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Assessment of Flexibility in Forming Technology in an Uncertain Sales Market Framework

T. Ederer · J. Avemann · S.O. Schmitt · U. Lorenz · P. Groche

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Abstract We evaluate the economic competitiveness of dedicated and flexible forming technologies under various trends of demand. A taxonomy is developed to categorize these demands depending on time resolution and level of uncertainty. Further, the influence of external, technology independent factors is investigated. Discrete optimization and dynamic programming are employed to find the optimal technology selection for each demand scenario. This work is motivated by the current situation of forming companies, where unexpected variations in demand can heavily affect the profitability of production technologies.

Keywords discrete optimization · uncertain demand · forming technology

1 Introduction

In the last two decades production technology is more and more affected by turbulent company surroundings. Product life cycles are shortening and the number of product variants is increasing [9]. This is triggered by an increasing speed of technological progress, customer demands for individualized products as well as global production [26]. The possibility to quickly exchange information and low transport times

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Thorsten Ederer / PD Dr. Ulf Lorenz
Dolivostr. 15, 64293 Darmstadt
Tel.: +49 (0)6151 16-3487 / 16-2961
Fax: +49 (0)6151 16-3954
E-mail: ederer/lorenz@mathematik.tu-darmstadt.de

Jörg Avemann / Sebastian O. Schmitt / Prof. Dr. Peter Groche
Petersenstraße 30, 64287 Darmstadt
Tel.: +49 (0)6151 16-75143 / 16-3956 / 16-3056
Fax: +49 (0)6151 16-3021
E-mail: avemann/s.schmitt/groche@ptu.tu-darmstadt.de

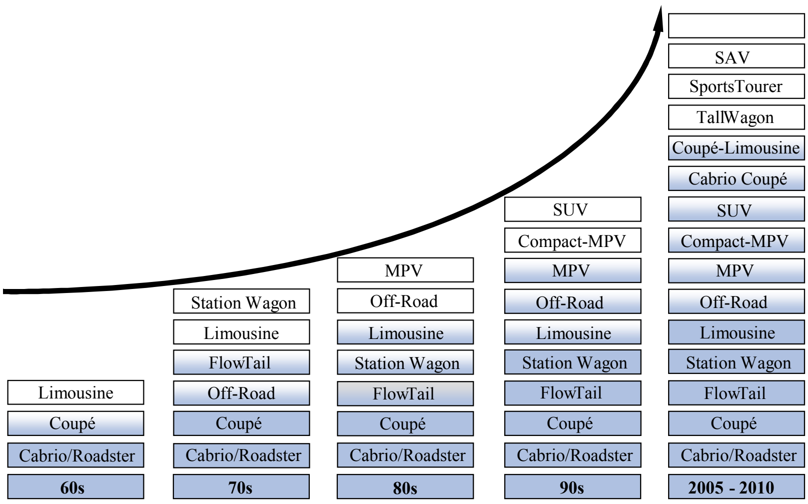


Fig. 1 Variant development for passenger vehicles [15]

strengthen the influence of global competition [26]. As a consequence of the shortening product life cycle, process life cycle and equipment life cycles diverge, which results in a challenge for process and equipment planning [19]. While the number of product variants is increasing, sales volumes are heavily fluctuating and hardly predictable [9]. Figure 1 displays the development of variants considering the example of passenger cars. While in the sixties only three variants were available today a broad number niche vehicles exists. For the future a further increase to between forty and fifty variants is expected [27]. Figure 2 shows sales volumes of some exemplary SUVs. It becomes apparent that the sales volumes are subject to high fluctuation which makes forecasting difficult and often inaccurate.

Besides uncertainties of the sales market a broad range of other influence factors exists. Varying prices, qualities and availabilities of raw materials and semi-finished products represent uncertainties of resources. Varying process characteristics e.g. due to wear as well as the qualification level of employees are influence factors that substantially result from inside the company. Environmental influence factors are e.g. changes in the legislation or in certification standards which can affect the demand for specific products or the processes a company may employ [20].

Forming technology as a branch of production technology is usually focused on mass production. The according production methods and processes are characterized by a very high productivity and utilization of material. With regard to the emerging shortage of energy and raw material forming technology provides the prerequisites to serve mass markets, as they are emerging in e.g. India or China, in an efficient way. On the other hand, the highly specialized processes require high invests in machines, high development efforts for tools as well as large set-up times. This hinders a quick response to changing market requirements such as changing products, product variants or lot sizes. As a consequence in the past many forming companies focused on a narrow product spectrum and few customers. A survey among the members of the

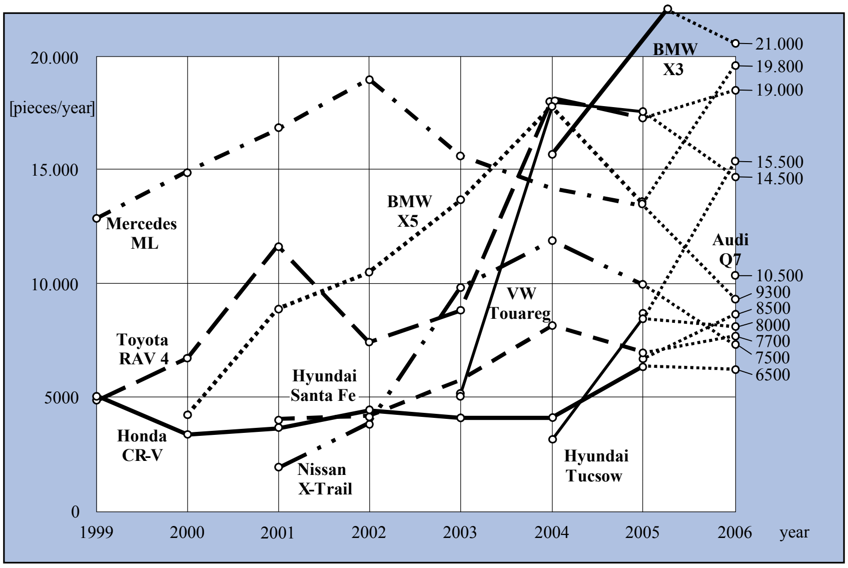


Fig. 2 Sales figures for suburban vehicles [15]

industrial association of sheet metal forming companies in Germany showed that the average revenue per customer is two million Euro. At average 80 % of the revenues are made with 17.3 % of the customers. 81 % of the sheet metal forming companies are depending on customers from the automotive branch.[1]

Against the background of the described market developments the forming industry is now confronted with the challenge to master the turbulent market surrounding and to simultaneously remain its high productivity and efficiency. Flexible production systems provide an approach to meet this challenge. According to Slack, flexibility is defined as the bandwidth of conditions at which a system can be operated [23]. These may allow the cost efficient adaption of production lot sizes as well as adaptions of the product spectrum or quality. Accordingly, the economic evaluation of investments in flexible production systems considering uncertainty is crucial.

2 Evaluation of investment opportunities under uncertainty

In the following a short overview of evaluation methods for investments is given. These are evaluated in regard to their adequacy for the economic assessment of flexible and dedicated machines in a forming company. This usually faces a two stage problem. It has to consider a strategic as well as an operational aspect making investment decisions. On the one hand it has to identify the optimal machine and on the

[1] The survey was conducted by the Institute of Production Engineering and Forming Machines of the *Technische Universität Darmstadt* in cooperation with the German industrial association of sheet metal forming companies. The survey was returned form 33 companies representing a sample of more than 5 % of the industry.

other hand it has to find the optimal employment for its machine portfolio. Thereby, information which is gathered after the time of the initial investment has to be considered. Technical interdependencies between varying influence factors, such as the demand, and the systems possibilities to react have to be considered.

The *discounted cash flow* (DCF) method is a standard for the evaluation of investments under uncertainty [11]. The *net present value* (NPV) of an investment is calculated using a risk free discount rate. To consider uncertainty a risk premium is added to the risk free rate lowering the net present value. Hence, probability distributions are reduced to a single figure often oversimplifying a risk evaluation. Further, the DCF method does not consider a company's option to react after an investment has been made. DCF assumes the passive commitment to an operation strategy, which is made at the time of the investment. Information that is gathered after the time of the initial investment is not regarded. This often leads to an undervaluation of the NPV [28]. Thus, the standard DCF method is not suitable for analyzing investments in uncertain markets. The *internal rate of return* (IRR) is the discount rate which results in a NPV of zero. To consider uncertainty, future payments can be adjusted by a risk premium. As a modification of the NPV method the IRR exhibits similar disadvantages as those described for the DCF.

In the real option approach, evaluation methods for financial options are applied to investments in production facilities [16]. In case of demand modeling, the value of the investment depending on the demand structure is defined as an underlying. The possibility to act after the time of the initial investment is represented in the model by the possibility to exercise or abandon an option [3]. Abele et al. [1] proved that the real option can be applied to value the flexibility of production machines. Different types of production system flexibility such as machine or routing flexibility can be represented by different types of options and modeling strategies [4]. The Black and Scholes Model is commonly employed for option pricing which assumes a geometric Brownian motion of the underlying [17]. This is, however, not adequate for many investment situations of production companies. The demand for a product may depend on unexpected occurences such as the outcome of an election, which cannot be sufficiently described by only considering an expected value and a standard deviation. Real option modeling using decision trees on the other hand may not be suitable for the calculation of complex problems.

The standard methods described above do not consider technical aspects. Against the described background, optimization under uncertainty may constitute a beneficial extension. A model can be developed which reflects technical production conditions. Hence, pay-offs need not be estimated, but can be calculated considering varying influence factors. In particular, the optimal solution of such a model does not only consist of a selection of machines from a given portfolio, but also of an optimal utilization strategy for these machines in every considered market scenario. Thereby, it can be assured that the flexibility potential of each machine is optimally exploited. Furthermore, uncertainty can be handled in different ways, e.g. by optimizing an expectation value or by doing a worst case analysis. Adaptions to the model are straightforward, which allows for later changes of the target functions or the consideration of enhanced technical aspects as well as market conditions.

3 Problem Statement

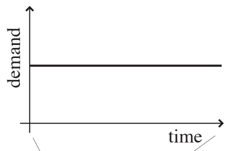
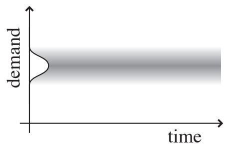
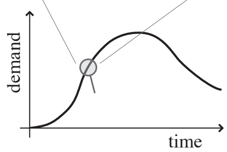
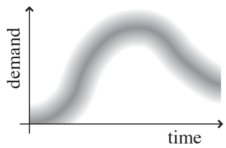
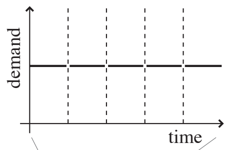
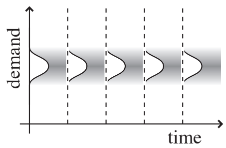
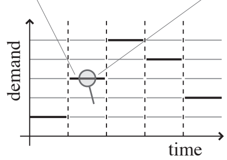
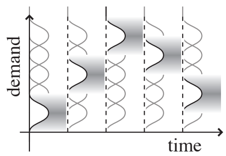
In the context of increasingly uncertain markets and the recent development of flexible production systems, there is a need to study the worth of flexibility for an investment. Some authors have already investigated this problem, e.g., Gupta et al. [13] modeled a two-stage stochastic program to find the optimal mix of dedicated and flexible manufacturing capacities, and Van Mieghem [25] studies the optimal investment in flexible manufacturing capacity based on several market parameters. However, these approaches are fairly theoretical. In this paper, we present a similar, but more practice-oriented mathematical model to support the investment decision between dedicated machines and flexible production systems, and verify this model in a case study with a realistic machine portfolio.

The basic assumption of our investigation is that a company wants to establish a new product or enter a new market. Assuming it has no capable process chains or the existing ones are working at full capacity, the company has to invest in one or several new machines. Thereby, it has to ensure that the investment ammortizes over a certain period of time, and, if possible, a worthwhile profit should remain. However, the company faces a market with unknown price structures, unclear costs of production and uncertain customer demands. Which technology option – cheaper dedicated machines or a more costly and more flexible production system – is the best investment? To answer this question, we must formalize *a*) the properties and costs of the production technologies, *b*) the market characteristics and the customer demand and *c*) our assumptions on the course of actual production.

The value of a flexible investment may heavily depend on the customer demand. To that end, our idea is to identify the best investment decision for *every* possible demand trend. Of course, we have to concentrate on a restricted feature set of the demand distribution, but we do not think that a few individual parameters such as the mean value or the variance of the demand suffice to base a purchase decision on. That means we have to find a satisfying compromise between versatility and computational overhead. Therefore, we classify possible demand models by their degree of abstraction.

Table 1 shows a taxonomy of market demands for a varying time resolution and levels of uncertainty. The left column of the demand distributions shows how the border cases of a constant and a very fluctuating deterministic demand trend translate to the realm of discrete time periods: On the one hand, a fixed demand spans over several time periods, which corresponds to the use case where operational decisions are carried out much faster than the demand can vary. On the other hand, it may be necessary to adjust each production step to a recent change in the demand level. In practice, a realistic demand distribution will usually have some properties of both cases, i.e. the demand will change perceptibly over time, but rather slow compared to operational control. The right column shows the stochastic equivalents of those cases. Here we have the additional complication, that the demand can only approximately be predicted, such that the exact value has to be observed near-term. To simplify the stochastic case in detail, we can assume without loss of generality that each observed demand attains one of finitely many discrete values and stays constant for the remaining period.

Table 1 Taxonomy of market demands

		demand distribution	
time	resolution	deterministic	stochastic
continuous trend	fine		
	coarse		
discrete periods	fine		
	coarse		

In the long-term production planning often only the deterministic case is considered. On top of that, a specific demand trend is often solely presumed. In the following, we are interested in multiple demand patters as in the discrete and coarse time resolution. We call the grid indicated by gray bars the *deterministic demand grid* (DDG) and all possible demand patterns that can possibly result from it will be evaluated. Afterwards, fluctuating demand scenarios are investigated employing the *stochastic demand grid* (SDG) on the same time level, i.e., patterns of the DDG where each demand level in itself is uncertain.

4 Model Formulation

As a preliminary step, we present a *mixed-integer linear program* (MIP) [22] for a deterministic version of the specified problem. That is, we formulate an extension of a single-product single-machine model [5, 6] with multiple technology variants to find the best investment decision given fixed market parameters and an upfront known demand. Thereafter, we discuss how the model can be extended further to handle uncertain market parameters. We denote index sets and model parameters as uppercase letters, whereas indices and model variables are depicted as lowercase letters.

4.1 A deterministic mixed-integer program

Let D_t be the (exactly) anticipated customer demand for each time period $t \in T = \{1,\dots,n\}$. The production is required to satisfy this demand and can be conducted by some technology variants $m \in M = \{1,\dots,k\}$ (which may either be dedicated system or technology options of a flexible system, depending on the parameter set) with corresponding lot sizes L_m. Production of a machine m in time period t is indicated by binary variables $z_{t,m}$.

Excess products (which may result from unsuitable lot sizes or deliberate preproduction) can be stored intermediately. They are remembered by the integer variables s_t (for the stock taken over from period t to period $t+1$). The stock may in principle be arbitrarily large, however, it causes stock holding costs C^H per product and time period (cf. equation 14). If the demand cannot be satisfied by the current production, it must be taken from the current stock.

$$s_t = s_{t-1} + \sum_{m\in M} L_m \cdot z_{t,m} - D_t \qquad \forall\, t \in T \tag{1}$$

A machine can only produce if it has been set up beforehand, but it can only be set up if it has been bought. We call a machine that has been set up *ready* and use the binary variables $r_{t,m}$ as indicators. Consequently, b_m are buying indicators.

$$z_{t,m} \le r_{t,m}, \quad r_{t,m} \le b_m \qquad \forall\, t \in T, m \in M \tag{2}$$

We require that exactly one machine must be ready at each time period, which is a nontrivial assumption with some implications: On the one hand, at times individual machines may have to be ready without producing – however, that is indiscriminative since it does not cause any additional costs (cf. equation 14). On the other hand, two machines cannot produce at the same time. In case of a flexible production system this is an obvious requirement, because setting up different tools is mutually exclusive. For dedicated machines this restriction is motivated by the machine's integration into the production process – the simultaneous operation of several identical tools in a process chain is usually regarded as impractical because of synchronization and maintenance issues and therefore avoided.

$$\sum_{m\in M} r_{t,m} = 1 \qquad \forall\, t \in T \tag{3}$$

The need for machine setups is indicated by the binary variables $w_{t,m}$, which describe if machine m undergoes a change from not being ready in time period $t-1$ to being ready in time period t. This binary product of two readyness indicators can be reformulated as a set of three linear constraints.

$$\begin{aligned} w_{t,m} &\le r_{t,m} \\ w_{t,m} &\le 1 - r_{t-1,m} \qquad \forall\, t \in T, m \in M \\ w_{t,m} &\ge r_{t,m} - r_{t-1,m} \end{aligned} \tag{4}$$

The initial investment i is composed of the basic technology costs C^0 (at least for the flexible system) and the indiviual costs C^I_m of all necessary machines.

$$i = C^0 + \sum_{m \in M} C^I_m \cdot b_m \tag{5}$$

The cash flow in every time period results from the selling price P of products delivered to the customer less several expenses, which consist of the stock holding costs (C^H), variable costs of the products (C^V_m), fix costs for each machine and (C^F_m), and costs for switching between machines (C^S_m). Note that a machine being ready does not contribute any significant costs on top of it's fix costs.

$$\begin{aligned} f_t = P \cdot D_t - C^H \cdot s_t - \sum_{m \in M} C^V_m \cdot L_m \cdot z_{t,m} \\ - \sum_{m \in M} C^F_m \cdot b_m - \sum_{m \in M} C^S_m \cdot w_{t,m} \end{aligned} \qquad \forall\, t \in T \tag{6}$$

We seek a combination of investment decision and production strategy to maximize the net present value, i.e. the profit resulting from the present values (with respect to the interest rate R) of all cashflows f_t after the investment is payed off. Of course, the project should be rejected in practice if the optimal objective value was negative – however, we do not require this with an additional model constraint.

$$\textit{maximize} \qquad \text{NPV} = -i + \sum_{t \in T} \frac{f_t}{(1+R)^t} \tag{7}$$

The net present value is a linear function of several amounts of money and therefore a very suitable objective function for a linear program. Also, if we are interested in internal rate of return, we can avoid formulating a nonlinear objective function by iteratively solving this model with varying interest rate R instead.

4.2 Inclusion of Uncertainty

A general shortcoming of linear programs like the presented one is that the input parameters are static, which amounts to the necessity to make exact predictions about the future, e.g. about customer demands or selling prices. However, one cannot avoid or prevent uncertainties of these parameters in practice and thus has to live with a high risk of misjudging the model input. This hurdle can be overcome with modern techniques for optimization under uncertainty, such as stochastic programming [18] or quantified programming [10]. We do not give a formal description, but present the more intuitive *deterministic equivalent program* (DEP) [7], i.e. an exponentially large MIP which has the same first-stage solution as the stochastic version of our original MIP.

Suppose we want to consider a seldom varying demand, i.e. it is usually constant but may change at the beginning of each year to one of several possible values. This results in a total of $|\mathscr{S}| = \#demands^{\#years}$ scenarios (at least if the number of possible values does not differ between years). Let each scenario have the probability of occurence p^σ. On the contrary, operating decisions can be made on a much smaller scale, e.g. once a day. If we assume all scenarios to be equally likely, the DEP for this problem takes the following form:

maximize

$$\text{NPV} = -i + \sum_{\sigma \in \mathscr{S}} p^\sigma \cdot \sum_{t \in T} \frac{f_t^\sigma}{(1+R)^t} \tag{8}$$

subject to

$$i = C^0 + \sum_{m \in M} C_m^I \cdot b_m \tag{9}$$

$$s_t^\sigma = s_{t-1}^\sigma + \sum_{m \in M} L_m \cdot z_{t,m}^\sigma - D_t^\sigma \qquad \forall\, \sigma \in \mathscr{S}, t \in T \tag{10}$$

$$z_{t,m}^\sigma \leq r_{t,m}^\sigma, \quad r_{t,m}^\sigma \leq b_m \qquad \forall\, \sigma \in \mathscr{S}, t \in T, m \in M \tag{11}$$

$$\sum_{m \in M} r_{t,m}^\sigma = 1 \qquad \forall\, \sigma \in \mathscr{S}, t \in T \tag{12}$$

$$\left.\begin{aligned} w_{t,m}^\sigma &\leq r_{t,m}^\sigma \\ w_{t,m}^\sigma &\leq 1 - r_{t-1,m}^\sigma \\ w_{t,m}^\sigma &\geq r_{t,m}^\sigma - r_{t-1,m}^\sigma \end{aligned}\right. \qquad \forall\, \sigma \in \mathscr{S}, t \in T, m \in M \tag{13}$$

$$\begin{aligned} f_t^\sigma = {} & P \cdot D_t^\sigma - C^H \cdot s_t^\sigma - \sum_{m \in M} C_m^V \cdot L_m \cdot z_{t,m}^\sigma \\ & \ldots - \sum_{m \in M} C_m^F \cdot b_m - \sum_{m \in M} C_m^S \cdot w_{t,m}^\sigma \end{aligned} \qquad \forall\, \sigma \in \mathscr{S}, t \in T \tag{14}$$

$$\text{"nonanticipativity constraints controlling the time resolution"} \tag{15}$$

The changes to the determinstic program mainly consist in upper indices σ traversing the set of scenarios $\mathscr{S}$. One distinguishes between the so-called first-stage variables b (the buying indicator) and i (the investment costs), which have to take the same value regardless which scenario will occur in the future, and so-called second-stage variables, which are duplicated for each possible scenario. Since most variables are second-stage, the DEP has nearly $|\mathscr{S}|$ as many variables *and* $|\mathscr{S}|$ as many constraints as the original program.

The given formulation without nonanticipativity constraints[2] would imply that the scenarios are completely decoupled. However, this amounts to an oracle, which can predict the demand for all coming years at once, right after the machines have been purchased. A more realistic assumption would be a less omniscient oracle, which can

2 The model already includes some nonanticipativity since the first-stage variables take the same value over all scenarios. However, the given compact-view formulation avoids introducing explicit constraints, as opposed to a split-variable formulation [24].

only predict the demand for a single year at the beginnning of each year, without knowing anything about the more distant future. One can achieve this formulation by adding more constraints to the DEP, which force some scenario-duplicates of decision variables to be equal, e.g. $z_{t,m}^{\sigma_1} = z_{t,m}^{\sigma_2}$ if the demand trends D^{σ_1} and D^{σ_2} do not differ *before* the time period t.

Note that market parameters like the selling price and the stock holding costs are not incorporated as uncertain quantities. We investigate how different combinations of these parameters influence the optimal investment decision, thus it is instrumental to iteratively solve several models with varying determinstic values for these parameters. Of course, we thereby assume that they can be easier predicted and are more long-term consistent than the actual customer demand.

5 Solution Approach

The presented MIP has a moderate amount of several thousand variables and constraints, and poses no challenge to sophisticated MIP solvers [14] on modern hardware. However, we are going to analyze the influence of various market parameters and demand trends on the optimal investment decision. This approach is tremendously time-consuming: As to market parameters, we consider various combinations of selling prices, stock holding costs and interest rates. For each fixed market, we compare all yearly-varying demand trends for five discrete demand levels and five years, resulting in $5^5 = 3125$ customer demands. At this point, there are so many individual MIPs to solve, that the overall computation time makes our analysis intractable. To make matters worse, the stochastic case with three possible demand levels in each year results in a DEP with approximately $3^5 = 243$ as many variables and constraints as the original MIP, moving the required computation time out of our reach. Therefore, we had to introduce further simplifications.

A reasonable way to reduce solution times is to decompose the problem into a master problem and suitable subproblems. Since the master problem has to be solved for roughly a million instances, we need to eliminate as much computational overhead as possible in the subroutines. An interesting observation regarding the determinstic MIP is that for fixed variables b and i (that is, for a fixed investment decision) all remaining variables are indexed over the time periods, and the only constraints linking variables of different time periods apply to *discrete* variables of *neighbouring* time periods. Thus, the problem structure suggests *dynamic programming* [8] to preprocess the optimal production strategy for fixed purchase decisions, fixed market parameters and fixed demand. The idea works out as follows:

Recall that the investment decision has been fixed and suppose time has already elapsed till the last time periods. (It does not matter for this argument if the past production has been optimal or not.) For the last production decision we have to cope with the currently ready technology variant and with the current stock, but no other variables of the original problem affect, what the best production decision for this time period is. (Note that even though the initial amount of money depends on the previous production, the following decision does not.) Now, we can compute a mapping $\phi_t(r_{t-1}, s_{t-1}, D_t, \dots)$ which specifies the best course of production for each possible initial situation, the current demand and the usual model parameters. Given such a mapping for the last time period, we can reuse it for the second to last time periods, since we now know the follow-up costs of the residual situation the current production decision causes. In the first time period, the initial stock is empty and no machine is ready yet. Therefore, one has to make a single production decision based on the costs that this decision causes in the following time periods.

Thus, we now have a two-step process of computing a decision mapping and then resolving the involved costs. The memory needed to save ϕ is quite high, but grows only linearly with the number of days processed. The number of intermediate computations is quadratic in the number of technology variants, stock items and demand levels, but does not depend on the number of time periods. Note that in the original problem, the number of demand trends grew polynomially with the number of time periods and exponentially with the number of demand levels. Even though the subproblems are still time-consuming, we could cut down the overall computation time by a substantial amount. However, the arguments hold only in the determinstic case – for the stochastic version, we had to solve an additional problem.

At each turn of the year, we assumed the demand may change to one of many possible values. Similar to the transition from a MIP to a DEP, the increase in computational overhead is considerable. We can avoid this penalty by adding the additional assumption that the stock is not carried between years. (It does not matter if we force the stock to be used up or if we allow a clearance sale to a reduced price.) This allows us to decouple the processing of individual years completely, which not only saves the stochastic overhead, but also reduces the memory usage of the individual dynamic programs. In terms of the DEP, this stock clearing amounts to trivializing all nonanticipativity constraints (c.f. equation 15) after the purchase nonanticipiativity: Since the optimal production strategy does no longer depend on the production in previous years, there is no real advantage in knowing the exact demand more than a year in advance.

6 Case Study: Flexibility in Forming Technology

Until now, the notion of *dedicated* and *flexible* production systems is still very vague. In the following, we give a concrete example of a modern flexible production system and apply the developed optimization model to assess it's benefit compared to comparable dedicated machines.

In different areas of manufacturing such as assembly and chipping, various concepts for flexible production are state of the art. However, machines are either designed for mass production of a limited product spectrum or specialized for small batch production with predefined tool movement. Especially in forming technology, machines are either capable to cover a wide demand spectrum or to produce product variants in an economic way. The driven *degrees of freedom* (DoFs) for the relative movement of work piece and tool are analyzed in the following classification (cf. fig. 3) [12]. It becomes apparent, that with a rising number of DoFs equipment, product and process flexibility increases meanwhile demand flexibility decreases. Machines with a large number of DoFs are downward compatible but their drive systems

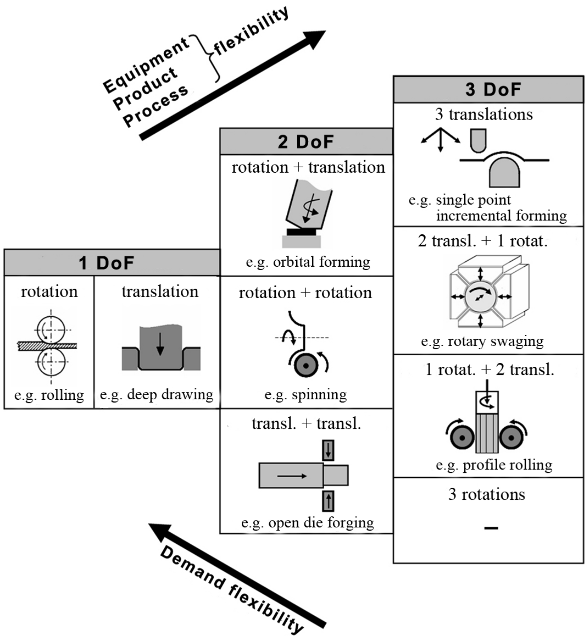


Fig. 3 Forming process classification by used degrees of freedom [12]

are limited in their productivity. For this reason the total flexibility in terms of adaption to changing market conditions is very restricted [21].

In order to resolve this conflict, it is necessary to develop new technologies which provide the called total flexibility. According to the introduced classification according to the number of DoF it is required to establish forming systems which provides a high quantity of DoF and offers concurrently the suppression of selected DoF if required. Thereby productive and flexible processes can be realized on a single machine without the investment for other production systems in case of change overs. An example for a machine that provides the described possibilities is the so called *3D ServoPress*, which will be described in the following. The assembly and the lever system of a prototype of this machine are displayed in figure 4.

The 3D Servo Press consists of three independent lever systems which are star-shaped arranged in a 120° angle to each other. In the center of the machine two spindles are located which are connected to each lever system. The design of the lever systems enables a way bound operation of the machine with the eccentric drives, a force bound mode with the spindles as well as a combination of the two different operation modes. Implementing the two different operation modes in one machine is an approach to enable highly productive process with the way bound drive as well as flexible ram movements with the force bound drive. The applied actuators are servo motors which are capable to perform a predefined ram motion including for example a stand still at the lowest ram position the so called bottom dead center. This characteristic can be used to adapt the motion profile of the ram to the process re-

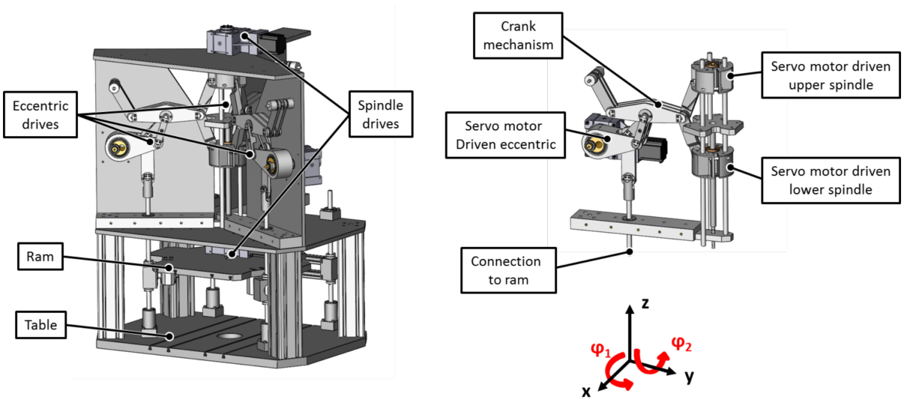


Fig. 4 Prototype of the 3D Servo Press [12]

quirements and to implement for instance joining processes into the process chain. The star-shaped arrangement of the lever systems enables the 3D Servo Press to perform an enlarged movement spectrum of the ram compared to conventional presses. Examples for flexible processes using these characteristics are presented by Groche et al. [12].

In order to compare conventional forming machines, which are dedicated for a limited process spectrum and solely provide a single technology with the 3D Servo Press as a multi-technology machine with an increased production spectrum, various technology options were developed to produce a selected work piece. Therefore, influences on the production process and the selection of the technology option such as demand scenarios affecting the cost effectiveness of the developed production processes are analyzed.

The different production steps as well as the required semi-finished parts and the work piece are shown in figure 5. Dependent on the current demand situation respectively the demand forecast, the shown technology options have their individual economic advantages. In case of a prototype production or small batch series, the first technology option is economical superior to the second and the third option. The shown orbital forming process uses a tube as a semi-finished part and the tube is formed by an operation with 3 DoF before it is removed by an ejector. This process is characterized by a low investment in the production system but high costs for the semi-finished part as well as high production cycle times. The second technology option is often applied for medium lot sizes. The costs for the semi-finished part are comparable to the orbital forming process. Investments for the production system including machine and tool as well as the setup-costs are higher than for the first process but the cycle time is less. The cycle times of the third technology option are comparable to the second one. The investments for the production system are the highest among the shown options. The semi-finished part is in this case a part of solid material, which reduces the material

Using conventional production systems for the shown technology options, different production systems with various technological specifications would be required.

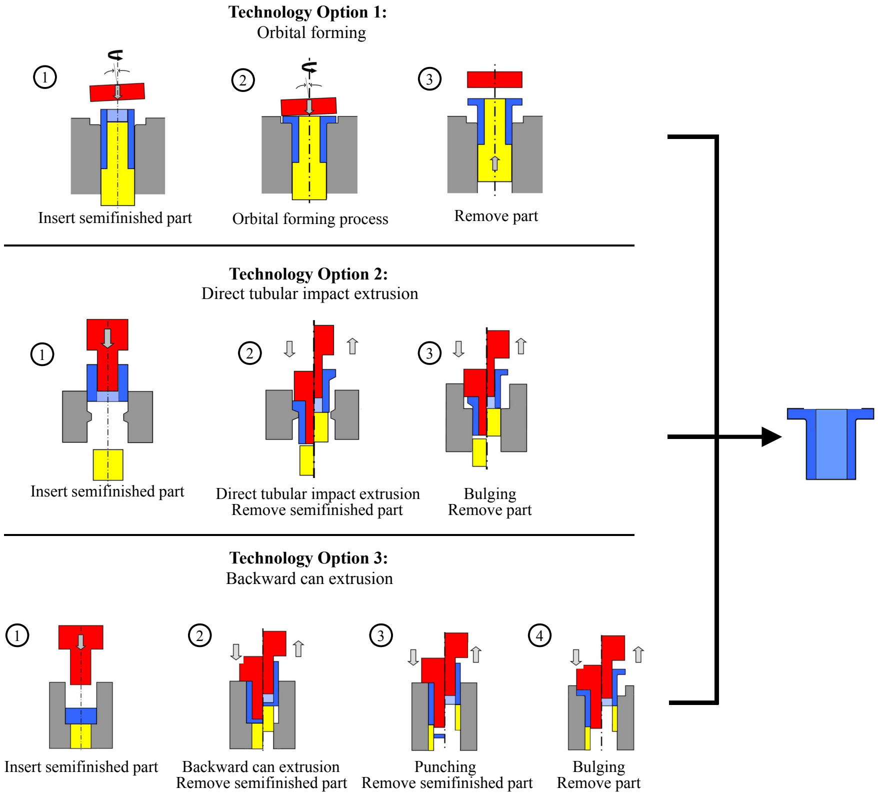


Fig. 5 Example technology options for socket production [2]

In case of changing demand situations, a change-over between different technology options is essential to ensure an economical production and to meet the customer's demand. A change-over between conventional machines is attended by the investment for the machine itself and tools which are necessary to perform the forming operations [2].

Due to the above described technological specifications the 3D Servo Press is capable to perform all shown technology options. For the different technology options solely new tools are required. Investments in new machines to cover various demand ranges are not necessary.

6.1 Example Data Set

We focus on just three technology variants: orbital forming, direct tubular impact extrusion and backward can extrusion. These variants have increasingly higher investment costs, fix costs and setup costs, but also much larger lot sizes and therefore lower variable costs. As a rule of thumb, the latter technology variants compensate for their expensive investment and operation if only the overturn is sufficiently high.

Table 2 Comparison of the production technologies

#	technology variant	lot size	production costs in €	
			variable costs	setup costs
1	orbital forming	960	1.20	25
2	tubular impact extrusion	24 000	1.00	170
3	backward can extrusion	28 800	0.80	315

Table 3 Investment costs for machines and tools

#	technology variant	investment costs in €		fix costs in €	
		dedicated	flexible	dedicated	flexible
1	orbital forming	600 000	10 000	1320	120
2	tubular impact extrusion	850 000	60 000	1680	480
3	backward can extrusion	1 000 000	110 000	1800	600
	basic technology		900 000		1200

Table 2 shows an overview of some examplary capacities and costs, which are chosen comparable to real production systems. We assume that all values in this table do not differ between the dedicated machines and the flexible technology.

The acquisitions of dedicated and flexible technologies follow two different philosophies, which are summarized by table 3. In the case of dedicated production systems, each technology variant is resembled by a corresponding machine that can essentially be purchased and used as is. For example, if one needs the technology variants 1 and 3, the investment costs sum up to 1.6 M€. In the case of flexible production, one needs to pay a basic cost for the flexible framework even before any technology variant is selected. Together with the required tool for a production technology, the investment costs are therefore always higher than their dedicated equivalent. However, the basic technology is a one-time investment regardless of the number of desired technology variants. Thus, the total investment for the flexible system with technology variants 1 and 3 boils down to 1.02 M€, which is *less* than for the dedicated counterpart. This amounts to the flexible production system being a reasonable investment if the flexibility of multiple technology variants is inevitably needed.

7 Computational Results

With the given machines, we determined for all possible demand patterns and for different market parameters which technology investment is economically advantageous. Selling prices were varied between 0.5 € and 10 €, holding costs between 0.01 € and 0.1 € and the interest rate between 1 % and 10 %. Depending on the choice of objective function (NPV or IRR), we will see that some details differ, but the overall insights are very similar. On a side note, many general observations are surprisingly in line with the theoretical predictions of Van Mieghem [25], despite his rather different model assumptions. First of all, we analyze the results for deterministic demand trends.

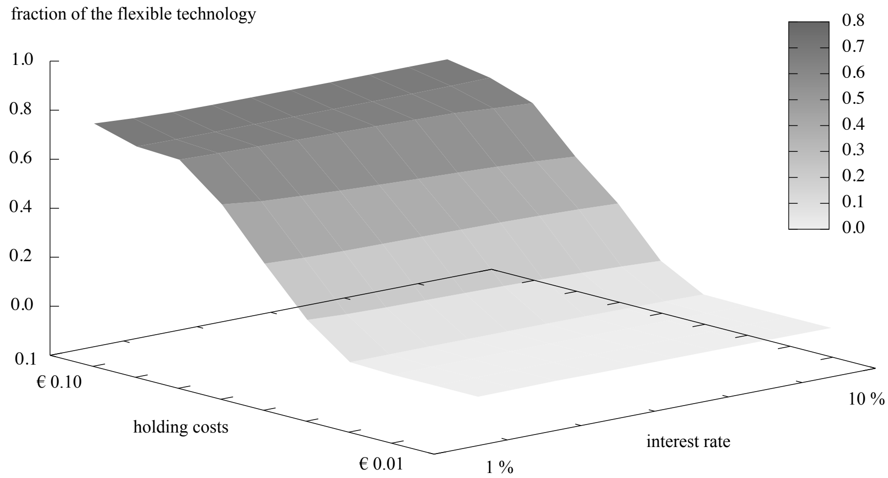


Fig. 6 NPV-optimal investment decisions for deterministic demand scenarios

7.1 Optimal investment decisions for predictable demand trends

For each fixed combination of selling price, holding costs and interest rate, there are 3125 demand patterns in total. We can summarize the results for these patterns by computing a "flexibility ratio", i.e. we determine the fraction of all demand patterns where the flexible technology with any combination of tools leads to a better NPV than all combinations of dedicated machines would. Note that when comparing different NPVs, the product selling price can essentially be ignored, since the optimal production strategy does not depend on it. We must only ensure the price is high enough that the investment becomes profitable over the given time period.

Figure 6 shows the fraction of flexible technology investments as as function of holding costs and interest rate. The darker and higher the surface, the more attractive is the flexible technology compared to it's conventional alternatives. The choice between dedicated and flexible technologies seems to strongly depend on the cost of storage. This seems reasonable, because in general, flexible technologies are better at adapting their production to the current demand, which results in less products to store on average. The interest rate on the other side seems to be less important (the given ranges). At least, one can note a slight decrease of the flexible fraction for increasing interest rate, and this trend goes on for even larger interest rates. This is plausible, since a high interest rate suggests that far-future gains and losses are negligible compared to near-future ones, i.e. a dedicated machine for the near-future demand is a reasonable investment.

Since changes between realistic interest rates have nearly no influence on the investment decisions, now we compare the NPV-optimal investment decisions to IRR-optimal ones. Thereby, the interest rate ceases to be a market parameter, but instead the selling price becomes relevant, since it affects the ratio between overall profit and investment cost. As a rule of thumb, the NPV might be a good objective function

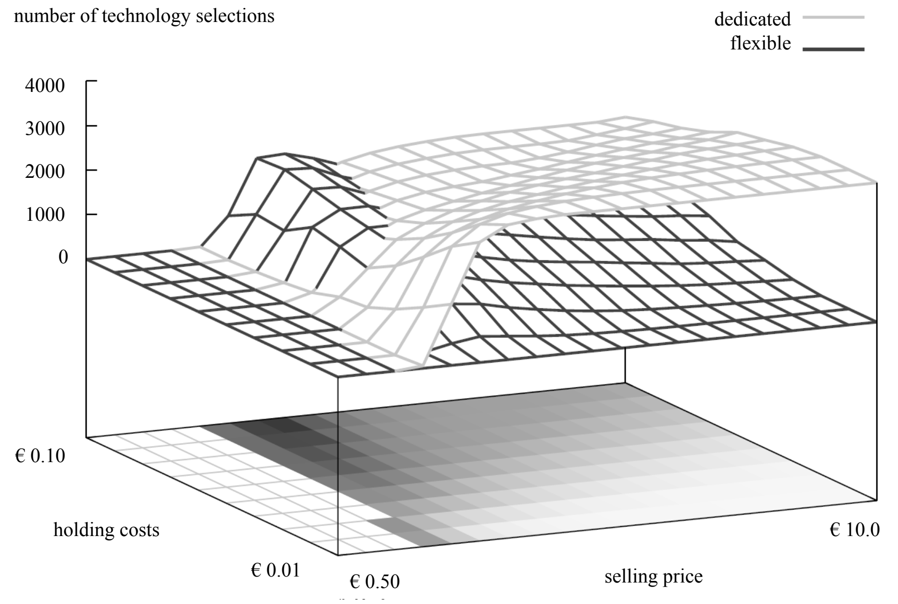


Fig. 7 IRR-optimal investment decision for deterministic demand scenarios

to maximize the returned capital of a single project, while an IRR-optimal purchase decision might render the project more attractive for investors. From an academical point of view, we find it interesting to compare both results.

Figure 7 shows the number of IRR-optimal technology selections as a function of selling price and storage costs. The gray surface depicts the ratio of dedicated machines, whereas the black surface depicts the flexible machines' ratio. The *shadow* gives the difference of both curves: The darker it is, the more beneficial is a flexible investment. We see that the ratio of dedicated machines approaches 100 % if the selling price is high and the storage costs are low. However, the ratio of flexible machines increases with falling selling prices and rising storage costs, and they even become economically advantageous on average.

Similar to the NPV-optimal investment, high storage costs force both technologies to adapt their production to the current demand. Otherwise, storage costs and capital lockup effects hurt the companies' profit. The influence of the selling price can be attributed to the internal rate of return's tendency to favor lower initial investments – if the products can be sold for a high price, the losses of missing flexibility become irrelevant compared to the overall profit. Summarizing, a criterion for choosing the flexible technology seems to be low profit margins.

In the following, we analyze the influence of the demand pattern. One might argue that it would have been completely sufficient to compare statistical properties of the demand trend. Therefore, let's compare the best investment decisions for demand trends with specific mean values and standard deviations. Figure 8 (top) shows the fraction of demand trends with the flexible machine being the best choice as a function of the average demand. The black line depicts the combined fraction over all

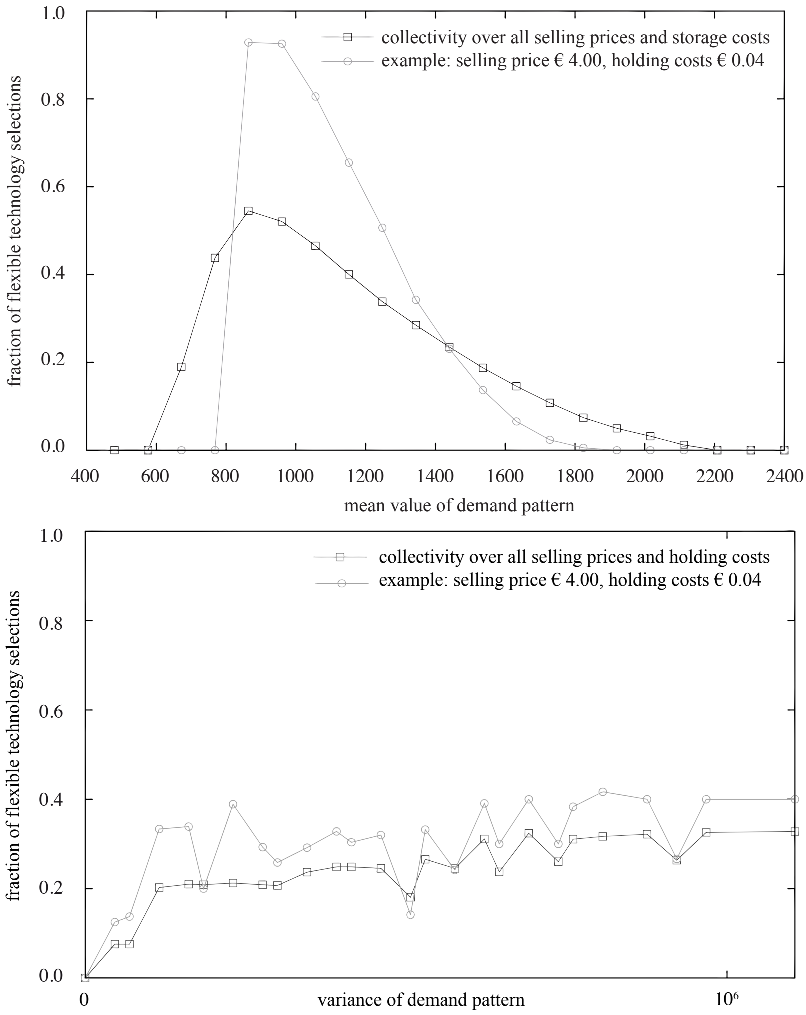


Fig. 8 Technology selection as functions of the demand average and variance

market parameters and the gray line is an example for a fixed selling price and storage cost. If the average demand is very high or very low, then the dedicated technology is apparently by far the best choice. In both cases, the demand is nearly constant, which is exactly what the dedicated machines are designed for. The flexible technology takes its highest ratio at an demand mean value of about 1000 units per day. This is reasonable, since demand trends in this category cannot completely be satisfied by the smallest dedicated machine (the demand has to be higher than its lot size in about 1-2 years) and the other dedicated machines cause high stock holding costs and capital lockup effects. Flexible technologies can show their strengths in such transition regions.

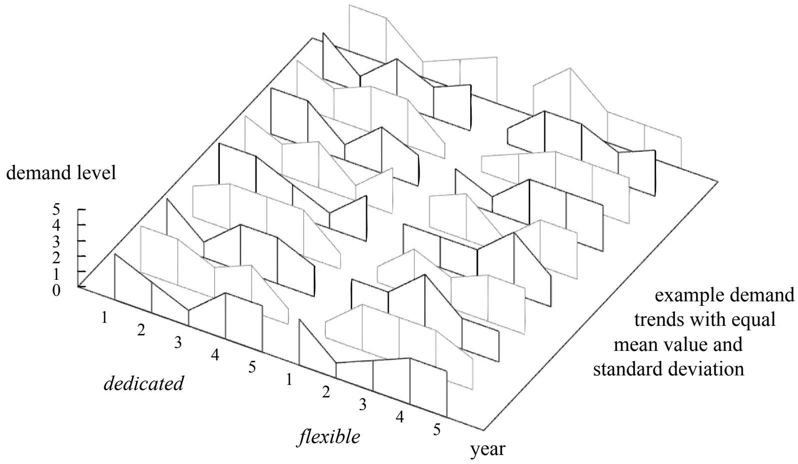


Fig. 9 Examples of demand patterns with similar statistical properties

Figure 8 (bottom) shows the flexible technologies' fraction as a function of the demand standard deviation. In the same way as before, the black line is the collective result over all selling prices and storage costs, and the gray line is an example for fixed market parameters. We see that the fraction of flexible machines decreases when the deviation of demand levels approaches zero. This finding is in line with the constant demand trends of the previous figure. For nonzero standard deviation of the demand trend, it seems overall as though a higher variance implies a higher fraction of flexible machines, but the tendency is weak. Thus, the demand standard deviation is no good indicator for an investment decision, even though it is in widespread use as a measure of volatility.

We have seen that the mean value and standard deviation of the demand trend can be utilized as a rough indicator for the investment decision. However, which technology is the best investment for a given demand cannot be derived from these parameters alone. We can conclude this from figure 9. For fixed selling prices and fixed storage costs, it shows a selection of demand trends with a fixed mean value and a fixed standard deviation, i.e. a set of demand trends which cannot be distinguished in the previous figures. The trends are grouped by their best technology choice. We do not see any relevant characteristic based on which one could have manually grouped them this way. We can summarize the results of our investigation as follows: If the product margins are high or the demand is more or less constant, a dedicated machine might be preferred. If the product margins are low, a flexible production system should be favored in most cases. However, these are only statistical arguments, so to not take chances, an investor might be better of to optimize the investment decision for his individual demand forecast. Anyway, we saw that for moderate product margins and nontrivial demand trends, there's nothing else for it but to assess the possible investment alternatives in consideration of the given market situation.

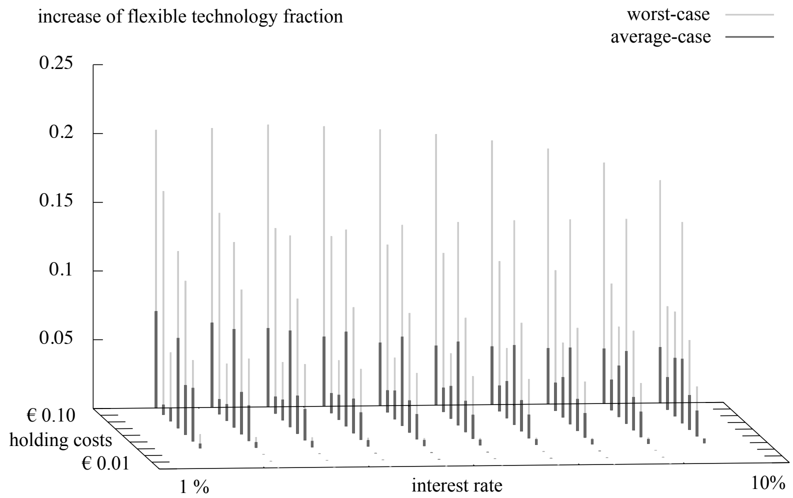


Fig. 10 change in NPV-optimal investment decisions for stochastic demand scenarios

7.2 Optimal investment decisions for uncertain demand trends

Now we discuss the results for uncertain demand scenarios. Remember that each demand of the five-year demand trend can be one level higher or lower than expected with a probability of 25 % each. An optimal solution regarding the expected objective value (i.e., an average-case analysis) is certainly the most relevant result for practical investment decisions under uncertainty, but it might be interesting to also consider a worst-case analysis. So instead of choosing the technology option which maximizes the return rate in average, we are also interested in the technology option which maximizes the worst possible return rate. That means, this technology option is able to cope with unexpected changes in the prospected demand and to guarantee a certain minimal return rate.

Figure 10 shows the changes to the flexible technology fraction compared to the deterministic case (figure 6). Black bars indicated the fraction's increase for average-case-optimal investments and gray bars for worst-case-optimal investments. Apparantly, the flexible technology becomes more appealing if the customer demand cannot completely be predicted. In detail, hedging against unexpected demand fluctuations seems to be an even better argument for investing in a flexible technology than maximizing expected profits. While the interest rate again shows only a slight influence on the statistical outcome, high storage costs favor a large increase of the already high fraction. Note however that there is a irregularity at 0.08 € and 0.09 €, which is caused by a change in the optimal tool selection for several demand trends. Such effects depend on the actual costs and lot sizes of the production move to other market parameters if we vary the input data.

Figure 11 shows the change of the number of flexible technology selections compared to figure 7 when optimizing the expected IRR. Again, no production is possible for very low selling prices. The first impression is that the flexible technology

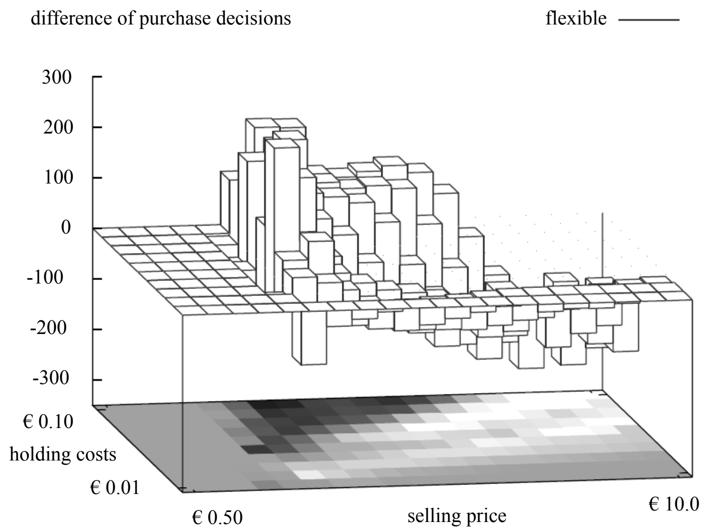


Fig. 11 Change in technology selections for stochastic demand scenarios

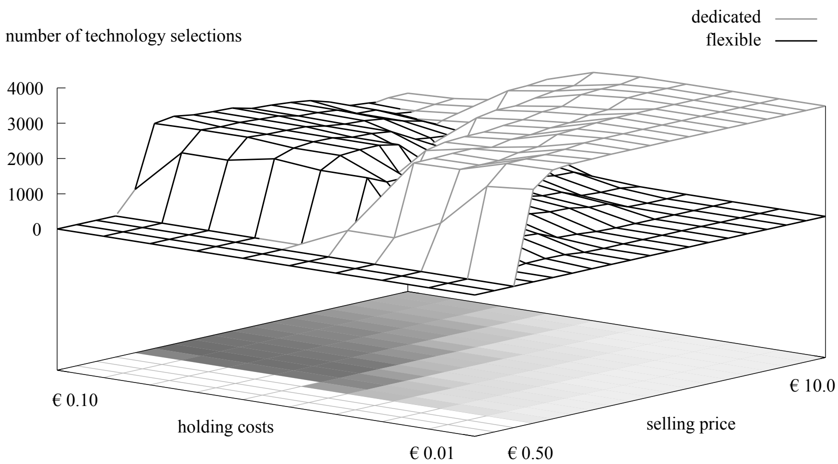


Fig. 12 Worst-case-optimal investments for stochastic demand scenarios

becomes more attractive at low selling prices and high storage costs, i.e. at market parameters where it already was advantageous. However, it's ratio *decreases* further in parameter regions where the dedicated machines have been the better investment in the determinstic case. That means, even though stochastic demand makes the problem "harder", the decision between both technology options becomes "easier".

Figure 12 shows the new number of technology selections as compared to figure 7. For the majority of market parameters, there is clearly a best technology option for almost all possible demand trends. There is only in a small gap with middle-sized profit margins, where the actual demand pattern seems to have an influence on

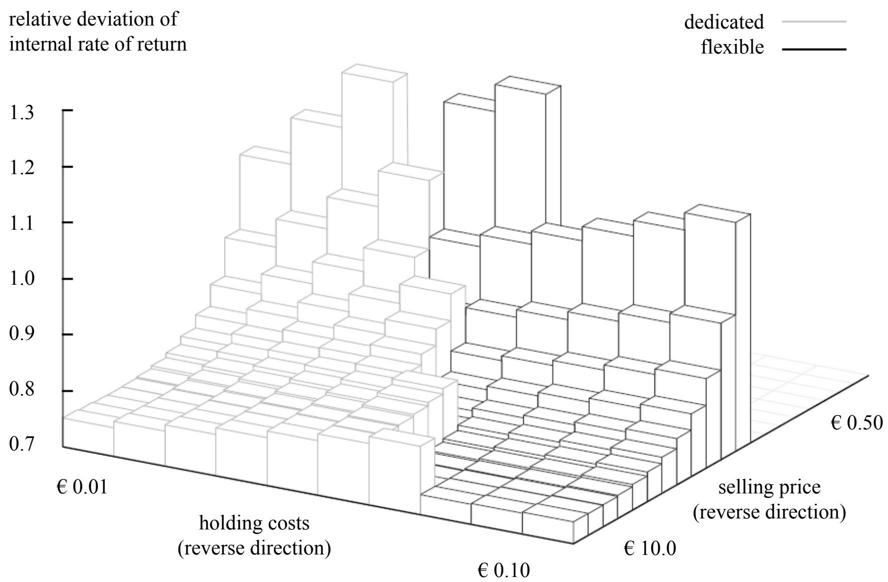


Fig. 13 Relativ IRR deviation regarding the average-case optimal investment

the investment decision. Note that this region of equally-likely investments for both technology options has moved to higher profit margins compared to the result for deterministic demands.

That there are still some market parameters where dedicated machines cause a higher worst-case return rate than a flexible technology essentially means, that they generate sufficiently high profits such that accepting possible losses by an uncertain demand is preferable to the flexible technology's higher upfront costs. At market parameters, where the flexible technology is worst-case optimal but *not* the best average-case choice, the investor should evaluate the actual risk of demand fluctuations and try to enhance his demand forecast. In the case of doubt, he can invest in the flexible technology, thereby accepting lower expected profits for secureness.

To support this interpretation, figure 13 shows a measure for the risk of each technology's investment. (In this illustation, the axes are reversed to depict all bars.) The investment decision for this plot is based on an average-case optimization for the IRR, i.e., the amount of black or respectively gray bars can be deduced by comparing the figures 7 and 9. On the vertical axis, the span of possible return rates which can result from fluctuations in the prospected demand pattern is given as percentage deviation from the expected internal rate of return. Near the gap between both technology options, the bars differ by approximately 10 % of the expected IRR – regardless of the actual market parameters. This has an interesting implication: Even if the flexible technology provides only a slightly better expected profit on average, in particular it also assures that the profit will not fluctuate as much in the future.

8 Conclusions

Our goal was to evaluate the economic competitiveness of dedicated and flexible production systems under various market parameters. A taxonomy has been developed to categorize demand trends depending on time resolution and level of uncertainty. We developed a mathematical model in order to determine the optimal technology investment by taking the production strategy into account. Input data for this model are a machine portfolio, given market scenarios, and demand patterns according to the mentioned taxonomy. To solve the model, conventional integer programming techniques can be applied, but by decomposing the problem and using a dynamic programming algorithm, we could speed up the solution process significantly.

The model has been verified by means of a case study from the field of forming technology comparing dedicated forming machines with the flexible 3D Servo Press. The results can be summarized as follows: If the demand trend does not vary over time, a dedicated machine can be employed. If preproduction is disadvantageous because of high stock holding costs or capital lockup effects, a flexible production system is more appropriate. The choice between dedicated and flexible technologies becomes easier if the demand trend is uncertain and this effect becomes stronger in a worst-case analysis. Even if dedicated machines provide a higher expected return of investment, the flexible technology promises a smaller risk regarding undesirable demand fluctuations. Regardless of the choice of NPV or IRR as objective function, the statistical results about the influence of uncertainty are still valid.

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