*Transdisciplinarity and the Future of Engineering*
*B.R. Moser et al. (Eds.)*


*doi:10.3233/ATDE220676*

# Data-Driven and Real-Time Prediction Models for Highly Iterative Product Development Processes

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**Abstract.** Some high-level technical products are associated with transdisciplinary simulation-driven design processes. Therefore, their design process involves many stakeholders and is prone to frequent changes, leading to a highly iterative process with a long lead time. Despite the decades of statistical approximations and metamodeling techniques on prediction models, companies are still striving to achieve fully automated real-time predictions in early design phases. The literature study shows a gap in existing methods such as not being fully real-time or suffering from high dimensionality. This paper presents a generic model for the development process of such described products and motivation for such modeling through a series of semi-structured interviews with an automotive sub-supplier company. The proposed process model points to the digital verification in every design loop as the bottleneck which is then confirmed by interviewees. As alternative solutions to overcome the problems, a method for data-driven and real-time prediction models is presented to enable the designer to foresee the consequence of their decision in the design phase. To evaluate the method, two examples of such real-time meta-modeling techniques, developed in an ongoing research project are discussed. The proposed examples confirm that the framework can reduce lead time spent on digital verification and therefore accelerate the design process in such products.

**Keywords.** Data-driven, Prediction models, Design automation, Simulation-driven design, CAD/CAE

## Introduction

For many industries, long development lead time has been one of the critical issues, and reducing this time has been a goal for decades. For instance, by the late 1980s, leading Japanese auto firms (most notably Toyota and Honda) were developing major new car platforms in 36 months and replacing existing product generations every four years. European and US auto firms were taking approximately 60 months to develop similar products, expending considerably more resources and replacing existing product generations every eight or more years [1]. This rapid development gave the leading Japanese firms significant advantages in forecasting consumer preferences and offering newer designs (on average), faster paybacks, and more innovative products incorporating newer technologies [2].

The development lead time has been also aggravated by the emergence of some high-level technical products that are highly dependent on digital engineering tools in their development process. For these products, virtual models and simulations are the only means of validation before production [3]. Simulations range in a broad spectrum

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with different granularity levels, from the simulation of a component under a specific load, contact, and boundary conditions to the process simulation in product development loops. Simulations are usually considered where observing the real-world case is expensive or impossible, where analytical solutions are too complicated, or costly to be validated. The granularity level of a simulation is coupled to its model, which is defined as a simpler representation of a system and is used to study the behavior and performance of a system, for instance, to reduce the chances of failure in meeting requirements [4]. Simulations are powerful transdisciplinary tools for digitally verifying the design in early conceptual phases, before moving to physical prototyping or full extent production [5]. Approaching step by step to the solution and repeating each completed step to incorporate new information [6, 7] makes the nature of the development work with simulations iterative. It can be argued that increased reliance on simulations leads to repeating them more often. Additionally, the traditional design-build-test iterations are shifting to incorporate simulation verifications in as early stages of the product development process as possible which introduces even more iterations. As a result, the highly iterative product development process exacerbates the long-existing developing lead-time problem.

This paper studies a group of high-level technical products with transdisciplinary, highly iterative, and simulation-driven design processes and aims to increase the knowledge on certain characteristics associated with these types of design processes. The research question is to identify the problems associated with such design processes and review what current strategies and supports exist to address those identified problems in such design processes. Section 2 presents performed interviews with an automotive supplier company which resulted in a generic design process model for the design process that is presented in section 3. Results indicate major characteristics as well as the bottleneck for such development processes. Section 4 presents a potential solution as a generic method that can be used in the early stages of the design process. The method is validated by the case company as they expect this envisioned solution to improve the development lead time in their design process. The last section includes current strategies and supports and categorizes them into two umbrella groups. Shortcomings with each of the groups are studied and suggestions for future work that can address each shortcoming are presented.

## 1. Related work

All intelligent systems fall into the category of the soft computing approach that helps the designers' decision-making process, with rough but fast estimation. There are many definitions of what is considered intelligent behavior. But most of them agree on having previous data as verified facts and some kind of reasoning engine as the starting points [8]. Metamodeling or surrogate modeling techniques such as response surface, inductive learning, kriging, etc are considered soft computational techniques [9, 10]. Unlike hard computational methods that use numeric modeling, symbolic logic and reasoning, and precise models, soft computational-based methods use imprecise models and approximate reasoning and functional optimization and random search to reach for a solution [11].

Metamodeling or surrogate modeling techniques have been historically used to reduce computational time in design processes by building approximation models, mapping design space inputs to objective outputs. However, two issues usually challenge the research field. On one hand, a high number of design requirements and constraints make the decision space large and highly nonlinear which challenges the mentioned mapping. On the other hand, for high-level technical products, the requirements are not very solid (often the designers have a vague view of them) in the early phases which makes the process prone to curse of dimensionality.

Data-driven design is about making design decisions based on data analysis and interpretation. Chiarello et al defined data-driven as "Using computational systems to extract knowledge from structured and unstructured data" [12]. In the literature, this definition that attempts to take advantage of past solutions is considered data-driven. An example of taking advantage of past solutions is the case-based reasoning (CBR) paradigm, which was firstly introduced in design by [13]. CBR helps to find a good starting point for design by searching among past solutions and finding the closest alternative to the problem at hand and therefore it is considered among decision support systems (DSS) [14]. Engineering design not only aims to consider past solutions but to go further and generate a new alternative, the ones that never existed, in a feasible design space.

There has been a lot of other efforts to introduce data science into the design process. Fan et al. [15] constructed a prediction model for the vehicles' shape design. First, the profile curves of the side view for a large number of existing product samples in the marketplace were collected based on the required criteria an evaluation score is attributed to each concept. A support vector machine was trained using the 35 control point coordinates of the vehicle profiles as input data and the evaluated scores as the output value. Optimal training parameters of the regression model were determined using a grid search of cross-validation. In another attempt to use Artificial Neural Networks (ANN) as a shape design tool, Wang et al. [16] used a type of unsupervised ANN (i.e. with no feedback) namely, a self-organizing map (SOM) for constructing a topological feature map in designing sneakers. SOM is a data visualization technique that can be used to deal with high-dimensional data, consolidate the relationship between requirements from customers and formal elements from designers and formulate a customer-oriented product concept. A feature-based shape-morphing process was implemented for the design of a new style of sneakers. A model to blend the features was constructed in SolidWorks CAD by choosing any two different shapes from the SOM map. This research added a vast variety of shapes and designs of sneakers from the selected SOM feature map to help designers create many different styles in a short amount of time. Additionally, there are other reports in the literature [17] that Variational Auto Encoders, Generative Adversarial Networks, Convolutional Neural Networks, and several other AI-based methods have been employed to model a simulation or shape forming process.

## 2. Research design and the interviews

A case study approach is used together with design research methodology (DRM) to investigate the challenges of the design process in the case company. The DRM methodology is used to support a more rigorous research approach by helping to plan and implement design research [18]. In this way, this study is mainly presenting the results of the two initial phases of the research project in DRM, 'Research Clarification' and 'Descriptive Study 1'. The discussion includes suggested areas for future research that can be further developed for the next two phases i.e., 'Prescriptive Study' and 'Descriptive Study 2'.

The studied company is an automotive supplier that owns a large share of the market for specific safety-related products in the world. Based in northern Europe, the company has manufacturing plants in more than 50 countries and more than 70000 employees worldwide. The important safety-related products are of standard and customizable types and can meet all various demands in the competitive automobile industry. This company is referred to as the case company throughout this paper.

As shown in Table 1 fourteen people were interviewed for a wide range of roles involved with the development and production work in the company. The interviews were one hour each and held online. This was for two reasons, first and for most, it was due to the ongoing Corona pandemic situation around the world, and second, some of the respondent employees were located in different countries.

**Table 1.** Roles of the staff interviewed in the case company.

| | | | |
|---|---|---|---|
| 1 | Senior Simulation Engineer | 8 | Project Engineering Leader |
| 2 | Quality Coordinator | 9 | Tech Center Group Manager |
| 3 | Simulation Group Team Leader | 10 | Customer Technical Manager |
| 4 | Simulation & System Engineering Manager | 11 | Development Group Leader |
| 5 | Project Engineering Leader | 12 | Senior Design Engineer |
| 6 | Simulation Engineer | 13 | Customer technical manager |
| 7 | Product Manager Quotation Leader | 14 | Simulation engineer |

The semi-structured interview method is used to allow the interviewer to express their feelings and give distinct examples instead of solely shallow answers and add in-depth insight into the challenges. Some characteristics for a semi-structured interview that were taken into consideration are; flexible questions, specific data gathering from all respondents, a large part of the interview guided by a list of questions or issues to be explored, no predetermined wording or order exists [19]. A typical process after data collection via interviews involves identifying challenges that are mentioned by different interviewers. The identified challenges were at the end presented to the respondents and the received feedback was taken into the consideration. Moreover, a process model for the identified challenge was produced to enable understanding and in-depth study of it.

Aside from these interviews, three workshops with engineers in the company were designed to closely study how they work in practice. Two workshops with CAD designers and one with a simulation engineer in the company. These workshops overall helped to add depth to our understanding of the development process in the case company.

## 3. Challenges in the current design process

This section presents challenges that are faced by the development work and are raised during the interviews. All of the interviewees unanimously exerted that the long development lead time is the most challenging aspect of their work today. Managerial level interviewees claimed that they are doing a lot of manual work within the development process and therefore sought to automate tedious manual tasks. On the other hand, interviewees with engineering and more practical roles argued that they are doing a lot of development loops and therefore sought to reduce the number of iterations on the tasks. Iterations are historically considered a major source of increased product development lead time [20]. In the interviews, it was also mentioned that because of the nature of the products, developers strive for flawless launch by continuously correlating design with virtual and physical testing. Which leads to performing these verifications iteratively. Therefore, a product with such an iterative process in the case company takes two years to be developed and launched. To understand where this long developing lead time is initiated this research focused on the design process of the case company as an example to identify the reason behind this lag. It was understood that the design process for these products is experiencing 50-60 loops in the design process. In the simplest form, a three-step product development process i.e. Design-Build-Test cycles, [2] is used as inspiration to build a development process model of these high-level technical products and the result is shown in Figure 1.

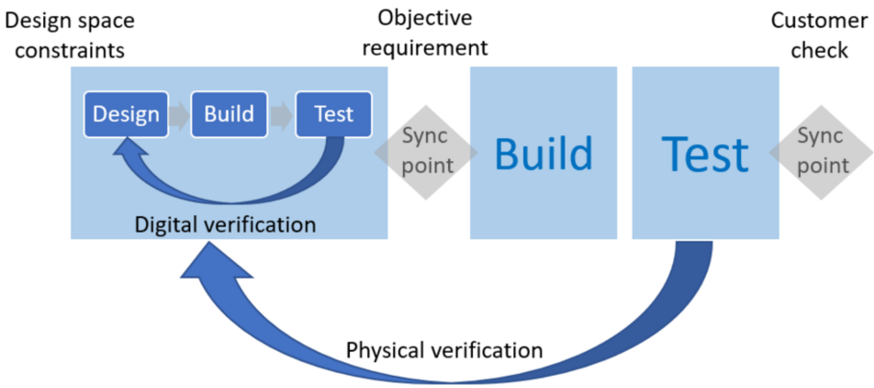


**Figure 1.** The generic product development model for iterative and simulation-driven products.

As it can be inferred from the figure, the work from design space constraints to objective requirements is iterative (inner loop). This can be due to the complexity of the product, difficulty at satisfying all the design requirements simultaneously, or having constraints with opposite effects on one requirement. As an example, when a CAD model parameter is changed, and the objective CAE simulation result fails in satisfaction of the requirements. This loop is concerned with the requirement satisfaction in digital tools and therefore it is called the *Digital Verification* loop. Moreover, the work between prototype testing and the development process is also iterative (outer loop) which is usually due to the dynamic nature of the customer requirements or lack of correlation with physical tests. For example, failure in physical prototyping or zero series can be visualized with the outer loop. The naming *Physical Verification* follows the same convention as most performed requirement satisfaction tests are physical in this loop. Overall, the two loops constitute a highly iterative process (two loops, 5-10 each) for the case company which is a common property among those groups of products under study in this research.

In the early design phases (conceptual phase) many requirements from customers are not yet solid and they are prone to change as the design becomes mature. After many design loops and digital verifications and when the requirements are better shaped the design process moves to physical verifications as well and a hybrid form of the process is continued. Within later iterations where the concept is solidified the process changes to physical verification only, and in the process no digital verification is performed anymore. The transition from digital verification to physical verification is not crisp and well-cut, but more of a grayscale. As the development matures more physical tests are performed. These physical tests are simplified tests that are being performed on test rigs. But toward the end of the process, real-world scenarios with real products are used for physical verification.

Another discussion point that was raised during the conducted interviews was the envisioned solution for the mentioned challenge. In total 10 out of 14 respondents expressed that at least one of the solutions below for this accelerating or shortening the long development lead time.

1. Design automation to do the iterations automatically.
2. Data-driven approaches to avoid iterating.

Both tracks are part of a bigger category namely intelligent systems for engineering design which was mentioned in the previous section but the application and their final result are different. In the design automation path, computerized engineering supports such as code scripts are utilized to connect engineers' knowledge and reasoning to the design process. Automation levels are different and range from the built-in coding environment of the CAD and CAE software to the utilizing external APIs that connect different engineering supporting tools to each other. However, the main goal is to accelerate the process of digital verification (see Figure 1).

Design Automation (DA) can be used to address repetitive design tasks, integrate tools and datasets, and simplify and standardize more complicated processes, achieving significant savings in development lead time and cost [21]. A mapping between approaches in design automation eases the understanding in the industry concerning what type of tasks can be automated. And what approaches in DA are suitable for what kind of tasks [22]. However, the development of DA applications is generally undertaken by domain engineers who may not have formal knowledge in engineering or software development training, with subsequent development processes lacking the structure of formalized methodologies, and important principles can be neglected [23]. Another shortcoming with this path is that in practice even if everything in the development becomes automated, each task still needs to be performed by the machine and that still would require the time for reading into the processor and processing and writing back the results. For instance, in a finite element analysis, even if everything is automated, a lot of time still is required for reading the geometry, discretization, solver run time, post-processing, and creating a report. Therefore, this approach cannot resolve the problem of long development lead time.

In the Machine learning path, the engineering knowledge and reasoning are captured in a statistical function like a black box. In this way, the trained machine learning algorithm will be able to prevent iterative simulations by predicting their results. For instance, meta-modeling techniques use statistical methods to map some inputs to simulation output and the resulting network can predict a result for the suggested design within an acceptable error margin.

## 4. The proposed solution

This section presents envisioned solutions for addressing the long development lead time problem of the high-level technical products. The idea of the solution comes from the interviews, literature study, and the development process model presented in the previous section. As mentioned, many design loops are required for satisfying all of the requirements in the design process.

In both mentioned tracks, a real-time prediction model right after design or simultaneously at the same time with the design will prevent a large amount of manual work and will accelerate the design process. Envisioned model for real-time prediction is shown in Figure 2. The objective with such a real-time prediction model is not only about the fast evaluation of different design alternatives which will be gained. This model can also help with cutting quotation lead-time, quality-ensure the design process, capture tacit design knowledge, ensure producibility and robustness.

Since in the early phases, only the digital verification is being performed and the company does not have crisp information on the requirements, the precision of the proposed design does not require to be very high. This enables a Set-based working method, where the design space can be explored to find solutions that are feasible from several aspects [24]. For instance, these early design loops are aimed to estimate a rough cost or engineering analysis. In many situations, it is enough to know (with 70-80 percent confidence) that the design will pass the requirement. This fact enables designers to use approximating methods to predict the performance of a proposed concept within an acceptable precision. This approximation capability is well aligned with the second path because using machine learning leads to prediction models. Therefore, an embedded data-driven and real-time prediction model is the heart of this method that can perform the digital verification loops while the design task is under development.

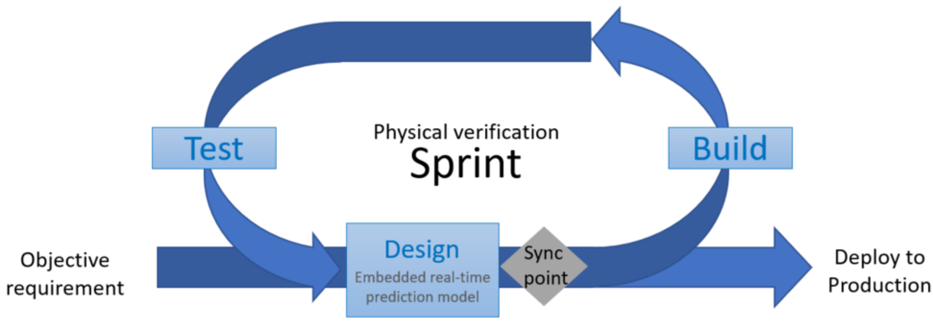


**Figure 2.** Envision model for addressing lead time with embedded real-time prediction ability.

A data-driven solution is about decisions making based on data analysis and interpretation or "Using computational systems to extract knowledge from structured and unstructured data" [12]. Our proposed method will be placed in a CAD environment and act as a traffic light for each requirement. When the designer gets the green light for all the requirements the design will move into the physical verification loop. This can be seen as a prototyping sprint that will generate agility for development work.

Using such models in the design process can help to map the design inputs to outputs just as performing the digital verifications. Moreover, it will potentially reduce the lead time as it will prevent many iterations in the design loop. Asking the company representatives about the proposed method, they confirmed that this can help them "avoid all the simulations" and "reduce the number of iteration loops" and therefore reduce the development lead time in the conceptual design phase. To overcome these problems there are several approaches in the literature that we categorize and give examples for each of them and also mention shortcomings of each category and future improvement that can be focused on in next studies.

## 5. Discussion and examples

The embedded data-driven and real-time prediction model during the design process, without any need for simulating the product's behavior, can evaluate the objective output in real-time. As discussed in previous sections, early versions of the data-driven prediction models were metamodeling or surrogate modeling methods that have been around for quite a long time. They are mainly aimed to reduce the computational cost by mapping a simulation and creating an alternative model to replace CAE work. However, seldom metamodeling techniques rarely rely only on CAD as input, and they usually incorporate many types of data types. The difference between our proposed method and the conventional techniques is highlighted when considering hindrances for applying a prediction tool in the design process namely *Dimensionality* and *Parameterization* which are identified during the performed workshops with the case company. It was discovered that the engineers in the case company are not using fully defined parameterized CAD models because it will limit them in addressing the requirements and lower their flexibility.

In CAD work, dimensionality and parameterization are discussed to be the root cause of the iterative characteristics. The company does not use a fully defined CAD model for the design process, and this increases the dependency of the design work on the experience and creativity of the designer. The utilized geometrical shapes in high-level technical products are complex and making them defined will lead to high dimensionality and will consequently limit the designer and prevent flexibility in addressing the changing requirements. The CAE work is also highly dependent on the experience of the simulation engineer. Different employees have various comfort levels regarding the different meshing software and finite element solvers and thus employees are using different procedures to do the same work. This work also depends on the work culture in different countries. For example, one simulation could be done in two different ways in two different countries.

In a complex design problem, mapping the output parameters to the input variables is not always a straightforward process. For instance, choosing the number of hidden layers to determine the complexity of the network if not chosen correctly may result in underfitting and overfitting the training data [25]. As another instance, it is difficult to see how changing one particular parameter, affects the output (Since we can have coupled parameters or variables). This limits the possibility to isolate and capture the relations between variables and reduces the chance of having a full model that truly represents the system. Another problem is the need for high accuracy in high-level technical products that requires a large number of training data available to train the network to the desired accuracy level. Due to the size of the system and the number of parameters affecting the output, it is not possible to train networks well, which often leads to simplification and generalization of the design knowledge. Consequently, the level of abstraction makes the model useless for real-life applications and practical industrial applications. Despite all aforementioned shortcomings, the majority of designers still express their convenience about getting every possible support during the design process, even when it comes to managing generalized or approximated design models [26].

Several approaches are identified in the literature that has tried to address mentioned shortcomings. These methods are categorized below and the advantages and disadvantages of each group are discussed through examples. Some potential improvements for each category as a form of future studies are proposed.

### *5.1. Order reduction*

Order reduction is a category of methods that attempt to use better parameters in the studies which will result in using fewer parameters. Sensitivity analysis methods such as Principal Component Analysis [27] or analysis of variance (ANOVA) [28] together with Taguchi are widely used dimension reduction strategies to select the most important parameters and reduce the dimensionality of the models. Yet, there is a shortcoming with mentioned methods to avoid high dimensionality. It is not possible to use CAD model parameters as inputs and the designer usually selects a couple of the most effective parameters as input. Considering how large the number of parameters and constraints in a real CAD can be, and how small each of those parameters can affect the simulation output, running higher-order Taguchi arrays add up to existing computational complications. Order reduction methods need to be developed that are not focused on using the direct CAD model parameters but instead try to extract features that have a higher correlation with objective output. Feature extraction has been used in data science to improve the quality of the inputs. This concept can also improve the engineering application of data science. This will enable much efficient mapping between input and output and will make the mapping independent from the parameterization.

### *5.2. Avoiding parameterization*

Mapping inputs to output by avoiding parameterization can be done by training machine learning algorithms that are using other forms of inputs as their input. For example, Rahman et al. used the designer's sequential design behavioral data stored in the design action log file (.JSON) of a CAD program to train a machine-learning algorithm and predict the next stage in the process as immediate design action [29]. Another example to avoid parameterization is to use image regression to map some images of the design in the conceptual phase to the objective requirement. This method has been shown to have good performance in the literature on predicting the age of people from images of their faces [30] and also to predict house prices from input images of that house [31]. One suggestion for future work is to use images of the CAD design as input to map to simulation outputs. In this way, designers will be able to predict the consequences of the decisions in the design phase in real-time. For our future studies, we will focus on an image processing machine learning prediction model that for instance can be embedded into a button in CATIA so after every design concept, confirm or rejects the proposed design changed based on the predictions it is making for the objective outputs.

## Conclusion

The design process of a group of high-level technical products with transdisciplinary, iterative, and simulation-driven characteristics is studied. Using semi-structured interviews, it was found out that these products suffer long development lead time. Studying the development process in the case company led to a generic process model for such iterative and simulation-driven design processes and their associated bottleneck. This model, literature, and further discussions and workshops, were utilized to envision a generic solution to overcome the identified problem with embedded real-time prediction capability. The solution is validated through experts. Examples of the solutions that can addresses the problem area are identified in the literature and categorized and shortcomings with each category are discussed. For each category, a suggestion for future studies is also proposed.

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