A REVIEW OF MANUFACTURING RESOURCES PLANNING MODELS UNDER DIFFERENT UNCERTAINTIES: STATE-OF-THE-ART AND FUTURE DIRECTIONS

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ABSTRACT

The main purposes of this paper are to enhance the understanding of manufacturing resources planning models under uncertain conditions by documenting the current state of affairs, and to stimulate a fruitful future research direction by identifying gaps between the relevant issues and the literature available in reputable journals. This paper is a comprehensive and up-to-date review of the existing literature on manufacturing resource planning models under uncertainty. The authors have found that the combined effects/ impacts of the uncertainty factors on the system parameters have yet to be thoroughly studied. So far no research has been conducted into developing mathematical model(s) to study the uncertainty issues holistically in multi-period, multiple product, and multi-stage environments for manufacturing resources planning in association with commonality.

OPSOMMING

Die primêre doel van hierdie artikel is om die insig in vervaardigingshulpbronbeplanning onder onsekerheid te bevorder. Die huidige stand van sake word ondersoek en gapings word uitgewys aan die hand van literatuur beskikbaar in gesaghebbende joernale. Die outeurs bevind in die studie dat die sisteemparameters en die invloed van onsekerheid daarop nog nie voldoende bestudeer is nie. Geen navorsing is nog onderneem om wiskundige modelle te ontwikkel om op holistiese wyse die impak van onsekerheid in multi-periode, veelvoudige produk en multi-stadium omgewing te bestudeer nie.

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1. INTRODUCTION

The fundamental concern of manufacturing resources planning is to guarantee that the most promising quantity of the item is released at the best time, at the lowest cost, within the given constraints of the system, such as availability of the needed resource(s). Planning in a manufacturing environment is commonly carried out on the basis of material requirements planning (MRP) logic [1-3]; but the MRP logic has a major shortcoming in being unable to deal with uncertainty.

MRP, manufacturing resource planning (MRP II), enterprise resource planning (ERP), and ERP II are used to control production-planning activities, and have been widely implemented in contemporary manufacturing enterprises. They become the central systems in manufacturing environments within which production data such as demand, supply, product, inventory, accounting, costing, lead-time, and routing are kept in an integrated manner. The same MRP logic is used in MRP II and ERP in their production-planning modules [4]; thus their inability to cope with and respond to uncertainty remains, and the planned order release (POR) schedules are different from those generated from an MRP system [1, 5]. Also, MRP logic does not take capacity constraints into account [6, 7]. As MRP planning systems do not offer a solution to these fundamental issues, planners frequently have to adjust their planning [8]. In addition, implementation of these systems is very expensive and time-consuming. According to Fortune 500 companies, it costs US$30 million in licence fees and US$200 million in consulting fees – not to mention additional millions in computers and networks – and can take three years or more before the system yields its maximum benefit [9]. It was estimated that the spending on ERP systems in 1998 was about US$17 billion [10]. Therefore these planning and control tools are neither suitable nor affordable for SME/SMIs.

Today’s manufacturing enterprises must be responsive and able to tackle uncertainty quickly and robustly in order to sustain and enhance business competitiveness. In order to respond to uncertain demand, supply, and production processes, the role and performance of a production planning and control system within a manufacturing enterprise is a vital issue [11].

In general, optimisation problems include uncertainty in the problem structures, which are usually defined by probability distributions. Uncertainty causes a loss of dependability in the output of models, and therefore constrains the applications of models, especially multi-stage models, where uncertainty may increase and accumulate. Consequently the primary issues of concern in this review are: i) to identify the uncertainty factors in the manufacturing area, ii) to enhance the understanding of manufacturing resource planning models under uncertainty by documenting the current state of affairs, and iii) to instigate fruitful future research by identifying gaps between the relevant issues and the available literature.

2. METHODOLOGY

The criteria for choosing articles for this review are as follows. First of all, the article must have been published in a peer-review/archival journal, proceedings, or edited book. Second, to avoid never-ending revision of this article, June 2009 was selected as the cut-off date. Third, only articles with ‘uncertainty’ and ‘MRP’ or ‘manufacturing’ or ‘production’ as a part of their titles were selected. The exceptions are those articles that explicitly deal with ‘uncertainty’, but whose authors decided for some reason not to use ‘uncertainty’ in the title. The inclusion of such articles is inevitably ad hoc. Consequently it is possible that more such articles exist that are not surveyed in this article. Fourth, no restrictions were imposed on the field of the surveyed journal. This should allow a comprehensive set of viewpoints on uncertainty in different fields. For the mathematical modelling, the articles with ‘model’ and different combinations of ‘uncertainty’, ‘production/manufacturing’ and ‘MRP’ as a part of their titles were selected. According to these criteria, an attempt has been made to collect all the available journal articles. However, it is always possible that some articles are missing from this list. Figure 1 shows the number of articles that have been cited in this paper by year of publication. The article sources and names of the major journals are given in Tables 1 and 2 respectively.

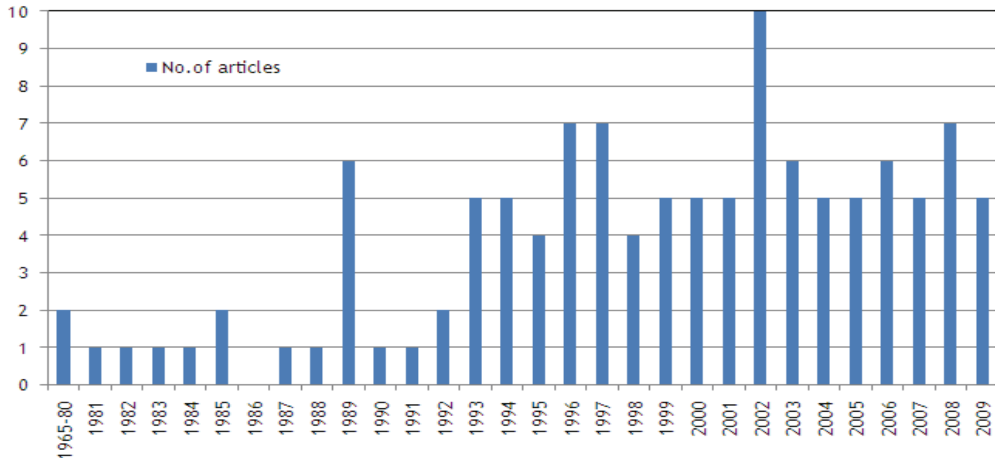

Figure 1: Article map (by year of publication)

Source	Number
Journal	92
Proceedings	8
Book	15
Web	1

Table 1: Definition of uncertainty

Name of the Journal	Number
International Journal of Production Economics	19
European Journal of Operational Research	12
International Journal of Production Research	10
Management Science	5
Journal of Operations Management	4
Fuzzy Sets and Systems	4
International Journal of Advanced Manufacturing Technology	4
International Journal of Production Planning and Control	2
Journal of Intelligent Manufacturing	2
Journal of Global Optimization	2
Other journals	28

Table 2: List of major journals

3. UNCERTAINTY

'Uncertainty' refers to measuring the degree of difference between models and the respective real systems' values, or between the estimation of variables and their true values. The uncertainty can be caused by the errors associated with the model itself and by the uncertainties of the model inputs. One of the challenges of multi-stage manufacturing systems is the propagation and accumulation of uncertainty, which influences the conformity of the outputs. Modern manufacturing enterprises face increasing pressure to respond to production dynamics caused by the disruption of uncertainty [12]. This section reviews the perspectives sources and factors for uncertainties in manufacturing systems.

3.1 Perspectives, sources, and factors of uncertainty

Uncertainty means different things to different people. For example, the error-estimation for a measurement is referred to as uncertainty [13]. Yen and Tung [14] attributed uncertainty mainly to a lack of perfect understanding with regard to phenomena or processes. Ayyub and Gupta [15] characterised uncertainty as an inseparable companion of any measurement at the experimental level, and as the vagueness and incompleteness of understanding of complex real problems at the cognitive level. Zhao et al. [16] defined uncertainty as the differences or errors between models and reality. Oberkampf et al. [17] described uncertainty as a potential deficiency in any phase or activity of a modelling process due to lack of knowledge. Delaurentis and Mavris [18] defined uncertainty as incompleteness in knowledge (either in information or context) which causes model-based predictions to differ from reality in a manner described by some distribution functions. Zimmermann [19] defined stochastic uncertainty as the unknown of the future state of a system due to lack of information, and fuzziness uncertainty as the vagueness concerning the description of the semantic meaning of events, phenomena, or statements themselves. Some researchers referred to uncertainty as a form of disturbance [20-22]. More definitions of uncertainty found in the literature are listed in Table 3.

Definition	Ref.
Uncertainty is defined as any unpredictable event that disturbs the production process in a manufacturing system that is planned by MRP, MRP II, or ERP system.	[5]
Uncertainty is defined as any unplanned events that occur during production, which disrupt orders execution.	[12]
Uncertainty can be defined as any unpredictable event in manufacturing environments that disturbs operations and performance of an enterprise.	[23]
Uncertainty can be defined as any unpredictable event that disturbs the operation and production in a manufacturing system.	[24]
Uncertainty is the dissimilarity between the amount of information required to execute a task and the amount of information already infatuated.	[25]
Situation where the current state of knowledge is such that (1) the order or nature of things is unknown, (2) the consequences, extent, or magnitude of circumstances, conditions, or events are unpredictable, and (3) credible probabilities to possible outcomes cannot be assigned.	[26]
Degree to which available choices or the outcomes of possible alternatives are free from constraints. Situation where neither the probability distribution of a variable nor its mode of occurrence is known.	

Table 3: Definition of uncertainty

The definitions in the literature indicate that context and intent are important factors in determining the viewpoint taken. This is not surprising, since uncertainty is present in all engineering models, regardless of the type of phenomena under study. Control system design, structural design, and financial forecasting are examples (both within and outside the bounds of engineering) of the wide range of activities where uncertainty modelling and management play a central role.

An important part of managing uncertainty is identifying as many sources/factors of uncertainty as possible. Koh and Saad [12] identified eight uncertainties that are most likely to affect customer delivery performance. The factors pertinent to uncertainty reported in different issues of publications are summarised in Table 4.

Ho [27] categorises uncertainties into two groups: (i) environmental uncertainty, and (ii) system uncertainty. Environmental uncertainty includes uncertainties outside the production process, such as demand uncertainty and supply uncertainty. System uncertainty is allied to uncertainties within the production process, such as operation yield uncertainty, production lead-time uncertainty, quality uncertainty, failure of production system, and changes to product structure, to mention a few. Uncertainty can also be classified differently from the viewpoint of its sources, as below:

i. Natural uncertainty, also referred to as inherent uncertainty and physical randomness, which is due to the physical variability of a system [14, 28, 29]
ii. Model uncertainty due to simplifying assumptions in analytical and prediction models, simplified methods, and idealising representations of real performances [14, 18, 28, 30, 31]
iii. Measurement uncertainty resulting from the limitation of measurement methodologies and the capability of measurement systems [14, 18, 29]
iv. Operational and environmental uncertainty [14, 18]
v. Statistical uncertainty due to incompleteness of statistical data and the use of sampled information to estimate the characteristics of these parameters [28]
vi. Subjective uncertainty related to expert-based parameter selection, human factors in calculation, fabrication, and judgment [28]

Factor(s) of uncertainty	Reference
System uncertainty	[32-35]
Lead-time uncertainty	[11, 36-41]
Environmental uncertainty, supply uncertainty	[42-44]
Operation yield uncertainty	[45-47]
Interrelationship between levels	[48]
Demand uncertainty	[11, 33, 37, 38, 42, 49-65]
Probabilistic market demand and product sales price	[46, 57, 66, 67]
Capacity	[48, 55, 57, 68]
Resource breakdown / uncertainty	[11, 56, 59, 69, 70]
Changing product mix situation	[71]
Labour hiring, labour lay-offs	[67]
Quantity uncertainty	[72, 73]
Cost parameters	[41, 68]
Quality	[41, 47, 64, 74]

Table 4: Factors of uncertainty

The model uncertainty is further classified as i) input uncertainty (referred to as 'input parameter uncertainty'), external uncertainty, and precision uncertainty [30, 31]; ii) bias uncertainty, which is induced in transforming the physical principles of scientific theory into analytical or raw models for engineering use, and in transforming the analytical or raw models into numerical simulation models [31]; iii) model parameter uncertainty, arising from limited information in estimating the characteristics of model parameters [28, 75]; iv) model structure uncertainty [76], which is due to the assumption and simplification of the model structure.

4. MEASURES FOR AND EFFECTS OF UNCERTAINTY

Uncertainty can be measured by the frequency of its occurrence, and by analysing the relative contribution and resulting effect on delivery performance. It can quantify whether the impact is minor or major.

Uncertainties in manufacturing have heterogeneous effects due to the interrelationships between resources and operations. The lead-time and demand uncertainties are individually and interactively significant determinants of system performance [38].

A high level of lead-time and demand variability has a strong effect on both the level of optimal safety lead-times and optimal safety stocks. In the event of high demand variability and low lead-time variability, the lowest costs are obtained by using safety stocks. In cases with simultaneously high variability in demand and lead-time, the lowest cost was obtained by using safety lead-times. When uncertainty in processing time increases, the algorithmic scheduling policies become complex [77]. Again, increasing manufacturing flexibility leads to increased performance and to lower uncertainty [78].

Koh and Saad [1] have shown that poor supplier delivery performance, uncontrolled schedules/work-to-list, machine capacity shortages, finished products not being delivered, unacceptable product quality, and engineering design changes during or after production have significant effects on late delivery. The causes of uncertainty have compound knock-on effects on late delivery. Compound effects are more difficult to control, compared with knock-on effects. The occurrence of uncertainty at a different time does not change the characteristic and nature, but may change the effect.

Many conceptual and mathematical models are proposed and used to manage competitive production/manufacturing under conditions of uncertainty. This section reviews the factors, their effects, and the models found in the literature.

4.1 Conceptual models under conditions of uncertainty

Various techniques are used to tackle the effect of uncertainty, such as overtime production, subcontracting, outsourcing, holding safety stock, and keeping safety lead-time. These techniques are adopted to minimise the effect of uncertainty on delivery to the customer. Buffering and dampening are well-known techniques [1, 11, 20-22]. The buffering technique is a more physical arrangement, such as inventory buffer; while the dampening technique is a relatively intangible arrangement, such as safety lead-time [11, 79].

Safety stock and safety lead-time are the key robust techniques used by many researchers [73]. This justifies the research effort in applying safety stock or safety lead-time to manage uncertainty. But more system nervousness might be produced when using safety stock [80]. This finding aligns with the conclusion from Ho et al. [42]. Buzacott and Shanthikumar [81] found that the use of safety lead-time is preferred over safety stock when it is possible to make accurate forecasts of future shipment requirements over the lead-time. These findings limit the robustness of safety stock and safety lead-time, given the constraint of the lead-time variation information [11]. Within the MRP controlled batch-manufacturing environment (using simulation modelling), Guide and Srivasta [73] and Koh et al. [79] suggested the use of safety stock when faced with quantity uncertainty, or safety lead-time when faced with timing uncertainty. Overtime and multi-skilling labour techniques are also used by practitioners, although they have conflicting effects on delivery performances [79]. SMEs usually apply fire-fighting techniques to deal with uncertainty [79]. This implies that they do not manage uncertainty systematically, and hence do not prepare themselves for the future, when the same uncertainty might recur [1].

Vargas and Metters [52] proposed a 'dual-buffer' heuristic: the first for triggering production, and the second for replenishing stock internally. This outperforms a single buffer heuristic in tackling demand uncertainty. Ho et al. [42] developed an uncertainty-dampening framework to reduce system nervousness caused by external supply uncertainty, external demand uncertainty, and internal supply uncertainty. It was found that holding safety stock, safety capacity, and safety lead-time, as well as rescheduling, are useful to buffer and dampen these uncertainties. Ho and Carter [50] simulated static dampening, automatic rescheduling, and cost-based dampening techniques to tackle external demand uncertainty. They concluded that system improvement is dependent on the appropriate use of dampening techniques and lot-sizing rules. Holding safety capacity and rescheduling were also found to be the common buffering and dampening techniques used by many practitioners [11].

Pagell and Krause [82] suggested that there is no relationship between the measures of environmental uncertainty and operational flexibility, nor is there any relationship between an enterprise's performance and its effort to align the level of operational flexibility with its external environment. It means that fitness of flexibility in managing uncertainty depends on specific types of uncertainty and on an enterprise's environment.

Enns [83] investigated the effects of forecast bias and demand uncertainty in a batch production environment using integrated MRP planning and an execution test bed. The effects of uncertainty on delivery performance in an MRP-controlled batch manufacturing environment with multi-product and multi-level dependent demand is modelled using simulation [24]. Also an MRP order release timing logic is developed and modelled with a unique method called the tagging configuration, which is conceptualised from the parent and child in MRP systems [12]. The knowledge management approach is used by Koh and Gunasekaran [11] to manage uncertainty in manufacturing enterprises that use MRP, MRP II, or ERP for production planning. Manufacturing enterprises should simultaneously use both tacit knowledge of uncertainties and buffering and dampening techniques, along with the explicit knowledge that is generated by the intelligent agent, to manage uncertainty [11]. The effectiveness of the buffering and dampening techniques for specific types/sources of uncertainties, and their effects on delivery performance, are also investigated.

Newman et al. [84] proposed a dynamic equilibrium model to demonstrate the trade-offs and interrelationships between manufacturing flexibility innate in an enterprise's processes and infrastructure, the uncertainties faced by the enterprise, and the way in which the enterprise's processes and infrastructures are buffered with inventory, lead-time, and capacity. A trade-off between flexibility and uncertainty is required to achieve system agility [85].

Molinder [86] proposed simulated annealing to find good safety stock and safety lead-times under a stochastic demand and lead-time. He analysed the amount of lead-time and demand variability and the influence of the stock-out cost/inventory holding cost ratio. Mayer and Nusswald [41] proposed a simulation model with integrated quality factors with manufacturing cost and lead-times. The models considered a single stage production system.

With the existing manufacturing system's structures and constraints, considering also system reconfiguration and restructure, an agent-based approach was presented by Anosike and Zhang [71] to achieve optimised use of resources in a situation of changing demand distribution and product mix. A business model to manage the uncertainty in manufacturing, which is planning and scheduling of production using MRP, MRP, II or ERP, was proposed by Koh and Saad [1]. How, and to what extent, uncertainty disturbs was examined, and they diagnosed the underlying causes for uncertainty through a questionnaire survey.

The conceptual techniques are summarised in Table 5.

Technique	Reference
Buffering	[1, 11, 20-22, 24, 42, 73, 79, 81]
Dampening	[1, 11, 20-22, 24, 42, 50, 73, 79, 81]
Overtime labour, multi-skilling labour, and fire-fighting techniques (SMEs usually apply)	[1, 79]
Overtime production	[1, 11, 72, 79]
Subcontracting and outsourcing	[11, 72]
Dual-buffer	[11, 52]
Safety capacity and rescheduling	[11, 42]
Knowledge management approach	[11]
Questionnaire survey	[1]
Execution test bed	[83]
Simulation model	[24, 41, 86]
Agent-based approach	[71]
Dynamic equilibrium model	[84, 85]

Table 5: Conceptual techniques for uncertainty

Conceptual models are widely used in design and manufacturing. However, no models can completely capture all the characteristics of the simulated physical system. It is asserted that the values of the physical variables that describe the behaviour of the physical system in the Heisenberg uncertainty principle are impossible to specify accurately and simultaneously. Heisenberg's uncertainty principle states that it is impossible to know both the exact position and the exact velocity of an object at the same time.

Increased integration and simplification of both technologies and infrastructures can decrease internal uncertainty. Better integrated buyer/vendor relationships have been shown to reduce external uncertainty. The use of computers and numerical control manufacturing technology has also provided a potentially cost-effective means of accommodating manufacturing uncertainty through enhanced flexible automation.

4.2 Mathematical models under uncertainty

In order to address uncertainties, several mathematical models have been proposed. Examples include the interval model, the convex model, fuzzy sets, and random models. The interval model, introduced in the early 1900s, can give rigorous bounds for a solution when applied to different fields [87-93]. The convex model extended the interval model from one dimension to multiple dimensions, and has been used in construction engineering, mechanical engineering, structural engineering, mechanics, and other fields [94-98]. Fuzzy sets, introduced by Zadeh [99], were initially used in fields such as economics and the social sciences to address the uncertainties introduced by imprecise and vague information. Later they were extended to engineering areas [100-102]. The random model represents uncertainty through a probability mass function or a probability density function, and also has many applications in engineering [103, 104]. This section reviews the mathematical models within the limits of this article.

Mathematical programming (MP) approaches to cope with capacity constraints were devised by Billington et al. [43] and Chung and Krajewski [105]. They considered the lead-time as an implicit outcome of the alteration of demand and finite capacity. The model mainly deals with the scheduling problem in a multi-stage production system with some constraints but without any uncertainty. This moved many authors to substitute planning models in a rolling schedule context [8]. Spitter et al. [8] talked about the timing of production during the planned lead-times of items, and investigated the effects of production timing on safety stocks and inventory costs. Similarly, Belvaux and Wolsey [106] produced assorted models for lot sizing under capacity constraints, where the lead-times are implicit outputs of the optimisation procedure. Bourland and Yano [49] developed a multi-objective optimisation model that considers capacity slack, safety stock, and overtime, and that aims to minimise the expected cost per unit time of inventory, overtime, and set-up costs (where applicable). These models incorporated fluctuation in demand only. Ould-Louly and Dolgui [36] investigated a multi-period and multi-component supply planning problem for assembly systems with random lead-time and fixed demand. The lead-times of different types of components followed the same distribution in the model.

A manufacturing resource planning algorithm, matrix based formulation, which can handle limited production capacity, was presented by Harris et al. [107], but no information imperfection. Shabbir et al. [68] addressed a multi-stage capacity expansion problem with uncertainties in demand and cost parameters, and economies of scale in expansion costs. Choi and Enns [108] developed the relationship to establish the lot-sizes that minimise costs for single and multiple product cases under the particular production rate, as well as the link to determine both lot sizes and throughput rates that maximise profits. The model deals with variation in the arrival times of components; all other parameters are known with certainty. The combinatorial manufacturing resource planning (CMRP) model, with its concept of balancing machine productivity and human capability, and its step-by-step algorithm to reach a maximum profit solution under deterministic market demand, was constructed by Lan and Lan [66]. They extended the applicability of the CMRP model to achieve optimum manufacturing resource planning under the forecasts of probabilistic market demand and product sales price. Kim and Hosni [48] formulated a multi-level capacitated optimisation model and a relatively efficient heuristic in the MRP II environment, which considers work center capacities and interrelationship between levels in lot-sizing computation. The model provides an optimal lot size plan for small problems in deterministic situations, and does not allow for shortages – which is unrealistic. Escudero and Kamesam [51] originated a stochastic programming model for MRP with uncertainty in demand, which is given as a random parameter. Though the models considered multiple levels, an holistic view of uncertainty is absent.

Under demand uncertainty, i) Ben-Daya and Noman [60] developed integrated inventory inspection models with and without the replacement of nonconforming items discovered during inspection; ii) Arruda and do Val [59] presented a discrete event model of a multi-stage, multi-product production and storage, in which a single facility is used to produce various products; and iii) Lusa et al. [109] presented a multi-stage scenario stochastic optimisation model when planned working time is considered as annualised hours (AH). But these articles failed to attend to more frequent uncertain factors – such as lead-time, price, etc. – and their combined disruptions and interactions.

Grabot et al. [54] suggested the F-MRP (Fuzzy-MRP) model to handle the uncertainty and imprecision of demand passing through all the MRP II steps (material requirement planning, load balancing, scheduling). Mula et al. [55] presented a new linear programming model for medium-term production planning in a capacity constrained MRP, multi-product, multi-level and multi-period manufacturing environment. Mula et al. [57] developed a fuzzy production planning model to generate production plans under conditions of uncertainty in important parameters such as market demand, capacity, and costs data. Interaction and combined impacts were not included in the conclusions.

Xu and Li [69] created a modelling schema to address the manufacturing resource for process planning, especially for process reasoning. A robust optimisation model for a medium-term planning horizon was developed by Leung et al. [67] to solve multi-site production planning problems with uncertain data. Robust optimisation includes two distinct constraints: a structural constraint, and a control constraint. Structural constraints are formulated using the concept of linear programming, and input data are free of any noise; while control constraints are taken as an auxiliary constraint influenced by noisy data. The proposed model is more practical for dealing with uncertain economic scenarios than with production parameters.

Models for the optimum batch quantity in a multi-stage system with rework process were developed for two different operational policies by Sarker et al. [110]. The mathematical expression of this model was corrected by Cárdenas-Barrón [111]. The models deal with optimal batch-sizing when rework is considered in a stable system. A model of the EOQ type was developed and analysed by Dobos and Richter [112], in which a producer serves stationary product demand. This demand is met by producing or procuring new items, as well as by recycling some of the used products that come back to the producer at a constant rate. They examined a production/recycling system with a predetermined production-inventory policy, and assumed that there was no difference between newly-produced and recycled items – which is not realistic. Dobos and Richter [113] extended the model with a quality parameter. The models mainly emphasised inventory issues rather than the production system.

Kogan and Lou [114] considered a multi-stage, continuous-time dynamic model for multistage production and a one-product-type system, which is an extension of the classical single-period newsboy problem. Products flow from one stage to the next. It is assumed that the demand during the planning horizon is unknown, but that the cumulative demand at the end of the planning horizon is known. The objective is to adjust production rates during the planning horizon in order to minimise total costs. No uncertainty is considered, apart from imperfect in demand.

Kim and Gershwin [47] proposed the Markov process model that integrated quality and productivity. They considered only one line of production, so this cannot be extended or applied to multiple production lines. Dalal and Alghalith [46] modelled for production decision-making under price and production uncertainty.

Tang and Grubbström [65] investigated the possibility of establishing a method for a Master Production Schedule (MPS) under stochastic demand, evaluated the replanning action, and provided a model for estimating appropriate MPS parameters (like length of replanning interval, length of time to freeze the plan, etc.). Uncertainty in parameters other than demand was ignored. Leung [115] generalised a number of integrated models with or without lot streaming and with or without complete backorders under the integer–multiplier coordination mechanism, and then individually derived the optimal solution to the three- and four-stage model. The models confirm parameters without uncertainty.

Chen and Chang [116] introduced a Fuzzy Economic Production Quantity (FEPQ) model with defective results that cannot be repaired. In this model, a fuzzy opportunity cost, and trapezoidal fuzzy costs for either crisp production quantity or fuzzy production quantity, are considered.

Balakrishnan and Cheng [56] reviewed cellular manufacturing, an important application of Group Technology (GT), under conditions of multi-period planning horizons, with demand and resource uncertainties. They addressed the change in demand over time caused by product redesign and uncertainties due to volume variation, part mix variation, and resource unreliability.

Based on the authors' observations, the broad classifications of the uncertainty models are: conceptual models (yield factor, safety stock, safety lead-time, etc.), artificial intelligence-based models (fuzzy set theory, fuzzy logic, multi-agent systems, etc.), simulation models (the heuristic method, network modelling, queuing theory, etc.) and analytical models (mathematical programming, stochastic programming, etc.). Forty-nine articles are cited in this section, which is roughly 43% of the total citations. Figure 2 shows the number of articles surveyed for mathematical models, and their distribution by year of publication. The authors believe that this collection and distribution of articles is sufficient to ensure the identification of the 'flavour of the month', and to identify the gaps in the literature in the area of concern. (In Appendix A the authors compare some major models.)

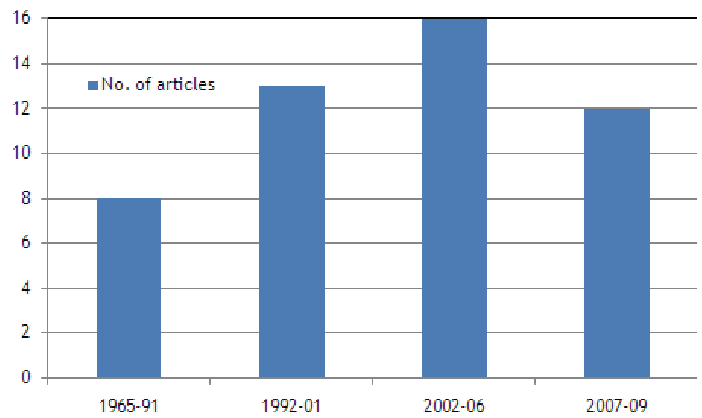

Figure 2: Distribution of articles surveyed for mathematical models

5. DISCUSSION AND RECOMMENDATIONS

Manufacturing planning and control entails the acquisition, use, and allocation of limited resources in production activities so as to satisfy customer demand over a specified time in the most efficient and effective way. Planning and control problems are inherently optimisation problems, where the objective is to develop a plan that meets demand at a minimum cost, or that meets demand and maximises profit. The available planning tools (MRP, MRP II, ERP, ERP II, etc.) are very good for scheduling, but completely ignore the uncertainty, capacity, and component commonality issues. Managing uncertainty effectively and efficiently requires balanced planning and control. The consideration of uncertainty is vital to harvest benefits and to maintain competitive outputs. One must understand which uncertainty to tackle, and how to tackle it, in order to obtain the maximum improvement of the system.

Any planning problem starts by specifying the customer demand that is to be met by the production plan. In most contexts, future demand is only partially known at best, and often is not known at all. Consequently, one relies on a forecast of future demand. To some extent, any forecast is inevitably inaccurate, and one must decide how to react to this demand uncertainty. Most of the optimisation models described in articles treat demand as being known; as such they must be periodically revised and rerun to account for forecast updates. In some studies, the demand is considered as stochastic, or random data as an independent or dependent variable. The identification of the relevant costs is also an important issue. For production planning, one typically needs to determine the variable production costs, including setup related costs, inventory holding costs, and any relevant resource acquisition costs. There might also be costs associated with imperfect customer service, such as when demand is back-ordered. There are limited production resources that cannot be stored for any length of time. Also, there may be uncertainty associated with the production function, such as uncertain yields or lead-times. The selection of the time period (big bucket) and planning horizon (small bucket) is another event that requires painstaking attention. The choice of planning horizon, appropriate cost parameters, the lead-times, service level, safety stocks, input quality, etc. under uncertainty need to be analysed in an holistic manner, and incorporated into models for production and resource-related decisions.

In earlier studies [69, 115-136], the benefits of component commonality in manufacturing systems were associated with a decrease in inventory, lowered the costs of proliferated product lines, mitigated the effects of product proliferation on product and process complexity, reduced the cost of safety stock, decreased the set-up time, increased productivity, improved flexibility and permitted greater operating economies of scale. It alsofacilitated quality improvement, enhances supplier relationships, reduces product development time, risk,-pooling and lead-time uncertainty, simplifies planning, schedules, and controls, streamlines and speds up product development process, lowersthe setup and holding costs, offers high variety while retaining low variety in operations, lowered the manufacturing cost, and obtains design savings. Jans et al. [137] validated the importance of the development costs and unit production costs in the component commonality decision. But the commonality issue is completely ignored in the existing models.

From the study and discussion, it is clear that very little research has been conducted in the field of multi-stage production systems under uncertainty and commonality. So far no research has been done into developing any holistic model to study the uncertainty issues in multi-period, multiple products, and multi-stage environments for manufacturing resources planning. The effects of the incorporation of component commonality in the aforesaid models, and on the system parameters, remain unexplored, and thus need research attention.

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Appendix A: Comparison of mathematical models

Study	Model/problem	Level	Factor of uncertainty
Billington et al. [43] and Chung and Krajewski [105]	Production scheduling problem	Multistage	None
Spitter et al.[8]	Timing production in LP model	Multistage	Demand
Belvaux and Wolsey [106]	Lot-sizing problem	Multistage	Demand
Bourland and Yano [49]	Economic lot scheduling problem	Single stage	Demand
Kim and Hosni [48]	Capacitated optimization model	Multistage	None
Harris et al. [107]	Matrix based formulation for MRP problem	Multistage	Demand
Shabbir et al. [68]	Multi-period investment model	Multistage	Demand and cost
Choi and Enns [108]	Capacity-constrained lot-sizing problem	Multistage	Arrival time of component is uncertain
Ould-Louly and Dolgui [36]	Multi-component supply planning problem	Multistage	Lead-time
Lan and Lan [66]	Combinatorial manufacturing resource planning (CMRP) model	Multistage	Demand & sales price
Grabot et al. [54]	Fuzzy MRP model	Multistage	Demand
Mula et al. [55]	Linear programming model	Multistage	Demand, capacity & cost
Mula et al. [57]	Fuzzy production planning model	Multistage	
Xu and Li [69]	Meta modelling paradigm	Multistage	None
Leung et al. [67]	Robust optimisation model	Multistage	Capacity, workforce, storage & resource
Ben-Daya and Noman [60]	Integrated inventory inspection models	Multistage	Demand
Arruda and do Val [59]	Discrete event model	Multistage	Demand
Sarker et al. [110]	Operational policies models	Multistage	None
Lusa et al. [109]	Scenario stochastic optimisation model	Multistage	Demand
Dobos and Richter [112]	Production recycling system	Multistage	None
Dobos and Richter [113]	Production recycling system	Multistage	Quality
Kogan and Lou [114]	Continuous-time dynamic model	Multistage	Demand
Chen and Chang [116]	Fuzzy Economic Production Quantity (FEPQ) model	Multistage	Production quantity
Dalal and Alghalith [46]	Production decision	Multistage	Price and productivity
Tang and Grubbström [65]	Master Production Schedule	Multistage	Demand
Leung [115]	Integrated production inventory system	Multistage	No
Sarker et al. [110] and Cárdenas-Barrón [111]	EPQ inventory model	Multistage	None
Kim and Gershwin [47]	Markov process model	Multistage	Quality & productivity