MULTI-OBJECTIVE ROBUST OPTIMIZATION
USING
IOSO TECHNOLOGY
PART II: REAL LIFE EXAMPLES

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Abstract: This paper presents the main capabilities of IOSO (Indirect Optimization based on Self-Organization) technology algorithms, tools and software, which can be used for the optimization of complex systems and objects, including air engine and aircraft. IOSO implements a novel evolutionary response surface strategy. This strategy differs significantly from both the traditional approaches of nonlinear programming and the traditional response surface methodology. That is why, IOSO algorithms have higher efficiency, provide a wider range of capabilities, and are practically insensitive with respect to the types of objective function and constraints. They could be smooth, non-differentiable, and stochastic, with multiple optima, with the portions of the design space where objective function and constraints could not be evaluated at all, with the objective function and constraints dependent on mixed variables, etc. The capabilities of IOSO software are demonstrated using examples of solving complex multi-objective (up to 9 simultaneous objectives) problems, which are solved in deterministic and robust design optimization statements. The results of this paper show the Pareto set probability statement, which decreases technical risks when developing modern objects and systems with the highest level of efficiency.
1 INTRODUCTION

Any optimization research requires at least two components. First, one needs the object itself or its analogue (a mathematical model) that will make it possible to quantitatively evaluate how design parameters affect the efficiency of the object. Second, an appropriate technique for the optimum solution search is required.

Multidisciplinary optimization problems are distinguished from the others by the fact that mathematical analysis models for different disciplines are usually developed by different authors, and are implemented using different algorithmic programming languages and hardware platforms. These factors significantly complicate the solution of such problems since implementing the scheme “mathematical model - optimization algorithms” inevitably encounters technical or organizational problems. This explains why software products designed for searching extremum using different-class mathematical models are being developed so intensively. Achieving this goal assumes proper customizing data exchange between the mathematical model and the optimization program. The well-known software products on the market are iSIGHT by Engineous Software Company, VisualDoc by Vanderplaats Research & Development, Inc. (VR&D), Epogy by Synaps Company and others. These packages are currently used for solving real-life optimization problems.

This paper presents the some examples of usage IOSO tolls and software for real-life optimization problems. Currently, our algorithms and software are effectively applied to the following problems:

• Design optimization (obtaining the most effective technical solutions by means of multi-dimensional optimization of design parameters of the system being investigated according to one or more criteria);
• Obtaining optimal management of complex systems at a wide range of varying conditions and purposes of functioning;
• Design optimization of controllable systems (simultaneous optimization of design parameters and control laws);
• Comparative analysis of different solutions and grounds for choosing a particular technical option.

This paper demonstrates the optimization of parameters for engine systems in aircraft either Deterministic or Robust Design Optimization (RDO) statements for multi-objective problems.

2 MULTIDISCIPLINARY OPTIMIZATION OF AIRBREATHING ENGINE

The purpose is to obtain the totality of Pareto-optimum combinations of air engine and aircraft parameters. This means that we must use a mathematical model of air engine and aircraft that allow defining objectives and constraints for different design variables of air engine and aircraft. We used analysis codes of air engines and aircraft for this research which was developed and presented earlier\(^1\)\(^2\). The analysis code of air engines allows one to define the performance characteristics of the engine for given parameters of engine operation process. It means that we can calculate specific fuel consumption and thrust, with external resistance included, for any flight operating modes of aircraft; weight, size engine’s parameters; engine’s life period; level of engine noise; design, operating mode and maintenance costs of the engine...
for the current value of the operation process engine parameters.

Performance characteristics of an aircraft are calculated by using a mathematical model developed by the Central Institute of Aircraft Motors (CIAM)\(^2\). This model allows one to define the main objectives of subsonic and supersonic aircraft for given design parameters and performance characteristics of an engine, and the geometry of aircraft, at the various variants of flight conditions and different operating modes of aircraft. For example, we can calculate passenger-by-kilometer fuel consumption, direct maintenance expenditures, maintenance costs, terrain noise level, take-off runway, maximum of altitude, maximum Mach number for different parameters of the operation process of the engine, and the different geometry of aircraft.

For this research we have completed two separate analysis codes and have used external batch-mode executable modules for our optimization procedure\(^1\). Thus, we have a complex multidisciplinary optimization problem.

As shown in the preliminary analysis, while solving design problems (one for aircraft and engines, for example) incomputable areas of values of objective function and constraints may exist. This can be conditioned by both the impossibility of project existence at a certain combination of design variables, and the instability of numerical schemes used as mathematical models. This can even lead to the crash of the user’s application. For example, Fig. 1 shows the topology of the engine’s fuel consumption rate during cruising flight and some constraints in the area of extremum as dependent on the bypass ratio and low-pressure ratio of the engine’s fan. The dark area on the right corresponds to incomputability areas of the mathematical model. In this case the incomputability area is conditioned by the fact that at certain combinations of the bypass ratio and fan pressure ratio it is impossible to ensure coordinated work of the engine’s elements (increasing both of these parameters the turbine’s power is insufficient to move the fan). The existence of such areas usually substantially complicates the solution of optimization tasks and in some cases makes finding extremum impossible.

Figure 1. Topology of objective and constraints.
In this case, we have multidisciplinary optimization problems with a crash analysis code. Generally, it is a multi-objective constrained non-linear optimization problem with a region that can use crash analysis codes. We used IOSO NM 1.0 software for this research, which allowed the solution of this type of optimization problems\(^3\). We tried to find the best design (Pareto set), including, first, multi-point operating modes of aircraft and air engine, second, different flight programs of aircraft (really we use 5 different flight programs according to the requirements of designers). This means that we have no design operating mode for aircraft and air engine. We must improve some integral objectives, which describe the efficiency of this complex object (aircraft + power system) including each operating mode (a set of different operating modes of flights).

Note that all this research must be considered as preliminary analysis for choosing a set of alternative technical solutions and concepts, which can be used for more detailed research in the future using high fidelity analysis codes (2D and 3D models). Thus, this is the first stage of the design of new modern aircraft and air engines. We are sure that this approach can be used for the next step. We have experience using procedures in this area as well\(^{4,10}\).

2.1 Deterministic optimization

**Purpose:** to obtain the totality of Pareto-optimum combinations of air engine and aircraft geometry parameters for regional subsonic jet.

**Problem features:**

**Design variables:** - total compressor pressure ratio; low pressure compressor (fan) pressure ratio; bypass ratio; temperature before turbine, parameters of control system, and geometry parameters of aircraft (total 10 design variables).

**Objectives:** the main efficiency indexes of aircraft (passenger-by-kilometer fuel consumption, direct maintenance expenditures, terrain noise level, take-off runway etc. (total 8 objectives).

**Constraints:** design requirements of aircraft, maximum temperature before turbine, maximum pressure in exit of compressor, stall margins of both compressor at all operating modes, etc (total 26 constraints).

As example, Figure 2 shows Pareto set for Obective #1 and Objective #4. It can be seen that all points of Pareto set allow a higher level of efficiency then is required (1.0 is required level). Figure 3 shows objectives for each point of the Pareto set. We think that this set can be used for choosing the best technical solution.

Note that each point of the Pareto set corresponds to a different operating mode for engine parameters and the geometry parameters of the aircraft.

For example, Figure 3 show distribution of objectives for some different points of the Pareto set. Maybe point # 8 is the best because in this case we can improve all objectives by more then 2 %. That is why this design was chosen for the solution of Problem #2.
2.2 Robust design optimization

We used deterministic statements for the last problem. It means that we have no information about the probability of the realization of these results. That is why we cannot be sure that this efficiency can be realized in practice. It is very important to minimize the risk of realization failure to develop a modern complex system and objects. It is well-known that we can use a probabilistic approach for the solution of these problems\textsuperscript{11-15}, which are known by the name Robust Design Optimization (RDO). It means that we must use probabilistic objectives for this optimization problem and calculate these criteria by each interaction. We used distributions of design variables for this RDO solution, which was based on many years of aircraft and engine development. As shown the analysis of each design parameter has a different distribution. We have approximated this experimental data and used it for numerical research.

In this research we chose the probability of an objective as the stochastic criteria, because this type of stochastic criteria can guarantee high quality determination solution for Robust Design Optimization\textsuperscript{15}. For this research case we have multi-objective constrained optimization problems with a crash analysis code. For this research we used IOSO RM 1.0 software\textsuperscript{16}.

\textbf{Purpose:} to research the possibilities of design requirements for commercial supersonic aircraft ensuring the use of probability objectives.

![Figure 2. Pareto set of regional subsonic jet](image)

![Figure 3. Points of the Pareto set for a regional subsonic jet.](image)
**Problem features:**

**Design variables:** - total compressor pressure ratio; low pressure compressor (fan) pressure ratio; bypass ratio; temperature before turbine, parameters of control system, and geometry parameters of aircraft (total 10 design variables).

**Objectives:** the probabilities of main efficiency indexes of aircraft (passenger-by-kilometer fuel consumption, direct maintenance expenditures, terrain noise level, take-off runway etc. (total 8 objectives).

**Constraints:** many design requirements of aircraft, maximum temperature before turbine, maximum pressure in exit of compressor, stall margins of both compressors at the all operating modes, etc. (total 26 constraints).

The first part of this problem includes the solution of this problem in a deterministic statement. An example of a deterministic solution is Figure 4, which shows the Pareto set for flight and altitude flight capabilities (this is circular label). Then we test all these Pareto points in a probability statement using the distribution of each design variable. Then we defined the value of objectives for different levels of probability using numerical random research for a given distribution of each design variable. For this estimation we used 10000 numerical calls. The main results are shown in Figure 4 (square label, yellow is the level of the requirements of this project).

![Figure 4. Pareto set for range of flight and altitude flight capabilities for: a) deterministic statement, and b) Robust Design Optimization statement.](image)

First, one can see that the Pareto set in a probabilistic statement is very small. It means that we have low level of compromise between these objectives. As shown in analysis we have the same situation for other objectives. Second, both objectives are decreased. This means that one cannot ensure the level of efficiency, which was reached by a deterministic statement. Moreover, we cannot ensure the requirements of the project (1.0). This is impractical because the project cannot reach the required efficiency. In other words, a deterministic solution is a nice project,
but we must understand that it is a project on paper only. We can never reach this level of efficiency if we try to realize this project for real-life objects. Note that each company has their own level of development and production. This means that we must develop a particular project using the specific uniqueness of this company, which has its own cycle of development and production for each object. In our case we use probabilistic properties for design variables only. In real-life we must use information about the accuracy of the analysis code, which we use for developing each object. For example, each company has variable levels of accuracy for their computer code analysis. The experimental research is also used for the development of modern objects with various levels of accuracy. Moreover we must have a clear understanding that we cannot consider all physical phenomena during the development of a project.

You can find many different statements and results for the solution of RDO problems in other papers. Some of these problems can be solved if we use probabilistic statements. The general ideas of the RDO approach are explained next. We must find design variables, which allow us to ensure a high level of probability for the realization of a project. It means that we must find design variables where we have a low level of divergence of objectives for a given level of production (this includes all aspects which we discussed earlier). Note that the purpose of robust analysis and robust design optimization are very different. Robust analysis means that we study some current solutions near one point only. This point is the extrema of objectives. Robust design optimization means that we must find solutions (design variables), which ensure the best value for efficiency with maximum or given levels of probability for this object.

Figure 4b shows Pareto set for Robust Design Optimization. Comparative analysis (Fig.4a and Fig.4b) is shown next. First, the RDO approach allows finding a solution, which can be realized with high-level probability. Second, we have compromises between these objectives. It means that we can choose a different solution from the Pareto set, which has different levels of efficiency for aircraft. Third, if one compares the results of a deterministic and RDO approach, we can ensure the highest-level of realizing the efficiency for aircraft for the same level probability. Fourth, we cannot ensure design requirements with probability P = 100%, but we can realize the project parameter with a probability P=98% (nearby P = 100%). Moreover, we have a Pareto set for this project with alternative variants which can be realized with probability P > 98%. This means that we have a level of freedom connected with choosing some alternative projects.

Note that this Robust Design Optimization problem has 8 objectives (each was considered as probability criteria) and 10 design variables. For example, Figure 5 and Figure 6 show a Pareto set for different levels of the probability. It can be seen that for probability P = 90% we have many points in the Pareto set, which ensures successful realization of design requirements. Note that a deterministic procedure can guarantee a needed level of design requirements with the probability of only P = 50%.
Figure 5. Pareto set of objectives for Robust Design Optimization (Probability of realization is $P = 10\%$).

Figure 6. Pareto set of objectives for Robust Design Optimization (Probability of realization is $P = 90\%$).

Figure 7. Change of flight range and altitude flight capabilities depending on the probability of realization.
Figure 7 illustrates the main particularity and quality of Robust Design Optimization. For design requirements we can ensure the probability of realization $P = 98\%$ for a range of flight conditions if we used the RDO procedure. For a deterministic statement we can only have $P = 63\%$. Thus, a deterministic approach cannot guarantee the needed level for range of flight, because probability $P = 63\%$ is a lower level and guarantee of the requirement level for range of flight is an important contingency in statistical terms. Note that a deterministic solution for range of flight can be 0.95 only for the same level of probability $P = 98\%$. In other words, we cannot ensure the needed range of flight if we use a deterministic procedure. However, we can find it if we use the Robust Design Optimization approach. We have a different situation with altitude capabilities. Both approaches have approximately the same level of altitude capabilities for the same value of probability. Why? First, it is very easy to reach the level of this requirement. Second, all points of the Pareto set for the deterministic case allows us to ensure an increment of altitude capabilities more then 5\% with reference to the requirement level.

This means that we have some reserve of altitude capabilities, which can be used for the improvement of probability for a deterministic solution. Thus, the requirement for altitude capabilities is not critical for this project. We can ensure a higher level of this objective (altitude capabilities) without decreasing other objectives. Typically, probabilistic research and robust analysis decrease the efficiency of objects (for example, the decrease of flight range in this case). But, for altitude capabilities we have a large reserve of increment. It is enough to guarantee a high level of probability for the robust analysis stage. Thus, the results of RDO research give us very important information about an object. First, what is the possibility of improving each objective? Second, which objectives decrease the efficiency of the project? The last question is more important for practice. Can we exchange the formulas in this problem or must we find a new technical solution for this design (for examples, different configuration of aircraft, another schema of engine, including additional design variables etc)? This information can help us to formulate this statement in a more correct form for future research.

Fig.8 illustrate distribution for some design in research area of the Pareto set variables for a deterministic and robust design optimization statement. You can see that we have a different distribution of design variables for these cases. That is why we cannot define the robust design optimization solution if we use a deterministic approach only. If we solved this optimization problem in a deterministic statement, then we can try to use this solution for Robust Design Optimization. However, we cannot guarantee that this solution can to ensure probabilistic properties of this objective in general. This solution is not the best solution for robust design optimization problems.
Figure 8. Pareto set of objectives for Robust Design Optimization with 10% probability of realization.

3 CONCLUSIONS

A new robust optimization algorithm (IOSO) was shown to be a highly efficient and reliable tool for multi-objective optimization in deterministic and probabilistic statements. We tried to demonstrate that robust design optimizations ensure for a higher level of probability of realization for real-life technical solution.

A Pareto set in probabilistic statements allows for a decreased technical risk of development for new modern higher qualitative objects and systems. All of this research demonstrates some of the possibilities of IOSO tools and software.

The examples relate specifically to air engine and aircraft. However, this technology has been highly successful in use for many different areas and it can be used in a wide range of fields.

REFERENCES