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A Path Specification Approach for Production Planning in Semiconductor Industry

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ABSTRACT

This paper explores a new approach for modeling of decision-making problems that involve uncertain, time-dependent and sequence-dependent processes which can be applied to semiconductor industry. In the proposed approach, which is based on probability theory, approximate sample paths are required to be specified by probability and statistic characteristics. Completely specified sample paths are seen to be elementary and fundamental outcomes of the related experiment. The proposed approach is suitable for modeling real processes more accurately. A case study is applied to a single item production planning problem with continuous and uncertain demand and the solution obtained by the approximate path specification method shows less computational efforts and practically desirable features. The application possibility and general plan of the proposed approach in semiconductor manufacturing process is also described in the paper.

Key Words : Uncertainty; Path specification; Decision model; Production planning

1. Introduction

Uncertainty of events needs to be considered appropriately in many decision-making models. These models may relate to production planning, materials requirement planning, job scheduling, project scheduling, and capacity expansion planning etc. Random modeling methods have been often used to account for uncertainty in decision-making problems. Solutions can be obtained by stochastic programming, deterministic approximation, simulation and other suitable techniques for such models. When the random variables change continuously with time, we may use stochastic processes such as Brownian motion (BM) and the generalizations such as geometric BM, Fractional BM, Levy Process, Ito process as modeling tools. We can easily find application examples of such tools in many cases in the literature. One reason for random modeling is that models become amenable to exact theoretical analysis to greater depth. We shall review a few studies of this nature. This is indicating rather than being exhaustive and the variety of decision models with stochastic processes has been employed to deal with uncertainty.

Bather proposed an inventory model in which inventory level is a BM [1] which is a pioneering work. A (s, S) type policy is proposed to minimize long run expected cost per unit time considering a fixed ordering cost, linear inventory holding and backlogging cost. A number of inventory models with demand patterns have been presented by different studies. For example, Sulem discussed a similar model in which cumulative demand is a BM with a drift [2] and Berman et al. analyzed a model with the parameters in the BM and that is state dependent [3].

Capacity expansion decisions for electricity generation, transportation, health service and education, etc., undoubtedly, is also important and practical problems. Change of the demand with time, expansion lead times and economies of scale in expansion become important in capacity expansion decisions.

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Many research works have focused on capacity expansion decision models with stochastic demands, and more particularly, BM/ geometric BM demand, etc [4, 5].

Jagannathan discussed a linear programming formulation in which the requirement vector is assumed to be a stochastic process, one particular case being BM [6]. The properties of deterministic equivalent of formulations are derived. The results are applied to a multi-item production planning problem. Szmerekovsky presented a single machine scheduling model where reward for completing a job varies as a BM [7]. Kannianen deliberated on the question of appropriateness of using a geometric BM to model properly discounted projects [8].

An alternative approach to model uncertainty has been fuzzy theory [9]. Complexity and chaos theory, vagueness theory and possibility theory, etc. may be used to model uncertainty. However, no particular theory may be considered as a universal tool for dealing with uncertainty in all contexts.

In this paper, we present a new approach that is based on basic principles of probability but do not have assumptions such as independence of the random variables, etc. It aims to use process knowledge to a larger extent. This makes it more general and is suitable to a number of real-world situations and it can also be applied to semiconductor industry.

Rest of the paper is organized as follows. In the next section, we show the assumptions underlying the proposed approach. In Section 3, a case study of the proposed approach is illustrated with a model of production planning. Some concluding remarks describes in section 4.

2. The Path Specification Approach

Consider a continuous time domain and uncertain process $\{W(t):0 \le t \le T\}$, $W(t) \in R$, $W(t) < \infty$, $T < \infty$. This process underlies the decision model and is an input of it. The following properties are assumed for , and the related decision model:

i) $W(t)$ is specified with some approximate sample paths (ASP), $S_i(t)$, $0 \le t \le T$, $i = 1, 2, \ldots, k$. The i^{th} ASP has probability p_i $(0 < p_i \le 1)$, and the total summation of p_i is 1. ASPs are the elemental and fundamental outcomes of the random experiment. Fig. 1 shows ASPs of some hypothetical processes.

ii) In a realization of $W(t)$ in [0, T], the ASP which shows a minimum of maximum absolute deviation from the observed path is considered to occur. In notation, let $A(t)$ be the actual and observed path. Then, a path is to minimize $\max_{0 \le t \le T}\{|S_i(t) - A(t)|\}$ where it is considered to be realized. Ties, if any, may be broken in proportion of the probabilities of the paths.

iii) Let $f(w(t), x_1, x_2, \ldots, x_n)$ be a function that includes the decision variables $x_1, x_2, \ldots, x_n(\in R)$ as parameters, and is calculated in [0, T]. Average of the function is given by the following equation:

$$\mu_{(f)} = \sum_{i=1}^{k} p_i f(S_i(t), x_1, x_2, \ldots, x_n) \qquad (1)$$

Variance and standard deviation are,

$$V_{(f)} = \sum_{i=1}^{k} p_i (f(S_i(t), x_1, x_2, \ldots, x_n) - \mu_{(f)}) \qquad (2)$$

$$\sigma_{(f)} = \sqrt{V_{(f)}} \qquad (3)$$

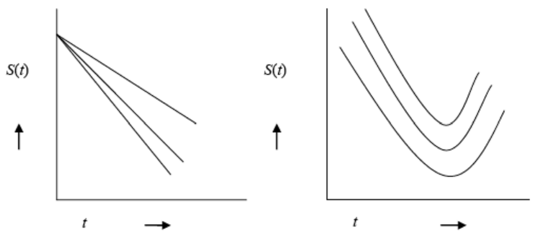

Fig. 1. Examples of Approximate Sample Paths.

The decision problem requires to determine optimal values of $x_1, x_2, \ldots, x_n$ and to minimize $\mu_f + \lambda_{\sigma(f)}$, $\lambda \ge 0$. A solution with less average and less variation at the same time is sought. We may not consider other types of objectives as practical requirement.

It may be noted that we do not have any random variable to describe the process-paths being the outcomes of the random experiment. The deviations from the sample paths may be modeled with random variables, or in other ways. We may get the practical interpretation of μ_f and σ_f using the long-term frequency interpretation of the probabilities. If one of the ASPs occurs exactly in every realization of the process, the values are average and standard deviation of the function over a large number of realizations of the process. But there can be noises. Deviations from μ_f and σ_f would decrease as noises decrease. Such deviations can be quantified by imposing further properties on the noises. If ASPs are forecast with sufficient accuracy, this may not be required practically in most cases.

There is no need to verify the values of the variable $W(t)$ at different time points which are independent or otherwise, since complete paths over the horizon are specified.

A number of decision models can be modeled within this framework. It is also clear that some modifications in the above approach can be made quite readily, e.g., $W(t)$ is a vector and t is indexed discretely. But, characteristics as a discrete sample space with a small number of outcomes add to the easy comprehensibility of the approach.

3. An Application In Producton Planning

In this section, we consider a single item production planning problem with continuous and uncertain demand and describe the usefulness of the proposed approach. Uncertainty of demand, supply and other conditions is an important issue for production planning and materials requirement planning. Mula et al. presented a survey of research dealing with uncertainty in production planning [10]. Random modeling and stochastic programming or deterministic approximation have been used [11, 12] and fuzzy theory modeling is also used [13].

We apply the path specification approach derived by probability and statistics characteristics, as given in the preceding section, to the following production planning problem.

Consider an item which has continuous and uncertain demand. ASPs are forecasted in (T = 12 months) with past data, with subjective estimates, and/or utilizing process knowledge. Forecasting gives some ASPs along with the probabilities. These represent possible demand rate fluctuation for the item in and are given in these instances as follows:

i) S_1(t) = 1 (constant);

ii) $S_2(\mathrm{t}) = \begin{cases} 1,\ 0 \le t \le 6 \\ 0.8,\ 6 < t \le 12 \end{cases}$;

iii) $S_2(\mathrm{t}) = \begin{cases} 1 - 0.1t,\ 0 \le t \le 5 \\ 0.5 + 0.1t,\ 5 < t \le 12.1t \end{cases}$;

The paths are shown in Fig. 2 (along with the approximately optimal solution obtained). Each path has equal probability of 1/3. Production rate is constant in a month but can vary over the months. Production rate for the *i-th* month ([0, 1]) is the first month, etc.) is denoted as $x_i(\ge 0)$, i = 1, 2, ..., 12. The conditions of the problem are described as follows:

(a) Maximum production rate possible is 1.5/unit time.

(b) Initial inventory (I_0) is 0.25 and at any point of time and the level of inventory should be greater than and equal to this. A cost is proportional to the square of the difference, when inventory level goes below 0.25. The time which the level continues is incurred. The proportionality constant (c_1) is 3.0.

(c) Inventory holding cost (c_2) is 1.0/unit/month.

(d) Further, there is a cost of changing the production rate from one month to the next. It is proportional to the square of the difference of the rates. The proportionality constant (c_3) is 2.0.

(e) Other production costs do not change with time.

(f) The objective function is average cost incurred plus 25% of standard deviation of cost incurred. This has to be minimized.

3.1. Optimization Model

The problem can be written as the following equation. Let $I_k(y)$ be the inventory position at time y, if demand follows the path $S_k(t)$ (exactly). That is, $I_k(y)$ = Initial inventory + Total production up to time y – Total demand up to time y.

$$I_k(y) = I_0 + (x_1 + x_2 + \ldots + x_i + (y-i)x_{i+1})$$
$$- \int_0^y S_k(t)dt,\ i \le y < i+1,\ i = 0, 1, \ldots, 11 \qquad (4)$$

Cost incurred for the path is

$$f(S_k(t), x_1, \ldots, x_n) = c_1 \int_0^T (I_0 - min\{I_0, I_k(t)\})^2 dt + c_2 \int_0^T \max(\{I_0, I_k(t)\}) dt + c_3 \sum_{i=1}^{12} (x_{i+1} - x_i)^2 \quad (5)$$

From this, average cost ($\mu_{(f)}$) and standard deviation of cost ($\sigma_{(f)}$) can be calculated. We need to minimize $\mu_{(f)} + \lambda\sigma_{(f)}$ with $\lambda = 0.25$, $0 \le x_i \le 1.5$ $i = 1, 2, ..., 12$.

3.2. Solution Search Method

Due to the structure of the problem, it is not possible to solve it analytically. We solve it with a random search method. In the random search method, some variables are changed randomly while the others are changed in a known manner. The best solution obtained till some iterations is further improved with generating further points randomly and around the obtained solution. The variables x_1, x_2 and x_3 are changed with uniform increments in the range while other variable values are generated randomly. An approximately optimal solution is obtained as follows: $\{x_1 = 1.03, x_2 = 1.03, x_3 = 0.71, x_4 = 0.91, x_5 = 1.05, x_6 = 1.07, x_7 = 0.72, x_8 = 1.0, x_9 = 1.22, x_{10} = 1.02, x_{11} = 1.32, x_{12} = 1.24\}$, with objective function value 7.46 where average cost is 7.01 and standard deviation of cost is 1.83.

3.3. Validation of the Solution

Suitability of the obtained solution is verified with a simulation experiment. ASPs are perturbed adding a chaotic signal, which has been used [14]. First, we have a chaotic signal noise as,

$$z_{j+1} = 4z_j(1 - z_j), j = 0, 1, 2, \ldots \quad (6)$$

with $z_0 = 0.2$, 0.3, 0.4, for three cases. This is altered as,

$$\tilde{z}_{j+1} = (0.5 - z_{j+1})/5, j = 0, 1, 2, \ldots \quad (7)$$

and added to the sample paths.

It may be seen that $0 < z_j \le 1$, $j = 0, 1, \ldots$; and hence, $-0.1 \le \tilde{z}_j \le 0.1$, $j = 0, 1, \ldots$. Such $\tilde{z}_j$ noises are added at time points $0.05j$, $j = 0, 1, \ldots$. Actual cost incurred is calculated for each of the perturbed sample paths for the solution and a comparative solution such as $\{x_1 = x_2 = \ldots = x_{12} = 1.0\}$. This is shown in Table 1. In Table 1, the solution is denoted as Sol.1 and the comparative solution suggested is denoted as Sol.2. As shown in Table 1, the comparative solution gives less cost in case of ASP 1 occurring; but the cost may increase steeply for other ASPs. Sol.2 has less or almost equal cost except ASP 1 and significantly less standard deviation. Thus it can be considered as a more "balanced" solution that would not lead to very high cost in any situation.

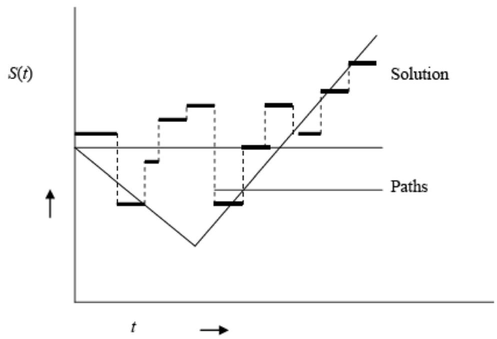

Fig. 2 Approximate Sample Paths and a Solution for the Numerical Example.

Table 1. A Comparison of Solutions

S. No	z_0	ASP	Cost (Sol.1)	Average cost	Cost (Sol.2)	Average Cost
1	0.2	1	2.95		4.93	
2	0.2	2	6.58	7.07	6.59	7.01
3	0.2	3	11.68		9.52	
4	0.3	1	3.26		4.63	
5	0.3	2	6.89	7.32	6.56	6.91
6	0.3	3	11.82		9.64	
7	0.4	1	2.99		4.92	
8	0.4	2	6.62	7.11	6.54	7.01
9	0.4	3	11.69		9.56	

3.4. Application Possibility of the Proposed Approach in Semiconductor Industry

To survive in highly competitive business environments of these days, semiconductor companies should operate their facilities at the maximum effectiveness and efficiency, and this can be done thorough careful production planning and scheduling, among other approaches. In general, the semiconductor manufacturing process is composed of four major stages, wafer fabrication(FAB), probing or electric die sorting (EDS), assembly and final test Among the four stages, wafer FAB is considered as the most complex production stage requiring a lot of time and involving hundreds of operations with complicated production characteristics such as various resource constraints, reentrant flows, limited number of tools, time-dependent and sequence-dependent processes, sequence-dependent setup times, unexpected machine breakdowns, yield loss, uncertain demand and so on. Therefore, for achieving the maximum effectiveness and efficiency of the manufacturing process, effective and sophisticated production planning and scheduling methodologies must be developed for the FABs and probing facilities. The proposed approach in this study can be applicable to a two-level hierarchical production planning and scheduling method of the semiconductor manufacturing as a higher level decision model. The two-level hierarchical production planning and scheduling method can be divided into two stages in which the higher level (aggregate level) decision is made for production planning and the lower level (disaggregate level) decisions is made for detailed scheduling. In the proposed method, we model the production planning using the proposed path specification approach and we adopt an iterative scheme to obtain a good and feasible production plan. That is, in each iteration, a production plan is obtained from the ASP model and a priority rule-based scheduling in the FAB, and schedule and the production plan are evaluated with the discrete-event simulation to satisfy the objectives in the lower level (disaggregate level) decision model. An iterative scheme is adapted for obtaining and feasible production plan.

4. Conclusion

We have proposed a new approach to model a decision model with a process state which changes with time uncertainty. In the approach, complete sample paths over the time horizon are seen as the outcomes of the underlying random experiment. Forecasts are required to give such sample paths. The application of the approach is described with an example of a production planning problem. It is seen that, the solution generated may be regarded as a suitable solution.

The proposed approach has the desirable features as:

i) It is devised to focus on the major trends in the process instead of noise in it;

ii) It has the flexibility to model realistic processes closely without the need of having unrealistic and restrictive assumptions. It allows us, for example, to consider more complicated objectives in alignment with the practical requirements;

iii) The models are amenable to numerical solution methods which can be implemented easily;

iv) No particular demand pattern etc. is assumed theoretically for a process. Forecasts for the process would use past data and practitioners' insights about the process crucially;

v) Noise in a process need not be a random variable and can be modeled in various ways as appropriate;

vi) It is intuitively appealing and the underlying principles are understood easily. Practitioners can get conversant with it readily.

We feel that, for effective application of a method, the last point mentioned is particular importance.

The proposed approach the limitations that exact theoretical analysis is not much possible. We do not have a technique to get forecasts as required in it combining past data and practitioners' process knowledge efficiently. Furthermore, it may also be difficult to automate forecasts and decisions when process knowledge is considered to be an important component in forecasting. The above issues may be studied in future research.

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