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Models for production planning under uncertainty: A review ☆

J. Mula*, R. Poler, J.P. García-Sabater, F.C. Lario

CIGIP (Research Centre on Production Management and Engineering), Polytechnic University of Valencia (SPAIN)

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Abstract

The consideration of uncertainty in manufacturing systems supposes a great advance. Models for production planning which do not recognize the uncertainty can be expected to generate inferior planning decisions as compared to models that explicitly account for the uncertainty. This paper reviews some of the existing literature of production planning under uncertainty. The research objective is to provide the reader with a starting point about uncertainty modelling in production planning problems aimed at production management researchers. The literature review that we compiled consists of 87 citations from 1983 to 2004. A classification scheme for models for production planning under uncertainty is defined.

Keywords: Manufacturing; Production planning; Uncertainty modelling

1. Introduction

Galbraith (1973) defines uncertainty as the difference between the amount of information required to perform a task and the amount of information already possessed. In the real world, there are many forms of uncertainty that affect production processes. Ho (1989) categorizes them into two groups: (i) environmental uncertainty and (ii) system uncertainty. Environmental uncertainty includes uncertainties beyond the production process, such as demand uncertainty and supply uncertainty. System uncertainty is related 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 some. In this paper, we will use this typology of uncertainty.

Along the years there have been many researches and applications aimed at to formalize the uncertainty in manufacturing systems (Yano and Lee, 1995; Sethi et al., 2002). The literature in production planning under uncertainty is vast. Different approaches have been proposed to cope with different forms of uncertainty. A brief general classification is shown in Table 1.

In an effort to gain a better understanding of the ways of managing uncertainty in production planning, and to provide a basis for future research, a broad review of some existing research on the topic has been presented.

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*Corresponding author. Escuela Politécnica Superior de Alcoy, Plaza Ferrándiz y Carbonell, 2, 03801 Alcoy (Alicante) Spain. Tel.: +34 96 652 84 23; fax: +34 96 652 84 65.

E-mail address: fmula@cigip.upv.es (J. Mula).

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Table 1
Classification for the general types of uncertainty models in manufacturing systems

Conceptual models	*Analytical models*
Yield factors	Hierarchy processes
Safety stocks	Mathematical programming:
Safety lead times	(LP, MILP, NLP, DP, and MOP)[a]
Hedging	Stochastic programming
Overplanning	Deterministic approximations
Line requirements planning	Laplace transforms
Flexibility	Markov decision processes
Intelligence artificial based models	*Simulation models*
Expert systems	Monte Carlo techniques
Reinforcement learning	Probability distributions
Fuzzy set theory	Heuristic methods
Fuzzy logic	Freezing parameters
Neural network	Network modelling
Genetic algorithms	Queuing theory
Multi-agent systems	Dynamic systems

[a]LP = linear programming; MILP = mixed-integer linear programming; NLP = nonlinear programming; DP = dynamic programming; MOP = multi-objective programming.

Table 2
Classification scheme for models for production planning under uncertainty

Research topic	Number of citations
1. Aggregate planning	Artificial intelligence models [8] Simulation models [2]
2. Hierarchical production planning	Analytical models [3]
3. Material requirement planning	Conceptual models [9] Analytical models [6] Artificial intelligence models [4] Simulation models [10]
4. Capacity planning	Analytical models [4] Simulation models [1]
5. Manufacturing resource planning	Analytical models [7] Artificial intelligence models [5] Simulation models [2]
6. Inventory management	Analytical models [10] Artificial intelligence models [5]
7. Supply chain planning	Conceptual models [1] Analytical models [5] Artificial intelligence models [5]

In a general way, we have selected papers to include in this survey based on two main criteria:

(i) Midterm tactical models are the focus of our work. These models address planning horizons of 1–2 years and incorporate some features from both the strategic and operational models.
(ii) It is applied on real-world problems, and mainly, on manufacturing systems.

We describe briefly what each paper is but we do not describe with detail or formulate the models that have been considered. The motivation of this work is not to identify every bibliography and extended review of them rather it is intended to provide the reader with a starting point for investigating the literature on how best to manage with uncertainty in different production planning problems.

The objective of this paper is to (i) review the literature, (ii) classify the literature based on the production planning area and the modelling approach, and, (iii) identify future research directions. This paper is organized as follows. In next section, a classification scheme for models for production planning under uncertainty is introduced. Then, previous research on incorporating uncertainty in models for production planning is reviewed and classified. Finally, the conclusions and directions for further research are given in Section 4.

2. Classification scheme for models for production planning under uncertainty

Table 2 illustrates a classification scheme for the literature review on models for production planning under uncertainty. This classification scheme is based on two aspects: (i) the production planning area, and, (ii) the modelling approach. Seven major production planning categories are defined: aggregate planning, hierarchical production planning, material requirement planning, capacity planning, manufacturing resource planning, inventory management, and supply chain planning. Also, four modelling approaches are identified: conceptual, analytical, artificial intelligence, and simulation models. These four modelling approaches were originally defined by Giannoccaro and Pontrandolfo (2001).

A total of 87 citations on models for production planning under uncertainty were reviewed. The majority of the citations were found in journals (80.46%), proceedings, conferences and others (8.05%), books (10.34%) and published PhD Thesis

Table 3
Summary of citations on models for production planning under uncertainty

Source	Number of citations	% Total
Annals of Operations Research	2	2.30
Books	*9*	*10.34*
Computer and Chemical Engineering	1	1.15
Computers and Industrial Engineering	2	2.30
Decision Sciences	1	1.15
Engineering Costs and Production Economics	1	1.15
European Journal of Operational Research	*8*	*9.20*
Fuzzy Sets and Systems	3	3.45
IEEE Transactions on Systems, Man and Cybernetics	2	2.30
IIE Transactions	1	1.15
International Journal of Agile Manufacturing	1	1.15
International Journal of Flexible Manufacturing Systems	1	1.15
International Journal of Operations and Production Management	2	2.30
International Journal of Physical Distribution and Logistics Management	1	1.15
International Journal of Production Economics	*16*	*18.39*
International Journal of Production Research	*13*	*14.94*
Journal of Operations Management	2	2.30
Journal of the OR Society	1	1.15
Management Science	4	4.60
Operations Research	3	3.45
Proceedings (Conferences)	4	4.60
Production and Inventory Management	2	2.30
Production Planning and Control	1	1.15
Statistica Neerlandica	1	1.15
Technical Reports	3	3.45
Thesis	1	1.15
TOP (published by SEIO, the Spanish Statistical and Operations Research Society)	1	1.15
Total	87	100

(1.15%). Three journals, *International Journal of Production Economics, International Journal of Production Research,* and *European Journal of Operational Research* accounted for 42.53% of the citations (see Table 3).

Table 4 shows the distribution of the reviewed models by modelling approach (C = conceptual, A = analytic, AI = artificial intelligence and S = simulation) and by year. From the 87 reviewed models, 35 are analytical models, 27 are models based on artificial intelligence, 16 are simulation models and, lastly, 9 are conceptual models.

3. Research on models for production planning under uncertainty

The reviewed works are ordered chronologically, according to the approach detail, inside each classification criterion.

3.1. Conceptual models

3.1.1. Material requirement planning (MRP)

MRP/MRPII (Orlicky, 1975; Vollmann et al., 1988) is one of the methodologies for production planning and control more used by companies. Also, a great interest has been detected by the research community to incorporate uncertainty in the MRP systems.

The concept of 'yield factor' is used to embrace system uncertainties. A composed yield factor relates the quantities of required inputs to satisfy a demand of specified output when the system uncertainties cause losses of articles in different levels of the production process. The composed yield factor therefore is a function of the production factors in the different stages of the process. Hegseth (1984) considers a production process in series with uncertainty. The author uses a deterministic formulation that implies production factors for different stages of the operation. The bill of materials is

Table 4
References by modelling approach and year

	1980–1989	1990–1999	2000–2004	Total
C: Conceptual models	2	4	3	9
A: Analytical models	12	19	4	35
AI: Artificial Intelligence based models	9	8	10	27
S: Simulation models	11	3	2	16
Total	34	34	19	87

modified using the yield factors, and the material planning is carried out after this modification. New and Mapes (1984) also address uncertain production losses. The authors consider processes with high losses and high variability in losses like, for example, the production of integrated circuits. They propose a model that relates the quantities of inputs and outputs to a random yield factor. New and Mapes study different approaches based on safety stocks, safety times, and hedging to treat such losses. Murthy and Ma (1991) review more research literature about MRP models with uncertain quality. The denominated overplanning approach is used to embrace the uncertainties related to product quantity and quality. In this approach, more products than those specified in the master production schedule (MPS) orders are executed, so that the process can satisfy possible demand excesses. An overplanning excess can cope with possible demand variations, but to expense of an increment in inventory costs, while insufficient overplanning reduces inventory costs but can result in backorders costs.

Donselaar (1992) introduces and evaluates an alternative concept called line requirements planning (LRP) for material coordination in a stochastic environment. LRP is based on the 'level' concept introduced by Clark and Scarf (1960). The essence of LRP is the fact that demand information from the final customer is transferred directly to each of the stages in supply chain, so that the final information of demand is not distorted. Donselaar et al. (2000) compare the performance of MRP and LRP systems in a stochastic environment, performance being estimated by the service level, inventory levels and the planning nervousness. The results of the experiment show that both MRP and LRP concepts of planning possess important characteristics for stochastic environments, but development of new models that combine these characteristics is called for.

For specific industries (aeronautics, electronic equipment, etc) that suffer from long and uncertain production lead times, Hatchuel et al. (1997) develop a model, referred to as dynamic anticipation approach (DAA), based on a classical hierarchical two-stage decomposition of the planning and scheduling process. The planning stage uses a combined PERT/MRP approach, whereas job shop control uses a dynamic scheduling rule.

Bertrand and Rutten (1999) investigate three different production-planning procedures that make use of recipe flexibility to cope with uncertainty in demand and supply. The procedures are computer simulated through an experimental design.

Caridi and Cigolini (2000) provide a new methodology for dimensioning an overall buffer against uncertainty in demand in MRP environments. For this purpose, a set of recommended guidelines is reported to dimension and position safety and/or strategic stocks within products bills of materials and manufacturing pipelines.

3.1.2. Supply chain planning

Das and Abdel-Malek (2003) propose a method for estimating the level of supply chain flexibility as a function of varying demand quantities and varying supply lead times. The model provides estimates of the annual procurement cost in a given buyer–supplier relationship.

Table 5 summarizes the conceptual models reviewed, in relation to (i) the type of uncertainty, (ii) the research topic and (iii) the approach detail.

3.2. Analytical models

Production planning problems are one of the most interesting applications for optimization tools using mathematical programming. The idea of incorporating uncertainty in mathematical models appears initially with Dantzig, well known as 'the father of linear programming' (Dantzig, 1955).

3.2.1. Hierarchical production planning

One of the important advances in the field of production planning by means of mathematical programming was the concept of hierarchical production planning (Hax and Meal, 1975). Hierarchical production planning has attracted wide research activity, including the addition of parameters with uncertainty. Gfrerer and Zäpfel (1995) present a multi-period hierarchical production-planning model with two planning levels, i.e. aggregate and detailed, and with uncertain demand. Meybodi and Foote (1995), on the other hand, develop a multi-period model for hierarchical production planning and scheduling with random demand and production failure. Zapfel (1996) presents a hierarchical model that can be incorporated in a MRPII system to program the production with demand uncertainty.

3.2.2. Material requirement planning

Büchel (1983) considers a planning procedure based on stochastic use ratios for optional parts

Table 5
Classification scheme for conceptual models

Author (s)	Uncertainty	Research topic	Approach detail
Hegseth (1984)	[5]OYU	Material requirement planning	Composed yield factor
New and Mapes (1984)	[5]OYU		Safety stocks. Yield factor
Murthy and Ma (1991)	[5]OYU		Overplannig
Donselaar (1992)			
Donselaar et al. (2000)	[1]DU		Line requirements planning (LRP)
Hatchuel et al. (1997)	[4]LTU		Dynamic anticipate approach (DAA) based on MRP/PERT integration and sequencing dynamic rules
Bertrand and Rutten (1999)	[2]EU		Recipe flexibility
Caridi and Cigolini (2000)	[1]DU		Safety stocks
Das and Abdel-Malek (2003)	[2]EU	Supply chain planning	Supply chain flexibility

[1]DU = demand uncertainty; [2]EU = environmental uncertainty; [3]SU = system uncertainty; [4]LTU = lead times uncertainty; [5]OYU = operation yield uncertainty; [6]SLTU = supply lead time uncertainty.

when their demand is stochastic. The 'use ratio' for a specific component is the ratio between the component demand and the total demand for all final products. Small ratios (and/or a small number of customer orders) cause considerable demand variations that require high safety stocks. Büchel demonstrates how the use ratios could be included in MRP to reduce the uncertainty in demand.

Burstein et al. (1984) consider a multi-stage production process in series with quantities of known demand, but with uncertainty in delivery dates. The authors propose a dynamic lot-sizing approach based on stochastic dynamic programming.

Wacker (1985) develops a statistical model that estimates the average and variance of the outputs of final products and components due to uncertainties. The author uses a safety stock approach. In a make-to-order environment, the safety stocks of final products do not alleviate the uncertainty in demand. The model uses a standard 'forecast error' for components as an estimate of the safety stocks. The author comments that a MRP system should not imply sophisticated control measures to monitor environmental and system uncertainties, but it should incorporate these variations in the same system.

Wijngaard and Wortmann (1985) study different approaches for MRP with stochastic uncertainties. The authors consider a multi-stage production process with convergent and divergent nodes. They introduce three forms to generate looseness among the stages, and subsequently compare three approaches: (i) safety stocks, (ii) safety times and (iii) hedging.

Yano (1987) uses an analytic approach to embrace the problem of stochastic lead times. First, it determines optimal planned lead times in an assembly operation with uncertain process times. The author uses a nonlinear programming formulation.

Escudero and Kamesam (1993) propose a model for MRP with uncertainty in demand, in a multi-product, multi-level, multi-period manufacturing network environment. They use scenarios to characterize the uncertainty in demand, resulting in a stochastic programming model.

3.2.3. Capacity planning

Bitran and Yanesse (1984) propose deterministic approximations to a non-sequential capacity planning model and analyse its effectiveness when the demand is characterized by standard probability distributions.

Eppen et al. (1989) model the strategic capacity planning problem of a major automobile manufacturer. They use a stochastic programming approach based on demand scenarios with emphasis on longer-range decisions regarding facility selection for manufacturing.

Paraskevopoulos et al. (1991) describe a production capacity planning problem with uncertain demand. They use a robust approach avoiding the inherent complexities in a nonlinear stochastic formulation.

Karabuk and Wu (1999) develop a strategic capacity planning model for a major semi-conductor manufacturer. They formulate a multi-stage stochastic program with recourses, where demand

and capacity uncertainties are incorporated via a scenario structure.

3.2.4. Manufacturing resource planning

Billington et al. (1983) study the interaction among lead times, lot sizing, and capacity constraints in a production process with complex bills of materials and uncertainty in demand and lead times. The authors propose a mixed-integer linear program. The model calculates the required lead times based on the demands, available capacity, while also reducing work-in-process inventory. The computational effort required to obtain the solution depends on the model size, and this can be eased by compression of the bills of materials.

Escudero et al. (1993) analyse different modelling approaches for the production and capacity problem using stochastic programming. Next, Escudero and Kamesam (1995) develop linear programming models for stochastic planning problems and a methodology for solve them. They use a production problem with uncertainty in demand, characterized by scenarios in a test case.

Kira et al. (1997) propose a hierarchical approach to model the multi-period and multi-product production programming problem with a finite set of demands through stochastic linear programming.

Rota et al. (1997) present a mixed integer linear programming model to address the uncertain nature and complexity of manufacturing environments. Their proposed model includes capacity constraints, firm orders, demand forecasts, and supply and subcontracting decisions for a rolling horizon planning process.

Grubbström (1998) provides an overview over theoretical developments of MRP/MRP II systems for which input–output analysis combined with the Laplace transform has been a useful methodology. Based on this approach, Grubbström (1999a, b) determines optimal safety stock levels in multi-level MRP systems with capacity requirements when the market demand is stochastic. The objective is to maximize the net present value (NPV) of the cash flow associated with production and demand. In Grubbström and Tang (1999) this work is extended to the case that the time interval of demand is Gamma-distributed.

3.2.5. Inventory management

Models for distribution-inventory coordination approach the inventory management problem like production–distribution systems. The objective is to determine the optimal inventory policy for the whole system. These models are known as multi-level inventory models. The theory of multi-level systems embraces, essentially, the problem of uncertain demand in different levels of the planning process, and allows for random delivery times (although in this case the theory is less developed). On the other hand, it is, mainly, oriented towards materials since the intention to include capacity constraints has not been very successful (Zijm, 2000). Many authors, Eppen and Schrage (1981), Federgruen and Zipkin (1984), Van Houtum et al. (1996) and Diks and De Kok (1996), study multi-echelon inventory problems in non-serial systems in a stochastic setting. Rosling (1989) and Langenhoff and Zijm (1990) prove the correspondence between non-serial systems and serial systems. The central idea is that decisions on production quantities of common components can be made while postponing the decision on how to allocate these quantities to specific products as long as possible (Zijm, 1992). Ganeshan (1999) considers a three-stage supply chain with multiple suppliers replenishing a central warehouse that distributes to a large number of retailers. The author determines a reorder point that minimizes the logistics costs under customer service constraints. Kelle and Milne (1999) develop a multi-echelon inventory distribution system and develop a quantitative tool to analyse the effect of demand variability on ordering inventory policy, demand parameters and logistics costs.

Ould-Loudy and Dolgui (2004) propose a mathematical formulation, based on Markov chains to measure the average cost, and a new generalized Newsboy model to solve a multi-period and multi-component supply planning problem for assembly systems with random lead times and fixed demand.

3.2.6. Supply chain planning

Escudero (1994) proposes a model for supply chain planning with uncertainty in demand based on stochastic programming. The work by Schumann Consortium (1998) addresses the problem of automobile industry supply chain management through stochastic programming and via scenario modelling. Koutsoukis et al. (2000) develop a decision support system for supply chain planning decisions. The system has an embedded decision engine that uses a two-stage stochastic program as a paradigm for optimization under uncertainty. Lario et al. (2001) describe the modelling via scenarios as a tool for supply chain planning with environmental uncertainty in an automobile industry supply chain. Also, Gupta and Maranas (2003) address the problem of tactical planning of supply chains under demand uncertainty using a stochastic programming based approach.

Table 6 summarizes the analytical models reviewed in relation to (i) the type of uncertainty, (ii) the research topic and (iii) the approach detail.

3.3. Artificial intelligence models

3.3.1. Aggregate planning

Fuzzy modelling is an approach based on the fuzzy set theory (Bellman and Zadeh, 1970). In this approach a distinction is made between randomness and imprecision. The authors question the use of the probabilistic approach, as in their view imprecision does not equate to randomness in many situations.

Table 6
Classification scheme for analytical models

Author (s)	Uncertainty	Research topic	Approach detail
Gfrerer and Zäpfel (1995)	[1]DU	Hierarchical production planning	Hierarchical processes
Meybodi and Foote (1995)	[1]DU, [3]SU		Multi-objective programming
Zapfel (1996)	[1]DU		Hierarchical processes integrated with MRPII
Büchel (1983)	[2]EU	Material requirement planning	Statistical. Stochastic usage ratios
Burstein et al. (1984)	[2]EU		Stochastic dynamic programming
Wacker (1985)	[2]EU, [3]SU		Statistical. Safety stocks
Wijngaard and Wortmann (1985)	[2]EU, [5]OYU		Statistical. Safety stocks. Safety lead times. Hedging.
Yano (1987)	[4]LTU		Nonlinear programming. Safety stocks
Escudero and Kamesam (1993)	[1]DU		Stochastic programming
Bitran and Yanesse (1984)	[1]DU	Capacity planning	Deterministic approximations
Eppen et al. (1989)			Stochastic programming
Paraskevopoulos et al. (1991)			
Karabuk and Wu (1999)	[2]EU		
Billington et al. (1983)	[2]EU, [3]SU	Manufacturing resource planning	Mixed integer linear programming
Escudero et al. (1993)	[1]DU		Stochastic programming
Escudero and Kamesam (1995)			
Kira et al. (1997)	[1]DU		
Rota et al. (1997)	[2]EU		Mixed integer linear programming
Grubbström (1999a, b)	[1]DU		Laplace transforms and input–output analysis
Grubbström and Tang (1999)			
Eppen and Schrage (1981)	[2]EU	Inventory management	Multi-level inventory system
Federgruen and Zipkin (1984)			
Van Houtum et al. (1986)			
Diks and De Kok (1996)			
Rosling (1989)			
Langenhoff and Zijm (1990)			
Zijm (1992)			
Ganeshan (1999)			
Kelle and Milne (1999)			
Ould-Loudy and Dolgui (2004)	[6]SLTU		Markov process. Newsboy model
Escudero (1994)	[1]DU	Supply chain planning	Stochastic programming
Schumann Consortium (1998)	[1]DU		
Koutsoukis et al. (2000)	[2]EU		
Lario et al. (2001)	[1]DU		
Gupta and Maranas (2003)	[1]DU		

[1]DU = demand uncertainty; [2]EU = environmental uncertainty; [3]SU = system uncertainty; [4]LTU = lead times uncertainty; [5]OYU = operation yield uncertainty; [6]SLTU = supply lead time uncertainty.

Rinks (1981) develops algorithms for fuzzy aggregate planning using fuzzy conditional 'if-then' statements. The robustness of the fuzzy aggregate planning model under varying cost structures is examined in Rinks (1982a). A detailed set of fourty production rate and work force rules is presented in Rinks (1982b). Turksen (1988a, b) uses interval-valued membership functions to define linguistic production rules for aggregate planning over the point-valued membership functions proposed by Rinks. Ward et al. (1992) develop a C-language fuzzy controller that uses the Rinks discrete membership functions for aggregate planning, and closely reproduce his results.

Gen et al. (1992) propose a fuzzy model with multiple objectives for aggregate planning, with objective function coefficients, technological coefficients, and resource right-hand side constraints represented by triangular fuzzy numbers.

Wang and Fang (2001) discuss the limitations of applying classical mathematical programming techniques to solve medium-term production planning problems, and propose a fuzzy linear programming model to solve an aggregate planning problem with multiple objectives where the product price, subcontracting cost, manpower level, production capacity and market demand are considered fuzzy. The fuzzy parameters are represented by trapezoidal fuzzy numbers.

3.3.2. *Material requirement planning*

Lehtimäki (1987) studies MPS in a MRP environment that maximizes the fuzzy customer satisfaction level from the perspective of a multi-objective decision problem. The objective of maximizing customer satisfaction is ambiguous and can be modelled using fuzzy set theory.

Lee et al. (1990, 1991) propose a way to understand the effects of demand fuzziness in MRP systems where demand cannot be represented as a random parameter, and makes a comparative study of three lot-sizing algorithms: part-period balancing (PPB), silver-meal, and Wagner–Whitin. The uncertain demand is modelled using fuzzy sets. The authors demonstrate that a fuzzy set theory approach can model uncertainty, fuzziness and/or subjectivity in the PPB algorithm successfully.

Du and Wolfe (2000) propose an active MRP system in real time. The active MRP system uses a hybrid architecture that includes an object-oriented database, fuzzy logic controllers, and artificial neural networks. Fuzzy logic controllers are combined with an object-oriented database, such as an integration of dynamic and static knowledge. Artificial neural networks are used to learn 'if-then' fuzzy rules and to simulate fuzzy membership functions. The artificial neural networks are combined with the fuzzy logic controllers for the inventory classification. The active MRP system analyses the safety lead times, safety stocks and plans dynamically and it specifies the release and end dates for each requirement, programmed reception and planned order.

3.3.3. *Manufacturing resource planning*

Sommer (1981) uses an approach based on fuzzy dynamic programming to solve a real production-planning problem. Linguistic sentences, such as 'the stock should be zero in the best of cases, to the end of the planning horizon' and to 'diminish the production capacity as continually as possible', describe the fuzzy aspirations of the planner. Fuzzy dynamic programming is used to determine the production levels and optimal inventories.

Miller et al. (1997) develop a fuzzy linear programming formulation to determine the production plan of a fresh tomato packing company. Three types of operators are applied: the 'min-operator' (Zadeh 1965), 'fuzzy and' (Werners, 1987) and 'compensatory and' (Zimmermann and Zysno, 1980), i.e. the convex linear combination of the min-operator and max-operator. The 'compensatory and' operator provides better results although the differences are relatively small. The authors show that the average cost obtained by linear programming is approximately 10 times superior to the costs obtained by the fuzzy model.

Hsu and Wang (2001) propose a possibilistic programming model to manage production-planning problems in assembly to-order environments. The proposed model considers forecast smoothing, material coordination and production activities. The costs, material obsolescence, and time value of money are considered fuzzy. The fuzzy parameters are represented by triangular possibility distributions. Then, the authors substitute the fuzzy objective function by three deterministic functions with the following objectives: to minimize cost, to maximize the possibility to obtain the lowest cost, and to minimize the risk of obtaining the highest cost.

Reynoso et al. (2002) propose a MRP II approach based on fuzzy set theory. This approach, called F-MRP (Fuzzy-MRP), distinguishes between uncertain and imprecise demand and considers both of them. The uncertain demand is given when the demand occurrence is not certain. While the imprecise demand happens when the demand quantity is not known with accuracy.

Mula (2004) provides a new linear programming model, called MRPDet, for medium-term production planning in a capacity constrained MRP for a multi-product, multi-level and multi-period manufacturing environment. Subsequently, this model is transformed into 15 fuzzy models based on different approaches of fuzzy mathematical programming, where the cost coefficients in the objective function, the market demand, the required capacity, and the available capacity can be considered (depending on each model) vague and/or ambiguous. Finally, the models are tested using real data from an automobile seat manufacturer.

3.3.4. Inventory management

Kacprzyk and Staniewski (1982) embrace the inventory control problem in an infinite planning horizon. The inventory system is represented by a fuzzy system, with fuzzy inventory levels, inputs and outputs. The authors develop an algorithm that determines an optimal strategy to determine the reinstatement of existent inventory levels.

Park (1987) studies the economic order quantity (EOQ) model from a fuzzy set theory perspective. The order and inventory costs are modelled by trapezoidal fuzzy numbers. The author suggests rules to transform the fuzzy cost information in precise inputs for the EOQ model. Hojati (2004) evaluates the probabilistic-parameter EOQ model of Lowe and Schwarz (1983) and the fuzzy parameter EOQ model of Vujosevic et al. (1996). The author uses simulation to compare the results.

Porter et al. (1995) develop a genetic algorithm to solve an inventory-production-distribution problem. The objective is to determine optimal stock levels, production quantities, and transportation quantities to minimize total system costs.

Samanta and Al-Araimi (2001) propose a model based on fuzzy logic for inventory control. The model considers a periodic revision of the inventory with a variable order quantity. The control module combines fuzzy logic with a proportional-integral-derivative (PID) control algorithm. This model simulates the decision-making support system to maintain the final product inventory at the desired level, considering the demand variations and the dynamics of the production system.

3.3.5. Supply chain planning

Petrovic et al. (1998, 1999) describe the fuzzy modelling and simulation of a supply chain in an uncertain environment. Their objective is to determine the stock levels and order quantities for each inventory during a finite time horizon to obtain an acceptable delivery performance at a reasonable total cost for the whole supply chain. Customer demand and external supply of raw material are represented by fuzzy sets. Petrovic (2001) develops a simulation tool, SCSIM, for analysing supply chain behaviour and performance in the presence of uncertainty modelled by fuzzy sets.

Fox et al. (2000) present two applications: the coordination of a team in a virtual enterprise, and the analysis of coordination mechanisms to cope with unexpected events that perturb operations of a supply chain. They view a supply chain as a system of intelligent agents, each being responsible for one or more activities and interacting with the others in planning and executing according to its responsibilities.

The consortium for integrated intelligent manufacturing planning-execution (CIIMPLEX) was formed to develop a framework for intelligent integrated manufacturing planning-execution, where manufacturing plans can be based on real-time capacity information; and create an open application architecture to enable manufacturing software applications to deliver integrated planning-execution solutions (Chu et al., 2000).

Table 7 summarizes the artificial intelligence based models reviewed in relation to (i) the type of uncertainty, (ii) the research topic and (iii) the approach detail.

3.4. Simulation models

3.4.1. Aggregate planning

Thompson and Davis (1990) and Thompson et al. (1993) present an integrated approach to model the uncertainties present in aggregate production planning. They formulate a linear programming model in which the uncertainty in costs, capacities, lead times and demand are modelled using Monte Carlo simulation techniques. They evaluate six production strategies but no disaggregate processes are carried out.

3.4.2. Material requirement planning

Callarman and Hamrin (1983) compare dynamic rules to determine the production lot sizes for

Table 7
Classification scheme for artificial intelligence models

Author (s)	Uncertainty	Research topic	Approach detail
Rinks (1981, 1982a, b)	²DU, ³SU	Aggregate planning	Expert system using fuzzy linguistic parameters
Turksen (1988a, b)			
Ward et al. (1992)			Fuzzy logic controller based on Rinks' model
Gen et al. (1992)			Fuzzy multi-objective linear programming
Wang and Fang (2001)			Fuzzy linear programming
Lee et al. (1990, 1991)	¹DU	Material requirement planning	Fuzzy set theory
Lehtimäki (1987)	²EU		
Du and Wolfe (2000)	²EU, ³SU		Oriented to objects database, fuzzy logic controllers and artificial neural networks
Sommer (1981)	³SU	Manufacturing resource planning	Fuzzy dynamic programming
Miller et al. (1997)	²DU, ³SU		Fuzzy linear programming
Hsu and Wang (2001)	³SU		
Reynoso et al. (2002)	³SU		Fuzzy set theory
Mula (2004)	²EU, ³SU		
Kacprzyk and Staniewski (1982)	³SU	Inventory management	Inventory as a fuzzy system: algorithm with a fuzzy conditional sentence
Park (1987)			
Hojati (2004)			Fuzzy arithmetic. Cost information modelled by fuzzy trapezoidal or triangular numbers and transformed in precise inputs
Porter et al. (1995)	²EU, ³SU		Genetic algorithm
Samanta and Al-Araimi (2001)	²DU, ³SU		PID control algorithm based on fuzzy logic
Petrovic et al. (1998, 1999, 2001)	²EU	Supply chain planning	Fuzzy arithmetical operations
Fox et al. (2000)	²EU, ³SU		Software agents
Chu et al. (2000)	²EU, ³SU		Software agents

¹DU = demand uncertainty; ²EU = environmental uncertainty; ³SU = system uncertainty; ⁴LTU = lead times uncertainty; ⁵OYU = operation yield uncertainty.

articles with independent demand in a single-stage MRP system. The authors study three methods: EOQ, Wagner–Whitin, and PPB. The authors conclude that the PPB procedure is the best for lot sizing in a single-stage inventory system with uncertainty in demand. The authors modelled the uncertainty in demand using probability distributions.

De Bodt and Wassenhove (1983) study decision making concerning lot sizing, safety stocks and the effect of costs under a single-level MRP environment with uncertainty in demand and a rolling horizon. The authors demonstrate that the forecast errors have an important effect on the relative costs of the lot sizing and safety stock decisions, and that the differences in the estimated costs are significant for different techniques in the presence of forecast errors. Also, their results show that the safety stock and lot-sizing policies are important for companies that use MRP under an uncertain environment.

Grasso and Taylor (1984) examine the impact of operation policies on MRP system with uncertainty in lead times. Their simulation modelling approach studies the impact on the total cost of four factors: lead time variability, safety stock level, safety lead times, and lot-sizing rules on total cost.

John (1985) discusses the cost of inflated lead times on the operation of a MRP system. The author uses a simulation model with several stochastic parameters for customer demand and lead times. Their study demonstrates the necessity to reduce the lead times, since high lead times generate high costs.

Melnyk and Piper (1985) propose a forecast method for the uncertain lead times which is issued from the used methods for random demand. The authors establish planned lead times as the observed average of lead times, more a multiple of the standard deviation of the error distributions of the lead times. Through simulation experiments, they show how the margins in lead times influence the lot-sizing effectiveness, and in turn, how the lot sizing influences the effectiveness of the margins of the lead times in MRP.

Marlin (1986) develops a stochastic simulation model for a MRP/job shop system. The model, carried out with SIMSCRIPT II.5, closes the loop between the releasing of orders via MRP and order execution, for a production line and external suppliers. The model simulates two types of demand uncertainty, the quantity and the delivery date. To address the uncertainty in demand quantity, Marlin uses the yield factor approach developed by Hegseth (1984).

Carlson and Yano (1986) investigate a MRP system with rolling horizon and uncertainty in demand. The authors assume that forecast errors are normally distributed. They develop a heuristic method and demonstrate that a significant increment exists in the lot-sizing cost due to the necessity of rush preparations, and that safety stocks at the component level reduce the necessity of rush preparations, and are therefore, effective.

Kurtulus and Pentico (1988) extend the yield factor approach (Hegseth, 1984) through simulation in a MRP environment.

Anderson and Lagodimos (1989) consider the problem of predicting service levels in a single-stage MRP system, where the quantity of the demand is uncertain. The authors develop an analytic expression to estimate the service level in make-to-stock environments, and study how the service levels are affected by the level of safety stocks.

Kadipasaoglu and Sridharan (1997) develop simulation models to study the instability of MRP systems. The objective of these experiments is to analyse the impact of the process parameters (lot size, rolling planning, etc.) on the MRP execution in an uncertain environment. One of the proposed approaches to solve this problem is to freeze certain periods of the MPS. Also, Xie et al. (2003) investigate the performance of MPS freezing parameters in multi-item single-level systems with a single resource constraint under demand uncertainty.

Table 8
Classification scheme for simulation models

Author (s)	Uncertainty	Research topic	Approach detail
Thompson and Davis (1990)	[1]DU, [3]SU	Aggregate planning	Linear programming with uncertainty modelled using Monte Carlo techniques
Thompson et al. (1993)			
Callarman and Hamrin (1983)	[1]DU	Material requirement planning	Probability distributions. Lot sizing.
De Bodt and Wassenhove (1983)	[2]EU		Safety stocks
Grasso and Taylor (1984)	[3]SU		Safety stocks. Safety lead times
John (1985)	[2]EU, [3]SU		Inflated lead times
Melnyk and Piper (1985)	[4]LTU		Margins in lead times
Marlin (1986)	[2]EU, [5]OYU		Safety stocks. Safety lead times. Yield factor
Carlson and Yano (1986)	[2]EU		Heuristic method. Safety stocks
Kurtulus and Pentico (1988)	[5]OYU		Yield factor
Anderson and Lagodimos (1989)	[2]EU		Analytical expression. Safety stocks
Kadipasaoglu and Sridharan (1997)			Freezing parameters
Xie et al. (2003)	[1]DU		
Huang et al. (1985)	[4]LTU	Manufacturing resource planning	Network modelling using Q-GERT
Huang et al. (1985)	[2]EU, [5]OYU		Theory of queues with Q-GERT

[1]DU = demand uncertainty; [2]EU = environmental uncertainty; [3]SU = system uncertainty; [4]LTU = lead times uncertainty; [5]OYU = operation yield uncertainty; [6]SLTU = supply lead time uncertainty.

3.4.3. Capacity planning

Wilhelm (2000) presents a dynamic and continuous production model called automatic production control based on methods of control theory. The objective is to develop a feedback control for capacity planning with defined control and reference variables based on logistical objectives. The program is tested via simulation with data from an automotive supplier.

3.4.4. Manufacturing resource planning

Huang et al. (1982) develop a simulation model to incorporate the basic logic of MRP in a production process, using a Q-GERT simulation and network modelling language. The objective is to provide the necessary information for material and capacity requirement planning, and control of a production process with uncertainty. The simulation model provides answers to questions related to the production decisions of each facility, and production capacity and lead times, in order to satisfy a specified demand for final products. Huang et al. (1985) extend the simulation model based on the theory of Queues with Q-GERT that integrates MRP with plant control in a production process.

Table 8 summarizes the simulation models reviewed in relation to (i) the type of uncertainty, (ii) the research topic and (iii) the approach detail.

4. Conclusion and further research

This paper has presented an exhaustive literature survey about models for production planning under uncertainty. The production planning area and the modelling approach were the taxonomy criteria used.

The analytical modelling approach, in particular stochastic programming was the most frequently encountered. In the case of dynamic programming, few models were found and were mainly theoretical. Most of the analytical models addressed only one type of uncertainty, and assumed a simple structure of the production process. For more complex processes, with many different final products and more than one type of uncertainty, the analytical approach is replaced by methodologies based on artificial intelligence and simulation.

Although many works use simulation approaches to model uncertainty, very few studies exist on the comparative evaluation of the advantages and inconveniences of different simulation languages. With respect to artificial intelligence models, those based on fuzzy set theory represent an attractive tool to aid research in production management. Lastly, conceptual models with different approaches complete the taxonomy.

Although an extensive literature on models for production planning under uncertainty was reviewed, a need for further research is identified: (1) investigation of new approaches to modelling of uncertainty. Uncertainty is impossible to be completely removed from supply chains, and also from each link of the chain (Mula et al., 2005). Optimization problems in the context of production planning in a supply chain, and hence under conditions of uncertainty, are, in general, very complex. For such reason, new approaches for production planning and control are required to manage the uncertainty within each company of the chain. Moreover, it can help supply chains that operate in uncertain environments to be more agile. In our opinion, artificial intelligence based models have a particular interest to the practitioners in order to address the production planning problems under uncertainty. Our position is that fuzzy set theory is, in general, an appropriate methodology which can suppose a great advance in the current production planning systems (see Mula et al., 2006), (2) development of new models that contain additional sources and types of uncertainty, such as supply lead times, transport times, quality uncertainty, failure of production system and changes to product structure, etc. since models with uncertain demand have received more attention in comparison to other types of uncertainty, (3) investigation of incorporating all types of uncertainty in an integrated manner, (4) development of empirical works that compare the different modelling approaches with real case studies, (5) development of a comparative evaluation of the existent models for the different manufacturing systems.

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