Benefits of an Integrated Hierarchical Data Structure for Automotive Demand and Capacity Management

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***Abstract*— The demand and capacity management (DCM) is an essential component of the automotive supply chain management. DCM synchronizes resource requirements with capacities and restrictions of the supply chain and production system. Those requirements result from future or already realized market demands. One major challenge of the DCM is the uncertainty and volatility of the market demands. Other challenges are product variety and supply chain complexity. Here, efficient data management increases transparency and can support the DCM processes effectively. In this context, this contribution analyses the benefits of an integration of distributed product data into a hierarchical tree structure against the background of complexity reduction. The results of this study prove that a hierarchical integrated information model provides an optimized basis for a scenario-based DCM planning process. Data from a German automotive manufacturer served as basis for this evaluation.**

Keywords- product structure; automotive production; demand and capacity management; optimization; complexity.

I. INTRODUCTION

To compete in international markets, automobile manufacturers, i.e., original equipment manufacturers, OEMs, tend to offer their customers buying incentives, a huge variety of models which can be further individualized by several hundred options, i.e., colors, assistance systems, etc. Furthermore, OEMs constantly update their product range in an increasing frequency [1]. Though customers have to deal with the variety of models, they tend to expect that vehicle orders can still be customized shortly before actual production and that the produced car is rapidly delivered on the planned date [2][3].

Here, logistics plays an important role. Nowadays, suppliers do not only produce simple components, but also develop complex modules [4]. The competence of the car manufacturer has shifted to product marketing, the coordination of suppliers, assembly of supplied parts, and the distribution of the end product [5]. Therefore, the integrated management of the automotive production and supply chain is critical for the OEM. The anticipation of the future market demand, the timely derivation of resource and component requirements as well as the integrated and coordinated capacity planning are indispensable prerequisites [6]. Most critical, resource requirements resulting from anticipated or realized market demand need to be synchronized with resource capacities and restrictions of the production and procurement system by an effective demand and capacity management (DCM). DCM processes identify demand- and capacity-asynchronies and implement appropriate countermeasures in a timely manner. DCM acts as an essential interface between market, production and supply chain processes [7][8]. Nevertheless, it is obviously impossible to predict the exact future vehicle orders, as customers can choose from billions of possible configurations for each car type [9][10]. Today, regional and central sales departments of the OEM forecast sales volumes for the models offered in the different sales regions (e.g., number of VW Golf Trendline 2.0

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TDI) and sales quotas for the selectable options (e.g., ratio of vehicles with xenon light or navigation system).

Fig. 1 depicts the interdependences of demand and capacity information. The compatibility of options for a respective car is described by a complex set of technical rules, while the relationship between the fully-configured car type and the corresponding parts is described by the bill of material (BOM). Capacity constraints and restrictions exist on sales level, production level and supply chain level. To balance volumes and quotas with constraints and restrictions in order to identify possible bottlenecks, it is necessary to bridge the gap between demand information and capacity information [11][12][13]. Forecast uncertainty, demand volatility, rapid product changes, as well as changes in the supply chain complicate this task significantly.

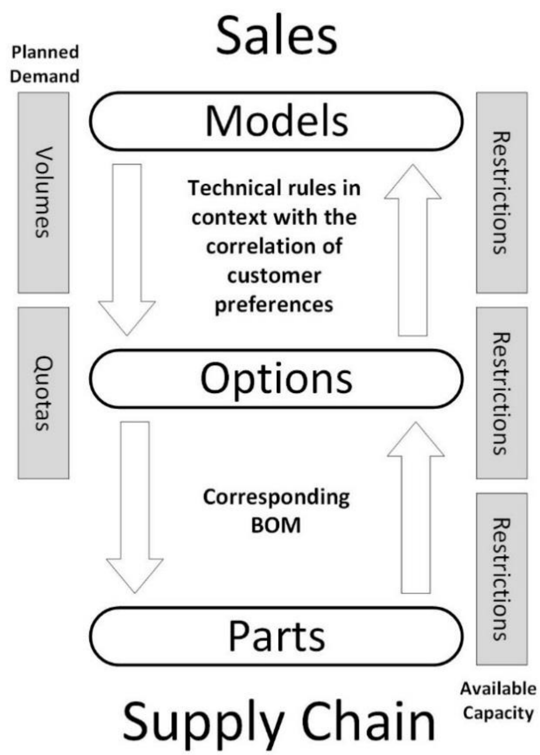

Figure 1. Bridging the gap between demand information and capacity information

Furthermore, the relevant data is typically kept in a highly fragmented information landscape. For example, part demand is typically gradually derived from sales figures in a number of sequential processes taking into account a variety of systems [14][15]. Since automated processes only allow the identification and reporting of formal inconsistencies, typically an experienced human planner has to review the process.

As it is easily understood, an integrated information base could reduce the complexity and increase transparency of the DCM processes immensely. So, highly innovative systems integrate all related data from sales to supply chain into a consistent and integrated information structure, thus providing the essential basis for a continuous DCM process. In this context, this paper analyses the benefits of a hierarchical tree-based data structure for the integration of distributed product data against the background of complexity reduction and transparency increase.

In the next Section, the state of the art of information structures for automotive DCM is presented. Afterwards, an introduction to specific data optimization methods is given in Section 3. Section 4 analyses the complexity reductions gained by these optimization methods. A conclusion including a summary and a perspective on future research and development is given in Section 5.

II. State of the Art in Automotive DCM Processes

This Section illustrates the state of the art in automotive DCM processes. The DCM process is initiated by the sales department predicting medium-term and future market demands [16]. Here, model volumes and option quotas for hundreds of sales regions worldwide must be planned. These figures are integrated with order volumes and translated into a production program for all sites. The planning complexity of this step is tremendous due to the variety of products. For example, a typical mid-class series (e.g., VW Golf, BMW 1 Series, Audi A3) offers about 30 to 50 different car models (car type of a specific series with typically body type, engine and gear system specification) with about 400 to 800 options. This results in several thousand volumes to be planned for car models in sales regions in a specific time period (e.g., month, week or day depending on planning granularity) and some 10 million option quotas. Furthermore, technical restrictions prohibit options for specific models (e.g., no 17’’ tires for convertibles), force specific combinations of options (e.g., LED head light only in combination with LED back lights) or prohibit combinations (e.g., a navigation system rules out all other radios). In addition, sales constraints and customer preferences need to be included. This complex planning can often only be handled by the integration of human experience and intuition (cf. [17]).

Even more so, a huge amount of the resulting resource requirements for production or logistics (supply of parts) are not only depended on single model volumes and quotas for options, but on a particular combination of model, options and sales region. Therefore, some part volumes are hard to predict until the exact configuration of the vehicle, i.e., the order, is known. Nevertheless, as lead times in global supply networks can be long, a certain amount of vehicle parts has to be ordered long before customer orders are known (cf. [16]).

Consequently, the DCM process is challenging and characterized by conflicting goals: because of market dynamics, a huge number of possible vehicle configurations and correlations among vehicle models, options, and parts, the planning itself is already complex [18]. Sales departments are forced to react to volatile markets, increased global competitions, and changing customer requirements: flexibility and reactivity is requested. Production is interested in a stable production program, which guarantees both high capacity utilization and optimal operating results. Material planning wants to fix part requirements as early as possible to avoid bottlenecks proactively as well as to negotiate the flexibility of suppliers appropriately.

This conflict can be named the dilemma of automotive DCM. Typically, it is solved by planning cycles of four to six weeks, which are based on numerous workshops and committee meetings between sales, programming- and material planning [18][19]. The consequence is insufficient flexibility in reaction to market changes. Furthermore, the program is adjusted manually between program approvals and even after program freeze, within the so-called frozen period. However, these adjustments cause a lack of program stability and poor transparency on future demand for parts on supply side. The probability of bottlenecks increases and induces additional internal costs, as well as deterioration of the delivery service to the customer.

There are two theoretical approaches for the integration of these sequential planning processes in an effective holistic DCM process.

The first one is the early inclusion of selected critical resource restrictions into the sales and program planning. The planning variables, i.e., model volumes and option quotas, typically include several million variables. Furthermore, technical rules and BOM rules relate these planning variables to part demands and thus capacity restrictions. For example, a capacity restriction may exist which limits the number of a specific powerful battery. Unfortunately, the selection of this battery may depend on several combinations of options, e.g., the battery is only selected if specific electronical options are chosen. To derive restrictions on model volumes and option quotas all BOM rules and technical rules that relate directly or indirectly to that battery have to be analyzed. In the worst, case this amounts to a significant proportion of the overall number of rules, for a midrange model about 15,000 technical and 600,000 BOM rules. Even more so, partially unmanageable correlations exist between option quotas and model volumes. These result not only from technical restrictions, but also from product strategy, customer preference, and marketing strategies. A customer preference as the choice of navigation system and hands-free module shall be given as an example for such correlations. These two options are independent from the viewpoint of the customer. But historical data has shown that most customers (80%) who choose the navigation system also select the hands-free module; customers who do not select the navigation system rarely choose the hands-free module [20].

As a result, not all restrictions may be deterministically traced back to the decision variables. This is aggravated by ramp-ups and run-outs (continuous change in options, models, etc.), dynamic changes in capacity information, multiple use of parts, parts commonality strategies and other restrictions that may change daily. The complete derivation of restrictions on planning variables harbors an immense complexity and is not deterministically feasible. The selection of historically critical restrictions is not sufficient.

Consequently, the most promising perspective of an effective holistic DCM process is seen in scenario-based real-time planning. Starting from a planning scenario, resources and component requirements are derived and capacity bottlenecks are identified and disclosed.

The basis for this is a consistent and holistic information model, which consists of all planning information for the planning process. The simplest form of the DCM information model is divided into three data partitions: the planning scenarios, the resource information, and the product structures. Resource and part requirements are then derived from planning scenarios by propagation of the product structure from models and options to parts. Typically planned orders are applied here.

To make fast and qualified statements about the feasibility of a scenario, the integrated DCM requires the application of smart quantitative methods to derive future resource requirements from market requirements.

In [17], an evaluation of a number of publications has been performed, that have introduced innovative processes and methods for DCM (e.g., approaches of [11][21][22][23]) and developed an approach that applies planned orders that are applicable for calculation of part demand for the automotive industry.

These algorithms have been implemented and validated at several German OEMs. The respective tool suite is now known under the name of OTD-DCM, where OTD refers to the basic instrument OTD-NET (order-to-delivery and network simulator, cf. [23]). To reduce the amount of data of BOM rules and to optimize their terms, the next Section presents optimization methods that are partially used in this approach.

III. Hierarchichal Product Structure and Optimization Methods used in the DCM

As described in Section 2, the possible number of BOM rules for a fully specified car amounts to over 600,000. Hence, it is necessary to assure consistency and avoid redundancy in and between all data entities when integrating data into one data structure. Inconsistencies occur for example when subsets of technical rules contradict each other so that orders cannot be specified fully. Hence, it is necessary to adapt planning-relevant information regarding structural requirements and to verify their consistency before they are processed. As a result, the implemented data processing in OTD-DCM has been based on the principle of generating a hierarchically-linked structure of variant clusters (cf. [24]). Here, a variant cluster contains by definition a subset of allowed vehicle variants (typically car models), that have common properties (example: sales region=Germany, body=medium class sedan, engine=150hp diesel, transmission=automatic, and trim=comfort). The first pre-optimization of the product structure is the generation of a hierarchical data tree where tree levels are based on subsequently detailed variant cluster specifications. The tree structure is an intuitively attractive approach because of its proximity to car design principles. Tree levels may be defined based on for example the model type, target country, engine type (see Fig. 2).

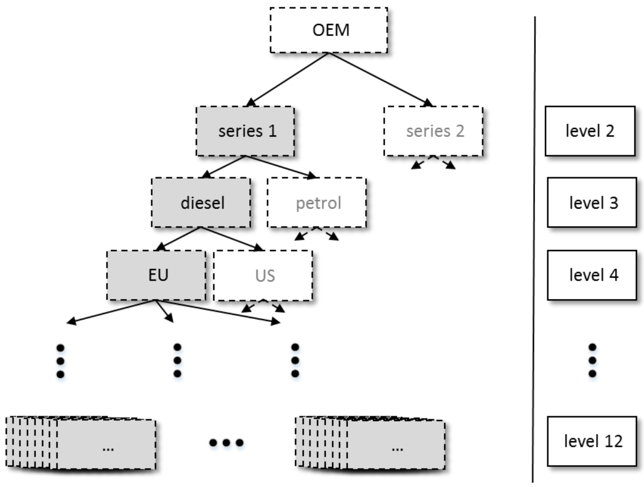

Figure 2. Extract of the generated tree structure

Each level can have one to several nodes, depending on the level and type of car (e.g., gasoline, diesel, electronic for the fuel nodes). As all product information have a specific temporal validity, these dynamics have to be handled within this tree structure [17].

This paper especially focuses on the processing and thus complexity reduction of rules when integrating product data into this hierarchical structure. Technical rules represent the technical feasibility by Boolean expressions, e.g., "if motor = 90 kW then suspension = 6-speed manual gearbox". BOM rules follow the same Boolean schema but link options to part demands, e.g., "if motor = 90 kW and radio = "Radio Basic" then parts 5678973 and 5678974". The mentioned optimization has been subdivided into three optimization steps.

- The first objective has been to identify all forced options, i.e., the options that have necessarily to be chosen for a specific variant cluster (e.g., every car for the German market has necessarily a specific exhaust system). Therefore, principally allowed options for one variant cluster are reduced by non-feasible options. This is done by checking intelligently selected, partly specified theoretical configurations against all applicable technical rules. If a contradiction occurs, the option will be deleted from the set of allowed options. When this process leads to only one possible option from a set of alternative options, this option is set as forced.
  An inner inconsistency is identified if the last identified forced property violates a technical rule. An outer inconsistency is identified if a positive demand quota for an option has been planned, but the option itself is technically not allowed. Another outer inconsistency is identified, if the sum of all planned quotas for all allowed options within a subset of alternative options in a specified time period does not equal 100%.
- The second optimization step reduces the number and the length of rules by application of the Identity Law of the Boolean algebra (cf. [25]). It should be noted that these steps are valid only for one variant cluster and a specified, fixed time period. Therefore, these steps need to be executed for each variant cluster and all relevant time periods. The OTD-DCM implementation is able to shorten rules by merging several BOM or technical rules that belong to more than one resource, i.e., workstations, assembly lines and more [17][26][27]. Next, this second optimization step aims to further reduce the actual length of all rules by Boolean simplification of terms. In contrast to the first step, it is used for each rule separately. If the optimized length of the rule is shorter than the original one, it is replaced by the new representation. Example: The Boolean expression "$\neg$ ($\neg$A $\wedge$ B $\wedge$ $\neg$C)" will be reduced to "$\neg$B $\vee$ A $\vee$ C".
- The third and last optimization step tries to identify commonalities for nodes in the hierarchical product structure. For example, rules which are valid for each child node of one variant cluster are moved upwards to the parent node and deleted from all children. The preliminary condition for this step is that all derived variant clusters share this rule over the same time period. Example: The forced option "Owner's manual in German language" may be valid for all variant clusters within the sales market = Germany. Hence, it can be transferred upwards to the variant cluster "variants - German" [17].

The analysis of the complexity reductions which these methods provide, will be presented in the next Section.

IV. Analysis of Complexity Reductions

The evaluation of the previously described optimization steps has been executed on real data for two middle class series from a German OEM. It should be noted that these two car series represent only a small fraction of the OEM portfolio and the analysis is limited here on BOM rules only. In the following the parameter $n(l)$ is defined as the number of tree nodes on a level. A tree node represents a variant cluster as described in the previous Section. The respective sum of BOM rules before optimization are defined as $r^{pre}(l)$ and after optimization as $r^{post}(l)$. The number of average rules per tree node within a level is defined as

$$a^{pre}(l)= r^{pre}(l) / n(l) \tag{1}$$

and

$$a^{post}(l)= r^{post}(l) / n(l). \tag{2}$$

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A null-entry rule characterizes a rule without condition, i.e., this rule is valid for the whole variant cluster. Accordingly, the total number of null-entry rules on a specific level l before optimization is defined as $v^{pre}(l)$ and on a specific level l after optimization as $v^{post}(l)$.

The results in Table 1 illustrate, that the lowest level of the hierarchical product structure contains all existing BOM rules $r^{pre}(l)$ before all optimization steps. Levels 1 to 11 do not contain rules because these levels have been added artificially to the product structure in the first pre-optimization step in order to construct the primary tree structure. After optimization, several BOM rules have been hoisted to higher levels resulting in $r^{post}(l)$.

Furthermore, the overall number of rules is reduced from 1,076,428 to 111,070, which amounts to a reduction of 89.7% in relation to the original number.

The reduction as well as the average ratio of rules per node are recognizable by comparing $a^{pre}(l)$ and $a^{post}(l)$. The weighted average considers the number of nodes of the whole tree per level, where the reduction in this case also results in 89.7% coincidentally. This analysis proves the immense complexity reduction by application of the OTD-DCM hierarchical product structure.

TABLE I. INDICATORS WITHOUT OPTIMIZATION (PRE) AND WITH OPTIMIZATION (POST)

level l	$n(l)$	$r^{pre}(l)$	$r^{post}(l)$	$a^{pre}(l)$	$a^{post}(l)$	$v^{pre}(l)$	$v^{post}(l)$
1	1	0	38	0	38	0	35
2	2	0	4,389	0	2,194	0	2,554
3	3	0	1,204	0	401	0	425
4	3	0	0	0	0	0	0
5	4	0	1,293	0	323	0	498
6	4	0	0	0	0	0	0
7	5	0	1,047	0	209	0	111
8	8	0	4,101	0	512	0	845
9	8	0	0	0	0	0	0
10	8	0	0	0	0	0	0
11	12	0	1,501	0	125	0	416
12	184	1,076,428	97,497	5,850	529	287,841	7,324
	sum	**sum**	**sum**	**weighted average**	**weighted average**	**sum**	**sum**
	242	1,076,428	111,070	4,448	458	287,841	12,208

Nevertheless, rules at parent nodes are valid for all child nodes. When a specific variant cluster at lowest level is regarded (for example, for generation of fully specified planned orders) it is necessary to take into account all valid rules for this specific node. Thus, rules on the upper levels need to be propagated downwards to all child nodes and have to be considered when calculating the total number (sum) of valid rules for one variant cluster.

TABLE II. PROPAGATED RULES PER VARIANT CLUSTER AT LOWEST LEVEL (LEVEL 12)

propagated rules - level 12	**pre-optimization**	**post-optimization**
sum	1,076,428	813,823
average ratio	5,850	4,423
median	6,734	4,725
minimum	3,007	2,653
maximum	7,522	5,344

Table 2 shows that the propagated number of rules on the lowest level. The total number is still significantly smaller than the original number. The reduction of the number of rules is still about 24.4%.

V. CONCLUSION AND FUTURE WORK

An integral component of the automotive supply chain management is DCM, where resource requirements, resulting from future or already realized market demands, are synchronized with capacities and restrictions of the supply chain and production system. Because it is impossible to predict the exact future vehicle orders, part demand is typically gradually derived from sales figures in a number of sequential processes involving a variety of systems as well as experienced human planners. In this paper, the integration of the respective distributed product data into a hierarchical tree structure has been analyzed against the background of complexity reduction.

It has been demonstrated that by choosing a hierarchical tree structure the total number of BOM rules could be reduced by a factor of 10 (reduction of 89.7%). Furthermore, the number of BOM rules relating to a variant cluster could be reduced by 24.4% in the current case. In summary, the hierarchical integrated information model provides more transparency as redundant and surplus information is dramatically reduced. Thus, it proves to be an optimized basis for a scenario-based DCM planning process for the automotive industry which relies on transparent and consistent data. A sound DCM process will increase program stability and transparency on future part demand. Bottlenecks and the resulting deterioration of delivery service levels will be decreased. Furthermore, all applications using the information model will save computation time and memory space [17].

Since only a small information model of two car series has been considered here, an analysis of a full product spectrum may be necessary to provide greater insights into the effects of the optimization steps. The chosen tree structure is an intuitively attractive approach because of its proximity to car design principles. Nevertheless, when targeting an integrated product structure, product characteristics from other departments like sales, productions and logistics need to be taken into account. Here, a more generalized graph structure instead of the applied tree structure may hold further benefits in terms of complexity reduction. Against this background, generic graph structures will be analyzed in the near future.

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References

[1] J. Schuberthan and S. Potrafke, “Die Anforderungen des Kunden…,” in F. Gehr and B. Hellingrath, eds. Logistik in der Automobilzulieferindustrie: Innovatives Supply Chain Management für wettbewerbsfähige Zulieferstrukturen. Springer, p. 9, 2007.

[2] D. Alford, P. Sackett, and G. Nelder, “Mass customization - an automotive perspective,” International Journal of Production Economics, vol. 65(1), pp. 99-110, 2000.

[3] E.-H. Krog and K. Statkevich, “Kundenorientierung und Integrationsfunktion der Logistik in der Supply Chain der Automobilindustrie,“in H.Baumgarten, ed. Das Beste der Logistik: Innovationen, Strategien, Umsetzungen, Springer, p. 187, 2008.

[4] A. Trojan, “…und die Auswirkungen auf den 1st-Tier-Lieferanten,” in F. Gehr and B. Hellingrath, eds. Logistik in der Automobilzulieferindustrie: Innovatives Supply Chain Management für wettbewerbsfähige Zulieferstrukturen. Springer, p. 12, 2007.

[5] S. Meißner, “Logistische Stabilität in der automobilen Variantenfliessfertigung,“ Lehrstuhl für Fördertechnik Materialfluss Logistik, Technische Universität München, Germany, p. 1, 2009.

[6] R.T. Yu-Lee, ”Essentials of Capacity Management,” John Wiley and Sons, Inc., p. 3, 2002.

[7] E.-H. Krog, G. Richartz, R. Kanschat and, M. Hemken, “Kooperatives Bedarfs- und kapazitätsmanagement der Automobilhersteller und Systemlieferanten,“ Logistik Management, vol. 4(3), p. 47, 2002.

[8] D. Arnold, H. Isermann, A. Kuhn, H. Tempelmeier, and K. Furmans, Handbuch Logistik, 3rd ed., Springer, p. 472, 2008.

[9] M. Holweg and F. K. Pil, “The Second Century: Reconnecting Customer and Value Chain through Build-to-Order”, MIT Press, p. 165, 2004.

[10] F. Klug, “Logistikmanagement in der Automobilindustrie: Grundlagen der Logistik im Automobilsbau“, Springer, Berlin, Germany, p. 49, 2010.

[11] T. Stäblein, “Integrierte Planung des Materialbedarfs bei kundenbeauftragsorintierter Fertigung von komplexen und variantenreichen Serienprodukten,“ Aachen, Germany, Shaker, 2008.

[12] T. Zernechel, „Gestaltung und Optimierung von Unternehmensnetzwerken: Supply Chain Management in der Automobilindustrie,“ in F. Garcia, K. Semmler, and J. Walther, ed. Die Automobilindustrie auf dem Weg zur globalen Netzwerkkompetenz: Effiziente und flexible Supply Chains erfolgreich gestalten“, Berlin, Germany, Springer, p. 372, 2007.

[13] J. Gebhardt, H. Detmer, and A.L. Madsen, “Predicting Parts Demand in the Automotive Industry — An Application of Probabilistic Graphical Models,” Proc. Int. Joint Conf. on Uncertainty in Artificial Intelligence (UAI’03, Acapulco, Mexico), Bayesian Modelling Applications Workshop, Morgan Kaufman, San Mateo, CA, USA, 2003.

[14] H. Meyr, “Supply Chain planning in the German automotive industry,” OR Spectrum, vol. 26(4), p. 453, 2004.

[15] T. Stäblein, “Integrierte Planung des Materialbedarfs bei kundenbeauftragsorintierter Fertigung von komplexen und variantenreichen Serienprodukten,“ Aachen, Germany, Shaker, p. 35, 2008.

[16] T. Zernechel, „Gestaltung und Optimierung von Unternehmensnetzwerken: Supply Chain Management in der Automobilindustrie,“ in F. Garcia, K. Semmler, and J. Walther, ed. Die Automobilindustrie auf dem Weg zur globalen Netzwerkkompetenz: Effiziente und flexible Supply Chains erfolgreich gestalten“, Berlin, Germany, Springer, pp. 367-378, 2007.

[17] A. Wagenitz, K. Liebler, and S. Schürrer, “A Holistic Approach to Demand and Capacity Management in the Automotive Industry,” in Proceedings of tge 21st International Conference on Production Research, Stuttgart, Germany, p. 101, 2011.

[18] H. Meyr, “Supply Chain planning in the German automotive industry,” OR Spectrum, vol. 26(4), pp. 447-470, 2004.

[19] J. Diercks. *IT verliert Kontrolle über Geschäftsprozesse*. [Online]. Available from: : http://heise.de/-1244454 [last accessed 17 May 2016], 2011.

[20] K. Liebler, “Eine prozess- und IT-gestützte methode für die Produktionsplanung in der Automobilindustrie,“ Dissertation, Dortmund, Germany, Praxiswissen Publications, p. 105, 2013.

[21] S. Ohl, “Prognose und Planung variantenreicher Produkte am Beispiel der Automobilindustrie,“ Düsseldorf, Germany, VDI, 2000.

[22] H. Wagner, „Kollaboratives Bedarfs- und Kapazitätsmanagement am Beispiel der Automobilindustrie: Lösungsansatz zur Sicherstellung der Wandlungsfähigkeit,“ 1st ed., Huss, 2006.

[23] A. Wagenitz, “Modellierungsmethode zur Auftragsabwicklung in der Automobilindustrie,“ Dissertation, Technische Universität Dortmund, Germany, 2007.

[24] K.-U. Meininger, “Abstraktionsbasierte Bereitstellung bereichsübergreifender Planungsdaten für die Produktionsplanung bei Serienfertigung variantenreicher Erzeugnisse,“ 1st ed., Idstein, Germany, Schulz-Kirchner, p. 32ff, 1994.

[25] R. L. Goodstein, Boolean Algebra, Mineola, New York, Dover Publications, 2007.

[26] K. Liebler, “Eine prozess- und IT-gestützte Methode für die Produktionsplanung in der Automobilindustrie,“ Dissertation, Dortmund, Germany, Praxiswissen Publications, p. 101, 2013.

[27] K. Liebler, “Eine prozess- und IT-gestützte Methode für die Produktionsplanung in der Automobilindustrie,“ Dissertation, Dortmund, Germany, Praxiswissen Publications, p. 110, 2013.

