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Technology design of composite parts

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Materials

ABSTRACT

Purpose: Purpose of this paper is to optimize the design of the manufacturing technology process of large composite plastic products. One of the key problems is how to integrate computer-based product design and planning of the technology process.
Design/methodology/approach: In the current study the Neural Network meta-modelling technique has been used. The optimization of the plastic sheet and its strengthening layer thickness has been performed using the surrogate design model. For modeling and structural analysis of derivative products CAE (ANSYS) and CAD (Unigraphics) systems are used. The Finite Element Analysis simulation was performed with optimal thickness values to verify the prediction accuracy of a surrogate model.
Findings: The optimization model is proposed to control and analyze the calculated technology planning route, the optimal vacuum forming processes, the technology of post-forming operations, strengthening and assembling operations. The design of the new products is tightly integrated with manufacturing aspects. The product family of the large composite plastic products together with the derivate products and their production technologies is designed using proposed methodology. The optimization of the plastic sheet and its strengthening layer thickness has been performed.
Practical implications: The most of the methods described in this study are now under development and industrial testing. Development of manufacturing (operation) plans for a product family is of great practical importance with many significant cost implications. In design of derivative products for the product family, the nonlinear optimization is used and the detailed description of the product is established. The proposed approach is exemplified by the development of a family of products in Wellspa Inc.
Originality/value: Value of this paper is that developed optimization model controls and analyzes the calculated technology planning route.
Keywords: Composites; Plastic forming; Manufacturing technology management; Artificial neural networks

1. Introduction

Nowadays, advanced CAD/CAE/CAM tools are becoming increasingly used in companies. The computer-based methods are used to support engineering decision making processes. The computer simulations of product and process performance are carried out. Any undesirable conditions are modified, and the simulation is performed again. The simulations enable to optimize the product and manufacturing processes.

Progress in design search and optimization (DSO) has continued steadily in past forty years, and by now, a formidable range of optimization methods is available to the engineers. In general, design optimization may be defined as the search for a set of inputs that minimizes (or maximizes) objective function under given constraints. It is subject to constraints in accordance with given relationships among variables and parameters and constraints of manufacturing system parameters and resources. These functions may be represented by simple expressions, complex computer simulations, or large-scale experimental facilities. Challenges to design multiple products simultaneously, have led to the collaborative multidisciplinary design optimization (MDO) [1, 2, 3, 4].

The aim of the current study is to develop general principles applicable to design of products and their manufacturing processes, to use the multidisciplinary design optimization approach enabling rapid and effective design decisions. The underlying focus of proposed methodology is to develop formal procedures for exploiting the synergistic effects of the coupling of different product development and technology planning decisions and existing experience into the design process.

The simulations or observations of learning methods must be applied for evaluation of the relationship (Response Surface Model-RSM) between design results and parameters with the best precision and the least cost. For practical design problems the hybrid learning methods integrating both, classification (or pattern recognition) and regression (or function approximation) paradigms, are recommended to develop and use [2]. Neural networks and other methods of inductive learning are possible tools for extensions and generalizations of classical regression methods for this case. For modeling the decisions of technology planning processes the use an artificial feed-forward neural networks and Radial Basis Function Network are proposed [5, 6].

2. Product design

It is recommended to split the product design process into two layers: a product family planning layer, and the layer for optimization of the design parameters of derivative products.

The objective of the product family planning is to optimize the sales volumes and module combination pattern [7]. For optimal planning of the volumes of product family and module combination, the model was developed. The model maximizes net profits and is subject to upper and lower bounds of market demand and capacity constraints. Using the optimization model, new additional functions of the market needs; required investments; possible market growth; and production costs for each product are determined [7]. Based on obtained results, the company Wellspa Inc. developed two additional functions and the present sales justify the made decisions.

In product family modeling phase, general guidelines for product structural calculations and optimization are defined [7]. In design of derivative products for the product family, the nonlinear optimization is used and the detailed description of the product is established. For modeling and structural analysis of derivative products CAE (ANSYS) and CAD (Unigraphics) systems are used. It is important to emphasize that the design of new product is tightly integrated with technological aspects. For example, the bathtub is produced in two stages – in the first stage the shell is produced by vacuum forming, and in the second stage the shell is strengthened by adding glass-fiber-epoxy layer. In the vacuum forming process, the final shell thickness in different areas may differ, so this has to be taken into account in structural analysis of the product [8, 9].

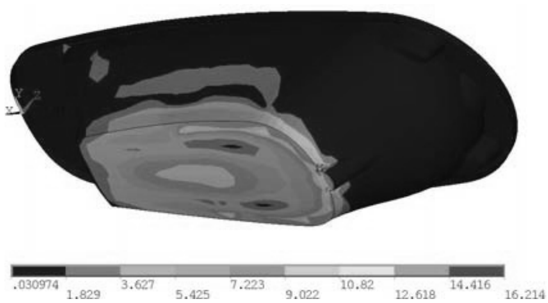

Fig. 1. The equivalent stress plot after optimization of the composite structure

When considering optimal thickness of the strengthening layer, obviously it should be different in different areas. In the current study 12 areas of bathtub were considered. Fig. 1 shows the equivalent stress plot for the loaded model, which indicates the stress concentrators and is used to optimize the glass-fiber reinforcement thickness in the given areas [10, 11]. In the current study, for design exploration and for the surrogate design model, the Neural Network meta-modeling technique was used.

3. Technology planning

Development of manufacturing (operation) plans for a product family is of great practical importance with many significant cost implications. The planning encompasses development of feasible manufacturing plans, evaluation of different feasible solutions and selection of the optimal plan(s).

For finding out optimal technology route we have to cut down the structure of the technology process into different process segments, meaning that we have to solve different sub systems, like finding out the optimal vacuum forming technology, the technology for post-forming operations (trimming, drilling the slots and cut-outs into the part, decoration, printing etc), strengthening (reinforcing) and assembly. An example of a generalized structure of the manufacturing plan for a product family is represented in Fig. 2 [12].

In Fig. 2 Op1,1 represents reverse draw forming with two heaters; Op1,2 represents straight vacuum forming; Op2,1 represents automatic trimming with saws; Op2,2 represents automatic trimming with 5-axis NC routers; Op2,3 represents manual trimming with saws; Op3,1 represents manual reinforcement; Op3,2 represents automatic reinforcement; Op4,1 represents sub-assembling; Op5,1 represents assembling.

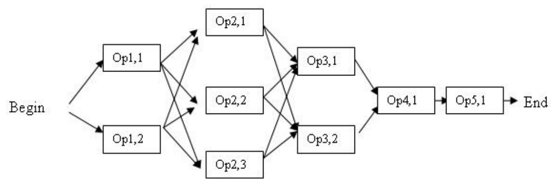

Fig. 2. The structure of the technology process

Artificial Neural Network is used for modeling the decisions of technology planning processes for each operation. ANN copes well with incomplete data and imprecise inputs. A non-linear input-output mapping is accepted for modeling. Neural Networks are composed of nodes (neurons) connected by directed links. Each link has a numeric weight W_{ji} associated with it. A mathematical model for a neuron could be represented as:

$$a_i = g(\sum_{j=0}^{n} W_{j,i} a_j), \quad (1)$$

Where: a_j is the output activation of the unit j; g is the activation function of the unit (the sigmoid and linear functions are used as activation functions).

The "classical" measure of the network performance (error) is the sum of squared errors. Different ANN training algorithms were investigated: a multilayer feed forward networks with one hidden layer, the Sigmoid (for hidden layer) and linear activation functions (for output layer). Back-propagation and the Levenberg-Marquart approximation algorithms were selected as more suitable. The use of the artificial feed-forward neural networks and Radial Basis Function Network is proposed [5, 6, 13]. The attempt is made to tackle the problem in a practical and integrative way.

The first process in the technology route is vacuum forming. Vacuum forming (thermoforming) uses heat, vacuum, or pressure to form plastic sheet material into a shape that is determined by a mould [14, 15].

In the vacuum forming process, the knowledge and the experience of engineers (process personnel) is of great importance. Geometrical complexity, depth of draw, level of surface detail required, ribbing, fillets, stress concentration, shrinkage, expansion, and undercuts are all factors that must be carefully considered when creating component design and design of the vacuum forming operation.

The quality of formed parts is seriously affected by the moisture absorbing ability of the material. The materials known as hygroscopic, if not pre-dried prior to forming, could have moisture blisters which will pit the surface of the sheet [14, 16].

Successful design of the thermoforming operation can best be accomplished by controlling the critical parameters associated with the process. These parameters include: sheet properties, heating conditions, and parameters of the forming operations.

For vacuum forming, it is necessary to accept the significant thinning in the sheet material accompanying the process [15]. The thickness variations are potentially large for a part (Fig 3). Therefore, it is often important to control the thickness variations in order to meet functional requirements of the part.

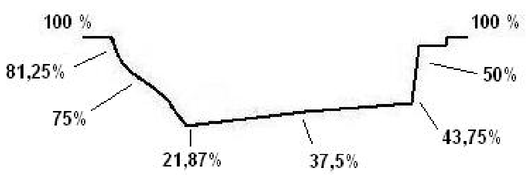

Fig. 3. Wall thickness reduction in a 3.2 mm thick FF0013 Plexiglas

The methods used to control thinning are: Selection of forming scheme; Use of surface lubrications; Modification of the die or part design to minimize local stress concentrations; Post-forming strengthening (reinforcing), etc.

For analyzing the suitable vacuum forming process, the heating zone variations should be also calculated. The temperature and working time for each heating zone depends on the part, material structure, geometry and parameters [17, 18]. For experimental analysis the product with four independent zones and with controlled temperature was used, the temperature variation was 290-340˚C. For better understanding in Fig. 4 is brought out temperature variations depending on different zones.

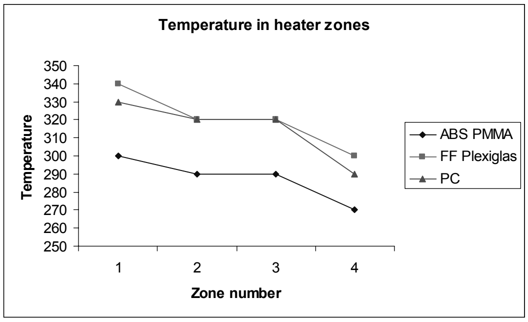

Fig. 4. Temperature differences in heating zones

To solve the different sub systems the selection parameters for each technology have to be determined. Table 1 shows short list of the parameters for vacuum forming processes. Those parameters were used also in the ANN training.

Using the selection parameters (Table 1), the ANN trained for each technology (like vacuum forming processes, acrylic cutting technologies and reinforcement) was used. For illustrating of the point the Table 2 is presented. There are three variations: {0 - Not usable, 1- Reverse draw forming with two heaters, 2- Straight vacuum forming }.

Where: *Geom* is the geometric complexity; *Log(nP)* is the number of parts; *Dim* is the dimension of vacuum forming bench table; *Thick* is maximal material thickness; *SQ* is surface quality; *PT* is part texture; *UC* is undercuts; *I* is investments.

Thermoformed parts are trimmed in several ways: with matched shearing dies, steel rule cutting dies, saws, routers, hand knives, and 3- and 5-axis NC routers. The trimming tasks has two different possibilities {yes = 1, no = 0}, if the trimming output is 1, manual or automatic trimming can be used. In case of automatic trimming process saws or 5-axis NC routers can be used. For finding out the optimal trimming method, different processes have to be analyzed and possible defects determined. The analysis resulted in optimal input parameters for the neural networks tasks.

Reinforcement tasks have two choices: {yes, no}; in case of "yes" the manual or automatic reinforcement can be used. In order to obtain sufficient training data for the neural networks used for optimization tasks later, the series of finite element analysis, to simulate and optimize the reinforcement ply thickness, were performed.

The following formulation of the task can be given:

Find the feasible operation sequences for a product family that gives us: maximum profit and minimize the manufacturing time; and is subject to the following constraints: capacity constraints for all workstations; use of materials; use of technologies.

Table 1.
Selection parameters for vacuum forming processes

Parameter and mark	Description
Dimensions (L and B):	L x B; 280x430, 680 x 760 mm up to 2000 x 1000 mm
…	…
Draft angle (α):	α; α >5 ˚
…	…
Heating zones (Z):	Z; 1 < Z < 4

Table 2.
Vacuum forming training mode

Sample	Vacuum forming	Geom	Log (nP)	Dim	Thick	SQ	PT	UC	I
1	1	1	2	1	0	2	1	2	2
…	…	…	…	…	…	…	…	…	…
20	2	1	2	2	1	2	1	2	1

The results of the technology planning optimization task, represent the list of operations used to manufacture the proposed family together with the data of the used resources.

Applying above mentioned methodology, it is possible to find out the optimal set of technologies, maximizing the profits, minimizing the production time and costs.

4. Conclusions

The objective of the current study is to investigate how to optimize the large composite plastic parts manufacturing processes. The computer-based product design has been integrated with the process planning. For optimal selection of technology, the corresponding optimization model has been proposed. The optimization model has been created to control and analyze the calculated technology planning route, the optimal vacuum forming process, post-forming operations, strengthening (reinforcing) and assembling operations.

The design of the new products is tightly integrated with manufacturing aspects. In the current study, for design exploration, the Neural Network meta-modelling technique has been used. The optimization of the plastic sheet and its strengthening layer thickness has been performed using the surrogate design model. The final FEA simulation was performed with optimal thickness values to verify the prediction accuracy of a surrogate model. In this manner the optimization time was shortened considerably.

The most of the above described methods are now under development and industrial testing. To facilitate these developments, it is important to provide effective techniques and computer tools to integrate an increasing number of disciplines into design system in which the human ingenuity combines with the power of computers in making design decisions.

The proposed approach is exemplified by the development of a family of products in Wellspa Inc. The demonstrated examples ascertain the validity and effectiveness of the proposed method.

Acknowledgments

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