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Automated Derivation of Optimal Production Sequences from Product Data

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Abstract

Customer specific, individual products nowadays lead to larger product variance and shorter time to market. This requires efficient production system planning. In addition, due to a larger system complexity, each iteration of the planning process itself gets soaringly complex. Time constraints and complexity, therefore, emphasize the necessity of supporting humans in planning modern production systems.
Especially the determination of the production sequence holds immense potential and tends to get even more complex within specific production technologies. Exemplarily, this article focuses on welding sequences. Here, domain knowledge from product development and production planning needs to be holistically integrated. Furthermore, implicit, historic knowledge needs to be formalized and used in today's planning tasks.
This article introduces a methodical approach and a corresponding toolchain to derive optimal production sequences from customer product data which is validated using welding processes. For this, firstly, a reference system is build up consisting of historic product data (e.g. part list, CAD data) and corresponding production system characteristics (e.g. number and specifications of machines). The main aspect is to use similarities between the new product variant and assemblies from the reference system, to determine implications of product specifications on the process sequence. Overall, such restrictions can be displayed using Model-Based Systems Engineering. Relevant information (e.g. weld seam lengths) can be used to compute the optimal weld seam order regarding minimal cycle times, for example. This requires a parametric encoding of product and production system. In a nutshell, this approach covers the automated derivation of an optimal production sequence for new product variants, based on system information and product similarities, to tackle time constraints and complexity by suggesting initial planning drafts.

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Keywords: Automated Production Planning; Computer-aided Design; Operations Research; Methodical Approach.

1. Introduction

In the age of digitalization, manufacturing companies are more than ever confronted with new challenges but also opportunities leading to a successful digital transformation [1]. Here, success largely depends on operational excellence [2], resulting in a high potential in optimizing production processes. Due to shorter product life cycles, the frequency of developing and planning products and production systems increases. In addition, because of the demand for a shorter time-to-market and individual products, manufacturers nowadays need to reduce time and maximize efficiency in engineering processes. [1] To cope with increasing product variants and system complexity, new methods and tools supporting humans in production planning are required [3].

Especially the determination of optimal product variant-specific production sequences holds immense potential and tends to get even more complex within specific production technologies. Here, a holistic view of product properties and their impact on production is of central importance [4]. Detecting these interdependencies between product variants and their corresponding production sequences requires an integration and formalization of domain knowledge which is afterwards reusable in production planning tasks.

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Finally, not only the generated optimal production sequences but also the optimization of planning processes and the resulting increase in efficiency, quality and sustainability by means of Zero Defect Manufacturing [5] brings immediate competitive advantages for manufacturing companies [2].

Problem Description:

Production process planning deals with the question of how requirements and features of the product to be manufactured can be implemented and realized [6]. It also involves the product-related, repetitive activity of planning production systems. Here, the term *production system* is much discussed and can be used in many ways: In general, production can be divided into four levels: production network, site/factory, area/process sequence and process/workstation [7]. Within this article, a *production system* contains several process steps and, therefore, refers to the level of process sequences.

In planning process sequences and especially with product variant-specific production systems, there are many repetitive activities. This article, thus, aims at supporting users in automatically planning new production systems based on already designed new product variants (Fig. 1.).

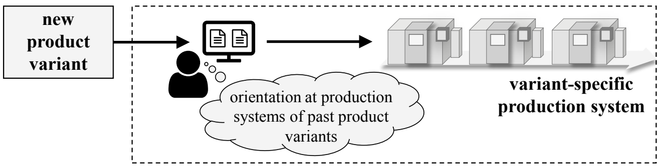

Fig. 1. Problem Description: Production system planning.

Here, the overall goal is to generate optimal production sequences by means of maximizing or minimizing a target function. Disciplines such as *Operations Research* (OR) provide methods for solving optimization problems in general. With deriving variant-specific production sequences it is necessary to efficiently use the knowledge generated by repetition and follow the assumption that similar products are accompanied by similar production sequences. Therefore, a *determination of product similarities* could help making sense of variant-specific parts and their impact on production using a *reference system*, containing information about past product variants. In addition, a formalization of planning rules by explicitly modeling interdependencies between product and production system is missing in practice. [8] Here, *Model-Based Systems Engineering* (MBSE) represents a methodology established in product design that could also lead to advantages in the planning of production systems.

In a nutshell, due to an increasing number of product variants production system planning is a repetitive but complex process that calls for an integrative approach to support automatically deriving variant-specific production sequences from product data utilizing knowledge from past variants.

Structure of Work:

Section 2 summarizes a comprehensive review of relevant literature. The methodical approach for the automated derivation of production sequences is outlined in Section 3. Early findings from applying the method are described in Section 4. Section 5 gives an overview about current research activities extending the approach.

2. Literature Research

This section provides an overview of literature describing the relevant state of the art in deriving production sequences and the sub-domains stated above.

2.1. Automated Derivation of Production Sequences

As early as 1989, algorithms for generating mechanical assembly sequences are developed [9]. Nowadays, the focus mainly lies on automatic assembly sequence planning by means of manual assembly tasks [10–12]. Eng et al. [13] use various criteria based on the feasibility of the assembly direction, the assembly itself, and costs. Dini and Santochi [14] describe an assembly scheduling software system. Most literature uses data from *Computer-Aided Design* (CAD) Software as an input description of the product. Following this, Leo Kumar [15] reviews the state of the art regarding artificial intelligence in *Computer-Aided Process Planning* (CAPP). Trommer [16] proposes a method for an early evaluation of production sequences in product development.

2.2. Reference System

In literature dealing with product development, reference systems are often found in general [17,18]. Albers et al. [17] describe a method for developing products in generations based on a reference model. With a focus on product variants rather than product generations, shared modular product designs are used [7,19], with the most prominent example being Volkswagen's "MQB". In production, the usage of reference systems such as Demeester et al. [20] remains rare.

2.3. Determination of Product Similarities

There are many ways to determine product similarities. Linguistic methods compare standardized text modules of quantitative and qualitative requirement types [21–23]. Krahe et al. [24,25] use machine learning to compare geometric similarities based on point clouds. Schuh et al. [26–28] pursue a minimization of the cost of change by comparing products' *bill of materials* (BOM). Most literature determining product similarities is based on extracting features from CAD. There is extensive literature on feature recognition [29–31]. However, the focus mainly lies on extracting features rather than connections between parts (also referred to as *joints*). Sarivan et al. [32] consider a product model with weld joints for an automated welding robot programming.

2.4. Model-Based Systems Engineering in Production

MBSE is mainly used in the field of developing mechatronic systems [33,34]. Gönnheimer et al. [35] propose to derive turnkey production systems based on a product modeled in MBSE. Their focus, however, lies on change management i.e., a traceability analysis between functions, components, and features of the product as well as manufacturing and assembly processes, machines, and their relations in production [36]. As first, Akundi and Lopez [8] review the application of MBSE to manufacturing and production engineering systems.

2.5. Operations Research in Production Planning

The optimization of production sequences is an important part of production system planning [37]. Mathematical optimization algorithms, however, are mainly used in production control, more specifically scheduling [38,39] and sequencing [40] orders. Sparse applications in production planning are given by Xue et al. [41] or Wang and Tian [42] assessing manual assembly sequence planning optimization.

2.6. Conclusion of Related Work

To summarize, the literature study conducted allows for the following conclusion: There is a large body of knowledge on the subject of *automated derivation of production sequences* from product data. However, the focus mainly lies on assembly sequences regarding manual assembly tasks or manufacturing sequences based on feature extraction. The consideration of (automated) joining processes (referring to DIN 8593-0) remains absent.

The idea of *reference systems* primarily originates from product development. In combination with an automatic *determination of product similarities*, however, this enables a data driven classification of product variants in order to look at their impact on corresponding production sequences. To formalize these correlations, *MBSE* helps explicitly modeling interdependencies between product and production.

3. Methodical Approach

Following the findings from the previous section, the approach presented in this article supports users in automatically planning new production systems based on already designed new product variants using knowledge and interdependencies from past product variants.

3.1. Overall Approach

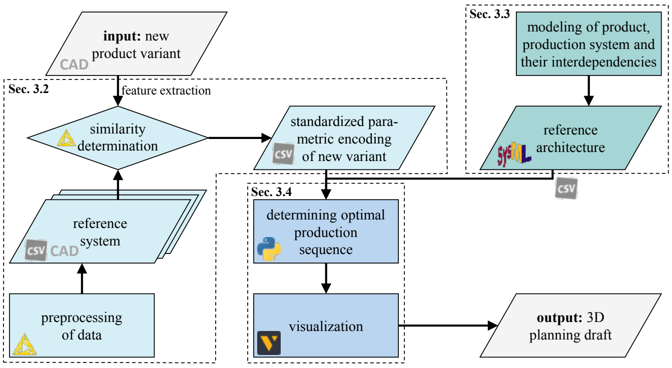

Fig. 2. Visualization of methodical approach.

Fig. 2 visualizes the procedure which consists of three main steps: Based on the variant to produce, firstly, similarities between the new product variant and the reference system – consisting of past variants – are determined (Sec. 3.2). The resulting parametric encoding of the product is combined with relevant information from the model-based reference architecture (Sec. 3.3) which formalizes interdependencies between product and production system. Lastly, the optimal production sequence corresponding to the new variant is being derived and a rough visualization of the resulting production system is generated (Sec. 3.4). Further details regarding the three steps are given in the following sections.

3.2. Reference System and Similarity Determination

A key first step in deriving production sequences is to determine similarities between product variants. This approach follows the assumption that similar products are accompanied by similar production sequences. Existing approaches (see Sec. 2) are mostly limited to extract features from product data (CAD) and afterwards match features to production processes. CAD feature extraction reaches its limits when it comes to joining features such as weld seams. This approach explicitly considers joints between parts and (sub-) assemblies. That proposes a central challenge: In most CAD assemblies, other than screw connections, weld, solder or adhesive joints for example are not explicitly modeled. Therefore, in order to consider these features as well, one needs to know which assembly parts shall be connected. This necessity calls for a classification of parts of the new customer variant using a reference system, containing information about past product variants and their corresponding production sequences.

Here, a standardized, parametric encoding of product and production properties as well as their interdependencies is advantageous and should contain all relevant information for planning. Examples include the assembly structure, parts and their features and connections on product side as well as the number of operations, their order and the assignment of features to production steps on production side. With this information available, there are four key steps in order to automatically consider e.g. weld, solder or adhesive joints based on past product variants:

Investigation of differentiators: A preprocessing of part properties helps determining attributes in which the parts differ.

Classification of parts: To make sense of the parts of the new product variant, similar parts from new and past variants must be identified. This matching can be based on geometric, semantic (e.g. same or similar part names) or property-based (e.g. material or weight) similarities.

Transferring part joints: For past product variants, joints between parts are known. Once all parts from the new variant are classified and assigned to the reference system, joints known from past variants are transferred to the new variant.

Determination of feature and joint properties: In the same way as extracting features (e.g. holes) alone is not sufficient, specific feature/joint properties need to be derived from CAD data (e.g. diameter with holes/length with weld seams [32]).

The resulting standardized, parametric encoding of the new product variant is also necessary in order to select the relevant planning restrictions supported by the reference architecture, as discussed below.

3.3. Reference Architecture

The aim of this approach is to utilize implicit knowledge from past product variants and their corresponding production sequences. Since an extraction of this knowledge solely from the reference system (Sec. 3.2) would need an extensive amount of data, which – in industrial practice –is typically not available, this approach suggests the explicit modelling of a product and production architecture as well as their interdependencies. Coming from current distributed document-based planning processes, a holistic model-based approach brings consistency and the opportunity to formalize planning rules. The reference architecture, hence, consists of at least:

- Product model in general, consisting of e.g. assembly structure, parts, feature classes, attributes and relations.
- Production model in general, consisting of e.g. site-dependent information, processes according to DIN ISO 8085, modules, resources, attributes and relations.
- Interdependences between product features and production processes (e.g. hole and drilling).
- Effects of product specifications on the necessity of specific production processes (e.g. variant drivers and associated process steps).
- Interactions between several production processes (e.g. restrictions and sequence).
- Specific relationships between attributes of the product and attributes of the production resources (e.g. part dimensions and machine installation space).

The combination of variant-specific information from Sec. 3.2 and complementary planning rules from Sec. 3.3 forms the input for the determination of the optimal production sequence corresponding to the new product variant.

3.4. Determining Optimal Production Sequences

When looking at production processes, there are a lot of possibilities to formulate optimization targets. With the planning scenario assessed in this article (Sec. 1) where product properties are already determined and fixed, optimality regarding production cycle times and resource investment costs are of central importance. Based on the variant-specific features and joints, three key questions need to be considered to determine optimal production sequences:

(1) Which production steps are necessary at all and how long will they take?
(2) In what order should the steps be performed?
(3) Which resources are necessary and what specifications must these have?

The answers to question (1) and (2) arise from the combination of variant-specific parts and joints (Sec. 3.2) and their model-based connection to related process steps and resources (Sec. 3.3). Question (2) results in an optimization problem where all resulting operations from question (1) need to be assigned to as little resources as possible still lacking behind the targeted customer cycle time.

Given the optimal solution is determined and properties of the necessary resources are known (3), the resulting standardized parametric encoding of the production system can be visualized as an early planning draft.

4. Method Application and Toolchain

Following the methodical approach presented above, this section touches upon some examples of the current state of the art regarding its application. The built toolchain can be taken from Fig. 2 and will be further assessed in the following.

4.1. Reference System and Similarity Determination

An initial step in order to build up the reference system is to determine suitable parameters for a standardized encoding of product variants, corresponding production sequences and their interdependencies. A standardized *comma-separated value* (CSV) representation allows for easily reading and writing files using different applications later on. Fig. 3 shows an excerpt from an example encoding. This demonstrates the generality of the method by including several joint types (DIN 8593-0), where type 1 refers to weld seams as the application example.

```
                    product(){
num_parts:            3
part_width:           [0.1, 0.5, 0.8]
part_length:          [0.2, 0.5, 0.7]
num_joints:           5
joint_type:           [0, 1, 1, 1, 1]
weld_seam_length:     [0.1, 0.5, 0.2, 0.1]
weld_seam_to_part:    [[1, 0, 1, 0],
                       [0, 1, 0, 1],
                       [0, 0, 1, 1]]
...}

                 production_system(){
num_machines:         4
machine_type:         [1, 2, 2, 2]
machine_order:        [1, 2, 3, 4]
machine_buffer:       [3, 1, 1, 1]
cycle_time:           [0.5, 0.3, 0.3, 0.3]
...}

                 interdependencies(){
weld_seam_to_machine: [[0.0, 0.0, 0.0, 0.0],
                       [1.0, 0.4, 0.0, 0.0],
                       [0.0, 0.6, 0.0, 0.0],
                       [0.0, 0.0, 1.0, 1.0]]
...}
```

Fig. 3. Excerpt from the standardized parametric encoding.

Another key step before determining variant similarities is to investigate how the individual parts differ. Using part properties from Fig. 3, a clustering of the data reveals which attributes are suitable to separate functional part types that each product variant has. Quick wins can be scored here using a data analytics software, such as KNIME [43]. Fig. 4 shows an exemplary KNIME workflow and Fig. 5 one resulting scatter plot, which reveals that the attributes *part_width* and *part_length* are helpful to distinguish part type 1 from type 2 and 3. However, to reliably separate types 2 and 3 without misclassifications other attributes (e.g. weight or material of the parts) are necessary.

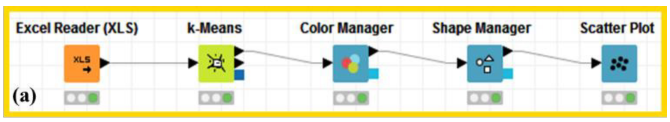

Fig. 4. KNIME workflow.

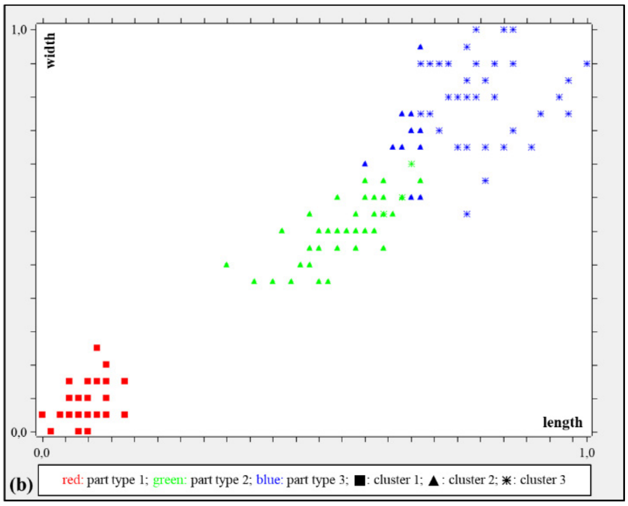

Fig. 5. Clustering of product data.

4.2. Reference Architecture

With the aim of explicitly modeling product and production system, the model-based reference architecture is implemented using Systems Modeling Language (SysML). This allows to represent (among other things) interdependencies between attributes. Fig. 6 consists of an excerpt from the reference architecture that shows besides general references (i.e. parts can contain weld seams which are realized by welding processes): (1) how product dimensions influence machine installation space, (2) how material restricts usable production technologies and (3) how weld seam length and welding robot speed results in the time needed to complete the weld seam. The latter is particularly important for determining the cycle-time-optimal production sequence.

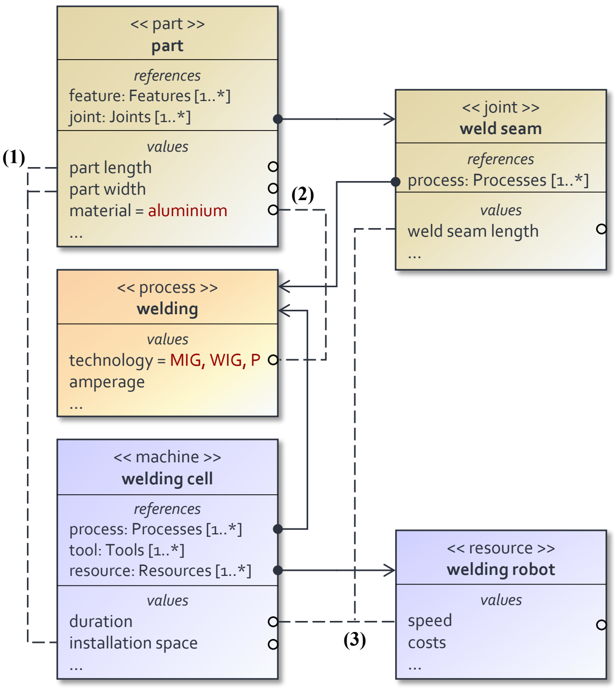

Fig. 6. Excerpt from the reference architecture.

4.3. Determining Optimal Production Sequences

With variant specific information in combination with references from Sec. 4.2, it can be determined which production steps are needed at all. The central challenge now is in which order features and joints should be realized. For this, a given number n of features and joints need to be assigned to M machines. Each feature/joint has a processing time t_i and predecessor features/joints $pre(j)$ with $i, j = 1, \ldots, n$. This results in the minimization problem regarding cycle time CT:

$$\min CT = \min(\max_m \|\textstyle\sum_i^n t_i * x_{i,m}\|) \tag{1}$$

with the variables:

$$x_{i,m} \coloneqq share\ of\ i\ assigned\ to\ m \tag{2}$$

$$h_{i,m} \coloneqq 1\ \forall\, m\ with\ 0 < x_{i,m} \leq 1, else\ 0 \tag{3}$$

and the exemplary secondary conditions:

$$x_{i,m} \in [0,1];\ \textstyle\sum_m^M x_{i,m} = 1 \tag{4}$$

$$\begin{gathered} max_m\, m * h_{i,m} - min_m\, m * h_{j,m} \leq 0 \\ \forall h_{i,m}, h_{j,m} \neq 0, \forall i \in pre(j), \forall m \in M \end{gathered} \tag{5}$$

In order to minimize cycle time and machine invest, a search algorithm can be used to determine the minimum number of machines M. Maximum and minimum values known from customer cycle time, processing time and maximum invest limit solution space and calculation effort. The algorithm recursively increases the number of machines, compares adding parallel and sequential machines regarding throughput time and can be implemented using e.g. Python. This results in a NP-hard problem which can be solved using a solution heuristic that assigns features and joints to machines.

Ultimately, given the variant-specific production sequence and the needed machine properties, a visualization of the solution as an early planning draft is to be generated. To give the reader a better idea of the desired result, Fig. 7 (a) gives a 3D-visualization of the Learning Factory at wbk using Visual Components. Fig. 7 (b) especially shows the modular structure of resources that allows for an automatic generation.

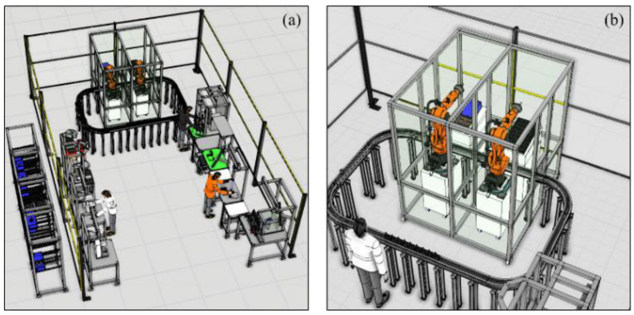

Fig. 7. (a) Learning Factory Global Production; (b) Modular cells.

5. Summary and Outlook

This article describes a methodical approach and examples from its application to automatically derive production sequences from variant-specific product data. Here, it uses knowledge from past product variants and explicitly considers joints (e.g. weld seams) in addition to classic features. The approach supports humans in production system planning based on already designed new product variants. To address the demand for shorter time-to-market, once a software demonstrator has been implemented, a quantitative efficiency analysis will be conducted to prove the validity of the approach.

Current and future research shall focus on implementing machine learning classifiers (e.g. Decision Trees) with KNIME in order to classify customer variant-specific parts using the reference system. In addition, the reference architecture is constantly extended by adding new planning rules and references. Equally, more secondary conditions (e.g. late increase in weight or quality aspects) are added to the optimization problem which is implemented using Python. Lastly, an interface for an automatic initialization of the modular visualization using Visual Components is built up.

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