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The Volkswagen Pre-Production Center Applies Operations Research to Optimize Capacity Scheduling

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Abstract. The Volkswagen Pre-Production Center (VPC) is responsible for the entire prototype assembly of the Volkswagen brand. In their assembly sites, however, they often cannot employ their manufacturing staff to the full utilization level, and therefore, the manufacturing volume is low. Maximizing the manufacturing volume for a given available capacity is a frequently pursued objective in industrial manufacturing. The planning task of capacity scheduling contributes to this objective by deciding on resource allocation and the selection and scheduling of orders. We were asked to evaluate possible operations research/management science (OR/MS) solutions for their capacity scheduling problem. To this end, we developed a prototype for capacity scheduling based on binary integer programming. After the prototype had revealed high improvement potential, we developed a spreadsheet-based decision support system (DSS) for daily capacity scheduling. The schedules generated by the DSS were substantially better than the solutions generated by the current manual procedure, in terms of both accomplished manufacturing volume and planning effort. After successful test implementation and rollout, the VPC estimated the annual cost savings to lie in the six-digit Euro range. Meanwhile, we continue spreading OR/MS methods to neighboring departments of the VPC.

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Keywords: automotive assembly • prototype • capacity scheduling • decision support system • spreadsheets

At its site in Wolfsburg, Germany, Volkswagen dedicates more than 14,000 employees to pursue innovation in the Research and Technical Development departments of the Volkswagen group. The *Volkswagen Pre-Production Center* (VPC) as a part of Technical Development is responsible for the coordination and manufacturing of prototype vehicles of the *Volkswagen brand* (VW). These prototype vehicles are frequently presented to the public at automotive exhibitions or internally as concept or design models to the management board. The most considerable number of prototypes, however, is dedicated to technical tests before the pilot-run series of the specific car models. With its 1,400 employees, the VPC accounts for the timely completion of approximately 4,000 VW prototype vehicles annually.

Grown historically at times with lower product variety, the current organizational structure of the VPC's manufacturing department is characterized by several autonomous *organizational units* (OUs). One master craftsperson leads each OU with around 30 skilled workers and is responsible for the timely completion of the orders centrally assigned to the OU.

Traditionally, the OUs focused on a fixed set of car models and could consequently gain experience with their models. In today's prototype vehicles, however, a high degree of novel technology is common among all vehicle segments, and virtual prototype models assist the workers throughout the assembly. As a consequence, the VPC reduced the specialization of OUs, and workers can now build any vehicle model. The organizational structure with several autonomous OUs, however, has been retained.

In past years, the VPC has faced an increasing demand for manufacturing capacity, considerably exceeding internal capacity supply. This tremendous increase is mainly due to an increasing product variety worldwide, along with more extensive tests of mechanical functionality and an increase in electric vehicle components. In order to ensure the timely completion of all orders despite these developments, external manufacturing has become an attractive option lately.

At the VPC, the decision on whether to outsource an order is the task of the centralized function of capacity scheduling. In their capacity scheduling process, they

decide on the executing OU and the assembly period of each order. These decisions are driven by the available internal and external manufacturing capacity and the timely completion of each order. Currently, the planning task is carried out manually and requires significant data management effort because several stakeholders are responsible for data maintenance. As a consequence, the capacity scheduling process is limited to the supervision of (exogenous) due dates. The manufacturing department therefore suffers from large fluctuations in personnel utilization at generally lower utilization levels and the low internal manufacturing volume associated with it. Decisions on the internal and external manufacturing and scheduling of orders do not consistently follow the aim of maximizing the internal manufacturing volume. To reduce costs spent on external manufacturing of orders, management seeks measures to increase the internal manufacturing volume.

The VPC asked the authors of the contribution at hand to evaluate possible operations research/management science (OR/MS) solutions for their capacity scheduling. Particularly fascinated by the combinatorial complexity of their problem and the peculiar characteristics of their manufacturing system, we developed and implemented, in cooperation with the VPC, a prototype for capacity scheduling based on binary integer programming. In order to solve the prototype for real-world settings, we had to simplify it. However, it demonstrated that the VPC could substantially increase its manufacturing volume by utilizing a dedicated planning approach. Based on these preliminary results, the VPC subsequently decided to launch a spreadsheet-based decision support system with user-friendly functionality and generalized assumptions we developed for every-day planning.

Theoretical Foundations of Automotive Product Development

Early in the automotive value chain, manufacturers are concerned with the development of novel products for potentially emerging future markets. With a focus on decision making in product development, Krishnan and Ulrich (2001) provide an extensive survey on research in this domain. They propose to divide the decisions in product development into four stages: (S.1) *concept development*, (S.2) *supply chain design*, (S.3) *product design*, and (S.4) *production ramp-up and launch*. In order to provide an initial understanding of the decisions in automotive product development and recent research associated with it, we present examples of recent research associated with the product development stages in the automotive industry in the following.

Concept Development (S.1)

The (S.1) *concept development* stage is concerned with product differentiation and addresses the definition of the products' target value, the core concept, and the determination of the number of product variants (Krishnan and Ulrich 2001). In the automotive industry, decisions on future product portfolios are at the heart of the *concept development* stage. Recently, several authors have focused on the market introduction of alternative fuel technologies (Kieckhäfer et al. 2014, Kieckhäfer et al. 2017, Oliveira et al. 2019). Moreover, strategic assortment planning and supply chain design decisions are integrated (Bertsimas and Mišić 2017, 2019; Jonnalagedda and Saranga 2017, 2019; Umpfenbach et al. 2018a, b).

Supply Chain Design (S.2)

The (S.2) *supply chain design* decisions include (S.2.1) *supplier selection*, (S.2.2) *production system design*, and (S.2.3) *distribution system design* (Krishnan and Ulrich 2001). The (S.2.1) *supplier selection* refers to vertical integration and outsourcing decisions (Novak and Stern 2009, Agrawal et al. 2017, Tsay et al. 2018, Moheb-Alizadeh and Handfield 2019, Zhou et al. 2019). In (S.2.2) *production system design*, particular attention is given to the production network design, thus focusing on the manufacturers' internal supply chain. Approaches in this domain assume a loss of productivity at the plant level due to the launch of novel products (Fleischmann et al. 2006, Gopal et al. 2013, Egelman et al. 2017, Ziegler et al. 2019). The (S.2.3) *distribution system design* is concerned with the location of distribution facilities between plants and customers (Geoffrion and Graves 1974). Şen et al. (2010) and Kchaou Boujelben et al. (2016) report on successful applications of distribution system design in industrial practice.

Product Design (S.3)

The (S.3) *product design* stage then focuses on the design of single products rather than portfolio design. *Product design* decisions predominantly relate to the engineering community. Typically, selected design parameters of the product are improved in an iterative trial-and-error manner (Papalambros 1995, Krishnan and Ulrich 2001). To account for the iterative nature of *product design*, Thomke (1998) specifies it as an iterative four-step cycle consisting of (S.3.1) *design* (i.e., choosing the level of a product's attributes), (S.3.2) *build* (i.e., developing the (physical or virtual) apparatus required to conduct the necessary experiments), (S.3.3) *run* (i.e., testing the prototypes in their use environment), and (S.3.4) *analyze* (i.e., identifying opportunities to improve the product design) phases. To the best of the authors' knowledge, recent research with applications to the automotive industry only

addresses (S.3.3) the *run* phase. Here, several articles are concerned with test scheduling problems in the automotive industry and relate to decisions on the number of required prototype vehicles, their configuration, and the resulting test schedules (Chelst et al. 2001, Hsu et al. 2004, Bartels and Zimmermann 2009, Reich et al. 2016, Shi et al. 2017). The capacity scheduling problem we consider in our manuscript is categorized into the (S.3.2) *build* phase.

Production Ramp-up and Launch (S.4)

The final stage of product development refers to (S.4) *production ramp-up and launch*. In this phase, the timing of the product launch is considered, and multiple factors are traded off, for example, completeness of development and threat of competitor entry to the market (Kalish and Lilien 1986, Thomke 1998). Glock and Grosse (2015) provide a review of decision support models for production ramp-up. Almgren (2000), Wochner et al. (2016), and Becker et al. (2017) report on successful applications of OR/MS methods in this field.

As illustrated in our overview, much research is associated with OR/MS in the stages of product development in general and automotive product development in particular. The capacity scheduling problem we consider is part of the *product design* stage. In this stage, the scheduling of technical tests has recently attracted attention. Before conducting tests on the prototype vehicles, however, automotive manufacturers are committed to their assembly. To the best of the authors' knowledge, no existing research addresses the processes of automotive prototype assembly from an OR/MS perspective. The same holds for the domain of assembly of prototypes in industries in general. In the next section, we will illustrate the problem setting we faced at the VPC.

The Problem Setting

Capacity scheduling is conducted daily with a rolling-horizon planning period of 60 days in which compliance with capacity restrictions is ensured. The VPC pursues a single-shift system for both administration and manufacturing employees. Manufacturing is conducted on weekdays except for public holidays and annual work holidays. The latter is specific for the Volkswagen site in Wolfsburg, Germany.

A release date and a due date are associated with each order. The assembly of any order cannot start before its particular release date. Several factors have an impact on the determination of the release date, for example, the delivery date of hardware components or software products required for assembly, or preliminary clarification of technical requirements. The prototype vehicles are manufactured for different

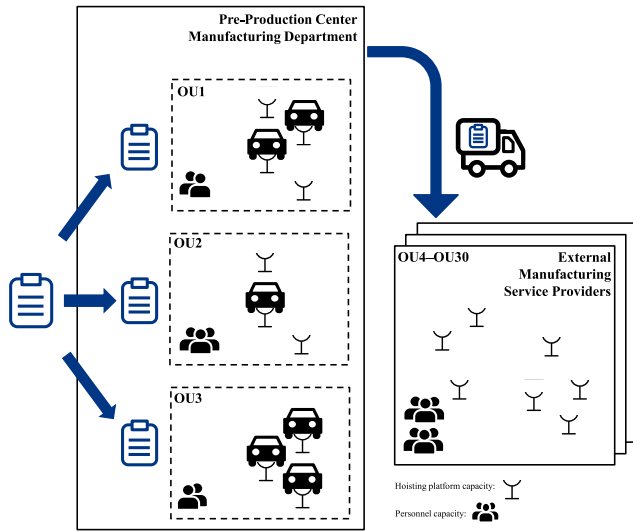
internal customers of the Technical Development departments, for example, for test runs of specialized equipment or management and exhibition presentations. Because of the high priority of these occurrences, potential delays strictly have to be avoided, which means the due date is firm.

The VPC holds responsibility for each VW prototype vehicle and coordinates the timely completion of each order by either internal OUs (preferred) or external manufacturing service providers. Consequently, an OU has to be determined for each order. To accept orders for internal manufacturing, the availability of two limited resources has to be ensured.

First, a sufficient capacity of power-driven hoisting platforms is required. Hoisting platforms are stationary devices to lift vehicles by their frames. In the VPC, they are needed to enable underbody work. Each OU maintains a certain number of hoisting platforms. The prototype vehicles have to be assigned to one of these hoisting platforms throughout their assembly. Only one vehicle can be assigned to a hoisting platform at a time. Because the assembly of any order cannot be interrupted once having been started, the car cannot be released from the hoisting platform and remains lifted until its assembly is finalized. As hoisting platforms are stationary, the hoisting platform capacity of each OU differs from other OUs.

Second, each OU has a certain number of skilled workers, providing a predetermined personnel capacity in each period that fluctuates according to the individuals' vacation entitlement. The volume of work caused by the assigned orders must not exceed the available capacity in any period. The master craftsmen maintain the disciplinary responsibility for their skilled workers and the punctual completion of their orders. Therefore, the master craftsmen conduct the scheduling of their resources on a technically more detailed level and operate autonomously. Personnel can only move within an OU. Within each OU, however, the master craftsmen can flexibly assign their personnel among the orders allocated to the associated OU. A general illustration of the planning problem is given in Figure 1.

The assembly effort associated with each order can be determined only a few days before the planned start date because changes in technical requirements can occur on short notice. For planning purposes, however, the order has to be assigned to either of the OUs well in advance, for example, to enable the picking and shipping of parts. Therefore, capacity scheduling has to rely on estimates of the orders' assembly effort. This estimation is based on prior experience with similar projects and is measured in hundreds of staff hours.

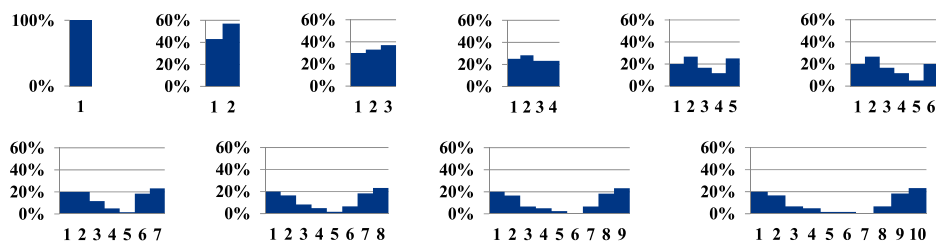
Figure 1. (Color online) The Planning Problem of the Volkswagen Pre-Production Center

Notes. Each order is coordinated, scheduled for assembly between release date and due date, and assigned to organizational units (OUs). Because external manufacturing service is costly, the internal manufacturing volume is sought to be maximized. Internal allocation is constrained by two resources: personnel and hoisting platform capacity.

Within the range of release and due dates, the actual duration of the assembly activity (usually three weeks) can be influenced by scaling the assignment of skilled workers. Consequently, the duration of an assembly activity of any order can be shortened by allocating more personnel, resulting in a high period-wise personnel effort (and vice versa). The resulting effort per period, however, does not run linearly among the assembly periods. This is due to interrelations within the considered planning process described above. The centralized capacity scheduling function allocates orders among OUs and specifies the associated start and end dates of the assembly. Subsequently, each OU is responsible for the execution of the assembly tasks associated with the assigned orders before the due date.

Therefore, they schedule the required assembly tasks within the OU on a technically more detailed level. In this setting, start and end effects arise within the decentralized OUs. For that reason, they focus on visible progress on the vehicles during the first periods. In the last periods, the unfinished work must be completed to comply with the due date. To anticipate this behavior of the subordinate OUs, the VPC observes the share of finished work over the assembly. Based on their findings, they use a deterministic function to assign the overall assembly effort among the single planning periods in their centralized approach. The resulting effort per period therefore depends on the estimated assembly effort and the duration of the assembly activity. We provide exemplary trends in Figure 2.

As described above, the due date of the prototype vehicles is firm. The VPC has taken various technical and organizational measures to achieve high process reliability and responsiveness of their value chain, ensuring the timely completion of prototypes. Referred to as the “Transparent Prototype,” critical parts and components are labeled using radio frequency identification (RFID) already at the suppliers. The state and location of the parts and components are henceforth monitored. This high degree of transparency in the logistics chain serves to avoid delays in the provision of parts and components. In the assembly area, the VPC uses a monitor at each hoisting platform providing the workers with a virtual three-dimensional copy of the respective vehicle. This technology assists the workers in case they are unsure about the correct assembly of individual parts. Both RFID and the virtual prototypes therefore help to enhance process reliability and responsiveness using technical measures. On the organizational side, steps are taken to mitigate the effect of employee absences. Once the VPC anticipates reduced personnel availability, the expected personnel capacity in each period is reduced by 10%. Consequently, the VPC utilizes only 90% of the expected capacity. Because of the decentralized structure

Figure 2. (Color online) The Relative Personnel Requirement (Ordinate) Caused in the Periods of Assembly (Abscissa) Depends on the Overall Duration of the Assembly Activity

Notes. In the figure, the bar charts represent typical assembly effort profiles for different overall durations of the assembly activity (i.e., modes of assembly), ranging from 1 to 10 periods. These 10 profiles illustrate the typical durations of assembly activities at the VPC. Irrespective of an order's overall duration, however, its effort results to 100%. Relatively high effort arises in earlier and later periods of the assembly activity. This can be observed particularly well for orders with a long duration. Independent of the latter, any order requires one hoisting platform throughout its assembly. Time units on the abscissa are illustrated in periods, and effort is scaled arbitrarily for confidentiality reasons.

of OUs, each OU does detailed scheduling of the necessary work to compensate for a possible delay in the progress of a particular vehicle, as described earlier. Using these measures, the VPC ensures timely completion of each vehicle and thus customer satisfaction.

Generally, the components required to assemble a prototype vehicle are sourced ready-for-assembly. Particular parts, however, have to be manufactured by the VPC itself for a specific order and function. A car dedicated to the testing of driving characteristics, for example, is not required to feature a car dashboard designed to increase customer perception of the car's quality. Because these processes cannot be scaled arbitrarily with higher personnel commitment, the duration of the assembly activity cannot be reduced below a specific limit. Consequently, a lower bound on the assembly duration applies to each order.

Finally, each order has a predetermined cost internally by the VPC for the assembly services provided, independent of whether the vehicle is assembled in-house or externally. The VPC aims to increase the economic efficiency. The internal personnel capacity, however, is assumed fixed in the short term. Capacity scheduling seeks to avoid (costly) outsourcing activities by maximizing the internally accomplishable manufacturing volume.

Related Work

According to the classification of the automotive product development phases and the description of the problem setting in the preceding sections, we consider the (S.3.2) *build* phase within automotive product development. To date, no recent research has addressed the application of OR/MS methods to the assembly phase of vehicle prototypes from a practical perspective. Academically, the problem can be classified as a resource-constrained project scheduling problem (RCPSP). In the RCPSP, the project to be scheduled may comprise several independent activities. Each activity can, generally, start and end in each of the considered periods. The activities consume a prespecified quantity of resource units of one or several resource types. Each activity is associated with a predetermined duration and consumes a constant amount of resource units throughout its periods. The resource types are renewable; that is, their limited capacity is available in each period at a constant level. Finish times of each activity have to be determined to minimize the finish time of the last activity subject to the precedence relations between activities and the constrained resource capacities (Demeulemeester and Herroelen 2002). Recognized reviews of the vast body of academic literature on project scheduling are, for

example, given by Brucker et al. (1999), Herroelen (2005), and Hartmann and Briskorn (2010).

The RCPSP, however, suffers from too restrictive assumptions to represent the capacity scheduling problem we face at the VPC. Although resource capacities are available at a constant level in the RCPSP, the personnel capacity of the VPC varies in time. Therefore, our approach requires consideration of dynamic resource capacities (*generalized resource constraints*). In the RCPSP, one project is scheduled. In our approach, we interpret each vehicle as an independent project that has to be coordinated (*multiple projects*). Furthermore, we decide on an internal or external realization of each order and opt for an internally beneficial portfolio (*project selection*). During the planning, the technical requirements of the vehicles are known only on an aggregated basis, and their capacity requirements rely on estimates. Therefore, we interpret each vehicle as a project comprising only one (assembly) activity. Activities may be performed utilizing multiple modes where each mode represents an alternative combination of activity duration and its resource request per period (*generalized activity concepts*). This relates to the different assembly effort profiles introduced in Figure 2 in which each bar chart characterizes one of the potential modes. Each project (and thus activity) depends on release and due dates (*generalized temporal constraints*). Moreover, we pursue maximization of the internal manufacturing volume of selected projects, whereas time-related objectives (e.g., minimization of makespan or tardiness) are most typical when scheduling multiple projects (*alternative objective*).

We particularly emphasize the *project selection* extension. Whereas RCPSP requires detailed scheduling of one project, our problem additionally comprises project selection decisions regarding the internal and external project portfolios. We therefore need to integrate decisions about the internal and external project portfolios and their scheduling. In academic literature, research associated with integrated project selection and scheduling problems is scarce. Chen and Askin (2009) propose an approach to simultaneously decide on a beneficial portfolio of general research or development projects and the selected projects' schedule, aiming at profit maximization. Their approach is extended by Amirian and Sahraeian (2017) toward a multiobjective formulation to additionally consider the minimization of total costs and unused capacity. Tofghian and Naderi (2015) suggest a multiobjective approach toward project selection and scheduling to maximize profit and minimize resource use between two consecutive periods. Shariatmadari et al. (2017) propose maximizing profit

of the selected projects and additionally decide on an increase or decrease in resource capacities at pre-specified costs. Kumar et al. (2018) take mutual exclusiveness and mutual complementarity of projects into account.

All of the contributions above propose opting for profit maximization, which is an objective similar to the maximization of the manufacturing volume we pursue. These publications, however, commonly consider the activity duration as constant. Furthermore, a constant load of the resources over the activity's duration is assumed to conduct an activity. Therefore, recent approaches toward simultaneously selecting and scheduling projects are not suited to model the dynamic effort per period as required for our approach (Figure 2).

To the best of the authors' knowledge, Kolisch and Meyer (2006) are the only ones to develop an approach to simultaneously select and schedule projects where the load of the resources is dynamic and depends nonlinearly on the chosen duration of the activities. However, they do not consider release dates of the jobs or activities and assume the resource capacity to be constant among all periods. For our problem setting, we require the consideration of release dates and dynamic capacities. Furthermore, Kolisch and Meyer assume each resource type to be identically loaded by an order. Therefore, they do not provide a suitable approach to differentiate hoisting platform capacity (one capacity unit required per order and period) and personnel capacity (dynamic requirement throughout the assembly of the associated order). Based on the review of related work, we decided to develop a customized approach to the capacity scheduling problem the VPC faced in order to allow for expedient real-world decision support and evaluate the potential in terms of higher internal manufacturing volume.

The Prototype

As approximately 500 orders have to be allocated among 30 OUs, the VPC faces a tremendous number of possible order allocations in their capacity scheduling every week. We consequently decided to utilize OR/MS approaches for a systematic evaluation of reasonable solutions. To this end, we developed a binary integer programming model (BIP) as a first step and compared the results of the current (manual) planning procedure with the results from mathematical programming. We provide the model formulation in the appendix.

The objective function of the BIP maximizes the internal manufacturing volume. Constraints ensure that each order is assigned to exactly one OU and receives a feasible assembly period (i.e., start of assembly following the release date, completion prior to

the due date, and minimum duration respected). Both personnel and hoisting platform capacities must not be exceeded in any OU and period. Orders must not be reallocated once having been started. We assume the resource requirements of each order in each period, as well as the resource capacities, as predetermined and deterministic. Whereas personnel capacity is dynamic, we parameterize hoisting platform capacity as constant. Furthermore, we assume each period to comprise one day in a real-world setting. For model simplicity, we make further assumptions: although we model the internal OUs with their personnel and hoisting platform capacity over time explicitly, we consider the multitude of external manufacturing service providers as one OU with unlimited personnel and hoisting platform capacities. This is in line with industrial practice as coordination of the outsourcing process requires the manual request of available capacities from the external manufacturing service providers before order assignment. The overall capacity of manufacturing service providers in the region, however, is virtually unlimited. Because our generic model formulation maintains limited capacity for each resource type and OU, we parameterize the external capacities using a sufficiently large number. The modeling approach is further based on the following assumptions: (i) Orders are characterized by their volume, release date, due date, and minimum duration. (ii) The volume of each order is assumed to distribute among the distinct periods of its assembly activity according to the predetermined assembly effort profiles (Figure 2) depending on their duration. (iii) OUs maintain independent hoisting platform and personnel capacities, which cannot be interchanged. (iv) Each order may generally be assigned to each OU and hoisting platform. (v) The necessary equipment and tools are available at each hoisting platform. We validated these assumptions in close cooperation with experts of the VPC, who confirmed that the model corresponds accurately to the real-world system.

We implemented the BIP in Java 8 and used the Java CPLEX API (version 12.7.1) as its solver. We read input data from and wrote results to Microsoft Excel spreadsheets using the Apache POI Java API. All computations were run on a personal computer with Intel Core i7-4710MQ CPU @ 2.5 GHz and 8 GB RAM.

Before the evaluation of the results of our optimization approach, we needed to find the parameters of the real-world decision situations to generate instances for our model. We could gather the spreadsheet files of 52 consecutive weeks serving as the basis for the manual planning process. From these files, we were able to extract personnel and hoisting platform capacities for the three internal OUs. The data also contained information on fixed and planned order

allocation, their estimated manufacturing volume and effort per period, and realized start and end dates. Unfortunately, we could not reconstruct information on release dates, due dates, and the minimum duration of orders from the data provided by the VPC. In order to allow for a fair comparison of both planning approaches, we assumed the orders' assembly duration to be fixed as determined by manual planning.

Because the constructed real-world instances were still too large to solve the BIP model, we made a further simplifying assumption and merged the three internal OUs. This aggregation offers more flexibility in assigning the orders to personnel and hoisting platforms. On the one hand, the solutions obtained were thus likely to overestimate the potential of the model-based planning approach when comparing it with the manual planning currently conducted at the VPC. On the other hand, this approach allowed us to get an initial understanding of reasonable solutions to the planning problem.

The comparison of the plans obtained by the BIP with the manually generated plans revealed that on average over all 52 instances the value of the objective function (total manufacturing volume) increases by 38.7%, with a minimum improvement of 18.8% and a maximum improvement of 68.8% (Table 1). This is mainly due to better utilization of the personnel available at the VPC ($R^2 = 0.93$), which increases between 7.9% and 68.1% and on average, by 35.9%. The average hoisting platform utilization, though, can only be increased slightly by 0.6%. For 23 instances, the hoisting platform utilization even decreases in favor of higher utilization of the personnel capacity. Overall, the potential for increasing the internal manufacturing volume was found to be limited if the personnel utilization in a manually determined plan exceeded a value of 80%, indicating personnel capacity to be the limiting factor. This holds for 6 out of the 52 instances. In all other cases, the hoisting platforms

are operated at their capacity limit, or the results of manual planning allow for better utilization of both resource types, respectively.

With regard to the characteristics of the portfolio of orders, on average, more orders (+10.4%) with a longer duration of the assembly activity (+12.3%) as well as more hours of assembly per order (+31.9%) are selected by the BIP for internal assembly compared with the manual planning. As expected, the results reveal essential interdependencies between the figures analyzed. The average number of orders selected for internal assembly decreases with an increasing average duration of the assembly activity per order and an increasing average of assembly hours per order. Because of these interdependencies, some of the figures become negative for some instances, making the interpretation of the results ambiguous.

As a consequence, we additionally compared the orders selected for internal assembly with those that are outsourced to external manufacturing service providers. We show the results in Table 2. Regarding the duration of the assembly activity per order, we find that the mean average duration of assembly activity of an order assembled internally is lower than the duration of outsourced orders. This holds for both manual planning (19.3 days versus 22.9 days) and the BIP (21.5 days versus 22.6 days). In 19 out of 52 instances, the orders allocated internally by the BIP are characterized by a higher average duration. Thus, selecting orders with a long duration of the assembly activity seems to have a positive influence on the performance of the internal assembly plan. An even more pronounced influence can be obtained for the mean average hours of assembly per order. Here, in contrast to the manual plan, the BIP selects orders for internal assembly with substantially higher average hours (208.0 hours of assembly per order compared with 140.3 hours for external manufacturing). The number of instances for which the internal average hours of assembly per order exceed the external

Table 1. Evaluation of the Plans Obtained by Applying the Binary Integer Programming Model (BIP) for All Instances in Terms of the Relative Deviation Between BIP Solutions and Manual Planning for Different Parameters (Mean, Minimum, and Maximum Values) Reflecting the Performance of the Optimization Approach and the Characteristics of the Internal Portfolio of Orders Assembled

Improvements	Mean	Min	Max
Performance measures			
Total manufacturing volume (objective function)	38.7%	18.8%	68.8%
Utilization of personnel capacity	35.9%	7.9%	68.1%
Utilization of hoisting platform capacity	0.6%	−12.3%	18.9%
Characteristics of orders assembled internally			
Number of orders assembled	10.4%	−10.3%	34.1%
Average duration of assembly activity per order	12.3%	−6.5%	47.7%
Average hours of assembly per order	31.9%	7.8%	57.9%
Average hours of assembly per period	18.0%	2.7%	54.7%

Table 2. Comparison of the Orders Selected for Internal and External Manufacturing for Manual Planning and the Application of the Binary Integer Programming Model (BIP) for All Instances

Improvements	Manual	BIP
Average duration of assembly activity per order		
Mean internal	19.3	21.5
Mean external	22.9	22.6
# Instances internal > external	0	19
Average hours of assembly per order		
Mean internal	159.2	208.0
Mean external	153.8	140.3
# Instances internal > external	27	52
Average hours of assembly per period		
Mean internal	9.4	11.4
Mean external	7.5	6.8
# Instances internal > external	52	52

Note. The results for the average hours of assembly per period suggest the advantage of the BIP for planning purposes.

average hours of assembly per order increases from 27 to 52 instances in the case of the BIP.

Subsequently, we decided to analyze a further key metric, namely, average hours of assembly per period, which is determined based on the ratio of the hours of the assembly to the duration of the assembly activity for every single order. From Table 1 we can derive that this figure has a positive value for all 52 instances. Moreover, the average hours of assembly per period of the orders selected by the BIP for internal manufacturing have a strictly higher value compared with those assembled by external manufacturing service providers (Table 2). Although this also holds for the manual plans, the BIP plans reveal a much higher deviation between the internal and the external mean average hours of assembly per period (11.4 hours versus 6.8 hours) compared with manual planning (9.4 hours versus 7.5 hours). Probably unaware, the manual planner seemed to select orders with high average hours of assembly per period for the internal portfolio of orders yet without tapping the full potential compared with the BIP.

To increase the total internal manufacturing volume as intended by the VPC, we came up with the idea of introducing a general planning rule to determine preferred orders for internal assembly based on our findings. Choosing orders particularly with long duration yields no consistently beneficial solution throughout all instances—this rule aims at utilizing hoisting platforms over time but neglects the personnel capacity. Choosing orders with particularly many hours aims to utilize the personnel—this rule neglects the hoisting platform capacity over time. Therefore, we considered the trade-off between the two resource types as essential and suggested selecting those orders that have a high ratio of hours of the assembly to its duration. In utilizing this planning rule,

orders generating as much manufacturing volume (hours) as possible per unit of hoisting platform capacity and time unit should be chosen.

The Decision Support System

After we presented the above results to managers of the VPC, they wanted to exploit (some of) the potential of the model-based planning approach. The prototype implementation, however, raised some drawbacks regarding its implementation for everyday use. First, the BIP model suffered from the unjustifiable aggregation of OUs toward one internal and one external OU. Second, Java code could impose security issues on the Volkswagen IT systems; that is, a lengthy approval process is required. Third, the use of additional commercial software, for example, CPLEX, should be avoided.

We consequently agreed on developing a tailored planning algorithm for the problem. In industrial practice, support systems are frequently based on spreadsheets (LeBlanc and Grossman 2008). The VPC also maintains preference toward spreadsheet-based solutions because planners are familiar with their functionality, and the spreadsheet software package is available in the corporation. Additionally, the integration of spreadsheet solutions is uncomplicated and assumed not to induce security issues. We consequently decided to implement our decision support system (DSS) in Microsoft Excel and utilize Visual Basic for the algorithm. Besides the detailed consideration of their organizational structure, the VPC identified further requirements that a comprehensive DSS should meet. These requirements represent additional constraints for the resulting DSS compared with the BIP.

Requirement (R.1)

First, the VPC desired the planning algorithm to maintain adherence to the enterprise resource planning (ERP) data. If an order has not been considered in capacity scheduling, the algorithm, therefore, proposes an initial allocation and scheduling of the particular order. The planner returns this information to the ERP system after its approval. Once one initially planned the order, the DSS should henceforth maintain this allocation if feasible regarding capacity restrictions.

Requirement (R.2)

Second, desirable allocations may be determined based on corporate policy decisions. Irrespective of a beneficial allocation, decision makers may require the assignment of particular projects (i.e., a set of similar vehicle orders) to be preferentially (or even exclusively) manufactured in a particular (internal or external) OU or in a certain assembly period. The plan has to adhere to these decisions. When facing internal unused

capacity, orders may be reallocated from external to internal OUs (reinsourcing). Here, decision makers may maintain preferences regarding the external OUs from which orders should preferably (or not at all) be retrieved. A comprehensive DSS, therefore, requires a rank order for retrieving orders from external manufacturing locations.

Requirement (R.3)

Third, further dynamic effects have to be considered in the planning approach. The outsourcing process requires preliminary lead time for contractual and logistical preparation. Consequently, orders with a planned start date within a specified period in the future (e.g., one week) must not be reallocated from internal to external OUs.

Requirement (R.4)

Fourth, the interface to the operational system should be as close as possible. We therefore stored the required order data in a data warehouse. The data are updated every two hours to process recent information. Using a structured query language (SQL) server query within the spreadsheet-based solution, we receive the order data from the data warehouse. The data warehouse contains, for example, information regarding both planned and realized start and end dates and the assigned OU of each order.

Requirement (R.5)

Fifth, a user-friendly interface is required that allows for hands-on interaction and improves the system's acceptance among the users. We opted to use colors to indicate different events in the planning tool consistently throughout the DSS. For example, we indicate whether data are allowed to be manipulated manually, such as planning results in blue-shaded cells, or may not be manipulated manually, such as external information shown in white-shaded cells. Furthermore, we highlight updated information visually after the data synchronization using orange-shaded cells. Additionally, a feasibility check of data from the data warehouse is implemented to indicate inconsistent data sets using red-shaded cells. Differences between the ERP data and the results of the planning algorithm are highlighted in yellow-shaded cells (Figure 3). The resulting quality of the plan generated by the algorithm is to be reported visually subdivided by OU. Here, personnel and hoisting platform utilization is of particular importance (Figure 4).

During the concept phase of the DSS, we faced two significant challenges: determining the structure and interface of the spreadsheet model and developing an efficient planning algorithm. First, we introduced the main sheet comprising all relevant information on

orders, that is, information from the data warehouse and the planning results. The main sheet additionally serves to control the automated functions such as data synchronization and launch of the planning algorithm. Although we obtain information on orders from the data warehouse, no exogenous source exists for information on OUs or preferences of decision makers. Therefore, we introduced additional sheets for the administration of master data to maintain the number of available hoisting platforms and personnel capacity over time. Additionally, decision makers may determine desirable OUs for particular vehicles based on (arbitrarily detailed or aggregated) project codes. Furthermore, they may provide a rank order of external OUs to prioritize the reallocation of orders from external to internal OUs in case of internal unused capacity (reinsourcing). An archive contains completed orders and additionally serves as a taboo list of orders that have been entered erroneously and are not (or no longer) to be taken into account.

The algorithm utilizes a tripartite approach for capacity scheduling: (1) *initialization*, (2) *constructive method*, and (3) *improvement method*. During the (1) *initialization*, order information in the DSS synchronizes with the data warehouse, and changes in data are highlighted. We use an object-oriented approach and convert order information from the spreadsheet into Visual Basic objects, which we utilize for the subsequent calculations.

Within our (2) *constructive method*, we adapt the well-known *greedy drop heuristic* introduced by Ignizio (1980), which is particularly well suited for 0-1 selection problems. After disregarding capacity constraints, each order is assigned to an OU and assembly period. The initial allocation is based on either existing ERP data (preferential) or the decision makers' preferences (subordinate). This approach maintains existing allocations as preferred. However, it typically results in unbalanced solutions among OUs. Throughout the planning horizon, high overutilization of the internal OUs occurs predominantly, while periods with idle capacity may also exist. Therefore, we firstly strive for a more even distribution of overload. For each internal OU, we identify periods with idle capacity and assign an order from a simultaneously overloaded OU. We choose the order to be reassigned according to the planning rule derived from applying the BIP. Thus, the DSS selects the order with the highest ratio of hours of assembly to duration of assembly activity subject to the conditions that (i) its assembly period exceeds the overloaded period, (ii) it has not been fixed, and (iii) it may feasibly be assigned to the OU experiencing idle capacity. This procedure is repeated until the reassignment of internal orders can utilize no idle capacity.

Figure 3. (Color online) Main Sheet of the Decision Support System (DSS)

Vehicle No.	Order	Organization	Desired Start	Desired End of Assembly	Technical description	Annotation	Model	Volume	Priority	Date	Date	CW	CW	Days	Fraction	OU	Fraction	Start of Assembly	ZPT	without E-2P6	with E-2P6
VW100001	55388	H18	18.04.2017	02.06.2017			299			18.04.2017	02.06.2017	16	25	45		MS1					
VW100002	55416	H18	23.01.2017	14.04.2017			299			23.01.2017	14.04.2017	4	13	81		MS1					
VW100003	55383	H18	15.05.2017	19.05.2017			299			15.05.2017	19.05.2017	20	21	4		MS2					
VW100004	55780	H18	15.05.2017	19.05.2017			299			15.05.2017	19.05.2017	20	21	4		MS1					
VW100005	56384	H18	14.08.2017	08.09.2017			299			14.08.2017	08.09.2017	33	40	25		MS1					
VW100006	56095	H18	14.11.2017	08.12.2017			299			14.11.2017	08.12.2017	46	2	91		MS1					
VW100007	57647	H18	18.12.2017	27.04.2018			170			18.12.2017	27.04.2018	4	14	91		MS1					
VW100008	57979	H18	01.02.2018	06.07.2018			320			01.02.2018	06.07.2018	1	10	146		MS2					
VW100009	56952	H18	02.01.2018	16.02.2018			320			02.01.2018	16.02.2018	2	11	30		MS2					
VW100010	57276	MS2	22.01.2018	23.02.2018			310			22.01.2018	23.02.2018	4	13	32		MS2					
VW100011	56952	H18	02.02.2018	07.03.2018			320			02.02.2018	07.03.2018	5	15	33		MS2					
VW100012	57276	MS2	02.02.2018	15.03.2018			310			02.02.2018	15.03.2018	5	15	33		MS2					
VW100013	57277	OSP	05.02.2018	21.09.2018			100			05.02.2018	21.09.2018	6	18	238		OSP					
VW100014	56952	OSP	08.02.2018	27.04.2018			320			08.02.2018	27.04.2018	5	15	85		OSP					
VW100015	56952	OSP	08.02.2018	27.04.2018			320			08.02.2018	27.04.2018	5	15	85		OSP					
VW100016	57481	MS1	09.02.2018	25.05.2018			350			09.02.2018	25.05.2018	6	16	105		MS1					
VW100017	57276	MS2	12.02.2018	16.03.2018			310			12.02.2018	16.03.2018	7	16	28		MS2					
VW100018	56952	OSP	12.02.2018	27.04.2018			320			12.02.2018	27.04.2018	7	17	14		OSP					
VW100019	57481	MS2	19.02.2018	06.04.2018			310			19.02.2018	06.04.2018	8	18	45		MS2					
VW100020	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100021	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100022	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100023	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100024	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100025	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100026	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100027	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100028	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100029	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100030	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100031	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100032	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100033	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100034	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100035	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100036	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100037	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100038	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100039	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100040	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100041	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100042	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100043	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100044	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100045	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100046	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100047	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100048	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100049	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100050	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100051	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100052	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100053	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100054	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100055	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100056	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100057	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100058	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100059	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100060	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100061	57481	MS1	19.02.2018	23.03.2018			350			19.02.2018	23.03.2018	8	18	31		MS1					
VW100062	57481	MS1	19.02.2018	23.03.20																	

Figure 4. (Color online) The Utilization of Personnel and Hoisting Platforms Is Reported Using Utilization Diagrams Individually for the Different Organizational Units (OUs) in the Decision Support System (DSS)



Source. Used with permission from Microsoft.

Note. Colors are used to differentiate between the resource types. Available and utilized hoisting platform capacity is illustrated on the right-side scale using lines. Personnel utilization is illustrated on the left-side scale differentiated by completed orders, started orders, and planned orders using bars. Diagrams are generated using Visual Basic functionality. Data illustrated are generated arbitrarily because of confidentiality reasons.

Compared with the BIP, the DSS picks orders with a similar ratio of hours of the assembly to its duration based on the planning rule implemented in the constructive method. The improvement method generally selects more and shorter orders.

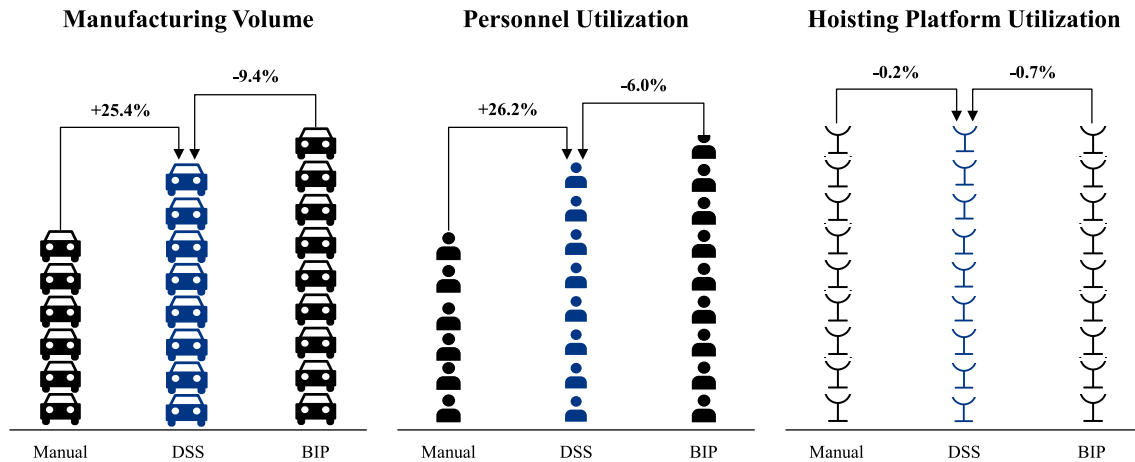
Based on the obtained results, we estimated the cost savings potential for the VPC at up to €2,000,000 per year, which would be paid to external manufacturing service providers otherwise. Thus, we attribute the full savings potential to the reduced amount of outsourcing activities. Although the number looked quite impressive, we communicated that it is subject to the extent to which the VPC manually refines the plans based on the decision makers' preferences (R.2). Furthermore, the extent of dynamic effects to be considered in the planning approach (R.3) may negatively affect the quality of the resulting feasible plans.

Beyond the improved quality of the plans and the resulting cost savings potential, the application of the DSS exhibits further benefits compared with the BIP and manual planning. Although all three approaches can handle more than 500 orders to be scheduled, which is entirely sufficient for the VPC, only the DSS allows assigning the orders to a reasonable number of OUs within a short time. As in manual planning,

30 different OUs are modeled in the DSS, enabling the consideration of 27 external manufacturing service providers working for the VPC (Figure 4). Although the effort of the manual planner is roughly five hours a day, the DSS needs, on average, 356 seconds (min: 246 seconds, max: 494 seconds) to determine a feasible plan for each of the considered instances. Similar solution durations are obtained for the BIP (mean: 271 seconds, min: 139 seconds, max: 445 seconds). The BIP, however, is limited to just one internal and one external organizational unit and therefore suffers from limited usability.

Regarding daily use in the VPC, all three approaches can be considered to be easily adaptable to change. Mainly, this holds for a short-term adjustment of the considered orders and a midterm adjustment of the personnel and hoisting platform capacity, which are the most likely aspects underlying change. However, the approaches substantially differ in terms of their ease of use. Manual planning heavily relies on expert knowledge of the planner. Because of the high complexity and effort to manage all necessary data and determine feasible plans, nobody else can act in place of the responsible planner. For the BIP, expert knowledge is also required because the

Figure 5. (Color online) Comparison of the Results of Our Decision Support System (DSS) with Manual Planning and the Results of Our Prototype Based on Binary Integer Programming (BIP) in Terms of Obtained Mean Values for Internal Manufacturing Volume, Personnel Utilization, and Hoisting Platform Utilization over All 52 Instances



Note. Levels are scaled arbitrarily because of confidentiality reasons.

planning approach is implemented in Java and makes use of CPLEX as a solver. Only members of the academic team have this knowledge—none of the employees of the VPC do. In contrast, the application of the DSS is hands-on thanks to its implementation in Microsoft Excel as well as its interfaces to the company-wide ERP system and the comprehensive planning functionality realized with the help of Visual Basic. For these reasons, the tool proved to be easily applicable for several employees of the VPC after a brief introduction, which allows them to cover for the responsible planner in case of absence.

Test Implementation, Impact, and Rollout

In the next step, we agreed with the management of the VPC on a pilot test in which our planning tool was fed with ERP data to generate schedules for 60 days with a rolling planning horizon. The resulting plans were compared twice a week with the worksite planners. These meetings, on the one hand, served to validate the generated schedules and to build confidence in the DSS. On the other hand, we gave tutorials on how to use the DSS, and specific instructions were made available in an Excel sheet.

During the two-month pilot test, we experienced some challenges as most of the logic of the DSS is implemented in Visual Basic and works in the background. To solve this, we invested much time in explaining the theory behind the model, the underlying assumptions, and the implemented planning rules. This helped the members of the VPC, who were not familiar with OR/MS methods, to get a better understanding of our planning approach.

At the end of the pilot test, we were able to convince the worksite planners and also the managers at the VPC that our tool can be used for capacity

scheduling to support everyday planning. As expected, the generated plans exhibited excellent quality and significantly increased the utilization of personnel and, thus, the internal manufacturing volume. However, they needed to be manually refined owing to specific corporate requirements and preferences mentioned above, resulting in a less efficient allocation of orders to internal and external OUs. As a consequence of these adjustments, the VPC estimated the cost savings to lie in the six-digit euro range per annum.

In addition to these cost savings, a further substantial benefit resulted from a decreased internal planning effort, which gives the VPC more time to concentrate on the continuous improvement of their planning processes. Mainly, this holds for the planner responsible for capacity scheduling at the VPC. Whereas formerly it took this person roughly five hours a day to determine feasible plans, she can now concentrate on tasks of higher quality. This has resulted in considerably improved data management and data transparency, making the application of the DSS even more valuable. The deployment of the tool therefore did not lead to any cost savings in personnel but did lead to more effective utilization of the planner.

A further positive impact related to the rollout of the DSS is the improved maintenance of the planning data by the responsible employees. Because we based the planning on ERP data, higher data transparency and improved data control mechanisms were established. Therefore, employees have gained a common understanding of the importance of data maintenance. Based on the tool, they can directly perceive what their data are used for and how bad data negatively influence planning quality.

Enablers of Project Success

During the project, we faced several challenges in developing the DSS, rolling it out at the VPC, and convincing all stakeholders of our ideas and the approach taken. In this context, we figured out the following enablers that heavily contributed to the success of the project; these enablers might serve as essential lessons learned for executives and modelers.

The first significant milestone in the cooperation between the VPC and these authors is a relationship of mutual trust and the general openness of the VPC to OR/MS methods developed by academia. This was first established well in advance of the project. In a series of workshops with managers of the VPC, we discussed a variety of particular planning problems. For a selection of these planning problems, we presented state-of-the-art solutions from academia and played several customized business games. For example, we played the “beer distribution game” to introduce the bullwhip effect and to sensitize the importance of coordination of corporate processes (Sternan 1989). Also, we asked the managers to manually determine solutions to a simple (S.2.2) *production system design* problem we developed. Subsequently, we presented an optimization model that outperformed the managers’ solutions regarding both quality and time. This way, the managers experienced the limitations of manual planning approaches in complex decision situations and the potential of OR/MS methods as a suitable approach to overcome these limitations.

Because of these workshops, we gained the valuable support of the management of the VPC from the beginning, facilitating a successful composition and collaboration of the project team and the deployment of effective project management, and gained access to all critical data sources. The project team was composed of the head of VPC’s assembly department, the planner responsible for capacity scheduling, an assembly employee, the head of data acquisition, an employee of the IT department, and the authors of this contribution. The assembly employee helped us considerably to understand all processes and requirements based on his comprehensive and longstanding experience in assembling prototype vehicles. The IT employee was mainly responsible for database queries in consultation with further team members. This fruitful cooperation between the planning department, the IT department, and academia was of the utmost importance for project success and would not have been possible without the full support of management.

Concerning the project management, we decided to utilize an agile procedure following the Scrum framework well known from software development projects. To this end, the work was broken down into

small prioritized tasks to be completed within short time intervals. Moreover, intensive communication was supported among all team members about the project status, the need for modifications, and the next steps. By that, we enabled close cooperation as well as quick response and high adaptability to changing requirements, resulting in a perfect fit for the tool and high acceptance among all stakeholders during the course of the project.

We identified quick achievements to be equally crucial for the success of the project. At the beginning of the project, especially the employees concerned with capacity scheduling were skeptical about our model-based approach because the tool interferes with and partially restricts their daily business routines. In this context, quick achievements helped us to convince the employees of the immediate benefits resulting from the application of the novel planning tool. The manual planner mainly benefits from the possibility of concentrating on tasks of higher quality, as described earlier. Moreover, the work of the manual planner and the team’s work is supported by a good overview of all relevant data, which are in line with the ERP data, and a hands-on and meaningful visualization of key metrics such as the utilization of personnel and platforms of a specific OU. These features also allow for quick achievements for the management, immediately improving their reporting tasks on key metrics such as assembly durations and the number of orders assembled.

Conclusions

The managers of the VPC had been well aware that the utilization of their manufacturing personnel could be improved to reduce costs for external manufacturing services. They could not estimate the full cost-saving potential associated with improved capacity scheduling. Given the complexity of the planning problem at hand and the variety of requirements and constraints from industrial practice that needed to be taken into account, they asked the authors of the contribution at hand for support. The outcome of this collaboration is a well-suited decision support system for capacity scheduling based on OR/MS methods that has proved its potential for better utilization of internal resources and a reduction of outsourcing activities.

Although we were able to formulate a BIP prototype for the capacity scheduling problem, it would not have been possible to utilize this within an adequate DSS. This is mainly because of the unjustifiable aggregation of OUs toward one internal and one external OU, which was required to achieve adequate computational efforts. Indeed, developing a spreadsheet-based solution using a heuristic approach ensured the acceptance of the DSS by the worksite planners and managers. Even though this approach

does not yield optimal solutions, it is easy to understand and operate, is well suited for integration in the existing systems, and realizes a significant *proportion of the illustrated potential* for improvement.

Because of the documented applicability of the DSS for industrial planning purposes at the VPC, it was decided to transfer our considerations into neighboring departments in the next project phase. Currently, we are working to improve capacity scheduling in the logistics department. This way, interdependencies between assembly and logistics can be taken into account, with additional potential for improving the utilization of internal resources by a better match of material demand and supply. Moreover, we started discussions with a department responsible for prototype vehicle management on how to utilize OR/MS methods in order to reduce the total number of prototype vehicles required for testing purposes.

Acknowledgments

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Appendix Notation

The initial evaluation of the inherent potential of the planning problem under consideration is based on binary integer programming. In the following, we provide the notation of sets and parameters.

We define the following sets and subsets:

- P : set of orders, index $i \in P = \{1, \dots, n\}$.
- $P_{revise} \subseteq P$: subset of orders that may be reassigned by the decision makers.
- $P_{freeze} \subseteq P$: subset of orders that may not be reassigned.
- K : set of organizational units, index $k \in K = \{1, \dots, \bar{k}\}$.
- $K_{internal} \subseteq K$: subset of internal organizational units.
- $K_{external} \subseteq K$: subset of external organizational units.
- G : set of resource types, index $g \in G = \{1, \dots, \bar{g}\}$.
- T : Set of time periods, indices $s, e \in T = \{1, \dots, \bar{t}\}$.
- A : Set of feasible assembly durations in periods, indices $l, d \in A = \{1, \dots, \bar{d}\}$.

We use the following parameters:

- V_i : assembly hours required for order $i \in P$.
- r_i : release date period of order $i \in P$.
- d_i : due date period of order $i \in P$.
- p_i : minimum duration of order $i \in P$ in periods.
- OU_i : organizational unit to which order $i \in P_{freeze}$ is assigned.
- ζ_{lgld} : units of resource type $g \in G$ demanded by order $i \in P$ in its assembly period $l \in A$, where i is assembled in $d \in A$ periods with $l \leq d$.
- c_{gkt} : available capacity units of resource type $g \in G$ in organizational unit $k \in K$ and period $t \in T$.

Optimization Model

To model the capacity scheduling problem under consideration, we consider the following decision variables.

- $\alpha_i = \begin{cases} 1, & \text{if order } i \in P \text{ is produced internally;} \\ 0, & \text{else.} \end{cases}$
- $x_{ikse} = \begin{cases} 1, & \text{if order } i \in P \text{ is assigned to organizational} \\ & \text{unit } k \in K, \text{ for start period } s \in T \text{ and end} \\ & \text{period } e \in T; \\ 0, & \text{else.} \end{cases}$

We determine the allocation and scheduling of the orders by solving the following binary integer programming model:

$$\max \sum_{i=1}^n \alpha_i \cdot V_i \quad (\text{A.1})$$

subject to

$$\sum_{k \in K} \sum_{s=1}^{\bar{s}} \sum_{e=1}^{\bar{e}} x_{ikse} = 1 \quad \forall i \in P. \quad (\text{A.2})$$

$$\sum_{k \in K} \sum_{s=1}^{\bar{s}} \sum_{e=1}^{\bar{e}} s \cdot x_{ikse} \geq r_i \quad \forall i \in P_{revise}. \quad (\text{A.3})$$

$$\sum_{k \in K} \sum_{s=1}^{\bar{s}} \sum_{e=1}^{\bar{e}} e \cdot x_{ikse} \leq d_i \quad \forall i \in P_{revise}. \quad (\text{A.4})$$

$$\sum_{k \in K} \sum_{s=1}^{\bar{s}} \sum_{e=1}^{\bar{e}} (e - s + 1) \cdot x_{ikse} \geq p_i \quad \forall i \in P_{revise}. \quad (\text{A.5})$$

$$\sum_{k \in K_{internal}} \sum_{s=1}^{\bar{s}} \sum_{e=1}^{\bar{e}} x_{ikse} = \alpha_i \quad \forall i \in P. \quad (\text{A.6})$$

$$\sum_{i=1}^n \sum_{s=1}^{\bar{s}} \sum_{e=t}^{\bar{e}} x_{ikse} \cdot \zeta_{i,g,t-s+1,e-s+1} \leq c_{gkt} \quad \forall g \in G, k \in K, t \in T. \quad (\text{A.7})$$

$$x_i \text{OU}_i r_i d_i = 1 \quad \forall i \in P_{freeze}. \quad (\text{A.8})$$

$$\alpha_i \in \{0,1\} \quad \forall i \in P. \quad (\text{A.9})$$

$$x_{ikse} \in \{0,1\} \quad \forall i \in P, k \in K, s, e \in T. \quad (\text{A.10})$$

This binary integer programming model maximizes the overall manufacturing hours produced internally, which is associated with the orders allocated to internal organizational units. Whether an order $i \in P$ is allocated to an internal organizational unit is denoted in binary variables α_i (A.1). The binary decision variables x_{ikse} encode all relevant information on each order. Constraints (A.2) ensure that order $i \in P$ is assigned to exactly one organizational unit $k \in K$, for start period $s \in T$ and completion period $e \in T$. A release date period r_i and a due date period d_i are associated with each order $i \in P$. Constraints (A.3) ensure that each order must not start before its release date period. Constraints (A.4) denote that each order must be completed prior to or on its due date period. Each order is associated with a minimum duration of p_i periods. Compliance of the chosen start and end periods with the minimum duration is observed by constraints (A.5). Constraints (A.6) define variables α_i such that $\alpha_i = 1$ if order $i \in P$ is assigned to an internal organizational unit; $\alpha_i = 0$, otherwise. The available resource capacities must not be exceeded in any organizational unit or period. This is guaranteed by constraints (A.7). Orders with start of assembly realized in

Pseudocode of the Constructive Method

```
// distinguish between started, finalized, and future orders
For Each order  $x$ 
    If assembly of  $x$  has finalized Then
        Assign  $x$  to set of finalized orders  $S_f$ .
    Else If assembly of  $x$  has started Then
        Assign  $x$  to set of started orders  $S_s$ .
        Assign and fix start date and OU of  $x$  as realized, assume end date as provided in ERP.
        Reserve remaining capacity requirements.
    Else
        Assign  $x$  to set of terminable orders  $S_t$ .
    End If
Next
// compute the initial assignment of terminable orders
For Each  $x$  in  $S_t$ 
    Assign planned start and end dates of  $x$  as given in ERP.
    If planned OU of  $x$  is given in ERP Then
        Assign  $x$  to given OU.
    Else
        Assign  $x$  to decision maker's preferred OU.
    End If
Next
// reallocation of orders among internal OUs to balance capacity overload
For Each period  $t$  in planning horizon
    For Each internal  $OU_1$ 
        For Each internal  $OU_2 \neq OU_1$ 
            If personnel or hoisting platforms overloaded in  $OU_1$  and  $t$  and idle personnel and hoisting
            platform capacities in  $OU_2$  and  $t$  Then
                For Each  $x$  in  $S_t$ 
                    If  $x$  is assigned to  $OU_1$  and planned start date of  $x < t$  and planned end date of  $x > t$ 
                    and OU of  $x$  is not fixed and  $OU_2$  is not taboo for  $x$  Then
                        Add  $x$  to temporary set  $S_{temporary}$ .
                    End If
                Next
                While idle personnel and hoisting platform capacities in  $OU_2$  and  $t$ 
                    Reassign order  $x \in S_{temporary}$  with the highest hourly density to  $OU_2$ .
                    Remove  $x$  from  $S_{temporary}$ .
                End While
                Clear  $S_{temporary}$ .
            End If
        Next
    Next
Next
// drop orders until assignments are compliant with capacities in any internal OU and period
For Each period  $t$  in planning horizon
    For Each internal  $OU_1$ 
        If personnel or hoisting platforms overloaded in  $OU_1$  and  $t$  Then
            For Each  $x$  in  $S_t$ 
                If  $x$  is assigned to  $OU_1$  and planned start date of  $x < t$  and planned end date of  $x > t$  and
                OU of  $x$  is not fixed and  $x$  is not forced to internal assembly and outsourcing lead time
                is respected
                Then
                    Add  $x$  to temporary set  $S_{temporary}$ .
                End If
            Next
            While personnel or hoisting platforms overloaded in  $OU_1$  and  $t$ 
                Reserve order  $x \in S_{temporary}$  with the lowest hourly density for subcontracting.
                Remove  $x$  from  $S_{temporary}$ .
            End While
            Clear  $S_{temporary}$ .
        End If
    Next
Next
```


Pseudocode of the Improvement Method

// compute relevant orders subject to improvement

For Each x **in** S_t **If** x is reserved for outsourcing **Then**Add x to temporary set $S_{reserved}$.**Else If** x is assigned to external OU **Then**Add x to temporary set $S_{external}$.**End If****Next**

// preferential improvement: re-insource orders reserved for outsourcing (but not yet assigned to particular OU)

For Each x **in** $S_{reserved}$ **For Each** internal OU_1 **For scenario** = 1 **to** 21**Case** 1: Increase originally planned start date by 1.**Case** 7: Increase originally planned start date by 7.**Case** 8: Decrease originally planned end date by 1.**Case** 14: Decrease originally planned end date by 7.**Case** 15: Increase originally planned start date and decrease originally planned end date by 1.**Case** 21: Increase originally planned start date and decrease originally planned end date by 7.**If** planned end date of x – planned start date of $x > 0$ **and** assignment of x to OU_1 is compliant with hoisting platform and personnel capacities **Then**Assign x to OU_1 .Continue with next x .**End If****Next scenario****Next****Next**

// subordinate improvement: re-insource orders with yet assigned external OU

For Each OU_1 to be re-insourced prioritized**For Each** x **in** $S_{external}$ **If** x is assigned to OU_1 **Then****For Each** internal OU_2 **For scenario** = 1 **to** 21**Case** 1: Increase originally planned start date by 1.**Case** 7: Increase originally planned start date by 7.**Case** 8: Decrease originally planned end date by 1.**Case** 14: Decrease originally planned end date by 7.**Case** 15: Increase originally planned start date and decrease originally planned end date by 1.**Case** 21: Increase originally planned start date and decrease originally planned end date by 7.**If** planned end date of x – planned start date of $x > 0$ **and** assignment of x to OU_2 is compliant with hoisting platform and personnel capacities **and** OU_2 is not taboo for x **and** outsourcing lead time is respected **Then**Assign x to OU_2 .Continue with next x .**End If****Next scenario****Next****End If****Next****Next**

prior periods must not be reassigned to a different OU or end period by constraints (A.8). Constraints (A.9)–(A.10) serve to define the domain of the decision variables.

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Verification Letter

Peter Bartels, Director, Pre-Production Center, Volkswagen AG, 38436 Wolfsburg, Germany, writes:

“I am writing to you on behalf of the Pre-Production Center of Volkswagen AG in Wolfsburg, Germany, to confirm the application of OR/MS and its results as reported by Christian Weckenborg, Karsten Kieckhäfer, Thomas S. Spengler, and Patricia Bernstein.

“The decision support system developed by the team of Mr. Spengler accurately depicts our needs: increase in personnel utilization by advanced planning logics along with more accurate and robust allocation of personnel, and decrease in planning effort due to automated planning. By using the developed decision support system, we expect an annual reduction of costs in the six-digit euro range due to fewer outsourcing activities and decreased internal planning effort.

“We are highly satisfied with the achievements of Mr. Spengler’s team. Their results motivate us to continuously collaborate with university researchers in the OR/MS field on innovative topics such as the one submitted to your journal. We are currently expanding our collaboration with Mr. Spengler’s team and work on additional promising topics in order to further improve the planning processes at the Pre-Production Center.”

Christian Weckenborg is a PhD student at the Chair of Production and Logistics at the Institute of Automotive

Management and Industrial Production at Technische Universität Braunschweig, Germany. He holds an MSc degree in industrial engineering with majors in operations management and economics. His research interests are in the design and control of manufacturing systems, focusing on mixed-integer modeling and optimization.

Karsten Kieckhäfer is a professor of production and logistics management at FernUniversität in Hagen, Germany. He holds a diploma in industrial engineering and a PhD in business administration, both from Technische Universität Braunschweig, Germany. His research is mainly centered on modeling and analyzing problems of production, logistics, and sustainability management. His work has been published in *Transportation Science* and *European Journal of Operational Research*, among others.

Thomas S. Spengler is a professor of production and logistics management and director of the Institute of Automotive Management and Industrial Production at Technische Universität Braunschweig, Germany. His research interests cover the conceptual development and implementation of techno-economic models for decision support. His work has been published in a variety of academic journals, including *Transportation Science*, *European Journal of Operational Research*, and *Journal of Cleaner Production*.

Patricia Bernstein is the head of the manufacturing department of the Pre-Production Center of Volkswagen in Wolfsburg, Germany. She is responsible for the logistics and manufacturing of the entire prototype assembly of the Volkswagen brand and accounts for the timely completion of approximately 4,000 prototype vehicles annually. She received her MSc in international business from Maastricht University, Netherlands.