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An automated packaging planning approach using machine learning

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Abstract

The manufacturing industry is highly affected by trends of mass customization and increasing dynamics of product life-cycles which result in a large set of part variants. Thus, the required effort for logistics planning and, in particular, for packaging planning is increasing. This paper proposes an approach to automate the assignment of packaging for an individual part based on its characteristics using machine learning. We use the historical data of product parts and their packaging specifications to train our two-step machine learning model. Consequently, the model is able to propose a packaging with an accuracy of 84% in comparison with real-world data.

Keywords: production planning; packaging planning; machine learning; model building; case study

1. Introduction

The manufacturing industry is highly affected by trends of mass customization and dynamics of product life-cycles [1]. Consequently, the variety of individual parts, sub-assemblies and product components increased to meet customers' requirements [1]. To overcome these challenges, the manufacturing industry has developed an integrated supply chain network to enable a continuous supply of parts [2]. When supplying parts, the packaging (1) enables the transport and storage of parts, (2) protects both the parts and the environment and (3) enables the identification of parts [3,4]. However, each part has its individual characteristics (e.g. geometry, weight) and requires suitable packaging. Thus, the effort and complexity for logistics and packaging planning has increased dramatically.

In contrast, within the last years, machine learning (ML) has been adapted successfully across various industries. ML algorithms aim to optimize the performance criterion which evaluates the efficiency of fulfilling a given task by learning from (historical) data [5]. The field of ML can be separated into supervised and unsupervised ML. Unsupervised ML tries to discover unknown patterns (e.g. clustering), while supervised ML requires a set of labels to classify or regress the labels using algorithms [6].

Nevertheless, it is far from trivial to formulate, develop and implement a ML model. This requires both business and data understanding, as well as the right algorithms and concepts. Also, for production planning, a variety of applications and case studies exists [7,8]. However, none of the approaches focuses on the packaging planning process.

This paper seeks to propose an approach to automate packaging planning by formulating a packaging planning problem using supervised ML. It also contributes to the literature by:

- Identifying and developing relevant features both for part and packaging characteristics using the literature.
- Translating underlying decisions into separate ML models: packaging classification and fill rate regression.
- Evaluating the feasibility of the approach using real-world data of the automotive industry.

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The remainder of this paper is organised as follows. Sec. 2 briefly summarises the packaging planning theory. Then, the approach is presented in Sec. 3 and applied within a case study in Sec. 4. Sec. 5 discusses the advantages and limitations. Finally, Sec. 6 concludes this paper and presents an outlook for future work.

2. Packaging planning theory

This section presents a short overview of the current practice of packaging planning. This includes related definitions and packaging concepts, the packaging planning process, and the packaging decision-making.

2.1. Definitions and concepts

The term packaging is frequently used in different applications and scenarios, and consequently there are various definitions and perspectives. This issue has been identified and addressed by the DIN 55405 (2014). We briefly summarise the definitions as follows [9]:

- **Packaging goods**: the parts which are packed
- **Packaging**: the container which holds the packaging goods
- **Package**: the packaging including the packaging goods
- **Packaging aids**: protective layers inside the packaging

Packaging is separated into primary packaging (e.g. small load carrier) and secondary packaging (e.g. load unit for transport). According to Rosenthal (2016), the main packaging characteristics are size (e.g. small load carriers), type (e.g. standard or special packaging) and material (e.g. plastic or metal) [10]. Consequently, the set of possible packaging designs is large. In this paper, we focus on primary packaging.

2.2. Packaging planning process

The packaging planning process aims to select a packaging and to determine the fill rate of parts. The current practice presents various packaging planning processes with individual activities. Existing packaging planning processes share the main activities of characterizing the parts, comparing and evaluating existing packaging concepts, and selecting the most suitable packaging. Only in case of special requirements (e.g. oversized parts), will a special packaging type be developed. When packaging with its characteristics (e.g. size) is defined, the fill rate of parts per packaging can be calculated. The whole packaging planning process is repeated for each individual part and the results are documented in related information systems. During the planning progress, the rough planning result is transferred to a detailed planning result. We summarize the process in Fig. 1.

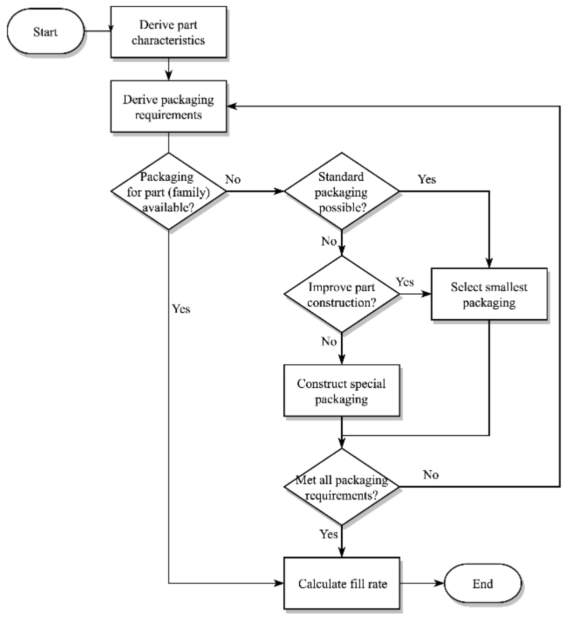

Fig. 1. Packaging planning reference process based on [10, 11, 12].

2.3. Packaging decision making

During this process, two main decision points can be identified: (1) select a certain packaging and (2) calculate the fill rate. According to Boeckle [13] and Schulz [14], the part (e.g. size, weight) is the main driver for the packaging decision [13, 14]. Other factors include the logistics functions, the suppliers and the legal conditions [13,14,15].

Based on the packaging decision, the fill rate of parts can be calculated. In operations research, the container loading problem (CLP) has been formulated. CLP aims to maximize the number of parts with the geometric constraints that parts lie entirely inside the packaging bin and they do not overlap [16]. However, it has to be stated that more than the geometric characteristics have to be considered [16, 17]. Furthermore, with very few exceptions, publications in the area of CLP deal with small rectangular items [16].

Thus, in the automotive industry, both physical and virtual simulation techniques are applied. Physical simulation requires physical prototypes of the parts and is cost-intensive [18]. Virtual simulation uses existing computer-aided design (CAD) files of parts and determines the fill rate [10,11,18]. To do so, a detailed CAD file is required, and the experience of packaging planners is required to select the packaging.

2.4. Interim conclusion

We conclude that the packaging planning process is a standardized process to select the packaging and calculate the fill rate. The process is repeated for each part. Further on, the decision-making requires additional information (e.g. weight, quality requirements) besides the mathematical optimization of the geometric objective function. It can be stated that the process can be supported using software but expert knowledge is still required.

3. Approach

In the following section, we formulate the packaging planning process and the decision-making within the process using supervised ML. Our approach and the structure of this section are based on the well-known cross-industry standard process for data mining (CRISP-DM) framework [19].

3.1. Data understanding

The decision-making of the packaging and the fill rate is significantly influenced by the part characteristics (cf. Sec. 2.3). To apply ML, we need to understand and formulate the characteristics as features for the ML algorithm. Thus, we reviewed existing literature of packaging planning with focus on part characteristics. Other factors, e.g. supplier, are not in the scope. The findings are used to develop the part and packaging model shown in Fig. 2.

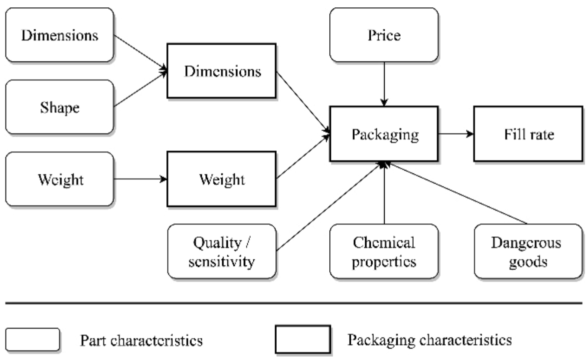

Fig. 2. Part and packaging relation model based on [12, 14, 20-23].

We translated the findings into a set of 11 part features. Additionally, we calculated the volume, three shape features and the bounding box density (cf. Table 1).

Table 1. Prepared feature set of part characteristics.

Category	Feature	Description
Dimensions	Length	Length of the bounding box
	Width	Width of the bounding box
	Height	Height of the bounding box
	Volume	Bounding box volume
Shape	Length/Width	Part shape
	Height/Length	Part shape
	Height/Width	Part shape
Weight	Weight	Weight of the product
	Weight/Volume	Bounding box density
Quality / sensitivity	Quality index	Quality requirements indicator
	Electrostatic	Electrostatic protection
Price	Part price	Part price
Dangerous goods	Dangerous goods	Dangerous goods indicator

3.2. Data preparation

The step of data preparation aims to prepare the existing data into the predefined schema for ML. For our given problem, we decide to use supervised ML because we want to train the ML model based on historical packaging assignments of planners. To apply supervised ML, we need to prepare the input data into a set of features. In contrast, the label represents the outcome of the model.

Therefore, we use the prepared feature set of part characteristics and merge the historical packaging planning results. We use the packaging and the fill rate as labels. This is required to enable the algorithm to learn from the knowledge of packaging planners. To complete the step, the master data of the packaging are extended (e.g. size).

Afterwards, invalid data has to be cleaned (e.g. drop empty rows). Finally, we created a set of 11 features, two labels and additional packaging information.

3.3. Modelling

We present an approach to formulate an ML model based on the labelled feature set. Based on the understanding of the packaging planning process and the underlying decision making, we split the model into two sub-models:

- **Packaging classification model:** Which packaging is suitable based on the part characteristics?
- **Fill rate regression model:** What is the expected fill rate of parts for the selected packaging?

Based on the part and packaging relation model, we formulated the input features for both tasks (cf. Sec 3.2). Firstly, the packaging classification model uses the 11 features and the packaging label for training. Thus, it can classify an unknown packaging (e.g. for future planning activities). Secondly, the fill rate regression model uses the 11 features and the fill rate label. However, as the fill rate mainly depends on the size of the packaging itself, the result of the classification (the packaging) is used as input for the regression model. The proposed design of the ML model is shown in Fig. 3.

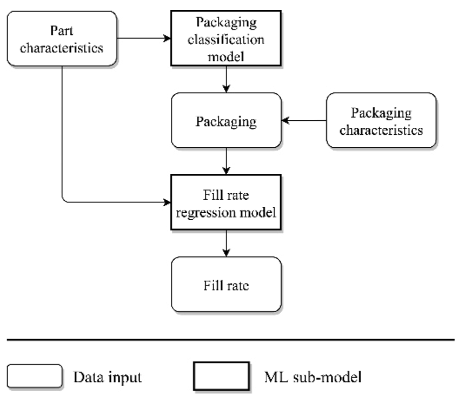

Fig. 3. Design of the ML model.

In addition to the design of the model, both ML sub-models require the selection of an ML algorithm and the related hyper parameters. Subsequently, we need to select an algorithm for the classification model (e.g. decision tree, support vector machine) and the regression model (e.g. linear regression). In theory, there are plenty of different algorithms with a variety of hyper parameters that can be combined with boosting or ensemble techniques. In industry, the random forest (RF) algorithm is applied widely due to its robustness and ease-of-application [24]. For now, we decided to use the RF both for the classification (RF classifier) and the regression (RF regressor). To select the right parameters, we applied a grid search of the (1) number of trees in the forest, (2) the maximum depth of each tree, (3) the maximum set of features, (4) bootstrapping and (5) the internal quality measurement and split criterion. For the regression, we applied a one hot encoder for the packaging categories to translate the categorical feature into separate features.

4. Case study

Within this section, we outline the application and evaluation of the approach within a case study. The case study has been conducted at an original equipment manufacturer (OEM) in the automotive industry.

Before working on the ML model, we conducted four workshops with experts to understand the packaging planning process, the relevant criteria for decision-making and the historical data. The experts broadly agreed on the process found in the literature, and additionally, that decision-making is mostly based on historical packaging. Within this stage, we analyzed, cleaned (e.g. part weight of 0.0) and prepared the data. In total, we selected a random set of 2,500 parts with packaging assignments. Thus, no conclusion of the overall distribution about parts and packaging can be made.

To assess the quality of the ML model, we separate 500 parts for testing purposes. The remaining 2,000 parts are split into a training and validation set, and are evaluated using cross validation (3-fold cross validation). Next, we present the results of the classification model (cf. Sec. 4.1) and the regression model for the fill rate (cf. Sec. 4.2).

4.1. Packaging classification model

The packaging classification model aims to classify a packaging based on the features of each part (cf. Sec. 3.3).

During the interviews and the data exploration, we identified 293 different packaging variants for the 2,500 parts. Only 9.3% is standardized packaging (e.g. small load carrier), but the standardized packaging covers 71% of all parts. Due to the high variance of existing packaging, we categorized the packaging into 9 categories for this case study (cf. Table 2).

Table 2. Packaging categories used in the case study.

Category	Size	Dimensions
Small load carrier (SLC)	Small	<= 400mm x 300m
	Medium	<= 600mm x 400mm
	Large	> 600mm x 400mm
Large load carrier (LLC)	Normal	<= 1200mm x 800mm
	Extra large	> 1200mm x 800mm
Heavy Load	-	-
Special	Small	<= 400mm x 300m
	Medium	<= 600mm x 400mm
	Large	> 600mm x 400mm

Further on, a quality index is not available in the data. However, the experts mentioned that the part price can be used to reflect the quality requirements: the more expensive a part, the higher the probability that there is a higher quality requirement. Thus, we used the part price of the product as a quality indicator. After the grid optimization, the average accuracy of the packaging classification model on the test data (n = 500) is 84.4%. The result of the classification model is displayed in the confusion matrix in Fig 4 which outlines three findings. Firstly, the invalid classifications are mostly related to the same packaging categories (e.g. SLC, special packaging) with different sizes (e.g. small, medium, large). Secondly, the heavy load packaging was classified with a high accuracy. The ML model learned the relation between volume and packaging weight. Thirdly, the overall distribution between standardized packaging and special packaging has been learned very well.

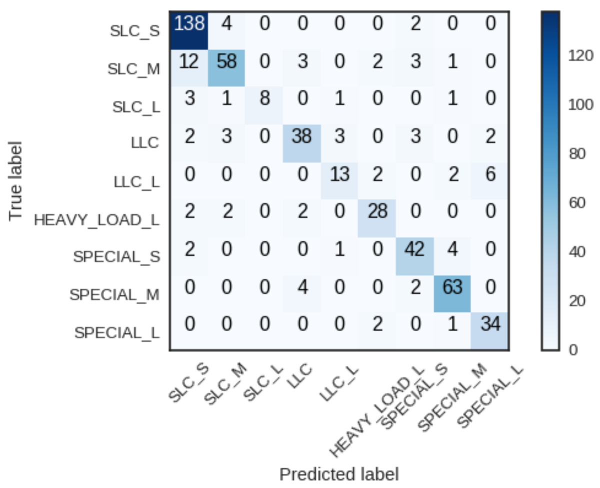

Fig. 4. Confusion matrix of the classification model on the test data.

Finally, we evaluate the importance of the individual features. The feature importance ranking of the classification model is shown in Fig. 5. The most important feature of the trained model is the part price which reflects the quality requirements. The second group covers volume, length and weight of the part. Thus, we can conclude that the ML model successfully learned a valid set of important features. Also, the

ML model strengthens the understanding in the literature, namely that the problem cannot be reduced to the mathematical optimization of the volume of the part and packaging.

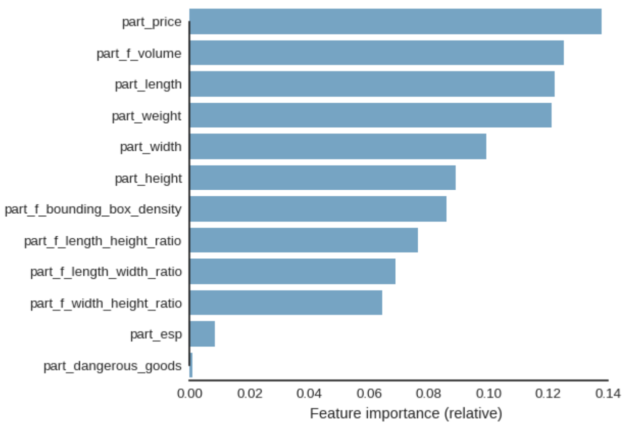

Fig. 5. Feature importance of the packaging classification model.

4.2. Fill rate regression model

The objective of the fill rate regression model is to calculate the fill rate based on the part characteristics and the packaging. As the fill rate depends on the packaging, e.g. dimensions of the packaging (cf. Sec. 3.3), we provide the correct packaging for the evaluation. To do so, we compared three different scenarios (cf. Table 3).

Table 3. Feature set for the regression model.

Scenario	Total number of features	Root squared mean error (RSME)
1. Packaging volume	12	529
2. Packaging length, width and height	14	524
3. Packaging length, width, height and category	14 + 9 (hot encoded)	542

The regression model performs the best in the second scenario with the packaging length, width and height (root squared mean error (RSME) of 583). A possible reason might be that the variety of input features in scenario 3 cannot be learned in a sufficient manner when using the training set size. This can be underlined by the fact, that the distribution of the fill rate is very large (median 64, while the maximum is 25,000).

To further interpret the range of validity, we compare the actual fill rate (based on packaging planners) and the predicted fill rate (cf. Fig. 6). This allows us two findings: Firstly, the lower the fill rate, the lower the absolute error. With an increasing fill rate, also the deviation between the actual fill rate and predicted fill rate increases too. Secondly, there are still outliers with invalid predictions in both directions (prediction is higher than the actual fill rate, and vice versa). To summarize, the regression model is less robust than the classification model.

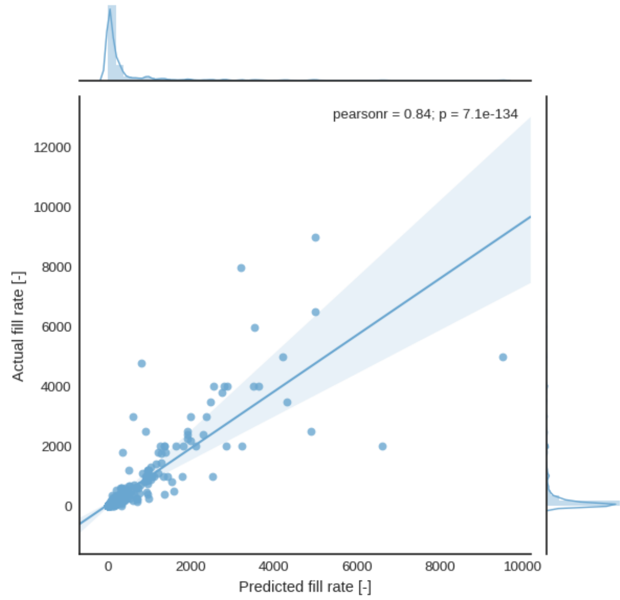

Fig. 6. Actual vs. predicted fill rate of regression model on the test data.

5. Discussion

In the following section, we discuss the strengths and weaknesses of the model both from the technical machine learning perspective and from the packaging planning perspective.

We can identify three strengths of the ML model. Firstly, the approach can automate activities during the rough planning stages. However, the detailed planning cannot be replaced. In addition to the packaging planning process, experts highlighted the chance to use the approach for other planning cases (e.g. during the change management process). Secondly, the approach is capable to learn and predict using the bounding box of the part, and does not require a precise CAD file or other information (e.g. CLP). Thirdly, as the process can be automated, the bottlenecks of manual evaluation can be eliminated. Thus, the process can be reengineered so that, for example, every change of the product structure and underlying parts, are evaluated instantly. Consequently, the risk of outdated planning results decreases.

Nevertheless, the approach shows limitations. Firstly, currently only part characteristics are considered. Existing supplier information and special requirements are neglected. Secondly, with the dependency between the two sub-models, the result of the packaging classification has a significant role on the fill rate. Currently, there is no validation of packaging result yet. Thirdly, the performance of the regression model varies. Especially when the fill rate is high, the error rate increases. Thus, the packaging planning experts have to evaluate the fill rate after the prediction, in particular for high fill rates. Fourthly, if the packaging process changes, the ML model has to be trained with updated data.

6. Conclusion and outlook

In this paper, we provide an approach to automate packaging planning. Therefore, we reviewed the existing packaging planning theory to understand the process and the underlying information required for decision making. Our proposed model combines a classification and regression model to determine the packaging and the fill rate. To do so, we reviewed the literature to provide and construct relevant features. We successfully evaluated the approach with real-world data. While the classification model performs with an overall accuracy of 84.4%, the regression model has an overall RSME of 524.

Our research provides an initial approach and future research is required. Firstly, additional features, such as including the supplier or logistics process, have to be integrated. Secondly, different algorithms other than the RF and sampling techniques have to be evaluated. Thirdly, we only focused on the ML model. In the future, a combination of our approach with existing techniques such as CLP or simulation have to be integrated and evaluated.

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