ELSEVIER
Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 52 (2016) 145 – 150
www.elsevier.com/locate/procedia

Changeable, Agile, Reconfigurable & Virtual Production

Predicting Future Inbound Logistics Processes using Machine Learning

Dino Knoll[a]*, Marco Prüglmeier[b], Gunther Reinhart[a]

[a]*Institute for Machine Tools and Industrial Management, Technical University of Munich, Munich, Germany*
[b]*Bayerische Motoren Werke Aktiengesellschaft, Munich, Germany*

* Corresponding author. Tel.: +49-89-289-15550 ; fax: +49-89-289-15500. *E-mail address:* dino.knoll@iwb.mw.tum.de

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.

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016

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].

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016
doi:10.1016/j.procir.2016.07.078

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.

2. Approach to predict future inbound logistics processes

The developed approach integrates both the perspectives of strategic and tactical inbound logistics planning and ML into one system. Starting with the (1) creation of an inbound logistics ontology and the identification of inbound logistics processes' features, the (2) system modelling and evaluation completes the initial set-up. Afterwards, logistics planners are (3) formalizing planning scenarios which will be (4) used to predict and recommend future logistics processes (see Fig. 1).

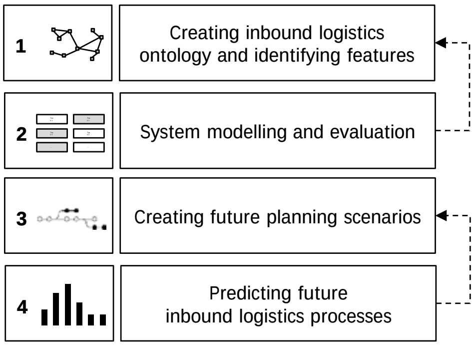

Fig. 1. Approach to predict future logistics processes

2.1. Creating inbound logistics ontology and identifying features

Modelling inbound logistics planning tasks to predict future inbound logistics processes using ML requires understanding of logistics planning tasks and business processes. Only if required information (features) are available and included in the data set, a ML model can extract knowledge of the data which can be re-used for predicting future inbound logistics processes. Therefore, the first step is to systematically identify and structure relevant information related to inbound logistics processes. This structure of information can be represented in an inbound logistics ontology. The term ontology describes a formal specification of a shared conceptualization to create a shared view [30]. While inbound logistics planning in an organization is mainly influenced by (1) assembly line production, (2) product development and (3) purchasing and sales [7], the ontology decouples logistics knowledge from organizational structure. This inbound logistics ontology can be set up by framing existing supply chain ontologies [31, 32] and extending relevant information in context of inbound logistics planning. Information included in the inbound logistics ontology can be separated into (1) *logistics process information* (e.g. source, sink) and (2) *supporting information* (e.g. container type, product's volume). The type of information can be classified into (1) describing information and (2) assessing information (see Fig. 2). While the description includes visible information, the assessment evaluates the performance by generating *key performance indicators* (KPIs) for each section. Latter is required to assess the quality of inbound logistics processes and to classify processes by benchmarking both for planners and ML models.

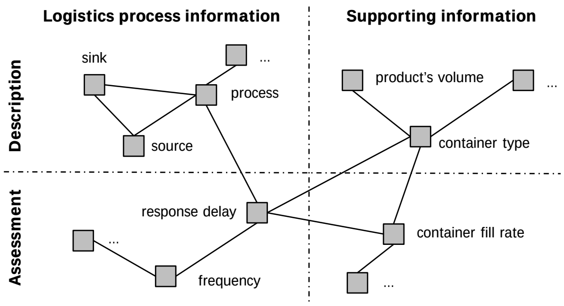

Fig. 2. Classification of inbound logistics ontology's information

After the structure of the ontology has been created, existing data from various sources can be transformed into information in the ontology. This ensures a consistency of information and decouples changes in data sources. Currently, there is a huge amount of data created, recorded and stored which can be re-used for further inbound logistics planning. This existing data (e.g. master data, transactional data and sensor data) can be summarized using the term *Digital Shadow* (a.k.a. Digital Twin). The Digital Shadow describes the digital representation of the production, the order processing, the product development and other areas nearby production [28]. Creating logistics process information and supporting information using the Digital Shadow, the inbound logistics ontology is the basis for further system modelling.

The inbound *logistics process information* is the key objective which needs to be described within the inbound logistics ontology. The inbound logistics processes include the material flow from sources (suppliers) to sinks (assembly line production) across various stations (e.g. warehouses and supermarkets) and can be separated into location-based (e.g. source and sink) and time-based (e.g. delivery frequency) components. At all steps, material numbers generate transactional data by scanning barcodes [33]. Instead of only using error-prone master data, analyzing transactional data can be used to (1) derive and visualize the material flow (e.g. Sankey diagram) for each material number automatically with a high accuracy and (2) to identify inbound logistics processes.

Besides the transparency about inbound logistics processes, the Digital Shadow can be used to assess the inbound logistics processes using KPIs. The KPIs for inbound logistics processes can be separated into internal and external point of view and short-term and long-term horizon [34]. For example, Kleijnen & Smits identified the fill rate, confirmed fill rate, response delay and stock delay as the main logistics KPIs [35]. It has to be identified which KPIs (1) can be used as features for ML to classify inbound logistics processes and (2) can be generated automatically using the Digital Shadow. This is necessary as too much information (features) can overextend the ML model which decreases the accuracy of results [13]. If the calculation needs to be done manually, the effort for calculating the KPIs might be non-economical.

The second category is *supporting information*. Supporting information are required for a ML model to extract generalized knowledge from implemented combinations of products and inbound logistics processes. The supporting information can be separated into (1) product information, (2) packaging information, (3) supplier information and (4) production program and production plant. These supporting information can be both combined with logistics process information and with other supporting information to perform different planning tasks. For example, product information such as price, geometry, weight and the link to the product structure can be matched to logistics process information (e.g. process type) or to packaging information (e.g. container type, size and fill-rate of material numbers). Using this generalized knowledge, future inbound logistics processes can be predicted.

2.2. System modelling and evaluation

After creating an inbound logistics ontology, structured information and knowledge can be used to create a *system model* which predicts future inbound logistics processes. As inbound logistics processes depend on multiple planning tasks and ML is limited to certain types of tasks, there is not only one ML model which predicts inbound logistics processes at once.

In Systems Engineering, *mathematical models* are used to formulate a set of assumptions, variables, formulas and equations to model relationships between system variables (input and output) in a simplified manner for a certain purpose [36, 37]. By decomposing the planning tasks in sub-models, an integrated system model can be developed. This integrated system model enables a cooperation between the sub-models and combines mathematical models with ML models (see Fig. 3). The cooperation can be enabled both between different mathematical models and ML models [38].

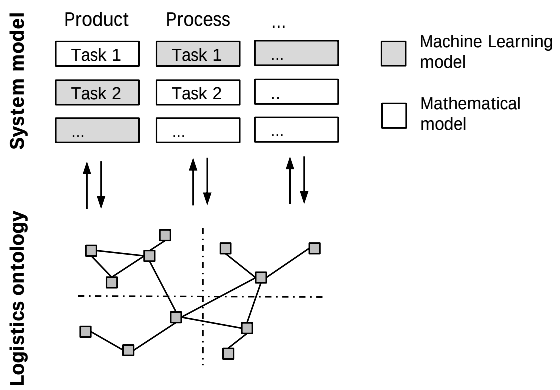

Fig. 3. Inbound logistics system model

While mathematical models are created by manually modelling the relation between input and output, ML models are set-up differently [13]. The key for implementing ML is the identification of features and choosing an optimal ML algorithm. Creating a ML model can be done using different ML algorithms (e.g. support vector machines, random forests or neural networks). While all ML models have different characteristics regarding accuracy based on the data set, there is no algorithm which outperforms all others at any time [13].

Therefore, a central research question is to identify features and algorithms which perform the best for each of the tasks at inbound logistics planning. After the ML algorithm has been chosen, the training of the ML model can be started. To ensure that the model works correctly, the data set will be divided into training and validation data. The validation data is required to evaluate how accurate the ML model performs on the data set. Thus it is required to classify tasks which (1) fit to ML models, which can be (2) solved better using mathematical models and which (3) cannot be modelled (e.g. coordination tasks). Therefore, a method which identifies required logistics planning tasks, assesses the ability to model each task and afterwards to derive recommendations how to model each task needs to be developed.

An example planning task is the selection of packaging containers for each material number. This can be done using a mathematical model which uses the volume of the material number to calculate the required space. By dividing the packaging container's volume by the material number's volume, the container fill rate can be calculated. ML models can be used to predict the container fill rate by a set of existing material numbers and container fill rates. Using the ontology, the relevant features (e.g. product and container volume) can be provided to the ML model. This offers the advantage to integrate implicit knowledge about volume used for container inlays or dead space. Combing both models leads to an integrated system by enabling a cooperation of different models. However, this emphasizes the risk that ML models learn both good and bad inbound logistics processes. To overcome the issue, experts need to assess the quality of an inbound logistics process in advance. This quality assessment with KPIs will be used to train the ML model only to recommend superior logistics processes across production plants and material numbers (benchmark effect). As result, this enables both the ML model and the logistics planner to (1) identify different inbound logistics processes for same products and material numbers (e.g. different plants) and (2) similar material numbers which could be delivered using the same inbound logistics processes (e.g. same material type). After the training stage, the ML models' prediction will be evaluated by experts. This stage can be separated into the (1) accuracy of the ML model using validation data and the (2) business knowledge intensive evaluation by experts.

As result, the system model covers required tasks to predict and recommend future inbound logistics processes using a cooperation of ML and mathematical models.

2.3. Creating future planning scenarios

Based on the initial set-up of inbound logistics ontology and the system model, future inbound logistics processes can be planned by the logistics planner. As the logistics planner cannot interact directly with the system model, the *view model* will be introduced as an interface for logistics planners. Within the view model, the logistics planner can create planning scenarios. Using the system model, each planning scenario can be decomposed and mapped to one or multiple models (tasks). As each model is linked to the inbound logistics ontology, required information can be provided. Non-available information can be imputed by information from history using the ML models. This offers the possibility for flexible planning, as the manual effort can be shifted to creating and evaluating planning scenarios while planning tasks can be executed automatically by the system model (see Fig. 4).

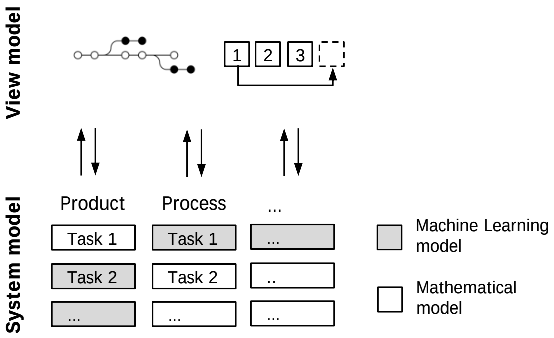

Fig. 4. Inbound logistics view model

As shown in the inbound logistics ontology, there are logistics process information and supporting information. This implies that there exist various triggers for planning inbound logistics processes. For instance, triggers can be (1) new products and material numbers, (2) changed products and material numbers, (3) re-located assembly steps, (4) changed suppliers' source locations or (5) a changed production volume. For each change, there are different implications for inbound logistics processes which needs to be checked and verified.

Re-locating assembly steps to other line-cycles results in changed displacement locations for material numbers at the assembly line. Adjusting the sink of inbound logistics processes requires a verification if there is enough physical space available at the new location or if there are any effects on previous logistics steps (e.g. re-sequencing material numbers in supermarkets). Creating transparency by predicting future inbound logistics processes enables inbound logistics planners entering a feedback loop with assembly line planning and evaluating implications (e.g. costs) for inbound logistics.

2.4. Predicting future logistics processes

After planning scenarios have been created, the prediction can be done by the system model which evaluates the planning scenario(s). Based on the hypotheses that knowledge from existing inbound logistics processes can be extracted, this knowledge can be transferred to future logistics processes. As the system model and all relevant sub-models are decomposed from organizational structure, it is possible to share logistics knowledge across different production plants inside the production network. In consequence, a benchmark of logistics processes across production plants based on KPIs can be enabled. At strategic and tactical logistics planning it is required to engineer and evaluate inbound logistics process alternatives for each material number. To predict future inbound logistics processes, the system model integrates this shared knowledge to identify best matching logistics processes using supporting information in the inbound logistics ontology (e.g. packaging containers). Afterwards, the ability of integration can be calculated using logistics KPIs (e.g. warehouse capacities) of the production plant (see Fig. 5).

```
Plant = sys_model.getPlant()
PlanningScenarios = sys_model.getPlanningScenarios()
For Each PlanningScenarios As Scenario
    MaterialNumbers = Scenario.getAffectedMaterials()
    For J < MaterialNumbers Do
            Packaging = pa_model.classify(geometry, weight, …)
            Process = pro_model.classify(Packaging, price, frequency, ...)
            IntegrationAbility = sys.calculate(Process, Plant, …)
    End For
End For Each
```

Fig. 5. Pseudo-code for predicting future inbound logistics processes

As inbound logistics processes depend on the packaging containers, the containers need to be defined before the inbound logistics process can be predicted [10]. Therefore, a *packaging model* predicts packaging containers by analyzing existing combinations of material numbers (e.g. product's volume and weight) and packaging containers (e.g. container types, fill rate) in the inbound logistics ontology. Combing information about containers, sources and sinks with additional information about material numbers (e.g. variants, price), the inbound logistics process can be predicted.

In the last step, an *integration model* calculates the ability to integrate the inbound logistics process into the production plant. Depending on the planning scenarios, different impacts for the inbound logistics processes in the production plant will be induced. To assess the implications and to calculate an ability of integration, it is required to combine the shared inbound logistics process knowledge (e.g. similar implemented inbound logistics processes) with production plant specific knowledge (e.g. warehouse capacities). Using this knowledge in combination, the integration model can calculate an ability of the integration for inbound logistics processes into the production plant. As a result, the inbound logistics processes with KPIs of similar, existing inbound logistics processes and the ability of integration will be provided to the inbound logistics planner. The KPIs create transparency about decisions made by system model and enables the logistics planner to understand, select and confirm the recommended inbound logistics processes. Using ML models, existing knowledge of inbound logistics processes can be re-used in order to reduce planning effort for each material number. In case the logistics planner is introducing new logistics processes (e.g. the integration of a new technology), these inbound logistics processes will be trained to the ML model afterwards to enable a continuous improvement over time.

3. Conclusion and Outlook

In this paper an approach for predicting future inbound logistics processes is presented. The main objective was to support inbound logistics planning using ML. The idea of ML is to extract knowledge during the training which can be transformed to future inbound logistics planning tasks. The approach is separated into the (1) initial set-up of the logistics ontology and the system model, and (2) the planning and prediction of future logistics processes. The approach integrates both concepts and presents a structure how the objectives could be achieved. Nevertheless, future research activities are required to implement the approach in industry. While this approach has not been implemented yet, there are several steps required: (1) creating a logistics ontology by identifying relevant information and relationships, (2) modelling the system by analyzing tasks, (3) evaluating and classifying ability of implementing ML models for these identified planning tasks, (4) identifying algorithms for ML models and (5) evaluating this system model with data.

Acknowledgements

The Bayerische Motoren Werke Group (BMW Group) funds this research and development project. We extend our sincere thanks to the BMW Group for the generous support of the work described in this paper.

References

[1] Abele, E., & Reinhart, G. (2011). Zukunft der Produktion. München: Hanser.
[2] Coronado Mondragon, Adrian E.; Lyons, Andrew C.; Michaelides, Zenon; Kehoe, Dennis F. (2006): Automotive supply chain models and technologies: A review of some latest developments. In: Journal of Ent Info Management 19 (5), S. 551–562. DOI: 10.1108/17410390610703675.
[3] Melo, M. T.; Nickel, S.; Saldanha-da-Gama, F. (2007): Facility location and supply chain management – A review. In: European Journal of Operational Research 196 (2), S. 401–412. DOI: 10.1016/j.ejor.2008.05.007.
[4] Gudehus, T., & Kotzab, H. (2012). Comprehensive Logistics. Springer.
[5] Klug, F. (2010). Logistikmanagement in der Automobilindustrie: Grundlagen der Logistik im Automobilbau. Springer.
[6] Schuh, G., & Stölzle, W. (Eds.). (2008). Anlaufmanagement in der Automobilindustrie erfolgreich umsetzen: Ein Leitfaden für die Praxis. Springer.
[7] Schedlbauer, M. J. (2008). Adaptive Logistikplanung auf Basis eines standardisierten, prozessorientierten Bausteinkonzepts. Lehrstuhl für Fördertechnik Materialfluß Logistik (fml) TU München.
[8] Schneider, M. (2008). Logistikplanung in der Automobilindustrie: Konzeption eines Instruments zur Unterstützung der taktischen Logistikplanung vor "Start-of-Production" im Rahmen der Digitalen Fabrik. Springer.
[9] Glöckner, M., Mutke, S., & Ludwig, A. (2015). Engineering and Evaluation of Process Alternatives in Tactical Logistics Planning.
[10] Klug, F. (2011). Automotive supply chain logistics: container demand planning using Monte Carlo simulation. International Journal of Automotive Technology and Management, 11(3), 254-268.
[11] Esmaeilikia, M., Fahimnia, B., Sarkis, J., Govindan, K., Kumar, A., & Mo, J. (2014). Tactical supply chain planning models with inherent flexibility: definition and review. Annals of Operations Research, 1-21.
[12]Durchholz, J. (2014). Vorgehen zur Planung eines schlanken Logistikprozesses: Wertstromdesign für die Logistik. Lehrstuhl für Fördertechnik Materialfluß Logistik (fml) TU München.
[13] Domingos, P. (2012). A few useful things to know about machine learning. Communications of the ACM, 55(10), 78-87.
[14] Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques.
[15] Jain, A. K., Duin, R. P., & Mao, J. (2000). Statistical pattern recognition: A review. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 22(1), 4-37.
[16] Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: a review. ACM computing surveys (CSUR), 31(3), 264-323.
[17] Dutton, D. M., & Conroy, G. V. (1997). A review of machine learning. The Knowledge Engineering Review, 12(04), 341-367.
[18] Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD process for extracting useful knowledge from volumes of data. Communications of the ACM, 39(11), 27-34.
[19] Wirth, R., & Hipp, J. (2000). CRISP-DM: Towards a standard process model for data mining. In Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining (pp. 29-39).
[20] Bolton, R. J., & Hand, D. J. (2002). Statistical fraud detection: A review. Statistical science, 235-249.
[21] Harding, J. A., Shahbaz, M., & Kusiak, A. (2006). Data mining in manufacturing: a review. Journal of Manufacturing Science and Engineering, 128(4), 969-976.
[22] Köksal, G., Batmaz, I., & Testik, M. C. (2011). A review of data mining applications for quality improvement in manufacturing industry. Expert systems with Applications, 38(10), 13448-13467.
[23] Choudhary, A. K.; Harding, J. A.; Tiwari, M. K. (2009): Data mining in manufacturing. A review based on the kind of knowledge. In: J Intell Manuf 20 (5), S. 501–521. DOI: 10.1007/s10845-008-0145-x.
[24] Sim, S. K., & Chan, Y. W. (1991). A knowledge-based expert system for rolling-element bearing selection in mechanical engineering design. Artificial Intelligence in Engineering, 6(3), 125-135.
[25] Kim, P., & Ding, Y. (2005). Optimal engineering system design guided by data-mining methods. Technometrics, 47(3), 336-348.
[26] Kusiak, A., Kernstine, K. H., Kern, J. A., McLaughlin, K. A., & Tseng, T. L. (2000, May). Data mining: medical and engineering case studies. In Industrial Engineering Research Conference (pp. 1-7).
[27] Schallow, J.; Ludevig, J.; Schmidt, M.; Deuse, J.; Marczinski, G. (2014): Zukunftsperspektiven der Digitalen Fabrik. Verständnis, Umsetzungsstand und Entwicklungsmöglichkeiten der digitalen Produktionsplanung. In: wt Werkstattstechnik online 2014 (3), S. 139–145.
[28] Günther Schuh, Matthias Blum, Jan Reschke, Martin Birkmeier (2016): Der Digitale Schatten in der Auftragsabwicklung. In: ZWF - Zeitschrift für wirtschaftlichen Fabrikbetrieb 111 (1 - 2).
[29] Andrew McAfee; Erik Brynjolfsson (2012): Big Data - The Management Revolution. Exploiting vast new flows of information can radically improve your company's performance. In: Harvard Business Review.
[30] Guarino, Nicloa; Staab, Steffen; Studer, Rudi (2009): Handbook on Ontologies. Berlin, Heidelberg: Springer.
[31] Hellingrath, B., Witthaut, M., Böhle, C., & Brügger, S. (2009). An organizational knowledge ontology for automotive supply chains. In Holonic and multi-agent systems for manufacturing (pp. 37-46). Springer.
[32] Fayez, M., Rabelo, L., & Mollaghasemi, M. (2005, December). Ontologies for supply chain simulation modeling. In Proceedings of the 37th conference on Winter simulation (pp. 2364-2370). Winter Simulation Conference.
[33] Willibald A. Günthner (2007): Neue Wege in der Automobillogistik - Die Vision der Supra-Adaptivität. Springer.
[34] Krauth, E., Moonen, H., Popova, V., & Schut, M. C. (2005, May). Performance Measurement and Control in Logistics Service Providing. In ICEIS (2) (pp. 239-247).
[35] Kleijnen, J. P., & Smits, M. T. (2003). Performance metrics in supply chain management. Journal of the Operational Research Society, 507-514.
[36] Liu, D. (2015). Systems Engineering: Design Principles and Models. Crc Press.
[37] Bender, E. A. (2012). An introduction to mathematical modeling. Courier Corporation.
[38] Seo, M., Hajishirzi, H., Farhadi, A., Etzioni, O., & Malcolm, C. (2015). Solving geometry problems: Combining text and diagram interpretation. Proceedings of EMNLP, Lisbon, Portugal