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Predicting Future Inbound Logistics Processes using Machine Learning

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Abstract

Manufacturing industry is highly affected by trends of globalization and increasing dynamics of product life-cycles which results in global supply chain networks. For inbound logistics, a high variance of parts from different suppliers and locations needs to be delivered to the assembly line. Planning these inbound logistics processes depends on frequently changing information of product development, assembly line planning and purchasing. Currently, a high amount of time is spent for gathering information during planning and existing knowledge from previous planning processes is scarcely used for future planning. Therefore, this paper presents an approach for predictive inbound logistics planning. Using machine learning, generic knowledge of logistics processes can be extracted and used to predict future scenarios.

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Keywords: Artificial Intelligence; Algorithm; Logistics; Modelling; Knowledge Management; Production Planning; Predictive Model

1. Introduction

Manufacturing industry is highly affected by trends of globalization, increasing dynamics of product life-cycles [1] and mass customization [2]. Challenged by a massive pricing pressure and requirements to support individual customer needs, manufacturing companies responded by outsourcing manufacturing steps to suppliers [2]. In consequence, global supply chain networks have been established. While supply chain management spans all movements and storage of raw materials, work-in-process inventory and finished goods from point-of-origin to point-of-consumption [3], inbound logistics is focused on supply from first tier suppliers to assembly line inside manufacturing plants. As a result for inbound logistics, a high variance of material numbers from different suppliers and locations needs to be delivered to the assembly line.

1.1. Inbound logistics planning

Logistics has to provide the right quantities of goods most efficiently at the right place in the right order within the right time [4]. Meeting these demands requires inbound logistics planning in advance. Inbound logistics planning covers all inbound logistics processes and required resources. This planning process can be separated into strategic (long-term), tactical (mid-term) and operational (short-term) planning of logistics before start of production [5, 6, 7, 8]. *Strategic inbound logistics planning* generates an initial evaluation for feasibility of different plant and supplier locations to integrate new products into production network [6]. *Tactical inbound logistics planning* focusses on the engineering of logistics process alternatives and their evaluation [9]. Especially the flexibility of these processes to adopt changes, for example in volume, needs to be assessed during the tactical logistics planning. To ensure this flexibility, underlying resources such as packaging containers [10], storages and in-house transportation elements have to be investigated and selected to find an optimal logistics process alternative [11]. As a result, the inbound logistics processes include both the material flow outside and inside the manufacturing plant [6]. At the *operational inbound logistics planning* stage, these pre-selected logistics processes and resources will be continuously detailed and integrated into the production plant by pre-series processes during the ramp up [7].

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While there exist further descriptions of planning stages, e.g. rough, detailed and executive planning [12] and there is no distinct separation between these stages in literature, all stages are dependent on the input of assembly line planning, product development process and purchasing sourcing decisions [6]. Especially at the strategic and tactical stage, information about products and related material numbers is uncertain and changes occur frequently [8]. This leads to a continuous logistics planning process of integrating material numbers, monitoring changes, evaluating implications and in consequence updating and re-assessing planned inbound logistics processes.

Recent developments in information technology offer the possibility to better integrate existing, historical data for future planning tasks to support inbound logistics planning.

1.2. Machine Learning

Machine Learning (ML) describes a system that automatically learns programs from data [13]. Instead of manually creating programs, a ML model will be trained with an existing data set. Afterwards, the ML model is able to perform learned tasks on new data. Enabling learning from data requires a collection of example cases and relevant input features (see Tab. 1).

Table 1. An example data set for classification with known labels [14]

Case	Feature 1	…	Feature n	Class
1	10	…	1.75	Good
2	20	…	2	Bad
3	15	…	1.3	Good

This implies, ML requires a sufficient size and quality of data which can be used to train the model [13]. Nevertheless, even if there is enough data available, ML is limited to certain types of tasks which could be learned from data. These types of ML tasks can be separated into two different categories: (1) supervised learning and (2) unsupervised learning [15, 16]. *Supervised learning* is the classification of data with labeled patterns or the prediction of continuous values (regression) in a data set [16]. At supervised learning input features are always linked to a target value (label or continuous value). In contrast, *unsupervised learning* is the clustering of unlabeled data to separate data into different groups aiming to identify new interdependencies [16].

In industry, the most significant application of ML is *Data Mining* (DM) [14]. DM describes the applied discovery of knowledge within databases [17] and includes the process of data understanding, data preparation, modelling, evaluation and implementation [18, 19]. DM applications have been widely implemented for different tasks across several industries, for example at web search, spam filters, fraud detection or drug design [13, 20]. In manufacturing industry, applications for manufacturing system design, engineering design, shop floor control, fault detection and quality improvement or maintenance exist [21, 22, 23]. In engineering design for example, the selection of rolling bearings [24], the identification of optimal product design for fixture layout [25] or the prediction of product costs [26] have been successfully implemented. According to Harding et al. [21], decisions while executing these engineering tasks are often based on historical data, information and knowledge. Therefore, engineering design is a prime area for DM applications although as yet only a few papers have been reported [21].

1.3. Shortcomings

The complexity for planning an increasing amount of inbound logistics processes based on frequently changing information during the planning stages is a major challenge. This is strengthened by the issues in information technology in the area of logistics planning [9]. A recent study outlined that 50% of the time of a planner in manufacturing industry is used for collecting and preparing information. Only 20% of the time is used for planning tasks [27]. Identified causes are (1) missing support of planning software, (2) missing connection and consistency of data and information and (3) the missing re-use of previously generated knowledge [27]. In Industry 4.0, there is a massive increase of data available in production, logistics and supply chain networks (e.g. barcodes and RFID) [23, 28]. Information technology is driving this development by cheap hardware for data storage and sensors combined with enormous performance increases [29]. Currently this increasing amount of data is scarcely used in for planning tasks [27] even though ML could be used as an integral part of supply chain planning [23]. Especially at strategic and tactical inbound logistics planning, there is a high repetition of recurring planning tasks for each material number caused by frequently changing information. Instead of automating these planning tasks by manual programming, ML offers potential for further use of previously generated knowledge within successfully implemented inbound logistics processes. Applications of ML for business processes across various industries and planning tasks (engineering design) in manufacturing industry have been successfully implemented but none for strategic and tactical inbound logistics planning.

1.4. Objectives

In consequence, an approach to predict future inbound logistics processes using ML at a strategic and tactical stage of inbound logistics planning will be presented in this paper. The approach aims to integrate ML into logistics planning tasks by systematically combining a generalized ML modelling process [18, 19] with business knowledge of inbound logistics planning. The contribution of the paper is to create an integrated view of required steps to (1) pre-select features in inbound logistics planning context and to set-up ML. By extracting knowledge from existing, implemented inbound logistics processes, the knowledge stored inside ML models can be re-used for future inbound logistics planning. This set-up is used (2) to automatically predict future inbound logistics processes and to integrate underlying tasks such packaging container planning and assessment of ability for integration into the production plant. This enables a transformation of manual planning tasks into an automated approach to predict future inbound logistics processes.