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Procedia CIRP 41 (2016) 159 – 164

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48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015

A framework for multi-level modeling and optimization of modular hierarchical systems

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Abstract

Most products and *manufacturing systems* (MS) have an inherent hierarchical structure. They are composed of multiple subsystems, such as machines, process components, or resources. In order to optimize the control parameters of such systems, manufacturing planners often follow a global black-box approach. The optimization, thus, neglects the hierarchical structure encoded in the model. All subsystems and their components have to meet individual constraints and show specific uncertainty in their output. By extracting the information, which modules violate the constraints, the optimization algorithm could focus on the parameters of this specific module. Moreover, the planner can define objectives evaluating the robustness or sensitivity of a specific solution based on the knowledge of the hierarchical dependencies and about the uncertainty in the outputs. To accomplish this, the structure of the optimized system must be known to the respective methods applied.
In this paper, the dependencies of the subsystems are defined by means of a tree structure. Based on this structure, different possibilities to define and solve the corresponding optimization problem are introduced. In addition, a concept for addressing the robustness of an MS with regard to the uncertainty of the components within the optimization model is proposed. As a practical example, a hot compaction process for manufacturing thermoplastic composites is formalized using the tree structure. Individual nonlinear empirical models simulate the input-output behavior of each subsystem. Based on this formalization, the results of single- and multi-objective optimization methods are compared and their strengths and weaknesses are discussed.

Peer-review under responsibility of the scientific committee of 48th CIRP Conference on MANUFACTURING SYSTEMS - CIRP CMS 2015

Keywords: Computer aided process planning (CAPP); Decomposition method; Optimisation

1. Introduction

The production industry has experienced a change from a supply-oriented to a demand-oriented design of products [1, 2]. An efficient adaptation of the manufacturing system and the available processes to the changing customer needs is an important requirement for industrial success [3].

Modular manufacturing systems (MS) may allow this flexibility to be achieved. By using individual models for each process or component (denoted as module in the following) and defining general interfaces to the preceding and subsequent modules, the input-output behavior can be accurately modelled while providing flexibility with respect to the combination of the individual modules. Moreover, problems can be localized within the MS, which assists in finding alternative solutions. In this context, the uncertainty in the MS represents an important factor, as it may lead to constraint violations, which are not regarded when considering only the production quality [4] under ideal conditions.

1.1. State of the art

In industrial practice, the planning of MS often relies on the experience of specific experts within the enterprise. Hence, research on externalizing the experiences and making it available for other employees has a long history [5].

The consideration of technology chains, i. e. sequences of processes a component has to run through before its completion, represents the first approach to utilize the concept of modularization during the formalization of the MS for planning tasks [6]. The planning engines behind these systems are usually based on qualitative rules. Usually, no continuous

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doi:10.1016/j.procir.2015.12.050

Nomenclature

d_i	desirability value for specification i
n	number of samples for uncertainty quantification
p_{set}	target press force of the press
p	local normal press force of the press
t_H	uniform heating time
t_M	masked heating time
F_{max}	maximum force absorbed in a 10 J impact test
T_{IR}	target temperature of the IR radiator fields
$T_{P,l}$	target temperature of the left tool half
$T_{P,r}$	target temperature of the right tool half
T_P	local temperature of the pressing tool

Abbreviations

CMA-ES	covariance-matrix-adaptation evolutionary strategy
DACE	design and analysis of computer experiments
DI	desirability index
IR	infrared
MS	manufacturing system
SMS	*S*-metric-selection-based
EMOA	evolutionary multi-objective algorithm
TI	technological interface

objectives for applying optimization methods do exist. If key performance indicators are considered, statically stored information, e. g. based on the recommended parameters of the tool manufacturer, is integrated using cost factors for the different resources and requirements [7]. The effect of the process parameters is therefore neglected.

In order to allow these effect to be considered, flexible and accurate surrogate models for the modules or the process chain can be used to approximate the parameter-dependent input-output behavior. In this context, global optimization approaches usually consider the complete MS as a black box whose performance is optimized. The respective modelling approaches, such as neural networks [8-11] or finite element simulations [12], imply a huge experimental effort for training or calibrating the underlying empirical, phenomenological or analytical models.

In order to reduce the complexity of the modeling task, which parameter space $D \in \mathbb{R}^d$ grows exponentially in the input dimension, Tönshoff et al. [13] have recommended the separated modeling of the processes within the process chain while considering the interactions between the process steps by means of *Technological Interfaces* (TI). These interfaces encode properties of the tools or workpieces that result from previous processes, but have an impact on later process steps. The complexity of the modelling is reduced without significantly reducing the complexity of the system. The experiments of Denkena et al. [13-17] have shown that the results of the multi-objective optimization of a multi-stage process chain can be significantly improved by considering the technological interfaces in comparison to a separated modeling of the processes without interactions. The combination with a monitoring-based approach, in which the deviations between the specified and the achieved workpiece properties are measured after each process step, allows even compensation processes to be utilized [18].

In a hierarchical approach for modelling complex energy flows in MS [19], the optimization is based on the identification of unnecessary energy consumers in the process chain. Based on a retrofitting approach, the corresponding components are exchanged or removed and the reduction of the energy consumption is validated by simulating the process chain with the new modules on a global level. In contrast to the approach proposed in this paper, the process parameters are fixed and therefore neglected during the optimization.

1.2. Scope and structure

In this paper, a framework for encoding, modelling and optimizing modular MS is presented and validated. The design and the methodical foundations of the framework are presented in section 2. To show the validity of the proposed approach, the modeling of the process chain for manufacturing self-reinforced thermoplastic single-polymer composites is considered within as a case study in section 3. Based on the implementation of the case study into the framework, the results of some selected algorithms and objective functions are presented and discussed in section 4. In section 5, these results are summarized and an outlook on further enhancements to the framework is presented.

2. Framework

In this section, the framework representing the basis for the flexible encoding and optimization of arbitrary MS is presented. The effects of the inputs of each module (process parameters and TIs) are integrated based on individual empirical models (section 2.1). A special focus is put on the flexibility and generality of the approach. Hence, arbitrary dependencies can be encoded using a tree-based structure (section 2.2). Based on the obtained hierarchy, the framework allows the uncertainty propagation within the MS to be quantified. To accomplish this, model-based uncertainty estimates and Monte Carlo sampling are combined (section 2.3). The foundations for the actual optimization of the MS are introduced in sections 2.4 and 2.5. First, objective functions evaluating the accordance with the specifications of the final product and the effect of uncertainty are defined (section 2.4). Then, the flexible single- and multi-objective optimization algorithms implemented for optimizing the defined objective functions are presented.

2.1. Modelling of the input-output behavior of the modules

An independent module represents each process or component of the MS. Within each module, an empirical model describes the input-output behavior of the respective process or component. As inputs, the model considers all process parameters to be adjusted for the respective process step or component. In addition, the model regards the dependencies to the preceding modules by means of TIs (cf. section 2.2.). They act as additional inputs of the model.

Empirical models are based on training data, which is interpolated or regressed in order to provide a continuous prediction. The required data is usually obtained by simultaneous and subsequent measurements in real-world experiments or by simulation studies. An experiment is hence either monetary or computationally expensive.

In order to provide accurate predictions based on a minimum number of experiments, models of the *Design and Analysis of Computer Experiments* (DACE) [20] were enhanced with regard to the requirements of manufacturing processes [21]. These models explicitly consider the uncertainty of the response with regard to both the model and the observation/measurement of the property value. Consequently, they not only allow the product properties and constraints to be predicted under ideal conditions, but also the respective uncertainty to be estimated.

2.2. Modelling of the process chain

In most cases, the process chains are the result of a synthesis process [22]. Within the synthesis, manufacturing functions are determined, and then modules implementing these functions are selected [21]. To accomplish this, either manufacturing engineers or expert systems can be used [23].

In line with this approach, the manufacturing functions determine the specification of the actual MS. For each manufacturing function, the user has to define a module implementing the respective functionality, where it is sometimes possible to omit single functions explicitly. If a specific module is selected, a link to the empirical surrogate models of its outputs, the dependencies to other (preceding) modules and the intervals for the process parameters have to be specified. The dependencies of each module have to be known as the TI inputs of the empirical model require a specification based on the outputs of the preceding modules. Examples for those outputs are either material properties determined by preceding processes or process conditions implied by integrated components. The framework automatically derives the optimization and evaluation sequence, as well as the formulation of the optimization problem, based on the local dependence information.

In the framework, it is assumed that the MS does not contain cycles, i. e. no modules are visited more than once. Consequently, the hierarchy expressed by the local dependence information can be formally expressed using a tree data structure [24]. For generating the tree, first the user explicitly specifies the core module. This module usually determines the final properties of the product. It hence acts as the root of the directed hierarchy tree, also called out-tree. From the root module, the framework performs a depth first search [24] following the dependencies specified in each module until it ends up in modules without any dependencies. These modules are denoted as leaves with regard to the tree structure. The algorithm buffers the visited modules with more than one child module in a queue [24]. The search continues until the buffer is empty. As the number of dependencies can be arbitrary, neither the tree is balanced nor is the number of child modules fixed.

2.3. Uncertainty quantification

The hierarchy tree derived using the methods of section 2.2 provides the basis for analyzing the propagation of uncertainties within the MS. Starting from the leaves, the outputs and the corresponding uncertainties are predicted. In case, the output follows a Gaussian normal distribution, as for instance if using the DACE models [20] proposed in section 2.1, only the corresponding mean and standard deviation are stored. Otherwise, a characteristic sample is created by means of Monte Carlo simulation; i. e. a finite set of random numbers from the respective distribution is created. As the size n of the set determines the approximation quality with regard to the estimated performance and the evaluation time during the optimization (cf. section 2.4), the user can specify n beforehand according to his specific needs.

Based on the distributions obtained from the leaf modules, the framework generates a set of inputs for evaluating the modules of the next level. To accomplish this, the framework combines all normally distributed inputs in order to compute a multivariate normal sampling of size n. In the current version, independence of the inputs is assumed. Whereas, this assumption can be easily dropped for the normally distributed inputs, the final sample combining normal and non-normal inputs would be much harder to generate. In the current version of the framework, this sample is directly constructed by combining the samples describing the remaining inputs with the multivariate one generated before.

In order to assess the uncertainty of the respective outputs, all samples are evaluated by means of the empirical model. The resulting output distribution can then be used to characterize the expected outcome and its uncertainty/ robustness. Moreover, the so-obtained non-normal samples can also be used as input(s) for the subsequent module.

2.4. Problem formulation

In order to optimize the MS, a formalization into a mathematical optimization problem is required. The framework performs this formalization automatically based on the specification of the final product and the constraints defined for each module. The user only needs to provide target values and tolerance ranges for each important property of the product. The framework then constructs continuous functions evaluating the agreement of the final product after the core module with each specification by means of Harrington's two-sided desirability function [25]. After this transformation, all the properties are comparable and on the same scale ($d_i \in [0, 1]$). Hence, a scalarization of the specification into an aggregated objective function is possible. As recommended for desirability functions, the *desirability index* (DI), i. e. the geometric mean of the individual desirability values d_i, is computed. This aggregation offers the advantage to prefer balanced solutions while penalizing products violating a specification. The latter property is utilized to directly integrate the constraints into the objective function. If at least one constraint within at least one of the modules is violated, the aggregated value is set to zero. Hence, no special constraint handling is required.

In case the quantification of the uncertainty is desired, the above procedure is applied for each design point in the input sample of the core module (cf. section 2.3.). As a result, n different desirability values are available. To allow the trade-off between the chance and risk of the MS to be judged by the user, different statistics can be computed over the sample. Typical choices are the mean, the standard deviation, and higher percentiles of the sample (for instance the 95 %-tile). The latter provides a threshold value, which is obtained within at least the given percentage within the sample.

2.5. Optimization methods

Due to the before-mentioned possibility to choose between different statistics of the sample and with a view to future requirements, such as energy efficiency, the framework is capable of performing single- and multi-objective optimization tasks. Whereas the former results in the proposal of a single optimum solution, the latter obtains a set of alternatives, from which the user can choose the desired setup.

For solving single-objective optimization problems, the MATLAB implementation of the Covariance-Matrix-Adaptation Evolutionary Strategy (CMA-ES) [26] including a restart-based adaptation of the population size [27] is applied. The CMA-ES is a well-established black box optimization approach, which has shown very good results in many benchmark studies [26, 27].

In a multi-objective optimization, the MATLAB implementation of the *S*-Metric-Selection-based Evolutionary Multi-Objective Algorithm (SMS-EMOA) [28] is used in order to approximate the set of optimal trade-offs. This algorithm has proven its superiority to other EMOA within comprehensive benchmark studies [29].

3. Case Study

The practicability of the framework is demonstrated based on a case study. In this study, a multi-station laboratory press including preceding heating steps for producing functionally graded products is modelled using the framework. Functionally graded products are made of a monomaterial, but are characterized by a continuous distribution of properties over at least one of the three spatial dimensions [23]. To accomplish this, complex thermo-mechanically coupled processes lead to differential thermo-mechanical loads inducing local transformations of the microstructure [23].

Based on the concept of functional gradation, products can be tailored to the requirements of their application. The framework assists the product planner during the process of planning and optimizing the process chain for manufacturing a specified component. In this case study, it is assumed that the synthesis of the process chain, i. e. the choice of the modules implementing the manufacturing functions, has already been performed – for instance by using the procedure proposed by Biermann et al. [22]. For the obtained MS, the properties of the final component are optimized with regard to the expected agreement, and also with regard to the robustness against stochastic variations within the MS. The latter is done for the first time in this paper.

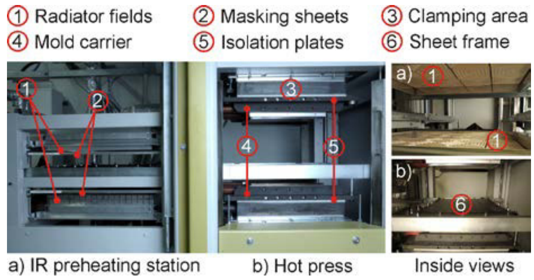

Fig. 1. Photographs of the MS considered in the case study.

The considered MS is shown in Fig. 1. It consists of two stations, three process steps, and four modules: uniform *infrared* (IR) preheating, partial masking and compression molding with a special molding tool. The first two steps are performed within the preheating station (a) directly connected to the press station (b). In the first process step, the layered textiles fixed within the sheet frame (6) are heated by IR-radiation (1) with target temperature T_{IR} and heating time t_{H}. For initiating the second process step, two rectangular masking sheets (2) made of aluminum are integrated between the radiators (1) and the frame (6), and the masking time T_{M} begins. The masking sheet shadows half of the surfaces in order to provide a thermal gradient into the component. After the masking time t_{M} is over, the sheet frame is automatically transferred to the press (b). Once in the press, the force-controlled compression molding with target press force p_{set} starts automatically.

The press offers a modular design allowing different molding tools to be integrated using the clamping area (3) and the corresponding mold carrier (4). The molding tool mainly determines the geometry of the final composite, but also the local normal press force and temperature during the molding process. The latter is particularly important with regard to the thermomechanical processing for manufacturing functionally graded products. Isolation plates (5) avoid thermal creeping into the clamping area.

The molding tool considered in the case study combines two separately heatable zones with target temperatures $T_{\mathrm{P,l}}$ and $T_{\mathrm{P,r}}$. In the center of the tool, a triangular insert with a height of 47.25 mm and an opening angle of 110° results in a reduced normal press force of $p = 0.696\ p_{\mathrm{set}}$ due to the distribution of the axially applied force at the angle section. The distribution of the temperature and the normal press force are shown in Fig. 2 for an exemplary setting of $T_{\mathrm{P,l}}$, $T_{\mathrm{P,r}}$ and p_{set}. The task of the case study is to find the parameter values for the modules of this specific MS (preheating, masking, press, molding tool) robustly resulting in the best possible agreement with an exemplary specification of the final product while meeting all the constraints of the individual modules.

Based on the geometry of the molding tool, a triangular component of size 350 mm × 350 mm was defined. As target property, the local impact resistance of the component, measured by the maximum force $F_{\max}$ absorbed within a 10 J impact experiment [21] had to be functionally graded. The respective gradation was motivated by potential future

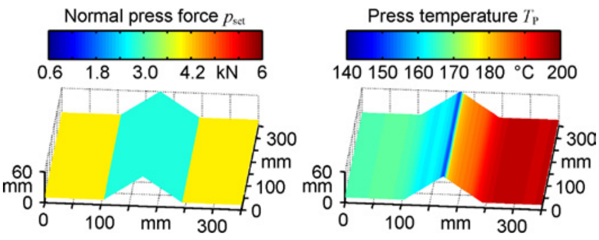

Fig. 2. Design of the molding tool and distribution of temperature T_P and the normal press force p over the tool for the exemplary process parameter setting p_{set} = 4 kN, $T_{P,l}$ = 170 °C, and $T_{P,r}$ = 190 °C .

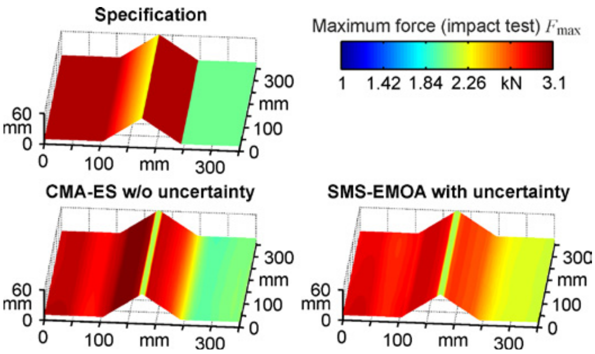

Fig. 3. Comparison of the target property values of the final product in the case study and the obtained ones based on the optimized parameter settings.

applications as interior door panels [30]. For the left flat part of the product, a high F_{max} = 3 kN was specified. The left half of the angle section should have a linear gradient starting with the high F_{max} and ending with F_{max} = 2.25 kN. The right part of the angle section should be more impact resistant (F_{max} = 3 kN), whereas the right flat part had to provide the lowest F_{max} = 2 kN. A tolerance of 0.5 kN was allowed for all specifications. This target specification is shown in Fig. 3.

4. Results

The input-output behavior of each of the four modules was internally described using DACE surrogate models [20]. Details on the experimental designs, the formal aspects of the models, and the experimental validation can be found in [21].

For the given MS, the compression molding process was defined as the core process step. Starting the depth first search from this module, the tree structure shown in Fig. 4 was obtained. The modules of processes or tools without predecessor or subcomponents were identified as leaves and were thus evaluated first. The masked preheating module was

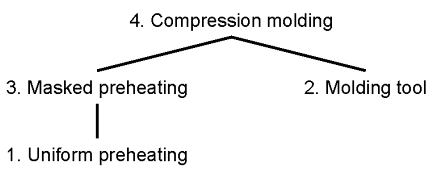

Fig. 4. Tree structure and optimization sequence for the MS of the case study.

buffered during the depth first search of the left path in Fig. 4. It is hence scheduled next per definition. The core process was evaluated as the last component in order to consider the influence of all its components and predecessors.

In the first optimization task considered, the uncertainty propagation was neglected. Only the predicted values of the TIs were passed to the parent processes of the module tree. Based on this formulation, the single-objective optimization using the CMA-ES results in a DI of 0.62, which corresponds to a good overall agreement with the specification.

In the second step, the uncertainty propagation was considered within a multi-objective optimization of both, the maximization of the mean and the minimization of the standard deviation over a sample of size n = 10 constructed using the methods of section 2.3. Compared to the evaluation based on the ideal TI values, the mean DI over the sample decreases to 0.59. The standard deviation of the DI values within the sample amounts to 0.038, thus, explaining the loss with regard to the single-objective evaluation.

The multi-objective optimization of both indicators by means of the SMS-EMOA resulted in the approximation of optimal trade-offs shown in Fig. 5. Despite using a population of 100 solutions, the SMS-EMOA found only seven nondominated trade-offs. As could be expected, the solution obtained by the CMA-ES represented an extreme solution. None of the candidates in the approximation (black dots in Fig. 5) provides a mean DI close to the one of the CMA-ES. These observations suggest evidence that both objective functions strongly correlate and that the elaborated adaptive variation applied within the CMA-ES is superior to the rather static one of the SMS-EMOA using real-coded genetic operators with fixed probabilities and step sizes.

Despite the potential problems in the variation of the solutions, the SMS-EMOA returned a set of trade-offs that significantly reduce the standard deviation within the DI values of the sample while only slightly deteriorating the mean. Moreover, the trade-offs show a strong knee towards the ideal point in the lower right corner of Fig. 5. The black arrow indicates the a-posteriori selected solution. This solution reduced the standard deviation to 0.013 – one third of the value of the CMA-ES solution. At the same time, the mean value was reduced to 0.52, which corresponds to a reduction of only 12 %.

Technologically, the solution selected from the trade-offs of the SMS-EMOA reduced the press force p_{set} from p_{set} = 6 kN to p_{set} = 3.6 kN and the press temperatures $T_{P,l}$ and $T_{P,r}$ from $T_{P,l}$ = 182.1 °C and $T_{P,r}$ = 183.5 °C to $T_{P,l}$ = 180.9 °C and $T_{P,r}$ = 179.9 °C. At the same time, it increases the

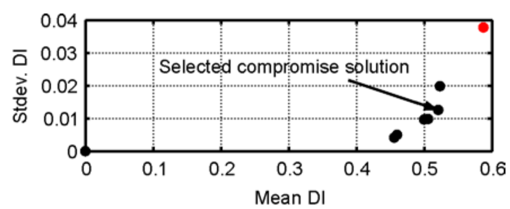

Fig. 5. Approximation of the optimum trade-offs obtained by the SMS-EMOA. Red color highlights the solution of the single-objective CMA-ES.

preheating time and makes use of the masking ($t_M = 21$ s instead of $t_M = 0$ s). These changes reduce the variation in the pressing temperatures T_P, which mainly determine the properties of the material [21]. They avoid the partial melting of the fibers and therewith the loss of the self-reinforcement. As shown in Fig. 3, also the overall variation within the values of F_{max} is lower for the SMS-EMOA solution.

5. Summary and Conclusion

In this paper, a framework for the multi-level modelling and optimization of hierarchical systems was proposed. The framework was applied to a case study on a MS for manufacturing functionally graded thermoplastic composites. It was shown that the internal algorithms for single- and multi-objective optimization are capable of optimizing small-size MS as the one considered in the case study. By using the methods for uncertainty quantification and propagation implemented in the framework, optimum trade-offs between the mean performance and its variation could be approximated. This allowed the decision maker an informed choice to be performed. In the considered case study, the variation could be reduced by 67 % while only 12 % were lost with regard to the mean performance.

In future work, the framework will be applied to MS involving more components and levels. To accomplish this, the generation of solutions within the SMS-EMOA will be improved. The availability of multi-objective optimization algorithms allows other objectives, such as energy efficiency, throughput, and costs, to be considered, as soon as models for these indicators do exist.

Acknowledgements

This work is funded as subproject C4 of the collaborative research center ‘‘3D-Surface Engineering’’ (SFB 708) and as subproject D5 of the transregional collaborative research center SFB/TR TRR 30 by the German Research Foundation (DFG).

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