White Paper - xT smart_DoE

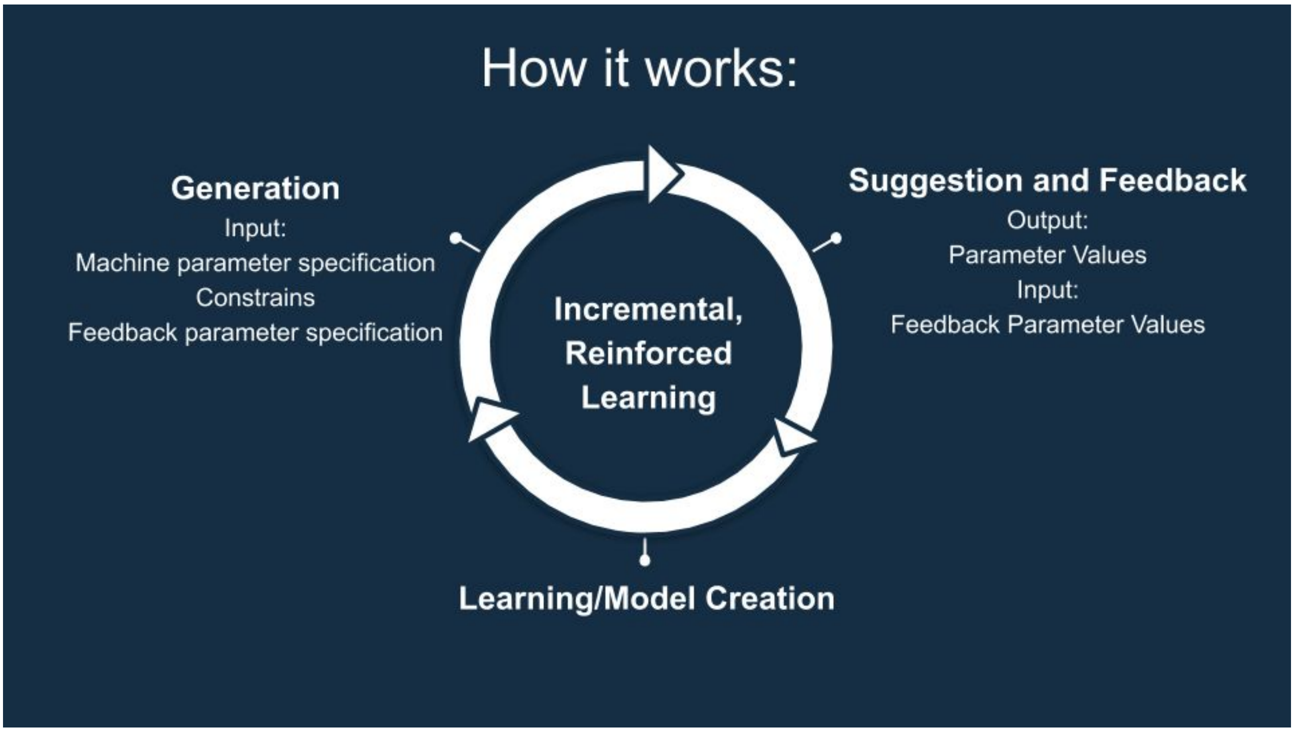
Finding optimal machine configurations or material compositions for a specific application is a complex and resource intensive task. Using classical techniques, the difficulty of finding machine configurations and material compositions scales exponentially with the amount of adjustable parameters and the number of material components. Especially in fields like additive manufacturing, CNC-machining and other manufacturing methods, where the number of machine parameters is high, such an approach leads to elevated costs and longer go-to-market time whenever an implementation of a new production process or material innovation is required. In areas like chemical production, biochemistry, and material science, increase in the complexity of material mixtures, results in rising costs and longer development time for new material compositions.

In many domains, e.g. additive manufacturing, a change in process parameters can alter material properties. That opens new innovation opportunities, at the same time requiring higher level of complexity. This complexity makes the use of advanced software solutions a necessity. As the machine configurations and the material compositions are strongly related in these fields, an effective process optimization always has to take both aspects into account. The main obstacle is that most software solutions available on the market are only good for either solving mixture type (e.g. material compositions) or factorial type (e.g. machine configurations) problems. In most cases, however, the goal is to manufacture a product with specific properties to solve a specific problem. Having a solution oriented approach in mind, both machine configurations and material compositions, although mathematically different, have to be optimized simultaneously in order to reach optimal product properties and to deliver the best functionality possible to the customer.

Out of these reasons we at Exponential Technologies Ltd. have developed a unique optimization software, called xT smart_DoE. Our software, similar to a classical Design of Experiment (DoE) software, guides the user through the experiments to accelerate the development process. However, unlike classical DoE software, our solution doesn't require statistical expertise from the user. Most industrial optimization problems are nonlinear in nature, that means that small changes of the input parameters can lead to significant changes in the result. The human brain is poorly equipped to solve these tasks, this is where artificial intelligence (AI) and machine learning (ML) algorithms can reveal their potential. Therefore, we use a combination of advanced AI and ML algorithms, that are extremely efficient at solving nonlinear problems. Using these algorithms we can accelerate the development of machine configurations and material recipes typically by a factor of 10.

The problem with most AI and ML based solutions available on the market is that they rely heavily on physical simulations and/or on big data. Physical simulations are in most cases only crude approximations of reality and assume perfect environmental conditions. This often leads to errors in the results of these simulations. Because of the nonlinearity of these problems, small errors can lead to huge deviations in the properties and functionality of the resulting product. Additionally, simulation based solutions have to be built for specific purposes and aren't easily adjustable. The obvious problem with a big data approach is the necessity of extensive data sets. However, in many R&D situations data points are not easily available and the quality of data can vary. That makes big data solutions not relevant for many R&D projects.

Having these issues in mind, we developed our solution specifically using small data algorithms that are very versatile and resilient. The resulting process is called incremental, reinforced learning. This allows us to adjust our software for many applications without any reprogramming. To set up a new experiment the user has to define the used machine and/or the material components by specifying the parameters, their maximal, minimal values and their step size. Further, search constraints can be defined. These search constraints are important to accelerate the development process, by excluding parameter regions already known to be of low probability for a good result. Our software also allows the definition of complex constraints, so constraints based on parameters which are a combination of adjustable parameters (e.g. laser energy deposition or build rate in SLM processes). As the final step, the user has to define his target function in the form of a formula, which defines how feedback is given to the software. Usually, this formula is also a complex function, consisting of several components (e.g. build quality factors, build rate, product properties). This complex target function is a mathematical representation of the objective of the optimization process. The setup of search constraints and the target function require expert knowledge and can also include subjective reasoning of the expert.



xT smart_DoE then generates the first sets of parameter values that the user manufactures and analyzes/measures afterwards according to the defined target function. The values of this evaluation have to be given back to the software. It then builds a model between the given parameters and the reached results. According to this model, the software then suggests the next parameter value sets. The user then repeats these steps until a suitable result is found. Typically we see good results within 3-5 cycles with 20 parameter value sets in each cycle. To put this in perspective, in an additive SLM process, that means 3-5 print jobs with 20 samples in each print job. The classical approach usually requires in the range of tenths to hundreds of print jobs.

To organize the R&D process and accelerate the experimental process even further, we have added a comprehensive Research Management System (RMS). The RMS helps to keep track of ongoing experiments and research activities and allows the users to share interesting finds.

xT smart_DoE has the potential to be further automated by using APIs to directly communicate with the machine and by automating the feedback (e.g. using optical tomography).

To find out more, visit our website www.x-t.ai or write us an email to info@x-t.ai.

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