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The design and production technology of large composite plastic products

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Abstract. The objective of this paper is investigation of the optimization of manufacturing technology processes of large composite plastic products. One of the key problems is how to integrate computer-based product design and planning of the technological process. An optimization model is proposed to control and analyse the calculated technology planning route, optimal vacuum forming processes, the technology of post-forming operations (like trimming and drilling of slots and cut-outs) and strengthening and assembling operations. Finite element analysis and artificial neural networks are included in the model used in the study. A family of large composite plastic products together with the derivate products and their production technologies is designed using the proposed methodology.

Key words: large composite plastic products, technological process, artificial neural networks.

1. INTRODUCTION

Nowadays, advanced CAD/CAE/CAM tools are widely used in many companies to support engineering decision making processes. They allow integrated use of information about different aspects of the latter, such as geometry of the product, manufacturing processes, available resources, pricing, supplier data, etc. Computer simulations of the product and process performance are carried out. Undesirable conditions are modified and the simulation is performed again. The simulations permit to optimize the product and manufacturing processes.

Progress in design optimization has continued steadily during the last forty years and by now a considerable number of optimization methods is available for engineers. In general, design optimization may be defined as the search for a set of inputs that minimizes (or maximizes) an objective function under given constraints. The objective function may be expressed as cost, product lead time, product efficiency, return on investment, or any combination of the product performance parameters. It is subject to constraints in accordance with given relationships among variables and parameters and constraints on the manufacturing system parameters and resources. This function may be represented by simple expressions or complex computer simulations. Challenges to design multiple products simultaneously have led to the collaborative multidisciplinary design optimization [1–5].

The aim of the current study is to develop general principles, applicable to the design of products and their manufacturing processes and to use the multidisciplinary design optimization approach for obtaining rapid and effective design decisions leading to better and more balanced solutions. The underlying focus of the 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 in the design process.

The simulations or observations of learning methods must be applied for evaluation of the relationship (response surface model) between design results and parameters with the best precision and the least cost. For practical design problems the hybrid learning methods, integrating the classification (or pattern recognition) and regression (or function approximation) paradigms, are recommended [3]. Neural networks and other methods of inductive learning are possible tools for extensions and generalizations of classical regression methods for this case. Artificial neural networks (ANN) are commonly used for learning and for generalization of the knowledge. For modelling the decisions in technology planning processes, the application of artificial feed-forward neural networks and the radial basis function networks are proposed [6,7].

2. PRODUCT DESIGN

It is recommended to split the product design process into two layers: the product family planning layer and the layer for optimization (for each fixed combination of functional features) of the design parameters of derivative products (product attributes optimization task). Under the introduction of these two layers, the product design is a hierarchical system of a mixed-integer programming model for the product family planning and a constrained non-linear programming model for the product attributes optimization tasks.

The objective of the product family planning is to optimize sales volumes and the module combination pattern for each derivative product [8]. The conditions of effective use of resources and fulfillment of market demands must be satisfied. For optimal planning of the volumes of a product family and module combination, a model was developed. The model maximizes net profits and is subject to upper and lower bounds of market demand and capacity constraints. Figure 1 shows examples of the derivative members of the product family of hydro-spa equipment.

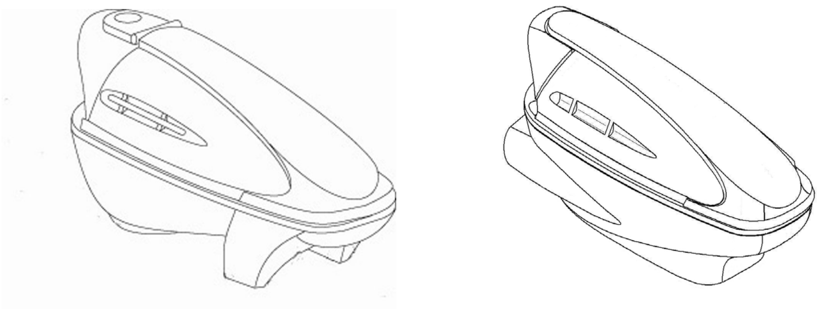
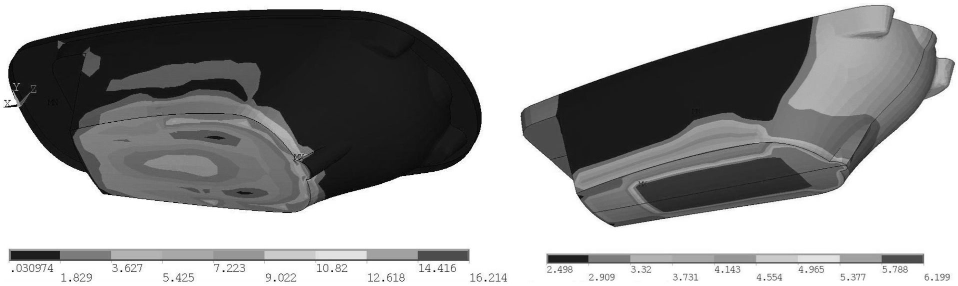


Fig. 1. Examples of the derivative products.

Using the optimization model, new additional functions of the market needs, required investments, possible market growth and production costs for each product are determined [8]. As a result, it is considerably easier to see the direction of investments and to determine profitable changes and modifications. Thus the delivery time and lead-time can be reduced. Based on the obtained results, the company Wellspa Inc. developed two additional functions of their product and the present sales justify the made decisions.

In the product family modelling phase, general guidelines for structural calculations and optimization of the product are defined [8]. Later, in design of derivative products for the product family, non-linear optimization is used and a detailed description of the product is created. For modelling and structural analysis of derivative products CAE (ANSYS) and CAD (Unigraphics) systems are used. It is important to emphasize that the design of new products is tightly integrated with technological aspects. For example, the bathtub (an essential part of the hydro-spa system) 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 a glass fiber epoxy layer on one side. In the vacuum forming process, the final shell thickness in different areas may differ significantly; this has to be taken into account in structural analysis of the product. The rate of thinning of the plastic sheet in forming operations can be determined from experience, special tests or simulations. When considering optimal thickness of the strengthening layer, obviously it should be different in different areas of the bathtub. In the current study, 12 areas of the bathtub were considered. Figure 2a 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 different areas. In the current study, for design exploration and for the surrogate design model (to provide an estimate for the strengthening layer thickness–structural response relationship), the neural network meta-modelling technique was used. The optimization is then performed using the surrogate design model. Finally, the FEA simulation with optimal thickness values is performed to verify the prediction accuracy of the surrogate model. Thus the time of optimization was shortened considerably.



(a) (b)

Fig. 2. The equivalent stress plot (a) and the thickness distribution after optimization (b) of the composite structure.

In optimization, the strengthening layer thickness was varied between 1 and 5 mm. The constraints for maximum equivalent stress in each layer and the total deformation were also defined and the volume of added material was minimized. In Fig. 2b, the final thickness of the structure after optimization is shown.

3. PLANNING OF THE TECHNOLOGICAL PROCESS

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). The technology planning model results in the optimal selection of technology operation sequences and parameters for the manufacturing of the product family.

For finding out optimal technology route we have to cut the structure of the technology process into different segments. It means that we have to optimize different subsystems, 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 assembling. An example of a generalized structure of the manufacturing plan for a product family is shown in Fig. 3 [9].

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

Choosing among different design alternatives of operations involves detailed analysis of existing knowledge and experience. A key factor in the selection process is representation of the knowledge in such a way that operation selection and design becomes a computer-supported process.

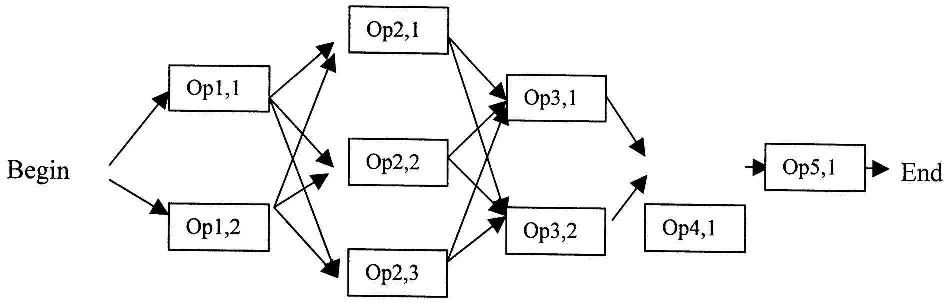


Fig. 3. The structure of the technology process.

An artificial neural network is used for modelling 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 used for modelling. Neural networks are composed of nodes (neurons) connected by directed links. Each link has a numerical weight W_{ji}, associated with it. A mathematical model for a neuron can be represented as

$$a_i = g\left(\sum_{j=0}^{n} W_{ji} a_j\right), \tag{3.1}$$

where a_j is the output activation of the unit j and g is the activation function of the unit (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 multi-layer feed-forward network with one hidden layer, the sigmoid function (for the hidden layer) and linear activation functions (for the output layer). Back-propagation and the Levenberg–Marquart approximation algorithms were selected as most suitable. Application of the artificial feed-forward neural networks and Radial Basis Function Network has been proposed in [6,7]. An 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 the plastic sheet material into a shape that is determined by the mould (Fig. 4). Sheet stock is heated to a temperature at which the plastic softens (but below its melting point). Using vacuum or pressure, the plastic is then stretched to duplicate the contours of the mould. Next, the plastic is cooled, by what it retains its shape. Finally, it is removed from the mould and trimmed as required to create the final product. Thermoforming is suitable for low to moderate production volumes (up to approximately 100 000 units per year) because, for example, tooling for injection molding can cost ten times as much.

In the vacuum forming process, the knowledge and the experience of engineers is of great importance. Geometrical complexity, depth of draw, level of

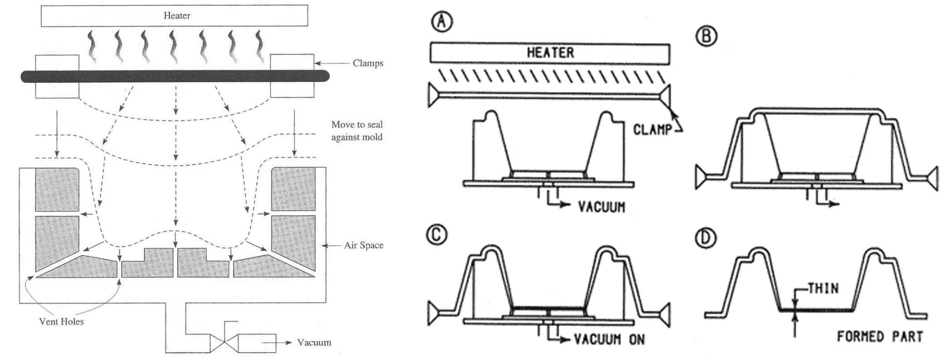
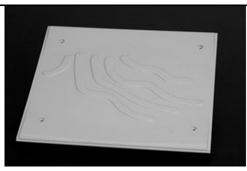


Fig. 4. Straight vacuum forming and forming steps [10].

the surface details required, ribbing, fillets, stress concentration, shrinkage, expansion, and undercuts are all factors that must be carefully considered when designing the components and vacuum forming operations. An example of typical components of vacuum forming is given in Fig. 5 (geometric complexity).

Simple parts: code 1	
	

Parts with medium complexity: code 2	
	

Complex parts: code 3	
	

Fig. 5. Typical vacuum forming parts.

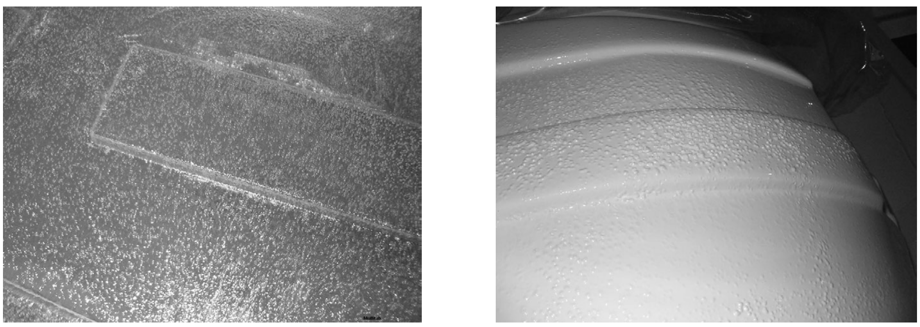
The quality of formed parts is seriously affected by the moisture absorbing ability of the material. The materials known as hygroscopic, if not pre-dried prior to forming, could have moisture blisters which will pit the surface of the sheet, resulting in a rejection of the part. For instance, ABS is able to absorb up to 0.3% moisture in 24 hours. In Fig. 6 some samples of wet material sheets after forming are shown. To overcome this problem it is sometimes necessary for hygroscopic materials to be pre-dried in an oven before forming. The drying temperature and duration of the drying time depends on the material and the thickness [[10,11]].

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.

The moulds are one of the most important elements of the forming process. One of the main advantages of vacuum forming is the significantly lower pressures as compared, for example, to the injection molding process. As a result, the vacuum formed tools can be produced economically from a wide range of materials to suit different prototype and production requirements. The prime function of a mould is to permit the machine operator to produce the necessary quantity of duplicate parts before degradation.

Selection of the best-suited mould material depends largely on the severity and length of the service required. If only a few parts are required, fairly low temperature plastics, wood or plaster can be used. However, if the quantity requirements and material temperatures are higher then ideally an aluminium-based resin or aluminium mould would be recommended.

For vacuum forming, it is necessary to take into account significant thinning of the sheet during the process. This thinning is a natural consequence of the deformations. For vacuum forming, elastic strains are negligible; therefore, the volume can be assumed to be constant. The thickness variations may be large (Fig. 7). Therefore, it is often important to control the thickness variations in order to meet functional requirements of the part.



(a) (b)

Fig. 6. Surface defects when the material was wet before molding: (a) Polycarbonate; (b) ABS.

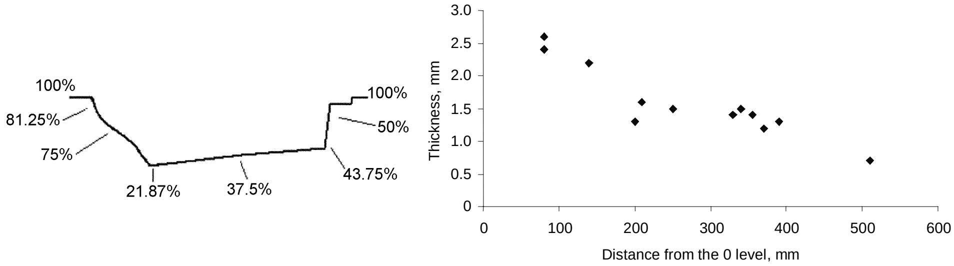


Fig. 7. Thickness variation of a 3.2 mm thick FF0013 Plexiglas plate after vacuum forming.

The designer can accommodate variations in the thickness if he knows in advance what they may be. We have analysed the thinning process with different materials like ABS, PMMA, white 2000BM 1516, polycarbonate ICE (UV) and acrylic FF0013 Plexiglas. In the study we mainly concentrate on the acrylic FF0013 Plexiglas, which is formed at the temperature 320–340 °C (heating time was 6 min and cooling time 2 min). The experimental product and wall thickness reduction is shown in Fig. 7.

The methods used to control thinning are the following:

- selection of the forming scheme;
- use of surface lubrication;
- modification of the die or part design to minimize local stress concentrations;
- post-forming strengthening (reinforcing), etc.

For analysing 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. For experimental analysis, the product with four independent zones and with controlled temperature was used, the temperature variation was 290–340 °C (Fig. 8).

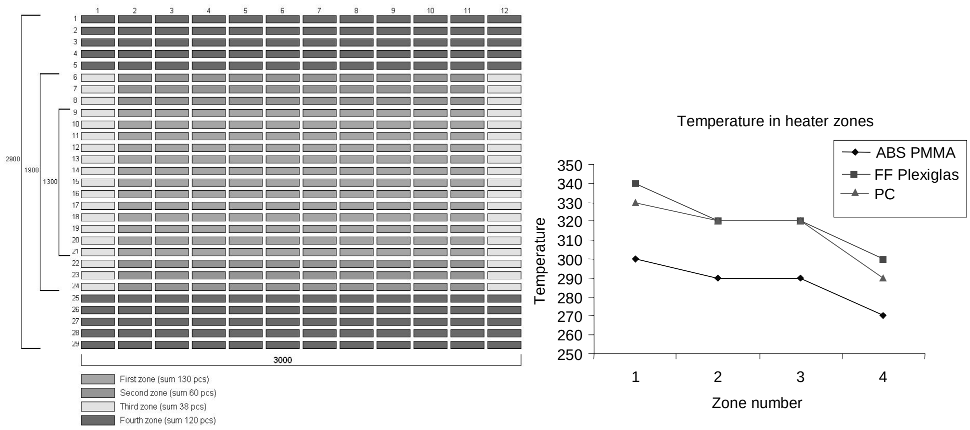


Fig. 8. Heater zones and temperature differences.

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

Using the selection parameters, the ANN was trained for each technology like vacuum forming processes, acrylic cutting technologies and reinforcement (Table 2).

In Table 2 the meaning of the acronyms is as follows: *Geom* – geometric complexity, *Log* (*nP*) – the number of parts, *Dim* – the dimension of the vacuum forming bench table, *Thick* – maximal material thickness, *SQ* – surface quality, *PT* – part texture, *UC* – undercuts, *I* – investments. There are three grades: 0 – not usable, 1 – reverse draw forming with two heaters, 2 – straight vacuum forming.

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 type of equipment best suited depends largely on the type of the cut, size of the part, drawing ratio, thickness of the material and the production quantity required. They are also factors to consider when determining the cost of such equipment. Below some of the more popular methods adopted are described.

Table 1. Selection parameters for vacuum forming processes

Parameter and mark	Description
Dimensions (L × B)	280 × 430, 680 × 760 up to 2000 × 1000 mm
Max depth of draw (H)	183, 220, 300 up to 800 mm
Max material thickness (D)	3.2, 4, 6, 7 mm
Undercuts (UC)	yes/no
…	…
Draft angle (α)	$\alpha > 5°$
Surface quality (Q)	low, medium, high
Batch size (N)	$1 \le N \le 10\,000$ ($0 \le \log N \le 4$)
…	…
Wall thickness after forming (h)	$0.7 < h < 3$ mm
Heating temperature (T)	$180 \le T \le 220$°C
Cooling time (C)	$3 < C < 7$ min
Heating zones (Z)	$1 < Z < 4$
Cooling points (P)	$2 \le P \le 5$

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
2	2	2	2	2	1	2	2	2	1
…	…	…	…	…	…	…	…	…	…
20	2	1	2	2	1	2	1	2	1

The trimming task has two possibilities {yes = 1, no = 0}; if the trimming output is 1, manual or automatic trimming can be used. In case of the automatic trimming process, saws or 5-axis NC routers can be used. For finding out the optimal trimming method, different processes have to be analysed and possible defects determined. The analysis resulted in optimal input parameters for the neural network tasks.

Reinforcement tasks have two options: {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, a series of finite element analysis to simulate and optimize the reinforcement ply thickness, were performed.

The optimization task can be formulated as follows: find the feasible operation sequences for a product family that gives maximum profit and minimizes the manufacturing time, and is subject to the following constraints: 1) capacity constraints for all workstations, 2) use of materials, 3) use of technologies.

The result of the technology planning optimization gives the list of operations used to manufacture the proposed production family together with the data about the used resources.

Applying the above mentioned methodology, it is possible to find the optimal set of technologies, to maximize the profits and to minimize the production time and costs. Testing of the proposed approach has shown that this approach determines a set of optimal process parameters for vacuum forming and post-forming operations quickly. As a result, parts of needed quality can be produced without relaying on the experience of the personnel.

4. CONCLUSIONS

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

The design of new products is tightly integrated with manufacturing aspects. In the current study, for design assessment, the artificial neural network meta-modelling technique has been used. Optimization of a 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 predicted accuracy of the surrogate model. In this manner the optimization time was considerably shortened.

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 the design system, in which the human ingenuity is combined with the power of computers in making design decisions.

The proposed approach has been applied for the development of a family of products in Wellspa Inc. Described examples illustrate the validity and effectiveness of the proposed method.

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Suuregabariidiliste plastdetailide tootmistehnoloogia planeerimine

Rein Küttner, Kristo Karjust ja Meelis Pohlak

On käsitletud suuregabariidiliste plastdetailide tootmistehnoloogia optimaalse planeerimise metoodikat. On püütud koos projekteerida tootepere, derivaattooted ja nende valmistamise tehnoloogiad. Samas on optimeeritud erinevaid alamsüsteeme, nagu vaakumvormimise ning lõikamise tehnoloogiad ja tugevdamise ning koostamise operatsioonid. Iga üksiku alamtehnoloogia protsessi planeerimissüsteemi modelleerimiseks on kasutatud närvivõrke; metoodika realiseerimiseks on kasutatud MS Exceli ja MatLAB'i keskkonda. Näitena on vaadeldud suuregabariidiliste plastdetailide tootmistehnoloogiat ettevõttes Wellspa OÜ.