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MULTI-PERIOD ROBUST CAPACITY PLANNING BASED ON PRODUCT AND PROCESS SIMULATIONS

Emre Kazancioglu
Kazuhiro Saitou

Department of Mechanical Engineering
2350 Hayward St.
University of Michigan
Ann Arbor, MI 48109, U.S.A.

ABSTRACT

This paper presents a method for allocating production capacity among flexible and dedicated machines based on uncertain demand forecasts of products in a production portfolio. Given multiple scenarios of future demands with the associated probabilities, the method provides alternative capacity allocations by quantifying the expected values of the product quality and cost. The product quality is estimated as the total performance variations from the nominal design for each product in a portfolio. The production cost is estimated as the total annual equivalent of investment and operation costs for each production period. A multi-objective genetic algorithm is utilized to compute the Pareto-optimal capacity allocations that quantify the trade-offs between the expected product quality and cost. Case studies on an automotive valvetrain production are presented, where, under the demand forecasts with low uncertainty, the allocation of flexible machines is encouraged only at production steps critical to quality and cost.

1 INTRODUCTION

The average number of products in a manufacturing firm's portfolio is increasing in an effort to provide the products accommodating the consumer preferences in today's highly segmented markets. To maintain their competitive positions, it is crucial for firms to accommodate demand changes for the products in their portfolio. The precise forecasts of market demands are extremely difficult, if not impossible, since they depends on many parameters such as the general state of the economy, competitors' products, and changes in customer preferences and expectations.

Firms' agility to emerging demands largely depends on how quickly and economically they can make adjustments in production capacity of each product in their portfolio. Since the acquisition (for increasing demands) or salvation (for decreasing demands) of existing production machines can take as long as one year in many industries, firms must either rely on forecasted demands that are prone to be erroneous, or seek quick remedies such as overtime and outsourcing that can only provide a short-term solution. While the use of flexible machining tools (FMTs) can provide the agility without a long lead time, their added cost over the dedicated machines must be carefully accessed in order to maintain adequate costs of all products in a portfolio. It is, therefore, of great interests to develop a decision-support tool for allocating production capacities among flexible and dedicated machines, such that production flexibility is introduced *only where it is necessary*. To be a practical aid for a decision maker, such a tool should be capable of quantifying a trade-off between quality and cost of products in a portfolio, under the presence of uncertainty in demand forecasts.

As an extension of our previous work (Kazancioglu and Saitou 2004) on simulation-based multi-period capacity planning, this paper presents a method for allocating production capacity among flexible and dedicated machines based on uncertain demand forecasts of multiple products in a production portfolio. The extensions are made in the incorporation of flexible machines (previously only dedicated machines are considered), and uncertainties in demand forecasts (previously demand forecasts are assumed accurate).

Given multiple scenarios of future demands with the associated probabilities, the method provides alternative capacity allocations (selections of numbers and types of production machines) by quantifying the expected values of the total quality and cost of all products in a portfolio. The product quality is estimated as the sum of performance variations from the nominal design for each product in a portfolio, obtained form computer analyses of product performances. The production cost is estimated as the sum of the annual equivalent of capital investment cost, operating cost, backorder cost, and holding cost at each production period. With the expected values of product quality and cost for multiple demand scenarios being two objectives, a multi-objective genetic algorithm (Coello, van Veldhuizen, and Lamont 2002) computes the Pareto-optimal capacity allocations that quantify the trade-offs between quality and cost objectives. Case studies on an automotive valvetrain production are presented, where, under the demand forecasts with low uncertainty, the allocation of flexible machines is encouraged only at production steps critical to quality and cost.

2 RELATED WORK

Multi-product capacity planning has been the area of active research. Below previous work is listed with the focuses on 1) the robust capacity planning in the presence of demand uncertainty, 2) the optimal allocation of flexibility, and 3) the use of simulation for modeling and optimizing complex manufacturing systems.

Eppen, Martin, and Schrage (1989) consider a multi-product, multi-plant, multi-period capacity planning problem where the appropriate type and level of production capacity at several locations are sought under risk. Paraskevopoulos, Karakitsos, and Rustem (1991) report on the significance of uncertainty in capacity investment, production and pricing decisions of firms and state that capacity expansion models need to consider uncertainty. Harrison and van Mieghem (1999) present a model to determine optimal investment strategies for a manufacturing firm that employs multiple resources to market several products to an uncertain demand. These works, however, rely on simple analytical models of dedicated production facilities, and do not address the issues of the optimal allocation of flexible production capacity.

Jordan and Graves (1995) claim, based on a simple model disregarding costs, that limited flexibility configurations have approximately equal benefits of total flexibility to cope with uncertain demand. Li and Tirupati (1994, 1995) examine a multi-product dynamic investment model over a finite planning horizon and state that the demand for each product in a portfolio can be met by investing on dedicated only, flexible only or some combination of dedicated and flexible capacity. Zhang *et al.* (2004) study a discrete-time capacity expansion problem involving multiple product families, multiple machine types and stochastic dynamic demand. Gigglio (1970) presented a method to help determine the optimal amount and timing of capacity expansions for situations where demand or facility life is stochastic. While the allocation of flexible production capacity is explicitly considered, these works lacks the detailed quantifications of product quality and its impact on production cost. Further, the analyses are limited to simple manufacturing systems due to the use of analytical models.

Production simulations, such as discrete-event simulations (Banks, Carson, and Nelson 1996), are used to model complex manufacturing systems which analytical models cannot handle. Thanks to the recent increase in computer speed, simulations have become a practical alternative to analytical models (Smith 2003, Eldabi and Paul 2001). Völkner and Werners (2000) state the appropriateness of simulation-based approaches in decision making with respect to complex dynamic systems and uncertain data. Kamrani *et al.* (1998) present a simulation-based methodology to design manufacturing cells using both design and manufacturing attributes, and demonstrate the superiority of simulation-based results to mathematical model due to its ability to incorporate higher details. Bermon and Hoon (1999) report Capacity Optimization Planning System (CAPS) used by IBM for semiconductor manufacturing, which finds the volume mix of products to maximize profits and the required production capacity. Saitou, Malpathak, and Qvam (2002) presented a simulation-based robust optimization of flexible manufacturing systems under forecasted product plan variation. Lee and Saitou (2002) extend this work by incorporating the redesign of the datum schemes of produced parts to improve their process similarity. While production models are realistic, these works also merely focus on production cost, with limited or no quantification of product quality as a result of capacity allocations.

In the present paper, discrete-event simulations and a surrogate model of detailed computer analyses are used to model production system and product performance, respectively. Using these simulations, the trade-offs between expected production cost and product quality under demand uncertainty are quantified as Pareto-optimal capacity allocations using a multi-objective genetic algorithm (Coello, van Veldhuizen, and Lamont 2002).

3 METHOD

Figure 1 illustrates an overview of the method. Given multiple scenarios of future demands with the associated probabilities, it provides, through multi-objective optimization, Pareto-optimal capacity allocations (selection of the types and numbers of machines) for each production period, with respect to the two objectives: the expected quality of all product types and the expected total production cost. The discrete event simulation simulates the production process until steady state, and calculates the investment and operation costs for all production periods. Using the part qualities in the finished goods inventory (FGI) obtained from the discrete-event simulation, the product model (a surrogate model of detailed computer analyses) calculates the distribution of product performances for each product type, based on which the product quality is estimated.

3.1 Production System Model

We consider a cellular manufacturing system where the machines performing the same process are grouped in a cell, with part buffers between cells for two subsequent processes. Figure 2 shows an example configuration of a three-

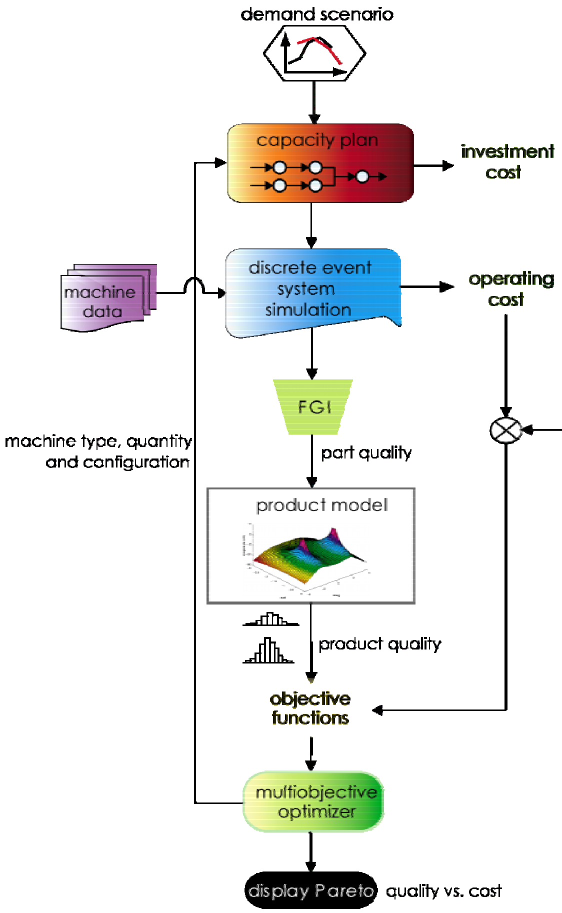


Figure 1: Overview of Method

cell production system with eight buffers. Each cell consists of one or more machines of a machine type, which specifies the following:

- process type (*eg*., cell 1, cell 2)
- product type (*eg*., A only, B only, both A and B)
- mean (μ) and standard deviation (σ) of process time [sec]
- setup time and cost [$]
- tolerance specification (μ and σ) on the relevant product parameters (such as dimensions)
- machine price and operating cost [$]

The design variable $\boldsymbol{x} = (x_{ijk})$ is the n-period capacity allocation for a production system with a given configuration, namely the number of machines of type k at cell j for the i-th period:

$$x_{ijk} \in \mathbb{Z}_0,\ i \in [1,n],\ j \in [1,m], k \in [1,l_j]\,, \qquad (1)$$

where $\mathbb{Z}_0$ is the set of non-negative integers, n is the number of periods, m is the number of cells, l_j is the number of available machine types at cell j. For instance, Figure 2 shows a 2 period (n = 2) capacity allocation of a 3-cell (m = 3) production system with three available machine types in each cell ($l_1 = l_2 = l_3 = 3$), which can be represented with 3x3x2=18 integer variables as in Table 1.

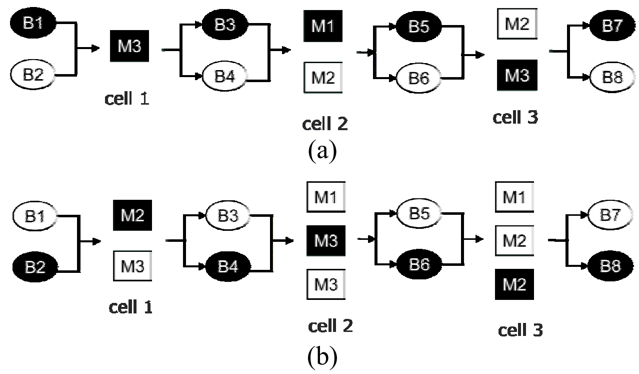


Figure 2: Example 2-Period Capacity Allocation of a 3-Cell Production System: (a) Period 1 and (b) Period 2

Table 1: Design Variables for Capacity Allocation in Fig. 2 (a)

$x_{111}=0$	$x_{121}=1$	$x_{131}=0$	$x_{211}=0$	$x_{221}=1$	$x_{231}=1$
$x_{112}=0$	$x_{122}=1$	$x_{132}=1$	$x_{212}=1$	$x_{222}=0$	$x_{232}=2$
$x_{113}=1$	$x_{123}=0$	$x_{133}=1$	$x_{213}=1$	$x_{223}=2$	$x_{233}=0$

It is assumed that every product type requires the processing at all cells before reaching FGI. Therefore, each cell must have at least one machine for each product type, which gives the following constraint:

$$\sum_{k \in MT_j^t} x_{ijk} \geq 1\,, \qquad (2)$$

where $MT_j^t \subseteq [1, l_j]$ is a set of machine types (dedicated or flexible) that can process the product type t in cell j.

For a given capacity allocation (specified by variable $\boldsymbol{x}$), the operation of the production system is simulated using a discrete event simulation, whose flow chart is shown in Figure 3. Simulation is chosen due to its flexibility in modeling various production system configurations, and the ease of recording the types of the machines used for each part going into FGI, which are required for estimating the quality of the finished products as described below. During the simulation, the process time for each machine is numerically sampled according to the normal distribution with the mean and standard deviation of the machine type. After simulating production until its steady state for each period in demand forecasts, the total amount of production and the utilization of each machine are calculated in order to estimate the operating cost.

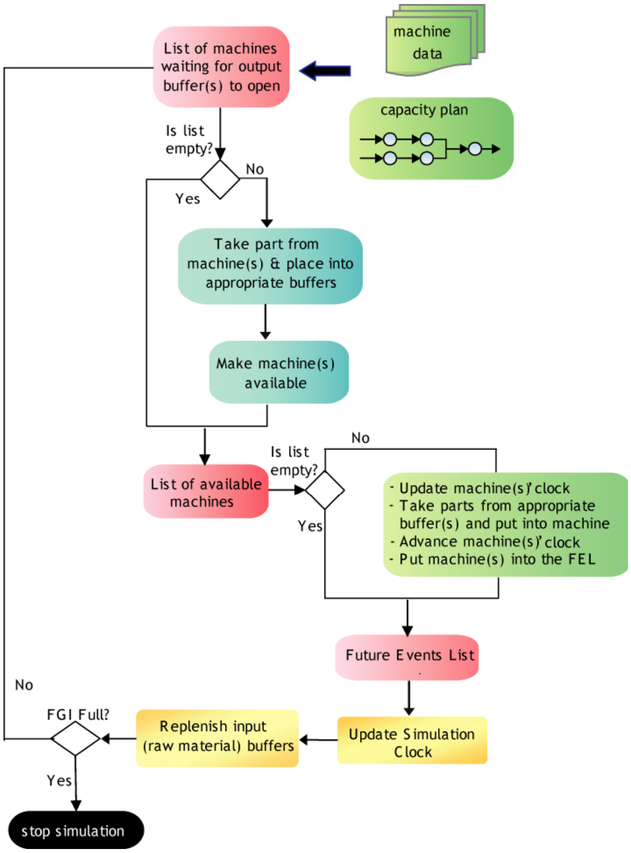


Figure 3: Flowchart of Discrete-Event Simulation

3.2 Product Model

The product model takes product parameters (*eg.* part dimensions) as inputs and calculates one or (typically) more measures of product performances. The model can be analytical, a simulation, or a surrogate model of an expensive computer analyses as adopted in the following case study.

The variations in product performances from their nominal values is depends on the variations of the input product parameters (eg., part dimensions). For a given capacity allocation (specified by variable $\boldsymbol{x}$), these variations of the input product parameters can be estimated by the tolerance specifications of the machines each part has gone through before reaching FGI. For instance, the variations of a part following the machined marked black in Figure 2 (a) depend on the tolerance specifications of M3 in cell 1, M1 in cell 2, and M3 in cell 3.

While the variations in production performances can be estimated by Monte Carlo sampling of the input product parameters based on the tolerance specifications of the machines, doing so within an optimization loop will be computationally very expensive due to the need of a large number samples to achieve sufficiently high statistical confidence. Since we are interested in the variations in product performances during steady-state production, the means and standard deviations of the product performances (denoted as μ_c and σ_c below) are estimated as follows:

1. **Before optimization**: For all possible sequences of machines a part can go though before reaching FGI, obtain the means and standard deviations of the input product parameters, and calculate μ_c and σ_c using Monte Carlo simulation. Record the results in a look up table.
2. **During optimization:** For each candidate capacity allocation specified by the optimizer, do the discrete-event simulation until steady-state to obtain FGI. Calculate μ_c and σ_c using the record of the machine types each part in FGI went through and the look-up table obtained in Step 1.

Since each part in FGI followed one of the machine sequences in the look-up table for which μ_c and σ_c are known, obtaining μ_c and σ_c resulting from all parts in FGI is equivalent to knowing the distribution of the samples consisting of the samples of several known distributions. This can be done by using the fact that for sufficiently large n_i and $n_{i+1,}$ the distribution of the $n_i + n_{i+1}$ samples consisting of n_i samples of $N(\mu_i, \sigma_i)$ and n_{i+1} samples of $N(\mu_{i+1}, \sigma_{i+1})$ is approximated by $N(\mu, \sigma)$ where:

$$
\begin{aligned}
\mu &= \frac{n_i\mu_i + n_{i+1}\mu_{i+1}}{n_i + n_{i+1}} \\
\sigma &= \sqrt{a+b} \\
a &= \frac{\sigma_i(n_i-1)}{n_i+n_{i+1}-1} + \frac{n_i n_{i+1}^2(\mu_i-\mu_{i+1})^2}{(n_i+n_{i+1})^2(n_i+n_{i+1}-1)} \\
b &= \frac{\sigma_{i+1}(n_{i+1}-1)}{n_i+n_{i+1}-1} + \frac{n_{i+1} n_i^2(\mu_i-\mu_{i+1})^2}{(n_i+n_{i+1})^2(n_i+n_{i+1}-1)} \ .
\end{aligned} \tag{3}
$$

Accordingly, the following iterative algorithm will calculate the mean and standard deviation of $n = \sum n_i$ samples consisting of n_i samples of $N(\mu_i, \sigma_i)$ where i = 1,2,…, m (Kazancioglu, 2004):

1. $i \leftarrow 1$.
2. Calculate μ and σ by Equation (3) (given below).
3. $n_{i+1} \leftarrow n_i + n_{i+1}$, $\mu_{i+1} \leftarrow \mu$, $\sigma_{i+1} \leftarrow \sigma$, $i \leftarrow i + 1$.
4. If $i = m$, return μ and σ. Otherwise go to step 2.

In the following case study, it is confirmed that this algorithm accurately calculates μ_c and σ_c comparable to the results of Monte Carlo simulation.

3.3 Demand Forecasts

Demand forecasts are given as an event tree with associated probabilities, where a probable demand (numbers of production for each product type) during the i-th period is associated with a node at depth *i,* and the probability that the demands at a node occurs is associated with the edge incident to the node. Figure 4 illustrates an example. Formally, demand forecast *DF* is a pair of set of demands *D* and set of probability *P*:

$$
\begin{aligned}
&DF = (D, P) \\
&D = \{\boldsymbol{d}_s \mid \boldsymbol{d}_s \in \mathbb{Z}_0^{nt}; s \in S\} \\
&P = \{p_s \mid p_s \in \mathbb{R}_0; s \in S; \sum_{|s|=k} p_s = 1 \text{ for } k \in [1, n]\},
\end{aligned} \tag{4}
$$

where *nt* is the number of product types in a portfolio, and $\mathbb{R}_0$ are the non-negative subset of real numbers. The elements in *D* and *P* are "indexed" with sequence *s* denoting to their paths from the root (see Figure 4 for examples):

$$S = \{s \mid s =< b_1, \ldots, b_l >; b_i \in \mathbb{Z}_0, i \in [1, l], l \in [0, n]\} \tag{5}$$

Demand scenario $\boldsymbol{ds}_s$ is a sequence of the demands in D along a path from the root to a node corresponding to ds. By letting $s = t \circ b, t \in S, b \in \mathbb{Z}_0$ (symbol "$\circ$" is the concatenation operator of two sequences), it can be recursively defined as:

$$
\boldsymbol{ds}_s = \begin{cases} < d_b > & \text{if } |t| = 0 \\ \boldsymbol{ds}_t \circ < d_s > & \text{otherwise.} \end{cases} \tag{6}
$$

In Figure 4, for example, $\boldsymbol{ds}_{<0,1,2>} = \boldsymbol{ds}_{<0,1>} \circ < d_{<0,1,2>} > = \boldsymbol{ds}_{<0>} \circ < d_{<0,1>}, d_{<0,1,2>} > = < d_{<0>}, d_{<0,1>}, d_{<0,1,2>} >$. Demand scenario $\boldsymbol{ds}_s$ with $|s| = n$ represents demand predictions of all *n* periods, which we refer to as a *complete* demand scenario. Similarly, the probability of occurrence $\boldsymbol{q}_s$ of demand scenario $\boldsymbol{ds}_s$ is defined as the product of the probabilities in *P* along the path:

$$
q_s = \begin{cases} p_b & \text{if } |t| = 0 \\ q_t \times p_s & \text{otherwise.} \end{cases} \tag{7}
$$

In Figure 4, for example, $q_{<0,1,2>} = q_{<0,1>} \times p_{<0,1,2>} = q_{<0>} \times p_{<0,1>} \times p_{<0,1,2>} = p_{<0>} \times p_{<0,1>} \times p_{<0,1,2>}$.

3.4 Quality and Cost Objective Functions

The first objective is the expected value of the weighted sum of the *coefficient of variation* of each performance criterion for each product type, under a given demand forecast *DF*:

$$
\begin{aligned}
&F_1(\boldsymbol{x}, DF) = \sum_{\substack{s \in S \\ |s|=n}} q_s f_1(\boldsymbol{x}, \boldsymbol{ds}_s) \\
&f_1(\boldsymbol{x}, \boldsymbol{ds}_s) = \sum_{i=1}^{nc} \sum_{j=1}^{nt} w_i^t \frac{\sigma_i^t}{\mu_i^t},
\end{aligned} \tag{8}
$$

where *nc* is the number of performance criteria, *nt* is the number of product types, μ_i^t and σ_i^t are the mean and standard deviation of criterion *i* of product type *t* obtained by the product model, and w_i^t is the weight of criterion *i* of product type *t*.

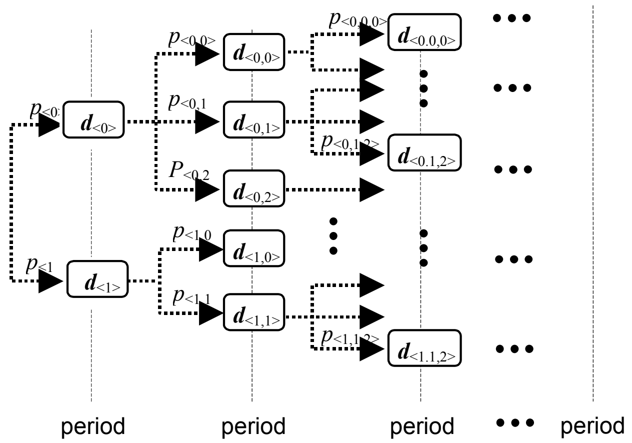


Figure 4: Example Demand Forecasts for *n* Periods

The second objective function is the expected values of the sum of the annual equivalent of capital investment cost (*IC*), salvage cost (*SC*), operating cost (*OC*), backorder cost (*BC*), and holding cost (*HC*) for each period (Park, 2001):

$$
\begin{aligned}
&F_2(\boldsymbol{x}, DF) = \sum_{\substack{s \in S \\ |s|=n}} q_s f_2(\boldsymbol{x}, \boldsymbol{ds}_s) \\
&f_2(\boldsymbol{x}, \boldsymbol{ds}_s) \\
&\quad = \varepsilon \sum_{i=1}^{n} \delta_i \{(1+\eta) IC_i + SC_i + OC_i + BC_i + HC_i\},
\end{aligned} \tag{9}
$$

where $\varepsilon = \eta(1+\eta)^n / \{(1+\eta)^n - 1\}$ is the capital recovery factor for equal payments during *n* periods with capital cost η, and $\delta_i = (1+\eta)^{-1}$ is the discount factor for the present value of future cash flows.

The capital investment cost IC_i for period *i* is the cost of new machines purchased at the *beginning* of period *i*, assuming there are no machines available at the beginning of period 1:

$$
IC_i = \begin{cases} \displaystyle\sum_{j=1}^{m} \sum_{k=1}^{l_j} c_{jk} x_{ijk} & i = 1 \\ \displaystyle\sum_{j=1}^{m} \sum_{k=1}^{l_j} c_{jk} \times \max(0, x_{ijk} - x_{(i-1)jk}) & i \in [2, n], \end{cases} \tag{10}
$$

where c_{jk} is the price of machine of type *k* in cell *j*.

The salvage cost SC_i for period *i* is the (negative) cost of exiting machines sold at its market value at the *end* of period i, assuming all machines are sold at the end of period n:

$$SC_i = \begin{cases} -\sum_{j=1}^{m}\sum_{k=1}^{j_j}\sum_{o\in O_i} c_{jk}\alpha^{A_{ijko}} & i\in[1,n-1] \\ -\sum_{j=1}^{m}\sum_{k=1}^{l_j}\sum_{o=1}^{x_{njk}} c_{jk}\alpha^{A_{njko}} & i=n\ , \end{cases} \qquad (11)$$

where α is the yearly percentage decrease in the market value of a machine, A_{ijko} is the age of the o-th machine of type k in cell j in period i. O_i is a set of max(0, $x_{(i-1)jk}$ - x_{ijk}) indices of machines of type k in cell j sold after period i.

The operating cost OC_i of period i is the sum of the product of the machine utilization, operating cost, and total operation time in a period:

$$OC_i = \sum_{j=1}^{m}\sum_{k=1}^{l_j}\sum_{o=1}^{x_{ijk}} u_{ijko}\times oc_{jk}(1+\lambda)^{A_{ijko}}\times t_i\ , \qquad (12)$$

where u_{ijko} is the utilization of the o-th machine of type k in cell j in period i, oc_{jk} is the operation cost of machine type k in cell j, λ is the yearly percentage increase in the operation cost, and t_i is the operating time. They are given as:

$$\begin{aligned} u_{ijko} &= bt_{ijko}/t_s \\ t_i &= \min(t_{\max}, d_i/n_i\times t_s)\ , \end{aligned} \qquad (13)$$

where bt_{ijko} is the operating time (busy time) of the o-th machine of type k in cell j in period i, t_s is the total operation time simulated, t_{max} is the maximum operation time, d_i is the demand in period i of scenario $\boldsymbol{ds}_s$, and n_i is the number of products produced in period i. The values of bt_{ijko}, t_s, and n_i are provided by the discrete event simulation of the production process.

The back order cost $BC_i = c_b\times\max(0,d_i-n_i)$ penalizes poor customer service due to unmet demand by a cost proportional to the amount of the demand that cannot be filled, where c_b is the back order cost. Similarly, an inventory holding cost $HC_i = c_h\times\max(0,n_i-d_i)$ is incurred when there is excess production, c_h being the unit holding cost.

3.5 Problem Formulation

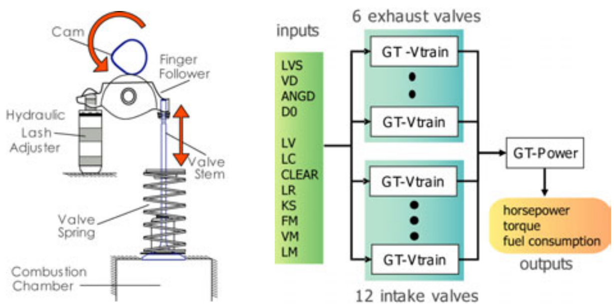
Based on the above equations, the problem can be written as the following multi-objective integer programming:

$$\begin{aligned} &\text{minimize } \{F_1(\boldsymbol{x},DF), F_2(\boldsymbol{x},DF)\} \\ &\text{subject to:} \\ &\quad \sum_{k\in MT_j^t} x_{ijk} \geq 1 \qquad (14) \\ &\quad x_{ijk}\in\mathbb{Z}_0,\ i\in[1,n],\ j\in[1,m], k\in[1,l_j]\ . \end{aligned}$$

This problem is solved using a multi-objective genetic algorithm (MOGA), an extension of GAs that do not require multiple objectives to be aggregated into a single value, (*e.g.* as a weighted sum). Instead of static aggregates such as a weighted sum, multi-objective genetic algorithms dynamically determine an aggregate of multiple objective values of a solution based on its relative quality in the current population, typically as the degree to which the solution dominates others in the current population (Coello, van Veldhuizen, and Lamont 2002).

4 CASE STUDIES

A case study is conducted on an automotive valvetrain production system. The main function of the valvetrain (Figure 5 (a)) is to control the flow of intake and exhaust gases with linear motion of valves, which is obtained by transforming the rotational motion of camshaft. The case study focuses on the production of valve stems and camshafts, and their effects on the horsepower, torque, and fuel consumption of the engine.



(a) (b)

Figure 5: (a) Valvetrain (Kazancioglu *et al*. 2003, Kazancioglu 2004); (b) Integrated Valvetrain-Engine Simulation

4.1 Product and Production System Models

The product model is a surrogate model (Artificial Neural Network) of an integrated valvetrain-engine simulation model of Ford Duratec 2.5L V6 SI engine, developed using commercial software GT-Vtrain and GT-Power (Kazancioglu *et al.* 2003; Kazancioglu 2004), shown in Figure 5 (b). The inputs are the selective dimensions of valves and cams: valve stem length (LVS), valve stem diameter (VD), cam lift duration angle (ANGD), and cam lift beginning angle (D0). The outputs are the horsepower, torque, and fuel consumption of the engine.

Figure 6 shows the cell configuration of the valvetrain production system with an example capacity allocation. It produce valve stems and cam shafts, and assembles them with engine blocks. The line for valve stems consists of cells 1 and 2 for machining LVS and VD, respectively. The line for camshafts consists of cell 3 for grinding cam lobes (controls ANGD) and cell 4 for assembling the finished cam lobes to camshaft (controls D0).

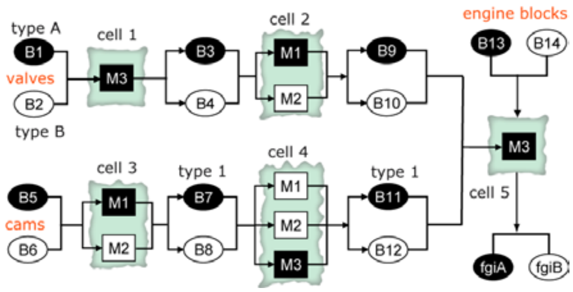


Figure 6: Valvetrain Production System

It is assumed that the system produces two (2) types of valvetrains, A and B, where type A valvetrains are made of type A valves and cams, and type B valvetrains are made of type B valves and cams. Machines types 1, 2, and 3 are valvetrain, a dedicated machine for type B valvetrain, and a flexible machine for both types changeover time of respectively defined as a dedicated machine for type A 20minutes with hourly changeover costs of $30-130. Note in call cells, the tolerances of the flexible machines are higher than the dedicated machines. Table 2 shows the machine data. Due to the complex requirements of the production simulation, an in-house software in Visual Basic with a Microsoft Excel front-end is developed (Kazancioglu, 2004).

Table 2: Machine Data for Valvetrain Production System

	Cell 1			*Cell 2*			*Cell 3*			*Cell 4*			*Cell 5*
Mach. Id.	**1-1**	**1-2**	**1-3**	**2-1**	**2-2**	**2-3**	**3-1**	**3-2**	**3-3**	**4-1**	**4-2**	**4-3**	**5-3**
μ_{PT} *[min]*	35	45	50	20	25	30	38	45	52	40	45	50	4
σ_{PT} *[min]*	1	1	1	1	1	1	2	2	2	2	2	2	0.5
OC [$/h]	10	15	20	5	7	12	12	20	26	12	20	25	5
ST [min]	n/a	n/a	20	n/a	n/a	20	n/a	n/a	20	n/a	n/a	20	n/a
SC [$/h]	n/a	n/a	50	n/a	n/a	30	n/a	n/a	130	n/a	n/a	130	n/a
P [K$]	200	270	350	150	200	300	350	500	650	300	500	650	60
Tol [mm]	0.015	0.002	0.001	0.03	0.025	0.01	0.003	0.002	0.001	0.5	0.15	0.07	n/a

In industries where there are rapid technological advances or dynamically changing customer preferences such as electronics and automotive industry, keeping inventory is risky since the products in stock may become obsolete before they are sold. As such, the case study assumed the production stops as soon as the demand is met at each period (a no back-order, no-inventory policy). Also, the input buffers providing raw materials never starve. The cost of capital, depreciation rate of machines and rate of increase operation cost are assumed 10%, 50% and 10% per year, respectively.

4.2 Demand Forecasts

Two, 3-period demand forecasts with different uncertainties are studied, where type B valvetrain replaces type A in time at different rates. Figure 7 shows the demand forecast with low uncertainties, and Figure 8 shows its most likely demand scenario, illustrating a slow replacement of type A by type B. Figure 9 shows the demand forecast with high uncertainties, and Figure 10 shows its demand scenario with the fastest replacement of type A. It should be noted that in both demand forecasts the demand for the period 1 is assumed to be known with no uncertainties (*i.e.*, $p_{<0>}$=1.0).

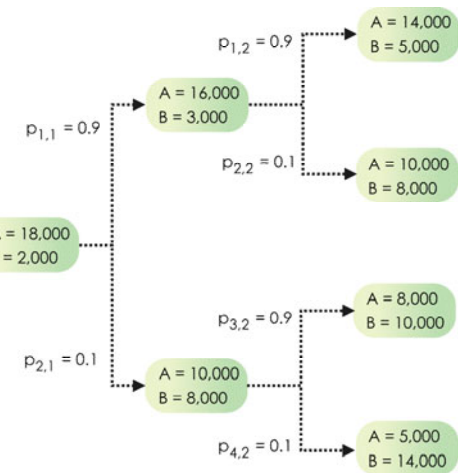


Figure 7: Demand Forecast with Low Uncertainty

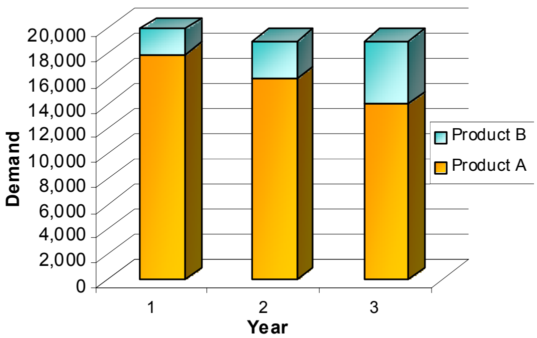


Figure 8: Most Likely Demand Scenario of the Demand Forecast in Figure 7

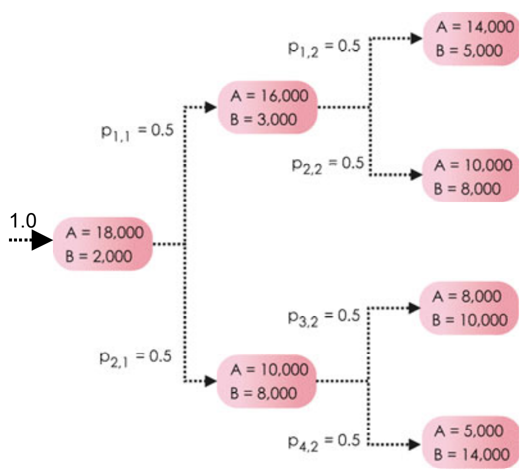


Figure 9: Demand Forecast with High Uncertainty

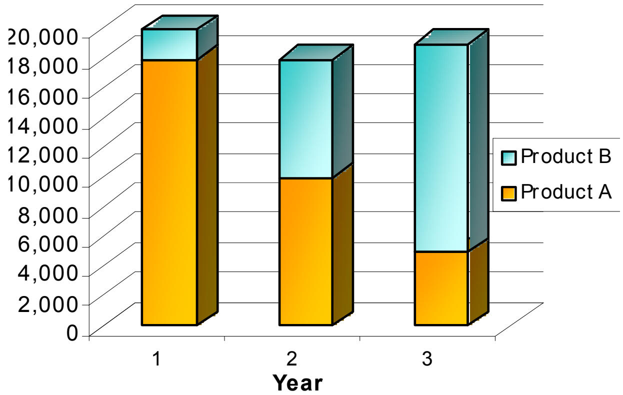


Figure 10: Demand Scenario of the Demand Forecast in Figure 9 with the Fastest Replacement of Product Type A

4.3 Results

Figure 11 shows the Pareto optimum results for high and low uncertainty forecasts, and Tables 3 and 4 list the 3-period capacity allocations corresponding to the options 1 (high uncertainty) and 2 (low uncertainty) indicated in Figure 11. As one might expect, the results suggest that the capacity allocations for the high uncertainty forecast must utilize more flexible machines (machine type 3), increasing the total cost of production. They also result in higher qualities, since the tolerance of the flexible machines are higher than the ones of the dedicated machines.

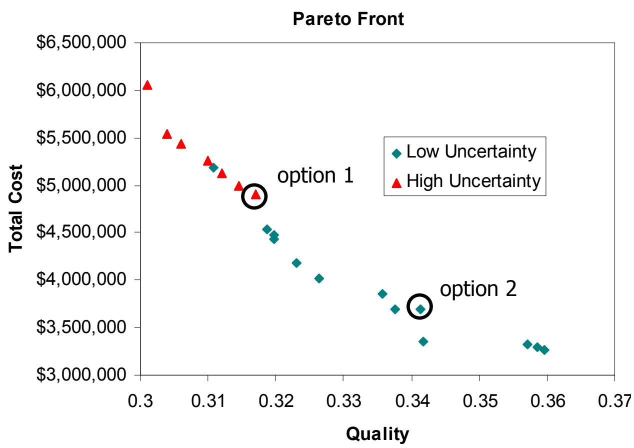


Figure 11: Pareto Optimum Results

Table 3: Capacity Allocation for Option 1 (High Uncertainty)

	Cell 1			*Cell 2*			*Cell 3*			*Cell 4*			*Cell 5*
Mach. Id.	1-1	1-2	1-3	2-1	2-2	2-3	3-1	3-2	3-3	4-1	4-2	4-3	5-3
Period 1	2	3	5	2	3	4	2	2	4	3	2	5	3
Period 2	2	3	3	2	2	3	2	2	3	2	2	4	3
Period 3	3	3	6	3	3	4	3	2	5	3	3	6	3

Table 4: Capacity Allocation for Option 2 (Low Uncertainty)

	Cell 1			*Cell 2*			*Cell 3*			*Cell 4*			*Cell 5*
Mach. Id.	1-1	1-2	1-3	2-1	2-2	2-3	3-1	3-2	3-3	4-1	4-2	4-3	5-3
Period 1	5	4	1	3	4	2	3	4	1	4	4	2	3
Period 2	3	3	1	3	4	1	2	4	2	2	4	3	3
Period 3	5	6	2	4	5	2	5	6	1	5	7	2	4

The results for the low uncertainty forecast, on the other hand, provide a wide range of alternatives: The capacity allocations with more flexible machines have higher product quality at the expense of higher total cost, whereas the ones with only dedicated machines have lower cost, at the expense of lower product quality. These low-cost, low-quality alternatives do not appear for the high uncertainty forecasts, due to the risk involved in committing to the dedicated machines, which would result in the very high production cost in some demand scenarios with dramatic demand changes.

5 CONCLUSION

This paper presented a simulation-based method for capacity allocation among flexible and dedicated machines based on uncertain demand forecasts. Given demand scenarios with the associated probabilities, the method provided Pareto-optimal capacity allocations based on the expected values of the product quality and cost. The product quality was estimated as the total performance variations for each product in a portfolio. The production cost was estimated as the total investment and operation costs for each production period. A case study on an automotive valvetrain production was presented. The analysis of the resulting Pareto optimal capacity allocations suggested that firms should invest on a larger percentage of flexible machines when there was high uncertainty in the future demand forecasts. Due to the use of simulations, the method can be easily customized for different product and production system characteristics.

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AUTHOR BIOGRAPHIES

EMRE KAZANCIOGLU received his MSc and Ph.D. in mechanical engineering from The University of Michigan, Ann Arbor in 2000 and 2004, respectively. His research interests include optimization, simulation and tools for strategic decision-making. Dr. Kazancioglu is currently with the Center for Strategy and Performance in the University of Cambridge as a postdoctoral research associate.

KAZUHIRO SAITOU received his PhD in mechanical engineering from the Massachusetts Institute of Technology (MIT) in 1996. From 1997 to 2003, he was an assistant professor in the Department of Mechanical Engineering at the University of Michigan, Ann Arbor, where he is currently an associate professor. His research interests include design automation and optimization, design for manufacture and assembly. He is a recipient of the 1999 CAREER Award from the National Science Foundation.