Proceedings of the TMCE 2004, April 13-17, 2004, Lausanne, Switzerland, Horváth & Xirouchakis (eds.)
 ISBN 90 5966 018 8

MULTI-PERIOD CAPACITY PLANNING FOR INTEGRATED PRODUCT-PROCESS DESIGN

Emre Kazancioglu
Department of Mechanical Engineering
University of Michigan,
USA
ckazanci@umich.edu

Kazuhiro Saitou
Department of Mechanical Engineering
University of Michigan,
USA
kazu@umich.edu

ABSTRACT

This paper presents an optimization-based method to aid capacity planning decisions by quantifying the trade-off between the capital and operating costs of a production facility and the quality of finished products. Given forecasted market demands during multiple production periods, multi-objective optimization selects the quantity and the types of production machines to be purchased during each period, which simultaneously maximize the quality of the finished products and minimize the total production cost during the periods. The product quality is estimated as the statistical variation from the performance targets obtained from the output tolerances of the machines that manufacture the components, via Monte Carlo simulation. The production cost is estimated as the annual equivalent cost of owning and operating a production facility during the production periods, obtained from the price of each machine and a discrete event simulation of production process. A case study with an automotive valvetrain is presented to illustrate the method.

KEYWORDS

Product-process design, robust design, capacity planning, discrete event simulation, Monte Carlo simulation, multi-objective optimization.

1. INTRODUCTION

With the increased number of players competing in a global market, it is becoming of crucial importance for companies to be able to accommodate changes in demand and customer preferences in a timely manner, by optimally allocating the capacity of their production facilities. However, short term, reactive planning that attempts to meet demands and quality requirements of immediate future only, usually compromises profits over multiple production periods due to the following reasons:

1. Incremental change in production capacity is benefited less by economies of scale.
2. Time lag between the purchase decision and the delivery of production machines may impede meeting demands.
3. Capacity expansion/retraction usually requires production to stop.
4. Allocating excess capacity early or preserving it in anticipation of future demand increase may be economically advantageous.

Despite increased uncertainty in long-term demand forecasts, it is often desirable to consider multiple production periods in order to meet fluctuating demand with minimum capital and operating costs.

On the other hand, if cost is reduced at the expense of quality, the brand image may easily be damaged and future demand may be jeopardized. However increasing product quality by investing on higher quality machinery drives the price of the product up. For smarter capacity planning decisions, therefore, it is important to understand the trade-off between the capital and operating costs incurred by the expansion/retraction of production capacity and the resulting changes in product quality.

As a computational aid to multi-period capacity planning decisions, this paper presents a method for quantifying product quality-production cost trade-offs via multi-objective optimization. Given market demand forecasts for multiple production periods, the method determines the quantity and types of production machines to be purchased during each period, which simultaneously maximizes the quality of the finished products and minimizes the total cost of production. The product quality is estimated as the statistical variation from the target performances obtained from the output tolerances of the machines that manufacture the components, via Monte Carlo simulation. The production cost is estimated as the annual equivalent cost of owning and operating a production facility during the production periods, obtained from the price of each machine and a discrete event simulation of production process. A case study with automotive valvetrain is presented to illustrate the method.

2. RELATED WORK

Capacity planning involves analysis and decisions to balance capacity at a production or service point with demand from customers and the methods vary according to the length of the planning horizon as long, medium and short term. Extensive research has been conducted on developing tools to make effective capacity planning decisions focusing on different aspects of the problem.

Bienstock and Shapiro (1988) presents stochastic programming approach to the optimal resource acquisition problem using a scenario based probabilistic future demand. Barchi et al. (1975) combine the production-inventory and capacity expansion problem by modeling it as a linear, integer problem. Bhatnagar et al. (1999) discusses a finite-horizon Markov decision process (MDP) model for providing decision support in semiconductor manufacturing on issues such as when to add additional capacity and when to convert from one type of production to another. Paraskevopoulos et al. (1991) demonstrate the existence of uncertainty influences the investment, production and pricing decision using a sensitivity approach. Asl and Ulsoy (2002) presents an optimal solution for the capacity management problem in Reconfigurable Machining Systems with stochastic market demand with time delay between the time capacity change is ordered and the time it is delivered, based on the Markov Decision Theory. Saitou et al (2002) uses a discrete-event simulation and a genetic algorithm to determine resource allocation in a multi-product production facility such that the production costs are insensitive to the changes in production volumes due to market demand fluctuations. This work is later extended in Lee and Saitou (2002), where the datum relationships in family of machined parts and the allocation of production resources are simultaneously optimized for robustness against production volume variations in a multi-period production scenario.

Although there is extensive research in capacity planning, the issues of product quality resulting from the change in production facility, has not been addressed. Also, most capacity planning literature use analytical models of production process which require many assumptions. The present method, on the other hand, utilizes multi-objective optimization and the simulation of production processes and product performances, which allows the examination of the trade-off between production cost and product quality for realistic production scenario.

3. METHOD

3.1. Overview

The developed method for multi-period capacity planning is illustrated in Figure 1. Given demand forecasts during the periods of interest and a selection of the types and numbers of machines, the production system model simulates the production process during the period, and calculates the capitol and operating costs and the tolerances of the product parameters (*e.g.*, component dimensions), which affect the product performance. These tolerances are fed into the product model, which calculates, via Monte Carlo simulation, the statistical distribution of the product performances. Based on the production cost and the performance distribution, a multi-objective optimizer determines the Pareto-optimal selections of the types and numbers of machines, with respect to performance variation and production cost.

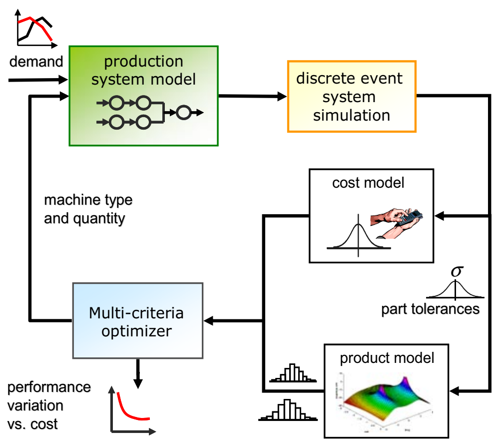

Figure 1 Overview of method

3.2. Production System Model

We consider a class of production systems which are comprised of cells of machines each performing one manufacturing operation, and part buffers between each cell. Figure 2 shows an example with three cells and five buffers. As illustrated in Figure 2, each cell consists of one or more machines. While machines in a cell perform the same manufacturing operation which affects one or more product parameters, they can be of different types. A type of machines is defined based on the following information:

- manufacturing operation
- process time (mean and standard deviation)
- tolerances of the relevant product parameters
- operating cost
- machine price

The topology of a production system can be represented as an incidence matrix $A = (a_{ij})$ of material flows (represented as arrows in Figure 2):

$$a_{ij} = \begin{cases} 1 & \text{if flows from cell } i \text{ to buffer } j \\ -1 & \text{if flows from buffer } j \text{ to cell } i \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Table 1 shows the incident matrix of the example system in Figure 2. During the optimization process, this matrix remains constant, whereas the types and quantity of machines in each cell are altered among the available choices, in order to maximize the product quality and minimize the production cost.

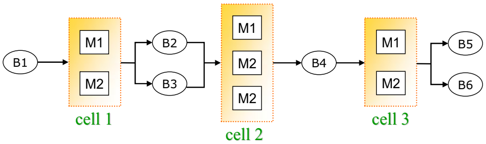

Figure 2 Example production system

Table 1 Incidence matrix of the example production system in Figure 2

	B1	*B2*	*B3*	*B4*	*B5*	*B6*
Cell 1	-1	1	1	0	0	0
Cell 2	0	-1	-1	1	0	0
Cell 3	0	0	0	-1	1	1

For a given selection of machine types and quantities, the operation of the production facility is simulated by a discrete event simulation (Banks, *et al*, 1996). The process time of each machine type is assumed as normally distributed with given mean and standard deviation, and accordingly sampled during the simulation. After simulating production for the periods with forecasted demands, the total amount of production and the utilization of each machine for each period are calculated, in order to estimate the operating cost as demonstrated in detail in the following section. In addition, the types of machines in each cell which are used to manufacture each product are recorded during the simulation, in order to estimate the quality of the finished product as described in the next section.

3.3. Product Model

The product model takes a set of product parameters (*e.g.*, component dimensions) as an input and calculates the statistical distribution of the product performances. The product model can be analytical, a numerical simulation, or a surrogate model of a computationally expensive numerical simulation as adopted in the following case study.

In the present study, the quality of the product is estimated as the statistical variation of the product performance. This can be calculated by Monte Carlo simulation of the product model with the product parameters sampled according to the tolerances of the types of machines used to manufacture each product.

3.4. Design Variables and Constraints

The design variables are the types and number of machines in each cell in the production system at each period. It can be represented as the number of machines of type k in cell j during period i:

$$x_{ijk} \in \mathbf{Z}, x_{ijk} \geq 0,\ i = 1,\ldots,n,\ j = 1,\ldots,m, k = 1,\ldots,l_j \quad (2)$$

where 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 example, let us consider the machine allocation problem using three periods ($n = 3$) and the production system in Figure 2 assuming there are two types of machines available in each cell (*i.e.*, $m = 3$, $l_1 = l_2 = l_3 = 2$). Then, the machine allocations shown in Figure 3 are represented as $3 \times 3 \times 2 = 18$ integer variables:

$$\begin{aligned} & x_{111} = x_{112} = x_{121} = x_{131} = x_{132} = 1, \quad x_{122} = 2 \\ & x_{211} = x_{231} = 0, \quad x_{212} = x_{221} = x_{222} = 1, \quad x_{232} = 2 \\ & x_{311} = 0, \quad x_{312} = x_{321} = x_{331} = 1, \quad x_{322} = x_{332} = 2 \end{aligned} \quad (3)$$

There must be at least one machine in a cell, which imposes the following constraint:

$$\sum_{k=1}^{l_j} x_{ijk} \geq 1; \quad i = 1,\ldots,n, j = 1,\ldots,m \tag{4}$$

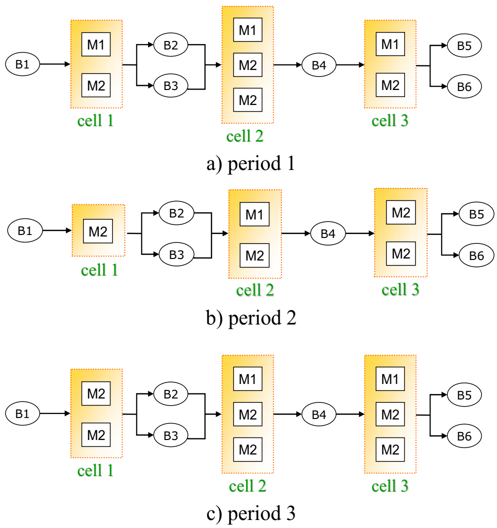

Figure 3 Example machine allocations for 3 periods

3.5. Objective Functions

The first objective function is the measure of product quality defined as the sum of the coefficient of variations of the performance criteria:

$$f_1 = \sum_{i=1}^{n_c} \frac{\sigma_i}{\mu_i} \tag{5}$$

where n_c is the number of performance criteria, μ_i and σ_i are the mean and standard deviation of the i-th performance criterion obtained by Monte Carlo simulation of product model. Alternatively, a weighted sum of σ_i can be used.

The second objective function is the estimation of the capital and operating costs of production, defined as the sum of the annual equivalent of capital investment cost (*AECC*), operating cost (*AEOC*), backorder cost (*AEBC*), and holding cost (*AEHC*) for all periods (Park, 2001).

$$f_2 = AECC + AEOC + AEBC + AEHC \tag{6}$$

Each cost term is given as:

$$\begin{aligned} AECC &= \varepsilon \sum_{i=1}^{n} \delta_i \{(1+\eta) IC_i + SC_i\} \\ AEOC &= \varepsilon \sum_{i=1}^{n} \delta_i OC_i \\ AEBC &= \varepsilon \sum_{i=1}^{n} \delta_i BC_i \\ AEHC &= \varepsilon \sum_{i=1}^{n} \delta_i HC_i \end{aligned} \tag{7}$$

where η is cost of capital of the project, ε is the capital recovery factor for equal payments during n periods given as:

$$\varepsilon = \frac{\eta(1+\eta)^n}{(1+\eta)^n - 1} \tag{8}$$

and δ_i is the discount factor which is used to compute the present value of future cash flows.

$$\delta_i = \frac{1}{(1+\eta)^i} \tag{9}$$

The capital investment cost IC_i of period i is the sum of the cost of machines purchased at the *beginning* of the period. Assuming there is no machine available at the beginning of period 1:

$$IC_1 = \sum_{j=1}^{m} \sum_{k=1}^{l_j} c_{jk} x_{ijk} \tag{10}$$

For the subsequent periods, the cost incurs only when new machines are purchased:

$$IC_i = \sum_{j=1}^{m} \sum_{k=1}^{l_j} c_{jk} \times \max(0, x_{ijk} - x_{(i-1)jk}); \quad i = 2,\cdots n \tag{11}$$

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

The purchased machines can be sold at their market value at the *end* of period i to if there is excess capacity for the next period, which can be represented as a negative salvage cost SC_i:

$$SC_i = -\sum_{j=1}^{m} \sum_{k=1}^{l_j} \sum_{o \in O_i} c_{jk} \alpha^{A_{ijko}}; \quad i = 1,\ldots n-1 \tag{12}$$

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 $\max(0,\ x_{(i-1)jk}\ \text{-}\ x_{ijk})$ indices of machines of type k in cell j sold after period i. There are no priorities set among machines as to which one is to be sold first. This is done intentionally since depending on the rate of market value depreciation and the rate of increase in the operating cost, fixed policies such as selling the oldest machines may be suboptimal. At the end of period n, all purchased machines are assumed to be sold:

$$SC_n = -\sum_{j=1}^{m}\sum_{k=1}^{l_j}\sum_{o=1}^{x_{njk}} c_{jk}\alpha^{A_{njko}} \tag{13}$$

However, depending on the type of a production system and the range of the periods considered, this assumption can be replaced with a more suitable one.

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:

$$OC_i = \sum_{j=1}^{m}\sum_{k=1}^{l_j}\sum_{o=1}^{x_{ijk}} u_{ijko} \times oc_{jk}(1+\lambda)^{A_{ijko}} \times t_i \tag{14}$$

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:

$$\begin{aligned} u_{ijko} &= bt_{ijko} / t_s \\ t_i &= \min(t_{\max}, d_i / n_i \times t_s) \end{aligned} \tag{15}$$

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, 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 penalizes poor customer service due to unmet demand by a cost proportional to the amount of the demand that cannot be filled:

$$BC_i = c_b \times \max(0, d_i - n_i) \tag{16}$$

where c_b is the back order cost. Similarly, the excess production incurs the inventory holding cost HC_i:

$$HC_i = c_h \times \max(0, n_i - d_i) \tag{17}$$

where c_h is the holding cost.

3.6. Optimization Problem

With the design variable, constraints, and objective functions defined in the previous section, the problem can be formulated as the follows:

$$\begin{aligned} &\text{minimize } \{f_1, f_2\} \\ &\text{subject to } \sum_{k=1}^{l_j} x_{ijk} = 1; \quad i = 1,\ldots,n,\ j = 1,\ldots,m \\ &\qquad x_{ijk} \in \mathbf{Z}, x_{ijk} \geq 0,\ i = 1,\ldots,n,\ j = 1,\ldots,m, k = 1,\ldots,l_j \end{aligned} \tag{18}$$

In the following case study, the problem is solved using a multi-objective genetic algorithm, an extension of genetic algorithms that do not require multiple objectives to be aggregated to 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[1] others in the current population. The results of the case study are produced with an implementation of non-dominated sorting genetic algorithm (NSGA-II) (Coello *et al.,* 2002), where the quality of a solution is measured in terms of the number of solutions dominating it in the current population. Interested readers should refer to (Coello *et al.,* 2002) for the details of the NSGA-II algorithm.

4. CASE STUDY: ENGINE VALVETRAIN

A case study is conducted on the valvetrain system of a Ford Duratec 2.5L V6 SI engine, released in 1994. The engine has a maximum power output of 125 kW at 6250 rpm and 220 Nm of torque at 4250 rpm and is used in the Mercury Mystique, Ford Contour and Ford European Mondeo. The main function of the valvetrain system (Figure 4) is to control the flow of intake and exhaust gases by opening and closing the valves, which is obtained by transforming the rotational camshaft motion into linear motion of the valve. 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.

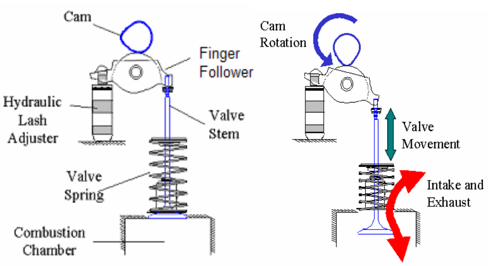

Figure 4 Valvetrain system (Kazancioglu, *et al.*, 2003)

[1] For a vector-valued function $\boldsymbol{f} = (f_1, f_2, .., f_n)$ to be minimized, a point $\boldsymbol{x}$ *dominates* $\boldsymbol{y}$ if $f_i(\boldsymbol{x}) < f_i(\boldsymbol{y})$ for all $i = 1,2,\ldots,n$.

4.1. Production System Model

Figure 6 shows the considered production system, which produces valve stems and cam shafts, and assembles them with engine blocks. The line for valve stem production consists of two cells for machining operations (cells 1 and 2), which correspond to the valve stem length (LVS) and valve stem diameter (VD), respectively. The line for camshaft production also consists of two cells for grinding cam lobes (cell 3) and assembling the finished cam lobes to camshaft (cell 4). Cells 3 and 4 correspond to the cam lift duration angle (ANGD) and cam lift beginning angle (D0), respectively. Table 2 shows the incidence matrix of the valvetrain production system.

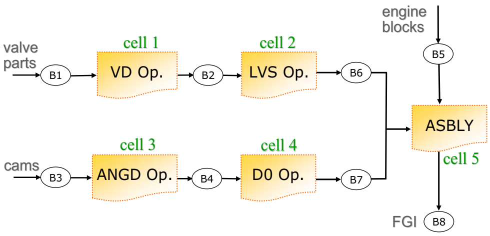

Figure 5 Valvetrain production system

Table 2 Incidence matrix of the valvetrain production system

	B1	*B2*	*B3*	*B4*	*B5*	*B6*	*B7*	*B8*
Cell 1	-1	1	0	0	0	0	0	0
Cell 2	0	-1	0	0	0	1	0	0
Cell 3	0	0	-1	1	0	0	0	0
Cell 4	0	0	0	-1	0	0	1	0
Cell 5	0	0	0	0	-1	-1	-1	1

The type of machines available for the production system is listed in Table 3. The processing times of the machine tools correspond to the time it takes to process one batch of parts which is 24 for both the valves and the cam lobes (4 cam shafts, 6 cam lobes on each).

4.2. Product Model

The product model of the case study is a surrogate model of an integrated valvetrain-engine simulation developed in the authors' previous work (Kazancioglu, *et al.*, 2003). The simulation, illustrated in Figure 6, uses commercial software GT-Vtrain and GT-Power. The inputs are the valve and cam parameters of the valves including VD, LVS, ANGD, and D0 which are the design variables of the case study, discussed in the previous section. The outputs are the horsepower, torque, and fuel consumption of the engine.

Table 3 Machine data of valvetrain production system in Figure 5

	Cell 1		*Cell 2*		*Cell 3*	
	M1	*M2*	*M1*	*M1*	*M2*	*M1*
mfg. operation	VD	VD	LVS	LVS	ANGD	ANGD
μ process time [min]	20	25	10	15	20	35
σ process time [sec]	5	1	3	1	5	2
operating cost [$/h]	30	40	15	20	50	100
machine price [K$]	200	270	150	200	350	500
tolerance	0.01	0.005	0.03	0.02	2	1

	Cell 4		*Cell 5*	
	M1	*M2*	*M1*	*M1*
mfg. operation	D0	D0	ASSY	ASSY
μ process time [min]	50	60	3	2
σ process time [sec]	5	2	10	10
operating cost [$/h]	50	100	50	75
machine price [K$]	350	420	60	60
tolerance	0.003	0.002	NA	NA

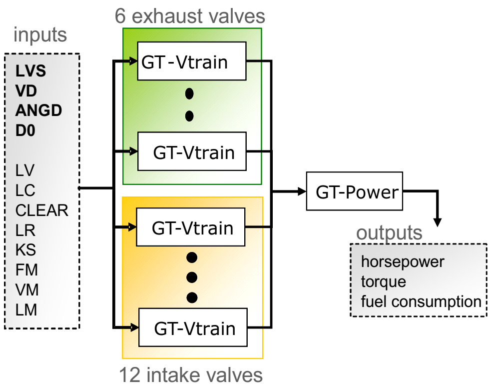

Figure 6 Integrated valvetrain-engine simulation

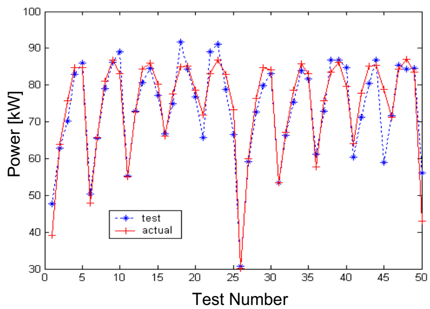

Figure 7 Horsepower output of the neural network model (dotted) and the simulation model (solid) (Kazancioglu, *et al.*, 2003).

Due to the excessive computational time to conduct Monte Carlo simulation, a surrogate model of the valvetrain-engine simulation is built using a feed forward neural network in MATLAB Neural Network Toolbox.

As training data for the neural network, pairs of the inputs and outputs of the valvetrain-engine simulation at 3000 rpm with full load are sampled by using the five-level full factorial design of the four parameters: LVS, VD, ANGD and D0. Each parameter is assumed to vary within $[0.975\mu\text{-}3\sigma, 1.025\mu\text{+}3\sigma]$, which is equally divided into the 5 ranges to define 5 factor levels. At each factor level, a value is uniformly sampled in the corresponding range. Figure 7 shows the horsepower output for 50 random unseen inputs, using the trained neural network model and the simulation model. The outputs of the neural network model match very well with the corresponding ones from the simulation model (Kazancioglu, *et al.*, 2003).

4.3. Optimization Problem

Three, one-year periods (n = 3) are considered as a horizon of the capacity planning. Since there are 5 cells (m = 5), each of which has two types of machine available (l_j = 2; j = 1,…,5), there are $3\times5\times2=30$ integer design variables. The quality objective f_1 is defined as the sum of the coefficient of variation of horsepower, torque and fuel consumption, obtained by the Monte Carlo simulation with the neural network model.

Table 4 shows the market demand for the three periods, which represents a situation where demand falls in the second period and picks up again in the third period. The following assumptions made for the valvetrain production during the three-year period:

1. Production stops as soon as the demand is met at each period. In other words, production for future demands is not allowed.
2. Time for the delivery of the purchased machines is not longer than one year.
3. The number of the machines of the same type should not exceed 5 in all periods. In other words, $x_{ijk} \le 5$.
4. Input buffers which provide raw materials never starve.

Table 5 lists the parameter values for the cost objective f_2. The backorder cost c_b is set to an extremely high value to enforce the demands to be met always. Considering the limited market for the machines for valvetrain production, α is also set to be very high. The holding cost c_h is zero since no inventory is allowed according to the above assumption.

Table 4 Market demand for valvetrain

	periods (year)		
	1	2	3
demand	30,000	15,000	35,000

Table 5 Parameter values for objective functions

	description	*value*
n	number of periods	3
η	cost of capital of the project	10 [%/year]
α	depreciation rate of machine value	50 [%/year]
λ	rate of increase in operation cost	10 [%/year]
t_{max}	maximum operation time	4320 [h]
c_b	back order cost	inf [$]
c_h	holding cost	0 [$]

4.4. Results

To demonstrate the importance of the multi-period planning and the quantification of quality-cost trade off, the results are presented for the following three cases:

1. **Case 1. Single-period, minimum cost planning:** Three capacity planning problems for the three periods are separately solved for minimum cost (*i.e.*, cost objective f_2 only).
2. **Case 2. Multi-period, minimum cost planning:** One capacity planning problem considering all three periods is solved for minimum cost (*i.e.*, cost objective f_2 only).
3. **Case 3. Multi-period, minimum cost-maximum quality planning:** One capacity planning problem considering all three periods is solved for minimum cost and maximum quality (*i.e.*, both quality objective f_1 and cost objective f_2).

Table 6 shows the parameters of multi-objective genetic algorithm used to obtain the results.

Table 6 Parameters of genetic algorithm

	Case 1	*Case 2*	*Case 3*
mutation probability	0.01	0.01	0.01
crossover probability	0.9	0.9	0.9
population size	25	25	45
max. # of generations	30	30	70

Table 7 shows the optimal values of cost objective function for Case 1 and Case 2, and Tables 8 and 9 show the optimal machine allocations for Case 1 and Case 2, respectively. The annual equivalent cost of Case 2 is approximately $250K less than that of Case 1. Ignoring the time value of money, this approximately adds up to $750K cost savings over the three-year planning horizon.

In Case 1, since an increase in the demand in the third period is not anticipated, a capacity retraction is carried out in the second period due to reduced demand. In Case 2, on the other hand, the demand information about the third term is available and it is more cost effective to keep the excess capacity in the second period in comparison to retracting capacity in the second period and than to expand it later again in the third period.

Table 7 Optimal cost for Case-1 and Case-2

	Case 1	*Case 2*
AEOC	$2,771,805	$2,759,349
AECC	$2,887,460.	$2,657,771
AEBC	$0	$0
f_2	**$5,659,265**	**$5,417,120**

Table 8 Optimal machine allocation for Case-1

	Cell 1		*Cell 2*		*Cell 3*		*Cell 4*		*Cell 5*	
	M1	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*
P 1	5	1	0	3	5	3	4	3	2	0
P 2	2	1	0	2	1	2	1	2	1	0
P 3	2	5	0	3	2	5	4	4	2	0

Table 9 Optimal machine allocation for Case-2

	Cell 1		*Cell 2*		*Cell 3*		*Cell 4*		*Cell 5*	
	M1	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*
P 1	5	1	0	3	2	5	4	3	0	2
P 2	4	1	0	3	2	5	3	3	0	2
P 3	5	2	0	3	2	5	4	4	0	2

Figure 8 shows the quality-cost trade off curve (Pareto front) obtained for Case 3. A square at the bottom-right indicates the optimum result of Case 2, which only minimizes cost. Tables 10 shows the values of the objective functions for Case 2 and of the two alternatives for Case 3 indicated on Figure 8. The optimal machine allocations for alternatives 1 and 2 are shown in Tables 11 and 12, respectively. Tables 11 – 13 summarize the standard deviations of the engine performance metrics for Periods 1, 2 and 3 respectively.

Both alternatives for Case 3 have better quality characteristics than Case 2, where quality was not considered during capacity planning. The results shows with approximately $550K additional investment to Case 2 result, the product quality increases about 10%, while approximately $350K to alternative 1 yields the quality increases of approximately 25%.

5. CONCLUSION

This paper presented an optimization-based method for capacity planning of production facilities considering the demand changes in multiple production periods and the trade-offs between the product quality and production cost. The method is then applied to a capacity planning problem in an automotive valve-train production. The results demonstrated the effectiveness of considering multi-period demand forecast and quantitative quality-cost trade-off in capacity planning decisions.

Future work will investigate the capacity planning problem in multi-product production lines under stochastic demands, which allows the quantification of quality-cost trade-off between flexible and dedicated production machines.

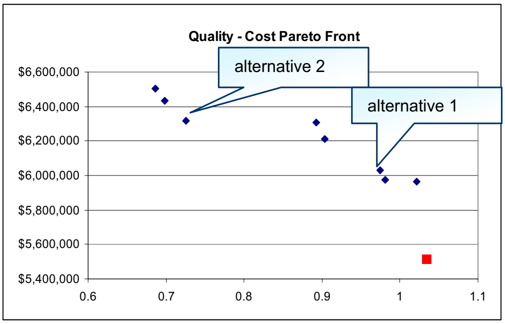

Figure 8 Quality-cost Pareto front for Case 3

Table 10 Optimal cost and quality objective function values of Case-2 and Case-3

	Case 2	*Case 3 – Alt 1*	*Case 3 – Alt 2*
AEOC	$2,759,349	$2,893,004	$2,797,127
AECC	$2,657,771	$3,081,844	$3,519,554
AEBC	$0	$0	$0
f_2	**$5,417,120**	**$5,974,849**	**$6,316,777**
f_1	**1.080**	**0.974**	**0.726**

Table 11 Optimal machine allocation for the alternative 1 in Figure 8

	Cell 1		*Cell 2*		*Cell 3*		*Cell 4*		*Cell 5*	
	M1	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*
P 1	5	1	0	3	2	5	4	3	0	2
P 2	4	1	0	3	2	5	3	3	0	2
P 3	5	2	0	3	2	5	4	4	0	2

Table 12 Optimal machine allocation for the alternative 2 in Figure 8

	Cell 1		*Cell 2*		*Cell 3*		*Cell 4*		*Cell 5*	
	M1	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*	*M1*	*M2*
P 1	0	5	0	5	5	5	0	5	0	2
P 2	5	0	3	0	0	5	0	5	0	2
P 3	3	5	0	5	2	5	5	5	0	2

Table 13 Comparison of engine quality results in Period 1

	Power (kW)		*Torque (N-m)*		*BSFC*	
	μ	*σ*	*μ*	*σ*	*μ*	*σ*
Case 2	87.08	10.61	203	20.73	243	39.74
Alt. 1	86.25	9.54	204	19.22	251	36.53
Alt. 2	87.38	2.89	207	7.06	246	18.21

Table 14 Comparison of engine quality results in Period 2

	Power (kW)		*Torque (N-m)*		*BSFC*	
	μ	*σ*	*μ*	*σ*	*μ*	*σ*
Case 2	86.72	9.25	208	18.42	249	40.53
Alt. 1	87.66	7.20	205	15.19	248	35.67
Alt. 2	87.27	4.95	204	13.18	249	30.44

Table 15 Comparison of engine quality results in Period 3

	Power (kW)		*Torque (N-m)*		*BSFC*	
	μ	*σ*	*μ*	*σ*	*μ*	*σ*
Case 2	86.497	9.02	208	17.3	244	39.8
Alt. 1	85.745	8.32	207	16.8	248	28.8
Alt. 2	86.62	8.29	206	16.4	251	36.1

ACKNOWLEDGMENTS

This research is supported by the US Army TACOM and the GM Collaborative Research Laboratory at the University of Michigan through the Dual Use Science and Technology Program on The Concurrent Design of Next-Generation Powertrains, Manufacturing Process and Materials. The authors acknowledge Mr. Karim Hamza for his contribution to the development of the MOGA code.

REFERENCES

Bienstock, D., Shapiro, J. F., (1988), "Optimizing Resource Acquisition Decisions by Stochastic Programming," *Management Science*, Vol. 34, No. 2, pp. 215-229.

Barchi, R. H., Sparrow, F. T., Vemuganti, R. R., (1975), "Production, Inventory and Capacity Expansion Scheduling with Integer Variables," *Management Science*, Vol. 21, No. 7, pp. 783-793.

Bhatnagar, S., Fernandez-Gaucherand, E., Fu, M. C., He, Y., Marcus, S. I., (1999), "A Markov Decision Process Model for Capacity Expansion and Allocation," *Proceedings of the 38th Conference on Decision & Control*, Phoenix, Arizona, USA.

Paraskevopoulos, D., Karakitsos, E., Rustem, B., (1991), "Robust Capacity Planning Under Uncertainty," *Management Science*, Vol. 37, No. 7, pp. 787-800.

Asl, F. M., Ulsoy, A. G., (2002), "Capacity Management In Reconfigurable Manufacturing Systems with Stochastic Market Demand," *Proceedings of 2002 ASME International Mechanical Engineering Congress and Exposition*, New Orleans, Louisiana, Paper No: IMECE2002-MED-32872.

Saitou, K., Malpathak, S., and Qvam, H., (2002), "Robust Design of Flexible Manufacturing Systems using Colored Petri Net and Genetic Algorithm," *Journal of Intelligent Manufacturing*, v. 13:5, p. 339–351.

Lee, B., Saitou, K., (2002), "Design of Part Family Robust-to-production Plan Variations based on Quantitative Manufacturability Evaluation," *Research in Engineering Design,* Vol. 13, pp. 199-212.

Banks, J., Carson, J., and Nelson, B., (1996), *Discrete-Event System Simulation*, Second Edition, Prentice Hall, New Jersey.

Coello, C. A. C., van Veldhuizen, D. A., and Lamont, G. B., (2002), *Evolutionary Algorithms for Solving Multi-Objective Problems*, Kluwer Academic/Plenum Publishers, New York.

Wu, J., and Azarm, S., (2001), "On a New Constraint Handling Technique for Multi-Objective Genetic Algorithms," *Proceedings of the Genetic and Evolutionary Computation Conference,* pp. 741-748.

Park, C. S., (2001), "Contemporary Engineering Economics," Ch.7-Ch.12, *Prentice Hall*, 3rd Edition, New York.

Kazancioglu, E., Wu, G., Ko, J., Bohac, S., Filipi, Z., Hu, S. J., Assanis, D., and Saitou, K., 2003, "Robust Optimization of an Automotive Valvetrain using Multiobjective Genetic Algorithm," Proceedings of the 2003 ASME Design Engineering Technical Conferences, Chicago, Illinois, September 2-6, DETC2003/DAC-48714.