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RESEARCH ARTICLE

Evaluating volume flexibility instruments by design-of-experiments methods

Matthias Walter[a]*, Thomas Sommer-Dittrich[b] and Jürgen Zimmermann[a]

[a]*Department for Operations Research, Clausthal University of Technology, Germany*; [b]*Research Centre Ulm, Daimler AG, Germany*

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Volume flexibility enables firms to cope with demand fluctuations but being flexible incurs costs. Hence, firms are challenged to choose economically adequate volume flexibility instruments. To tackle this challenge we present a three-step approach comprising a preliminary analysis and a model of a production system that takes into account different volume flexibility instruments. The model is solved minimizing production costs. For a multidimensional sensitivity analysis we use design-of-experiments methods in the third step to assess the impact of the instruments and their interactions. In a case study we apply our approach to a real life NP-hard production planning problem of a car manufacturer that is solved by approximate dynamic programming. Using design-of-experiments methods we gain managerial insights into the value of different combinations of volume flexibility instruments.

Keywords: volume flexibility; design-of-experiments methods; aggregate production planning

1. Introduction

Demand fluctuations are a concern for manufacturing firms as they — no matter whether they are certain or random fluctuations — severely impede smooth production and distribution execution. Volume flexibility is one answer to the challenge imposed on a firm by demand variability. Browne *et al.* (1984, p. 115) define volume flexibility as the capability to operate profitably at different output levels. Similarly, Gerwin (1987, p. 39) relates volume flexibility to the ability to smoothly change the aggregate output of production. Volume flexibility instruments are options of a firm's management to adjust the output level within the planning horizon. Examples for such instruments are additional shifts on Saturdays, hiring as well as firing temporary workers, short time, and changing param-

*Corresponding author. Email: matthias.walter@tu-clausthal.de

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eters of the production system, e.g. altering the cycle time in assembly line production systems.

After having investigated three manufacturing firms in a case study approach and having conducted a field survey Jack and Raturi (2002) concluded 'that volume flexibility has a positive impact on both delivery and financial performance.' Since it is known for long that flexibility is not a free good (cf. Stigler 1939, p. 311) the result of Jack and Raturi poses the following question to a firm: Which volume flexibility instruments should be selected and implemented? This question may be broken down into three research questions:

1. How large is the financial benefit of a volume flexibility instrument?
2. In which way do several volume flexibility instruments interact?
3. How sensitive are volume flexibility instruments to different demand fluctuations?

Although flexibility in general and volume flexibility in particular have been emphasized in academic research for more than 80 years (cf. Kaluza and Blecker 2005, p. 6) a clear and comprehensive theoretical framework is still missing and insights have not been diffused widely into practice because of the 'fuzzy and multidimensional nature of flexibility as a construct' (de Treville *et al.* 2007, p. 335). It is the aim of this paper to provide guidance for firms selecting volume flexibility instruments.

Usually, a firm has some volume flexibility instruments at its disposal. Consider a firm that can choose between three different shift models so far. A shift model defines whether only an early shift or even a late or a night shift have to work and specifies at which days of the week and how many hours a shift has to work. The firm thinks about negotiating an additional shift model with the workers' union. Before engaging in the negotiation process and offering compensation the firm must have an good estimate of how much it will save if the fourth shift model can be used. Consequently, the heart of our method is a model that represents the production process and incorporates all the volume flexibility instruments, e.g. the shift models and the hours bank — also known as working time account — when dealing with volume flexibility at the plant level. The model accounts for the relevant cost arising when production is executed given a production plan which specifies a shift model, extra hours, employments and other options for each period. Note that there is no unique model, as a model depends on the considered firm and situation. We present an exemplary model in our case study.

Coming back to the firm considering to opt for a fourth shift model, the valuation of the fourth shift model works in principle as follows. We optimize the production plan with respect to the restrictions of the model two times in separate runs. In the first run we only take into account the three shift models available to the firm so far. In the second run we optimize the production plan under the assumption that the fourth shift model is available. The difference in cost between the two production plans obtained from optimization reflects the value of the additional shift model.

The firm might also wish to raise the limit of unpaid extra hours that can be accumulated in the hours bank in times of high demand. Instead of paying for overtime the hours bank enables the firm to compensate for extra hours by shorter working times in periods of low demand while a constant weekly wage is paid independently of the actual working time. There is a wide spectrum of possible values for the upper limit, e.g. 100, 150 or 200 hours. Furthermore, there may exist an interaction effect between the number of shift models and the limit on accumulated extra hours: The fourth shift model may feature long working hours and may hence only be of advantage when a high limit on accumulated extra hours is chosen. Our method applies design-of-experiment methods to handle

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the myriad of possible specifications of a single volume flexibility instrument and the multitude of combinations of different instruments. The analysis is framed in a factorial design of experiment that allows us to scrutinize interactions between instruments.

As volume flexibility is one answer amongst others to cope with demand fluctuations we briefly discuss why volume flexibility is favourable in **Section 2**. In **Section 3** we clarify the difference between measurement and valuation of volume flexibility and review related literature. In **Section 4** we describe our method which we subsequently apply in **Section 5** in a case study conducted with our industry partner, a major European car manufacturer. For an assembly line we present a model that accounts for five volume flexibility instruments which are valued by design-of-experiments-methods. While the case study is based on known demand fluctuations, an extension of our approach to uncertain demand forecasts is outlined in **Section 6**. A summary and an outlook conclude this paper in **Section 7**.

2. The need for volume flexibility

In order to cope with demand variability it is crucial to recall the reasons for and the patterns of this phenomenon. Quite often seasonal fluctuations in demand are a characteristic of a product. Think of scarves that are rather sold in autumn and winter than in hot summer months. A second major cause for variable demand for a product is the life cycle of the product itself, i.e. the typical rise and fall of the demand curve between product launch and market exit. Third, the business cycle causes fluctuations in aggregate demand for a product, and hence affects the number of orders arriving at every single producer. Impacts stemming from the three sources mentioned so far can be forecasted to some extent. However, there is a fourth reason for demand volatility that comprises short-term effects such as price shocks, tax cuts and hikes, devastating test reports or sales promotion efforts of competitors. Those effects do not reveal a typical pattern or occur on a regular basis and are therefore difficult to anticipate.

Bearing these causes in mind a firm may manage both certain and random demand variability in four different ways. At first, a firm might operate at a constant output level and meet excess demand by inventory or with delay when backlogs occur. Secondly, a firm could try to eliminate demand fluctuations by engaging in marketing activities applying pricing and promotion policies. This idea stems from the concept to reduce or even eliminate the need for flexibility by controlling the environment (cf. Simon 1977, pp. 25 et seqq.). However, both strategies have a limited scope and do not fulfil customer needs. Thirdly, a firm producing several products could balance its product portfolio in such a way that the demand fluctuations of the single commodities cause almost constant total capacity requirements. This strategy necessitates product mix flexibility, which is defined as the ability to produce different items at the same time and at changing ratios over time (cf. Gerwin 1987, p. 39, and Gottschalk *et al.* 2004). Though, if a firm manages its portfolio primary for the purpose of constant capacity usage it may ignore its strengths and fail to meet customer needs.

The fourth way to encounter demand fluctuations is to use volume flexibility instruments in order to adjust capacity to demand. Establishing volume flexibility instruments basically means to reduce fixed costs. Hence, if the firm adjusts its capacity upwards this action is reversible in short time without loss and if the firm decreases its capacity by say 10% the costs incurred so far will fall by almost 10%. Faißt (1992) analyses volume flexibility instruments that are related to workforce flexibility. Askar *et al.* (2007) state

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examples for volume flexibility instruments applicable at the plant level.

The shortcomings of the three alternatives mentioned first make volume flexibility a favourable feature. Furthermore, the benefit of volume flexibility rose in recent years. Over the last decades demand became more and more volatile due to faster technological progress and quicker changing customer preferences as a consequence of globally interlinked societies. This development called for a higher degree of volume flexibility and was reflected in the outcomes of negotiations between employers and employees. Ozaki (1999) for example summarizes studies which cover countries across the whole world that give impressive evidence for the increasing flexibility in employment and working time. Already in the mid-eighties manufacturing companies made an effort to boost their capacity adjustment capabilities (cf. van Deelen 1989). Considering European plants of car manufactures Lehndorf (2001) gives empirical evidence for the increase of volume flexibility. This development is accompanied by a transition from build-to-stock to mass customization or even build-to-order production in some industry lines (cf. Feitzinger and Lee 1997, and Sharma and LaPlaca 2005, respectively). Holweg and Pil (2001) stress that a build-to-order strategy will fail without volume flexibility. Salvador *et al.* (2007) also claim that, besides mix flexibility, volume flexibility is a prerequisite for a successful build-to-order strategy.[1]

Altogether, the developments expose firms to the situation to choose and establish appropriate volume flexibility instruments. The choice should be based on a valuation of volume flexibility instruments. This task is not easy as 'flexibility is a complex, multidimensional, and hard-to-capture concept' (Sethi and Sethi 1990, p. 289). We shed light on the issues related to flexibility, its measurement and valuation in the next section.

3. Flexibility: measurement and valuation issues

In this section we clarify the difference between measurement and valuation of flexibility after some general notations on flexibility.

Due to the complex nature of flexibility a large body of related literature exists. Flexibility has been approached by disciplines as economics, decision science, strategical management, and manufacturing management (cf. Upton 1995, p. 207). The latter discipline comes close to our perspective. For surveys within the field of manufacturing management we refer to Gupta and Goyal (1989), Sethi and Sethi (1990), and De Toni and Tonchia (1998). Even within one discipline there is lack of an univocal nomenclature and a unitary model of flexibility (cf. Sethi and Sethi 1990, p. 289). Thus, it is no surprise that Slack (1987) who interviewed managers found out that a comprehensive understanding of flexibility is scarce. However, de Groote (1994) provided a framework which could integrate previous models of flexibility and which is applicable in our case, too, as we will demonstrate later on.

Slack (1987) distinguishes two dimensions of flexibility, namely response and range flexibility. Response flexibility accounts for the time (and cost) needed to adjust to change, e.g. to adjust the output level. Range flexibility describes the range of states a system can adopt or — with a slightly different meaning — the variety of available alternatives for the adaptaption of the system to changes. Koste and Malhotra (1999, p. 78) point out the necessity not only to consider the total range or the total number of states a

[1] A noteworthy aspect of the qualitative empiric research of Salvador *et al.* (2007) is that the authors reveal side effects of steps intended to increase only mix or only volume flexibility. Those side effects can be conflicting or synergistic, i.e. promote one type of flexibility at the expense of the other or support both types.

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system can adopt but also the difference between the states. This difference has to be considered when flexibility is measured. In regard to valuing flexibility, this difference as well as the number of possible states may have no impact. Defining flexibility as the capability to adapt to change, **measuring flexibility** means to quantify this capability in terms of time, cost, and range. **Valuing flexibility**, in contrast, means to quantify the financial benefit of this capability, either ex post given historic data or ex ante given a set of realistic scenarios for the development of the firm's environment. To illustrate the distinction we consider a firm that exhibits some volume flexibility instruments. Measuring may certify the firm a high degree of volume flexibility when the instruments enable the firm to quickly adjust output levels over a wide range incurring only moderate costs. Nevertheless, this volume flexibility is not of any value to the firm if it operates in a stable environment where demand is almost constant. In the following we will have a closer look at measures and ways of valuation of volume flexibility.

There are different proposals for measuring volume flexibility (cf. Suarez et al. 1996). These proposals include the response as well as the range dimension and often refer to both dimensions (cf. Gerwin 1993, Koste and Malhotra 1999). Stigler (1939) introduced an ordinal measure to compare the volume flexibility of production systems: the flatter the average cost curve of a production system the more volume flexible the system is. Other measures were proposed by Azzone and Bertele (1987) and Son and Park (1987), for example. Gupta (1993) pointed out the difficulties in measuring flexibility and recommended the value of flexibility as a surrogate measure. A high value of flexibility for a firm indicates that its current flexibility is low and vice versa. Recently, Olivella et al. (2010) assessed working time flexibility, a component of volume flexibility, using three measures, one of them relating to the range dimension and another relating to the response dimension. As it seems there is no mutual consent in the literature. None of the measures proposed in literature including the synthetic ones leads the way. For our method we will take the response as well as the range dimension into account.

Gottschalk *et al.* (2004) propose the ratio of relative change in output to time needed for the change as a key figure to measure response flexibility on a time basis. A similar definition of a key figure can be given with respect to cost. The general definition of those key figures indicates the need for a detailed context-sensitive analysis. Such an analysis is a preliminary step of our method. Though, it is not our goal to get a precise measure. But the analysis helps us to incorporate the relevant aspects of an instrument into our model aimed at valuation.

In regard to valuing flexibility Kulatilaka and Marks (1988) distinguish the strategic value from the option value of flexibility. Whereas the former embodies power in negotiations the latter represents the benefit of adaptation to changing conditions which is the value we are interested in. Kulatilaka (1988) presented a stochastic dynamic programming model to maximize the expected net present value of uncertain cash flows. He applied the model to a system offering the flexibility instruments to postpone the initial investment, switch between two operating modes, and abandon the investment.

Wild (1995) evaluates in-plant agreements between employers and employees. The agreements differ from one another with respect to the characteristics of volume flexibility instruments, e.g. the number of shift models and the daily working times. He applies a stochastic dynamic programming model to solve a multi-objective optimization problem. One objective — termed volume flexibility — is to minimize the daily deviation of actual personnel capacity from required capacity to fulfil demand, another one is to minimize

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labor costs accrued for fix period wages, shift allowances and extra hours. His model can be used to value volume flexibility instruments by setting an aspiration level for the deviation objective and minimizing labour costs.

Khouja (1998) takes on the measure of Stigler (1939) to determine the optimal investment in volume flexibility. He assumes a quadratic average cost curve. Different degrees of volume flexibility are represented by a single parameter C_1. The costs accrued for creating a degree of volume flexibility described by C_1 are given by $g(C_1)$. An optimal C_1, i.e. an optimal degree of volume flexibility is determined using Monte Carlo simulation. Though, the method falls short of linking the variable C_1 and the cost function $g(C_1)$ to volume flexibility instruments.

Recently Baykasoğlu (2009) proposed an abstract generic measure of flexibility that incorporates volume flexibility besides other types of flexibility related to a system. Since the measure accounts for uncertainty in the environment of the system it actually is a valuation. Applying this way of valuation asks for heavy aggregation which does not seem suitable for instruments that are repeatedly used over time.

A methodical way to value flexibility instruments under complex conditions was presented by Barad and Even Sapir (2003) who analysed a military logistics problem that comprised combat units located at different positions. They expressed the value of flexibility as the probability that no shortage occurred at combat units during a replenishment cycle. Increasing the number of linkages between combat units enabling shipments between them was one instrument that supported flexibility. For each instrument Barad and Even Sapir considered a low and a high level, e.g. zero and three linkages between combat units. They calculated the shortage probability for all the combinations of levels of the instruments. Though only a small number of levels was investigated, they could draw conclusions in regard to the effect of instruments and their interactions because the combinations were chosen systematically using design-of-experiments methods. In the next section we will refine this method and explain the power of systematically varying the availability of instruments for an efficient analysis. An additional contribution of our paper is that we combine this method with optimization techniques.

4. Methodology

In this section we outline our method that determines the impact of different volume flexibility instruments and their interactions. We apply design-of-experiments methods that are widely used in the fields of science and engineering when the impact of several input variables on a response variable has to be estimated. Design-of-experiments methods are characterized by purposefully altering the input variables to gain maximum insight with a small number of experiments (cf. Montgomery 2005, Box *et al.* 2005, or Kleppmann 2006, for an application in logistics cf. Barad and Even Sapir 2003, for an application to in-store sales promotion cf. Bell *et al.* 2009).

Our input variables, also called factors, are the volume flexibility instruments introduced in Section 1, e.g. extra hours. For each factor only a small set of levels is considered, e.g. 100 (t_1) and 200 (t_2) hours for the upper limit of the hours bank. The response variable is the minimum total cost (π) incurred by the production schedule which exploits the factor levels. Coming back to the framework of de Groote (1994) mentioned in Section 3 and using his notation the benefit of a higher upper limit for the hours bank can be expressed as the difference $\pi(t_2, e) - \pi(t_1, e)$ where e denotes a particular environment, in our case it represents a particular demand. Each environment e is characterized by its

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level of diversity.

As a rule it is not possible to conduct an empiric analysis to value several volume flexibility instruments because time series data of a production system represent only a few degrees of volume flexibility and exhibit many variables not controlled for. Therefore, we conduct an experimental analysis that allows us to systematically vary factor levels for an arbitrary set of instruments. Since the time horizon has to span at least one year due to seasonal effects and the damage potential of improper factor levels is tremendous, experiments cannot be carried out on real production systems. Hence, we carry them out on a mathematical model that incorporates the relevant characteristics of the production system.

Design-of-experiments methods are typically used when a model of the considered system does not exist. ***They allow to identify the relevant factors affecting a dependent stochastic response variable. The identified factors are included in a preliminary model. In contrast, our method requires a complete model of the system including potentially relevant factors. Furthermore, such a complete model may lack stochastic response variables and may hence be deterministic, i.e. the numerical value of the response variable can be calculated given values for the factors.*** Nevertheless, design-of-experiments methods are still necessary to identify relevant factors because the complexity of the model inhibits a thorough understanding of the consequences of changes in factor levels. These changes are model parameter changes that are usually examined applying sensitivity analysis. And that is just what design-of-experiments methods provide by purposefully altering the input variables. Hence, a model and the experiments are the crucial features of our method that comprises three steps.

Step 1: Preliminary analysis

A preliminary analysis is required to model the production system including the volume flexibility instruments properly. At the outset volume flexibility instruments deemed to be suitable in the broadest sense ought to be selected. This preliminary selection of instruments should not be too restrictive as it is for the experiments to find out the really suitable ones. The analysis of instruments must comprise the response aspect as well as the range aspect. In regard to response flexibility costs are crucial. Note that 'fixed' costs are incurred for creating and maintaining volume flexibility and 'variable' costs arise when a volume flexibility instrument is utilized (cf. Eversheim and Schaefer 1980, pp. 246 et seq.). The range flexibility offered by a volume flexibility instrument can be expressed in product units and number of output levels and the step size. It has to be compared with the expected range of product demand and the expected levels of product demand, respectively. The analysis can enable us to judge whether a volume flexibility instrument should be taken into account or not. Though, an instrument should only be excluded if it is dominated by other instruments. This, however, is not easy to see due to the multitude of dimensions of flexibility and the complexity of single dimensions (e.g. of range flexibility). Hence, the main benefit of an detailed analysis is the basis it provides for the model needed for valuation.

Step 2: Model building and algorithm design

Next, a mathematical model has to be developed which captures the features of all the volume flexibility instruments. The decision variables of the model will fix the production

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schedule and determine the number of hires and fires etc., i.e. the decision variables will describe the usage of the volume flexibility instruments. The objective function has to consider all relevant costs that arise due to the use of instruments, e.g. paid extra hours, shift allowances and costs for changing the production speed. Furthermore, the objective function has to account for relevant costs incurred for excess capacity or loss of demand. As real life production systems can differ considerably from one another, a model has to match the special features of the considered production system.

The model type and the problem size will affect the choice of an algorithm. In case of a mixed integer program a branch-and-bound procedure or a heuristic method could be applied. In case of non-linear restrictions dynamic programming can be adequate. The task of the algorithm is to determine a feasible production schedule that minimizes the objective function.

Step 3: Applying design-of-experiments methods

First, we consider the 'simple case' where we obtain a linear optimization problem $\mathcal{P}$ and instrument levels are represented by right-hand sides b_i of restrictions $i \in \{1, \ldots, m\}$ (e.g. extra hours $\leq$ 100h). In such cases solving the dual problem $\overline{\mathcal{P}}$ may provide sufficient information. The optimal dual value corresponding to a restriction of $\mathcal{P}$, the so called shadow price, reflects the savings in production costs when the restrictions' right-hand side is increased by one unit (e.g. from 100h to 101h). For well-behaving linear problems the total effect of increasing two right-hand side values b_i is equal to the sum of the corresponding dual values because the second derivative of the dual objective function with respect to any combination of two b_i is equal to zero, i.e. interaction effects do not occur. For ill-behaving problems though, an interaction effect may exist for two instruments whose dual values are equal to zero. Furthermore, in regard to Lagrangian dual problems this approach does not work for a wide range of problems such as many mixed integer non-linear programs, where a duality gap exists.

For those cases we suggest a (fractional) factorial experiment. For this experiment we consider each instrument at two levels. The low level refers to the less flexible specification of an instrument. This specification can even represent the lack of the instrument. The high level refers to the more flexible state.

Experimental runs are conducted for different combinations of factor levels to determine the corresponding system response. In our case the experiment is conducted as a series of optimization runs. The minimum total cost of production obtained represents the response that is used to estimate factor effects. If the response is a stochastic variable due to stochastic input data such as an absenteeism rate, for each level combination several runs should be conducted to prevent erroneous conclusions. If the optimization problem is deterministic or the solution of replicated runs is too time-consuming only one response per level combination will be determined.

For the experiment we use the following notation: Let k be the number of factors and for each factor $i = 1, \ldots, k$ a low level $(-)$ and a high level $(+)$ are specified.

An one-factor-at-a-time experiment starts with a baseline run where all k factors are at their low level. Then k runs are executed in which the factors one by one are set to their high level while the other $k-1$ factors stick to the low level. The main drawback of an one-factor-at-a-time experiment is that interactions between instruments cannot be captured. To remedy this shortcoming factorial designs can be applied. In full factorial designs runs for every level combination are executed. In fractional factorial designs only a fraction of the complete set of runs is conducted where the runs are systematically

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chosen to yield as much information as possible. Full and fractional factorial designs facilitate a multidimensional sensitivity analysis.

As an example we consider an experiment with $k = 3$ factors A, B, and C, each at two levels. A full factorial design for these factors is called a $2^k = 2^3$ design that comprises eight runs for a single replicate as depicted in Table 1.

[Table 1 about here.]

The main effect of factor i is defined as the average difference in the response of runs with i at its high level and with i at its low level. When the run label represents the corresponding response value, the effect of factor A, denoted by A, is calculated as follows:

$$A = \frac{a + ab + ac + abc}{4} - \frac{(1) + b + c + bc}{4}$$

If significant interaction occurs the experimenter cannot rely on the main effect as it strongly depends on the level of other factors. To calculate an interaction effect consider factor A and B. Their interaction effect, denoted by AB, measures the difference between the effect of A when B is at its high level and the effect of A when B is at its low level. Note that AB also measures the difference between the effect of B when A is at its high level and the effect of B when A is at its low level.

$$AB = \frac{\frac{(abc-bc)+(ab-b)}{2} - \frac{(ac-c)+(a-(1))}{2}}{2} = \frac{\frac{(abc-ac)+(ab-a)}{2} - \frac{(bc-c)+(b-(1))}{2}}{2}$$

The interaction effect ABC describes the average difference between the interaction effect AB when C is at its high level and the effect AB when C is at its low level. The signs of the responses required to calculate interaction effects are shown in the corresponding columns of Table 1.

The relation between response value y and level combinations (x_A, x_B, x_C) can also be described by a multiple linear regression model, where $x_i = -1$ refers to the low level of factor i and $x_i = 1$ to the high level of factor i:

$$y = \beta_0 + \beta_1 x_A + \beta_2 x_B + \beta_3 x_C + \beta_4 x_A x_B + \beta_5 x_A x_C + \beta_6 x_B x_C + \beta_7 x_A x_B x_C + \epsilon$$

For discrete factors x_i is restricted to the values 1 and -1. For continuous factors it is bounded by these values assuming a linear relationship between the factor and the dependent variable y within the boundaries. The β-values have to be estimated from the observations y. β_0 can best be estimated by the average response of all runs, $\beta_1, \ldots, \beta_7$ are best estimated by the half of the corresponding effect, e.g. $\beta_4 = \frac{1}{2}AB$. In case of a stochastic response and replicated runs, ϵ represents the random error, i.e. the residual between the observed response and the response determined by the model. The residuals are also not equal to zero when high order interactions have been excluded from the model. This exclusion is common as interactions of more than two factors are very rare.

To identify significant effects we check if the hypothesis $\beta_1 = \ldots = \beta_7 = 0$ can be rejected. To accomplish this we use analysis of variance techniques where the total sum of squares, i.e. the total squared deviation of single responses from the mean response value, is partitioned into deviations that derive from effects and random deviations. A

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test value is defined by the ratio of the mean sum of squares related to effects to the mean sum of squares related to random error. The test value is compared to a quantile of the F distribution. If the mean deviation caused by an effect exceeds the mean random variability in responses to a certain degree, i.e. if the test value is greater than the quantile of the F distribution it can be concluded that this effect is significant.

As the number of runs required for a full factorial design grows exponentially in the number of factors it may be efficient to use fractional factorial designs. Having outlined our methodology we will apply it to volume flexibility instruments considered for a real life production system in the following section.

5. Case study

Our case study stems from the production system of a major European car manufacturer who assembles cars to fulfil orders and forecasted demand. We consider a paced assembly line with identical unit cycle time at every station. The model of the production system presented below is described in detail by Askar (2008). It is used for aggregate planning, i.e. for simultaneous planning of the workforce level and production volume in every period when demand is known or estimated in advance (cf. Nahmias 2005, pp. 108 et seqq.). Hence, we focus on the value of volume flexibility instruments with respect to predictable changes in demand. Afterwards we outline how the approach can be extended to the case of uncertain demand forecasts.

5.1. *Preliminary analysis*

To model the assembly process and to select volume flexibility instruments that may decrease production costs we have to identify the parameters that determine the output level and the related costs. Main parameters are the cycle time and the operating time. The latter is related to the workforce size as working time regulations have to be obeyed. We establish mathematical relations between the parameters and the output level on the one hand and between the parameters and the costs on the other hand. Each parameter is constrained by technical conditions or contracts that constitute the degree of volume flexibility (cf. Figure 1).

[Figure 1 about here.]

For the planning horizon of two years our industry partner considered two demand scenarios that reveal typical seasonal patterns of a car market (cf. Figure 2). The management identified five instruments $A, \ldots, E$ promising a cheaper production plan:

- A *Additional cycle time:* Instead of only one unit cycle time, instrument A offers the opportunity to switch to a smaller cycle time, i.e. to a higher production speed.
- B *Additional shift models:* In the inflexible state two 2-shift models and one 3-shift model are available. In the flexible state two additional 2-shift models and two additional 3-shift models are available offering distinguished operating and working times.
- C *Allowing more extra hours:* Instrument C increases the maximum number of accumulated extra hours from 100 to 200 hours.
- D *Longer balancing period:* In the flexible state the period within which the hours bank has to be balanced is expanded from one year to two years.
- E *Allowing more temporary workers:* The maximum share of temporary workers in the

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total workforce is increased from 10% to 15%.

[Figure 2 about here.]

Instruments A and B enable the car manufacturer to reach more output levels. Implementing both options might be redundant. Instruments C and D allow the firm to choose shift models with high working times for a longer time period without hiring additional workers to facilitate shifts off. Instrument E is supposed to decrease costs in two ways: The substitution effect of the instrument allows to replace some permanent workers by less paid temporary workers, the adaptation effect allows to better adjust workforce size, especially in downturns because permanent workers are usually not laid off.

To assess these five instruments a model is required that determines production costs depending on the availability of the instruments. We present such a model in the next section.

5.2. *Optimization model*

The notation used in the optimization model is summarised in Table 2. We consider the production of a car on a single model assembly line. The demand for all periods $t \in \mathcal{T}$ is given by D_t. The quantity produced in period t is denoted by P_t, it may differ from D_t to allow for smoothing. However, the cumulated deviation is limited by an upper bound UB_t and a lower bound LB_t (cf. Constraints (3)). The production volume is limited by the available capacity which depends on the unit cycle time $ct_t \in \mathcal{CT}$ and the operating time TO_{t,sm_t} that takes into account calendar information and the shift model $sm_t \in \mathcal{SM}$ selected for period t (Constr. (4)). A shift model sm defines which shift groups $SG \in \mathcal{SG}(sm)$ have to work. The set of shift groups comprises the early shift, the late shift, and the night shift. Additionally, a shift model specifies at which days and how many hours a shift group has to work and the required share of floaters, denoted by $ShF_{sm,SG}$, who replace workers during their breaks.

The required workforce level essentially depends on the number of stations necessary to assemble a car. Let TA_t denote the assembly time of a representative car, the required net workforce level $W^{net}_{t,SG}$ for shift group SG of shift model sm_t can be calculated from Constr. (5). Additional workers are required to compensate for workers who are on sick leave and vacation. When the share of absent workers is expressed by ShA_t, we obtain the total staff demand per period W^{total}_t from Constr. (6). The required number of workers in period t has to be met by permanent staff WP_t and temporary staff WT_t (Constr. (7)). Let the hirings and dismissals in period t be denoted by ΔWP_t for permanent workers and ΔWT_t for temporary workers. These decision variables allow to formulate flow Constr. (8) to link workforce levels of consecutive periods. For temporary workers the corresponding flow equations hold. Initial values for $t = 0$ are known. Due to limited training capacity the number of employments per period must not exceed the level $WCap_t$ (Constr. (9)). The share of temporary workers is limited to ensure a certain quality level and to comply with in-plant agreements reached with the staff association. Let ShT_t denote the maximum share of temporary workers. Then Constr. (10) have to hold for every period.

The actual total working time TW^{act}_t that is performed in period t is calculated from the actual working times of each shift group SG, denoted by $TW^{act}_{t,SG}$, taking into account the number of workers needed on the shop floor (Constr. (11)). Let TH^{contr}_t be the number of hours a worker is supposed to work per period according to his labor contract or a collective agreement. The total sum of contracted hours TW^{contr}_t in period t is calculated

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in consideration of the whole workforce except for those workers who are on vacation or on sick leave (Constr. (12)). In general, the actual working time does not equal the contracted hours. The difference is recorded on an hours bank where overtime and shifts off are averaged over the workforce. The hours bank balance is denoted by THB_t. Workers who are laid off at the beginning of period t are paid for their overtime. Consequently, their overtime is cancelled from the hours bank (Constr. (13)). Note that Constr. (13) are non-linear constraints. The recorded extra time must not exceed an upper limit THB_t^{UL} and after a certain period of time the hours bank has to be balanced, i.e. accumulated extra hours have to be compensated for by time off. Reducing overtime can be managed by hiring additional workers that allow shifts off for a part of the workforce. The upper limit as well as the regular balancing can be expressed by Constr. (14).

The costs C_t incurred in period t can be partitioned in variable production costs including costs for smoothing, C_t^{prod}, wages C_t^{wage}, allowances C_t^{allow}, e.g. for night and Saturday shifts, costs for compensating for overtime, C_t^{ovti}, and costs for changes C^{change} (Constr. (15)). Apart from variable unit production costs c_t^v we consider costs for earliness, c_t^e, and tardiness, c_t^t, i.e. costs for storing and shortage costs (Constr. (16)). When the wages are calculated we account for wage differences between permanent and temporary workers who earn $WageP_t$ and $WageT_t$, respectively (Constr. (17)). To derive the costs for shift allowances we distinguish several shift types $ST \in \mathcal{ST}(sm_t)$, namely early, late, night, and Saturday early shift. For each shift type ST the actual working hours $TW_{t,ST}$ are determined. Again, we discriminate between permanent and temporary workers. The shift allowances AP_{ST} and AT_{ST} for permanent workers and temporary workers, respectively, depend on the shift type ST (Constr. (18)). If the workforce level is reduced and extra hours were accumulated on the hours bank, the permanent and temporary workers who leave the company receive $WageP_t^{ovti}$ and $WageT_t^{ovti}$, respectively, for every extra hour (Constr. (19)). Finally, we consider costs that arise whenever a variable changes from period to period. These change costs comprise costs for altering the unit cycle time, $C_t^{change,ct}$, the shift model, $C_t^{change,sm}$, the number of shift groups, $C_t^{change,SG}$, and a change in the workforce level, $C_t^{change,W}$ (Constr. (20)). The decision variables are constrained in Constr. (21). The overall aim stated in the objective function (1) is to minimize the total discounted cost of production, y, for the planning horizon. Denoting the cost of capital by i the discounted costs y are defined in Constr. (2).

$$\text{Minimize} \quad y \tag{1}$$

subject to

$$y = \sum_{t \in \mathcal{T}} C_t \, (1+i)^{-t} \tag{2}$$

$$\sum_{\tau=1}^{t} D_\tau - LB_t \leq \sum_{\tau=1}^{t} P_\tau \leq \sum_{\tau=1}^{t} D_\tau + UB_t \qquad t \in \mathcal{T} \tag{3}$$

$$P_t \leq \frac{TO_{t,sm_t}}{ct_t} \qquad t \in \mathcal{T} \tag{4}$$

$$W_{t,SG}^{net} = \frac{TA_t}{ct_t} \, (1 + ShF_{sm_t,SG}) \qquad SG \in \mathcal{SG}(sm_t), \quad t \in \mathcal{T} \tag{5}$$

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$$W_t^{total} = \sum_{SG \in \mathcal{SG}(sm_t)} \frac{W_{t,SG}^{net}}{(1 - ShA_t)} \qquad t \in \mathcal{T} \qquad (6)$$

$$WP_t + WT_t \geq W_t^{total} \qquad t \in \mathcal{T} \qquad (7)$$

$$WP_t = WP_{t-1} + \Delta WP_t\,, \quad WT_t = WT_{t-1} + \Delta WT_t \qquad t \in \mathcal{T} \qquad (8)$$

$$\Delta WP_t^+ + \Delta WT_t^+ \leq WCap_t \qquad t \in \mathcal{T} \qquad (9)$$

$$WT_t \leq WP_t \frac{ShT_t}{1 - ShT_t} \qquad t \in \mathcal{T} \qquad (10)$$

$$TW_t^{act} = \sum_{SG \in \mathcal{SG}(sm_t)} W_{t,SG}^{net}\; TW_{t,SG}^{act} \qquad t \in \mathcal{T} \qquad (11)$$

$$TW_t^{contr} = TH_t^{contr}\,(WP_t + WT_t)\,(1 - ShA_t) \qquad t \in \mathcal{T} \qquad (12)$$

$$THB_t = \frac{TW_t^{act} - TW_t^{contr}}{WP_t + WT_t} + \frac{THB_{t-1}\;\min\{WP_{t-1} + WT_{t-1}, WP_t + WT_t\}}{WP_t + WT_t} \qquad t \in \mathcal{T} \qquad (13)$$

$$THB_t \leq THB_t^{UL} \qquad t \in \mathcal{T} \qquad (14)$$

$$C_t = C_t^{prod} + C_t^{wage} + C_t^{allow} + C_t^{ovti} + C_t^{change} \qquad t \in \mathcal{T} \qquad (15)$$

$$C_t^{prod} = c_t^v\, P_t + c_t^e \left(\sum_{\tau=1}^{t} P_\tau - \sum_{\tau=1}^{t} D_\tau\right)^+ + c_t^t \left(\sum_{\tau=1}^{t} D_\tau - \sum_{\tau=1}^{t} P_\tau\right)^+ \qquad t \in \mathcal{T} \qquad (16)$$

$$C_t^{wage} = WageP_t\; WP_t + WageT_t\; WT_t \qquad t \in \mathcal{T} \qquad (17)$$

$$C_t^{allow} = \sum_{ST \in \mathcal{ST}(sm_t)} TW_{t,ST}^{act}\, W_{t,SG(ST)}^{net} \left(\frac{WP_t\, AP_{ST} + WT_t\, AT_{ST}}{WP_t + WT_t}\right) \qquad t \in \mathcal{T} \qquad (18)$$

$$C_t^{ovti} = THB_{t-1}^+ \left[(WP_{t-1} - WP_t)^+\; WageP_t^{ovti} + (WT_{t-1} - WT_t)^+\; WageT_t^{ovti}\right] \qquad t \in \mathcal{T} \qquad (19)$$

$$C_t^{change} = C_t^{change,ct} + C_t^{change,sm} + C_t^{change,SG} + C_t^{change,W} \qquad t \in \mathcal{T} \qquad (20)$$

$$sm_t \in \mathcal{SM}, \quad ct_t \in \mathcal{CT}, \quad \Delta WP_t \in \mathbb{Z}, \quad \Delta WT_t \in \mathbb{Z} \qquad t \in \mathcal{T} \qquad (21)$$

[Table 2 about here.]

Theorem 5.1: *Problem (1) - (21) is NP-hard.*

Proof: By restriction we demonstrate that the outlined problem contains a weight-constrained shortest path problem (WCSPP) which is known to be NP-hard (cf. Garey and Johnson 1979, p. 214). Let the states of the production system reachable in every period correspond to the set V of nodes of a directed graph $G(V, A, l, w)$. The states are characterized by the components sm_t, ct_t, WP_t, and WT_t with $t \in \mathcal{T} = \{1, \ldots, T\}$.

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Additionally, V contains a single source node s associated to $t = 0$. Arcs $a \in A$ connect nodes of period t with nodes of period $t + 1$ for $t = 0, \ldots, T - 1$. Hence, the graph is free of cycles. The arcs are associated with lengths l and weights w. The lengths l correspond to costs for wages, allowances etc. The weights w correspond to the change in accumulated overtime between any two states and can be negative. Let THB^{UL} be a constant upper bound on the total weight. Finding a feasible production plan with minimum total costs for our problem requires to determine a shortest path from s to each of the nodes reachable in period T with a total weight not greater than THB^{UL} in every period. □

Hassin (1992) stated pseudo-polynomial algorithms based on dynamic programming to solve the WCSPP. To solve our problem we apply the dynamic programming approach described by Askar (2008) where the time periods t are associated with the stages. The state space is constituted by the variables sm_t, ct_t, WP_t, WT_t and augmented by additional state variables THB_t and $\sum_{\tau=1}^{t} (P_\tau - D_\tau)$ required to record the accumulated overtime and the accumulated deviation of production from demand (cf. Bertsekas 2000, pp. 34 et seqq.). Further state variables assure that a certain number of periods elapses between consecutive changes of shift models and cycle times. The algorithm is not exact because discretization is used to reduce the number of states and decisions: The workforce level is discretized, for recorded extra hours and for the cumulated deviation of production from demand intervals are distinguished. The step size of discretization determines the trade-off between solution quality and solution time. Since our problem has not to be solved weekly a 'near-exact' algorithm that emphasizes solution quality seems suitable.

5.3. *Design-of-Experiments analysis*

With the experimental designs outlined in Section 4 we investigate the five instruments deemed suitable for the car manufacturer. Table 3 summarizes the characteristics of the instruments.

[Table 3 about here.]

For the full factorial design $2^5 = 32$ runs had to be conducted for each demand scenario. The design and the results of the runs for scenario 1 are depicted in Table 4.

[Table 4 about here.]

Since we consider a deterministic case a single replicate of the runs is exhaustive. However, a single replicate does not provide a random error which is required for an analysis of variance. To circumvent this problem, effects of high-order interactions can be pooled as an estimate of error because main effects and low-order interactions usually have a dominant impact on a system response. Table 5 shows the analysis of variance for a model that only accounts for main effects and 2-factor interactions. The analysis indicates that the main effects A, B, D, and E as well as the interactions AB and BD are significant, while instrument C does not exhibit an effect on costs.

[Table 5 about here.]

Though, adopting this approach runs the risk of missing significant high-order interactions. Therefore, in the first step of our analysis we use a normal probability plot to

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graphically identify the major effects.[1] For this plot effects are ordered according to magnitude. Then each effect is plotted against its cumulative percentage. Negligible effects are supposed to be normally distributed with mean zero. Hence, they will fall along a straight line in the plot, whereas important effects have non-zero means and stand out from the straight line. Figure 3 depicts the normal probability plot for scenario 1 that does not exhibit significant high-order interactions.

[Figure 3 about here.]

In the next step the important effects A, B, D, E, AB, and BD that stand out from the straight line in Figure 3 are considered in the regression model whereas negligible ones are pooled as an estimate of error. The estimated coefficients of the important effects are stated in Table 6.

[Table 6 about here.]

The factors A, B, D and E for themselves and interaction BD decrease costs, their coefficient estimate is negative. Interaction AB exhibits a small positive coefficient estimate as it marginally increases costs. The largest savings by far can be realized when instrument B, an additional cycle time, is available. On average, exploiting this option yields a saving of 7.2 million € (twice the coefficient estimate). Dominant interaction effects would favor different levels for the corresponding factors. However, interactions do not play a major role here. The joint availability of instruments A and B exhibits low redundancy. Altogether factors A and B decrease costs. Hence, the high level can be chosen for both factors. Interaction effect BD is also small: Cycle time changes are slightly supported by a longer balancing period as higher production speed allows the use of a 2-shift model with long working hours instead of a 3-shift model with less working time for an individual worker. Similar results are obtained for demand scenario 2. In both cases instruments B, E, and A facilitate large cost savings. If more than one scenario for future demand is likely decision makers can for example weight the results of each scenario or apply a minimax decision rule to minimize the maximum possible cost given a negotiation strategy or a budget for investing in additional flexibility instruments.

6. Extension to uncertain demand forecasts

So far, we have assumed for each scenario that the corresponding demand is known. However, for a long planning horizon demand is usually a random variable and uncertainty about demand is increasing in time. Hence demand forecasts are prone to errors. A manufacturing firm may not revise its production schedule each day where production deviates from demand. Yet, when a forecast is updated the production plan can be adjusted to new information using volume flexibility instruments. The quality of this adjustment depends on the available instruments and on their features. If the option to change the cycle time is available this option offers more flexibility in case the cycle time can be changed at short notice than if prior notice has to be given well in advance.

To value volume flexibility instruments in such a setting our approach can be adapted as follows. An experimental run for a combination of factor levels can be conducted as a simulation run into which the optimization procedure of Section 5.2 is embedded. The

[1]Half-normal plots can also be used for this purpose and are recommended (cf. Montgomery 2005, p. 227). For reasons of demonstration we choose a normal plot.

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simulation starts with a production plan that results from an optimization subject to the initial demand forecast. We randomly determine the number of forecast updates $N < |\mathcal{T}|$ and the periods t_n^{fu}, $n = 1, 2, \ldots, N$, where a forecast update is obtained. For each period t_n^{fu} a reoptimization is executed taking into account that some variables are fixed for a certain number of subsequent periods since notice has to be given in advance. The revised production plan is executed until period t_{n+1}^{fu}. For each simulation run the total costs including costs for deviation of production volumes from the forecasted demand values are recorded as the response value y. Replicates for each level combination are easily obtained as stochastic simulation is used. Utilising the same random seed for each level combination and classifying stochastic forecast values as a random error, design analysis is straight forward.

Since we consider instruments that are used on a tactical planning level we propose to evaluate instruments with respect to demand forecast changes. However, short-term volume flexibility should be measured with respect to changes in actual demand.

7. Summary

In this work we put forward arguments why volume flexibility is of great advantage for many firms which are confronted with demand variability. Manager must select volume flexibility instruments for implementation which accrues costs because investments in technical equipment or compromises with unions are required. To support their decisions we propose a three-step method to value flexibility instruments. The method is based on a preliminary analysis and an optimization model of the considered production system and applies design-of-experiments techniques to identify the most useful instruments in an efficient way. A full or fractional factorial design allows to perceive interaction effects between instruments that may render a joint implementation of instruments either very valuable or redundant.

In a case study we applied the method to an assembly line of a major European car manufacturer. ***We assumed that demand changes were known in advance.*** Out of five instruments we found one very valuable instrument and one of no value. Furthermore, serious interactions did not occur in that case. We repeated the analysis for a slight variation of demand. The results were robust to this second demand scenario that represented another likely future market development.

Our method is also suited for unexpected changes in demand that can be integrated into our approach by simulation in combination with reoptimization (rescheduling). A stochastic input would provide replicates for each factor level combination and would favor fractional over full factorial designs. Comparing the relative value of a volume flexibility instrument for different firms would be an avenue for future research because our work suggests that the relative value is strongly related to firm specific parameters.

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Table 1. Design of a 2^3 full factorial experiment with columns showing signs to calculate main and interaction effects

Run	Label/ Response	Factor/main effect A	B	C	2-factor interaction AB	AC	BC	3-factor interaction ABC
1	(1)	−	−	−	+	+	+	−
2	a	+	−	−	−	−	+	+
3	b	−	+	−	−	+	−	+
4	ab	+	+	−	+	−	−	−
5	c	−	−	+	+	−	−	−
6	ac	+	−	+	−	+	−	−
7	bc	−	+	+	−	−	+	+
8	abc	+	+	+	+	+	+	+

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Table 2. Glossary of symbols (alphabetically ordered in each subsection)

Symbol	Meaning	Symbol	Meaning
Sets (index in brackets)			
$\mathcal{CT}$, (ct)	Cycle times	$\mathcal{ST}$, (ST)	Shift types
$\mathcal{SG}$, (SG)	Shift groups	$\mathcal{T}$, (t)	Periods
$\mathcal{SM}$, (sm)	Shift models		
Parameters			
AP_{ST}	Shift allowance for perm. workers	ShT_t	Maximum share of temp. workers
AT_{ST}	Shift allowance for temp. workers	TA_t	Assembly time per car
D_t	Demand	TH_t^{contr}	Contracted hours per worker
i	Cost of capital	$TO_{t,sm}$	Operating time
LB_t	Limit for cumulated shortfall	UB_t	Limit on cumulated overproduction
P_t	Production volume	$WageP_t^{ovti}$	Overtime pay of a perm. worker
ShA_t	Share of absent workers	$WageT_t^{ovti}$	Overtime pay of a temp. worker
$ShF_{sm,SG}$	Share of required floaters	$WCap_t$	Capacity for training new workers
Auxiliary variables			
c_t^e	Unit earliness cost	THB_t	Hours bank balance
c_t^t	Unit tardiness cost	THB_t^{UL}	Limit on the hours bank balance
c_t^v	Variable unit production cost	TW_t^{act}	Actual total working time
C_t	Total period costs	$TW_{t,SG}^{act}$	Actual working time of a shift group
C_t^{allow}	Total period costs for allowances	$TW_{t,ST}^{act}$	Actual working time of a shift type
C_t^{change}	Total period costs for changes	TW_t^{contr}	Total number of contracted hours
$C_t^{change,ct}$	Costs for change in cycle time	$W_{t,SG}^{net}$	Required net workforce
$C_t^{change,SG}$	Costs for change of shift groups	W_t^{total}	Required total workforce
$C_t^{change,sm}$	Costs for changing the shift model	$WageP_t$	Wage for a perm. worker
$C_t^{change,W}$	Costs for change in workforce size	$WageT_t$	Wage for a temp. worker
C_t^{ovti}	Total period costs for overtime	WP_t	Number of perm. workers
C_t^{prod}	Total period costs of production	WT_t	Number of temp. workers
C_t^{wage}	Total period costs for wages	y	Total discounted cost
Decision variables			
ct_t	Cycle time	ΔWT_t	Change in temp. workforce size
ΔWP_t	Change in perm. workforce size	sm_t	Shift model

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Table 3. Selected instruments for the analysis

Instrument	Description	Inflexible state (−)	Flexible state (+)
A	Number of shift models	two 2-shift models, one 3-shift model	four 2-shift models three 3-shift models
B	Number of cycle times	one	two
C	Upper limit on the maximum number of accumulated extra hours	100 hours	200 hours
D	Length of balancing period of the hours bank	one year	two years
E	Maximum share of temporary workers	10%	15%

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Table 4. Design and results of the 2^5 full factorial experiment

	Factor levels					Response
	A	*B*	*C*	*D*	*E*	
Run	Shift models	Cycle times	Extra hours	Balancing period	Temporary workers	Costs in €
1	−	−	−	−	−	160,819,583
2	+	−	−	−	−	158,208,635
3	−	+	−	−	−	153,411,104
4	+	+	−	−	−	151,484,794
5	−	−	+	−	−	160,819,583
6	+	−	+	−	−	158,208,635
7	−	+	+	−	−	153,411,104
8	+	+	+	−	−	151,484,794
9	−	−	−	+	−	160,803,175
10	+	−	−	+	−	157,195,206
11	−	+	−	+	−	152,382,054
12	+	+	−	+	−	150,475,420
13	−	−	+	+	−	159,452,827
14	+	−	+	+	−	157,094,095
15	−	+	+	+	−	151,549,638
16	+	+	+	+	−	150,324,720
17	−	−	−	−	+	156,890,731
18	+	−	−	−	+	153,918,834
19	−	+	−	−	+	150,243,582
20	+	+	−	−	+	148,113,986
21	−	−	+	−	+	156,890,731
22	+	−	+	−	+	153,918,834
23	−	+	+	−	+	150,243,582
24	+	+	+	−	+	148,113,986
25	−	−	−	+	+	157,283,229
26	+	−	−	+	+	153,733,287
27	−	+	−	+	+	148,104,869
28	+	+	−	+	+	147,150,140
29	−	−	+	+	+	157,109,899
30	+	−	+	+	+	153,833,385
31	−	+	+	+	+	148,091,044
32	+	+	+	+	+	147,150,140

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Table 5. Analysis of variance for scenario 1 (high-order interactions pooled as an estimate of error)

Source of variation	Sum of sqares	Degrees of freedom	Mean square	F-value	p-value
A^*: Shift models	43.008 E+12	1	43.008 E+12	287.60	**< 0.0001**
B^*: Cycle times	409.307 E+12	1	409.307 E+12	2737.13	**< 0.0001**
C: Extra hours	0.199 E+12	1	0.199 E+12	1.34	0.2660
D^*: Balancing period	6.525 E+12	1	6.525 E+12	43.63	**< 0.0001**
E^*: Temporary workers	99.176 E+12	1	99.176 E+12	663.21	**< 0.0001**
AB^*	3.658 E+12	1	3.658 E+12	24.46	**0.0001**
AC	0.154 E+12	1	0.154 E+12	1.03	0.3257
AD	0.066 E+12	1	0.066 E+12	0.44	0.5148
AE	0.018 E+12	1	0.018 E+12	0.12	0.7354
BC	0.009 E+12	1	0.009 E+12	0.06	0.8124
BD^*	2.055 E+12	1	2.055 E+12	13.74	**0.0019**
BE	0.091 E+12	1	0.091 E+12	0.61	0.4457
CD	0.199 E+12	1	0.199 E+12	1.33	0.2660
CE	0.172 E+12	1	0.172 E+12	1.15	0.2991
DE	0.227 E+12	1	0.227 E+12	1.52	0.2361
Residual (error)	2.393 E+12	16	0.150 E+12		
Total	567.255 E+12	31			

$R^2 = 99.58\%$, adjusted $R^2 = 99.18\%$, * and bold p-value indicate significance at a level of α =5%

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Table 6. Regression analysis for the important effects

Effect	Coefficient estimate	Standard error	t-value	$p-$value
Average response	$153,684,863$	$66,396$	2314.65	$<$ **0.001**
A: Shift models	$-1,159,308$	$66,396$	-17.46	$<$ **0.001**
B: Cycle times	$-3,576,429$	$66,396$	-53.86	$<$ **0.001**
D: Balancing period	$-451,543$	$66,396$	-6.80	$<$ **0.001**
E: Temporary workers	$-1,760,472$	$66,396$	-26.51	$<$ **0.001**
AB	$338,120$	$66,396$	5.09	$<$ **0.001**
BD	$-253,389$	$66,396$	-3.82	**0.001**

$R^2 = 99.38\%$, adjusted $R^2 = 99.23\%$, bold p-value indicates significance at a level of α =5%

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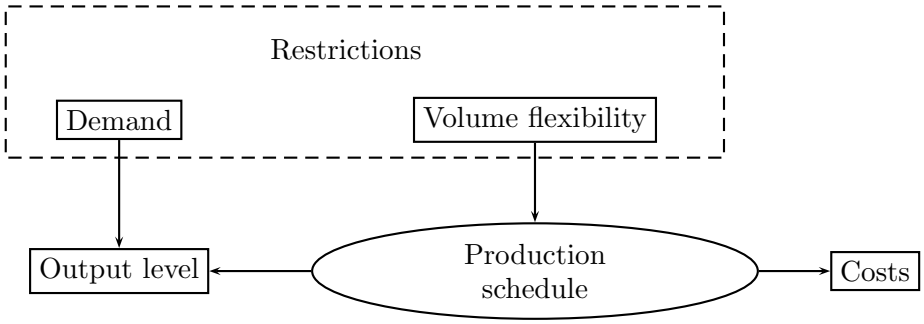

Figure 1. Objects of the preliminary analysis

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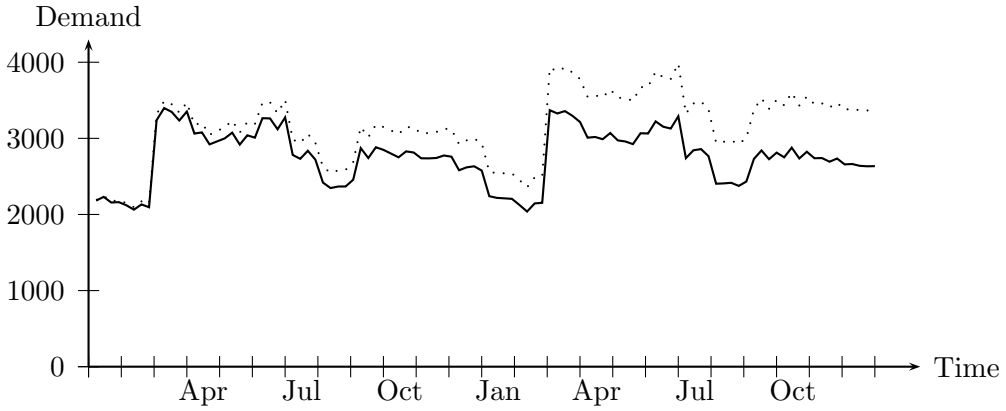

Figure 2. Investigated demand scenarios (solid line: scenario 1, dotted line: scenario 2)

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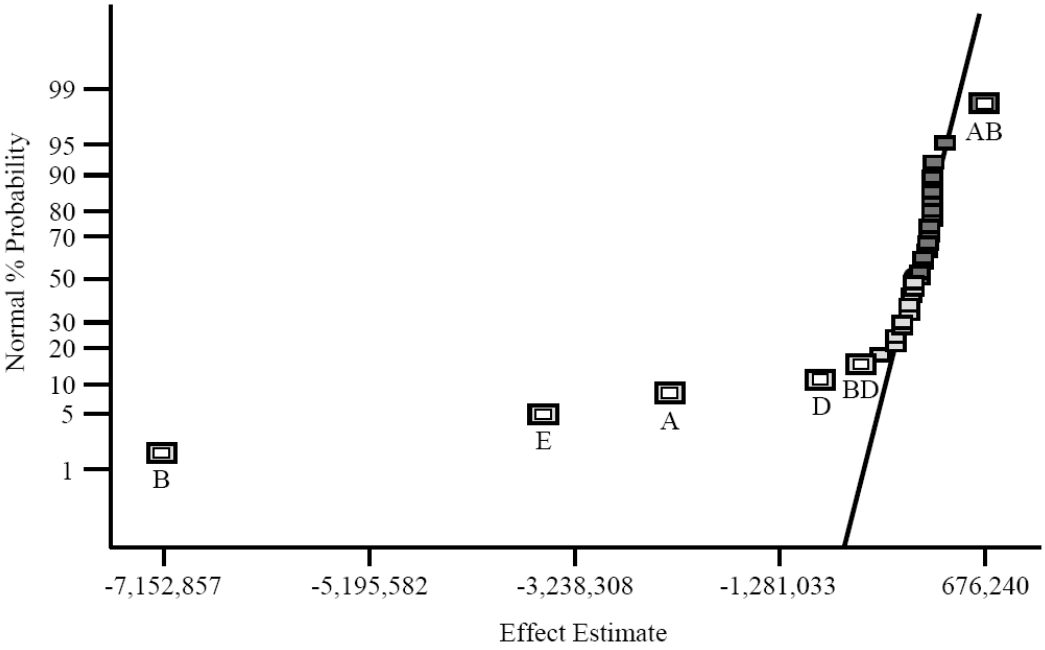

Figure 3. Normal probability plot of the effects for the full factorial design

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