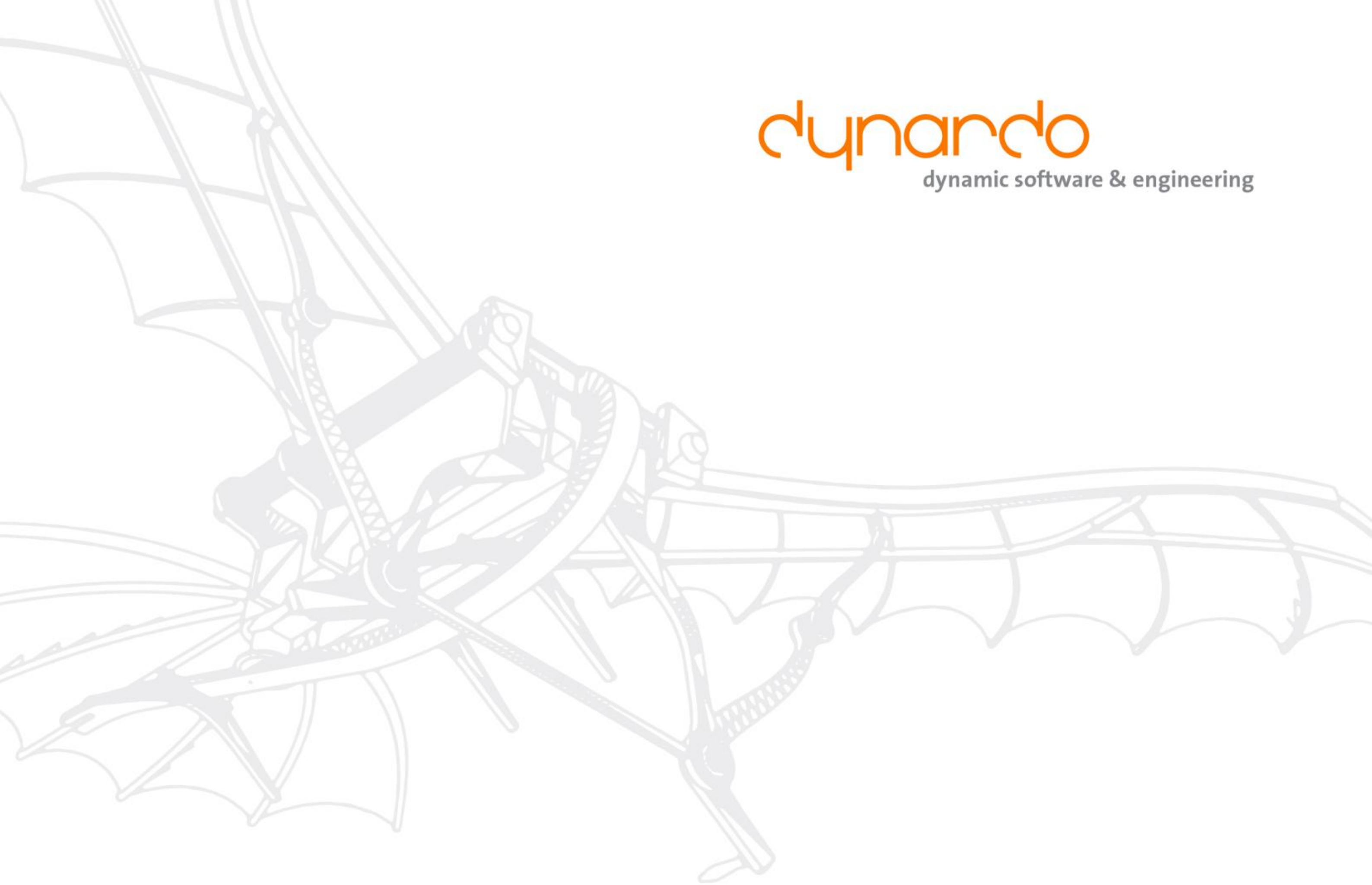

dynamic software & engineering

Lectures

Quest for the optimum

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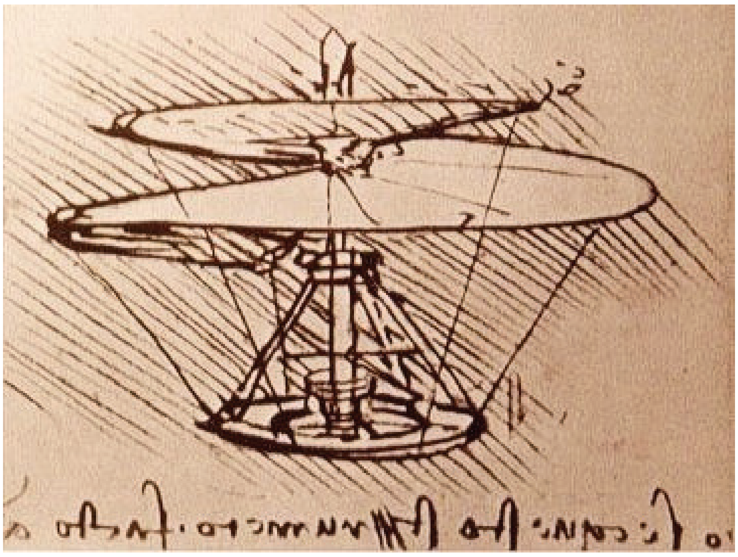
Quest for the optimum

Methods of CAE-based Robust Design Optimization in Virtual Product Development

The fact that innovation is often an imitation of nature in respect to technical matters is something even Leonardo da Vinci was aware of. An initial inspiration is followed by an evolutionary process of trial and error which maps the stations of technical progress. This progress includes technical revolutions such as the invention of the steam engine as well as the development of the combustion engine up until its optimized state of today. The basic principles of technological progress are the same as they were 500 years ago, yet today they function much quicker. Mathematical algorithms and rapidly increasing processing power allow for ever more realistic virtualizations, thus relocating the development completely in the virtual world. This relocation shortens the developmental period drastically. If we assume that the simulation in the virtual world is realistic enough to estimate product features, and design variant fabrication and calculation is automated, it is likely that Leonardo would have then developed strategies to optimize the trial and error process of virtual product development itself.

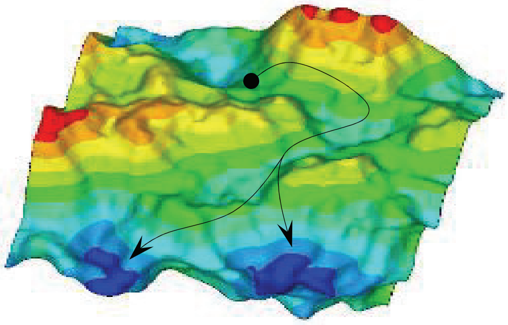



Left: da Vinci's design of a helicopter
Right: Leonardo da Vinci

This brings us to the topic of applications of optimization strategies in virtual product development.

The simplest solution to optimization would be producing, calculating and evaluating new variants until one is satisfied with the product features. To achieve this, one can create variants systematically, either through combinatorics or for all extrema of design parameters. Procedures of this kind are often referred to as Design of Experiments (DoE). It is also possible to create variants by chance, relying on a process of game theory - Monte Carlo simulation, for instance, - named after the famous casino in Monte Carlo. Either effort or chance could lead to success.

An engineer, however, is tempted to think ahead and wants to influence the process of improvement. Thus, many optimization strategies can be found.

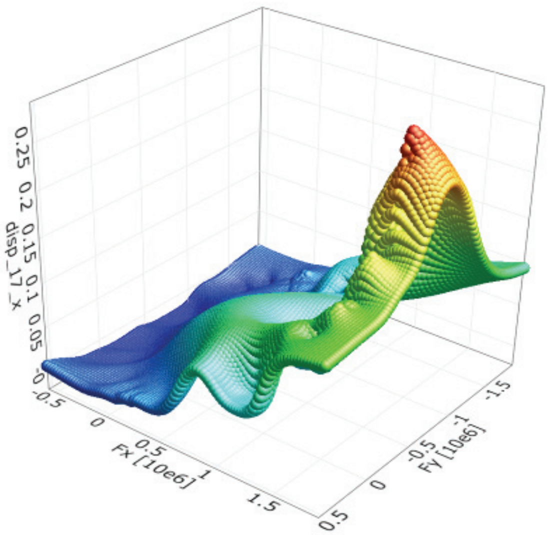


Optimization challenge: which algorithm finds the deepest valley?

One strategy forms gradients of design modifications by calculating small changes in every design variable and uses this information on the quest for the optimal design. Gradient-based processes are commonly called mathematical optimization processes. The success or failure of such mathematical optimization processes depends on determining significant gradients. Therefore, these processes require high detail in calculation and structure of the problem. In case these requirements are met, mathematical optimization processes are unbeatably quick in looking for the optimal design.

A second strategy watches nature closely and aims to understand the evolutionary process, then applies it to technological questions. This strategy led to numerous evolutionary optimization strategies: genetic algorithms that imitate evolution through genetic crossovers, evolutionary strategies that develop design through (coincidental) mutation or mechanisms that imitate a bee hive's intelligence when looking for food. Evolutionary optimization strategies are popular today due to their robustness. They achieve to improve a design almost every time, even when the results from the virtual world are inaccurate or single designs cannot be calculated successfully. It is extremely strenuous to verify whether the design improvement is significant or whether the optimization potential has reached its limit, which means that the convergence behavior leaves a lot to live up to in that respect.

Approximation models of the design spaces when optimizing are a good option in case a single design evaluation demands long calculation periods. These models are generally referred to as response surface methods. Response surfaces are fit into the sets of existing support points in the design space and the optimization is executed on these response surfaces. It is advisable to check whether the "optimal" designs bear up against recalculation, which forges the path in iterative or adaptive response surface methods.



Visualization of nonlinear correlations with Moving Least Square approximations.

Virtual worlds idealize reality and assume perfect surroundings. The elasticity modulus of steel, for instance, is assigned an idealized value, usually an average or a value of attributed probability, e.g. 5% fractile value. When a design is optimized and its performance is constantly evaluated below the ideal value of the elasticity modulus, its robustness has to be examined according to all scattering of important surrounding factors of the real world. This process is called robustness evaluation. To evaluate one design, all relevant scatterings are defined by stochastic parameters and using a random generator n-possible situations out of the set of possible design realizations are created, calculated and evaluated. Generating a set of possible designs based on distributional information of uncertain input values is referred to as stochastic analysis. Its results are evaluated with statistical measures; averages, standard deviations and variation coefficients are calculated. In case the scattering of important product characteristics is small, it is pronounced a robust design.

When we examine if the resulting scatter of product features is exceeding or falling short of defined states, we come to the topic reliability.

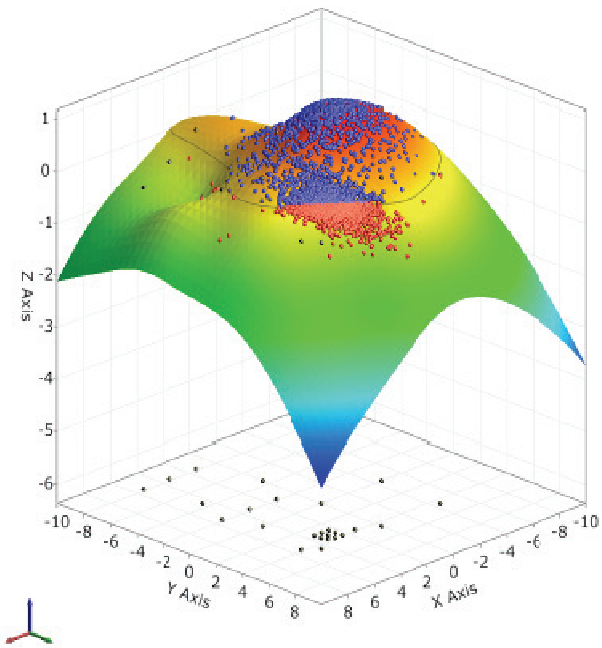


Image: Reliability analysis on the response surface (blue ok, red not ok)

A technical design should usually fulfill its functions reliably, yet at the same time be, for example, lightweight for economic reasons and save on energy. It is possible that these requirements contradict each other and an economic compromise has to be reached. For this matter, a design which works with a defined probability is desired.

Through the ages, engineers have been considering the reliability of their designs and have been depending mostly on experiences and approximating necessary safety distances. This can be illustrated by cathedral works of medieval times. During the Romanesque period, window openings were narrow and covered by semicircles. This construction was very safe from a static viewpoint. During the Romanesque period, however, facades became more and more delicate, the window openings and span widths became wider. Step by step, the master builders came closer to what was statically possible. In the process, the works on some churches could not be finished or collapsed. The experiences from then led to the formulation of construction rules, some of which are still valid today. With the help of these rules, safety distances have been established. They propose a sufficient distance to uncertainties of the foundation and the church building's geometrical deviation or material scattering.

Today, there are many rule sets which define safety distances for standardized constructions. Given the case that boundaries are fathomed or regulations on safety distances are missing, reliability often has to be demonstrated in the virtual world, accompanied by a few trials on the finished design. Numerical methods of reliability analysis finally link stochastic analytical methods with optimization algorithms in order to find and secure small probabilities.

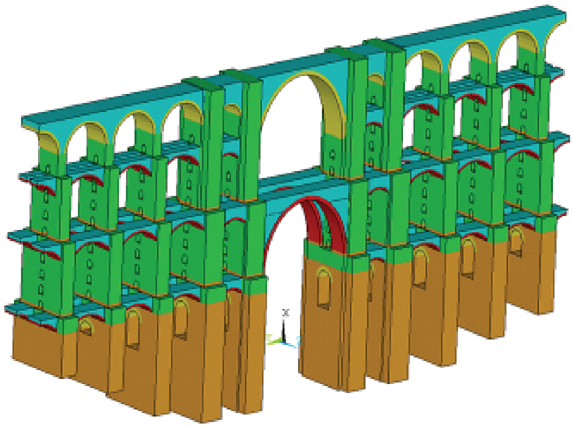


Image: The design of brick viaducts during the pioneering era of the railroad relied on the same rules as cathedral works. After 100 years the constructions are still completely safe.

When optimization strategies and the determination of robustness and reliability complement each other, the result is called robust design optimization. In the best case scenario, robustness and reliability can be proven for the optimized design. If necessary, security distances can be readjusted and optimization and reliability analysis are repeated. In extreme cases, robustness and reliability values influence the optimization task.

So, nothing new since Leonardo da Vinci? Based on a draft, a product's characteristics are still being improved through variation and the success of the concept is repeatedly reviewed under the aspects of uncertainties and imperfections – only that this now happens virtually and in many dimensions where different designs are evaluated simultaneously.

One small, yet delicate problem remains: the engineer seeks to understand how and why a randomly or methodically improved design is improved. This soon meets the limits of human dimensionality, as we live and think in three dimensions. High-dimensional correlations have to be reduced to mere 2 or 3-dimensional images and then verified.

How to start when introducing robust design optimization in your virtual product development? We recommend optiSLang - our premium software package for CAE-based sensitivity analysis, robustness evaluation, reliability analysis and robust design optimization. Best in class algorithms of all previously discussed technology is available and more important the technology is bundled in easy and safe to use flows to enable non-experts to explore design spaces and to perform robust design optimization.