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Workforce planning in production with flexible or budgeted employee training and volatile demand

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Abstract

Companies have to adapt their product portfolio to rapidly changing markets and high demand volatility. As a result, they need to invest in workforce learning and training measures to gain flexibility. Especially during ramp-up phases employees have to adjust their skill set to new production requirements. While traditional employee training models focus on a condensed period of training at the beginning of a production ramp-up, we aim to shed light on the effectiveness of more flexible concepts of training with a general availability of training measures during a product's life cycle. We budget training in two dimensions, (1) training capacity per period and (2) periods that do not allow training. To analyze the impact of different training scenarios, a multi-period workforce scheduling problem with workers who learn through learning-by-doing and training is considered. The model further incorporates forgetting. We distinguish a flexible and a budgeted training environment. In the budgeted setting, training measures are only available in the first periods of a production ramp-up to a limited extent. Data from a computational study with 600 scenarios and near-optimal solutions are analyzed statistically to derive insights into an employee's skill development. Overall, we investigate different training strategies under demand volatility and capacity scenarios and analyze the specific outcomes in order to provide managerial implications. Our results indicate that traditional budgeting of training measures has a negative effect on employee learning. The negative impact of budgeting is stronger when production capacity is scarce and demand cannot be fully satisfied.

Keywords Employee Skill Development · Budgeted Training · Workforce Scheduling · Demand Volatility · Learning and Forgetting

JEL Classification M11

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1 Introduction

Due to digitization and demographic changes, a variety of new challenges are arising for organizations (Wisner 1996; Surbier et al. 2014). Customers require updated products within shorter periods of time and, because of technological advances, production processes have often become more complex (Surbier et al. 2014). Since the 1990s, development times and product life cycles have been reduced substantially (Terwiesch and Bohn 2001). The Companies often have to develop new products and bring them to market in less than a year, which equals the market time window for selling many products. A famous example is the cell phone industry where new models are introduced every year. To address rapid changes in customer preferences and technology, companies have to be able to adapt to new market requirements if they are to keep up with the constant rate of change (Qin et al. 2015). Hence, to meet the challenges of fast-changing markets with high demand volatility, companies have to adjust not only their product portfolio and services, they also have to invest in the fast ramp-up of new production processes (Hansen and Grunow 2015). As these production processes are becoming increasingly interconnected, required employee skills are changing and existing skills might decrease in value over time (Letmathe and Schinner 2017).

Thus, project portfolio decisions should be based on the employees' competencies and take their targeted development into consideration (Gutjahr et al. 2010). If the proficiency of different products is known up-front or assessable during production, it is worthwhile for companies to focus on a specialized workforce when selecting project (Gutjahr 2011). However, especially during a product's ramp-up phase, which involves low production capacity and high demand, employees have to adjust their skill set to new requirements. Therefore, it is crucial for firms to invest in workforce learning and training measures (Terwiesch and Bohn 2001). Hence, employee skill development and competence management alongside concepts of learning and forgetting as well as different concepts of training should become an integral part of workforce management practices. Traditional employee training models focus on a condensed period of training at the beginning of employment or during the implementation of a new production process (Ally 2009). Such approaches limit training measures often by determining the available training budget and capacity and do not allow for training during the whole life cycle of a product. In this sense, companies have often a fixed budget of training measures that they can distribute among the work force. We aim to shed light on the effects of more flexible concepts of training which incorporate a general availability of training measures at all times. In order to compare traditional concepts of employee development with more flexible ones, we limit training measures in two dimensions. The training budget is defined by the available training capacity per period and periods which allow for training compared to those that prohibit training. Considering traditional, budgeted training, companies cannot react sufficiently flexibly to any demand oscillations. Thus, they are not able to use times of low demand for training in order to increase their skill levels. Moreover, high demand reduces the amount of time that can be used

for training; thus, training opportunities are forgone. Since budgeting often only allows for training measures in the first periods, employees cannot recover the missed training opportunities in later periods. As a consequence of production ramp-ups incorporating high and unknown demand (Terwiesch and Bohn 2001), the effect of budgeting training measures might increase with rising demand volatility and lower employee capacities.

Consequently, the question arises: What impact do demand volatility and the application of budgeted training measures have on the learning and training outcomes of employees in production systems? To analyze the impact of different training scenarios, a multi-period workforce scheduling model is considered with workers who gain experience by learning-by-doing and due to training or lose skill units through forgetting. Data from a computational study with near-optimal solutions obtained via GAMS and a Gurobi 7.5.2 solver are analyzed with General Estimation Equations (GEE) to derive insights on the production system's overall performance and skill outcomes depending on different training environments and demand volatility.

The remainder of the paper is structured as follows: Sect. 2 provides the theoretical background on production ramp-ups, learning theory, and types of training. In Sect. 3, we derive hypotheses for the main relationships of training and production outcomes with specific regard to employee training. We test these hypotheses with a set of simulated data generated through a mixed-integer optimization model that is presented in Sect. 4. The last Sects. 5 and 6 present the results of our analysis and discuss our findings.

2 Theoretical foundation

The implementation of new production processes, which can take up to a quarter of a product's life cycle, is known as the ramp-up phase and defined as the period '*between completion of development and full capacity utilization*' by (Terwiesch and Bohn (2001), p.1). They described three different kinds of ramp-up scenarios: plant ramp-up, product ramp-up, and process ramp-up. These are influenced by the same characteristics: uncertainty, high complexity (Surbier et al. 2014), interruptions, defects (Glock and Grosse 2015), low production capacity, and high demand volatility (Terwiesch and Bohn 2001). Hence the ramp-up phase is characterized by a trade-off between normal production and learning, which increases yields and decreases production times, which, vice versa, stimulates production output (Schultz et al. 2003). Since high demand oscillations are one of the main dynamic cost drivers, organizations have to build up safety stocks to cope with volatile demand patterns (Holweg et al. 2011). During ramp-ups, building these safety stocks is often impossible, as the productivity of the newly introduced production processes is low, and full capacity utilization is not possible in this phase (Schultz et al. 2003). However, the ramp-up phase is often also characterized by high demand for new products with customers willing to pay premium prices (Terwiesch and Bohn 2001). Research on demand volatility has especially been carried out in the field of forecasting to enable more precise predictions (e.g. Abolghasemi et al. (2020)). Although

demand volatility is of great importance for production scheduling and workforce planning, forecasting models require historical data on which to base calculations. Such data are often absent in production ramp-up situations (Huang et al. 2008). Since the combination of demand volatility and unstable production processes is challenging to control in ramp-up scenarios, companies need to invest in the factor ‘human resource’ in order to increase production output and workforce flexibility and thus be able to meet the customer demand and achieve long-term stability (Qin and Nembhard 2010). In this regard the production or project duration benefits from an even allocation of flexibility measures among available resources, i.e. workers or machines (Vairaktarakis 2003). However, employees’ time capacities are limited and cannot be extended flexibly to meet a given demand, thus these capacities limit production output per period. Hence, a trade-off between more efficient production by investing time into training and meeting customer wishes arises, especially when high demand volatility is present (Anderson 2001). Compared to capacity limits, capacity utilization can be increased due to learning and training when employees become more productive over time (Terwiesch and Bohn 2001; Qin and Nembhard 2010). High learning rates of workers in manufacturing production can lead to an increase in production quality as well as to a reduction in production costs and processing times (Yelle 1979; Dutton and Thomas 1984; Biskup 2008; Anzanello and Fogliatto 2011). These in turn enable workers to produce larger product quantities within the same time span (Argote and Ingram 2000). Therefore, in today’s changing production environments, a redesign of workforce planning, scheduling, and training approaches is indispensable and can help companies to maintain their competitive advantages (Qin and Nembhard 2015).

In 1936, Wright (1936) described the interdependency of the quantity produced and the time needed to execute a production task. By discovering that the amount of time workers need to produce one unit decreases in a log-linear relation to the cumulative number of goods produced, he developed the first learning curve model with a constant learning rate. Since this discovery, extensive research has been carried out on different types of learning curves (Yelle 1979; Dutton and Thomas 1984; Jaber et al. 2003; Biskup 2008; Anzanello and Fogliatto 2011; Hansen and Grunow 2015). Anzanello and Fogliatto (2011) compared univariate learning curve models, e.g. log-linear, exponential and hyperbolic learning curves, with multivariate approaches. Globerson (1987), Globerson and Gold (1997) and Grosse et al. (2015) discovered that the log-linear model with a non-complex mathematical structure nevertheless estimates production based on manual tasks with sufficient precision. Consequently, the log-linear model is the most widely used learning curve in production-based scenarios (Yelle 1979; Dar-El et al. 1995). In their review article, (De Bruecker et al. (2015), p.2) described the development of skills, as having a positive impact on an employee’s ‘*ability to perform certain tasks well*’. They identified the following factors as being positively affected by employee skills: processing time, production efficiency, product quality, and labor costs. Not only does the performance with respect to a single task increase, experienced workers at high skill levels are further able to adapt to changes in the production process more efficiently (Wright 1936).

In contrast to learning, forgetting has a negative influence on employee performance (Jaber et al. 2003; Digiesi et al. 2009; Dode et al. 2016). Thus, it decreases

the skill levels of a worker and therefore production efficiency. Teyarachakul et al. (2011) provide an overview of ways in which forgetting has been modeled in manufacturing settings, e.g. depending on the number of interruptions, experience or skill level gained previously, or the duration of an interruption. Moreover, forgetting curves were found to be mirror images of learning curves and to be dependent on the respective production task (Globerson et al. 1989). Jaber et al. (2003) presume that training measures cannot only foster learning but can also help to maintain achieved skill levels by counteracting any loss of skills by preventing forgetting.

In addition to learning-by-doing, skill enhancements and better capacity utilization can be generated by the training of employees (Carrillo and Gaimon 2000). According to Chen et al. (2010), training decisions entail at which point in time (i.e. when) which skills or production tasks (i.e. what) should be trained by which worker (i.e. who). Thus, in the context of training decisions, workers are assigned to training sessions. In order to develop employee skills, training measures are typically affected by two dimensions of costs: direct costs for the training sessions and opportunity costs, as workers cannot use the training time for production (Büke et al. 2016). To reduce overall costs, achieve shorter lead times, create higher product quality, and increase workforce flexibility, employees can be cross-trained (Inman et al. 2004; Yang and Kuo 2007). Cross-training enables workers to process different production activities which require distinct skills (Hopp and Van Oyen 2004). Compared to purely relying on the specialization of employee skills, a broader set of skills allows companies to better cope with demand volatility, which influences the mix and quantities of tasks to be performed. Although the resulting high level of workforce flexibility enables a company to meet stochastic demand by re-assigning employees to a variety of tasks, further costs for cross-training may arise: e.g., additional training costs and wage payments, decreased efficiency and productivity of an employee, as well as transfer costs (Qin et al. 2015).

Traditional training approaches aim to build knowledge in a condensed learning period at the beginning of the employment or a new production process (Ally 2009). Such budgeting approaches follow the rationale that learning should take place in the early phases of ramping up a new task and that follow-up learning does not need to be managed but happens somewhat automatically. In the same vein, sophisticated management of learning processes does not seem to be required, as initial learning takes place in the early phases of a ramp-up process and does not have to be planned in the later stages. However, in ramp-up scenarios, training and knowledge transfer can lead to a deceleration of the production process if not timed properly, as employees need to use their time for training instead of production (Szabó 2018). Therefore, it is of special interest to investigate the influence of more flexible training concepts, allowing workers to time training suitably under consideration of different markets and demand or capacity environments. Hence, the traditional budgeting approaches should be refined and potentially extended to the entire planning horizon of a product's life cycle.

Valeva et al. (2017) analyzed the extend to which employee learning and forgetting can be used to cope with demand volatility. They took three different demand variation scenarios into account to model the influence on production and capacity utilization, but they did not distinguish between different approaches to employee

training. Heimerl and Kolisch (2010) examined company skill targets at the end of the production phase to ensure sufficient skill development and to broaden a company's skill portfolio. Letmathe and Schinner (2022) analyzed how training measures can help to overcome the negative influence of demand volatility during production ramp-ups by showing that training measures can reduce the impact of demand volatility on skill development and productivity. These relationships are moderated by the available employee capacity. Their results show that if the time endowment of employees is sufficiently large, most of the training measures are used in the first periods of the ramp-up phase. In contrast to this, in scenarios with low employee time capacities, the number of training sessions undertaken appears to be rather constant in all periods.

Although the influence of novel training measures, which arise due to technological advances, has been investigated in the literature of Human Resource Development (Chalofsky et al. 2014; Noe 2010; Beardwell and Thompson 2017), to the best of our knowledge no such research has been carried out on the influence of the timing of training measures on workforce flexibility and workforce scheduling. We aim to contribute to the literature on workforce planning and ramp-up management by providing insights into the interaction between demand volatility and flexible training concepts compared to time-budgeted training. Furthermore, we focus on the interaction of training approaches and demand volatility in different employee capacity scenarios. We simulate demand volatility and different employee time capacity settings based on the approach of Letmathe and Schinner (2022). In contrast to the work of Letmathe and Schinner (2022) we include two scenarios to investigate the difference between flexible and traditional concepts of employee training. In the first setting, training measures are time-budgeted and training is only available in the first periods of production. This setting mirrors traditional concepts of employee skill development. In contrast, the second setting does not rely on a budgeted approach, i.e. employees can undergo training sessions in each period. Hence, workforce planning can react more flexibly to demand volatility.

3 Hypotheses

Considering the budgeted scenario, training measures are only available in the first periods of the planning horizon. Additionally, not only are the periods which allow for training limited but also the number of training sessions available per period. In consequence, we expect the number of training sessions undertaken by all employees in all periods to be significantly lower if the access to training measures is budgeted, compared to the scenario with flexible training. This assumption aligns with the results of Letmathe and Schinner (2022), who found the number of training measures to be close to constant during all periods with scarce employee capacities. The results of Valeva et al. (2020), who expect workers to train especially in periods of low demand, also support this finding. During the introduction phase of a new product, customers often pay premium prices with high demand. Thus, shortage costs are especially high during the ramp-up phase (Terwiesch and Bohn 2001). Such scenarios are especially relevant for

industries with innovative products, e.g. electronics, where initial demand is often unpredictable when a new product is launched (Fisher 1997). Henceforth, depending on the shortage costs, companies might forgo training opportunities rather than not meeting the given demand, even if employee training would not be available in later periods. Resulting from these expectations, the total learning output, which is the sum of learning-by-doing and learning through training, is expected to be significantly lower in the budgeted training scenario. As it is not possible to use training measures to prevent forgetting in the periods following the initial ramp-up and as production as well as learning depend on volatile demand, we expect forgetting to be higher in the budgeted scenario compared to the more flexible non-budgeted setting.

This expectation is in line with Jaber and Guiffrida (2008), who argued that training can prevent employees from forgetting and enables employees to maintain skill levels. Consequently, budgeting can lead to higher levels of forgetting and, thus skill units might decrease over time.

Throughout this paper, skill development is defined as the total learning output reduced by forgetting. Driven by the trade-off between learning-by-doing and training in the first periods of a production ramp-up and the lack of training measures to prevent forgetting and to foster employee skills in later periods, we assume the total skill development to be significant negatively impacted by budgeted training measures. Summarizing, we formulate the following hypothesis:

H1: The budgeting of training measures has a negative impact on skill development.

We model the amount of time needed to gain additional skills during a training session to be lower than gaining the same skill enhancement during production. Thus, a decision for learning-by-doing during production and against training sessions results in lower skill enhancement. Considering the trade-off between production and training measures, especially in the budgeted scenario, we expect the production quantity to decrease marginally because companies will use a minimum amount of time for training to profit from lower production costs and decreasing production time requirements in later periods.

Characteristic of scenarios with high demand volatility are oscillations between successive periods and uncertainty concerning the demanded amount (Huang et al. 2008). When companies have to face high volatility, they have to find a trade-off between meeting the given demand and investing in training opportunities in the respective periods. We expect companies to prefer to meet customer demand than to accept shortage costs. Thus, we predict a decrease in skill development regarding scenarios with high demand volatility. As training can also prevent forgetting, less training in high volatility scenarios might not only result in fewer newly adopted skill levels but might also lead to forgetting when workers are not assigned to a task for a longer period of time. Combining these factors, we derive the following hypothesis:

H2: Demand volatility has a negative impact on skill development.

Prior to the market introduction of a new product, not only is the actual demand per period unknown but also the general interest in the product itself. Therefore, companies face different intensities of demand volatility. We model the impact of different levels of demand volatility relative to the workforce capacity. Hence, employees have a limited amount of time units per period, which can be used either for training or production. In each capacity scenario, all employees work the same number of hours per period, i.e. they have the same capacity in every period. In a low-capacity scenario, the initial time endowments of employees barely suffice to meet a given demand. Thus, the trade-off situation between production and training intensifies, as workers need to increase their skill levels to be able to meet the demand in the following periods. At the same time, scarce capacity makes it more difficult to buffer production against demand volatility, as there is no slack for additional production. Considering a medium-capacity scenario, workers can satisfy the demand using their initial skill endowment but do not have any time remaining for training or production if the demand substantially exceeds the average demand. Hence, demand volatility still plays a limiting role but to a lesser degree than in low-capacity scenarios. High-capacity scenarios enable workers to produce goods and undergo training measures simultaneously in most periods. Moreover, they enable employees to obtain higher skill levels due to training. This results in improvements in production time and costs. At the same time, it is possible to buffer production against demand volatility.

According to the settings described above, we aim to shed light on the effects of budgeted training measures in the different employee capacity scenarios. We expect the impact of budgeted training measures on the amount of training to be negative in the low- and medium-capacity scenarios but to vanish regarding the high-capacity scenario due to better buffering opportunities. Thereby, employees develop more skills through training in the first periods in the high-capacity scenario to prepare for any forgetting effects in later periods. Hence, we expect the interaction effect of employee capacity and budgeting on skill development to be positive regarding increasing capacity endowments. To put it another way: Traditional budgeting approaches are less detrimental if a production system has sufficient capacity buffers. The mentioned expectations result in the following hypothesis:

H3: Employees' skill development is affected positively by the interaction effect of budgeting and employee capacity.

Budgeting for training measures reduces the ability to respond to skewed or low demand when employees are not enabled to achieve higher skill levels through targeted on-the-job learning. In times of high demand volatility, periods with high demand that deviates from the average demand are typical. Considering that periods of high demand are also possible in the first periods of observation, we expect a decrease in undertaken training measures that is caused by shortage costs. This will, in turn, lead to fewer opportunities to increase production efficiency through training. In the later periods, there will be fewer opportunities for employees to undergo training sessions, even when demand is low and surplus time capacities are available. Consequently, efficiency gains that are necessary to meet the demand in periods

with higher demand are forgone if budgeting and high demand volatility are present. Fewer opportunities for training in combination with unmet demand can therefore lead to a negative impact on employee skill development. Following this line of reasoning, we expect:

H4: Employees' skill development is affected negatively by the interaction effect of budgeting and demand volatility.

4 Methodology

To test the hypotheses concerning the influence of the budgeting of training measures and demand volatility, we use a mixed-integer optimization model based on Letmathe and Schinner (2022). This model contains the possibility of non-budgeted training and autonomous learning. Here, an extension of this model has been developed and then utilized to answer the formulated research questions. First, the model is introduced in Sect. 4.1; second, in 4.2, the parameters used for the simulation are depicted.

4.1 Model description

Let $i \in \{1, \dots, m\}$ denote the set of shop floor employees who can conduct a production activity $l \in \{1, \dots, L\}$ to produce products $j \in \{1, \dots, n\}$ in each period $t \in \{1, \dots, T\}$. Executing production activity l results in an output of l_j units of product j . Whereas each worker can theoretically perform each activity, each production activity allows the production of exactly one of the products relevant to meeting customer demand. Each employee i is characterized by a skill level for every production activity l in every period t , denoted by $z_{ilt} \geq 0$. Note, that this skill level can change over time due to training, learning-by-doing, or forgetting.

4.1.1 Skill development

To obtain a linear program we use a linear approximation for our learning curve by introducing discrete skill levels $k \in \{1, \dots, K\}$. Depending on the skill level k achieved due to skill units $z_{ilt} \geq 0$, the time required for processing production activity l , denoted by p_{kl} , and the production costs per unit, denoted by c_{kl} , differ. The required amount of skill units for processing production activity l at the skill level k is defined by $z_{kl}^{min} \geq 0$. In line with the learning curve theory, we assume production time and costs to decrease due to learning, i.e. with increasing skill levels. Forgetting and the two dimensions of learning are incorporated in the following ways:

First, we model learning-by-doing which occurs while executing production activity l in period t with skill level k , with $y_{iklt} \geq 0$ denoting the amount of product l produced in period t by employee i with skill level k . Employee i gains experience based on an individual linearized skill development or learning factor v_i . Second, we consider training measures with costs per training measure c_l and time units tr_l needed for one training unit. Both parameters depend

on the production activity l . Further, $u_{ilt} \geq 0$ denotes the total amount of training measures for production activity l of employee i in period t . The training effects, i.e. the gains in skill levels, occur proportionally to the time spent on training for each activity. In each period, worker i is equipped with a constant time capacity \overline{CAP}_i which can either be used for training or production, i.e. $\sum_{l=1}^L \sum_{k=1}^K p_{kl} \cdot y_{iklt} + tr_l \cdot u_{ilt} \leq \overline{CAP}_i \quad \forall i \in \{1, \dots, m\}, t \in \{1, \dots, T\}$.

As a counterpart to learning, we incorporate forgetting in our model. An employee i loses w_i skill units for a certain production activity l , according to his or her individual linearized forgetting factor, if she or he gains fewer than $fl_l > 0$ skill units for this production activity in the respective period. Thus, the amount of skill units forgotten depends on the length of the interruption, as it is possible that forgetting occurs in several successive periods, and on the experience gained so far due to the discrete skill level k . To display forgetting, we incorporate the binary variable fg_{ilt} with $fg_{ilt} = 1$ if employee i earns less than fl_l skill units due to training or processing of production activity l in period t , and $fg_{ilt} = 0$ if he does not lose skill units. Hence, we add the two constraints (1) and (2) to the model to determine if a worker i experiences forgetting effects for production activity l in period t measured by the binary variable fg_{ilt} . Constraint (1) ensures that forgetting effects are calculated if the threshold of fl_l produced units of product l is not reached by forcing $fg_{ilt} = 1$. The second constraint prevents forgetting effects to occur in case the sum of the unit production and the training sessions undertaken exceed the threshold fl_l . For this purpose, we chose the big M constant $M > 0$ to be a sufficiently large number in both inequalities. Note that we assume the forgetting threshold to be greater or equal to 1 to assure that forgetting effects are present if an activity is skipped in both, training or production.

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} \geq fl_l \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (1)$$

$$yt_{ilt} + u_{ilt} + M \cdot fg_{ilt} < (M + fl_l) \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (2)$$

Combining learning-by-doing, training, and forgetting, we derive the following constraint:

$$z_{ilt} = z_{il(t-1)} + yt_{ilt} \cdot v_i + u_{ilt} - w_i \cdot fg_{ilt} \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\}, \quad (3)$$

with $fg_{ilt} \in \{0, 1\}$ and $yt_{ilt} = \sum_{k=1}^K y_{iklt}$. The following constraints assure that workers only carry out production activities on those skill levels k that they have already achieved, with $r_{iklt} \in \{0, 1\}$.

$$z_{kl}^{min} - z_{ilt} \leq M \cdot (1 - r_{iklt}) \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (4)$$

$$y_{iklt} \leq M \cdot r_{iklt} \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (5)$$

A company skill level target $\phi_i \leq \sum_{l=1}^L z_{ilT}$ needs to be satisfied by every employee i . The target is embodied in the model to assure that the skill development does not

drop in the last period T and that company skill levels are sufficiently developed by the end of the planning horizon (Heimerl and Kolisch 2010).

4.1.2 Budgeted training measures

To budget training measures, we introduce a training sessions limit \overline{ucap}_t which restrains the total number of all training sessions for all production activities l and all employees i . We incorporate the following constraints into our model to analyze the effect of budgeted training and we omit these in the model not incorporating budgeting.

$$\sum_{i=1}^m \sum_{l=1}^L u_{ilt} \leq \overline{ucap}_t \quad \forall t \in \{1, \dots, T\} \quad (6)$$

In order to prohibit training in certain periods t , the capacity $\overline{ucap}_t = 0$ can be chosen, resulting in $u_{ilt} = 0$ for the respective periods.

4.1.3 Demand

In every period t , a demand D_{jt} for product j has to be satisfied. As storage is not possible, a shortage of product j , defined as $sh_{jt} = D_{jt} - \sum_{l=1}^L (a_{jl} \cdot ys_{lt})$, may arise and is penalized with shortage costs sc_j per unit (with $ys_{lt} = \sum_{i=1}^m \sum_{k=1}^K y_{iklt}$). The variable a_{jl} defines the number of products j produced by production activity l .

To simulate demand volatility, a randomization function is implemented in GAMS to create demand values for all periods and products depending on a given volatility level. The level of volatility determines an upper and lower boundary within which the demand can vary. Starting with a fixed demand D and a volatility level $dv \in \{1, \dots, D\}$, the set of possible demand values is given by $D_{jt} \in \{D - dv, D - dv + 1, \dots, D + dv\}$.

4.1.4 Objective function

We implement our Mixed-Integer-Program as a minimization problem, optimizing the total production costs over all periods $t \in \{1, \dots, T\}$. The total costs consist of production costs, training costs, and shortage costs.

$$\underbrace{\sum_{i=1}^m \sum_{k=1}^K \sum_{l=1}^L \sum_{t=1}^T c_{kl} \cdot y_{iklt}}_{\text{production costs}} + \underbrace{\sum_{i=1}^m \sum_{l=1}^L \sum_{t=1}^T c_l \cdot u_{ilt}}_{\text{training costs}} + \underbrace{\sum_{j=1}^n \sum_{t=1}^T sc_j \cdot sh_{jt}}_{\text{shortage costs}} \rightarrow \min \quad (7)$$

This model is developed to simulate the interplay of training measures, learning-by-doing, forgetting, and volatile demand. Therefore, it is not suited for operative workforce assignment in its current version.

4.2 Numerical example

In our simulation, $m = 4$ employees can process $L = 3$ production activities each to produce one of the $n = 3$ products during $T = 18$ periods. During the ramp-up phase, the new production processes are introduced. For the sake of simplicity, we assume that all workers i start with the same competence level $z_{i|0} = 30$ with respect to all production activities l . Employees can increase their competence level through learning-by-doing with an underlying learning rate $v_i = 1$ or through training. As described above, each training measure increases the skill units. A continuous scale of skill units is combined with $K = 4$ discrete skill levels which enable workers to perform production activities on a higher efficiency level, meaning that their production costs c_{kl} and time p_{kl} will decrease with a higher skill level k according to the following values:

$$p_{kl} = \begin{Bmatrix} 5 & 5 & 5 \\ 4.5 & 4.5 & 4.5 \\ 4.2 & 4.2 & 4.2 \\ 4 & 4 & 4 \end{Bmatrix}, c_{kl} = \begin{Bmatrix} 10 & 20 & 40 \\ 9 & 20 & 30 \\ 8 & 18 & 20 \\ 7 & 17 & 10 \end{Bmatrix}, sc_j = \begin{Bmatrix} 40 \\ 70 \\ 40 \end{Bmatrix}$$

The skill levels are set as follows: Level one starts at one skill unit, level two at 50 skill units, level three at 200 skill units, and level four, the highest skill level, starts at 500 skill units. Workers with skill level four cannot improve their performance in the respective production activity any further. However, higher skill levels also prevent forgetting. It is not possible, though, for workers to exceed 2500 skill units in any production activity, i.e. $z_{ilt} \leq 2500$. The values for c_{kl} were chosen to allow for different learning patterns which might be driven by different levels of task complexity (Shafiei-Monfared and Jenab 2011). For this purpose, a product produced with high efficiency gains due to learning ($l = 3$), an s-shaped model ($l = 2$) with slow learning at the beginning (Baloff 1971), and a moderate log-linear learning curve ($l = 1$), e.g. accounting for cognitive or manual tasks with high complexity (Dar-El et al. 1995; Shafiei-Monfared and Jenab 2011), are employed in terms of production costs. Note that cost learning effects include effects from employee learning, such as material handling and waste reduction (Lapr   et al. 2000), as well as effects from reengineering and incremental changes of production processes which are prominent in the s-curve model (Baloff 1971).

While learning-by-doing takes place during the production process and does not result in any further costs, two distinct kinds of training costs arise for training: on the one hand, the needed time $tr_l = 5$ and on the other hand, the monetary costs $c_l = 2$. The time utilized for training reduces the capacity available for production. Therefore, opportunity costs of lost production (shortage costs) arise. Forgetting occurs if an employee pursues a production activity or undergoes training fewer than $f_l = 10$ times in a period. In the case of forgetting, the workers' competence units decrease by $w_i = 10$ units. The company skill target for the end of the planning horizon is $\phi_i = 500$ skill units per worker.

Three features of the modeled production system factors are manipulated: the demand, employee capacities, and training availability. To simulate a stochastic

demand, a random distribution of period demands is applied. After choosing a stochasticity (demand volatility) level dv from 1 to 100, a random algorithm sets demands D_{jt} for all products j so that they sum up to 5400 over all 18 periods per product. Different time capacity levels of employees are applied in order to analyze the intensity of the demand volatility relative to the workforce capacity. The aforementioned three scenarios use the following time capacity \overline{CAP}_i per period: *low* = 200, *medium* = 375, and *high* = 550. These limits are chosen to simulate different impacts of demand volatility on production. In the low-capacity scenario, workers cannot meet the average demand of 100 units per period per product with their initial skill endowment. The medium-capacity scenario enables workers to meet the average demand exactly, while employees in the high-capacity scenario can meet the given demand and have additional capacity to be trained in each period.

The third manipulated factor is the budgeted training access. In the budgeted scenario, the training capacity limit for all employees together is set to $\overline{ucap} = 180$ per period in the first five periods. The following periods 6 to 18 do not allow for training measures.

Combining those factors, we receive 100 datasets based on the volatility simulation for each capacity level and each scenario, with and without budgeted training measures, resulting in 600 datasets in total with 10,800 data points due to the 18 periods of observation. To solve the above-described model we utilize the Gurobi 7.5.2. solver in GAMS. We terminate the runs when a gap of 4% is reached. The dataset obtained serves as the basis for the analysis which is performed in the following section.

5 Results and discussion

In the following a description of the applied analysis method in Sect. 5.1 and a descriptive analysis in Sect. 5.2 is presented. The section is hereinafter structured according to the hypothesis derived in Sect. 3. The influence of budgeting training measures on skill development is analyzed in Sect. 5.3. Further, we aim to shed light on the effects of demand volatility in Sect. 5.4 and, lastly, we analyze the interplay of budgeted training measures and the intensity of demand volatility and employee capacity in Sect. 5.5.

5.1 Analysis methodology

Throughout our analyses, *Generalized Estimating Equations* (GEE) are employed in order to investigate the effects of the above explained factors on the dependent variables and to test the previously formulated hypotheses. To do so, we used the open-source platform *R* (version 3.6.1) and the package *geepack* (Halekoh et al. 2006). Regression analyses with GEE are appropriate for the analysis of longitudinal data. Because of the normal distribution of the variables, we employ a *gaussian* family and use an *identitylink*. Due to the time-dependent nature of our variables, we use an AR(1) structure (Ballinger 2004).

Table 1 Coefficients from GEE regression training

Variables	All capacity levels			Different capacities		
	Linear	Quadratic	Interaction	Low (200)	Medium (375)	High (550)
Observations	N=10,800	N=10,800	N=10,800	N=3600	N=3600	N=3600
Intercept	50.866***	14.460***	28.992***	35.056***	90.424***	87.990***
Budget	-2.713***	-2.733***	-6.653***	-4.889***	-5.580***	1.053
Volatility	0.044***	0.042***	-0.182***	-0.069***	0.019	0.175***
Time	-4.858***	-4.852***	-4.850***	-1.729***	-6.130***	-6.906***
Capacity	0.052***	0.279***	0.237***			
Capacity ²		-0.0003***	-0.0003***			
Volatility*Capacity			0.001***			
Volatility*Budget			-0.049**			
Budget*Capacity			0.017***			

* Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 2 Coefficients from GEE regression learning-by-doing

Variables	All capacity levels			Different capacities		
	Linear	Quadratic	Interaction	Low (200)	Medium (375)	High (550)
Observations	N=10,800	N=10,800	N=10,800	N=3600	N=3600	N=3600
Intercept	127.368***	-88.072***	-87.746***	163.071***	300.047***	301.447***
Budget	0.196	0.572**	2.409***	1.474***	0.172	-0.035
Volatility	-0.067*	-0.062***	-0.086***	-0.023***	-0.163***	-0.0003
Time	0.773***	0.727***	0.727***	1.944***	0.374**	-0.149
Capacity	0.339***	1.684***	1.683***			
Capacity ²		-0.002***	-0.002***			
Volatility*Capacity			0.00007**			
Volatility*Budget			-0.002			
Budget*Capacity			-0.005***			

*Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

With regard to our previously formulated hypotheses, we use six dependent variables: *Training* (Table 1), *Forgetting* (Table 3) and *Learning-By-Doing* (Table 2), as well as *Learning Output* = *Training* + *Learning-By-Doing* (Table 4), *Total Skill Development* = *Training* + *Learning-By-Doing* - *Forgetting* per period (Table 5) and, lastly, *Achieved Skill Units*, which equal the sum of the achieved skill units over all activities for each period (Table 6). The expression ‘employees’ skill development’ utilized in the hypothesis focuses mainly on the variables *Total Skill Development* which combine *Training*, *Learning-By-Doing* and *Forgetting*. Table 7 in the appendix links the six dependent variables to the simulation model.

Table 3 Coefficients from GEE regression forgetting

Variables	All capacity levels			Different capacities		
	Linear	Quadratic	Interaction	Low (200)	Medium (375)	high (550)
Observations	N=10,800	N=10,800	N=10,800	N=3600	N=3600	N=3600
Intercept	18.183***	22.040***	20.717***	16.403***	33.647***	22.425***
Budget	1.209***	1.211***	-2.100**	-0.324	0.669	3.390***
Volatility	0.026***	0.026***	0.091***	0.085***	-0.038***	0.031***
Time	2.726***	2.726***	2.726***	3.050***	2.027***	3.101***
Capacity	0.016***	-0.008	-0.005			
Capacity ²		0.00003***	0.00003***			
Volatility*Capacity			-0.0002***			
Volatility*Budget			-0.012			
Budget*Capacity			0.011***			

*Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

Table 4 Coefficients from GEE regression learning output

Variables	All capacity levels			Different capacities		
	Linear	Quadratic	Interaction	Low (200)	Medium (375)	High (550)
Observations	N=10,800	N=10,800	N=10,800	N=3600	N=3600	N=3600
Intercept	175.035***	-73.847***	-59.310***	198.155***	390.298***	383.761***
Budget	-2.515	-2.447***	-5.627***	-3.448***	-5.635***	1.842**
Volatility	0.001	-0.029**	-0.262***	-0.092***	-0.145***	0.142***
Time	-4.164***	-4.068***	-4.068***	0.211***	-5.723***	-6.645***
Capacity	0.404***	1.966**	1.924***			
Capacity ²		-0.002***	-0.002***			
Volatility*Capacity			0.001***			
Volatility*Budget			-0.045**			
Budget*Capacity			0.015***			

*Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

The main explanatory variables are *Budget*, displaying whether training is budgeted $Budget = 1$ or whether unconstrained training is available $Budget = 0$, *Volatility* ranging from 1 to 100 in discrete steps, and *Capacity* taking values for the three capacity scenarios of 200 (low), 375 (medium), or 550 (high). Further, we include *Time* which reflects the periods during the planning horizon. For each dependent variable we conducted six GEE regressions displayed in Tables 1, 2, 3, 4, 5 and 6. The first three columns show models depicting the main effects only, i.e. on all 10,800 data points per variable and all capacity scenarios. The model in column 1 assumes a linear relationship between the employees' capacities. Similarly to Letmathe and Schinner (2022), we find a non-linear relationship when analyzing the

Table 5 Coefficients from GEE regression total skill development

Variables	All capacity levels			Different capacities		
	Linear N=10,800	Quadratic N=10,800	Interaction N=10,800	Low (200) N=3600	Medium (375) N=3600	High (550) N=3600
Intercept	157.039***	-95.782***	-79.911***	181.691***	356.584***	361.274***
Budget	-2.841	-3.595***	-3.570**	-3.099***	-6.255***	-1.515*
Volatility	-0.030	-0.055***	-0.354***	-0.178***	-0.107***	0.111***
Time	-6.831***	-6.787***	-6.787***	-2.832***	-7.748***	-9.745***
Capacity	0.384***	1.973***	1.928***			
Capacity ²		-0.002***	-0.002***			
Volatility*Capacity			0.001***			
Volatility*Budget			-0.032*			
Budget*Capacity			0.004			

*Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

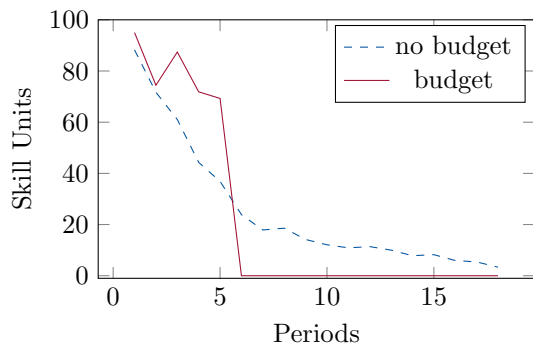
Table 6 Coefficients from GEE regression achieved skill units

Variables	All capacity levels			Different capacities		
	Linear N=10,800	N=10,800 Quadratic	Interaction N=10,800	Low (200) N=3600	Medium (375) N=3600	High (550) N=3600
Intercept	-896.802***	-3454.479***	-3222.401***	534.215***	642.943***	521.129***
Budget	5.111	17.789**	0.802	5.875	-17.664	37.930**
Volatility	-0.456	-0.488***	-4.627***	-2.102***	-1.213***	1.842***
Time	224.959***	223.649***	223.553***	142.324***	268.171***	263.153***
Capacity	3.861***	19.959***	19.312***			
Capacity ²		-0.021***	-0.021***			
Volatility*Capacity			0.012***			
Volatility*Budget			-0.626**			
Budget*Capacity			0.131**			

* Weakly significant ($p < 0.1$), ** significant ($p < 0.05$), *** highly significant ($p < 0.001$)

influence of employee capacity on training. For this purpose, the significance of the model for quadratic correlations is usually determined by the P -value (Twisk 2013). Here, the P -value is consistently highly significant for the quadratic variable *Capacity*. We model this non-linear relationship by using a quadratic term for *Capacity* and extend the models in columns two and three by the quadratic term *Capacity*² to better fit the quadratic u-shaped effects that we see in the data. Further, we compute the interaction variables *Volatility* * *Capacity*, *Volatility* * *Budget*, and *Budget* * *Capacity* to analyze the interplay of the manipulated variables and the

Fig. 1 Average Training Per Period



capacity scenarios in more detail. The latter three models (columns 4–6) comprise the main effects for the different capacity scenarios separately. Throughout our analysis, we focus on significant effects only. The quadratic term $Capacity^2$ is significant in all models. Therefore we analyze the effects displayed in the second columns and omit analyzing the results in the first columns, where a linear relationship is assumed. For the sake of completeness we display the models without $Capacity^2$ in the first columns.

5.2 Descriptive analyses

Before turning to the results of the multivariate statistics and the tests of the hypotheses, we first report some descriptive results for a better understanding of the underlying strategies for how companies can most efficiently cope with learning and training requirements in the different scenarios. In Fig. 1, the average training measures undertaken by all workers per period are displayed. The number of training sessions decreases over time in both scenarios; nevertheless, training measures are initially used more frequently in the budgeted scenario than in the flexible scenario, where they decrease continuously. Due to the model's assumption, workers in the budgeted scenario cannot train later than in period 5, whereas workers in the flexible scenario can be trained in all periods. Considering the development of forgetting, displayed in Fig. 2, we see contradictory behavior, which aligns with the findings from the average training measures. Overall, forgetting increases over time in both scenarios. However, in the budgeted scenario, workers forget less knowledge in the first five periods of observation compared to the flexible scenario. In period six, this effect changes, as workers forget more acquired knowledge in the budgeted scenario. The effect of more training and fewer forgetting in the first five periods results in a generally higher level of average achieved skills in the budgeted scenario. In both scenarios, but more pronounced in the flexible scenario, employees can use their time endowment in periods of low demand for training and prepare for periods with higher demand. The effect that workers achieve higher average skill levels in the budgeted setting is especially strong in the settings with low to medium volatility ($Volatility \leq 60$), shown in Fig. 3, and diminishes with higher volatility ($Volatility > 60$). Considering a volatility level of 100, the underlying trend lines

Fig. 2 Average Forgetting per Period

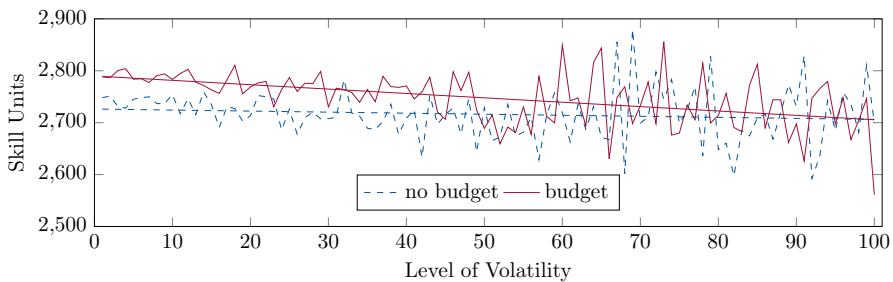
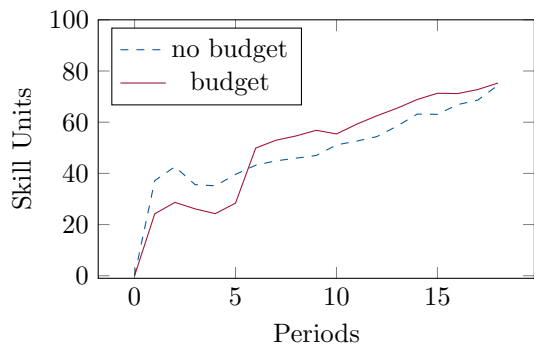
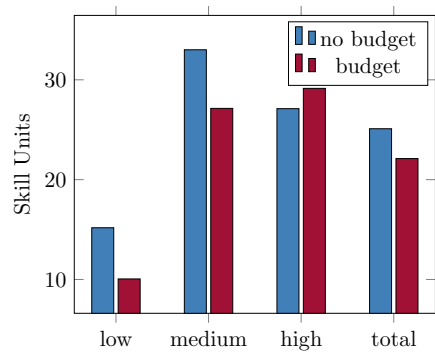


Fig. 3 Average Achieved Skill Level vs. Volatility

of budgeting and flexible training merge. Thus, if volatility and capacity allow for training, workers are trained more intensively in the first five periods in the budgeted scenario compared to the flexible scenario. Hereby, the forgetting caused by missing training opportunities in the later periods is counterbalanced. Since our model does not allow to build up inventory, the excess employee capacity during low demand can solely be used for training. In the budgeted scenario, this is only possible in the first five periods. In later periods the capacity cannot be used to counteract forgetting by training measures. Consequently, in times of low demand and budgeting, the available capacity cannot be used for neither training nor production. This results in excess unused capacity due to the fluctuations in demand. This results in excess, unused capacity due to fluctuations in demand. However, excess capacity must still be maintained for periods of high demand. The dynamics are visualized in Figs. 6, 7 and 8 in the appendix.

When turning to the three capacity scenarios, we find a difference in the absolute number of training measures (Fig. 4). By indicating an inverse u-shape curve, training is higher in the medium-capacity scenario and somewhat lower in both other scenarios. The lowest amount of training measures is undertaken in the low-capacity scenario. Based on the u-shaped influence of the capacity endowments employed, we modeled capacity as a quadratic term $Capacity^2$ in our GEEs to test whether this relationship has a significant impact. Surprisingly, we find the number of average training sessions to be larger in the budgeted than in the flexible scenario,

Fig. 4 Average Training per Capacity Scenario

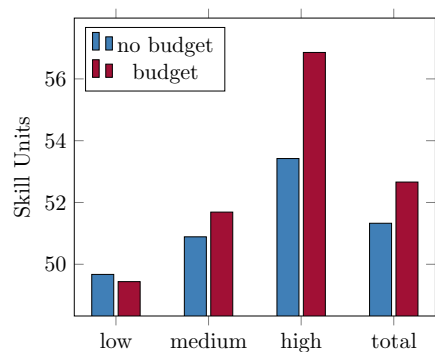


considering the high-capacity setting. Figure 5 reveals that forgetting increases with higher capacity. This relation can be explained through more intensive training in the first periods due to the higher time capacities available. More initial training leads to more forgetting in later periods. Not surprisingly, this effect is more pronounced in the budgeted scenarios, where training is squeezed into the first periods of the planning horizon. Each of the following sections evaluates the individual effects of learning, training and forgetting first and turns later to the compound variables learning output, skill development and achieved skill levels.

5.3 Influence of budgeted training measures

Focusing on the effect of budgeted training measures (*Budget*), we find evidence for the assumption that budgeting has a significant negative effect on *Training* ($p < 0.001$, column 2, Table 1). In contrast to *Training*, *Learning – By – Doing* is positively affected by budgeting training measures ($p = 0.018$, column 2, Table 2.) This effect can only be observed when including capacity as a quadratic term $Capacity^2$, as it is only significant in the low-capacity scenario ($p < 0.001$, column 4, Table 2) and vanishes with more employee capacity (columns 5 and 6, Table 2). This might be driven by possible efficiency gains due to training which reduce shortage costs in later periods to an extend that allows

Fig. 5 Average Forgetting per Capacity Scenario



missing the demand and paying shortage costs in earlier periods. The missing effect in the higher capacity scenarios might be driven by the fact that there is sufficient capacity endowment to meet the given demand and to allow for the amount of training needed for preventing higher shortage costs in later periods. Consequently, companies produce equally in both scenarios to meet the given demand, which further fosters comparable results for learning-by-doing. The contradictory effects of *Training* and *Learning – By – Doing* result in an overall negative effect of *Budget* on the compound variable *Learning Output*, again with a non-linear and significant influence of the capacity endowments *Capacity*² ($p < 0.001$, column 2, Table 4). Turning to the three capacity levels, we find that in the low and medium scenarios the missing opportunities for training lead to a negative influence of *Budget* on the *Learning Output* ($p < 0.001$, column 4 and 5, Table 4) whereas the budgeting leads to a positive effect in the high-capacity scenario ($p < 0.001$, column 6, Table 4). This effect aligns with the findings of the descriptive analyses which show that employees undertake more training measures in the first periods in the budgeted scenario compared to the flexible scenario (Fig. 1). The amount of extra training sessions is high enough to exceed the training measures utilized in the flexible scenario in the whole planning horizon, and thus, lead to a significant positive learning output for budgeting in the high-capacity scenario as well as in the whole dataset. Analyzing the effect of *Budget* on *Forgetting* (Table 3), we find that the absence of an all-time availability of training measures fosters the loss of workers' skill units significantly ($p < 0.001$, column 2 and 6 Table 3). The change of sign of the effects of the variable *Budget* throughout the different capacities illustrates the non-linear and significant impact of the capacity variable *Capacity*² ($p < 0.001$, column 2, Table 3). These findings are consistent with the assumption made by Jaber et al. (2003) that training measures might be used to keep skill units high and thus prevent forgetting.

When looking at the overall effect on the *Total Skill Development* (Table 5), which includes *Training*, *Learning – By – Doing* and *Forgetting*, we find a significant negative impact of budgeted training measures (*Budget*) with a non-linear and significant impact of the capacity endowment *Capacity*² ($p < 0.001$, column 2, Table 5). This negative impact persists in all scenarios while being only weakly significant in the high-capacity scenario ($p < 0.001$, column 4, 5 and 6, Table 5). This shows that extensive training in the first periods allows compensating the effect of forgetting in the later periods. Consequently, the results support H1, as the budgeting of training measures has a negative impact on skill development.

Surprisingly, the data reveal a positive effect of *Budget* on the overall *Achieved Skill Units* ($p < 0.001$, column 2, Table 6). This effect depends on the non-linear influence of the capacity and can only be observed in the high-capacity scenario. However, this effect is no longer significant when the relevant interaction effects are considered ($p = 0.9667$, column 3, Table 6). Thus, H1 is supported. Therefore, we now turn to the hypotheses to investigate the relevant effects triggered by our two manipulated variables—demand *Volatility* and employee *Capacity*.

5.4 Influence of volatility

Hypothesis H2 proposes that demand volatility has a negative impact on employees' skill development. Again, we look at the individual effects of *Training*, *Learning – by – doing*, and *Forgetting* first, and then consider the total effect on employee skill development. Surprisingly, we find that demand *Volatility* has a small but significant ($p < 0.001$, column 2, Table 1) positive impact on workforce *Training*. Analyzing the capacity scenarios, we find contradictory results. The impact of *Volatility* in the scenario with high demand intensity (low-capacity) is significant negative ($p < 0.001$, column 4, Table 1), not significant in the medium scenario, and significant positive ($p < 0.001$, column 6, Table 1) in the scenario with low demand impact (high-capacity). This effect is probably driven by the fact that high volatility at low capacity leads to high shortage costs, as the corresponding demand cannot be met when employees are trained extensively. At high capacity, the volatility can be absorbed and it is further possible to invest excess time in the training of the workers. Again, this effect on *Training* is accompanied by a non-linear and significant influence of *Capacity*² ($p < 0.001$, column 2, Table 1). *Learning – by – doing* is affected negatively by demand *Volatility* ($p < 0.001$, column 2, Table 2). This effect persists in the low- and medium-capacity scenarios ($p < 0.001$, column 4 and 5, Table 2). Employees are not able to meet the high demand which is strongly deviating from the average if high demand volatility is employed. This might affect especially the first periods, where no experience gains are present, caused by their time capacity restrictions. Additionally, we do not include storage in our model and it is impossible to produce goods in advance to meet later demand. Thus, production opportunities are forgone and learning-by-doing decreases with respect to a scenario with lower demand volatility. Moreover, an explanation for this might be, for example, that volatility leads to workers frequently having to change tasks, which means that specialization potential cannot be fully exploited. As a result, increases in skill levels through learning-by-doing are lower when volatility is high and can only be buffered by excess capacity in the high-capacity scenario in which *Volatility* has no effect (column 6, Table 2). Considering the combined variable *Learning Output* (Table 4), *Volatility* has a negative influence. In the low- and medium-capacity scenarios, the effect is significant negative. In the high-capacity scenario, again, training measures can be used in times of low demand to prepare for times with higher demand. Thus, a positive effect occurs ($p < 0.001$, columns 4,5 and 6, Table 4).

Similarly, we find significant positive effects on *Forgetting* due to *Volatility* ($p < 0.001$, column 2, Table 3), as workers miss opportunities for learning-by-doing and training, which both of which may prevent forgetting. Interestingly we find a significant non-linear effect of *Capacity*² ($p < 0.001$, column 2, Table 3) which is reflected by a u-shaped effect in the different capacity scenarios, since the effect of *Volatility* on *Forgetting* is positive in the scenarios with low- and high-capacity ($p < 0.001$, columns 4 and 6, Table 3), whereas *Forgetting* decreases with higher volatility in the medium scenario ($p < 0.001$, column 5, Table 3). This at first glance contradictory result can be interpreted by looking at various influence factors. Volatility at low capacity leads to frequent changes of tasks among the employees and thus to less specialization and more forgetting. The increase in forgetting at high

capacity on the other hand can be explained by the fact that more knowledge is built up and thus the possibilities of forgetting increase. The medium-capacity scenario, on the other hand, might use a good mix of specialization and training. Therefore, more volatility does possibly not lead to more forgetting here, but on the contrary to significant higher retention of the skills once they have been acquired.

For *Total Skill Development* (column 2 Table 5) and *Achieved Skill Units* (column 2, Table 6), we observe negative effects with increasing demand *Volatility*, similarly to the individual effects described above. This effect is visualized in Fig. 3. Hence, we find support for our second Hypothesis H2 in the whole data set ($p < 0.001$, column 2, Tables 5 and 6), as well as in the low- and medium-capacity scenario ($p < 0.001$, column 4 and 5, in Tables 5 and 6). Nevertheless, in the high-capacity scenario, we find a significant positive effect of increasing demand *Volatility* on the *Total Skill Development* ($p < 0.001$, column 5, Table 5) and the *Achieved Skill Units* ($p < 0.001$, column 5, Table 6). After discussing the results for the individual effects, this result should no longer be surprising.

5.5 Interaction effects with budgeting

First, we present the interaction effect between budgeting training measures and employee capacity. Second, we analyze the interaction between demand volatility and budgeting.

Since employees' time capacity is used for training and production, the effect of budgeting on skill development depends on employees' capacity endowment. The importance and effect of the capacity scenarios have already emerged from the presented analyses, which further emphasized the importance of the non-linear effect. These effects are underlined by a significant influence of the quadratic term *Capacity*² on all variables. In order to gain further insight on the influence of the moderating variable *Capacity* in combination with budgeting, we compute the interaction effect of *Budget * Capacity* on the variables describing employees' skill development. Analyzing the effect of the interaction variable on *Training* measures, we find a significant positive effect ($p < 0.001$, column 3, Table 1). The effect supports H3 and indicates that employees practice more during the initial periods if excess capacity (high-capacity scenario) is available and shortage costs can be kept at their minimum. These extra training measures might be connected to costs for the company, at least in terms of employee capacity.

For *Learning-By-Doing*, we do not find a significant negative effect for the interaction of budgeting and capacity *Budget * Capacity* ($p < 0.001$, column 3, Table 2). Interestingly, we find a positive interaction effect of *Budget * Capacity* on *Forgetting* ($p < 0.001$, column 3 Table 3), indicating that excess capacity leads to more forgetting. In this vein, Fig. 4 reveals that workers lose relatively and absolutely more skill units due to forgetting in the high-capacity scenario. On the one hand, the high employee capacity endowment allows for tactical training, in order to prevent forgetting in the flexible scenario. On the other hand, the plot in Fig. 5 shows that in the budgeted high-capacity scenario, absolutely more training measures are used, compared to the flexible setting. This is noteworthy, as training is only possible in the first five periods. Thus,

employees are initially trained to a higher skill level in the high-capacity scenario, which consequently results in more forgetting and is driven by the aim to avoid shortage costs in later periods.

Considering the compound variable *Learning Output*, the interaction variable *Budget * Capacity* has a significant positive effect ($p < 0.001$, column 3, Table 4), driven by the effect on *Training* ($p < 0.001$, column 3, Table 1). However, the data do not reveal a significant effect on the *Total Skill Development*, which incorporates *Forgetting* and thus a complementary effect to *Training*. Relating to the *Achieved Skill Units* of employees, we observe a significant positive interaction of *Budget* and *Capacity* ($p = 0.0022$, column 3, Table 6). These results provide partial support for H3. The achieved skill units are positively affected, as employees are initially trained to a higher skill level in the budgeted scenario in order to use the initial productivity gains as a buffer against future volatility and forgetting. Therefore, the total skill development per period is not positively affected as the higher achieved skill units decrease over time due to an increase in forgetting compared to scenarios without volatility. In this vein, employees do gain more skill units in absolute terms which are lost in the consecutive periods.

Turning to the effect of the interaction variable *Volatility * Budget*, which combines budgeting and volatility, we find a negative and significant impact on *Training* ($p = 0.003$, column 3, Table 1). On the one hand, this result might again be driven by the shortage costs which arise if production does not meet demand. Thus, production (reflected by the variable *Learning – by – doing*) is prioritized over *Training* and is not further affected by the combination of budgeting and volatility (column 3, Table 2). On the other hand, higher demand in the first periods does not only lead to unmet demand for the budgeted and flexible scenarios but moreover to foregone training opportunities in the budgeted scenario which cannot be offset in later periods. Thus, *Volatility * Budget* amplifies the negative influence on *Training*. Since it is not possible in the budgeted scenario to compensate for forgetting through training measures in the budgeted scenario any later than in period five, demand volatility in combination with budgeting does not have any further significant effect on *Forgetting* (column 3, Table 3). As a result, we receive a negative and significant impact on *Learning Output* ($p = 0.014$, column 3, Table 4), *Total Skill Development* ($p = 0.082$, column 3, Table 5) and *Achieved Skill Units* ($p = 0.0065$, column 3, Table 6). Therefore, hypothesis H4 is supported and we do find a negative influence of the interaction variable *Volatility * Budget* on the employees' skill development.

Due to the fact that the interaction variable *Volatility * Capacity* has extensively been studied by Letmathe and Schinner (2022), we omit analyzing this relation. Since the effects were significant in their study, we included the variable for the sake of completeness so that we could analyze the remaining effects in a more differentiated manner.

6 Conclusion

Summarizing our analyses of traditional (budgeted) versus flexible training approaches on production ramp-up under the influence of demand volatility and different employee capacity endowments, we find that the budgeting of training measures has a negative influence on the skill development of employees. In detail, employees are trained less frequently and lose more skill units due to forgetting when training measures are budgeted. This is reflected by an overall lower average skill development of the workforce compared to flexible training approaches. Moreover, employees achieve higher skill units in the budgeted scenario, as excess training measures in the first periods can be used to compensate for forgetting in later periods. Thus, additional costs for initial training arise. To simulate different intensities of demand volatility, three scenarios with different time capacity endowments of workers are employed. In the low scenario, workers cannot meet the average demand per period using their initial time endowment. Thus, skill improvements through training and learning-by-doing are necessary for workers to meet the demand in later periods and to prevent shortages. The time endowment in the medium scenario is sufficient to meet the average demand but does not leave much time for training. In the high-capacity scenario, training and production are simultaneously possible. These three scenarios allow for an extensive analysis of the training impact on employees' skill development, depending on the products' demand and its volatility. When looking at the interplay of budgeted training measures and capacity, we find distinctive effects, which can be explained by different influence factors. Considering employees with a small capacity endowment, respective to demand, assignments to training or production are mainly driven by the need to fulfill a given demand and to prevent shortage costs. In the high-capacity scenario, on the other hand, the buffer effect predominates, i.e. the negative effects of demand volatility can largely be offset by the available overcapacity.

Therefore, the influence of budgeting is strongest in the low-capacity scenario, as employee training has to be squeezed into the few available time windows, and initial training in the first periods is often not possible. Consequently, the impact diminishes with higher capacity. Thus, the skill development and the achieved skill levels, increase with capacity. If employee capacities suffice, workers are trained extensively in the first periods to reach higher average skill levels allowing for lower costs and higher productivity in subsequent periods. Overall, the amount of training in the first five periods in the budgeted scenario is much higher than the number of training sessions in the flexible scenario, where workers can be trained at all times.

As a consequence, decisions on employee training need to be based on the employees' time capacity in relation to product demand. In times of high demand pressure, flexible training measures contribute to the skill development of employees, they prevent forgetting, and they offer higher efficiency gains. With enough employee capacities, it is possible to reduce negative effects by training employees to a higher extent than is needed in the first periods. Therefore, an investment in flexible training measures that can be used in times of low demand, e.g. e-learning or mobile learning, can potentially contribute to a company's productivity if employee

capacities are fully utilized for meeting a given demand. Moreover, it can prevent costs for excess training measures undertaken in the first period which would not be necessary if employees have access to training when it is needed in order to prevent forgetting during all periods.

In summary, our research provides interesting insights into the interplay of employee learning, budgeting training measures, capacity restrictions, and demand volatility, which are also highly relevant in practice. The selected simulation scenarios make it possible to predict relevant interactions as a consequence of induced changes in the variables without making claiming general transferability of the results. Like any research, this article therefore has its limitations. Considering the results of our study, it should be noted that the used parameters were set by the researchers. Although these are derived using empirical results from the field and a former study by the authors, future research might validate the results using real shop floor data. Moreover, future research might include a setting that incorporates more employees and more tasks, or analyze the impact of flexible capacities to include overtime hours. The model considers categorical skills but assumes that each worker is able to perform any of the activities with her or his initial skill set. An extension to the study could model categorical skills in a way that demands employees to gain initial experience on the production task in order to be able to perform it. In this vein, effects of budgeted training measures on specialization and cross-training of workers could be evaluated. The production environment considered is a parallel production setting yielding multiple products. Analyzing the effects for serial production lines, i.e. assembly lines, provides further avenues for research.

Appendix A: Mathematical model

$i \in \{1, \dots, m\}$ denote the set of shop floor employees

$j \in \{1, \dots, n\}$ products

$t \in \{1, \dots, T\}$ period of the observation

$k \in \{1, \dots, K\}$ discrete skill levels

$l \in \{1, \dots, L\}$ production activities

a_{lj} number of units of product j produced after pursuing production activity l

\overline{CAP}_i time capacity of employee i in every period

c_{kl} production costs per unit for activity l at skill level k

c_l costs per training measure for production activity l

D_{jt} demand for product j in period t

fg_{lit} binary variable displaying if forgetting occurs for employee i and production activity l in period t

fl_t minimum amount of newly gained skill units in a period needed to prevent forgetting for activity l

M big M

p_{kl} processing time per unit for activity l at skill level k

r_{iklt} binary variable displaying if employee i is able to pursue production activity l at skill level k in period t

sc_j shortage costs of product j

sh_{jt} amount of shortage of product j in period t

tr_l time needed for one unit of training for production activity l

$u_{ilt} \geq 0$ total amount of training measures of employee i in period t for production activity l

v_i individual linear learning or skill development factor of employee i

w_i individual factor for forgetting of employee i

$y_{iklt} \geq 0$ amount of product l produced by production activity k by worker i in period t

yt_{ilt} amount of all production activity l performed by employee i in period t

ys_{lt} amount of all production activity l in period t

$z_{ilt} \geq 0$ skill units of employee i for production activity l in period t

$z_{kl}^{min} \geq 0$ required skill minimum

ϕ_i company skill target for employee i in period $t = T$

Table 7 Mathematical formulation of the dependent variables

Variable	Definition
Learning-by-doing	$\sum_{i=1}^m \sum_{l=1}^L y_{ilt} \cdot v_i \quad t \in \{1, \dots, T\}$
Training	$\sum_{i=1}^m \sum_{l=1}^L u_{ilt} \quad t \in \{1, \dots, T\}$
Learning-Output	$\sum_{i=1}^m \sum_{l=1}^L y_{ilt} \cdot v_i + \sum_{i=1}^m \sum_{l=1}^L u_{ilt} \quad t \in \{1, \dots, T\}$
Forgetting	$\sum_{i=1}^m \sum_{l=1}^L w_i \cdot fg_{ilt} \quad t \in \{1, \dots, T\}$
Total Skill Development	$\sum_{i=1}^m \sum_{l=1}^L y_{ilt} \cdot v_i - \sum_{i=1}^m \sum_{l=1}^L w_i \cdot fg_{ilt} + \sum_{i=1}^m \sum_{l=1}^L u_{ilt} \quad t \in \{1, \dots, T\}$
Achieved Skill Units	$\sum_{i=1}^m \sum_{l=1}^L \sum_{t=1}^T z_{ilt}$

$$\underbrace{\sum_{i=1}^m \sum_{k=1}^K \sum_{l=1}^L \sum_{t=1}^T c_{kl} \cdot y_{iklt}}_{\text{production costs}} + \underbrace{\sum_{i=1}^m \sum_{l=1}^L \sum_{t=1}^T c_l \cdot u_{ilt}}_{\text{training costs}} + \underbrace{\sum_{j=1}^n \sum_{t=1}^T sc_j \cdot sh_{jt}}_{\text{shortage costs}} \rightarrow \min \quad (8)$$

$$y_{ilt} + u_{ilt} + M \cdot fg_{ilt} \geq fl_i \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (9)$$

$$y_{ilt} + u_{ilt} + M \cdot fg_{ilt} < (M + fl_i) \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (10)$$

$$z_{ilt} = z_{il(t-1)} + y_{ilt} \cdot v_i + u_{ilt} - w_i \cdot fg_{ilt} \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\}, \quad (11)$$

$$\sum_{k=1}^K \sum_{l=1}^L p_{kl} \cdot y_{iklt} + \sum_{l=1}^L tr_l \cdot u_{ilt} \leq \overline{CAP}_i \quad \forall i \in \{1, \dots, m\}, t \in \{1, \dots, T\} \quad (12)$$

$$z_{kl}^{min} - z_{ilt} \leq M \cdot (1 - r_{iklt}) \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (13)$$

$$y_{iklt} < M \cdot r_{iklt} \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (14)$$

$$\phi_i \leq \sum_{l=1}^L z_{ilT} \quad \forall i \in \{1, \dots, m\} \quad (15)$$

$$\sum_{i=1}^m \sum_{l=1}^L u_{ilt} \leq \overline{ucap}_t \quad \forall t \in \{1, \dots, T\} \quad (16)$$

$$sh_{jt} = D_{jt} - \sum_{l=1}^L a_{jl} \cdot ys_{lt} \quad \forall j \in \{1, \dots, m\}, t \in \{1, \dots, T\} \quad (17)$$

$$ys_{lt} = \sum_{i=1}^m \sum_{k=1}^K y_{iklt} \quad \forall l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (18)$$

$$yt_{ilt} = \sum_{k=1}^K y_{iklt} \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (19)$$

$$fg_{ilt} \in \{0, 1\} \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (20)$$

$$r_{iklt} \in \{0, 1\} \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (21)$$

$$sh_{jt} \geq 0 \quad \forall j \in \{1, \dots, n\}, t \in \{1, \dots, T\} \quad (22)$$

$$u_{ilt} \geq 0 \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (23)$$

$$y_{iklt} \geq 0 \quad \forall i \in \{1, \dots, m\}, k \in \{1, \dots, K\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (24)$$

$$yt_{ilt} \geq 0 \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (25)$$

$$ys_{lt} \geq 0 \quad \forall l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (26)$$

$$z_{ilt} \geq 0 \quad \forall i \in \{1, \dots, m\}, l \in \{1, \dots, L\}, t \in \{1, \dots, T\} \quad (27)$$

On request, the GAMS code and the data will be provided by the authors.

Appendix B: Unused capacity

See Figs. 6, 7 and 8.

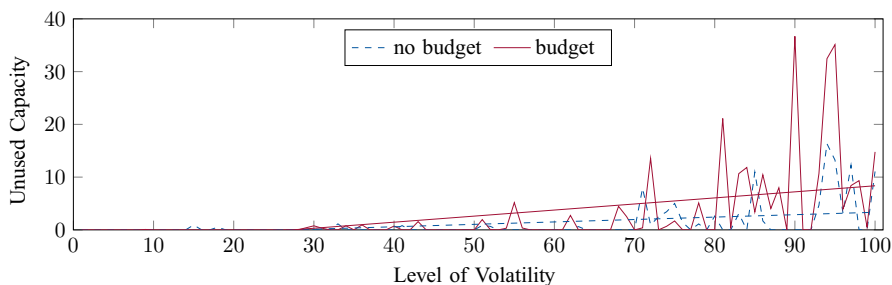


Fig. 6 Unused capacity—Capacity 200

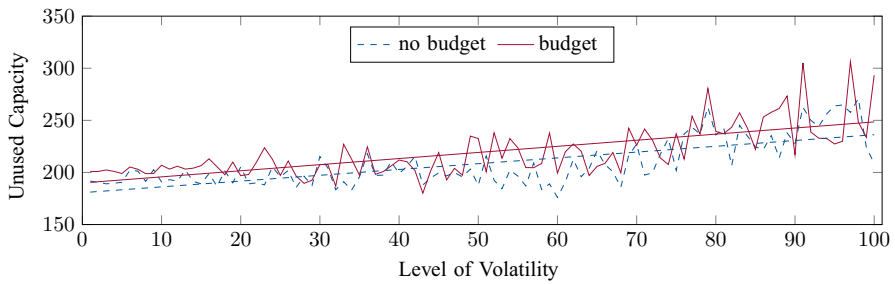


Fig. 7 Unused capacity—Capacity 375

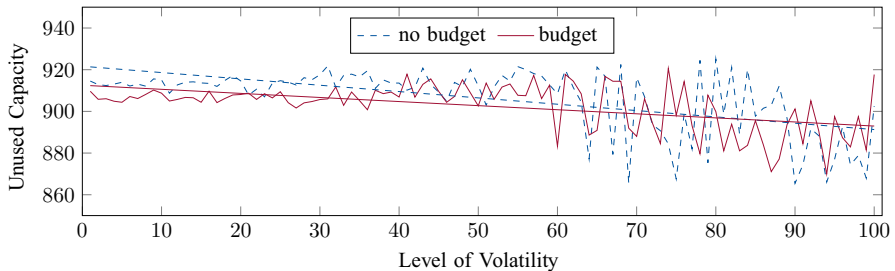


Fig. 8 Unused capacity—Capacity 550

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