next function is connected with the results the user obtained after the optimization. On the basis of these results, the expert system recommends certain changes in the optimization method parameters or even the change of the optimization method.

The decision tree is coded into database containing a question and possible users answers. The implementation is based on two classes. The decision tree leaf is stored with the use of the *Strategy_leaf* class. The object of the class contains information about the identification number of the leaf, question, possible answers and the number of child leafs connected with each answer. The sample tree is shown in figure 4. The *Strategy* class allows for loading the tree from file into database, creation of the tree leaf objects and communication with the user. The *GetLeaf* method returns a leaf with a current question and all possible answers. After presenting the question and answers to a user, the program calls the *SetAnswer* method with the number of a user's choice connected with the chosen answer. These two methods can be called one by one iteratively.

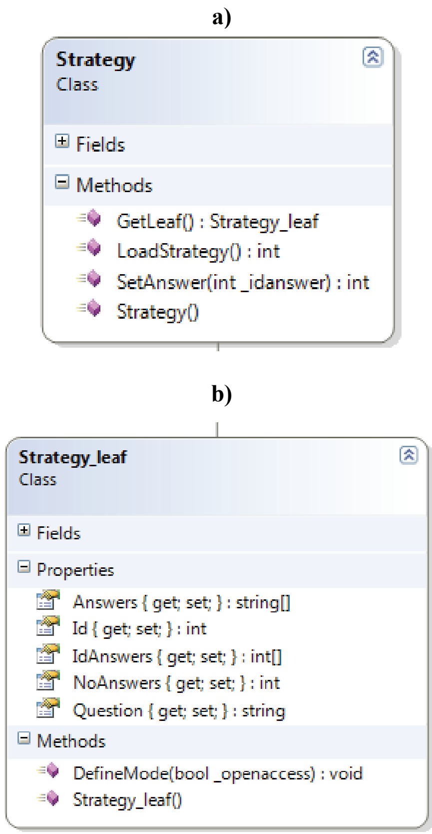

Fig. 4. The classes a) Strategy and b) Strategy_leaf

5. NUMERICAL EXAMPLE

The problem of optimal composite material design in multiscale modelling is considered as a numerical example. The objective function depends on the performance of the structure in macro scale. The design variables describe the shape of the microstructure. The model in two scales is presented in

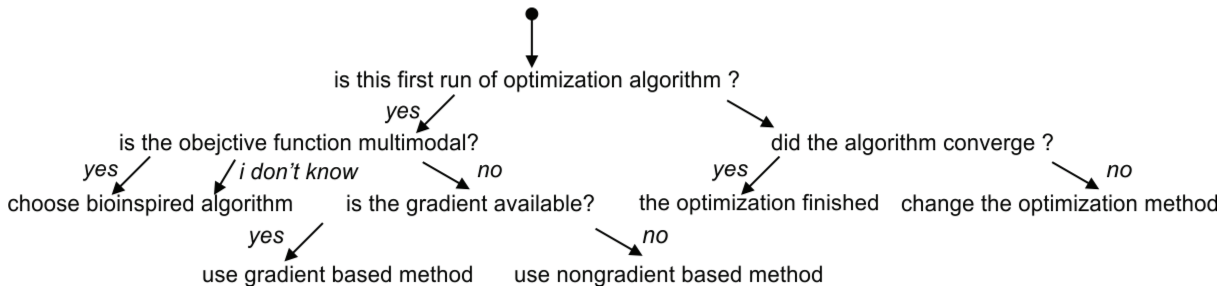

Fig. 5. *Example of a very simplified decision tree*

figure 6. The microstructure is build from two materials glass and epoxy. The geometry of the glass component is determined by the use of design variables. The NURBS curve was used to model the glass. The eight design variables were used. The design variables g_1-g_8 are coordinates of the control points of NURBS polygon (figure 6b).

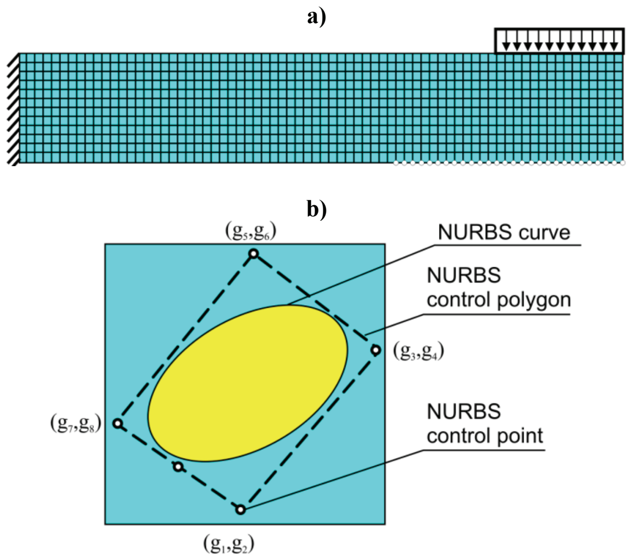

Fig. 6. *The model for a) macro, b) micro scale*

The objective function was formulated as minimum of displacement of the structure in macro scale. The constraints on the maximum ratio between glass/epoxy volume is given. In this paper the proposed strategy is used for the above problem. The problem was described with small number of variables and the parameterised NURBS curve. Quick scan through design space was performed just to take look on the objective function changes. The result of substituting two variables with the other six fixed ones is shown in figure 7. The scan was performed for some values of the g_1 and g_2 design variables (30x30 arbitrary points). It can be observed that objective function changes in non smooth way. The constraints which occur in the problem are nonlinear. The constraints were imposed with the use of penalty function. The next step is connected with the decision about metamodel usage. In the presented approach the metamodel doesn't exist and the time need to create the metamodel for a problem with eight design variables, nonlinear constraints and non smooth objective function value would require thousands of objective function evaluations. The authors decided to perform the optimization without metamodel. The chosen by the authors path in the strategy is shown in figure 8. The global sensitivity analysis were performed with the application of NISP toolbox for Scilab software (Baudin & Martinez, 2012). The resulting first order and total indices for each design variable are shown in figure 9. Since the design variables have similar influence upon the objective function value, so all the design variables will be used in the optimization problem solving. The strategy for choosing proper optimization algorithm was used and the path of choices made by authors is shown in figure 10. The objective function is multimodal (as shown in figure 7) therefore the the bioinspired algorithm was selected. The information about gradient of the objective function is not present, thus the hybrid bioinspired algorithm (bioinspired algorithm supported by classic gradient based algorithm) cannot be used. The problem seems to be complex due to nonlinear constraints and multimodal objective function so our choice is

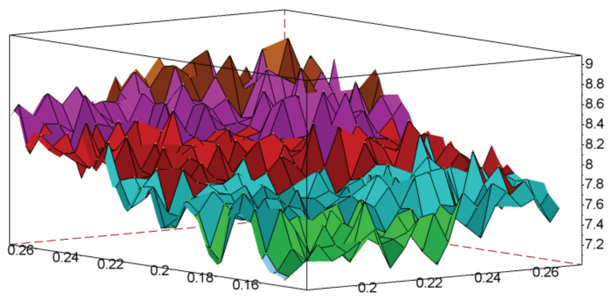

Fig. 7. *Objective function value in the function of g_1-g_2 design variables (g_3-g_8 had fixed values)*

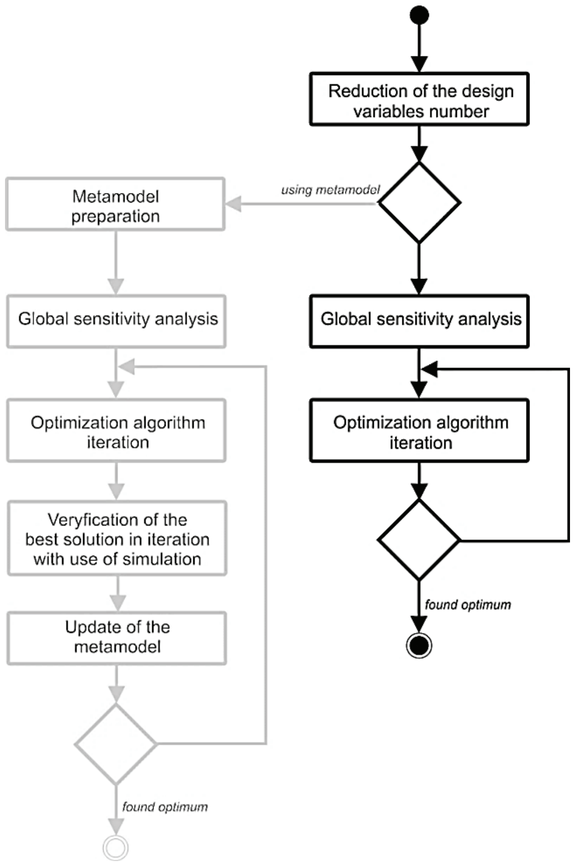

Fig. 8. The path in the strategy chosen by the authors

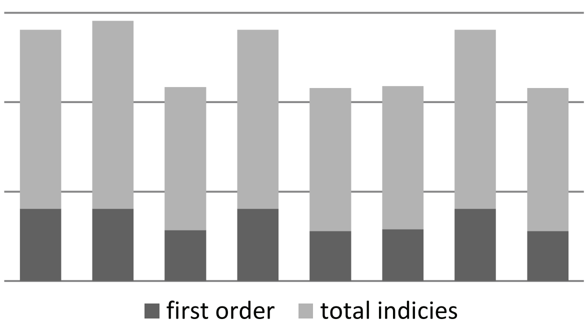

Fig. 9. Global sensitivity of the design variables g_1-g_8, shown as the first order and total indices

to use evolutionary algorithm as a one from the range of the bioinspired optimization algorithms. The parameters of the evolutionary algorithm were as follows: number of chromosomes 10, Gaussian mutation with simple crossover probability 90%, uniform mutation probability 10%. The detailed description of evolutionary algorithm and evolutionary operators can be found in paper by Kuś et al. (2011).

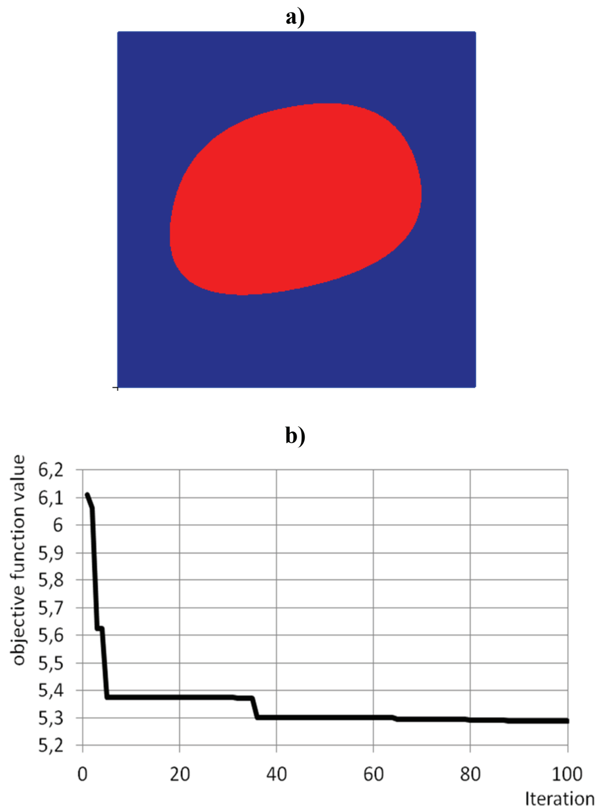

Fig. 11. a) Micromodel obtained with the application of evolutionary algorithm, b) Objective function value as function of iteration number.

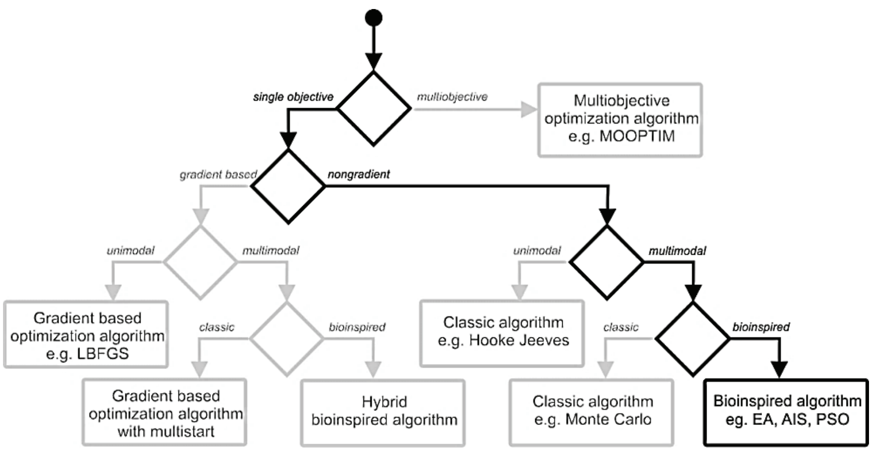

Fig. 10. The path chosen in optimization algorithms strategy

The resulting microstructure obtained during optimization is presented in figure 11a. The change of the objective function in the iterations of evolutionary algorithm is shown in figure 11b. The total number of objective function evaluations was equal to 1100. Comparing the total number of objective function evaluations to the thousands needed for creation of appropriate metamodel, it can be stated that here the optimization without using metamodel is faster. The statement is only true for the problem under consideration. For many other optimization problems the metamodels are essential part of the optimization strategy.

6. CONCLUSIONS

This paper discussed the strategy for optimization of processes. It focused on these steps during optimization which allow for the reduction of design variables and shortening of the computational time. Special attention was paid to the strategy of choosing a proper optimization algorithm. Moreover, the paper included an example of implementation of an expert system which helps users of the optimization system select optimization methods and their parameters.

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IDEA STRATEGII OPTYMALIZACJI DLA PROCESÓW PRZEMYSŁOWYCH

Streszczenie

Artykuł jest poświęcony strategii optymalizacji procesów. Przedstawiono w nim sposób redukcji liczby zmiennych projektowych, skrócenia czasu przy użyciu metamodeli. Omówiono użycie globalnej analizy wrażliwości w celu określenia najważniejszych zmiennych projektowych. W artykule przedstawiono strategię wyboru metody optymalizacji oraz podano przykładową implementację systemu ekspertowego wspomagającego użytkownika podczas stosowania jednej z przedstawionych strategii.

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