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ORIGINAL ARTICLE

# Aggregate production planning under uncertainty: a comprehensive literature survey and future research directions

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**Abstract**
This is the first literature survey of its kind on aggregate production planning (APP) under uncertainty. Different types of uncertainty, such as stochasticity, fuzziness and possibilistic forms, have been incorporated into many management science techniques to study APP decision problem under uncertainty. In current research, a wide range of the literature which employ management science methodologies to deal with APP in presence of uncertainty is surveyed by classifying them into five main categories: stochastic mathematical programming, fuzzy mathematical programming, simulation, metaheuristics and evidential reasoning. First, the preliminary analysis of the literature is presented by classifying the literature according to the abovementioned methodologies, discussing about advantages and disadvantages of these methodologies when applied to APP under uncertainty and concisely reviewing the more recent literature. Then, APP literature under uncertainty is analysed from management science and operations management perspectives. Possible future research paths are also discussed on the basis of identified research trends and research gaps.

**Keywords** Aggregate production planning (APP) under uncertainty · Management science methods · Literature on uncertain APP models

## 1 Introduction

### 1.1 Introductory overview

Aggregate production planning (APP) is a type of medium-term capacity planning that usually covers a time horizon of 3 to 18 months and its aim is to determine optimal level of production, inventory and human resources regarding the limitations of production resources and other constraints. The purpose of APP is (I) determining overall level of each product category to meet fluctuating and uncertain demand in near future and (II) adopting decisions and policies in regard to hiring, lay off, overtime, backorder, subcontracting, inventory level and available production resources.

APP has attracted considerable attention from both practitioners and academia [1]. Since the pioneering studies by Holt et al. [2] and Holt et al. [3] proposed linear decision rule and Bowman [4] suggested transportation method to deal with APP, researchers have developed different methodologies to handle the APP problem.

Figure 1 outlines the APP position among other types of production planning and control techniques and their interconnected relationships from a holistic perspective. As it can be seen from Fig. 1, in the hierarchy of production planning activities, APP falls between long-term strategic planning decisions such as new product development and short-term shop-floor scheduling practices.

Uncertainty is described by Funtowicz and Ravetz [5] as a situation of inadequate information, which can be present in three forms: inexactness, unreliability, and border with ignorance. Walker et al. [6] adopt a general definition of uncertainty as being any departure from the unachievable ideal of complete determinism.

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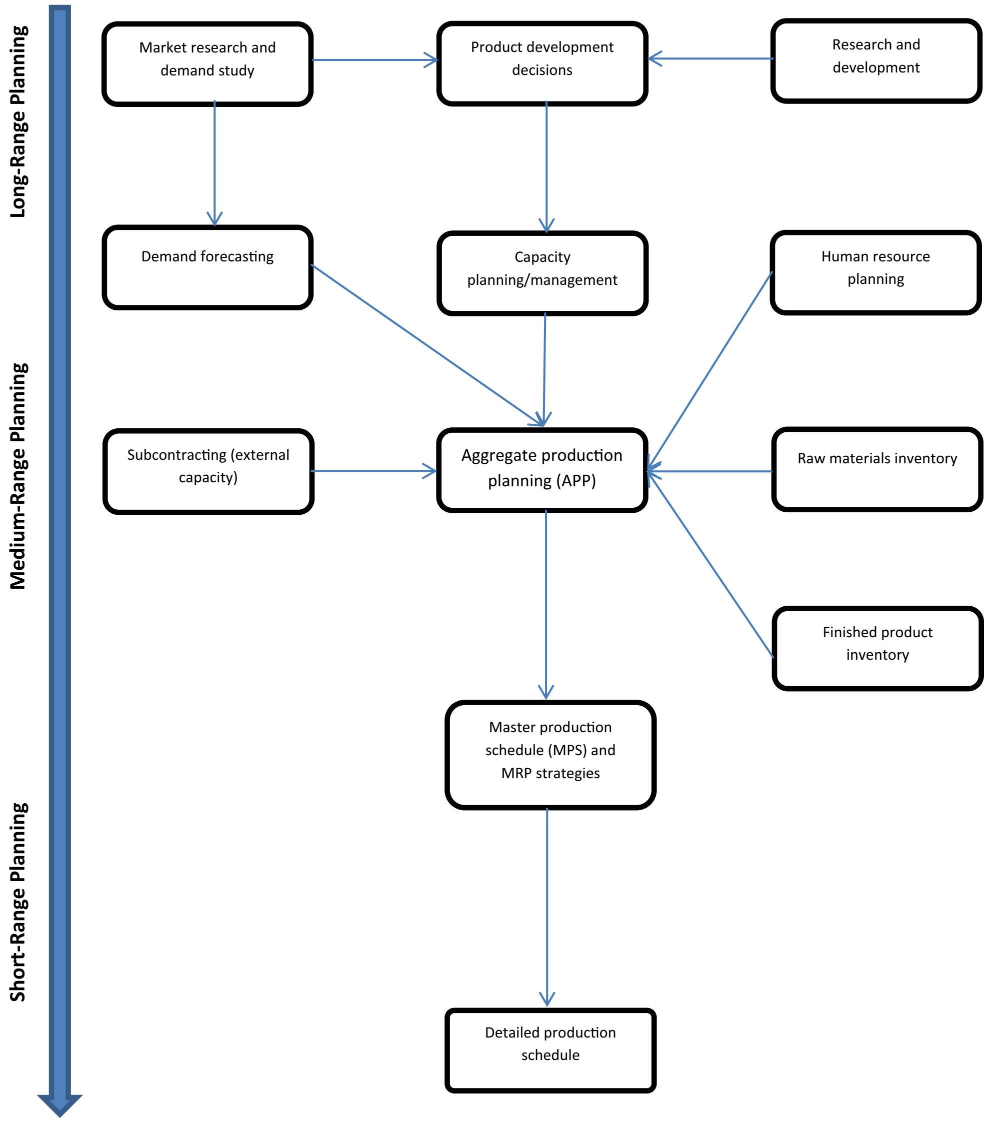


**Fig. 1** The diagram which shows APP relationships with other types of production planning and control activities

A large portion of the existing research studies the deterministic state of APP and ignores its inherent uncertain nature. This assumption may be valid in several APP decision-making problems where product demand exhibits a smooth pattern, i.e., demand has low coefficient of variation and workforce market, materials price and availability and other related factors show a rather consistent state.

However, in practical business environments, products usually have shorter life cycles, demand is uncertain and variable, customers' preferences are changing, production capacity is limited, workforce market condition is unstable, subcontracting may impose higher costs and has its own difficulties, raw materials supply is uncertain and increase in backorders leads to customers' dissatisfaction and makes them change their purchasing source. These all display the dynamic and uncertain characteristics of APP and the need to incorporate these uncertainties into the APP decision models. Therefore, the utilisation of traditional deterministic methodologies may lead to considerable errors and imprecise decisions.

A significant number of studies have been devoted to APP subject to uncertainty by considering different forms of uncertainty including stochasticity, possibilistic forms, fuzziness and randomness.

Figure 2 indicates APP literature map (diagram). The early management science approaches applied to study APP are categorised as (1) linear programming [7, 8], (2) linear decision rule [2, 3], (3) transportation method [4], (4) management coefficient method [9], (5) parametric production planning [10], (6) search decision rule [11], (7) simulation [12] and (8) tabular/graphical methods [13, 14].

Then, subsequent studies used different methods to deal with various kinds of APP problems, which can be divided into three general categories: (I) studies that apply deterministic management science techniques to APP decision-making problem, (II) research which incorporates uncertainty in

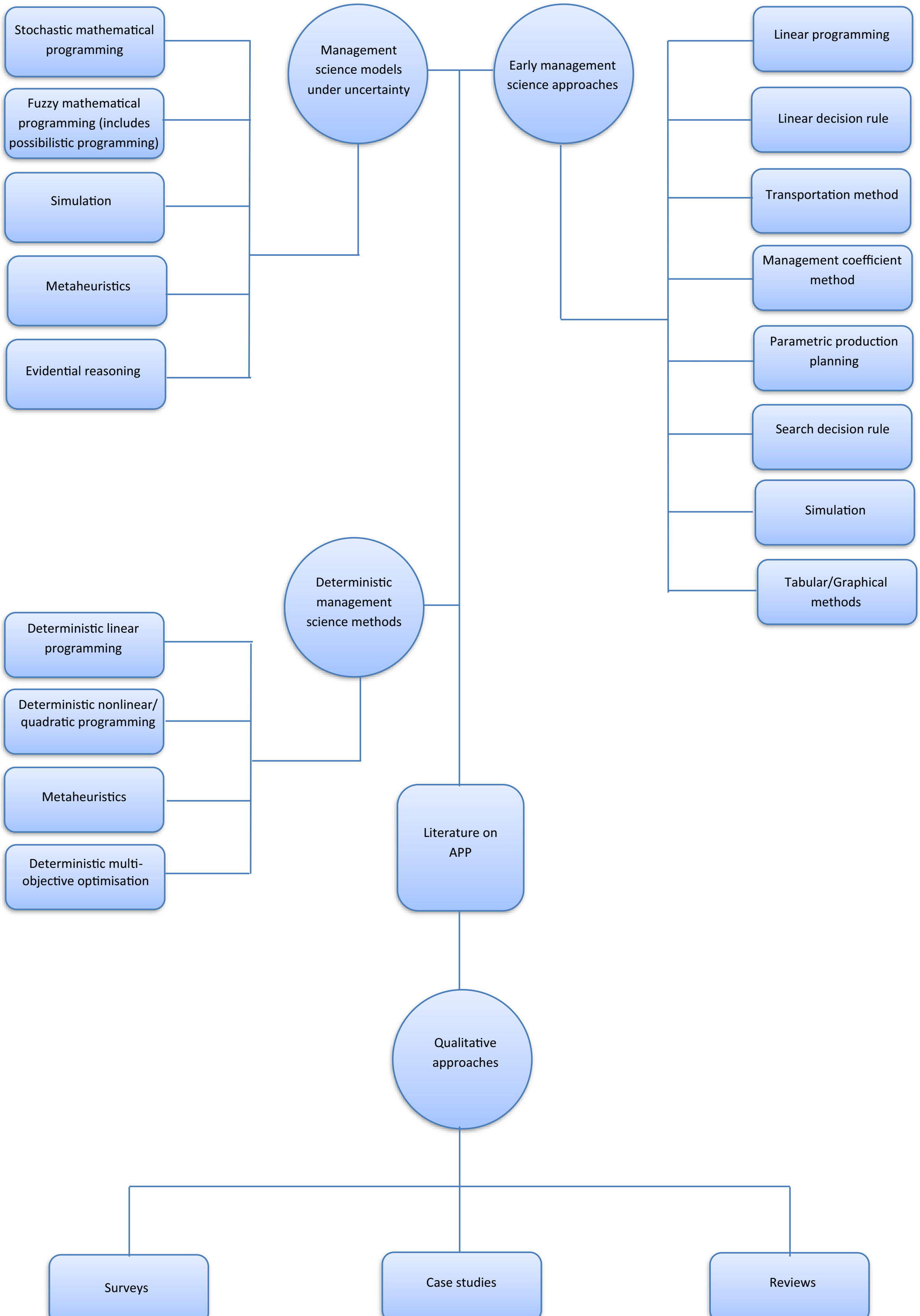


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**Fig. 2** APP literature map

management science methods to study APP problem (III) and, finally, research on APP that applies qualitative research approaches such as surveys and reviews instead of management science methodologies.

The abovementioned classic approaches to deal with APP such as linear decision rule, transportation method and management coefficient method which were popular in 1950s, 1960s and early 1970s are outdated and are very rarely used. Therefore, in the present research, the literature which has applied the subsequently developed approaches to handle APP are surveyed from about mid-1970s until October 2018.

As Fig. 2 shows, the management science methods that have been adopted in literature to study APP under uncertainty are generally classifiable into five main categories: stochastic mathematical programming, fuzzy mathematical programming, simulation, metaheuristics and evidential reasoning. Each of these categories could be divided into smaller subcategories, which will be described in detail in subsequent parts.

The paper is further organised as follows. The need for a literature survey on APP under uncertainty is justified in the next part. Section 2 gives a preliminary literature analysis, which includes classification plan and discussion on advantages and disadvantages of methodologies applied to study APP under uncertainty and succinctly reviewing more recent literature on APP under uncertainty. Section 3 and Section 4 analyse the surveyed APP literature from management science and operations management perspectives, respectively. In Section 5, conclusions are drawn, and possible future research directions are discussed.

### 1.2 The need for literature survey on APP under uncertainty

The researchers have been incorporating uncertainty in APP to make decision models which better represent the present-day turbulent industrial environments. The research on APP in presence of uncertainty has been growing constantly over the recent decades.

This is the first literature survey of its kind on APP under uncertainty. The authors have benefited from their decade-long experience of doing concentrated research on APP under uncertainty and their deep familiarity with APP literature to critically review and analyse a comprehensive set of relevant literature. Some of the major features of this literature survey which differentiates it from those conducted by Nam and Logendran [16] and Cheraghalikhani et al. [15] are as follows:

1. It presents in-depth discussions about the situations in which each management science methodology is applied to APP under uncertainty and strengths and weaknesses of these methodologies when applied to APP under uncertainty or similar problems.
2. Detailed statistical analysis of the literature categorically reveals the sources of uncertainty in APP models under uncertainty, the publication frequency and growth rate of the literature regarding each type of the applied management science methods.
3. In relevant sections, the types of industries that APP under uncertainty have been applied to, and the specific characteristics of these industries that may involve more uncertainty, type of manufacturing systems considered by the reviewed literature, e.g. process manufacturing and reconfigurable manufacturing systems, rolling horizon APP, incorporation of sustainability-related principles to APP models under uncertainty, type of APP strategies considered by the reviewed literature are presented, which together with abovementioned features provide research insights about recent research trends and research gaps for interested researchers.
4. We have linked the findings from the research trends and research gaps to the extensive set of proposed future research paths that are presented in Section 5. These recommendations on future research directions which are drawn based on recent research trends and existing research gaps will provide a basis for other researchers to make their own research agenda.

The authors decided to consider APP, as a central activity in production planning and control which was depicted in Fig. 1, instead of general production planning in order to provide an in-depth and focused literature analysis.

The current study considers the existing research on APP under uncertainty as a crucial and constantly growing part of the research about APP. The research on deterministic APP decision models would require a separate literature survey, again, to present another in-depth and specialised literature analysis.

### 1.3 Research method

Uncertainty has been incorporated in management science-based models of APP in different shapes including stochasticity, randomness, possibility, fuzziness and vagueness of the information. Search for the term “aggregate production planning (APP)” found a large number of published results but they were filtered by adding the words “uncertain/uncertainty”, “stochastic/stochasticity”, “possibility/possibilistic”, “random/randomness”, “fuzzy/fuzziness”, “probability/probabilistic” and “chance-constrained”. Then, by abstract and keywords reviewing, these publications were again filtered to make sure they really consider APP under uncertainty, although in many cases reviewing full texts was needed, since whether those studies have considered APP under uncertainty or deterministic APP have not been clearly mentioned in the abstract. We also reviewed the references section of these publications to find relevant literature to our study.

As of 19t October 2018, a total of 92 publications were surveyed, which include 73 journal articles (79.35%), 9 conference/proceedings papers (9.78%), 7 book chapters (7.61%), 2 PhD theses (2.17%) and 1 paper from Social Science Research Network (1.09%).

To get the relevant information from reviewed literature, we read the full texts and took notes of useful information that also helped us in grouping the literature into categories which will be detailed in next section.

## 2 Preliminary analysis of the literature

### 2.1 Classification scheme

As it was already mentioned in Subsection 1.1, the management science methodologies applied in the literature to handle APP under uncertainty can be classified into five main categories: stochastic mathematical programming, fuzzy mathematical programming, simulation, metaheuristics and evidential reasoning. Each of these categories is divided into sub-categories, which have been shown in Table 1.

In short, these categories and sub-categories are described as follows:

#### 2.1.1 Fuzzy mathematical programming

This class of models for APP in presence of uncertainty covers a wide range of mathematical programming models in fuzzy environment such as fuzzy linear programming, fuzzy nonlinear programming, fuzzy multi-objective optimisation and so forth. In this set of models, uncertainty is present in the form of fuzziness, which involves market demand, objective/goal values, constants, coefficients and constraints of the developed management science models.

Due to high similarity between fuzzy mathematical programming and possibilistic programming, in this study we consider possibilistic programming literature as part of fuzzy mathematical programming literature.

Possibilistic linear programming and possibilistic linear multi-objective optimisation methods belong to possibilistic programming sub-category. In general, the possibilistic programming models are recommended to deal with APP when the information about the forecasted demand, parameters and coefficients of the constructed mathematical programming models and objective function/goal values are imprecise in essence.

**Advantages** Fuzziness is equivalent to not having been clearly defined and having ill-defined boundaries. This can exist in many situations that involve human judgements and reasoning in terms of linguistic variables. Fuzzy sets and fuzzy logic can effectively handle such ill-defined situations which may be present in APP process. As fuzziness is generally different from randomness, fuzzy mathematical programming techniques can hardly be replaced with stochastic mathematical programming to handle the ill-defined situations or situations with imprecise information.

**Disadvantages** Despite the advantages of fuzzy mathematical programming approach to model APP, it suffers from disadvantages as well. The membership functions of fuzzy sets which represent linguistic variables resulting from decision makers' linguistic judgments, vague information, etc. are normally constructed based on experts' judgments that can vary from one expert to another. This, in turn, can make the resulting fuzzy mathematical models even more imprecise and un-robust. Based on personal experience of the authors, another shortcoming of fuzzy mathematical programming techniques is that, compared to stochasticity, it is a hard task to intuitively explain the fuzziness to business managers who

**Table 1** Classification of the methodologies applied to study APP subject to uncertainty

| Categories | Sub-categories |
|---|---|
| Fuzzy mathematical programming | Fuzzy multi-objective optimisation; fuzzy linear programming; fuzzy nonlinear programming; fuzzy logic control; fuzzy robust optimisation; approximate reasoning; possibilistic linear programming; possibilistic linear multi-objective optimisation; interactive possibilistic linear programming |
| Stochastic mathematical programming | Stochastic linear programming; stochastic nonlinear programming; stochastic multi-objective optimisation; robust optimisation; stochastic control; stochastic queuing; stochastic process |
| Simulation | Discrete-event simulation; system dynamics; Monte Carlo simulation |
| Metaheuristics | Genetic algorithm; tabu search; harmony search algorithm; particle swarm optimisation |
| Evidential reasoning | Belief-rule-based inference method |

may have little or very basic knowledge of mathematics and get them support your research project by involving in it or providing the necessary data.

### 2.1.2 Stochastic mathematical programming

It includes mathematical models for APP under uncertainty that apply stochastic linear programming, stochastic nonlinear programming, stochastic multi-objective optimisation and so on where demand for products, constants and coefficients of the mathematical programming models and decision variables are of stochastic/random nature. This group also includes mathematical programming models with probabilistic constraints or chance-constrained models.

**Advantages** As stated above, randomness and fuzziness, as two forms of uncertainty, are essentially different, and thus fuzzy mathematical programming can hardly be efficient in dealing with this kind of uncertainty. Present-day business environments are instable in nature, and deterministic APP models hardly fit these unstable, uncertain environments. APP models need to be built in such a way that includes the uncertainties. These uncertainties could be randomness of parameters/constants and decision variables which is not unusual in real-world production planning and control activities. An efficient method to handle randomness present in mathematical models of APP is stochastic mathematical programming.

**Disadvantages** Similar to fuzzy mathematical programming method, in stochastic mathematical programming, the subjectivity is still present regarding the fact that in many cases the associated scenario probabilities are estimated or modified subjectively by business managers with regard to their experience of specific events. This may affect the preciseness of the developed models.

In addition, from both theoretical and computational viewpoints, there are serious concerns with stochastic mathematical programming models.

The recourse approach, as a widely used stochastic programming technique, assumes that all constraints relating to different scenarios have equal probability of 1, or certainty, where the objective function represents the expected value with regard to different scenarios. From practical point of view, this does not sound robust, since when all constraints relating to different scenario are put together under the same mathematical programming model, it is as if they all happen simultaneously.

APP problems modelled by multi-stage stochastic mathematical programming techniques, e.g. stochastic dynamic programming, would normally need to deal with the curse of dimensionality due to rather large scale of real-world APP decision problems and typically due to the high number of scenarios involved.

### 2.1.3 Simulation

The simulation methods that have been proposed to run APP decision problem, where forecasted demand, objective/goal values, parameters/coefficients and constraints are supposed to be uncertain in their nature, can be divided into two main categories: discrete-event simulation (DES), which is essentially a discrete simulation method, and system dynamics (SD) which is probably the most famous continuous simulation technique.

SD treats the entities as continuous variables, while DES presents objects pictorially so that they can be visually tracked throughout the simulated system, a capability that SD lacks. Unlike SD that updates the state of the simulated system continuously, when DES is applied, the state of the system changes at discrete time points. Both simulation techniques' objective is to provide insights for decision makers on systems performance over time [17, 18].

**Advantages** Simulation modelling, whether applied to APP or other managerial decision-making activities, has several advantages in comparison with mathematical programming methods [19–24]: (i) unlike mathematical programming techniques that mostly operate based on average values, the simulation techniques can satisfactorily handle the transient effects in dynamic models, (ii) simulation is more flexible and needs less simplifying assumptions compared to mathematical optimisation or artificial intelligence, (iii) SD simulation models can easily consider the interactions and interrelationships between components of APP system which are decisions that are made in various parts of a manufacturing company, (iv) simulation techniques provide an adequate base for the construction of predictive and explanatory operational processes models, (v) simulation is able to show how a system behaves within a time period rather than just showing the final results and (vi) it allows the modeller to get insight on how the model under study actually works and realise the variables that are key performance indicators.

Additionally, as an extra advantage, DES and SD can easily be combined in building APP models to present an enhanced performance, as DES performs well when applied to operational, shop-floor activities, while SD is more suitable for aggregate/strategic level decision modelling; see [25] for example.

**Disadvantages** Although simulation is generally a powerful decision modelling tool with successful application record to APP, it also has disadvantages. Simulation does not basically provide the optimum solution and it can take long time to set the parameters to obtain near-optimal solutions. Providing accurate description of equations and formulas in order to indicate interrelationships between the simulated model's components is normally harder than mathematical programming. Furthermore, more complex simulation models may necessitate using computers with much higher processing capabilities and larger memory spaces.

#### 2.1.4 Metaheuristics

Due to the nonlinearity, combinatorial and large-scale nature of APP problems, metaheuristics have proved to be efficient techniques to solve APP problems with uncertain characteristics. In this group of APP models, uncertainty is present in decision variables, customer demand, objective function/goal values, constraints, constants and coefficients of the constructed management science models.

Among the metaheuristics, genetic algorithms (GAs), particle swarm optimisation (PSO), tabu search (TS) and harmony search (HS) algorithm have been used to deal with APP models in the presence of uncertainty.

**Advantages** Metaheuristics are always used for NP-hard models of APP, e.g. nonlinear programming, nonlinear multi-objective optimisation and large-scale linear programming where the ordinary optimisation methods could get trapped in local optima, and the computation time also could get unreasonably long. Another advantage of metaheuristics is that contrary to ordinary optimisation algorithms, by using metaheuristics, it does not really matter whether the constructed mathematical model is convex, differentiable and smooth or not.

The advantages of PSO are due to its simple concept/structure, robustness, quickness in getting solutions and high capability of bypassing the local optima [26]. Other advantages of PSO algorithm are relatively easier implementation, robustness when changing control parameters and computational efficiency in comparison with mathematical algorithms for heuristic optimisation [27]. When applying PSO, only a few parameters need to be set. it performs well in global search, scaling design variables have little impact on its performance and parallelising it for concurrent processing is not difficult [28–30].

GAs, the powerful tools that are inspired by biological mechanisms and theory of natural selection, have several useful features: (i) implicit parallelism, i.e. a property which enables GA to parallelly evaluate large number of schema patterns, (ii) ability to provide quick and reliable solutions to problems that can hardly be tackled with traditional methods, (iii) are easily interfaced and hybridised with other metaheuristic methods, (iv) bigger solution space, (v) complex fitness/adaptive landscape, (vi) finding global optimum is easier, (vii) having multiple objective function, (viii) efficient handling of noisy functions and (ix) ability to easily handle wide, not well-understood solution spaces [31–33].

No prior domain information such as objective function gradient is required when using HS algorithm. Unlike population-based evolutionary methods, only a single search memory is utilised in HS algorithm to evolve. Thus, the HS method is simple from algorithmic viewpoint [34]. Other advantages of HS algorithm are significantly easier implementation, less parameter adjustment, good performance in global search and fast convergence [35, 36].

To keep the search process record, TS algorithm uses a flexible memory [37]. Compared to systems with rigid memory or memory-less systems, this flexible memory helps exploiting search information more thoroughly. The flexible memory of TS algorithm is also helpful in intensifying and diversifying the search which leads the method towards optimal solution. The semi-deterministic nature of TS makes it both local and global search technique [38].

**Disadvantages** One disadvantage of metaheuristics is that they need high proficiency of coding/programming. In addition to high skilfulness in coding, the developers of metaheuristics need to simultaneously have a deep understanding of mathematical foundations of mathematical models under study and be able to present the solution process in algorithmic form.

In addition to weakness in local search, a disadvantage of PSO could be the premature convergence in below optimal points (Poli, Kennedy and Blackwell, 2007; [28, 29]). However, by coupling PSO algorithm suitable for discrete optimisation and chaos theory through which various chaotic maps are implemented for enlarging the search space and enhancing its diversity, Petrović et al. [39] proposed a mechanism to prevent the premature convergence of PSO.

GAs also have their own drawbacks, mainly (i) are not good at local search, (ii) premature convergence and (iii) may get trapped in near-optimal solutions. This is especially important when verifying the optimality of a solution on a problem is computationally impossible by using conventional methods, (iv) difficulties related to choosing a technique to suitably represent the problem, (v) problems related to choosing different parameters such as population size, crossover and mutation probabilities and the selection rule and its robustness, (vi) are not able to utilise gradients, (vii) information related to specific problem cannot be easily incorporated and (viii) are not effective terminators [31–33].

Despite the aforementioned strengths, HS algorithm is also weak at local search [34]. Other main defects of HS algorithm are premature convergence and lower speed of convergence [36]. It is noteworthy to mention that chaos disturbance strategy, parameter adaptive strategy and cluster analysis can be used to make the local convergence of the HS algorithm more speedy [35].

Main disadvantages of TS algorithm are that it is strongly dependent on the initial solution, and its search process is serial iterative [40].

#### 2.1.5 Evidential reasoning

Evidential reasoning (ER) approach which has been founded on the basis of Dempster-Shafer theory of belief functions is capable of dealing with information and knowledge which include varying levels of uncertainty, mainly coming from ignorance and incorrectness [41]. At present, only a single paper has been published on ER to APP, which employs a belief-rule-based inference (BRBI) method to handle APP decision-making problem with uncertain demand.

**Advantages** When applied to APP, by changing the values of relevant cost coefficients, BRBI sensitively makes effective planning strategies corresponding to each cost scheme. Even if the forecast is provided in interval forms, intended planning values are inferable from the belief rules with regard to different preferences. The belief-rule framework is concise and makes it possible for decision maker to easily improve it by directly adjusting the rule weights and thus belief degrees [42]. Contrary to regular multi-attribute decision analysis (MADA) methods that present an MADA problem under decision matrix structure, ER utilises a belief decision matrix where a distribution which depends on a belief structure is used for assessing the alternatives with respect to different attributes. The main benefit of this action is that it facilitates modelling both precise and imprecise data arising from ignorance and vagueness that can exist in subjective human judgments [43, 44]. The belief decision matrix enables the ER approach to take different formats of data with different form of uncertainties, e.g. single numerical values, discrete/continuous probability distributions and subjective expert judgments with associated belief degrees, as input. It also accepts data that is qualitative and incomplete [45–47].

**Disadvantages** The main disadvantage of ER approach to APP is that it is in absolutely beginning stage, and probably most of its strengths and weaknesses when applied to production planning and control are unknown.

The way the rules are generated impacts the consistency of a rule base. If the rules are inferred from expert knowledge, this issue would be assumed trivial. But if a noise-affected dataset is used to generate the rules, it can cause serious problems. Further investigations are needed to make sure there is consistency between rules generated with the intuition and common sense Yang et al. [44].

### 2.2 Concise review of the literature on APP in presence of uncertainty

In following subsections, the more recent literature about quantitative APP models under uncertainty is concisely reviewed. The studies have been reviewed in chronological order within each category.

#### 2.2.1 Fuzzy mathematical programming

The literature on application of fuzzy mathematical programming approaches in the APP context can be classified into studies which apply (I) fuzzy multi-objective optimisation, (II) fuzzy goal programming, (III) fuzzy linear programming, (IV) fuzzy nonlinear programming, (V) fuzzy logic control, (VI) fuzzy robust optimisation and (VII) approximate reasoning techniques.

As an explanation, although the fuzzy goal programming could be considered as a subset of fuzzy multi-objective optimisation but due to the significant number of publications that apply fuzzy goal programming to APP, it has been presented as a separate sub-division to show a clearer picture of the literature.

**Fuzzy multi-objective optimisation** Since APP problem always involves several criteria (objectives) and also due to the vagueness of the acquired information, fuzzy multi-objective programming has been widely used in this area.

Gholamian et al. [48] and Gholamian et al. [49] developed a fuzzy multi-site multi-objective mixed-integer nonlinear APP model in a supply chain under uncertainty with fuzzy demand, fuzzy cost parameters, etc. Sisca et al. [50] constructed a fuzzy multi-objective linear programming model for APP in a reconfigurable assembly unit for optoelectronics where product price, inventory cost, etc. are supposed to be fuzzy variables.

Fiasché et al. [51] developed a fuzzy linear multi-objective optimisation model of APP in fuzzy environment where the product price, unit cost of not utilising the resources, etc. are of fuzzy nature.

Zaidan et al. [52] hybridised fuzzy programming, simulated annealing and simplex downhill algorithm to make a multi-objective linear programming model of APP in a fuzzy environment so that operating costs, production capacities and forecasted customer demand are assumed to be fuzzy.

Chauhan et al. [53] developed a fuzzy multi-objective mixed-integer linear programming (FMOMILP) model for APP where many of the constants/parameters and objective values are regarded as fuzzy variables.

**Fuzzy goal programming** Jamalnia and Soukhakian [54] proposed a hybrid fuzzy goal programming approach that includes both quantitative and qualitative objectives with fuzzy aspiration levels.

Mezghani et al. [111] developed a fuzzy goal programming formulation of APP in an imprecise environment in which the concept of satisfaction function is used to explicitly incorporate the decision maker's preferences into the APP model. In their APP model, forecasted demand, capacity levels and aspiration levels are supposed to be fuzzy values.

Sadeghi et al. [55] proposed a fuzzy goal programming model of APP with fuzzy aspiration levels where coefficients and parameters of the model are assumed to be grey numbers.

**Fuzzy linear programming** Liang et al. [56] constructed a fuzzy linear programming model of APP, which attempts to minimise total production cost subject to constraints on inventory levels, workforce levels, etc. where objective function and its coefficients and constraints' upper/lower bounds are assumed to be fuzzy variables. A fuzzy mixed-integer linear programming model for APP with fuzzy demand, fuzzy warehouse space, fuzzy cost parameters and so forth in a multi-echelon multi-item supply chain network was developed by Pathak and Sarkar [57].

Omar et al. [58] investigated the benefits of applying fuzzy mathematical programming in APP context by developing a fuzzy mixed-integer linear programming model to APP with fuzzy demand, fuzzy cost parameters, etc. in a resin manufacturing plant, which considers both fuzzy and possibilistic uncertainties. Wang and Zheng [59] proposed a fuzzy linear programming method to APP in a refinery industry in Taiwan, which aims at maximising total profit so that market demand and cost items are characterised as fuzzy numbers.

A fuzzy linear programming model of APP with imprecise data which involves fuzzy demand and fuzzy cost items was suggested by Iris and Cevikcan [60].

**Fuzzy nonlinear programming** Chen and Huang [61] constructed a fuzzy nonlinear programming model for APP using the membership function of the fuzzy minimal total cost so that maximum workforce level and forecasted demand adopt fuzzy nature. An APP problem by considering learning effects and demand under uncertainty was studied by Chen and Sarker [62]. Then, their fuzzy nonlinear programming model was compared to two other models which had not considered learning effects and uncertain demand.

**Possibilistic programming** The literature on possibilistic programming approaches that have been utilised to study APP subject to uncertainty ranges from regular possibilistic programming methods to interactive possibilistic programming approaches.

**Ordinary possibilistic programming** Hsieh and Wu [63] proposed a possibilistic linear multi-objective optimisation approach to consider APP decision-making problem with imprecise demand and cost coefficients, which take triangular possibility distribution functions. Sakallı et al. [64] presented a possibilistic linear programming model for APP in brass casting industry. In the constructed model, demand quantities, percentages of the ingredient in some raw materials, etc. have imprecise nature and adopt triangular possibility distributions. Zhu et al. [65] developed an interval programming method to solve a multi-period, multi-product APP problem in which product demand and many of the coefficients are of imprecise nature.

**Interactive possibilistic programming** A multi-objective APP problem with imprecise demand, cost coefficients, available resources and capacity was studied by Liang [114] by applying an interactive linear multi-objective possibilistic programming model. The proposed model minimises total production costs and oscillations in workforce level.

Liang [113] presented an interactive possibilistic linear programming (i-PLP) method to solve APP problems where the objective function, forecasted demand, related capacities and operating costs adopt imprecise nature. The study aims at minimising total manufacturing costs subject to bounds on inventory, labour, overtime and so on for each operating cost category.

**Other fuzzy mathematical programming approaches** Turksen and Zhong [66], Ward et al. [67] and Rahmani et al. [68] proposed approximate reasoning schema to implement an expert system, C language fuzzy logic controller and robust fuzzy model, respectively, to study APP under uncertainty.

A robust fuzzy model for APP was developed by Rahmani et al. [68], which includes fuzzy customer demand and fuzzy cost items.

#### 2.2.2 Stochastic mathematical programming

The literature on stochastic mathematical programming approaches for APP in the presence of uncertainty includes stochastic linear programming, stochastic nonlinear programming, robust optimisation and stochastic control, which are reviewed concisely in this subsection.

**Stochastic linear programming** A stochastic linear programming method to handle APP with stochastic demand and stochastic cost parameters was proposed by Leung et al. [69]. Demirel et al. [70] applied mixed-integer linear programming to make a decision model for rolling horizon APP problem with flexibility requirements profile where demand is regarded as uncertain variable.

**Stochastic multi-objective optimisation** Chen and Liao [71] adopted a multi-attribute decision-making approach to select the most efficient APP strategy such that selling price, market demand, cost coefficients, etc. are assumed to be stochastic variables. Jamalnia et al. [72] proposed a novel stochastic, nonlinear, multi-objective optimisation decision model to APP decision-making problem based on mixed chase and level strategy under uncertainty where the market demand acts as the main source of uncertainty. By constructing stochastic, nonlinear, multi-objective optimisation models for five different APP strategies, Jamalnia [73] evaluated the performance of APP strategies under demand uncertainty with regard to eight different criteria.

**Stochastic nonlinear programming** Ning et al. [74] presented a multi-product nonlinear APP model by applying uncertainty theory where the market demand, production cost, and so on are characterised as uncertain variables.

Mirzapour Al-e-hashem et al. [75] and Lieckens and Vandaele [76] both suggested nonlinear mixed-integer programming methodologies to study APP decision problem in the presence of uncertainty. Mirzapour Al-e-hashem et al. [75] considered a multi-site APP problem in green supply chain with uncertain demand, while Lieckens and Vandaele [76] developed a multi-product, multi-routing model where a routing consists of a sequence of operations on different resources so that the uncertainty is associated with the stochastic nature of the both demand patterns and production lead times.

**Robust optimisation** Mirzapour Al-e-hashem et al. [77] and Mirzapour Al-e-hashem et al. [78] suggested robust multi-objective optimisation models to deal with APP problem with two objective functions that aims at minimisation of total costs and maximisation of the customer services with cost parameters, demand, etc. under uncertainty. The former is solved using LP-metrics method and the latter with a combination of an augmented ε-constraint method and genetic algorithm.

Niknamfar et al. [79] developed a robust optimisation model for aggregate production-distribution planning so that unit production and fixed costs for production units, unit storage and fixed costs for distribution centres, selling prices and so forth adopt uncertain nature in a three-level supply chain. Modarres and Izadpanahi [80] proposed a linear multi-objective optimisation model to APP with uncertain product demand which tries to minimise operational costs, energy costs and carbon emission. To deal with uncertain input data, a robust optimisation approach is also applied.

Entezaminia et al. [123] suggested a robust optimisation approach to handle a multi-site APP problem in green supply chain with regard to potential collection and cycling centres under uncertainty. Customer demand and cost parameters are supposed to be of uncertain nature. Makui et al. [81] implemented APP for products with very limited expiration dates. A robust optimisation method is also used due to inherent uncertainty of parameters of the constructed APP model.

**Stochastic control** Silva Filho [82] formulated APP problem as a chance-constrained stochastic control problem under imperfect information of states (i.e. the inventory levels).

**Aggregate stochastic queuing and stochastic processes** Kogan and Portouga [83] considered a multi-period APP in a news vendor framework where over/under production are random variables. Their stochastic process model minimises the expected total costs that includes productivity, overtime and over- and underproduction costs.

An aggregate stochastic queuing (ASQ) model was introduced by Hahn et al. [84] to anticipate capacity buffers and lead time offsets for each time bucket of the APP model where set-up times and processing times in the ASQ model are stochastic variables.

Hahn and Brandenburg [85] presented hierarchical decision support system for sustainable APP which is integration of deterministic linear programming and ASQ network models, and duration of operations processes and equipment failure rates are of stochastic nature.

### 2.2.3 Simulation

Simulation modelling of APP problem under uncertainty covers a spectrum from discrete-event simulation (DES) and system dynamics (SD) to fuzzy random simulation.

**Common discrete-event simulation** Tian et al. [86] applied a simulation-based approach to aggregate planning of a batch plant which produces concrete and asphalts so that fluctuating demand could be generated by using a statistical distribution, e.g. uniform and normal. Gansterer [87] investigated the impact of APP with demand under uncertainty in a make-to-order environment utilising a DES method within a comprehensive hierarchical production planning framework.

Altendorfer et al. [88] evaluated the effect of long-term forecast error on optimal planned utilisation factor for a production system with stochastic customer demand. Simulation is used to determine overall costs like capacity, backorder and inventory costs. Cebral-Fernández et al. [89] used DES to model complex shipbuilding manufacturing process. Their ongoing simulation model tries to minimise the effects of uncertainties present in shipbuilding processes.

**Other simulation modelling techniques** Khouja [90], Jamalnia and Feili [25] and Mendoza et al. [91] used Monte Carlo simulation, integrated SD and DES and SD respectively to consider APP subject to uncertainty.

Khouja [90] developed an APP framework to evaluate volume flexibility using Monte Carlo simulation with normally distributed demand.

By employing an integrated SD and DES, Jamalnia and Feili [25] evaluated effectiveness and practicality of different

APP strategies regarding total profit criterion where the forecasted demand was represented as random normal distribution.

Mendoza et al. [91] explored different APP strategies (such as production with maximum capacity and storing inventory to meet the demand without using overtime and subcontracting, resorting to hiring and lay off as the pure strategies to cover uneven demand, and flexible production plans using overtime and/or subcontracting) for a multi-product, multi-period APP problem by applying a SD model in a two-level, labour-intensive supply chain under demand uncertainty.

### 2.2.4 Metaheuristics

Different kinds of metaheuristics have been proposed by for APP in condition of uncertainty as follows.

**Genetic algorithms (Gas)** Fichera et al. [92] suggested possibilistic linear programming and GA as a decision support system for APP to assist decision makers in APP decisions in a vague environment where the constraints on balance equation for production, inventory and demand and total production capacity are of possibilistic form. The chromosome vector in their GA consists of variables for production amount, inventory level and workforce level. An interactive fuzzy genetic methodology to solve aggregate production-distribution planning in supply chain subject to the fuzziness of total profit, total expenses, etc. was developed by Aliev et al. [93], where a data structure called chromosome or genome is used to code decision variables. Since in their study binary coding is used, genomes that are equivalent to bitstrings each can store a potential coded solution. They convert fuzzy parameters to binary type and linked them up within a single bitstring.

**Tabu search (TS)** Baykasoğlu and Göçken [94] proposed a TS method to solve a fuzzy goal programming model of APP with fuzzy goal values. In solving fuzzy goal programming problem, they took three steps: (1) finding initial solution, which is an initial random feasible solution vector that satisfies all hard constraints, (2) changing the value of a decision variable that has been randomly selected from the solution vector to generate neighbourhood solutions and (3) selection of the current best solution vector. Baykasoglu and Gocken [95] proposed a multi-objective APP with fuzzy parameters and solved the model by employing fuzzy numbers ranking methods and TS. The fundamental search mechanism used by them is the TS algorithm of Baykasoglu et al. [96]. The TS algorithm entails several steps: (1) finding initial solution, (2) generation of neighbourhood solutions, (3) selection of the current best solution vector, (4) updating the best-known solution vector, (5) putting the accepted solutions on the tabu list, (6) aspiration criteria, which means accepting any move that improves the best-know solutions and (7) termination.

**Other metaheuristic approaches** Aungkulanon et al. [97] applied a harmony search (HS) algorithm with different evolutionary elements to solve a fuzzy multi-objective linear programming model for APP with fuzzy objectives. They developed various hybridisations of the HS algorithm, the Hunting Search Element on the Pitch Adjustment, Rate Novel Global Best HS Algorithm (NGHSA) and Variable Neighbourhood Search Element on the HS algorithm (VHSA), which employ different neighbourhood and global search mechanisms to generate new solution vectors that enhance accuracy and convergence rate of HS algorithm.

Chakrabortty et al. [98] solved an integer linear programming model of APP with imprecise operating costs, demand and capacity-related data by employing a particle swarm optimisation (PSO) approach. To make convergence faster and obtain better solutions, linear reduction of inertia weight as a modified version of PSO was applied in solving the APP model, where the algorithm stops when the maximum number of loops is reached.

### 2.2.5 Evidential reasoning

Li et al. [42] presented a belief-rule-based inference methodology for APP under demand uncertainty. The proposed model was implemented by using a paint factory example to conduct a comparative study and sensitivity analysis.

## 3 Management science perspective on APP under uncertainty literature

### 3.1 Source of uncertainty in APP models

As Table 2 indicates, the literature was analysed based on which type of the five main methodologies described in Subsection 2.1 they use and which elements are subject to uncertainty. Uncertainty could be present in different elements of the developed quantitative models for APP such as forecasted demand, objective function values, goals aspiration levels, constants/coefficients, constraints and decision variables. Although forecasted demand would also be represented under the coefficients/parameters category but because of the great number of the occasions it has been under uncertainty in the studied APP models, we represent it as a separate part to make the literature analysis more informative.

Table 2 shows that coefficients/parameters account for the highest frequency of the uncertainty in total, 79 (28.11%) out of 281 (100%), among the components of the APP models under study. That is, in total of 79 studies (publications), coefficients/parameters were subject to a form of uncertainty.

**Table 2** The source of uncertainty in APP models in the presence of uncertainty

| | Forecasted demand | Objective/ goal values | Coefficients/ parameters | Constraints | Decision variables |
|---|---|---|---|---|---|
| Fuzzy mathematical programming | 29 | 34 | 31 | 30 | 3 |
| Stochastic mathematical programming | 28 | 13 | 32 | 27 | 4 |
| Simulation | 11 | 2 | 11 | 3 | 0 |
| Metaheuristics | 4 | 5 | 4 | 5 | 2 |
| Evidential reasoning | 1 | 0 | 1 | 1 | 0 |
| Total | 73 | 54 | 79 | 66 | 9 |

Two of the highest frequencies of the coefficients/parameters under uncertainty, i.e. 32 (40.51%) and 31 (39.24%) out of 79 (100%), belong to the studies that apply stochastic mathematical programming and fuzzy mathematical programming methods, respectively. The third tier is represented by the literature that employs simulation techniques which contributes to 11 (13.92%) out of 79 (100%) occasions of the coefficients and parameter uncertainty, that is a sharp decrease compared to the first two highest frequencies.

Forecasted market demand comes in the second place among the elements of the surveyed APP models under uncertainty in terms of frequency of being uncertain, which adds up to 73 (25.98%) out of 281 (100%) in total. Similar to the coefficients/parameters case, fuzzy mathematical programming, stochastic mathematical programming and simulation modelling methodologies top the list for the number of occasions that forecasted demand characterised as uncertain in the reviewed literature with corresponding frequencies 29 (42.03%), 28 (34.78%) and 11 (15.94%) out of 73 (100%), respectively.

Constraints represent the third level of the uncertainty frequencies among the elements of the reviewed APP models in presence of uncertainty with total frequency of 66 (23.49%) out of 281 (100%). Again, similar to the two previously analysed APP model components, fuzzy mathematical programming and stochastic mathematical programming techniques make the highest contributions in terms of number of occasions that the surveyed research studies include uncertain constraints, which are 30 (45.45%) and 27 (40.91%) out of 66 (100%), respectively. But, unlike the two previously analysed elements of the APP models, now metaheuristics come in the third place with respect to the number of occasions that the surveyed literature includes uncertain constraints, i.e. 5 (7.58%) out of 66 (100%).

### 3.2 Trends for frequency of published research regarding each main category of the methodologies

Table 3 shows the number of publications in each decade regarding the respective methodologies applied in the literature to study APP in presence of uncertainty.

As is evident from Table 3, the two highest frequencies of the published research on APP under uncertainty belong to 2010s and 2000s with total frequencies of 47 (51.09%) and 24 (26.09%) out of 92 (100%), respectively. 1990s comes in the third place with total number of 13 (14.13%) publications out of 92 (100%). Generally, the total number of literature about APP subject to uncertainty has been increasing constantly from 1970s until 2010s.

In 2010s, the research that applies fuzzy mathematical programming and stochastic mathematical programming techniques accounts for 20 (42.55%) and 17 (36.17%) out of total publications in this decade, i.e. 47 (100%), which put them in the first and second orders, respectively. The studies that utilise simulation methods come in the third place with total frequency of 6 (12.77%) out of 47 (100%).

For the decade starting in 2000, of 24 studies (100%), the highest number, 14 (58.33%), goes to the literature which applies fuzzy mathematical programming to APP. Stochastic

**Table 3** The number of publications on APP under uncertainty over time

| | 1970–1979 | 1980–1989 | 1990–1999 | 2000–2009 | 2010–2018 | Total |
|---|---|---|---|---|---|---|
| Fuzzy mathematical programming | | 1 | 3 | 14 | 20 | 38 |
| Stochastic mathematical programming | 2 | 2 | 7 | 6 | 17 | 34 |
| Simulation | 2 | 1 | 1 | 2 | 6 | 12 |
| Metaheuristics | | | 2 | 2 | 3 | 7 |
| Evidential reasoning | | | | | 1 | 1 |
| Total | 4 | 4 | 13 | 24 | 47 | 92 |

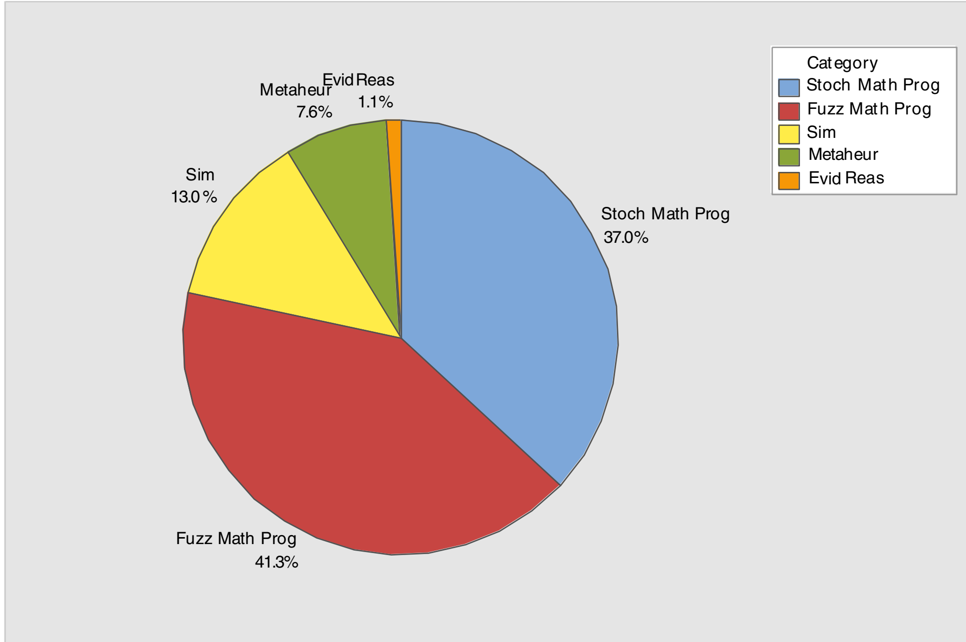


**Fig. 3** The share of each methodology from literature on APP under uncertainty

mathematical programming and both simulation and metaheuristic methods come in the second and third places with respective contributions of 6 (25%) and 2 (8.33%) out of 24 (100%).

In the time period 1990–1999, three of the highest frequencies of the studies about APP under uncertainty belong to stochastic mathematical programming, fuzzy mathematical programming and metaheuristics-based methodologies with corresponding frequencies of 7 (53.85%), 3 (23.08%) and 2 (15.38%) out of 13 (100%).

In terms of the total frequency of published literature on APP in presence of uncertainty with regard to the methodology applied, total number of the literature on fuzzy mathematical programming to APP for all decades, 38 (41.30%) out of 92 (100%), stays in the first place. The second and third levels of the frequencies, 34 (36.96%) and 12 (13.04%) out of 92 (100%), are represented by stochastic mathematical programming and simulation methods, respectively, which has been shown in Fig. 3.

The trend lines for the number of studies with respect to different methodologies they employ to study APP under uncertainty over a time period from 1974 to 2018 are presented in Table 4. If we suppose the trend line equation is $Y = a + bt$ where $t$ represents time in years, Table 4 shows the computed parameters of the trend lines.

The trend line for the time series on the number of publications about fuzzy mathematical programming models for APP in presence of uncertainty has the largest slope, i.e. 0.06568, which means the amount of this category of literature has had the highest rate of growth over time.

The regression line for the number of studies on stochastic mathematical programming to APP under uncertainty with the slope of 0.0434 shows the second steepest line during the last 44 years.

The trend lines for the frequencies of studies that apply simulation modelling and metaheuristics techniques to APP decision problem under uncertainty, with approximately equal slope 0.011, are less steep compared to those of fuzzy and stochastic mathematical programming which is indicator of relatively lower growth rate in the amount of literature in these areas.

### 3.3 Frequency of published research with regard to each sub-category of the methodologies

Table 5 shows the frequency of publications when each category of the management science methodologies for APP in presence of uncertainty are split into sub-categories. As it can be seen from the Table 5, under the fuzzy mathematical programming category, methodologies such as fuzzy multi-

**Table 4** Trend lines for different management science methodologies applied to APP under uncertainty

| Management science methodology | Parameters | |
|---|---|---|
| | $a$ | $b$ |
| Fuzzy mathematical programming | − 0.614 | 0.06568 |
| Stochastic mathematical programming | − 0.204 | 0.0434 |
| Metaheuristics | − 0.087 | 0.01092 |
| Simulation | 0.032 | 0.01071 |

**Table 5** The frequencies of studies regarding each sub-category of the methodologies applied to APP under uncertainty

| Methodology | Number of publications | Related references |
|---|---|---|
| Fuzzy mathematical programming | | |
| Fuzzy linear programming | 6 | Dai et al. [99], Liang et al. [56], Pathak and Sarkar [57], Omar et al. [58], Wang and Zheng [59], Iris and Cevikcan [60] |
| Fuzzy nonlinear programming | 4 | Tang et al. [100], Fung et al. [101], Chen and Huang [61], Chen and Sarker [62] |
| Fuzzy multi-objective optimisation | 11 | Lee [102], Gen et al. [103], Wang and Fang [104], Wang and Liang [105], Ghasemy Yaghin et al. [106], Gholamian et al. [48], Gholamian et al. [49], Sisca et al. [50], Fiasché et al. [51], Zaidan et al. [52], Chauhan et al. [53] |
| Fuzzy goal programming | 8 | Lin and Liang [107], Da Silva and Marins [136], Wang and Liang [108], Ertay [109], Tavakkoli-Moghaddam et al. [110], Jamalnia and Soukhakian [54], Mezghani et al. [111], Sadeghi et al. [55] |
| Fuzzy logic control | 1 | Ward et al. [67] |
| Approximate reasoning | 1 | Turksen and Zhong [66] |
| Fuzzy robust optimisation | 1 | Rahmani et al. [68] |
| Possibilistic linear programming | 4 | Wang and Liang [112], Liang [113], Sakallı et al. [64], Zhu et al. [65] |
| Possibilistic linear multi-objective optimisation | 2 | Hsieh and Wu [63], Liang [114] |
| Stochastic mathematical programming | | |
| Stochastic linear programming | 8 | Lockett and Muhlemann [147], Kleindorfer and Kunreuther [115], Günther [116], Thompson and Davis [117], Thompson et al. [118], Jain and Palekar [119], Leung et al. [69], Demirel et al. [70] |
| Stochastic multi-objective optimisation | 5 | Rakes et al. [120], Chen and Liao [71], Mezghani et al. [121], Jamalnia et al. [72], Jamalnia [73] |
| Robust optimisation | 8 | Leung and Wu [146], Kanyalkar and Adil [122], Mirzapour Al-e-hashem et al. [77], Mirzapour Al-e-hashem et al. [78], Niknamfar et al. [79], Modarres and Izadpanahi [80], Entezaminia et al. [123], Makui et al. [81] |
| Stochastic control | 3 | Love and Turner [124], Shen [125], Silva Filho [82] |
| Aggregate stochastic queueing | 2 | Hahn et al. [84], Hahn and Brandenburg [85] |
| Stochastic process | 2 | Silva Filho [126], Kogan and Portouga [83] |
| Simulation | | |
| Regular discrete-event simulation | 8 | Lee and Khumawala [127], McClain and Thomas [128], Lee et al. [129], Tang et al. [130], Tian et al. [86], Gansterer [87], Altendorfer et al. [88], Cebral-Fernández et al. [89] |
| Monte Carlo simulation | 1 | Khouja [90] |
| System dynamics | 3 | Dejonckheere et al. [131], Jamalnia and Feili [25], Mendoza et al. [91] |
| Metaheuristics | | |
| Genetic algorithms | 3 | Wang and Fang [132], Fichera et al. [92], Aliev et al. [93] |
| Tabu search | 2 | Baykasoğlu and Göçken [94], Baykasoglu and Gocken [95] |
| Harmony search algorithm | 1 | Aungkulanon et al. [97] |
| Particle swarm optimisation | 1 | Chakrabortty et al. [98] |
| Evidential reasoning | | |
| Belief-rule-based inference method | 1 | Li et al. [42] |

objective optimisation, fuzzy goal programming and fuzzy linear programming respectively represent the three highest numbers of studies: 11 (28.95%), 8 (21.05%) and 6 (15.79%) out of 38 (100%).

Of 34 publications about stochastic mathematical programming for APP, robust optimisation and stochastic linear programming techniques equally represent the highest share on the number of published research among others, i.e. 8

(23.53%). Stochastic nonlinear programming stays in the second order with total number of publications 6 (17.65%) out of 34 (100%).

Common discrete-event simulation as a subset of the simulation methodology in general has been utilised in research on APP in presence of uncertainty in 8 occasions (66.67%) out of 12 (100%), which is the greatest contribution among other simulation methods. System dynamics and Monte Carlo simulation with frequencies 3 (25%) and 1 (8.33%) out of 12 (100%) stay in the second and third places, respectively.

## 4 Operations management perspective on APP under uncertainty literature

### 4.1 Rolling horizon APP

Unlike fixed-horizon APP models, in rolling horizon APP models, the forecasted demand, planned production volumes, backordered orders and subcontracting quantity are updated constantly in each time period with regard to remaining time periods in the future. This is especially important regarding the fact that the forecasted market demand as the driving force in APP is not static and dynamically changes in each time period within the planning horizon. Dynamicity of market demand will automatically make the whole APP system dynamic as well.

Rolling horizon planning entails solving multiple and probably different optimisation problems within each planning period $t$, where these optimisation problems for each plan may have different initial conditions which in turn depend on the plan at period $t - 1$ [70].

Different measures can be incorporated into rolling horizon production planning models to reduce instability/nervousness that results from rolling horizon, mainly (1) quantifying nervousness in terms of cost and including it in objective function and (2) minimising oscillations in production volumes and the number of set-ups.

McClain and Thomas [128] evaluated the effect of different horizon lengths on their APP model performance. Kleindorfer and Kunreuther [115] studied APP problems with stochastic horizons and determined the optimal horizon lengths. However, none of these studies can be categorised as rolling horizon APP regarding the above-presented description of rolling horizon planning.

In general, very few published studies on rolling horizon APP exist in both uncertain and deterministic conditions.

Demirel et al. [70] created a rolling horizon-based APP model under flexibility requirements profile (FPR). In their mixed-integer linear programming formulation of APP under demand uncertainty, to avoid instabilities arising from rolling horizon, the FPR is, in fact, lower and upper bounds on planned productions. The parameters representing these bounds are called “flex-limits”. The overall results show that the proposed FPR framework has superior performance in terms of production stability compared to traditional APP models.

### 4.2 APP for reconfigurable manufacturing systems

Reconfigurable manufacturing systems (RMS) have been developed to respond to the requirements of manufacturing environments such as quicker response time/shorter lead time, increasing the product variants, lowering production volume and cost-effectiveness.

RMS are designed from the beginning for timely reaction to rapid change in structure, hardware and software components, so that quick adjustment of manufacturing capacity and functionality within a part family to respond the sudden changes in market requirements or business-related regulations becomes possible [133]. The purpose of RMS concept is to deal with the changes and uncertainties which are typical of modern manufacturing environments. This objective can be achievable by reconfiguration of hardware as well as software resources [134].

Only two published pieces of research have studied APP (whether deterministic or under uncertainty) from RMS viewpoint.

Jain and Palekar [119] considered APP problem in configuration-based manufacturing environment, in which machines and equipment’s lay-out can be re-arranged to form new production lines. Their APP model was implemented in a food processing company where the production processes are basically continuous, and products go through several production stages. At each stage, several machines are available, and creating new machine configurations to co-manufacture groups of products at various output rates is performed by combining these machines in different ways.

Sisca et al. [50] developed a fuzzy multi-objective APP model in a manufacturing environment of high mix, low volume products where Robotic Reconfigurable Assemble Units (RRAU) are integrated using different integration scenarios in a preexisting shop-floor. Each RRAU receives and storages raw materials, then processes the raw materials and finally storages the semi-finished products.

### 4.3 APP for process industries

In contrast to discrete manufacturing, process manufacturing is essentially continuous and uninterrupted. Examples of process industries include soft drink production, food processing and oil refinery. Due to the special features of process industries which may not allow keeping in process inventory and regarding the fact that unlike discrete manufacturing, process manufacturing is concerned with bulk of materials instead of individual units, ingredients rather than parts, formulas instead of bill of materials, production planning for process industries can be fundamentally different from that of discrete manufacturing.

Another important issue to consider in operations planning of process industries is that delays and breakdown of machines, which could stop the production process, can easily increase the amount of perished products and materials.

Among the reviewed literature, only Jain and Palekar [119] and Hahn and Brandenburg [85] have considered APP in process industries.

Jain and Palekar [119] applied stochastic linear programming method to study APP with resource limitation considerations in continuous food producing company, where keeping in-process inventories cannot be allowed due to cost considerations or shorter lifetime of the intermediate products. Additionally, the production process in their study is reconfigurable by re-arranging the machines and equipment.

Hahn and Brandenburg [85] developed a sustainable APP decision model for chemical process industry by applying stochastic queuing networks. In their model, work in progress (WIP) inventory may be allowed. Since chemical production processes normally operate in campaign mode, i.e. required production resources are assigned to the sequential production of batches of the same type for days or even weeks, by campaign planning their APP model is concerned with anticipating the impact of decisions related to production mix, production volume and production routing on campaign lead times and work in process inventories in stochastic manufacturing environment. Their model also tries to minimise carbon emissions and negative social impacts due to varying operating rates.

### 4.4 APP under uncertainty with sustainability considerations

Recently, literature on APP under uncertainty has started incorporating newer trends in operations management such as green supply chain management, energy saving and sustainability in general in APP models in order to optimise carbon emission, greenhouse gas emissions, energy consumption and overtime working hours.

This category of literature which can be classified as sustainability-related literature on APP under uncertainty includes Hahn and Brandenburg [85], Entezaminia et al. [123], Modarres and Izadpanahi [80] and Mirzapour Al-e-hashem et al. [75].

Practical requirements of the contemporary operations management which stems from stakeholders and government pressures and environmental and social activists' expectations necessitates taking into account the abovementioned sustainability-related factors in the developed APP decision models.

### 4.5 Literature with respect to the applied APP strategy

Table 6 presents the number of the published studies on APP under uncertainty with respect to different APP strategies, i.e. mixed chase and level, pure chase, pure level, modified chase, modified level and demand management strategies. As Table 6 shows, 100% of the surveyed literature applies the mixed chase and level strategy, i.e. 92 out of 92. Modified chase and modified level strategies with equal frequencies of 4 (4.35%) out of 92 (100%) and pure chase and pure level strategies with equal frequencies of 3 (3.26%) out of 92 (100%) come in the second and third orders respectively. The demand management strategy with total frequency of 1 (1.09%) out of 92 (100%) stays in last place. However, studies performed by Thompson et al. [118], Chen and Liao [71], Jamalnia and Feili [25] and Jamalnia [73] compared various APP policies in the presence of uncertainty and found out that the chase strategies family are the most effective strategies or are among the most effective strategies.

**Table 6** Comparing the research on APP in presence of uncertainty with respect to the utilised APP strategy

| | Mixed chase and level strategy | Pure chase strategy | Pure level strategy | Modified chase strategy | Modified level strategy | Demand management strategy |
|---|---|---|---|---|---|---|
| Stochastic mathematical programming | 34 | 1 | 1 | 3 | 3 | 0 |
| Fuzzy mathematical programming | 38 | 0 | 0 | 0 | 0 | 0 |
| Simulation | 12 | 2 | 2 | 1 | 1 | 1 |
| Metaheuristics | 7 | 0 | 0 | 0 | 0 | 0 |
| Evidential reasoning | 1 | 0 | 0 | 0 | 0 | 0 |
| Total | 92 | 3 | 3 | 4 | 4 | 1 |

### 4.6 Type of industries in which APP models under uncertainty have been applied more frequently

Table 7 shows the types of industries in which APP models under uncertainty have been applied in existing literature. Please note that some literature has used hypothetical numerical examples or has not stated the type of industry from which it has collected the data for APP model implementation. So, Table 7 only indicates the types of industries for the literature which has provided the relevant information.

As it can be seen from Table 7, three industries have been used most frequently as case studies by literature about APP under uncertainty. These industries in terms of frequency of application by literature on APP under uncertainty are machinery and machine parts manufacturing, food and drink industry and paint products with respective frequencies 11 (22%), 10 (20%) and 6 (12%) out of 50 (100%).

The paint products and wood and paper Industries have been taken as case studies from the research conducted by Holt et al. [2] and Mirzapour Al-e-hashem et al. [77], respectively, by subsequent researchers.

As it was already stated in Subsection 3.1, the uncertainty is mostly present in product demand in APP models in presence of uncertainty. Unsurprisingly, the market demand for products in abovementioned industries is normally highly variable. The market demand for machines including industrial manufacturing machines, cars and aero-engines and consequently the demand for their components could easily fluctuate due to economic growth, recessions, political instabilities, change in customers' preferences, fierce competitions in market and so on, which makes this industry a suitable case for implementing APP models under uncertainty.

Demand for food and drink products is also highly variable because of reasons which can range from seasonal factors to population growth/decline, change in consumption patterns and change in society's age construction. Similar to machines and machine parts industry, the high variability in food and drink products' demand makes it a suitable case study for APP in presence of uncertainty.

Customer demand for paint products, whether decorative or industrial paints, can oscillate as result of the rate of urbanisation and pace of development of the realty, automobile and infrastructure that in turn makes the demand volume uncertain and hardly predictable. Therefore, it is not a surprise that paint industry has been a favourite source of operational data for the literature on APP under uncertainty.

## 5 Conclusions and future research directions

In this research, a wide scope of literature on APP under uncertainty was analysed. This literature includes journal papers, book chapters, conference/proceedings papers and PhD theses which were classified into five main categories on the basis of the methodologies applied, such as stochastic mathematical programming and fuzzy mathematical programming. The uncertainties present in the constructed management science models are of sorts like stochasticity, fuzziness, impreciseness of the information and so on. First, the preliminary analysis of the literature regarding the classification schemes according to the abovementioned methodologies together with advantages and disadvantages of these methodologies were presented, and then recent literature was concisely reviewed. Finally, more detailed analysis of the surveyed literature from management science and operations management perspectives was followed.

Total numbers of studies which apply fuzzy mathematical programming and stochastic mathematical programming to APP in the presence of uncertainty come in the first and second places, respectively. The trend lines for the frequency of studies on fuzzy mathematical programming and stochastic mathematical programming to APP under uncertainty show the highest slopes. Very few published studies exist, whether in uncertain or deterministic modes, on APP for RMS, process industries and rolling horizon condition, sustainable APP and APP strategies other than the mixed chase and level strategy, which is indicator of sensible research gaps in these areas.

Possible future research directions according to in-depth literature survey in present study are recommended as follows:

- Forecasted market demand plays a central role in APP process. APP in practice is medium-range decision-making which normally covers a time horizon between 3 to 18 months. Thus, the rather long planning horizon can mean less accurate forecasting of the demand in the beginning of planning horizon. The diminished accuracy of demand forecast could lead to lost orders due to stock-out or over-stoking in case of overestimating the demand. In either cases, underestimating or overestimating the demand, the company will incur the relevant costs. Rolling horizon APP includes the possibility of updating/revising the demand in each time period and therefore modifying the errors in demand forecast.

  As it was already discussed in Subsection 4.1, very few published research on rolling horizon APP in both uncertain and deterministic conditions exists. More research on rolling horizon APP is needed to correct the above-described deficiency in APP models.
- Nowadays, manufacturing companies are concerned with rapid response to change in market demand and customer requirements to remain competitive. A company needs to be responsive to be able to meet changing market expectations by developing new products.

  By enhancing responsiveness for manufacturing systems, re-configurability facilitates quickly launching new

**Table 7** Type of industries considered in literature on APP under uncertainty

| Industry | The related published research | The relevant industry category | Frequency |
|---|---|---|---|
| Shipbuilding | Cebral-Fernández et al. [89] | Machinery and machine parts manufacturing | 1 |
| Vegetable production | Pang and Ning [135] | Food and drink industry | 1 |
| Home appliance | Jamalnia and Feili [25], Sadeghi et al. [55] | Appliances | 2 |
| General appliance | Aliev et al. [93], Niknamfar et al. [79] | Appliances | 2 |
| Paint company | Love and Turner [124], Shen [125], Li et al. [42], Hsieh and Wu [63], Turksen and Zhong [66], Dejonckheere et al. [131] | Paint products | 6 |
| Wood and Paper Industries | Mirzapour Al-e-hashem et al. [77], Mirzapour Al-e-hashem et al. [75], Gholamian et al. [48], Gholamian et al. [49], Entezaminia et al. [123] | Wood and paper industries | 5 |
| Precision machinery and transmission components | Wang and Liang [108], Wang and Liang [112], Liang [113], Liang et al. [56], Liang [114] | Machinery and machine parts manufacturing | 5 |
| Chemical process industry | Hahn and Brandenburg [85] | Chemical industry | 1 |
| Soft drink industry | Jamalnia et al. [72], Jamalnia [73] | Food and drink industry | 2 |
| Food products | Jain and Palekar [119], Kogan and Portouga [83], Ning et al. [74] | Food and drink industry | 3 |
| Garments | Chakrabortty et al. [98] | Garments | 1 |
| Vegetable oils | Zaidan et al. [52] | Food and drink industry | 1 |
| Chemical industry | Wang and Fang [132] | Chemical industry | 1 |
| Refrigerator manufacturing | Jamalnia and Soukhakian [54] | Appliances | 1 |
| Automotive supplier | Gansterer [87], Demirel et al. [70] | Machinery and machine parts manufacturing | 2 |
| Consumer goods | Kanyalkar and Adil [122] | General consumer goods | 1 |
| Oil production | Wang and Zheng [59] | Chemical industry | 1 |
| Lingerie production | Leung et al. [69] | Garments | 1 |
| Beer production | Lee and Khumawala [127] | Food and drink industry | 1 |
| Brass casting industry | Sakallı et al. [64] | Metallic, non-metallic and useful substances | 1 |
| Bolt, screw and nut production | Hahn et al. [84] | Machinery and machine parts manufacturing | 1 |
| Batch plant (asphalt production) | Tian et al. [86] | Asphalt production | 1 |
| Sugar mill | Da Silva and Silva Marins [136] | Food and drink industry | 1 |
| Aero-engine production | Tang et al. [130] | Machinery and machine parts manufacturing | 1 |
| Gear manufacturer company | Chauhan et al. [53] | Machinery and machine parts manufacturing | 1 |
| Mosquito expellant production | Chen and Sarker [62] | General consumer goods | 1 |
| Resin manufacturing | Omar et al. [58] | Food and drink industry | 1 |
| Smelting manufacturer | Modarres and Izadpanahi [80] | Metallic, non-metallic and useful substances | 1 |
| Calendar producing | Makui et al. [81] | General consumer goods | 1 |
| Cement production | Love and Turner [124] | Metallic, non-metallic and useful substances | 1 |
| Textile | Demirel et al. [70] | Garments | 1 |

Frequencies

| Appliances | Paint products | Wood and paper industries | Machinery and machine parts manufacturing | Metallic, non-metallic and useful substances | Food and drink industry | Garments | General consumer goods | Chemical industry | Asphalt production |
|---|---|---|---|---|---|---|---|---|---|
| 5 | 6 | 5 | 11 | 3 | 10 | 3 | 3 | 3 | 1 |

products on existing production facilities and reacting rapidly and cost-effectively to changes in marketplace and product specifications and system failures [137].

As very few published studies have considered APP for RMS, research on APP under uncertainty regarding the re-configurability of modern manufacturing systems would be interesting since the re-configurability can significantly reduce the negative effects caused by unstable business environments.

- Process industries such as oil refineries, beverage manufacturing and chemical processes which operate continuous, uninterrupted production processes, constitute a major part of industries. Because of especial features of process industries, e.g. stocking work in process inventory may not be allowed, and delays and stoppage in production process can easily lead to perished products/raw materials, these industries need their own type of production planning and control. Production planning of process industries can be specifically challenging when it is done using discrete-event simulation methods to simulate shop-floor activities due to continuity of the manufacturing process activities. However, each of the abovementioned challenges can open up a new future research path with regard to the fact that very few researches have considered APP, whether deterministic or under uncertainty, for process industries.
- In Subsection 4.4, the incorporation of sustainability-related issues in APP models in presence of uncertainty was discussed. This new path can be further extended by taking into account the circular economy principles in APP models, where instead of "take, make and dispose" mentality, the products and materials are recovered and regenerated when they reach the end of their service life.
- As it was already shown in Table 6, the absolutely prevalent APP strategy in the literature about APP in presence of uncertainty (and even in the literature on deterministic APP models) is the mixed chase and level strategy. However, the surveys conducted by Buxey [138–140] revealed that the most popular APP policy among operations managers is the chase strategy, which shows a gap between APP in academia and APP in practice. This also indicates an intense gap related to the lack of the studies about quantitative APP models under uncertainty based on other APP strategies such as chase strategy, level strategy and the demand management strategy.
- Several relative advantages of the simulation techniques over mathematical programming methods, e.g. coping with dynamic or transient effects, addressing interactions between different components of a system and the ability of providing a sufficient basis for developing explanatory and predictive models of operational processes, have been stated in the literature. Therefore, the relatively low share of the literature which apply simulation modelling to study APP subject to uncertainty (13.04%) and the least steep trend line of the frequency of the number of published research in this area over recent decades recommend the need to do extra research in this field to compensate the unfairly narrow share of the simulation methods.

  More specifically, even a single piece of research has not yet been published on agent-based simulation (ABS) to APP, whether in deterministic or uncertain manner. Nevertheless, ABS has been successfully applied to related areas such as production planning and control [141], advanced supply chain planning and scheduling [142] and inventory-production-transportation modelling [143]. In a supply chain context, APP involves different agents including focal firm, suppliers, customers and workforce market. In company-wide level, APP involves different units, such as operations management, human resource management, marketing management and purchasing and procurement departments, as agents. In both cases, these agents interact with each other via interrelationships. This feature makes ABS an effective tool in modelling and simulation of APP under uncertainty, e.g. with uncertain seasonal demand pattern. ABS has efficiently been utilised to production planning of both push and pull production systems, a feature that can be considered in future studies on APP in both uncertain and deterministic modes.
- APP in practical settings entails multiple objectivity and is of large-scale and combinatorial nature. In addition, factors such as quadratic cost functions, stepwise product price functions and learning curve effect in APP problems can make APP models nonlinear as well. Moreover, decision variables in APP problems can be integer. All this can make dealing with APP models computationally challenging in practice. Researchers may adopt decomposition methods or model the APP problem in such a way that the number of variables and constraints is reduced.

  Another efficient method to deal with these computationally challenging APP models is to recourse to metaheuristics. Different metaheuristics like PSO, GA, HS algorithm and TS have been applied by literature on APP under uncertainty to solve combinatorial APP problems. The advantages and disadvantages of these metaheuristic approaches were discussed in Subsection 2.1. However, despite the proven strengths of ant colony optimisation (ACO) such as providing positive feedback which helps quicker solution finding, and having distributed computation which avoids premature convergence [144], this well-established metaheuristic method has not yet been applied to handle APP models in presence of uncertainty. Applying the ACO to deal with computationally hard APP problem under uncertainty can be a future research path.
- Only a single journal paper has been published on evidential reasoning (ER) to APP in both uncertain and

deterministic manners. ER method can conjunctively combine multiple pieces of independent evidence with weights and reliabilities [47]. Regarding the capabilities of the ER in handling the uncertainty, this could act as a foundation stone to drive more research in this area.

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