MODELING JUST-IN-TIME PRODUCTION SYSTEMS:
A CRITICAL REVIEW

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ABSTRACT
Kanban-controlled serial manufacturing systems have recently received considerable attention. A large proportion of the literature on the topic is devoted to success stories. There is also an important modeling-based effort in gaining insight into the behavior of such systems, in identifying important success factors, and ultimately in optimizing various aspects of systems' performance. This paper focuses exclusively on model-based approaches in studying pull systems. Even though analytic models such as linear programming formulations or queueing approximations exist, the inherent complexity of pull systems makes simulation an essential tool in studying them. The objective of this paper is therefore to critically review selected papers that have recently appeared in refereed journals, highlight their approach, point out deficiencies, where appropriate, re-emphasize their message, and suggest new directions for research.

1 INTRODUCTION
Recently a considerable amount of attention has been focused on Japanese manufacturing systems, in particular the pull system and the just-in-time (JIT) approach [Schonberger 1982, 1983; Hall 1983; Zipkin 1991]. With this demand driven control, work is pulled through the system; that is, the succeeding stage withdraws items from the preceding stage according to the rate at which the succeeding stage consumes them. On a broader scale, a JIT orientation includes various action programs such as reduction of setup times and lot sizes, grouping of equipment into manufacturing cells, elimination of defects and other quality problems, extensive worker involvement and education, and close working relationships with a limited number of suppliers [Vollmann et al. 1988; p.245]. These initiatives are aimed at ultimately creating a pull system.

Although there are several ways of achieving a pull-type control system (e.g., order point/order quantity or base stock systems), it is most often implemented through kanbans. Criteria for judging successful JIT implementation include downtime reduction, inventory reduction, workspace reduction, increase in quality, labor utilization, equipment utilization, and increase in inventory turns [Mehra and Inman 1992]. Implementation issues, in particular, the transition from a push to a pull environment, are discussed in Miltenburg and Wijngaard [1991] and in Grünwald and Fortuin [1992]. A more theoretical discussion is presented in Zangwill [1987]. Suri and De Treville [1986] provide useful insights through simple congestion models.

It should be emphasized that the kanban system, by itself, is not crucial to improving performance. It is only one part of the overall JIT philosophy, which tries to shape a manufacturing environment with more uniform workflows and flexibility to adjust to changing capacity requirements through various factors such as lot sizes, setup times, yield losses, workforce flexibility, degree of product customization, and product structure [Krajewski et al. 1987].

The literature on JIT is largely one of cases. The most famous JIT examples are from firms with high volume, repetitive manufacturing environments such as the classic case of Toyota [Monden 1983; Shingo 1989]. In a recent literature review on the JIT philosophy, Golhar and Stamm [1991] identify some 860 articles published since 1970. (Many more have appeared since then.) Based on 211 articles that have appeared in refereed journals, they examine the role of culture in successful JIT implementations, compare the performance of JIT in relation to other approaches such as MRP and OPT, and classify the literature into broader categories that include implementation in manufacturing, kanban, human resource management, accounting, purchasing, and quality.

This paper is focused exclusively on models used in analyzing the problem associated with implementing and operating pull systems. The operational control problem includes implementing the kanban system to control the interaction between production and inventory levels in both deterministic and stochastic environments. Research on operational control problems of pull production systems relies heavily on simulation due to the inherent complexity of pull systems. Mathematical programming, stochastic analysis and queueing-theoretic approaches are only a few. Nevertheless, these analytical approaches based on simplified models yield valuable insight into the behavior of such systems and provide rough-cut analysis. The objective of the paper is thus
to critically review selected papers that have recently been published, highlight their approach, point out deficiencies, when appropriate, re-emphasize their message, and finally suggest new directions for research. Two other problem areas in implementation and control could also be identified [Deleersnyder et al. 1989]:

1. The identification of flow lines problem, which captures the conversion from a functional layout into a cellular layout.

2. The flow line loading problem, which involves the allocation of a viable amount of work to each flowline in order to avoid bottlenecks.

We do not address these problems here, as there exists an extensive literature on configuring and managing flow lines within a broader context. For instance, Morris and Tersine [1990] conduct a detailed simulation study to identify the factors influencing the attractiveness of a cellular layout compared to flow lines. An extensive review of cellular manufacturing is provided by Huang and Houck [1985], Okamura and Yamashina [1979], on the other hand, address the problem of effective utilization of mixed-model assembly lines to minimize line stoppages. Mittenburg [1989] also studies these lines with the objective of determining the sequence schedule for producing different products on the line while keeping a constant rate of usage.

Also excluded from this review are papers describing special tools for modeling and analyzing JIT systems. For example, Oguz and Dingir [1991] propose a decision support system to facilitate the analysis of such systems by providing a model base, a database, and a user interface. On the other hand, several papers discuss special constructs to simulate pull-type production systems [Sarker 1989; Mejabi and Wasserman 1992a,b; Muralidhar et al. 1992].

The paper is organized as follows: Section 2 describes our classification scheme. The selected papers are discussed within this scheme in Section 3. Summary of common themes together with some concluding comments are presented in Section 4.

2 CLASSIFICATION OF JIT MODELS

There is a large number of factors that have to be considered explicitly in describing a manufacturing environment. Krajewski et al. [1987] and, subsequently, Chu and Shih [1992] identify 41 system characteristics that appear as factors in analyzing manufacturing environments. They summarize these factors under eight major categories: inventory policy, process characteristics, product structure, customer influence, vendor influence, buffer mechanisms, facility design, and, inescapably, others. These are depicted in Table 5 of Chu and Shih [1992].

In somewhat abstract terms, we can classify the literature using the following elements:

S is the set of control mechanisms with s ∈ S,

X_s is the set of decision variables corresponding to control system s,

D is the set of external parameters,

P is the set of internal parameters.

Then, the mapping

f : (s, X_s, D, P) → R^k is the performance measure of interest. Examples of these modeling elements are given in Table 1. Several objectives for modeling and analyzing production systems can then be distinguished:

1. Comparison: Given D, P, and f, compare f(s', X_s', D, P) and f(s'', X_s'', D, P). For example, given a particular set of internal and external parameters and a performance measure, compare a push versus a pull system.

2. Evaluation: Given s, X_s, and f, evaluate f(s, X_s, D, P) as a function of D and P. For example, given a pull system and a performance measure, evaluate the sensitivity of f to internal and external parameters.

3. Static Optimization: Given s, D, P, and f, optimize f(s, X_s, D, P) as a function of X_s. For example, given a pull system, determine the number of kanbans that should be allocated to each of the workcenters to maximize throughput.

4. Dynamic Optimization: Given s(0), X_s(0), D(t), P(t), and f, optimize

\[ \int_0^T g(t) f(s(t), x_s(t), D(t), P(t)) \, dt \]

as a function of s(t) and X_s(t), where g(t) is a discount factor. For example, determine the least expensive way to switch from a push to a pull control system.

Different modeling and analysis techniques are used in addressing these problems. We will differentiate between deterministic and stochastic models. Stochastic models include analytic approaches such as Markov processes and queuing models as well as numerical approaches such as queuing approximations and computer simulation. Deterministic models, on the other hand, include linear programming formulations or dynamic programming methods. In the next section, we discuss these approaches in further detail.

3 REVIEW OF JIT MODELS

Research on operational control problems of pull production systems relies heavily on simulation. Mathematical programming, stochastic analysis and queuing-theoretic approaches are relatively rare. Selected papers are summarized in Table 2, where the objective of the study is depicted together with the adopted methodology for analysis. The table is also informative in showing where the majority of research in operational issues is clustered and where the big gaps—further research opportunities—can be found.

3.1 Deterministic Models

Luss and Rosenwein [1990] present a heuristic approach to determine the lot size for processing N items on a single bottleneck facility. The objective is to minimize the total inventory cost per unit time.

In a single-product, multi-stage environment, Kimura and Terada [1981] model a deterministic pull
system. They determine production quantity and work-in-process inventory analytically for each station. However, when the number of units indicated by a kanban is large, theoretical analysis becomes prohibitive and simulation is tried. As an alternative to kanban systems, a periodic pull control mechanism is also introduced [Kim 1985]. In a single-product, multi-stage environment, demand is modeled as a stationary stochastic process. The periodic pull system is formulated mathematically to determine the minimum stock level for each station in order to satisfy a pre-set stockout probability. Probability density functions for in-process material are provided.

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Bitran and Chang [1987] present a mathematical programming model in a deterministic, multi-stage, capacitated environment with a single product having an assembly-tree structure. Buffer stock capacity, the number of kanbans, is determined in order to minimize inventory carrying cost in the system at any point in time. With a similar approach, a near-optimal heuristic for computing the number of kanbans is also presented by Moeeni and Chang [1990]. Davis and Stubitz [1987] also deal with the determination of the number of kanbans. Discrete optimization and simulation are applied to configure the system.

Bard and Golany [1991] use a mixed linear-integer programming formulation to determine the number of kanbans at each workcenter in a multi-stage multi-product environment in order to minimize the total cost of inventory, shortage, and setup. An efficient algorithm is presented. Limited experimentation with real data yields considerably reduced operating costs compared to current company practice.

The kanban assignment problem is taken into a dynamic environment by Li and Co [1991] where an N-stage production system is analyzed over a planning horizon of T periods. The number of kanbans to be allocated to each workcenter is determined through a dynamic programming recursion based on the minimum cumulative cost from stage n to N.

A signal kanban is described for workcenters with relatively high setup times [Philipoom et al. 1990]. An integer programming approach is adopted for determining the optimal lot sizes to be used in conjunction with signal kanbans. A simulation model is subsequently employed to test the effectiveness of the integer programming models. It is concluded that the classical multi-product EOQ model would not always yield satisfactory results in a JIT shop.

Di Mascalo et al. [1991] propose Petri Nets as a unifying modeling framework for depicting and analyzing kanban controlled systems. Even though this approach has a well-established theoretical grounding, Petri nets quickly become too cluttered to support detailed modeling.

### 3.2 Stochastic Models
The discussion in this section centers around three
approaches: queuing and other Markovian models, approximations for congestion models, and computer simulation.

3.2.1 Congestion Models

Useful models for pull systems are provided by the finite-buffer tandem queues. As the finite buffer space between consecutive workcenters can be viewed as "kanban squares," the pull phenomenon can be represented through various blocking mechanisms. Tandem queues were originally studied by Hunt [1956] and Hillier and Boling [1967] in conjunction with automatic transfer lines.

More recently, blocking mechanisms as well as decomposition techniques to analyze individual stations in isolation and then to aggregate the results received considerable attention [Onvural and Perros 1986; Perros and Aliotik 1986; Aliotik and Perros 1986; Gershwin 1987; Aliotik 1989].

Studies related directly to manufacturing cells with limited buffers include Dubois [1983], Stidham and Aliotik [1984], Sarker [1984], Costa and Garetti [1985], and Elsayed and Hwang [1986]. Conway et al. [1988] conduct an extensive simulation study to analyze the impact of buffer allocation on system performance. Yao and Shanthikumar [1987] study the optimal input rate into a system of manufacturing cells in order to maximize the total throughput without causing excessive blocking.

Berkley [1991] asserts that the two-card kanban-controlled line is a generalization of the tandem queue. Through simulation experiments, he shows that the tandem queue serves as an upper bound for more general two-card systems. This is an interesting result in that the congestion model can be used to find the minimum number of kanbans required to achieve a desired production rate.

Using a cyclic queueing system, Sarkar and Zangwill [1991] present several surprising results concerning the effect of variability. They show cases where set-up reduction and processing rate increases may have adverse effects on inventory.

Markovian models have also found ready utility in depicting pull systems. For instance, Deleersnyder et al. [1989] model a general N-stage serial line as a Markov chain by taking capacity constraints, machine reliability, and demand variability into consideration. A 3-stage model is then used to illustrate the effects of the number of kanbans, the machine reliability, the demand variability, and safety stock requirements on system performance.

Suri and De Treville [1986] use a simple M/M/1/K model to illustrate the relationship between disruption and learning in a kanban-controlled production system. In their example, removing kanbans whenever throughput has recovered to the 90% level yields the steepest learning curve and the highest final throughput, with the cumulative throughput hardly different from that of the no-removal case.

Zipkin [1989] and Lee and Zipkin [1992] use a continuous-time Markov process to depict the operating characteristics of a pull system. The second paper also addresses the issue of quality problems and illustrates the value of early detection in preserving the system throughput.

Although simple and elegant, Markovian models suffer from the state space explosion problem. Jordan [1988] constructs a Markov chain model of an assembly system and introduces an approximation algorithm to avoid this explosion problem. His results are subsequently extended by Berkley [1990].


3.2.2 Approximation Techniques

The state space explosion problem is also addressed via various decomposition algorithms. In one such approach, Berkley [1992] decomposes a flow line into individual stations modeled as imbedded Markov chains. The analyses of individual workcenters are then aggregated to produce an approximation for the entire flow line. The impact of alternative numbers of kanbans and withdrawal cycle times are evaluated. Mitra and Mitrani [1990, 1991] introduce alternative decomposition schemes to analyze the relationship between throughput and inventory.

A different approach is adopted by Spearman et al. [1990], Spearman [1992], and Spearman and Zazanis [1992]. Through a sample path analysis, the latter two compare push and pull systems, and introduce an alternative hybrid control mechanism, CONWIP, which keeps WIP at a constant level. Through simulation, the former paper asserts that their system is more robust to environmental disturbances than a pure kanban-controlled system.

Another alternative is proposed by Jaikumar [1988]. The approach involves holding "emergency lots" in order to shield the system from such disturbances as machine breakdowns and yield losses.

Tayur [1993] expands on the work of Mitra and Mitrani [1990, 1991]. Through sample path arguments, he develops structural results for serial lines. These structural results characterize the dynamics of the systems, provide insight into their behavior, and, most importantly, significantly reduce the simulation effort needed to study them. These results hold in general as no assumptions are made on the processing time distributions, the number of cells, the total number of kanbans or on whether the machines are identical. Tayur [1993] also develops a heuristic procedure for the kanban allocation problem.

3.2.3 Computer Simulation

Simulation is still the most popular technique in studying pull systems due to inherent complexity of models with any appreciable degree of realism. Two important papers seem to have set the stage for further work. The paper by Huang et al. [1983] is usually taken as the benchmark in simulation studies analyzing kanban-controlled pull systems. On the other hand, the extensive simulation study by Krajewski et al. [1987] is not only a good example of a carefully designed set of simulation
experiments, but also provides valuable insights into the differences between various production control mechanisms in different environments.

Other simulation studies have also appeared in the literature: Ebrahimpour and Fathi [1985] and Gupta and Gupta [1989] adopt a system dynamics approach to investigate the impact of production stoppages, various inventory policies, variability in supply rates, variability in processing rates, increase in capacity, and unbalanced production lines on such measures of performance as throughput, shortages, and idle time. The former paper also looks at the effect of a gradual reduction of the number of cards.

Rees et al. [1989], Sarker and Fitzsimmons [1989], and So and Pinault [1988] compare the performance of various control mechanisms under different environmental conditions. Different operating rules are investigated in Meral and Erkip [1990] while different sequencing rules are tested in Berkley and Kiran [1991]. Periodic pull, as a modified approach to JIT production, is proposed and studied in Kim [1985] and in Lee et al. [1993].

Finally, Chaudhury and Whinston [1990] propose stochastic automata methods for modeling learning behavior. They claim that such an approach can be used with a Kanban-type control technique to make flow lines more flexible and adaptive in nature. They discuss the relationship of their control model to computational models such as neural computing.

As simulation plays a crucial role in modeling and analyzing pull systems, it is imperative that simulation studies are conducted with utmost care. A recent paper by Chu and Shih [1992] reveals important flaws in most simulation studies. The following seem to be the problems commonly encountered in published simulation studies:

1. Modeling randomness: Although many of the models contain various sources of variability (demand, processing times, machine availability, yield), it was found that there is no study which provides justification for or explains why and how a particular random variable was chosen.

2. Program verification and model validation: Though both of these processes are very tedious, they constitute an important stage in any simulation study. Inappropriate assumptions and/or inaccurate programs would render the study virtually useless. Among all the studies, it was found that only Krajewski et al. [1987] and Schroer et al. [1984, 1985] discuss validation and verification.

3. Design of Experiments: Most studies have been found to ignore experimental conditions such as the elimination of the initial transient (achieving steady-state conditions), the run length, and the number of independent replications.

4. Statistical output analysis: It is surprising that only four studies (Krajewski et al. 1987; Schroer et al. 1984, 1985; and Villeda et al. 1988) specify the method used to analyze the simulation output. Others just perform simple analyses or just ignore the issue.

The above findings are both surprising and alarming, as simulation is the most popular experimental technique in analyzing pull systems largely due to its ultimate flexibility. Such a lack of rigor in building these simulation models and analyzing their output renders the conclusions postulated in these studies, at best, questionable.

4 CONCLUDING COMMENTS

Computer simulation is recognized as the most powerful tool in analyzing JIT practice due to inherent complexities of such systems. Although computationally demanding, a simulation model can be used in comparing alternative manufacturing settings under the JIT philosophy, in assessing the impact of internal and external factors on pull-type production systems, and in contrasting the performance of the kanban system with other planning and control techniques.

However, these studies should be undertaken with care by devoting more attention to such issues as model verification and validation, experimental design, and statistical output analysis.

On the methodology side, robust approximation techniques with higher utility and generality are still needed. Such techniques will enable quick modeling and analysis of systems with arbitrary complexity, ultimately providing valuable insight into their behavior and furnishing some rough estimation of the performance measures of interest. These techniques would also reduce the effort required for conducting a simulation study by a considerable margin. In addition, such approximations could facilitate evaluation and optimization of production control systems of arbitrary complexity, reconciling the state-space explosion problem of analytical methods with the necessarily limited generalizability of simulation studies.

Finally, simulation-based optimization techniques should facilitate the design of kanban-controlled pull systems. In that aspect, methods such as Infinitesimal Perturbation Analysis [Glasserman 1991] and Frequency Domain Methodology [Schruben and Cogliano 1987; Jacobson 1988] should be useful in making it possible to conduct more efficient and effective simulation studies. From a methodology perspective, Table 2 clearly depicts the need for robust approximation techniques as well as simulation-based optimization methods.

Another important aspect of any model-based approach is to interpret the results in order to guide any implementation efforts. However, it is quite difficult to verify and compare individual results as each study used a different model with different assumptions, different experimental settings, and different measures of performance. As a result, the following questions should be addressed from a unified perspective under comparable experimental settings: Which measures should a company use to evaluate its JIT performance? Which factors are most important for successful JIT implementation? What will a JIT system perform better than other production systems? How should the transition from a push to a pull environment be managed? In addition, Table 2 exhibits the large gaps with respect to dynamic
optimization questions which should be viewed as promising research initiatives.

Satisfactory answers to the above questions are urgently needed in the light of the findings of Krajewski et al (1987), which were also confirmed by several other studies, that the key to improving performance is the environmental factors such as lot sizes, setup times, yield losses, workforce flexibility, degree of product customization, and product structure and not the kanban system itself.

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**AUTHOR BIOGRAPHIES**

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