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INTEGRATED EXPERIMENTAL DESIGN AND PARAMETER OPTIMIZATION UNDER UNCERTAIN PROCESS CIRCUMSTANCES

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Abstract – This paper presents an integrated experimental design and optimization methodology and its application in non-conventional machining process optimization. The introduced technique incorporates an efficient experimental settings generation module, a model building module based on the performed experiments and an optimization module using the built model. The application results show that the presented method is robust and is able to find optimal machining parameter values under uncertain process circumstances.

Keywords: non-conventional machining, experimental design, process optimization

1. INTRODUCTION

Most of the modern machining processes can only be described by numerous process variables due to the complexity of their technological background. This also means that the optimization of these processes requires such solutions that are able to successfully navigate in high-dimensional space in order to find the best parameter settings for a specific application of the machining technology. The task becomes more complex when in the field of non-conventional machining processes because their technologies are relatively new and partly unexplored. E.g. one of the problems that arose in the presented machining application is that the beginning and end of the process cannot be specified precisely. In other words the process breaks down into multiple smaller stages which behave differently from each other; therefore a comprehensive optimization cannot be applied and the different stages must be handled individually.

The paper contains five sections. After the introduction the second section presents experimental design and process optimization methods and applications. The third section describes the optimization methodology followed by the forth one reviewing the results achieved by applying the technique in the optimization of a non-conventional machining process. The last three sections are conclusions, acknowledgments and references.

2. EXPERIMENTAL DESIGN AND PROCESS OPTIMIZATION

Experimental design is often part of process optimisation tasks, because in many cases extensive measurements of the process are not possible and experiments are needed to obtain the necessary information. This section discusses typical experimental design and process optimization applications. For example Betta, dell'Isola and Frattolillo used experimental design techniques in the optimization of chain calibration [1]. They proposed a new method for designing the calibration which is more general respect to a conventional equally-spaced methodology and can be performed quicker. In another application experimental design and data-fitting techniques were applied to calibration of high-frequency electromagnetic field probes by D'Apuzzo, D'Arco and Pasquino [2]. Their approach reduces the amount of data needed to represent the calibration procedure by applying regression on the measured values. They could achieve better results than the by using linear interpolation which is suggested by the current standards.

Ezilarasan, Senthil kumar and Velyudham used Taguchi's experimental design [3] for analysing the process performances in machining of nickel based super alloy [4]. They determined important connections between the process parameters and also developed equations for the cutting force, flank wear and surface roughness. Multi-response optimization of non-conventional machining was the goal of Puhan, Mahapatra, Sahu and Das [5]. They applied a hybrid method of Principle Component Analysis (PCA), fuzzy inference systems and Taguchi method for optimizing material removal rate, tool wear rate, surface roughness and circularity.

Venkata Rao, Murthy and Mohan Rao analysed surface roughness, work piece vibration and metal removal volume to monitor the condition of the cutting tool [6]. They found that tool insert nose radius has the most influence on the work piece vibration and feed rate has the most influence on surface roughness and metal removal volume.

Taguchi method was used by Philip Selvaraj, Chandramohan and Mohanraj to optimize surface roughness; cutting force and tool wear [7]. Their revealed that the feed rate is the most significant parameter influencing the surface roughness and cutting force and tool wear is mostly influenced by the cutting speed. Masmiati and Sarhan also used the Taguchi approach to optimize cutting parameters in inclined end milling for minimum surface residual stress [8]. They found that as the machined surface inclination angle increases the microhardness also increases and the residual stress becomes more tensile. Meanwhile the axial depth of cut and the cutting speed have less influence on microhardness and residual stress.

It can be seen that Taguchi method is most often used for experimental design and in optimization of machining processes. Taguchi and other linear methods in one hand require a small amount of experiments to be performed but on the other hand have the disadvantage that they don't cover the whole, usually non-linear and non-convex parameter space. Selecting representative experimental settings from the multi-dimensional parameter space require the application of soft computing techniques that can greatly contribute to achieving a better optimization result.

3. THE PRESENTED METHODOLOGY

This section describes the presented methodology in details. The technique is recursive in nature and every step consists of three stages. The first stage is the design of experiment which aims reducing the possibility of finding a local minimum instead of the global one by covering the whole parameter space. During the second stage a model is built based on the data gathered from the performed experiments. This stage uses soft computing techniques for mapping the unknown dependencies among the process parameters and variables in order to allow the model based calculation of optimization objectives, too. Finally the third stage optimizes the process parameters using the previously built model(s). The optimization also requires the application of soft computing techniques for handling the uncertainty and unknown topology of the search space. These three stages are described individually in the following subsections.

3.1. Design of experiment

The first stage is to generate such experimental settings in the parameter space that are representative enough to provide as much information as possible for the model building stage and to cover the whole range of the possible machining parameters settings space. To achieve this goal a parameter value generator based method was applied to ideally cover the parameter space. The method randomly generates points in a way that the pair-wise distance between them cannot be smaller than a certain threshold. This threshold is not constant over the parameter space but it is calculated dynamically based on the given point's location. The algorithm generates points in the parameter space in a way that they are denser around a predefined experimental, quasi optimal point. This technique was introduced because in the given application field the expert from the field had a hypothesis about the possible area of the optimal point and this range is receiving higher priority in the selection of experiments around it. This not deterministic, unsure expert's opinion about the rough position of the optimal parameter values represents well the uncertainty in the whole process that is typical and acceptable in a non-conventional machining.

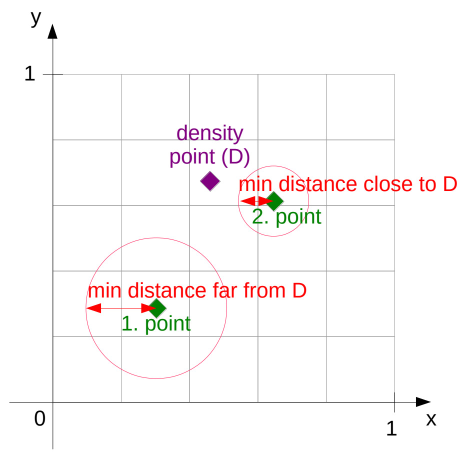

Fig. 1. Schema of the generated points in the parameter space.

Fig. 1. shows how the generated points are laid out in the parameter space. The circles around the points denote the area where other points cannot be generated. This area is smaller around the 2. point than around the 1. point because it is closer to the experimental, quasi-optimal point (D).

3.2. Model building

This stage is responsible for building a acceptable and applicable model of the process based on the data gathered by performing the experiments. The applicability of the model is highly influenced by how representative the experimental settings are in the parameter space. As in most cases of process optimization the dependencies among the process parameters and variables are unknown but models for them are required in order to allow the model based calculation of optimization objectives, consequently, soft computing techniques can be applied to model these connections with certain accuracy.

In the presented application an Artificial Neural Network (ANN) was used to build a model via a learning procedure. ANNs are robust computational models with relative high accuracy but they have the disadvantage that they are not easily interpretable. Neuro-Fuzzy systems solve this problem by providing an interpretable fuzzy structure. This type of system was used by Uros, Franc and Edi to estimate flank wear in end-milling [9] and other applications and detailed description about these systems can be found in [10].

3.3. Optimization

The final stage is to apply the built model for optimizing the process parameters. The model acts as a simulation for performing an experiment, so, a high number of experimental settings can be evaluated by a soft computing optimization technique quickly and in a very cheap way.

The presented application used the Simulated Annealing search algorithm for finding the optimal parameter settings. The optimization's objective function is composed of typical performance parameters of machining processes like machining time, tool wear rate, costs, etc.

3.4. Recursive optimization process

The previously introduced modules cannot guarantee to find the global optimum so they are applied recursively until the best solutions are no longer improving. The recursive application greatly reduces the possibility of finding a local minimum instead of the global one.

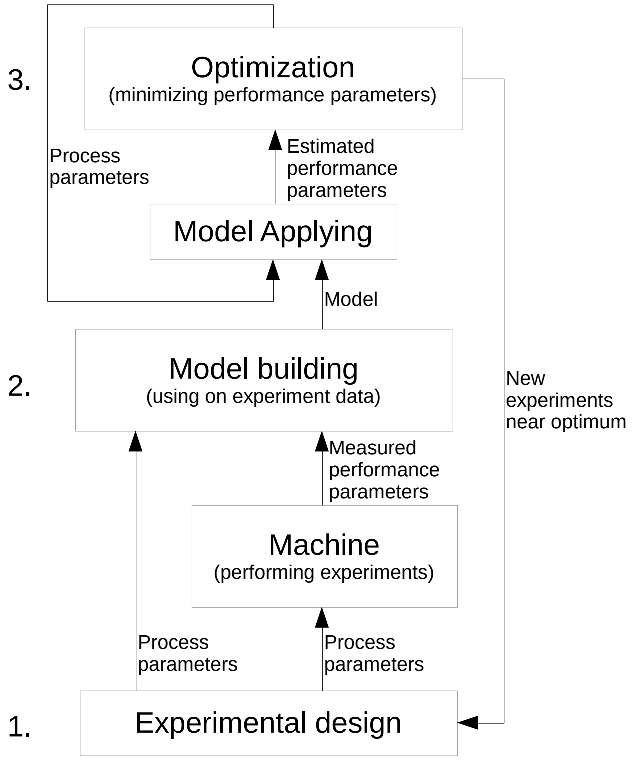

Fig. 2. Block diagram of the integrated experimental design and optimization methodology.

Fig. 2. shows the block diagram of the presented methodology. The first, second and third module was introduced in the previous sections. After the optimization stage new experiment settings are generated around the found optimum and the procedure starts from the beginning. This iteration is continued until there is no improvement between the new optimum and the previous one.

4. APPLICATION FIELD

This section gives an overview of the application's background. Non-conventional machining processes are characterized in the first subsection and the typical process optimization problem is discussed in the second one.

4.1. Non-conventional machining

As definition, non-conventional machining processes are either used in very specific industrial applications only or are based on such technologies that are not widely used yet. Naturally, it results, that in several cases these technologies can be very complex making more complicated and difficult to optimize their process parameters. Kolláth, Halaj and Kureková published a paper about the positioning accuracy of non-conventional production machines [11]. They specifically deal with machines employing parallel-kinematics structures (PKS) which are more flexible and accurate compared to the conventional structures. They show that this positioning technology introduces several theoretical problems thus making optimization tasks more complex.

4.2. Uncertain process conditions

Process optimization tasks often come with uncertain process conditions which should be handled in order to achieve near-to-optimal results.

- One of problem is that in certain cases the beginning and end of the process cannot be determined precisely. For example several machining processes behave differently in the beginning than near the end or during the main period of machining. This means that the process breaks down into multiple different stages which have to be handled individually. The presented application is relying on human rough judgment to determine the interval of the process stages to be optimized in each experiment.
- An important machining parameter is the tool wear that is difficult to determine in many cases. Usually some sort of rough estimation is used and they tend to be inaccurate.
- It is worth mentioning that an optimization task only contains a handful preselected process and performance parameters. In case of non-conventional machining these are determined by experts based on some years of experience but it cannot be guaranteed that important process parameters weren't left out thus reducing the overall performance of an optimization algorithm.

These are the most important uncertainties but each machining carries its own unique ones in addition to these.

It is important to mention that also technical diagnostics can reduce the uncertainty in process conditions by monitoring the process and providing a more exact feedback about the tool status or about the beginning and end of process stages. Bilski wrote about preprocessing methods for an artificial intelligence-based diagnostic module which minimize the number of features in the training and testing dataset [12]. This can yield better diagnostic performance and thus assisting process optimization tasks, too. Ciani and Catelani proposed a fault tolerant architecture to avoid the effects of Single Event Upset (SEU) [13]. Their solution can prevent SEU induced failure in avionic applications making them safer thus reducing uncertainty in the system.

5. APPLICATION RESULTS

The introduced concept was applied for a non-conventional machining process optimisation and the experiments were carried out with the cooperation of company specialised in non-conventional machining. As mentioned before as example, the process starting and ending point is not accurate it was estimated by process engineers as a rough estimation with some typical deviations, like early or delayed setting, missing start or end situations, etc. Also, the tool wear was not measured or estimated in an accurate way. Also in some cases the possible lower and upper limits of the process parameters were not given exactly. On the other hand the currently applied settings and also some ideas about the possible field of the assumed optimal machine settings drove the optimisation, too. The following paragraphs present the different stages of the optimisation process.

5.1. Experiment plan

The first stages of every iteration are the generation of experiment settings in the parameter space. In the first iteration there were 150 measurements and 10 more were added in each of the next iterations, as new experiments near the actually given optimal solution.

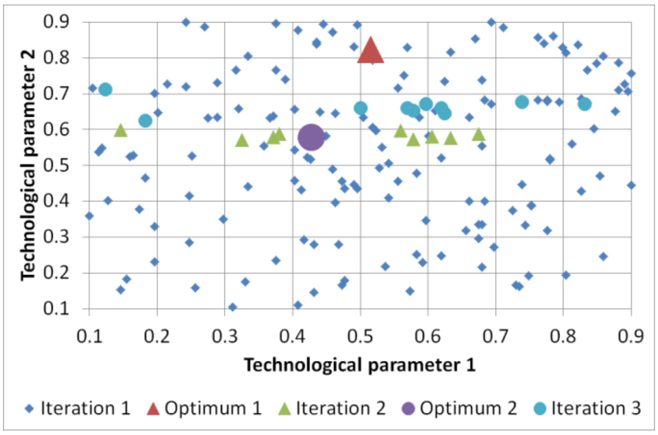

Fig. 3. Parameter space of two of the technological parameters (normalized values)

Fig. 3. shows the generated points in the first three iterations in the space of two of the technological parameters. *Iteration 1* denote the first 150 measurement points. This initial set were used in the next stages for building up the model between technological parameters and the process cost and resulted in the first optimum point denoted *Optimum 1*. Then 10 points were selected around the *Optimum 1*, these are denoted by *Iteration 2* (the new experiment points are generated around the optimum in a higher dimensional space, so in the selected two dimensions they may appear far). Then the next stages were repeated according to the methodology with the extended dataset which is the union of *Iteration 1* and *Iteration 2*. Subsequently the resulted optimum was *Optimum 2* and *Iteration 3* denotes the next 10 points to be added.

5.2. Model building

This stage follows iteratively the experiment generation and is using the generated technological parameter settings as inputs and the measured cost as output and building the model which will be used in the optimisation process.

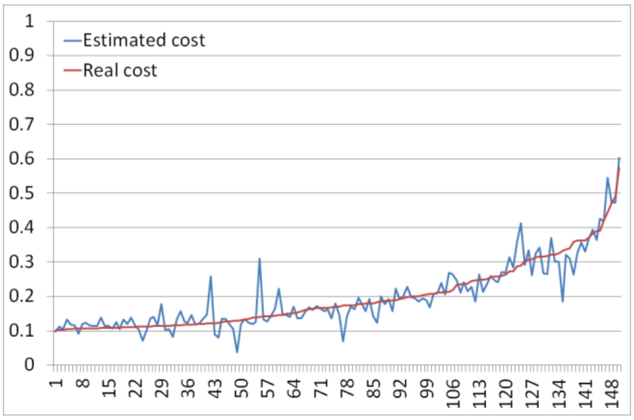

Fig. 4. Estimated cost of the trained model compared to the real cost (normalized values)

Fig. 4. shows the accuracy of the built cost model in the first iteration (first experimental runs). The model was trained with 150 samples and achieved 3.91% Mean Squared Error (MSE) in the first iteration. This accuracy can be considered satisfactory taking into consideration the uncertain process conditions, especially as the first experimental set.

5.3. Optimization

After building up the cost model by an ANN, the optimisation procedure can be started. This stage uses the previously built model to estimate the cost of any given point of the parameter space.

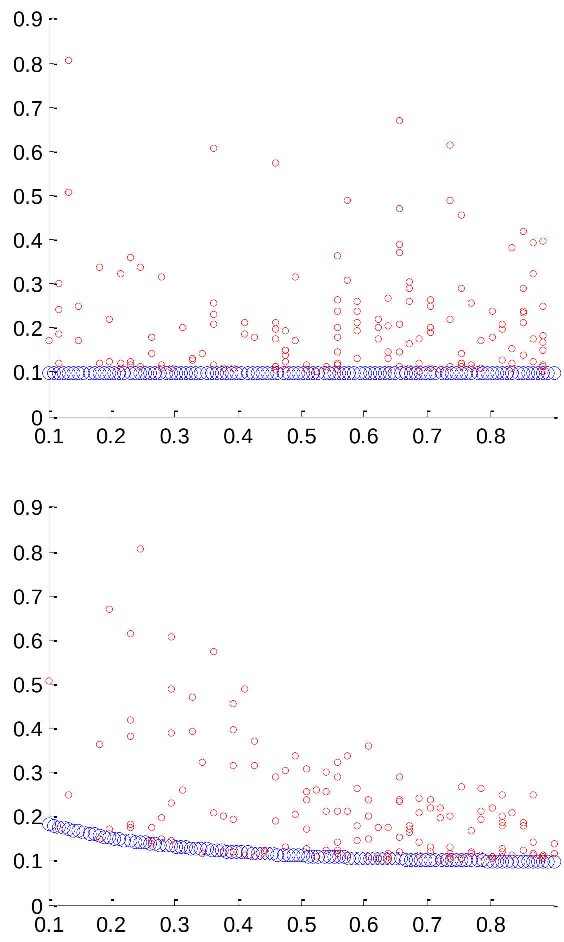

Fig. 5. Measured and estimated cost values as a function of two of the technological parameters (normalized values)

Fig. 5. shows measured and estimated cost values in the dimension of two parameters. The x axis denotes the range of a technological parameter and the y axis shows the corresponding cost value. Red circles mark the experimental settings of the given parameter and the measured cost, while the blue circles show the cost as the function of the given parameter having set the optimal values to the other parameters. In other words the blue circles show how the optimal cost changes depending on one of the parameters if the others are set to the optimal value found by the algorithm. The diagram on the top shows a technical parameter that has minimal influence on the cost, so it can be set to any value if the rest of the parameters are set to the optimal value. By contrast, the diagram on the bottom shows a technical parameter which is inversely proportional to the cost.

5.4. Iterated application

The previous three stages compose the core of the iterated methodology. These are repeated in order until a stable optimum point can be acquired.

Fig. 6. Estimated cost of the optimum and model error over the iterations (normalized values)

Fig. 6. shows how the cost and model error changes over the iterations. In the first few iterations the cost of the optimum is negative because the built model inaccurately learns from the experimental dataset of 150 points, consequently at the beginning there are not enough measurements to cover the whole space of technological parameters. As more and more measurement are done and added to the training dataset the model error grows, but the cost is becoming stable. The increase in the model error is relatively small and is inherited from the increased number of experimental measurement points and not from the significant model accuracy reduction.

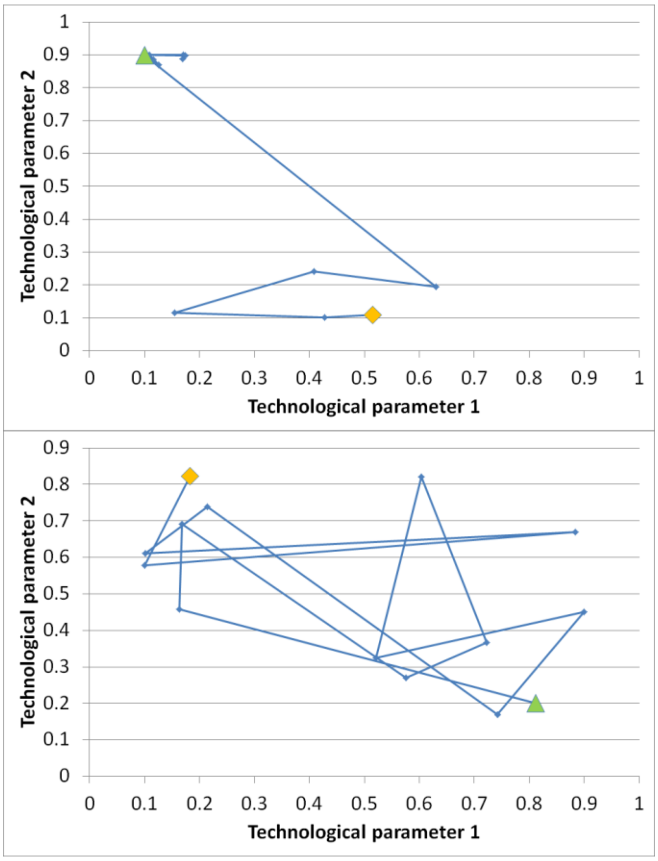

Fig. 7. Stability of the optimum points over the iterations (normalized values)

Fig. 7. shows two parameter pairs where the optimum points changes differently. The upper diagram shows the change of the optimum machining values in the space of two significant parameters, where the rhombus denotes the starting optimum and the triangle denotes the final optimum point. It can be seen that after the first few iterations the optimum reaches a stable point. By contrast the bottom diagram shows two parameters which have minimal influence on the cost and the optimum almost randomly changes its location over the iterations. This means that these parameters can be set almost to any value; they won't increase the cost of the process.

The application of the introduced iterative, soft computing based optimisation technique on the analysed non-conventional machining process served with the expected, continuously improving optimal values and with more stable optimisation points.

The productivity of the company in the selected process increased to around 300% but in daily production this rate is "only" around 200% because other (micro downtimes, human manipulations, positioning times, non-time based cost drivers) factors restricted the speed up of the whole production system. This significant results were received in case of non-conventional processes under uncertain machining conditions. The mathematical results and the doubling of the productivity of the firm proved the efficiency and effectivity of the novel, introduced algorithm. The fact the previous experimental design based optimisation trials (using various Taguchi methods) did not found the optimal machining setting but the current proposed solution was able imply that the proposed method can go beyond the classical methods, e.g. when dependencies among parameters are highly non-linear.

6. CONCLUSIONS

The paper presented an integrated, interative experimental design and optimization methodology and its successful application in non-conventional machining process optimization. An integrated recursive technique was presented consisting of three stages: the first for the experimental design, the second for model building and the third for process optimization. Non-conventional machining and typical problems of process optimization were discussed for presenting the background of the application.

Further research could be aimed at using Neuro-Fuzzy systems in the model building stage to yield a more interpretable structure of the inner connections between the process parameters, production costs and quality parameters. Other search algorithms can be applied in the optimization stage, too.

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