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Aggregate production planning: A literature review and future research directions

Ali Cheraghalikhani[a], Farid Khoshalhan[a] and Hadi Mokhtari[b*]

[a]*Department of Industrial Engineering, K.N.Toosi University of Technology, Tehran, Iran*
[b]*Department of Industrial Engineering, University of Kashan, Kashan, Iran*

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A B S T R A C T

Aggregate production planning (APP) is concerned with determining the optimum production and workforce levels for each period over the medium term planning horizon. It aims to set overall production levels for each product family to meet fluctuating demand in the near future. APP is one of the most critical areas of production planning systems. After the state-of-the-art summaries in 1992 by Nam and Logendran [Nam, S. J., & Logendran, R. (1992). Aggregate production planning—a survey of models and methodologies. *European Journal of Operational Research, 61*(3), 255-272.], which specifically summarized the various existing techniques from 1950 to 1990 into a framework depending on their abilities to either produce an exact optimal or near-optimal solution, there has not been any systematic survey in the literature. This paper reviews the literature on APP models to meet two main purposes. First, a systematic structure for classifying APP models is proposed. Second, the existing gaps in the literature are demonstrated in order to extract future directions of this research area. This paper covers a variety of APP models' characteristics including modeling structures, important issues, and solving approaches, in contrast to other literature reviews in this field which focused on methodologies in APP models. Finally some directions for future research in this research area are suggested.

1. Introduction

Aggregate production planning (APP) is the medium term capacity planning that determines minimum cost, workforce and production plans required to meet customer demands. APP simultaneously establishes optimal production, inventory and employment levels over a given finite planning horizon to meet the total demand for all products that share the same limited resources (Buffa & Taubert, 1972; Hax, 1978; Hax & Candea, 1984). Hax and Candea (1984) grouped production management decisions in their study into three broad categories: (i) Policy formulations, capital investment decisions, and design of physical facilities, (ii) Aggregate production planning, and (iii) Detailed production scheduling. Mula et al. (2006) defined seven major production planning categories. These categories are: aggregate planning, hierarchical production planning, material requirement planning, capacity planning, manufacturing resource planning, inventory management, and supply chain planning.

* Corresponding author
E-mail: mokhtari_ie@kashanu.ac.ir (H. Mokhtari)

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APP is one of the most critical areas of planning performed in the design of production systems (Nam & Logendran, 1992) and it has attracted considerable interest from both practitioners and academics (Shi & Haase, 1996). Interest in the APP models stems from the ability that such models provide control over production and inventory costs. In general, literature review is important because it highlights the key features that have emerged about the concept of reflective practice during the past years. In other words, literature review provides readers with a background for understanding current knowledge on a topic and illuminates the significance for the new study.

The first literature reviews on APP models were provided by Silver (1967, 1972), Foote and Ravindran (1988) and the latest was published by Nam and Logendran (1992). After the state-of-the-art summaries in 1992 by Nam and Logendran (1992), there has not been any systematic survey in the literature. Nam and Logendran (1992) conducted a survey of APP techniques and identified the most frequently used techniques including: (1) Trial and error methods, (2) Graphical techniques, (3) Parametric production planning, (4) Production switching heuristic, (5) Linear programming, (6) Goal programming, (7) Mixed integer programming, (8) Transportation method, and (9) Simulation models. Weaknesses and strengths of each technique were discussed by Nam and Logendran (1992). In addition, several researchers criticized the limitations of the existing methods in solving APP problems (Gilgeous, 1989; Buxey, 1993). Stockton and Quinn (1995) conducted a literature review and analyzed these limitations. The first purpose of this study is to propose a structure for classifying APP models in a systematic manner, and the second purpose of our study is to demonstrate the gaps existing in the literature in order to extract future trends and directions of this research area. Since it is not possible to survey all the literature associated with APP, we will concentrate our review on articles published in the last decade. In contrast to other literature reviews in this field which had focused on APP methodologies, this study covers a variety of APP models' characteristics including modeling structures, important issues, and solving approaches.

The rest of this paper is organized as follows. Two classification schemes for APP models including structural groups and important issues will be defined in the next section. Then, analytical discussions of the proposed structural groups and important issues will be discussed in section 3 and concluding remarks and directions for further research will be given in section 4, respectively.

2. Classification Schemes for APP Models

In this section a comprehensive classification scheme is presented, which categorizes the APP models into different structural groups based on the level of uncertainty that exists in the APP model. The input data for APP models can vary from deterministic, to stochastic and fuzzy sets. Another important criterion that affects the structure of APP model is the number of objective functions that a model contains. Based on these two criteria the structure of APP model could be categorized into six main structural groups. Fig. 1 shows these main structural groups in more detail.

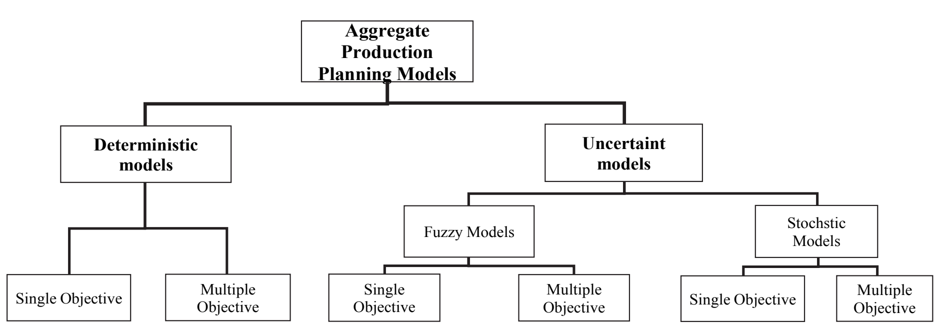

Fig. 1. Structural groups for APP models

Based on this categorization, we title the structural groups as abbreviated notations as follow.

- Structural group 1: Deterministic models with single objective
- Structural group 2: Deterministic models with multiple objectives
- Structural group 3: Fuzzy models with single objective
- Structural group 4: Fuzzy models with multiple objectives
- Structural group 5: Stochastic models with single objective
- Structural group 6: Stochastic models with multiple objectives

2.1. Deterministic Models

Any APP model includes several parameters such as market demand, production costs, inventory costs, labor costs, subcontracting costs, production rate, backorder cost, subcontracting restriction, product capacity, product sales revenue, maximum labor level, maximum capital level, etc. These parameters are used in objective functions and constraints of the APP models. In deterministic models, all of these parameters are assumed to be known prior to planning. Deterministic models are divided into two subdivisions including single objective and multiple objective models. In real-world situations, APP problems normally involve multiple, conflicting and incommensurable imprecise objective functions (Liang, 2007). Many researchers are becoming increasingly aware of the presence of multiple objectives in real-life problems (Vincke, 1992). The deterministic models which have been reviewed in this paper are listed in Table 1.

Table 1
APP models classification based on the type of data (deterministic/fuzzy/stochastic) and the number of objective functions (single-/multi-objective)

Deterministic/ Uncertainty		Objective function	Articles
Deterministic		Single	Aghezzaf & Artiba, 1998; Silva & JoÄOoisboa, 2000; Pradenas & Pe˜nailillo, 2004; Fahimnia et al., 2005; Pipery & Vachony, 2001; Singhvi & Shenoy, 2002; Techawiboonwong & Yenradee, 2003; Paiva & Morabito, 2009; Mazzola et al., 1998; Sillekens et al., 2011; Zhang et al., 2012; Ramezanian et al., 2012; Wang & Yeh, 2014; Chaturvedi & Bandyopadhyay, 2015; Erfanian & Pirayesh, 2016; Chaturvedi, 2017
		Multiple	Leung & Chan, 2009; Leung & Ng, 2007; da Silva et al., 2006; Ismail & ElMaraghy, 2009; Leung et al., 2003; Baykasoglu, 2001; Chakrabortty & Akhtar Hasin, 2013; Entezaminia et al., 2016; Abu Bakar et al., 2016; Mehdizadeh et al., 2018
Uncertain	Fuzzy	Single	Baykasoglu, 1999; Wang & Fang, 2000; Fung et al., 2003; Tang et al., 2000; Tang et al., 2003; Ning et al., 2006; Aliev et al., 2007; Chen & Huang, 2010; Liang et al., 2011; Chen & Huang, 2014; Iris & Cevikcan, 2014; Rahmani et al., 2014; Chakrabortty et al., 2015
		Multiple	Wang & Fang, 1997; Wang & Liang, 2005; Wang & Liang, 2005; Wang & Liang, 2004; Baykasoglu & Gocken, 2006; Liang, 2007; Sakallı et al., 2010; Baykasoglu & Gocken, 2010; Liang & Cheng, 2011; Sadeghi et al., 2013; da Silva & Silva Marins, 2014; Madadi & Wong, 2014; Gholamian et al., 2016; Fiasché et al., 2016; Chauhan et al., 2017; Zaidan et al., 2017; Mosadegh et al., 2017
	Stochastic	Single	Leung et al., 2006; Ganesh & Amoorthy, 2005; Wang & Liang, 2005; Hsieh & Wu, 2000; Leung & Wu, 2004; Leung et al., 2007; Mirzapour Al-e-Hashem et al., 2013; Jamalnia & Feili, 2013; Ning et al., 2013; Entezaminia et al., 2016; Makui et al., 2016; Zhu et al., 2017
		Multiple	Mirzapour Al-e-Hashem et al., 2012; Jamalnia et al., 2017

2.2. Uncertain Models

Galbraith (2007) 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. In real-world APP problems, the input data or parameters, such as demand, resources, costs, objective function coefficients, etc are imprecise in nature, because some information is incomplete or unobtainable (Wang & Liang, 2004). Mula et al. (2006) conducted a survey on uncertainty in production planning models including APP models from 1983 to 2004. To deal with uncertainty in APP models, fuzzy set theory and stochastic programming were employed.

Fuzzy Models: Fuzziness is a type of imprecision that has no well-defined boundaries for its description. It is particularly frequent in the area where human judgment, evaluation and decisions are important, such as decision making, reasoning, learning and so on (Bellman & Zadeh, 1970). Fuzzy sets theory is very applicable for dealing with such ill-defined situations in APP models. Some types of uncertainties, e.g. fuzzy demands, production capacities with tolerance, imprecise process time, etc. are usually encountered in the APP of manufacturing systems. It is unsuitable to describe these types of uncertainties by frequency-based probability distribution. Therefore, there is a need to formulate APP models by way of fuzzy set theory (Zadeh, 1965; Zimmermann, 1985) and fuzzy optimization methods (Rinks, 1982; Lee, 1990; Wang & Fang, 1997; Tang et al., 1999) in order to deal with some uncertainty in APP models. In Fuzzy APP models, the objective function can be classified into single objective and multiple objective functions. Some researchers and practitioners have been working on fuzzy single objective models, and some others have concentrated on fuzzy multiple objective models. In these two structural groups, APP model parameters such as market demand production cost, subcontracting cost, inventory carrying cost, backorder cost, product capacity, product sales revenue, maximum labor level, maximum capital level, etc. are all characterized as fuzzy variables. Fuzzy APP models are summarized in Table 1.

Stochastic Models: The stochastic models and methods are usually based on the concept of randomness and probability theory, and they are limited to tackling uncertainties with probability distributions (Tang et al., 2003). Some researchers have focused on single objective stochastic APP models (Leung et al., 2006; Ganesh & Amoorthy, 2005; Wang & Liang, 2005; Hsieh & Wu, 2000; Leung & Wu, 2004; Leung et al., 2007). The main problems with applying stochastic models are lack of computational efficiency and inflexible probabilistic doctrines which might not be able to model the real imprecise meaning of decision maker (DM) (Lai & Hwang, 1992). It is worth noting that, multi-objective stochastic models have not been found in the literature from 1998 to now. Finally, the most commonly used APP objectives are to minimize: cost, inventory levels, changes in work force levels, use of overtime, use of subcontracting, changes in production rates, number of machine set-ups, plant/personnel idle time etc.; and maximize: profits, customer service, machines utilization, sales, etc. Stochastic APP models are presented in Table 1.

2.3. Important Issues

Aggregate planning is a complex problem largely because of the need to coordinate interacting variables in order for the firm to respond to the demand in an effective way (Kumar & Suresh, 2009). Table 2 shows some of the basic issues discussed in every APP model along with a brief definition of them. The most general description of APP models assumptions have been characterized by Silver (1972) as follows:

1. Market demand is deterministic.
2. Production costs in any given planning period are strictly linear or are piecewise linear.

3. Costs incurred as a result of changes to production rates in any given period are also linear or piecewise linear.
4. Inventory should be limited over the entire planning horizon.
5. Carrying costs for this inventory can be varied for each planning period.
6. Back orders may or may not be allowed.
7. Other assumptions which apply to specific models are introduced as they are needed.

Table 2
Basic issues in APP models

Basic Issue	Definition
Market demand	Demand for each period that must be satisfied by product, inventory or backorder
Inventory	Products that are held in stock in each period
Backorder	Part of demand that has not been satisfied in each period
Production capacity	Maximum amount of products that can be produced in each period by system (for machine and manpower)
Warehouse space	The capacity of the warehouse for the holding inventory
Costs of production	Costs of production consist of regular time and overtime production and costs of inventory carrying and backorders
Subcontracting	Hire the capacity of other firms temporarily to make the component parts or products
Labor level	Number of workers in each period includes regular and overtime workers
Hiring and Layoff cost	Additional workers need to be recruited to handle extra production loading and redundant workers to be laid-off to reduce overheads.
Product Price	Selling price of products

Considering the above mentioned assumptions and basic issues, APP models aim to find a production rate and some level of work force that will minimize the costs associated with meeting a known demand. In addition to these primary issues which are regarded as the basis of APP models, there are also some extra issues (or assumptions), which are called "important issues" in this paper, that have been used in APP models. These issues have been considered in some studies and they will be discussed here. A brief list of these important issues is described here and each issue is then described in more detail.

- *Multiple Product Item*

To use APP, it is first necessary to group all product families into an aggregated or surrogate product. Based on this expression, usually only one product family is considered in APP models. But in most APP models more than one product family exists. These models are usually named as "Multiple Product APP Models". Many multiple product models exist in the APP literature.

- *Labor Characteristics:*

This is consistent with the production planning literature, in which the labor is typically modeled as a key resource in APP models (Mazzola et al., 1998). Some important characteristics of labor such as Learning Curve Effect, Labor Skill, Legal Restrictions, Labor Training, Labor Productivity and Utilization, Constant Level for Labors, Worker productivity & Productivity Loses etc. are considered in APP models. These labor-related issues are classified as "labor characteristic" issues. Each sub issue is described in more detail here:

- *Learning Curve Effect:* In assembly activities that requires more handy work, it has been observed that production time decreases as workers learn more about their work, ways of doing it and their experience increases. Cumulative average-time learning model has been used in considering the learning curve effects (Jamalnia & Soukhakian, 2009). Learning curve effects has been considered in formulating the APP model and lead to nonlinearity of the APP model (Jamalnia & Soukhakian, 2009; Wang & Liang, 2005; Wang & Liang, 2004).

- *Labor Skill:* In APP models, it is assumed that all workers are equivalent. This assumption contradicts real-life situations where some workers are more valuable than others and thus not equal where hiring and firing costs are concerned. Some APP models have considered different labor types to confirm with reality (da Silva et al., 2006; Fahimnia et al., 2005).
- *Legal Restrictions:* Legislations in many countries have posted considerable restrictions on the practice of firing labors. Legal Restrictions is also considered in some models as a new constraint for the model (da Silva et al., 2006).
- *Labor Training (Cost and Time):* Some labor training aspects such as length of training periods, training cost, required number of training periods per labor, etc. can be considered in APP models (da Silva et al., 2006)
- *Labor Utilization:* Efficient labor utilization is important in realizing a profit on every job. Labor utilization is defined as the hours worked divided by population. This concept is considered as a labor characteristic in some APP models (Baykasoglu, 2001; Leung et al., 2007)
- *Constant Level for Labors:* Firing workers frequently can bring about a negative impact on the implementation of total quality management. To overcome this, labors level can be considered constant over the planning horizon (Silva & JoÄOoisboa, 2000).

• *Degree of DM Satisfaction from Solution*

In an APP problem as a decision making problem, the decision maker's (DM) satisfaction can be considered to maximize DM satisfactory with the models solution. In some models this issue is considered as an additional issue in the APP model. This issue has not been considered in formulating the APP model, and has been used in the solving process (Baykasoglu, 1999; Fung et al., 2003; Tang et al., 2000; Tang et al., 2003; Ning et al., 2006; Wang & Liang, 2005; Wang & Liang, 2004; Wang & Fang, 2001; Liang, 2007 and Wang & Liang, 2005).

• *Product Characteristics*

Product characteristics are very important factors that have significant impact on customer satisfaction. Product characteristics vary considerably overtime and in different business environments. The main characteristics that have been investigated in APP models include product life cycle, perishability and defectiveness of products, and customer satisfaction level.

- *Product Life Cycle:* The product life cycle describes the stages that most products and industries are evolved from creation to maturation. The product life cycle portrays how sales volume for a product changes over its life time. Some products are in birth or growth stages and demand for them will frequently increase in each period and some products are in mature or decline stages and their sales will decrease in subsequent periods. This issue can be added to APP models for better demand forecasting (Jamalnia & Soukhakian, 2009).
- *Perishable Product:* APP models assume that demand does not have a significant growth during the planning horizon. APP models can be proposed for perishable products. Perishable products are products that dramatic growth occurs in their demand. In addition to ordinary products that are considered in APP models, APP models can be represented for perishable products (Leung & Ng, 2007).
- *Defective Product:* Defective product is defined as a product which has physical, and its quality, quantity or standard is reduced. Defective product is usually ignored in APP models, When it must be considered for more conformity with real conditions (Leung & Chan, 2009)
- *Customer satisfaction level:* Customer satisfaction level (or Customer service) is defined as an organization's ability to consistently meet the needs and expectations of its customers. This is important, since the amount of profit that a business earns depends a lot on it. This concept was initially introduced by Filho (1999) in APP models.

- *Setup decision:* Setup decision is the machine setting decision for operation such as tool setting, jigs and fixture setting etc. Ignoring setup decision completely at the aggregate level will result in an overestimation of the expected available capacity for the scheduling level. In many APP models presented so far in the literature, all capacities of each stage are aggregated and setup decision is not explicitly considered (Aghezzaf & Artiba, 1998). Thus setup time (Aghezzaf & Artiba, 1998) and setup cost (Leung & Ng, 2007) should be considered in APP models.
- *Multiple Manufacturing Plant:* APP models assume that products are produced in a single manufacturing plant, while multi-national companies have multiple manufacturing plants for their productions (Leung et al., 2003; Leung et al., 2006; Leung et al., 2007 and Leung & Chan, 2009). Normally, production costs such as labor cost and subcontracting cost etc. and other production parameters vary in different manufacturing plants.
- *Time value of money:* The time value of money is the value of money figuring in a given amount of interest earned over a given amount of time. This phenomenon is caused mainly by the potential time value of money using the compounding interest method for each of the cost categories (Wang & Liang, 2005). The time value of money can be applied for each of the cost categories in a model.
- *Machines Utilization:* Machine utilization is the amount of time the machine is used for production. Leung and Chan (2009) considered machine utilization as an objective function that must be maximized.
- *Financial Concepts:* Today's tough financial conditions worldwide clearly demonstrate the changing emphasis and trade-off between the products, facilities, capacities, work force and profitability in the industrial companies that struggle for survival. These financial conditions may be used in APP models as objective functions or constraints. Fung et al. (2003) and Tang et al. (2003) proposed APP models under financial constraints.
- *Supply Chain Concepts:* A supply chain is defined as "a network of facilities and distribution options that performs the functions of procurement of materials, transformation of these materials into intermediate and finished products, and the distribution of these finished products to customers. Based on this definition, APP is one of the most important activities in supply chain management (SCM)" (Aliev et al., 2007). The overall objective of the SC aggregate plan is to satisfy demand and maximize profit in supply chain (SC) (Aliev et al., 2007).
- *Multiple Product Market:* APP models usually consider a single market with customer demand and unique sale price, while there are companies which have multiple markets for selling their productions. In this case demand and sale price may vary for each market. Leung and Chan, (2009) and Aliev et al., (2007) considered multiple product markets in their models.

Taking into account the previous two classification schemes presented in Section 2.2, we classified researches that have considered different important issues in different APP models' structural groups that are described in section 2.1. Table 3 classifies the surveyed literature according to two classification schemes.

Table 3 and Fig. 3 show the number of studies associated with important issues used in various structural groups.

3. APP Models Analysis

Based on the two classification schemes described in section 2, previous studies will be analyzed, and future research trends in this area are proposed in this section. Fig. 2 shows the increasing trends in paper publications during the period 1998-2009. Table 4 compares the literature according to important issues in a different view. According to Table 4, three categories of analysis, i.e., (i) structural analysis, (ii) important issues analysis and (iii) solving approach analysis, can be performed.

Table 3
Important issues versus structural groups in reviewed articles

Important issues	Deterministic		Fuzzy		Stochastic	
	Single Objective	**Multiple Objective**	**Single Objective**	**Multiple Objective**	**Single Objective**	**Multiple Objective**
Multiple Product item	Aghezzaf & Artiba, (1998); Pradenas & Pe˜nailillo, (2004); Techawiboonwong & Yenradee, (2003); Paiva & Morabito, (2009); Mazzola et al. (1998); Sillekens et al. (2011); Zhang et al. (2012); Ramezanian et al. (2012); Erfanian & Pirayesh, (2016)	Leung & Chan, (2009); Leung & Ng, (2007); da Silva et al. (2006); Leung et al. (2003); Baykasoglu, (2001); Chakrabortty & Akhtar, Hasin (2013); Entezaminia et al. (2016); Abu Bakar et al. (2016); Mehdizadeh et al. (2018)	Filho, (1999); Fung et al. (2003); Tang et al. (2000); Tang et al. (2003); Ning et al. (2006); Aliev et al. (2007); Liang et al. (2011); Chen & Huang, (2014); Iris & Cevikcan, (2014); Chakrabortty et al. (2015)	Jamalnia & Soukhakian, (2009); Wang & Liang, (2005); Wang & Liang, (2004); Wang & Fang, (2001); Baykasoglu & Gocken, (2006); Liang (2007); Sakallı et al. (2010); Baykasoglu & Gocken, (2010); Liang & Cheng, (2011); Sadeghi et al. (2013); da Silva & Silva Marins, (2014); Madadi & Wong, (2014); Gholamian et al. (2016); Fiasché et al. (2016); Chauhan et al. (2017); Mosadegh et al. (2017)	Leung et al. (2006); Wang & Liang, (2005); Leung & Wu, (2004); Leung et al. (2007); Mirzapour Al-e-Hashem et al. (2013); Jamalnia & Feili, (2013); Ning et al. (2013); Entezaminia et al. (2016); Makui et al. (2016); Zhu et al. (2017)	Mirzapour Al-e-Hashem et al., (2012); Jamalnia et al., (2017)
Labor Characteristics	Silva & JoÄOoisboa, (2000); Fahimnia et al. (2005); Pipery & Vachony, (2001); Techawiboonwong & Yenradee, (2003); Mazzola et al. (1998); Sillekens et al. (2011); Zhang et al. (2012); Wang & Yeh, (2014)	da Silva et al. (2006); Ismail & ElMaraghy, (2009); Baykasoglu, (2001); Mehdizadeh et al. (2018)	Liang et al. (2011); Chakrabortty et al. (2015)	Jamalnia & Soukhakian, (2009); Wang & Liang, (2004); Wang & Liang, (2005); Liang & Cheng, (2011); Sadeghi et al. (2013); Madadi & Wong, (2014); Gholamian et al. (2016)	Leung et al. (2007); Jamalnia & Feili, (2013); Makui et al. (2016)	Mirzapour Al-e-Hashem et al., (2012); Jamalnia et al., (2017)
Degree of DM Satisfaction From Solution			Filho, (1999); Fung et al. (2003); Tang et al. (1999); Tang et al. (2000); Ning et al. (2006)	Wang & Liang, (2004); Wang & Liang, (2005); Wang & Fang, (2001); Liang, (2007); Zaidan et al. (2017)	Wang & Liang (2005); Zhu et al. (2017)	

Table 3
Important issues versus structural groups in reviewed articles (Continued)

Important issues	Deterministic		Fuzzy		Stochastic	
	Single Objective	Multiple Objective	Single Objective	Multiple Objective	Single Objective	Multiple Objective
Product Characteristics	Sillekens et al. (2011)	Leung & Chan (2009); Leung & Ng (2007); Entezaminia et al. (2016); Mehdizadeh et al. (2018)	Filho (1999); Chakrabortty et al. (2015)	Jamalnia & Soukhakian (2009), Liang & Cheng (2011); Sadeghi et al. (2013); Gholamian et al. (2016); Chauhan et al. (2017)	Mirzapour Al-e-Hashem et al. (2013); Jamalnia & Feili (2013); Makui et al. (2016)	Mirzapour Al-e-Hashem et al. (2012); Jamalnia et al. (2017)
Setup Decision	Aghezzaf & Artiba, (1998); Pradenas & Pe˜nailillo, (2004); Ramezanian et al. (2012)	Leung & Ng, (2007); Baykasoglu, (2001); Mehdizadeh et al. (2018)	Iris & Cevikcan, (2014)	Fiasché et al. (2016)	Mirzapour Al-e-Hashem et al. (2013); Makui et al. (2016)	
Multiple Manufacturing Plant	Chaturvedi, (2017)	Leung & Chan, (2009); Leung et al. (2003); Entezaminia et al. (2016)		Gholamian et al. (2016)	Leung et al. (2007); Leung et al. (2006); Mirzapour Al-e-Hashem et al. (2013); Entezaminia et al. (2016); Makui et al. (2016)	Mirzapour Al-e-Hashem et al. (2012)
Time value of money				Wang & Liang (2004); Wang & Liang (2005); Liang (2007); Liang & Cheng (2011); Gholamian et al. (2016)		
Machines Utilization		Leung & Chan (2009)		Baykasoglu & Gocken (2010); Fiasché et al. (2016)		
Financial Concepts	Paiva & Morabito, (2009); Sillekens et al. (2011)	Ismail & ElMaraghy, (2009)	Fung et al. (2003); Tang et al. (2003)	Sakallı et al. (2010); Fiasché et al. (2016)	Jamalnia & Feili, (2013)	Mirzapour Al-e-Hashem et al. (2012)
Supply Chain Concept	Pradenas & Pe˜nailillo, (2004); Paiva & Morabito, (2009); Chaturvedi & Bandyopadhyay, (2015)	Entezaminia et al. (2016)	Aliev et al. (2007)	Gholamian et al. (2016)	Mirzapour Al-e-Hashem et al. (2013); Entezaminia et al. (2016)	Mirzapour Al-e-Hashem et al. (2012)
Multiple Product Market	Sillekens et al. (2011)	Leung & Chan, (2009); Entezaminia et al. (2016); Mehdizadeh et al. (2018)	Aliev et al. (2007)	Sakallı et al. (2010); Chauhan et al. (2017)	Jamalnia & Feili (2013); Makui et al. (2016)	

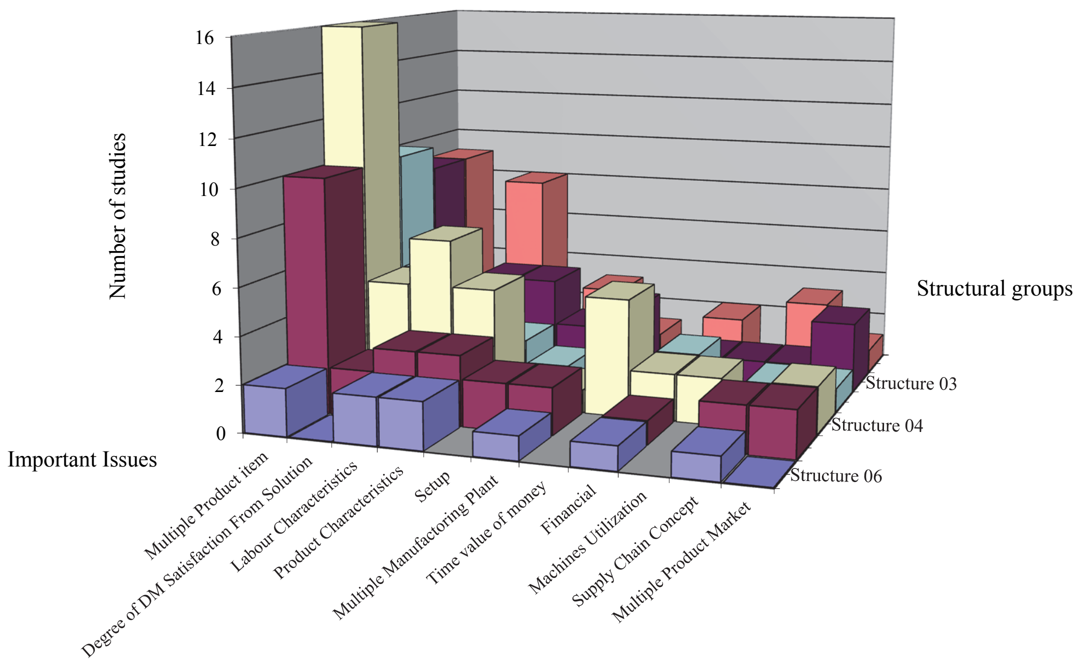

Fig. 2. Number of studies associated with important issues used in structural groups

3.1. Structural Analysis

According to Table 4, the number of deterministic models that have been considered in literature is more than two other types, but it is worth noting that practiontionars showed less interest in developing deterministic models. This decline may be due to the higher interest in developong APP models for real-life situations in which uncertainty is present in data parameters. An increase in the application of fuzzy logic to APP models has been reported, because it is not only a fuzzy useful tool for interacting with decision maker's viewpoints it can also deal with poor, incomplete, and uncertain information. Based on Table 4, stochastic APP models are less focused on than deterministic and fuzzy models. The first reason that researchers pay less attention to stochastic models may be due to difficulties of dealing with stochastic parameters.

The second reason is that the fuzzy set theory is more adaptable to uncertainty. It is worth noting that attention to stochastic models has recently increased. Furthermore, no paper has considered multi objective stochastic APP models. In addition, regarding the number of objective functions (single/ multiple objective), usage of multi objective APP models appears to have a higher growth rather than single objective APP models, because single objective APP models are unable to express production systems multiple and conflicting goals. Based on the APP model structures described above and associated analysis of each structure, it can be concluded that fuzzy and stochastic models, along with multi objective APP models, propose new directions for future work in this research area.

Table 4
An overview of the selected research on Production Planning Models in the literature from 1998 to now

Model Description		Paper	Important Issues											
Deterministic/	**Objective**		**MPI**	**LC**	**DDSfS**	**PC**	**SD**	**MMP**	**TVM**	**MU**	**Fc**	**SCc**	**MPM**	**Solving**
Deterministic	Single	Mazzola et al. (1998)	✓	✓										TSA
		Aghezzaf & Artiba (1998)	✓				✓							H
		Silva & JoÄOoisboa (2000)		✓										LDR
		Pipery & Vachony (2001)		✓										SS
		Singhvi & Shenoy (2002)												SS
		Techawiboonwong & Yenradee	✓	✓										SS
		Pradenas & Pe˜nailillo (2004)	✓				✓					✓		TSA
		Fahimnia et al. (2005)		✓										GA
		Paiva & Morabito (2009)	✓								✓	✓		SS
		Sillekens et al. (2011)	✓	✓		✓					✓		✓	H
		Zhang et al. (2012)	✓	✓										H
		Ramezanian et al. (2012)	✓				✓							GA&TSA
		Wang & Yeh (2014)		✓								✓		PSO
		Chaturvedi & Bandyopadhyay (2015)												H
		Erfanian & Pirayesh (2016)	✓											SS
		Chaturvedi (2017)											✓	H
	Multiple	Baykasoglu (2001)	✓	✓			✓							GP&TSA
		Leung et al. (2003)	✓					✓						GP
		da Silva et al. (2006)	✓	✓										SS
		Leung & Ng (2007)	✓			✓	✓							GP
		Leung & Chan (2009)	✓			✓		✓		✓			✓	GP
		Ismail & ElMaraghy (2009)		✓							✓			PM&EA
		Chakrabortty & Akhtar Hasin (2013)	✓											GA
		Abu Bakar et al. (2016)	✓											SAA
		Mehdizadeh et al. (2018)	✓	✓		✓	✓						✓	GA
Fuzzy	Single	Filho (1999)	✓		✓	✓								SP
		Wang & Fang (2000)												FP
		Tang et al. (2000)	✓		✓									FP
		Fung et al. (2003)	✓		✓						✓			ParP
		Tang et al. (2003)	✓		✓						✓			S
		Ning et al. (2006)	✓		✓									GA&NN&SP
		Aliev et al. (2007)	✓									✓	✓	GA
		Chen and Huang (2010)									✓			FP
		Chen & Huang (2014)	✓											FP&SS
		Iris & Cevikcan (2014)	✓				✓							FP
		Rahmani et al. (2014)												FP
		Chakrabortty et al. (2015)	✓	✓		✓								FP&PSO
	Multiple	Wang & Fang (2001)	✓		✓									FP
		Wang & Liang (2004)	✓	✓	✓				✓					PossP

Model Description		Paper	Important Issues											
Deterministic/	Objective		MPI	LC	DDSfS	PC	SD	MMP	TVM	MU	Fc	SCc	MPM	Solving
		Wang & Liang (2005)	✓	✓	✓				✓					PossP
		Baykasoglu & Gocken (2006)	✓											GA&TSA
		Liang (2007)	✓		✓				✓					PossP
		Jamalnia & Soukhakian (2009)	✓	✓		✓								FP&GA
		Sakallı et al. (2010)	✓								✓		✓	FP
		Baykasoglu & Gocken (2010)	✓							✓				TSA
		Liang & Cheng (2011)	✓	✓		✓			✓					GP
		Sadeghi et al. (2013)	✓	✓		✓								GP
		da Silva & Silva Marins (2014)	✓											GP
		Madadi & Wong (2014)	✓	✓										FP
		Gholamian et al. (2016)	✓	✓		✓		✓	✓			✓		FP
		Fiasché et al. (2016)	✓				✓				✓			FP
		Chauhan et al. (2017)	✓			✓							✓	FP
		Zaidan et al. (2017)			✓									FP&SAA
		Mosadegh et al. (2017)	✓											FP&GP
Stochastic	Single	Hsieh & Wu (2000)												PossP
		Leung & Wu (2004)	✓											SP
		Ganesh & Amoorthy (2005)												GA&SAA
		Wang & Liang (2005)	✓		✓									PossP
		Leung et al. (2006)	✓					✓						SP
		Leung et al. (2007)	✓	✓				✓						SP
		Mirzapour Al-e-Hashem et al. (2013)	✓			✓	✓	✓				✓		SS
		Jamalnia & Feili (2013)	✓	✓		✓					✓		✓	S
		Ning et al. (2013)	✓											GA&S
		Entezaminia et al. (2016)	✓					✓				✓		SP
		Makui et al. (2016)	✓	✓		✓	✓	✓					✓	SP
		Zhu et al. (2017)	✓		✓									SP
	Multiple	Mirzapour Al-e-Hashem et al. (2012)	✓	✓		✓		✓			✓	✓		SP&GA
		Jamalnia et al. (2017)	✓	✓		✓								SP

Abbreviations in Important issues: MPI stands for Multiple Product Item; LC denotes Labor Characteristics; DDSfS means Degree of DM Satisfaction from Solution; PC stands for Product Characteristics; SD denotes Setup Decision; MMP means Multiple Manufacturing Plant; TVM stands for Time value of money; MU denotes Machines Utilization; Fc means Financial Concepts; SCc stands for Supply Chain Concepts and MPM denotes the Multiple Product Market.

Abbreviations in solving Approach column: GA stands for Genetic Algorithm; GP denotes Goal Programming; TSA means Tabu Search Algorithm; PSO means Particle Swarm Optimization; SAA denotes Simulated Annealing Algorithm; SS stands for Solver Software (such as Lingo, Lindo, Microsoft Solver and Gams); PossP denotes Possibilistic Programming; FP means Fuzzy Programming; PM stands for Progressive Modeling; SP denotes Stochastic Programming; ParP means Parametric Programming; S stands for Simulation; NN means Neural Network; EA stands for Evolutionary Algorithm; H denotes Heuristic; LDR means Linear Decision Rules.

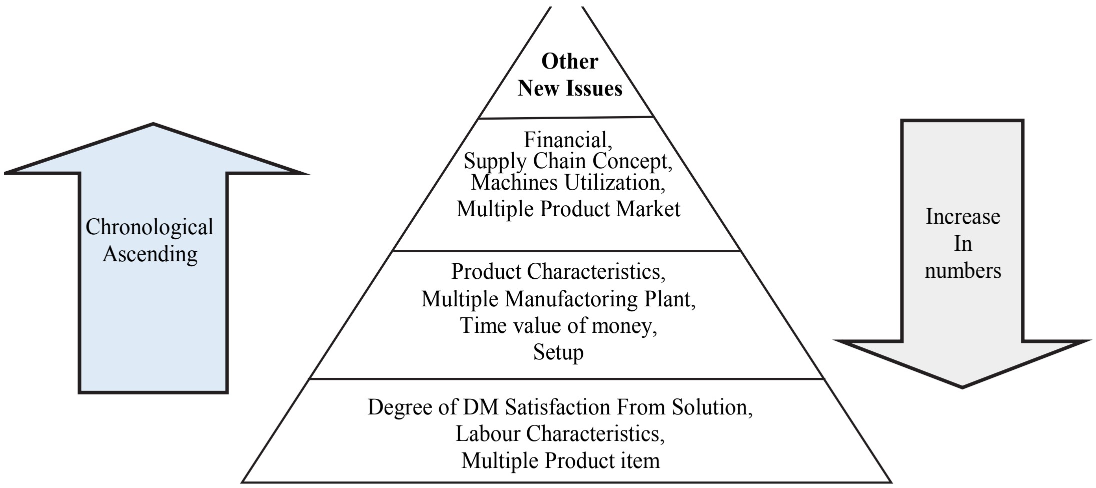

Fig. 3. Important issues according to the number of studies and the the publication date of studies

3.2. Important Issues Analysis

Important issues are summarized according to two criteria in the following figure. The first criterion is the number of studies that have considered the relevant issue, and the second criterion is the publication date of those studies. In Fig. 3, important issues that are located in upper levels are considered less frequently in APP models and are presented mostly in recent years. Unlike this, important issues that are located in lower levels are considered more frequently than other issues. Additionally, based on the above figure, moving up aside the issues shows the existing historical trends and tendencies in APP models.

For future research, important issues at the top of Fig. 3 can be regarded as an effective search direction for future work to improve the capabilities of APP models and their adaptation with real-life situations more than before. Multiple product items, the degree of DM satisfaction with the solution and labor characteristics are widely used in APP models because of their importance. That is why they are located at the bottom of the figure. On the other hand, financial concepts, supply chain concepts, machine utilization and multiple product markets have not been sufficiently taken into account by practitioners; therefore they are located at the top of Fig. 3. Therefore, we suggest important issues that are located at the top of the above figure besides other issues such as maintenance concept, transportation concept and other new concepts that can help APP models to provide greater adoption with real conditions of the production planning decision, for possible directions for future research. The end of section 3 has a list of some possible directions for future research in Table 6.

3.3. Solving Approach Analysis

Broad range of solving approaches used for different types of APP models can be easily found in the literature. Table 5 shows various types of solving approaches such as, Stochastic Programming, Fuzzy Programming, Goal Programming, Metaheuristics (including Neural Network, Simulated Annealing Algorithm, Tabu Search Algorithm, Genetic Algorithm) and Solver Software, which have been applied to various APP structures and issues. Solving approaches are used for solving six APP structural groups, an showed in Table 5. Table 5 is divided into three main regions, Deterministic approaches region, Fuzzy and stochastic region and Metaheuristic region. Metaheuristics algorithms are common approaches for solving deterministic models, fuzzy and stochastic models in APP literature. Solving approaches like Heuristic, Linear Decision Rules, Goal Programming, Progressive Modeling, Evolutionary Algorithm, Solver Software (such as Lingo, Lindo, Microsoft Solver, Gams, etc) are used for solving deterministic models, but Solver Software (such as Lingo, Lindo, Microsoft Solver, Gams, etc) and Goal Programming are used more often in this region to solve deterministic APP models. It is worth noting that Software (such as Lingo, Lindo, Microsoft Solver, Gams, etc) is used for single objective and Goal Programming is a more suitable technique for solving multi objective deterministic models. Possibilistic Programming, Fuzzy Programming, Stochastic Programming, Parametric Programming are located in the second region in Table 5. These approaches are used to solve fuzzy and stochastic APP models. Possibilistic Programming and Fuzzy Programming are mostly used for fuzzy models while Stochastic Programming and Parametric Programming are used for stochastic models.

As can be seen from Table 5, simulated annealing Algorithm, tabu search algorithm, genetic algorithm, neural network are located in the metaheuristic region. There is a trend in the APP models research area to use metaheuristic algorithms (i.e. (GA), (TSA) and (SAA), etc) for solving APP problems due to limitations imposed by the classical techniques. Metaheuristics are global optimization procedures and do not suffer from the many limitations faced by the classical techniques. More importantly, they have a problem independent nature; therefore these algorithms can be adapted to suit specific problem requirements. It is also worth noting that metaheuristic algorithms can be coupled with other mentioned classical approaches in regions one and two, and can be applied simultaneously with them. There is a trend in the research community to use metaheuristic algorithms (i.e. GA, TS, SA, NN) to solve APP problems due to limitations imposed by the classical optimization techniques as mentioned before. Metaheuristic algorithms can increase the ability of the optimization technique if they are used simultaneously. These methods are frequently used to solve the APP problems in recent decades.

Depending on the assumptions made and the modeling approach used, APP models can be quite complex and large scale. Therefore, there is a need to investigate the suitability of new modern metaheuristics for APP models. Three directions for future research in the solving approach of APP models are suggested here. The first is to use other metaheuristics that have not been used in APP models such as Ant Colony Optimization (ACO), Scatter Search Algorithm, Memetic algorithm, Invasive weed optimization (IWO), other Evolutionary Algorithm (EA), etc. It is worth noting that metaheuristics must be selected based on model features. The second direction is to use hybrid metaheuristics (i.e. GA&SA) to overcome their weaknesses as well as to increase their strengths. Finally, last suggestion is attached classical approaches which are used for solving deterministic, fuzzy and stochastic models (such as Goal Programming, Possibilistic Programming, Fuzzy Programming, Stochastic Programming) by metaheuristic algorithms to solve APP problems.

3.4. Directions for Future Research

Directions for further research proposed in section 3 which were obtained from analysis of relevant studies, are summarized in Table 6.

Table 5. Solving approaches used by different researchers for solving APP

Solving Approach	Abbreviation	Solving Approach	Deterministic Models		Uncertain Models			
					Fuzzy Models		Stochastic Models	
			Single Objective	Multi Objective	Single Objective	Multi Objective	Single Objective	Multi Objective
Neural Network	NN				✓			
Simulated Annealing Algorithm	SAA	Metaheuristic		✓		✓	✓	
Tabu Search Algorithm	TSA		✓✓✓	✓		✓✓		
Genetic Algorithm	GA		✓✓	✓✓	✓✓	✓	✓✓	✓
Heuristic	H		✓✓✓✓✓					
Linear Decision Rules	LDR		✓					
Goal Programming	GP			✓✓✓✓		✓		
Progressive Modeling	PM			✓				
Evolutionary Algorithm	EA			✓				
Solver Software (such as Lingo, Lindo, Microsoft Solver, Gams, etc)	SS	Deterministic approaches	✓✓✓✓✓✓	✓	✓		✓	
Possibilistic Programming	PossP					✓✓✓	✓	
Fuzzy Programming	FP				✓✓✓✓✓✓✓	✓✓✓✓✓✓✓✓✓		
Stochastic Programming	SP	Fuzzy and stochastic			✓✓		✓✓✓✓✓✓	✓✓
Parametric Programming	ParP				✓			
Simulation	S				✓		✓	

Table 6
Further researches on APP models

Structures	Important issues	Solving Approaches
Stochastic models (Single objective and Multiple objective)	Use of upper important issues in figure 3 for stochastic and fuzzy models	Use other metaheuristics that has not been used in APP models: Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Scatter Search Algorithm, Memetic algorithm, Invasive weed optimization (IWO), other Evolutionary Algorithm (EA), etc.
Fuzzy models (Multiple objective) Other types of uncertainty besides stochastic and fuzzy	New Important issue: Adding Transportation concept to APP; Other Human Resource Management concept (i.e. Motivation), Adding Maintenance concept to APP, Adding sustainability and green concepts to APP	Use hybrid metaheuristics (i.e. GA&SA) to increase their strengths
General suggestion	APP in advanced manufacturing system such as Flexible Manufacturing System APP in service-based firms (besides manufacturing firms) Integrated DSS System for APP Based on Decision Making tools And APP models	

In Table 6 four kinds of suggestions are proposed; namely, contained structures, important issues, solving approaches and general suggestion. Further work on Stochastic models (single/ multiple objective) multiple objective fuzzy models, and the application of other types of uncertainty besides stochastic and fuzzy for uncertain areas, are proposed for structure suggestions. For further research on important issues in APP, additional concepts such as maintenance decision (time and cost), and transformation decision (time and cost) between production plant and markets, sustainability and green concepts can be considered. Some general suggestions for APP models such as APP in flexible manufacturing systems and integrated decision support systems (DSS) based on decision making tools are showed in Table 6. Finally it should be noted that, APP models have not been proposed for any service-based firms other than manufacturing firms yet.

4. Conclusion

The aggregate production planning problem is an important part of the production planning process. APP greatly reduces the amount of data used during the planning process and therefore enables plans to be updated more frequently. Numerous APP models with varying degrees of sophistication have been introduced in the last four decades. The study conducted by Nam and Logendran (1992) categorized the literature on APP since early 1950 to 1990, and there has not been any systematic survey in the literature. In order to provide readers with a background for understanding current knowledge on a topic and illuminate the significance for new study, a well structured literature review was needed. In this paper a literature review that is characterized by a logical flow of ideas; current and relevant references with consistent, appropriate referencing style; proper use of terminology; and an unbiased and comprehensive view of the previous research on the APP models has been presented. The purpose of this review was to provide a systematic structure for classifying APP models and to demonstrate the gaps existing in the literature in order to extract future trends and directions of this research area.

In this paper a comprehensive classification scheme that categorizes the APP models from two perspectives has been presented. The first perspective is the structure of APP models which encompasses the level of uncertainty that exists in the APP model and the number of objective functions that a model contains. In deterministic models all of the model parameters are assumed to be known prior to planning.

The main concept of uncertain APP models is to tackle many problems in the real world where the input data or parameters are imprecise rather than exact. To deal with uncertainty in APP models, fuzzy set theory and stochastic programming were employed. APP models are divided into single objective and multiple objective models. The second perspective is based on some extra issues which are added to the basic issues of APP models. In addition to primary issues in APP models (such as market demand, backorder etc.), there are some further issues (i.e. multiple product item, labor characteristics, degree of DM satisfaction from solution, product characteristics, setup, multiple manufacturing plant, time value of money, financial concepts, supply chain concepts, multiple product market) that are considered in APP models. These issues are called important issues for classifying APP models.

Based on these two classification schemes, APP models are reviewed and three analysis categories including: structural, important issues and solving approaches for the purpose of extracting gaps and trends in the literature have been presented. Based on these analysis categories, finally four kinds of suggestions for further research on the APP models including structures, important issues, solving approaches and general suggestion, were pointed out. The main conclusion that can be drawn from this review is that, the role of aggregate production planning (APP) is a major factor in the operations management decision and this role is becoming more important with the increasing need for more comprehensive models that simultaneously consider different issues relevant to real-life problems. Therefore, there is still much room for the proposing of new APP models and solution approaches in order to help the decision-making process in production planning. It is hoped that this review will be beneficial to researchers in the production planning field, and will motivate additional work in this increasingly important subject.

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