Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 62 (2017) 129 – 134

www.elsevier.com/locate/procedia

10th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16

# Impacts of product-driven complexity on the success of logistics in the automotive sector

Veronika Feldhütter[a]*, Corinna Steck[a], Sven Hawer[b], Michael ten Hompel[b]

[a]*Fraunhofer Institute for Material Flow and Logistics, Joseph-von-Fraunhofer-Str. 2-4, 44227 Dortmund, Germany*
[b]*Institute for Machine Tools and Industrial Management, Technische Universität München, Munich, Germany*

* Corresponding author. Tel.: +49-176-2191-3718; *E-mail address:* veronika.feldhuetter@tu-dortmund.de

**Abstract**

Globalization and higher market heterogeneity have led to a substantial increase of model variety in the automotive sector. Caused by the necessity to integrate a growing number of models into existing plant structures a considerable increase of complexity is observable within the OEMs' manufacturing plants, especially in logistics. This often has a negative effect on the companies' processes and cost structures. To examine these impacts on logistics, structural equation modeling is used in this paper to determine causalities between indicators for product-complexity and logistics KPIs. Furthermore, a method for the operationalization of product-driven complexity is provided and implemented in a use case.

Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering

*Keywords:* Structural equation modeling; advanced data analysis; big data; pattern recognition; complexity

## 1. Introduction and motivation

Product complexity is one of the greatest challenges producing enterprises face these days [1]. Driven by the rising customers demand for individualized products [2] [3], the variety and number of product variants has increased significantly over the last two decades [4]. Another trend towards shorter technology [5] and product lifecycles [6] forces companies to deal with product complexity by way of reduced innovation and development periods [7]. In the automotive industry, the logistics sector in particular is affected by the increase in product complexity as a study by Göpfert et al. (2012) [8] shows. As a consequence, rising product complexity leads to more complex logistics systems [9]. The question arises to which degree product complexity is desirable so that the benefits for the costumer exceed the costs for managing logistical complexity [1]. However, no adequate key performance indicator (KPI) to measure the product-induced complexity of a company or a manufacturing plant has been developed so far [10]. To achieve this goal, the influencing factors have to be identified and quantified first [11]. Especially interdependencies between measurable complexity drivers have not yet been analyzed. With the development of new data-analytics methods such as structural equation modeling, tools from the field of "Big Data" are available today which open up new possibilities for tackling this challenge [12].

Accordingly, the goal of this contribution is to develop a quantitative model to predict the product-induced complexity of a logistics system in the automotive assembly based on data recorded over the last 6 years of production activity within seven international plants of a German automotive manufacturer. The model that has been developed makes it possible to calculate a KPI for product complexity, taking into account interdependencies between the influencing factors. After having discussed the present state-of-the-art for complexity quantification within logistics systems in chapter 2, we give an introduction into structural equation modeling in chapter 3. In chapter 4, we identify the influencing factors by conducting expert interviews. Based on the data gathered, a structural equation model using the partial-least-squares approach is developed to analyze the interdependencies by studying correlations between the influencing factors. We then validate the developed method in an industrial use case and discuss the results in chapters 5 and 6, before rounding up this paper with a conclusion and outlook in chapter 7.


Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2016.06.078

## 2. State of the art/literature

The term complexity is commonly used and is a research object in many research disciplines [13]. However, even a universal definition of complexity seems to be impossible [14]. This paper therefore focuses on five core-parameters: variety of elements, connectivity of elements [15], dynamics of a system [16], interdependencies [15] and fuzziness [17]. To further narrow down the scope of this paper, product-induced complexity regarding an OEM's in-house logistics is the object of investigation. The term product-complexity describes the complexity which is formed by the sum of product attributes with different characteristics and dependencies and which complies with the above mentioned core-parameters of complexity [18].

The first efforts to quantitatively measure complexity succeeded in 1965 and were made by Kolmogorov and Chaitin. Both stated, that the complexity of a system is linked with the length of the shortest program that reproduces the system [19]. In the last few decades, three approaches for the operationalization of complexity have emerged. Windt et al. developed a complexity vector that copes with the multidimensionality of complexity [20]. The fundamental idea of the vectorial approach is the comparability of different systems and system states using an ordinal scale [21]. For this approach, the dimensions of the vector are represented by complexity drivers, which are defined as parameters that influences a company's complexity directly or indirectly [22] [23]. Further approaches consider a system's entropy as a central weighting factor for complexity. Primarily used for the characterization of thermodynamical processes, the term can nowadays be assigned to thermodynamics, information theory and statistical mechanics [19]. In information theory, entropy is described as the amount of information that is necessary for describing a system's state [24]. It is therefore considered a measure for information content and can be used for the computation of a statistical process's or a system's degree of uncertainty [25]. With increasing uncertainty, system complexity rises, and consequently complex systems feature a higher entropy [24]. Becker, Meyer and Windt employ graph theory for the evaluation of complex manufacturing systems. Vertices and edges represent a material flow network that can be evaluated by graph-theoretical standard key performance indicators, but also conventional indicators for logistical performance. Regarding the complexity of supply chains, measures such as clustering coefficient, average node degree, or average path length are applied as complexity and robustness indicators in supply chains [26]. To determine the impact of complexity on logistical performance, Gießmann applies structural equation modeling and provides evidence for causalities between network complexity and a company's logistical success [27].

## 3. Methodological principles

In addition to a theoretical knowledge base, the reader is provided with a methodological background in order to understand the research methods applied.

In this paper a mixed methods approach consisting of qualitative and quantitative research methods is employed. Semi-structured expert interviews are conducted to identify the main drivers for product-complexity and their effective ranges within logistics. The survey data is a transliterated text that can be interpreted using sequential analysis, free interpretation, coding and qualitative content analysis [28]. In the latter case, which is applied in this paper, all important information is withdrawn and extracted from the original text.

Quantitative research differentiates between univariate, bivariate und multivariate statistics regarding the amount of variables considered [29]. Furthermore, it has to be determined if the variables are manifest, meaning directly observable or latent, i.e. not observable. In the case of latent variables, operationalization can be achieved using indicator variables. For the identification of causalities, multivariate statistics provides several approaches. A very common method is regression analysis. Its possibilities are versatile, but due to its assumptions and type of variables it is also limited. Regression only allows the inclusion of manifest variables, whereas no methods for the analysis of latent variables are supported [30]. Therefore structural equation modeling has established itself especially in business administration during the last few decades.

To analyze causal relationships between latent variables which are operationalized by manifest indicator variables, structural equation models are applicable. Their purpose is to test assumed relationships between variables as hypotheses. The graphic representation of variables and their relationships is referred to as "path model", a latent independent variable as "exogenous" and a latent dependent variable as "endogenous" [31].

A structural equation model (SEM) consists of two part-models, which represent the total construct's structure- and measurement equations [31]: the structure model describes coherence between latent variables, whereas the measurement model portrays relations between latent and manifest variables. Effect size as well as forecast data cannot be determined using covariance-based analysis; it rather serves for review and verification as well as to compare model assumptions and theories [32] [33]. In contrast, the variance analytical approach aims at discovering structures and relationships and identifying influencing variables [34]. Concerning requirements on data variance, the analytical approach has two main advantages: it is suitable for rather small sample sizes and imposes fewer requirements on statistical distribution [12]. Accompanied by the possibility of forecasting the impacts of complexity on logistical success, this is the reason why the variance-based approach, which is also known as Partial Least Squares (PLS), is applied in this paper. Fig. 1 describes the systematic process of PLS-SEM: