Generation of predictive configurations for production planning

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Abstract

We provide a production planning framework for variant rich customized products (such as automobiles, computers), by calculating entirely constructible configuration sets for future customer demands in a novel manner. Most of the established approaches analyse configurations out of historical order banks for estimating the appropriate set of future demands. In the current environment of rapidly changing designs and highly customized products, historical demands cannot easily be extrapolated to capture future market demand and may not even retain future product document restrictions. In this paper, our aim is to generate configuration sets such that (1) they represent customers buying behaviour (derived from configurations produced in the past and sales planning at aggregate level) (2) they are consistent with the product documentation. Configuration generation is formulated as guided search procedures which utilize the Satisfiability framework. Selection of configuration sets for planning is done by a large scale optimization model. We use column generation and other techniques to solve this large scale optimization model.

1 Introduction

In the customer focused order-fulfilment strategies such as Built-To-Order and Assemble-To-Order, mid to long term (6 months - 3 years) planning activities in production and logistics are supported with aggregate level of forecast from sales and marketing. Through sales forecast it is possible to get estimate of total volume for entire product line. In addition to this we get demand estimates for key attributes of the product [Srinivasan and Swaminathan, 1997]. For example, in case of automotive, attributes can be engine type, body style, air condition, and so forth. During the estimation demand characteristics of future customers, the dependencies between attributes and components provided by designers or customers may not have been considered [Olsen and Saetre, 1997]. Component dependencies by design can be found in product documentation and these will be reflected in the Bill-Of-Material system [Kaiser and Küchlin, 2001]. Dependencies from customer point of view may not be straightforward but these can be extracted from variants produced in the past. The important thing to note is that these dependencies change with continuous changes in the design (introduction of new feature, parts or components) and because of changing market, legislation and economic conditions.

Starting from sales planning inputs, the primary task of the production program planning activities is to know which parts and components need to be available at what time and in what amount, in order to produce the planned product units efficiently? This has to be done even when the company has not received any real customer orders.

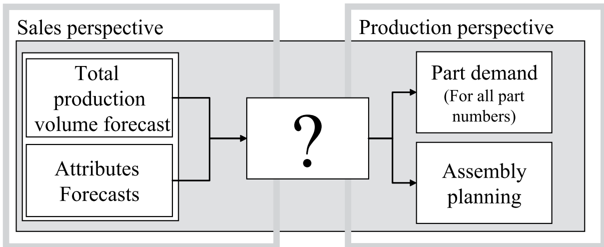

Figure 1: Need of methods for consistent transformation of information between sales and production planning

The derivation of part demand or workload at any assembly station may not be straightforward from the sales planning inputs. For example, one might get information from sales forecast that attribute parking assistance system and automatic lane departure system will be used in 50% and 40% of the cars respectively. This information may not be enough for calculation of the demand for a specific steering wheel. Selection of steering wheel may depend on if both attribute are selected together or individually. Assume that there is one steering wheel that will be used if both the above attributes are selected in the same configuration. From the sales planning as an independent forecast for attributes, the demand of this specific steering wheel may lie between 0% to 40%. Consequently, without additional assumptions, we cannot determine demands of all parts required for order fulfilment.

As shown in Figure 1 there is a need to build a medium which can transfer consistent information across various departments involved in the customer order processing to enable better program planning. One way to achieve this is by planning with fully specified customer configurations. As cus-

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tomer configurations are not available for mid to long term planning, most manufacturers use variants produced in the past to estimate the appropriate set of future demands. Due to the introduction of engineering changes and shifts in market expectation, variants produced in the past become statistically less significant to capture future customers demand characteristics. Also, engineering changes in the product make some configurations obsolete and cannot be re-produced exactly. Thus, simple extrapolation of historical demands to capture future demands characteristics may cause information distortion in the early stage of the production planning.

Our main aim in this paper is to provide an automated framework to supplement the historical configurations set in such a way so that the underlying configurations set can be more relevant to capture future demand characteristics. Once the desired configurations are generated we will select a target number of configurations to propose a production plan. The main challenge in defining future configurations of the product is that the solution space is huge (an enormous number of configurations are technically feasible). We will propose an integrated configurations generation and selection approach that will calculate only a few (as compared to the full solution space) configurations to complete the set of base configurations set for planning. In our work, we will argue that by considering sales estimates, engineering dependencies, production restriction and customer buying behaviour during configuration generation, the number of valid configurations can reduce significantly.

The rest of the paper is structured in following way: We will present a review of literature in Section 2 to motivate the need and use of product configurations in various planning activities across the organization. In Section 3 we will present formal problem descriptions with input data and their characteristics. In Section 4 we will discuss a heuristic for generating configurations directly from product documentation (i.e. the engineering document). The mathematical model building and solution methodology will be discussed in Section 5. Section 6 will describe initial computational experiments on industry size examples.

2 Literature Review

To manage product variety in mass customization techniques such as product differentiation and postponement are well studied approaches, offering flexible manufacturing for high variety product [Harrison *et al.*, 2004]. The basic idea is to design and manufacture the product in such a way so that variety can be introduced at the last stage of the production. The partially assembled standard products are produced till the point no differentiation is required. Final assembly is done based on customer configuration by adding specific product features. The work in progress (WIP) inventories are maintained to offer customer attractive lead time with required variety [Swaminathan and Tayur, 1998]. For a manufacturer who follows lean manufacturing or Just-in-Time (JIT) approaches, any kind of inventory either of individual parts or components or as a WIP is highly undesirable. As product technology and design changes continuously with respect to time, it might be difficult and costly to introduce variety at the end of the production.

Product configuration system has been a key enabler of mass customization by capturing the customer demand in most consistent way. Although, initial focus of configuration system was to provide significant reduction in customer order response time by enabling customer-product interface [Salvador and Forza, 2004]. As the customer order fulfilment process varies based on the product configurations, there is a need to utilize configurations technique in various planning and process design [Aldanondo and Vareilles, 2008]. Product configurations act as a medium to translate information between customer, sales, manufacturing and other supply chain players. For example maintaining consistent bill-of-material, or finding range of product with certain characteristics [Astesana *et al.*, 2010].

By utilizing product configurations in the early stage of planning hybrid order fulfillment strategies such as Virtual-Build-to-Order (VBTO) system can be created [Brabazon and MacCarthy, 2004]. The fundamental capability for a VBTO system is the ability to search the order fulfilment pipeline on behalf of the customer. These virtual (not created by end customer) configurations can be reconfigured with respect to actual customer configuration with minimum difference from customer preference. At the end, efficiency of systems such as VBTO mainly depends upon the correlation between the planned and real orders. If we are able to simulate configurations according to customers need, then we will get high level of satisfaction and smooth processes in customer order fulfilment.

It has been agreed in literature that efficient configuration system which co-ordinates and covers information from all available sources (e.g. sales, marketing, assembly, logistics, design, and customers) leads to significant gain in customer order fulfilment process [Trentin *et al.*, 2011]. However, most of the efforts in the past are devoted to use product configurations for reducing the lead time and maintaining customers buying behaviour. The generation of configurations has received considerably less attention. Hayler [Hayler, 1999] developed a sequential procedure for generating product configuration from rule based system. Products attribute classes (levels) are created and each virtual configuration selects attribute based on its forecast rates. The approach can be compared as a product configurator system. A product configurator is created form rule based design document. Selection of attribute from each step of configuration is supported by attributes selection rate, historical orders, association rules and experts experience. These permutation procedures often hamper the result quality and require manual intervention to match desired output. Stautner [Stautner, 2001] discussed configuration generation problem by identifying configurations form recent history through cluster analysis. Historical orders are modified in such a way so that it can fit in future planning requirements. The method involves manual procedure to create final configurations. In case of new product such as electric or hybrid cars which open new market segments for manufacturer and does not have customer history. The current available methods find difficulties in generating future product configuration which matches given input requirements from design, sales and production.

3 The planning problem

The major aim of this paper is the development of an automated procedure that supports production planning, part demand calculation and capacity management for the short-term as well as for a medium-term planning horizon up to two years from the start of production.

As discussed in the introduction, in a customer oriented production environment, planning may be done at an aggregate level such as modules or attributes. One problem in this method is that engineering constraints between attributes may not be taken into consideration. For example, selection of front bumper in the car may depend on body style type, headlamp, and optional feature and sensor mounted on the bumper. Drawing estimates of future bumper demand without consideration of such dependencies may give unreliable estimates.

This problem can be avoided if planning is based on complete products. However, drawing a small number of representative configurations from an enormously large set of possible configurations is a daunting task. One way to attack this problem is by utilizing customers demand in the past. Customer order history is an important input for capturing customer buying behaviour, required for future planning activities. In Figure 2 the planning tasks related to logistics and assembly are derived through extrapolation of configurations produced in the past. Once the fully specified configurations are known, assembly related processes can be optimized for the selected production program. From the logistics point of view, the most important outcome is the calculation of part demand, which is straightforward, once the product configurations are known. This method works only if the underlying configurations are able to fit with future demand characteristics.

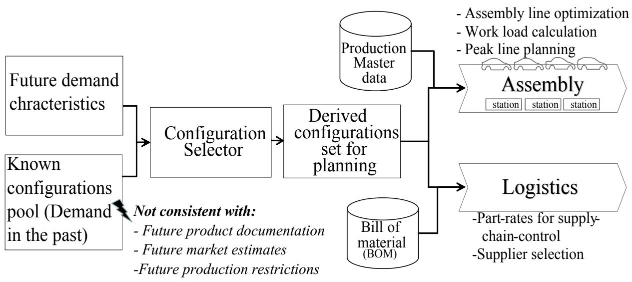

Figure 2: Current Planning: Generation of future customer configuration set through extrapolation of customer demand in past

Variant rich products (e.g automobiles) often receive highly individualized demand and undergo various engineering changes. The regular introduction of new features and short product life cycle make the task of capturing future demand characteristics out of production history a challenging one. In order to facilitate orders/configurations based planning we need to supplement the reference pool of historical production with some customer focused future configurations. To attain planning results of high quality, all the relevant information sources have to be considered, namely the valid list of the product features/attributes, rules for the correct combinations of the attributes, sample of variants produced in the past to capture customers' behaviour, future sales estimates to capture market changes, capacity restrictions and production plans that fix the total number of planned vehicles.

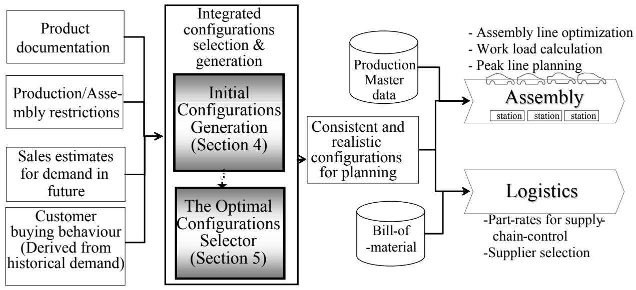

Figure 3: Proposed Framework: Calculation of consistent configuration sets as a foundation for efficient production planning

We propose a different planning set up to generate and select reference configurations for production planning. The main difference between the current (Figure 2) and the proposed methodology (Figure 3) is that current planning is restricted to create production programmes out of known configurations only, while in the proposed approach, we will generate product configurations as and when required, to capture future demand characteristics. This will result in a better match with market estimates and will be consistent with the engineering limitations. Configurations produced in the past can only appear in future planning if they are feasible with latest product documentation. Attributes dependencies in product documentation are maintained formally to support various engineering planning and can be used to automatically check the configurations feasibility. However, historical orders even after failing overall feasibility may contains some important relations among attributes reflecting customer buying habits. For this purpose we will use a data mining approach to identify interesting attribute combinations from the customer point of view, using historical sales data.

The goal of the paper is as follows. Given 1) product documentation 2) market estimates 3) customer behaviour and 4) assembly restrictions, the task is to generate and select valid configurations, which will lead to a production plan. The set of product configurations that are generated is utilized in planning the whole production process (full bill of material, i.e. a car in detail). The optimal configuration selector model (proposed in section 5.2) does not explicitly generate all (or a large number) configurations while it generates a relativity small number of configurations to sequentially build up the desired production plan. The initial configuration generation module (proposed in section 4) is used to provide a starting solution to the optimization model. Although, the optimization based module is able to generate and select configurations, an initial solution from heuristics will give a good starting point. Before describing the development of the solution methodology we list out important data sources and its characteristics.

3.1 Product Documentation

Product documentation is the most important input data for proposed framework and supplies two main sources of data:

1. List of available attributes of the product. For autmobiles, attributes can be power train, Hi-Fi equipment, parking assistant package, etc. Attributes also include labels or user manuals, which may not be crucial for planning but which are required during the creation of an automated framework for production planning such as automated computation of detailed part demand.

2. Rule for feasible combinations of attributes in the configuration. Product configuration can be defined as a list of selected attributes from given set of available attributes. Customer configurations can be produced by combining different attributes all together which are permitted by product documentation. It is important that while combining different attributes, we must fulfil the interdependencies between attributes, so that the feasible product configuration can be generated [Sinz *et al.*, 2003]. For instance, in the USA, some engines required special transmission types, this condition must hold during creating configuration with that particular engine.

Interdependencies among attributes are documented and maintained in the product technical document by a rule system. These rules are basically *propositional Boolean formulas* imposed against each attribute. These formulas are limited to logical operations ∨(OR), ∧(AND), ¬(NOT). Selection of attributes in a configuration is done through evaluating the respective Boolean formula. Table 1 shows an example of such documentation.

Attribute	Name	Rule	Description
1	Automatic climate control	$(2)\wedge(3\vee 4)$	attribute 1 only when attribute 2 is present and either attribute 3 or 4 is present
2	Air condition	TRUE	must be present in every variants
3	Comfort package	$\neg(4)$	attribute 4 should not be present
4	Performance package	$\neg(3)$	attribute 3 should not be present

Table 1: Rule based product document example

The customer order processing is controlled by evaluating the rule's formulae under the variable assignment induced by the customer order and executing suitable action based on whether the formula evaluates to *TRUE* or *FALSE*. [Sinz *et al.*, 2003] have presented a detailed description of one such product documentation; we will use a similar kind of product documentation in this paper. Product documentation describe product in flat structure over attributes (Boolean variables) and capture dependencies through propositional Boolean formulas.

3.2 Future market estimates

Sales and marketing departments continuously study the market behaviour and product positioning. This study enables them to give some demand estimates on key attributes of future products, which any way need to be calculated accurately for various marketing and vendor negotiation purposes. We assume that this information is available to us as an input to capture future market behaviour. We aim to generate configurations sets which represent the given estimates of attributes in the best possible way.

3.3 Assembly/ Production estimates

Product assembly is an important step in customer order fulfilment. Assembly is often restricted to be done on a number of predefined stations with certain work functions at each station. There are some limitations on the capacity and workload at each station. Due to these restrictions, order fulfilment can only be achieved for configurations that satisfy these restrictions. From the aggregate production plan, the total number of planned vehicles can be estimated and the final production plan is generated with the estimated number.

3.4 Customer behaviour

Customer buying trends are extracted by analyzing the product variants produced in the past. We first check the feasibility of variants that are already produced with respect to new product documentation rules. All feasible configurations will be candidates in the solution space. Nevertheless, configurations which are not feasible due to some engineering changes are analyzed on the level of attributes relations. We use the association rule mining technique to identify customer buying behaviour. All relations derived from the data mining approach are again verified with latest product documentation for its feasibility. Customer demand characteristics are calculated as joint or conditional selection rate of attributes, and these are controlled during the development of final production plan. The computation of customer behaviour trends from historical demand is not discussed in this paper and we assume that this information is already available as an input.

4 Configuration Generation

Configuration which satisfies rules from product documentation can be represented as Boolean vector satisfying a constraint system. We want some number of configurations which satisfy product's technical rules and are consistent with customers demand estimates in some way. e.g. we want N configurations which reflects customer demand estimates as best as possible.

As a first step we would like to generate valid configurations which can be use latter for some optimization problem. Generation of configuration involves finding TRUE or FALSE assignment for each attribute. In this section we will propose a guided search procedure which randomly generate configuration with some attribute selected in guided way and others then supplemented as per attribute selection rates form sales. Finally we solve a satisfiability problem with partial assignment of attributes. The satisfiability problem will result selection of generated configuration with some probability.

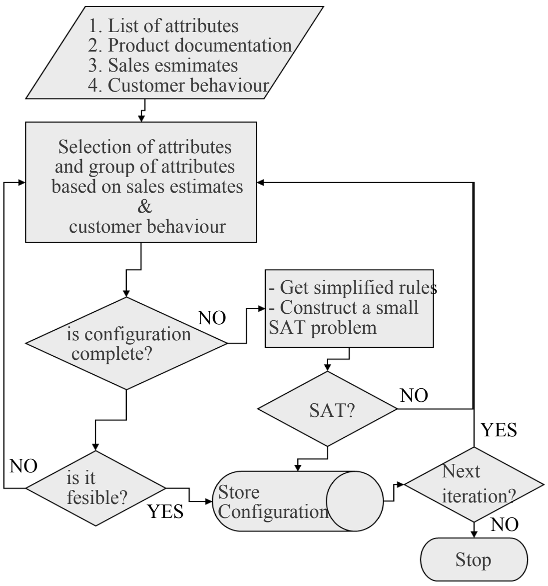

Figure 4: Steps for building up a configurations base

Figure 4 shows a flow diagram of building configurations sequentially. Selection of an attribute in the configuration may exhibit certain characteristics such as mutually exclusivity. For mutually exclusive attributes selection should be done through a multinomial choice. In general, the numbers of possible configurations in mass customization are huge. This motivates us to build a random search procedure to get a representative set of constructible configurations. In principle, first we arrange attributes (or group of attributes) in the decreasing order of their dependency index. The dependency index can be calculated by analysing the selection rule associated with the attribute. The attributes/group which has highest dependency will be selected first and will imply selection (not selection) of other dependent attributes. We will continue to do this process until all attributes assignment is not known. At the end we will check if generated configuration is feasible through evaluating rules with known configuration vector.

As soon as any attribute is selected in the configuration, we check the respective propositional Boolean formula (from product documentation) and select unassigned attributes from Boolean formula such that formula evaluates to *True*. This will keep some level of consistency during the configuration building process. We iterate through this process until a conflict or a steady state where no assignment is possible is reached. If the configuration finds assignment for all attributes, we finally check the overall feasibility of the configuration by evaluation all rules once again. The configuration will be selected with some probability of having a feasible configuration.

If the initial configuration is not able to extract all attributes assignment, we simplify all propositional Boolean formulas with known partial attribute settings and solve a satisfiability problem. Due to assignment of large number of attributes, the number of clauses and literals in satisfiability problems are minimized significantly. If the problem is not satisfiable we reject the configuration and start building a fresh configuration. The configuration generation runs until maximum number of iterations is reached or generated set of configurations is within specified range of attributes estimates.

The randomness in the configuration generation procedure will help in creating diversified configurations that will capture the customer behaviour of individualization in variant rich product. On the drawback side, there will not be any guarantee that the characteristics of generated configurations will improve with number of iterations. This lead us to think about a framework which selects generated configuration such that the target configurations set characteristics can be match as best as possible. At same time, the framework should also be able to generate missing configurations so that characteristics of the final set of configurations can be close to the target one. In the next section we discuss an integrated configurations generation and selection procedure.

5 Integrated configurations generation and selection

Heuristic approach discussed in section 4 does not provide answers for questions like 1) How many constructible configurations will be generated from the configuration generation heuristic? 2) How good the deviation between target and generated set of configurations will be? Although, approach can give a reasonable set of constructible configurations in short period of time this can be used as a starting solution for further optimization process. Based on the quality of starting solution the optimization model can generate missing configurations to complement reference configurations set. To facilitate optimization based approach for generation and selection of configurations we will first transform Boolean propositions from product documentation to a constraints system.

5.1 Transformation of logical rules to linear inequalities

Linear inequalities over Boolean variables are a widely used modelling technique. The main task during transformation of an attribute selection rule into a system of linear constraints is to maintain the logical equivalence of the transformed expressions. The resulting system of constraints must have the same truth table as the original statement. For every attribute we will introduce an the binary decision variable, is denoted by y_i. The connection of these variables to the propositions is defined by the following relations:

$$y_i = \begin{cases} 1 & \text{iff attribute i is TRUE} \\ 0 & \text{otherwise} \end{cases} \qquad (1)$$

Imposition of logical conditions linking the different actions in a model is achieved by expressing these conditions in the form of linear constraints connecting the associated decision variables. Some general transformations are presented in Table 2.

Our approach, in principle, involves identification of precise compound attribute rules of the problem and then processing it with developed equations. Before transformation,

Rule	Description	Constraints
$i \to j$	i implies j	$y_i - y_j \leq 0$
$i \leftrightarrow j$	i and j must come together	$y_i - y_j = 0$
$i \to (j \vee ... \vee n)$	if i is true then at least one attributes from j to n, must be true	$y_i - (y_j + ... + y_n) \leq 0$
$i \to (j \wedge ... \wedge n)$	if i is true then all attributes from j to n (say cardinality p) must be true	$(p)y_i - (y_j + ... + y_n) \leq 0$

Table 2: An excerpt of attribute selection rule transformation table

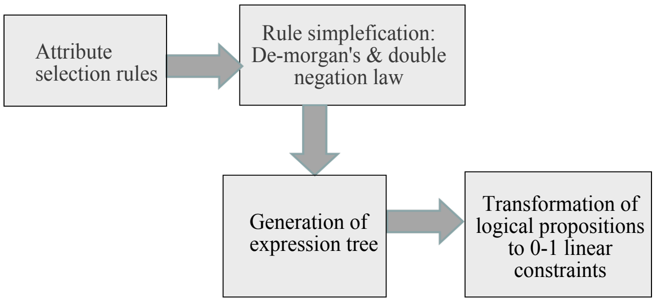

Figure 5: Block diagram for logical rules to inequalities transformation

we simplify Boolean expression through simple Boolean algebra, DeMorgan's Law. The logical rule is represented by a tree graph where attributes are associated with their common operator node. We traverse through the tree and prune the tree in such a way so that standard transformation equation (e.g. Table 2) can be applied. This pruning involves introduction of new auxiliary variables which helps in transformation process.

$$B[y] \leq b \tag{2}$$

As a result of transformation linear constraints sets are created as specified in Eq.2, where B is the constraint matrix contains all constrains originating from product documentation. All product configurations must satisfy Eq.2 in order to be feasible for production and can be a candidate for production plan.

5.2 The optimal configuration selection model

To create production plan based on detailed product configuration we need to list out some number of configurations (say K) in such a way that estimated characteristics of configurations can be match as best as possible. For example, let us assume that an automotive contains 1000 of attributes and we want to select 3000 configurations generated from available attributes. Our task will be to answer, does attribute i belong to the configuration j finally selected? This example will leads to s3 millions (a large number) of 0-1 type decision variables. We do know something about the portion of attribute (i's) in the final configurations (demand estimates from sales, customer behaviour etc.). So the objective function will be to minimize the positive deviation between selected and estimated values. General structure of above problem is defined over combinatorial optimization, with a very large number of variables that is quite difficult to solve.

Another possibility of formulation for given problem is to list all possible configurations with the given number of attributes. This runs into the hundreds of millions! Much larger than the previous formulation. We can define 0-1 variable over each configuration on whether it is selected or not. These feasible configurations has to be implicitly represented, i.e. not possible to list all of them explicitly. Surprisingly, this way of thinking is still useful. In this section we will develop an optimization model based on Lagrangian approach using column generation.

The Master Problem:
Let: i be i^{th} attribute, $i \subseteq \{1...I\}$, where I is the number of attributes
j be j^{th} configuration, $j \subseteq \{1...J\}$, where J is the number of unique configurations

Data
K = the number of configurations planned
D_i= Demand estimate for attribute i
C_i= Demand mismatch cost associated with attribute i
λ= Lagrange multiplier

$$A_{i,j} = \begin{cases} 1 & \text{if } i^{th} \text{ attribute is present in } j^{th} \text{ configuration} \\ 0 & \text{otherwise} \end{cases}$$

Decision variables:

$$X_j = \begin{cases} 1 & \text{if configuration } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

Z_i= Deviation between given demand estimate and calculated frequency for attribute i

Objective Function:

$$\textbf{P = Minimize} \sum_i C_i * Z_i + \lambda(\sum_j X_j - K) \tag{3}$$

Subject to

$$Z_i \geq \sum_j A_{ij} X_j - D_i \ldots \forall i \tag{4}$$

$$Z_i \geq D_i - \sum_j A_{ij} X_j \ldots \forall i \tag{5}$$

$$X_j = 0 \text{ or } 1 \tag{6}$$

The first sum of objective function in Eq. 3 tries to minimize mismatch cost of the positive deviation from desired demand estimates of the attributes. Second part of objective function ensures that selected number of configurations are closed to K, the desired number for planning. While, constraint Eq. 4 Eq. 5 ensure the feasible configuration set close to attribute demand estimates. Each attribute is associated with a demand mismatch cost. We fixed X_j to 0-1 type to support higher degree of individualization in the generated plan.

The above model is too large to solve by explicitly generating large number of configurations. A solution for such a large scale optimization can be found using column generation approach [Ben Amor and Valrio de Carvalho, 2005]. We can start with a possible set of X_j variables (may be more than K, generated from Section 4 or derived from history) Solving LP relaxation of the above problem to decide which of those X_j's are 1, and then try generate a new configuration which can improve the objective function value.

5.3 Implementation of the model

To start solving the model presented in Section 5.2 we use a fixed value of λ (this is because anyway we want approximately K configurations that are representative of the demand). Now we can solve the master problem with initial sets of X_j's. The question would be how to know if the current selection of configuration is good. For this, we will compute dual variable corresponding to constraints 4-5, with these values a sub problem is set up. The sub problem is basically a generation of new configuration for A_{ij} matrix which can be formulated as follows:

The Sub-Problem:
Data: W_i= Dual variable from LP relaxed of the optimal configuration selection model (5.2), associated with constraints 4-5 (note that for each i, one of them will be non-zero)
B= Set of constraints derived from product document (see Section 5.1)
Decision Variable

$$[y_j]_i = \begin{cases} 1 & \text{if } i^{th} \text{ attribute is present in new configuration} \\ 0 & \text{otherwise} \end{cases}$$

$[y_j]_i$= new configuration for j^{th} column of configuration matrix $A_{i,j}$

Objective:

$$\textbf{Maximize} \sum_i W_i * y_i \tag{7}$$

subject to:

$$B[y] \leq b \tag{8}$$

(i.e. y is a feasible configuration)

$$y_i = 0 \text{ or } 1 \tag{9}$$

The sub-problem is generate a possible new configuration j. If this new configuration j satisfies Eq. 10 the configuration j enter the pool.

$$\sum_i A_{ij} + \lambda - \sum_i W_i * y_i < 0 \tag{10}$$

Dual costs are recomputed by solving the master problem (Section 5.2) and the process terminates when no more configurations are found to be worth taking in. We use IBM ILOG Cplex engine to solve the sub-problem. The master and the dual problem may have to be solved multiple times before terminating criteria satisfies.

6 First evaluation results

In this section we discuss typical computation parameters and associated numbers with input data and decision variables. We tested our methods mainly on automotive data, for configuration based planning the granularity of the computation is plant/model series/body style (e.g. Bremen, C-class, Sedan). All input data and estimates are available or derived to same granularity. Total number of attributes are in the range of 500-1000. Typically selection rates of 100-200 key attributes are estimated from sales. Some attributes are related to production such as plant where production takes place, regularity laws, dependencies structure because of technical reason.

We target to generate production plan for weekly or monthly time frame and requite to simulate some thousand of configurations, typically 3-10 thousands of configurations in one computation. The generation of production plan with thousands of configuration need to be done by ensuring maximum correlations with given demand characteristics (e.g. sales estimates). The typical use of calculated configurations is to derivation of part demand or estimation of medium term workforce in assembly operations.

On an example with 130 attributes (for which attached selection rates are given), 900 total attributes and selection of about 3000 configurations, resulting problem has 10,000 variable and 15,000 constraints. The match between the target and achieved frequency of attributes in generated configuration set is defined by the ratio of target and gain frequency of attributes. If this ratio is equal to one, it is desirable.

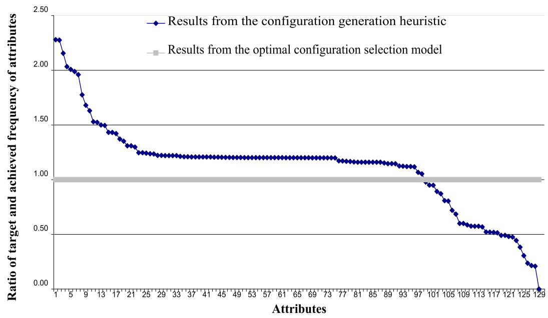

Figure 6: Attribute frequency match between target demand and gain rate in generated configuration set

Figure 6 provides comparison between results obtained after configuration generation heuristic (Section 4) and optimization based procedure (Section 5). The grey (light) line represents the best solution of the optimization model, which is very close to 1. The result from the configuration generation heuristic is plotted in a decreasing order of deviation from the target rate (in blue). We can see that some of the attributes are more than required and some less, but many are quite close to the desired target. This can perhaps be improved further in the satisfiability section of the algorithm, which allows different heuristic ways of completing orders.

In general, the heuristic provides a starting solution for our optimization model and helps in speeding up in the process of generating a configuration set for planning. The attribute selection rate obtained in generated configuration set matches reasonably with the target attribute demand.

7 Conclusion

In this paper we presented a production planning framework based on fully specified products which guarantees consistency among different planning tasks. The mathematical model that has been developed is capable of considering heterogeneous information generated by different planning departments. In this framework we are able to consider up-to-date product documentation at an early stage of program planning. The problem of find a valid set of configurations is formulated as an optimization problem by translating all logical conditions from the product document to algebraic inequalities. This transformation enables us to use the optimization framework effectively. The number of constraints generated during this transformation can be further reduced by simplifying the product rule system or through pattern identification in the product documentation.

The large variety in products implies that the construction of the set of customer-focused configurations is a large scale optimization problem. Our proposed column generation approach can be useful to get a good solution for this problem. The configuration generation heuristic is based on the guided search procedure that can be enhanced further to gain better speed and improve the result quality. Some other parameters like restrictions at the part level and assembly operation level are subjects of future research.

References

[Aldanondo and Vareilles, 2008] Michel Aldanondo and Elise Vareilles. Configuration for mass customization: how to extend product configuration towards requirements and process configuration. *Journal of Intelligent Manufacturing*, 19(5):521–535, 2008.

[Astesana *et al.*, 2010] Jean-Marc Astesana, Laurent Cosserat, and Helene Fargier. Constraint-based vehicle configuration: A case study. In *Proceedings of the 2010 22nd IEEE International Conference on Tools with Artificial Intelligence - Volume 01*, ICTAI '10, pages 68–75, Washington, DC, USA, 2010. IEEE Computer Society.

[Ben Amor and Valrio de Carvalho, 2005] Hatem Ben Amor and Jos Valrio de Carvalho. Cutting stock problems. In Guy Desaulniers, Jacques Desrosiers, and Marius M. Solomon, editors, *Column Generation*, pages 131–161. Springer US, 2005.

[Brabazon and MacCarthy, 2004] Philip G. Brabazon and Bart L. MacCarthy. Virtual-build-to-order as a mass customization order fulfilment model. *Concurrent Engineering: Research and Aplicxations*, 12(2):155–165, 2004.

[Harrison *et al.*, 2004] Terry P. Harrison, Hau L. Lee, John J. Neale, S. Venkatesh, and Jayashankar M. Swaminathan. Managing product variety through postponement: Concept and applications. In Frederick S. Hillier, editor, *The Practice of Supply Chain Management: Where Theory and Application Converge*, volume 62 of *International Series in Operations Research and Management Science*, pages 139–155. Springer US, 2004.

[Hayler, 1999] Christian Hayler. *Ein regelbasiertes System zur Generierung von Orders für Lagerfahrzeuge-Fallstudie bei einem deutschen Automobilhersteller*. PhD thesis, Universität Jena, 1999.

[Kaiser and Küchlin, 2001] A. Kaiser and W. Küchlin. Automotive product documentation. In *Proceedings of the 14th International IEA/AIE Conference, LNCS*, pages 465–475. SpringerVerlag, 2001.

[Olsen and Saetre, 1997] K. A. Olsen and P. Saetre. Managing product variability by virtual products. *International Journal of Production Research*, 35(8):2093–2108, 1997.

[Salvador and Forza, 2004] F. Salvador and C. Forza. Configuring products to address the customization-responsiveness squeeze: A survey of management issues and opportunities. *International Journal of Production Economics*, 91(3):273–291, 2004.

[Sinz *et al.*, 2003] C. Sinz, A. Kaiser, and W. Küchlin. Formal methods for the validation of automotive product configuration data. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 17(1):75–97, January 2003. Special issue on configuration.

[Srinivasan and Swaminathan, 1997] R. Srinivasan and J. M. Swaminathan. Managing configurable products in the computer industry: Planning and coordination issues. volume 22, pages 33–43. Sadhna:Academy Proceedings in Engineering Sciences, February 1997.

[Stautner, 2001] Ulrich Stautner. *Kundenorientierte Lagerfertigung im Automobilvertrieb: ergnzende Ansätze zum Supply-chain-Management*. PhD thesis, Universität Göttingen, 2001.

[Swaminathan and Tayur, 1998] Jayashankar M. Swaminathan and Sridhar R. Tayur. Managing broader product lines through delayed differentiation using vanilla boxes. *Manage. Sci.*, 44:161–172, December 1998.

[Trentin *et al.*, 2011] Alessio Trentin, Elisa Perin, and Cipriano Forza. Overcoming the customization-responsiveness squeeze by using product configurators: Beyond anecdotal evidence. *Computers in Industry*, 62(3):260–268, 2011.