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A Systematic Literature Review of Aggregate Production Planning (APP): Social and Economic Perspectives

Wan Yee Leong[1], Kuan Yew Wong[1*], Ali Anjomshoae[2]

[1]*Faculty of Mechanical Engineering, Universiti Teknologi Malaysia (Malaysia)*
[2]*Transportation Institute, Chulalongkorn University (Thailand)*

wyleong4@graduate.utm.my
[*]*Corresponding author: m-wongky@utm.my*
ali.an@chula.ac.th

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Abstract:

Purpose: The intricate interplay between economic dynamism and social cohesion is essential for holistic advancement and enduring societal welfare. This systematic review aims to critically evaluate APP literature with a focus on social and economic aspects. Previous APP studies have primarily focused only on the economic aspects, often overlooking the social aspects, leading to poor social performance and profit drop.

Design/methodology/approach: We reviewed the most recent APP papers published in the last 13 years from 2010 to 2023 and systematically classified them based on model type, solution approach, objective function, and social and economic parameters involved in the studies.

Findings: The outcome shows that most of the previous studies applied mixed-integer linear programming (MILP) methods in developing the APP models while stochastic and fuzzy methods are the most common approaches to deal with uncertainties. Among all the APP studies, only about one-fifth of them focused on both the economic and social aspects. Specifically, 21 cost parameters and 4 social parameters have been identified from the previous APP studies. The most common cost parameter is inventory cost while customer satisfaction level is the most prevalent social parameter.

Research limitations/implications: This article bridges the gap between economic and social considerations, offering a holistic approach to production management. It highlights the broader implications of APP by demonstrating economic benefits, alongside the social impacts.

Originality/value: This article presents a comprehensive review of APP studies from social and economic aspects. It provides insights into the application of social and economic parameters in APP and motivates more research interest or attention to address the social aspects of APP.

Keywords: systematic review, aggregate production planning, social, economic, production management, supply chain

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1. Introduction

Production planning is one of the key pillars of production management. It plays a vital role in a supply chain which is characterized by rapid changes in market demand, increase in product variety, decrease in product life cycle, and decrease in delivery time. Among the operational, tactical, and strategic planning, tactical planning serves as a crucial function in transforming demand forecasts into an achievable medium-term plan. Aggregate Production Planning (APP) is a type of tactical planning that has a time frame of 3 to 18 months, and its function is to determine the optimum production level for each planning period with the consideration of different production factors (Khalili & Alinezhad, 2021). APP strategies include changing the inventory level (Martínez-Costa, Mas-Machuca & García, 2013), varying the workforce size through hiring and firing of workers (Wang & Fang, 2001), varying the production rates through overtime and work shifts of employees (Demirel, Özelkan & Lim, 2018), subcontracting and applying part-time workers (Heizer, Render & Munson, 2017).

The APP problem representation is through mathematical modeling which provides approximate solutions for macro planning at the firm level (Nahmias & Cheng, 2009). Based on the literature, some systematic reviews of APP were found. (Aydin & Tirkolaee, 2022; Cheraghalikhani, Khoshalhan & Mokhtari, 2019). Several studies considered green production planning approaches, and those related studies were reviewed (Qasim, Wong & Saufi, 2023). On the other hand, APP was exclusively examined from the perspective of fuzzy mathematical programming in dealing with uncertainties (Qasim, Wong & Komarudin, 2024). However, to the best of our knowledge, there is a lack of comprehensive literature that reviews the APP studies, especially from the social and economic aspects. A review focusing on both of these dimensions provides a comprehensive understanding of the complex interactions and interdependencies that shape successful production planning. Thus, the study intends to fill this gap by reviewing the medium-term production planning approaches from economic and social perspectives with a classification scheme to provide future research directions to researchers and managers.

The following questions are the focus of the study:

RQ1: What are the mathematical model representation methods and solution approaches used to solve the previous APP problems?

RQ2: What are the objective functions that have been applied previously in APP?

RQ3: What are the parameters applied in the previous APP problems?

Knowing previous APP modeling methods, solution approaches and objective functions helps researchers and practitioners to build on existing knowledge related to APP. It raises awareness of the long-term impact of social and economic aspects in APP and promotes a general understanding of integrating both the economic and social parameters in APP models. Besides, insights into social and economic APP can be revealed and at the same time, this provides an opportunity to address identified shortcomings. This paper is further organized as follows. The APP backgrounds and concepts are presented in Section 2. Then, Section 3 explains the methodology, while distributions of reviewed papers are illustrated in Section 4, followed by the classification of APP studies and the review of previous APP studies in Section 5, results and discussion in Section 6, future research directions in Section 7, and lastly implications and conclusions in Section 8.

2. Backgrounds and Concepts

APP deals with planning and controlling different production management features. It includes production rates, capacity utilization levels, inventory levels, workforce levels, and outsourcing over a medium-term, multiple-period planning horizon. To achieve effective APP planning and controlling, various production activities related to inventory levels, machinery capacity, and workforce levels must be addressed to minimize the total costs while making the best resource utilization. Moreover, various methods and strategies are expected to be utilized in addressing demand fluctuation and its related costs (Jamalnia, Yang, Feili, Xu & Jamali, 2019). With this, APP is complex as it needs to coordinate the interacting variables to meet the demand and supply more effectively (Noegraheni & Nuradli, 2016).

APP is characterized by uncertainty based on a target industry's specifications (Aydin & Tirkolaee, 2022). The data such as customer demands, resources, and costs are inherently imprecise (Wang & Liang, 2004). In business practices, there are usually uncertainties in product demands and variables such as customer preferences, production capacity, and unstable labor market conditions (Goli, Tirkolaee, Malmir, Bian & Sangaiah, 2019; Zhu, Hui, Zhang & He, 2018). Besides, the increase in backorders and the uncertainty of raw material supplies can cause customer complaints and affect customers' satisfaction levels (Jamalnia et al., 2019; Demirkan & Durmuşoğlu, 2020). A highly unpredictable demand leads to frequent revisions of APP between each planning cycle (Jamalnia et al., 2019; Cheraghalikhani, Khoshalhan & Mokhtari, 2019). This induces instability within the production environment and may result in profit loss due to its adverse effects on labor and supply levels (Wang & Fang, 2001; Demirel, Özelkan & Lim, 2018).

APP extends beyond merely maximizing a company's performance. It also aims to achieve broader objectives such as minimizing production changes, permanent workforce size variation, and outsourcing while maximizing resource utilization. Therefore, it becomes imperative to have a well-defined objective function in an APP model (Attia, Megahed, AlArjani, Elbetar & Duquenn, 2022). A clear objective function ensures the alignment of APP with the specific goals and priorities of the organization, enabling more targeted and effective decision-making. Chen and Liao (2003) suggested that employing multiple objectives can represent a more realistic model. Generally, APP models focus on minimizing the total production costs such as costs of regular production, inventory, backordering, and outsourcing. In APP, the focus can be on profit maximization (Pradenas & Peñailillo, 2004), cost minimization (Zhang, Zhang, Xiao & Kaku, 2012), or a combination of multiple objectives (Leung & Chan, 2009; Nobari, Khierkhah & Hajipour, 2017). To avoid several kinds of human-centric issues, today's industries have put efforts into incorporating not only economic but also social aspects in APP.

Economic considerations, such as cost-effectiveness, profitability, and resource allocation, are central to production planning decisions and directly impact the financial health of organizations (Jamali, Faghih, Fathi & Rostami, 2023). Similarly, social factors, including labor practices, workplace conditions, and community engagement, are critical for ensuring ethical business conduct and fostering positive relationships with stakeholders. Financial success is assumed to be consistent with ethical and societal compliance (Baines, Brown, Benedettini & Ball, 2012). In advocating for the integration of social and economic aspects over environmental considerations in APP, it is essential to highlight the immediate and tangible benefits to both businesses and communities. By prioritizing social factors such as employee well-being, job security, and community engagement, companies can promote a positive work environment, enhance employee morale, and strengthen relationships with stakeholders (Rajabpour, Fathi & Torabi, 2022).

Additionally, focusing on economic aspects like cost-effectiveness, profitability, and market demand ensures business sustainability and growth, which in turn supports job creation and economic prosperity. Integrating social and economic perspectives ensures that production plans align with ethical standards, legal regulations, and societal expectations. Ignoring these dimensions not only limits the comprehensiveness of the review but also fails to address the broader implications of APP on society, equity, and long-term business success. However, most of the previous APP studies have focused on only the economic aspects of APP (Tirkolaee, Aydin & Mahdavi, 2023; Attia et al., 2022). There is a need for future research to address this limitation by incorporating social and economic parameters that shape the successful development of APP.

Several mathematical models that addressed APP problems with varying representation methods, solution approaches, and objective functions have been proposed in the last decades (Baykasoglu, 2001; Baykasoglu & Göçken, 2006; Mirzapour Al-e-Hashem, Baboli, Sadjadi & Aryanezhad, 2011; Gholamian, Mahdavi, Tavakkoli-Moghaddam & Mahdavi-Amiri, 2015). A theoretical or actual system is represented by mathematical models with various variables, equations, and inequalities, which are then solved analytically to study the effect of different APP components (Giordano, Fox & Horton, 2013). The mathematical models are either linear, nonlinear, stochastic, fuzzy, robust, or a combination of them, while there are several solution approaches applied to solve the models. Previous researchers have reviewed and analyzed various APP studies. However, those reviews lack a critical examination of the economic and social dimensions. By neglecting these dimensions, they overlook significant implications for stakeholders, including employees and communities at large (Aydin & Tirkolaee, 2022;

Qasim et al., 2023). Therefore, a more holistic perspective that encompasses economic and social issues is provided to have a comprehensive understanding of social and economic APP.

3. Research Methodology

This study utilized a Systematic Literature Review (SLR) of peer-reviewed scholarly articles published between 2010 and 2023, which are related to the topic of 'Aggregate Production Planning (APP)' that incorporates the economic and social aspects. The SLR process involves the research identification, selection, and critical assessment to address the research questions. In this study, the methodology follows the general principles, as proposed by Seuring, Yawar, Land, Khalid and Sauer (2020), Durach, Kembro and Wieland (2021), Khan, Parikh and Qureshi (2022) and Dhingra, Keswani, Sama & Qureshi (2024).

Figure 1 illustrates the SLR process of the study while Figure 2 shows the sampling process from databases.

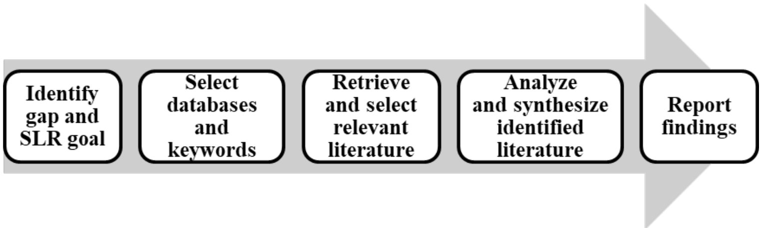

Figure 1. The flowchart of SLR

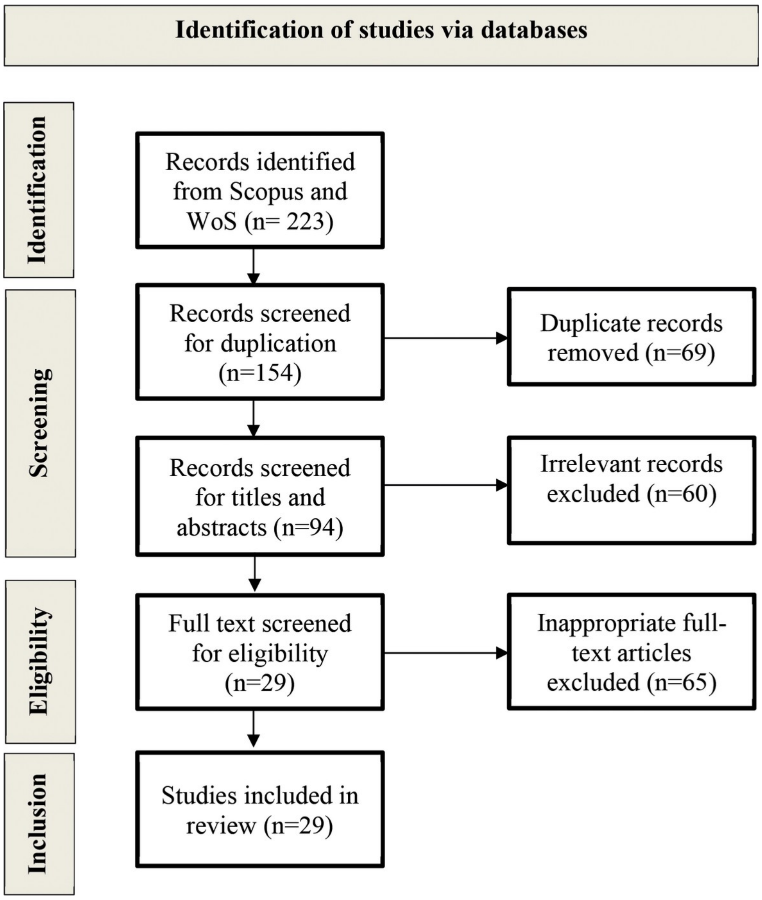

Figure 2. Databases sampling process

The SLR methodology steps to identify seminal work and extract the literature trends are explained in the following subsections.

3.1. Phase 1: Identify Gap and SLR Goal

Firstly, the research gap and SLR goal were identified. In addition, the research questions were developed to provide a clear focus for the study, thereby preventing results vagueness. In this study, the research questions were: 'What are the mathematical model representation methods and solution approaches used to solve the previous APP problems?' 'What are the objective functions that have been applied previously in APP?', and 'What are the parameters applied in the previous APP problems?'.

3.2. Phase 2: Select Databases and Keywords for Identifying Relevant Literature

The databases selected in this study were Scopus and Web of Science (WoS) due to a higher impact factor. To identify relevant papers, a combination of several keywords using Boolean operators (AND, OR) was applied to query the title, abstract, and keyword field. The keywords that were used as search terms include 'Aggregate Production Planning AND Socio-economic OR Social OR Economic'. These keywords were chosen because they were specific enough to return only articles related to the topic of either social, economic, or socio-economic APP from the search engines. This was to avoid generating articles that were out of the research scope.

3.3. Phase 3: Retrieve and Select Relevant Literature

With the keywords identified, a literature search of published articles was conducted by searching journal papers indexed in Scopus and WoS. The selection criterion of articles is that the research must have been published between 2010 and 2023 because this review is concerned with only the most recent economic and social APP studies within the 13 years. This is because there was still a lack of attention on social and economic APP studies before 2010. From the search, 223 papers were identified from the databases. By eliminating duplicate entries, the selection was narrowed down to 154 papers. Next, a preliminary assessment was conducted, and 60 papers were excluded based on titles and abstracts. Lastly, the full text of the remaining articles was analyzed, and 65 papers were excluded due to an unclear focus on social and economic APP. The final sample consisted of 29 studies published between 2010 and 2023. The year 2010 was selected as the starting year as 2010 is a year gap from Industrial Revolution (IR) 4.0 where a paradigm shift in manufacturing through decentralization and automation has been initiated (Krishnan, Khan & Alqurni, 2022), leading to job displacement, thus causing a rise in social issues which affected the economic aspects in APP. Since then, social aspects have been introduced in APP. With this, the related studies were reviewed.

3.4. Phase 4: Analyze and Synthesize Identified Literature

Next, the literature development trend was described through the distribution findings by applying frequency analyses of the selected articles according to year, journal, and country. The identified papers were then categorized according to different model representation methods, solution approaches, as well as the social and cost parameters involved in the studies. The analysis broke down specific studies into individual parts, describing how these parts relate to each other, while synthesis was aimed at finding associations between different selected studies. In particular, each article was studied in detail according to the research questions which were related to the mathematical modeling methods, solution approaches, objective functions, and parameters. Then, the key points from all the papers were compiled and analyzed to form a comprehensive review of APP from economic and social perspectives. Finally, the contents and contexts of each paper were analyzed through an inductive process to identify the main findings of each paper.

3.5. Phase 5: Report Findings and Future Research Directions

The final stage of the SLR process was the reporting of findings. The results were presented in the form of statistics, graphs, tables, and written discussions. This stage also discussed the overall SLR outcomes, research gaps, and future research directions.

4. Distributions of Reviewed Papers

4.1. Distribution over Time

The identified papers were 29 articles published between 2010 and 2023, as shown in Figure 3. In 2010, there was an APP study conducted by Baykasoglu and Gocken (2010). More recently, there were more contributions to this field of study (Tirkolaee et al., 2023; Al-Mohamed, Al-Mohamed & Ahmed, 2023). The development trend chart shows a constant growth in the number of papers from 2010 to 2012, however, there was no study conducted in the following year, 2013. The number of papers reached its peak in 2014, but it decreased in 2015, and there was a big drop to zero study conducted in 2016. From years 2017 to 2019, the number of papers remained constant. It rose in 2020 and remained constant again in the following year. Lastly, the number declined and showed a constant trend in 2022 and 2023.

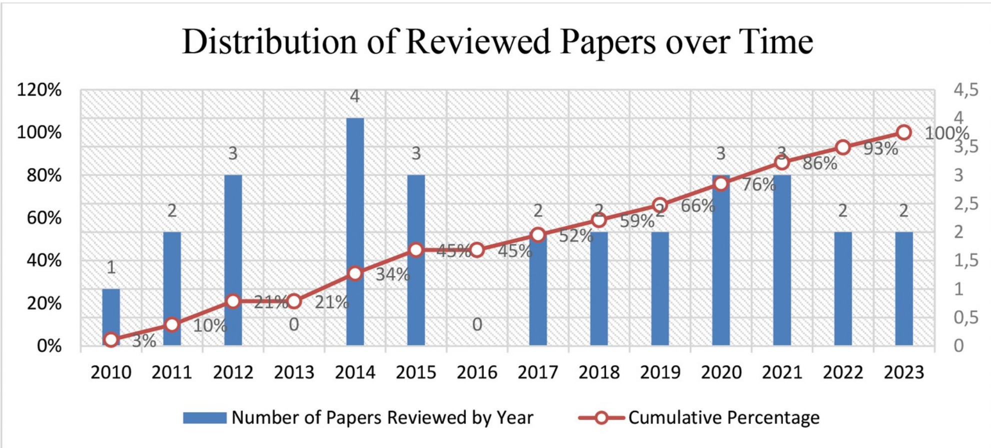

Figure 3. Distribution of reviewed papers over time

4.2. Distribution by Journal and Country

The journals that published APP studies are listed in Table 1. Computers and Industrial Engineering published most of the selected articles, followed by the International Journal of Advanced Manufacturing Technology, Computers and Operations Research, Expert Systems with Applications, Journal of Optimization in Industrial Engineering and Mathematical Problems in Engineering with more than one paper published.

Journal	Number of Papers Published
Computers and Industrial Engineering	4
International Journal of Advanced Manufacturing Technology	3
Computers and Operations Research	2
Expert Systems with Applications	2
Journal of Optimization in Industrial Engineering	2
Mathematical Problems in Engineering	2

Table 1. Number of papers per journal (n>1)

The selected papers were written by authors from various countries. Table 2 shows the geographic distribution of the corresponding authors, with Iran dominating the list. While the bulk of research appears to be concentrated in certain countries, there is still a diverse global interest in APP as evidenced by the studies from different countries across different continents including Latin America, Europe, Africa, and Asia.

Country	Number of Papers Published
Iran	11
Turkey	3
Indonesia	2
Algeria	1
Australia	1
Brazil	1
China	1
Germany	1
Malaysia	1
Mexico	1
Saudi Arabia	1
South Korea	1
Syria	1
Taiwan	1
Thailand	1
UK	1

Table 2. Number of papers published by authors per country.

5. Classifications of APP Studies

The following subsection describes the classifications of the previous APP models based on the model representation methods, solution approaches, objective functions, and both the social and economic parameters.

5.1. Classification by Mathematical Modeling or Representation Methods

One of the ways to classify the APP models is by the model representation methods. By this, the classification of mathematical models is either deterministic or non-deterministic. Deterministic models are models with unique parameter values where the same optimum solution is always generated for a given set of initial conditions. In contrast, non-deterministic models incorporate randomness and uncertainties in the values of parameters, where better parameter space sampling depends on retrials in obtaining the optimum solution (Dutta, 2016).

5.1.1. Deterministic Models

Deterministic models always generate the same optimum solution for a given set of initial conditions. In this research context, deterministic models are categorized into linear programming (LP) models and non-linear programming (NLP) models. According to Dutta (2016), LP models utilize a linear objective function as well as linear constraints. Certain LP models with some integer variables are named mixed-integer linear programming (MILP) models. On the other hand, NLP models utilize a non-linear objective function and/or non-linear constraints, while mixed-integer non-linear programming (MINLP) models are NLP models with the added restriction where some of its variables are integers.

5.1.2. Non-Deterministic Models

Nowadays, production environments are unstable, and deterministic APP models hardly fit these uncertain environments. To deal with this, APP models need to be built with the consideration of uncertainties such as parameters and constraints randomness which are quite common to be found in real-world production planning and control activities. In this context, non-deterministic models include stochastic, fuzzy as well as robust models and they are explained in the next subsection.

5.1.2.1. Stochastics Models

Stochastic models refer to the mathematical models that represent randomness and uncertainty with a random variation in one or more inputs over time (Dutta 2016). To deal with randomness, stochastic mathematical programming is applied. Previously, this method has been proposed by some researchers for solving multi-product, multi-period APP by applying stochastic LP or NLP, stochastic control as well as aggregate stochastic queuing, and stochastic processes, where product demands, constraint quantity values, and models' coefficients are of stochastic or random nature (Lieckens & Vandaele, 2014; Jamalnia, Yang, Xu & Feili, 2017; Demirel et al., 2018). Besides, this stochastic group also includes probabilistic constraints or chance-constrained models (Jamalnia, Yang, Xu, Feili & Jamali, 2019).

5.1.2.2. Fuzzy Models

Fuzzy models or fuzzy sets represent vagueness and imprecise information. These models can recognize, represent, manipulate, interpret, and utilize uncertain data and information. Fuzziness is equivalent to not having been clearly defined and having ill-defined boundaries. Normally, this exists when there are human judgments with linguistic variables. In the context of APP, fuzzy set theory has a significant place (Tang, Wang & Fung, 2000; Narasimhan, 1980). The uncertainties are presented in a fuzzy form, which involves market demands, objectives or goal values, coefficients, and constraints of the APP models. Fuzzy set theory can effectively handle such uncertainties, and it has been applied widely in solving APP problems (Mezghani, Loukil & Aouni, 2012; Zhu et al., 2018). The most common mathematical programming models in a fuzzy environment are fuzzy multi-objective, fuzzy LP, and fuzzy NLP models (Jamalnia, Yang, Xu et al., 2019).

5.1.2.3. Robust Models

Since the late 1990s, the robust method has been one of the most popular approaches to dealing with uncertainty optimization and control. In robust optimization, the uncertain parameters are described by discrete scenarios or a continuous range (Ahmed & Sahinidis, 1998). Subjectivity is usually present in the estimated scenario probabilities, or they are modified by business managers based on their experience of specific events. A robust model involves several scenarios to solve the APP problems from different views and perspectives. The model has two kinds of variables where one group of variables is independent of scenarios, and scenarios impact another group.

5.2. Classification by Solution Approaches

APP models can be solved by applying several solution approaches. One of the methods to solve the models is the exact method such as simplex and branch and bound while another approach is the software solvers including IBM ILOG CPLEX, GAMS, and LINGO. Other than that, there are certain very complicated APP problems with no guarantee of obtaining the optimum solution that can be solved by applying heuristics and metaheuristics. Heuristic is implemented with local search while metaheuristic is based on population or random search. Metaheuristics is an approach that does not rely on the type of problem. It is always used for a problem where an algorithm for solving it can be translated into one for solving any nondeterministic polynomial (NP) problem where the ordinary optimization methods could get trapped in local optima and the computation time could get unreasonably long. The most common metaheuristic methods for solving APP problems are Genetic Algorithm (GA), Tabu Search (TS), Harmony Search (HS), and Particle Swarm Optimization (PSO) (Fichera, La-Spada, Perrone & La-Commare,1999; Baykasoğlu & Göçken, 2006).

5.3. Classification by Objective Functions

Another way to classify an APP mathematical model is by its objective functions. An APP model can be categorized into two kinds namely a single-objective model and a multi-objective model according to the number of objective functions (Jang & Chung, 2020). A model is single-objective when it contains a sole objective function while a multi-objective model contains more than one objective function (Dutta 2016). In most of the conventional APP models, the developed models are single-objective where the monetary element is their focus (Chopra & Meindl, 2016; Nahmias & Cheng, 2009; Russell & Taylor, 2008; Stevenson, Hojati & Cao, 2007) and where the general objective function is minimizing the total cost (Noegraheni & Nuradli, 2016; Jamalnia, Yang, Xu et al., 2019; Leung, Tsang, Ng & Wu, 2007). However, cost is not the only factor to be considered in the APP problems. Some researchers focus on multi-objective mathematical modeling where cost and other aspects are included in the objective functions (Mohammadi & Nikzad, 2022; Tyas, Bakhtiar & Silalahi, 2021; Sazvar, Tafakkori, Oladzad & Nayeri, 2021).

5.4. Classification by Parameters

Previous APP studies have explored the application of social and economic parameters to understand the multifaceted nature of production planning decisions. Economic parameters such as labor cost, raw material cost, inventory cost, and production cost have been analyzed to develop APP mathematical models for optimal production planning. On the other hand, social parameters have been increasingly recognized as critical factors influencing production planning strategies (Ebrahimi & Fathi, 2017). Social parameters encompass aspects such as customer satisfaction level, work-family balance, employee safety, and gender equity. Some of the previous APP studies have investigated how social considerations can be integrated into APP. By incorporating both social and economic parameters, these studies have provided a comprehensive understanding of production planning practices, highlighting the importance of balancing economic efficiency with social responsibility to achieve a better business outcome.

5.5. Review of Previous APP Studies

The previous APP studies have been reviewed and categorized. Table 3 summarizes the previous APP studies from the year 2010 to 2023 according to different categories which are objective functions, model representation methods, and solution approaches. From the literature review, Baykasoglu and Gocken (2010) proposed a fuzzy multi-objective APP model, and the Tabu Search (TS) algorithm was applied to solve it using a numerical example. Next, Mirzapour Al-e-Hashem, Malekly and Aryanezhad (2011) developed a MINLP model with multiple objectives to handle a multi-period, multi-site, multi-product APP problem in the wood and paper industry and it was solved using LINGO. By using Genetic Algorithm (GA), and in a comparison with TS, Ramezanian, Rahmani and Barzinpour (2012) solved a MILP model for two-phase non-deterministic polynomial-time hard (NP-hard) APP systems. By using the same approach of GA, a multi-objective MINLP model for APP with uncertain demand was solved by Mirzapour Al-e-Hashem, Aryanezhad and Sadjadi (2012). Through a numerical example, Aungkulanon, Phruksaphanrat and Luangpaiboon (2012) applied the Variable Neighbourhood Search of the Harmony Search Algorithm (VHSA) to solve a fuzzy multi-objective LP APP model with several cost parameters.

Next, Wang and Yeh (2014) solved an integer linear programming (ILP) APP model by applying Modified Particle Swarm Optimization (MPSO) and compared it with standard PSO (SPSO) and GA, where the experimental results showed that MPSO gained the highest qualities in accuracy, reliability, and convergence. On the other hand, Gholamian et al. (2015) developed a fuzzy multi-objective MINLP model to address a comprehensive multi-site, multi-period, and multi-product APP problem under uncertainty and GAMS was applied to solve the socio-economic model. In the same year, Chakrabortty, Hasin, Sarker and Essam (2015) integrated PSO, GA, and fuzzy-based GA to solve an APP problem to minimize the total costs in a ready-made garment manufacturing company.

Entezamenia, Heidari and Rahmani (2017) solved a MILP model for an uncertain multi-site, multi-period, multi-product APP problem in a wood and paper company by applying IBM ILOG CPLEX. In 2018, a MILP model was developed by Mehdizadeh, Niaki and Hemati (2018) for an NP-hard APP problem with labor learning effect and machine deterioration, and it was solved by Subpopulation GA which was designed to solve large-size problems. Besides, Hahn & Brandenburg (2018) proposed a MILP model to focus on the issue of stochastic chemical production processes which was solved using IBM ILOG CPLEX. Furthermore, Rasmi, Kazan and Türkay (2019) presented a MILP APP model to focus on economic and social parameters in a household appliance manufacturing company and it was solved using a method called Generator of ND and Efficient Frontier (GoNDEF). On the other hand, Yaghin, Sarlak and Ghareaghaji (2020) used GAMS to solve a MINLP APP model under uncertainty with different cost parameters in the clothing industry.

Besides, Tyas et al. (2021) formulated a non-preemptive goal programming (GP) model for an APP problem with cost objective functions, and the model was solved using the LINGO software. Next, another multi-product APP problem was solved by Liu and Yang (2021) using Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to minimize total production costs and workforce instability. In 2022, a MILP APP model was presented by Attia et al. (2022) to minimize total production costs while fulfilling operational constraints and considering organizational learning. It was solved using IBM ILOG CPLEX and was validated in an Egyptian factory that produces electric motors for home appliances. Subsequently, Al-Mohamed et al. (2023) proposed a fuzzy GP model to address an APP problem in the sugar industry in a fuzzy environment. In the same year, Tirkolaee et al. (2023) introduced a MILP model considering cost parameters where the robust optimization technique was implemented to address demand uncertainty, and it was solved using GAMS in the soft drink industry.

Generally, the integration of social and economic parameters has been considered in APP studies. Table 4 reviews and summarizes all the economic and social parameters in each of the previous APP studies. All the parameters are listed where there are 21 cost parameters including production cost, raw material cost, labor cost, hiring cost, firing cost, training cost, inventory cost, transportation cost, backorder cost, backlogging cost, subcontracting cost, overtime cost, fixed cost, social investment cost, repair cost, setup cost, advertising cost, distribution cost, failure cost, workforce change cost, and work in progress (WIP) cost. On the other hand, the 4 social parameters from the previous APP studies are customer satisfaction level, employee safety, work-family balance, and gender equity.

Based on the literature, a two-stage stochastic programming model was developed by Mirzapour Al-e-Hashem, Baboli et al. (2011) to deal with an APP problem where production cost, labor cost, hiring cost, firing cost, training cost, transportation cost, inventory holding cost, and backordering cost were considered. Next, to deal with APP by considering the uncertain nature of the supply chain, a MINLP model was proposed by Mirzapour Al-e-Hashem, Malekly et al. (2011) where the minimization of total losses of the supply chain costs including production cost, hiring cost, firing cost, training cost, raw material cost, inventory holding cost, transportation cost, and backorder cost was its first objective function while the second objective function considered customer satisfaction through the minimization of the sum of the maximum amount of shortages among the customers' zones in all periods.

Next, Jamalnia et al. (2017) proposed a multi-objective APP model involving total revenue, production costs, labor costs, and customer satisfaction. In 2018, an optimization model was developed for an APP problem with the objectives of maximizing the profit, and minimizing the costs associated with repair, setup, failure, production, labor, hiring, firing, inventory, and backorder (Mehdizadeh et al., 2018). Furthermore, Rasmi et al. (2019) presented a multi-objective APP model to maximize the total profit where the parameters included the workers' salaries, hiring costs, firing costs, overtime costs, material costs, inventory holding costs, subcontracting costs, and backorder costs. At the same time, they minimized overtime working hours to ensure employees' safety and reduce work-family conflicts. On the other hand, more priority was given to hiring female workers to implement employee gender equity. Furthermore, the total stockouts were minimized to improve customer satisfaction levels.

In addition, Ramyar, Mehdizadeh and Hadji-Molana (2020) solved an APP model to minimize the total cost of the supply chain including inventory costs, production costs, labor costs, hiring costs, and firing costs. A multi-objective programming model for a multi-product APP problem was established by Liu and Yang (2021) to minimize total production costs associated with production, raw material, labor, training, inventory as well as overtime. Besides, a fuzzy goal programming model was developed by Al-Mohamed et al. (2023) to reduce the costs of production, labor, hiring, firing, and inventory in APP. Subsequently, a fuzzy goal programming model was developed by Al-Mohamed et al. (2023) to reduce the costs of production, labor, hiring, firing, and inventory in APP. Tirkolaee et al. (2023) proposed an APP model to minimize the parameters which were production cost, subcontracting cost, labor working cost, overtime cost, raw material cost, inventory holding cost, backorder cost, as well as hiring cost and firing cost of the workforce.

No.	Author (Year)	Objective Function			Model	Deterministic		Non-deterministic			Objective		Solution Approach
		Economic	Social	Socio-economic		Linear	Non-linear	Stochastic	Fuzzy	Robust	Single	Multi	
1	Tirkolaee et al. (2023)	✓			MILP					✓		✓	GAMS
2	Al-Mohamed et al. (2023)	✓			GP				✓			✓	GAMS
3	Attia et al. (2022)	✓			MILP			✓			✓		IBM ILOG CPLEX
4	Lahmar, Dahane, Mouss and Haoues (2022)	✓			ILP			✓			✓		NSGA-II
5	Liu and Yang (2021)	✓			MILP			✓				✓	NSGA-II
6	Gómez-Rocha, Hernández-Gress and Rivera-Gómez (2021)	✓			MILP			✓			✓		LINGO
7	Tyas et al. (2021)	✓			GP					✓		✓	LINGO
8	Yaghin et al. (2020)	✓			MINLP				✓		✓		GAMS
9	Jang and Chung (2020)	✓			MINLP					✓	✓		PSO
10	Ramyar et al. (2020)	✓			MILP			✓				✓	Harmony search & NSGA-II
11	Rasmi et al. (2019)			✓	MILP			✓				✓	GoNDEF
12	Yuliastuti, Rizki, Mahmudy and Tama (2019)	✓			MILP			✓			✓		Hybrid Simulated Annealing and Adaptive Genetic Algorithm (HSAAGA)
13	Hahn and Brandenburg (2018)	✓			MILP			✓				✓	IBM ILOG CPLEX
14	Mehdizadeh et al. (2018)	✓			MILP				✓			✓	SPGA
15	Entezaminia et al. (2017)	✓			MILP					✓	✓		IBM ILOG CPLEX
16	Jamalnia et al. (2017)			✓	MINLP			✓				✓	WWW-NIMBUS

No.	Author (Year)	Objective Function			Model	Deterministic		Non-deterministic			Objective		Solution Approach
		Economic	Social	Socio-economic		Linear	Non-linear	Stochastic	Fuzzy	Robust	Single	Multi	
17	Chakrabortty et al. (2015)	✓			ILP				✓		✓		PSO, GA, Fuzzy-based GA
18	Gholamian et al. (2015)			✓	MINLP				✓			✓	GAMS
19	Niknamfar, Taghi-Akhavan-Niaki and Hamid-Reza-Pasandideh (2015)	✓			MINLP					✓	✓		GAMS
20	Rahmani, Yousefli and Ramezanian (2014)	✓			MILP				✓		✓		LINGO
21	Madadi and Wong (2014)			✓	ILP				✓			✓	IBM ILOG CPLEX
22	Silva and Marins (2014)	✓			GP				✓			✓	GAMS
23	Wang and Yeh (2014)	✓			ILP			✓			✓		MPSO
24	Aungkulanon et al. (2012)	✓			MILP				✓			✓	VHSA
25	Mirzapour Al-e-Hashem et al. (2012)			✓	MINLP					✓		✓	GA
26	Ramezanian et al. (2012)	✓			MILP				✓		✓		GA & TS
27	Mirzapour Al-e-Hashem, Malekly et al. (2011)			✓	MINLP			✓				✓	LINGO
28	Mirzapour Al-e-Hashem, Baboli et al. (2011)	✓			MINLP					✓		✓	L-shaped method
29	Baykasoglu and Gocken (2010)	✓			MILP				✓			✓	TS
	Frequency	23	0	6		0	0	11	11	7	12	17	

Abbreviations: MILP: Mixed-integer Linear Programming; GP: Goal Programming; ILP: Integer Linear Programming; MINLP: Mixed-integer non-linear programming

Note: Models that consider only costs in their objective functions (even though with many cost elements) are categorized as single-objective, while models that include both the economic and social aspects in their objective functions are categorized as multi-objective. Models that include cost and non-cost elements in their objective functions and those that have a combination of maximization and minimization objective functions are categorized as multi-objective.

Table 3. Previous APP studies from year 2010 to 2023

No.	Author (year)	Cost																					Social			
		Production	Raw material	Labor	Firing	Hiring	Training	Inventory	Transportation	Backorder	Backlogging	Subcontracting	Overtime	Fixed	Social investment	Repair	Setup	Advertising	Distribution	Failure	Workforce change	Work in progress (WIP)	Customer satisfaction level	Employee safety	Work-family balance	Gender equity
1	Tirkolaee et al. (2023)	✓	✓	✓	✓	✓		✓		✓		✓	✓													
2	Al-Mohamed et al. (2023)	✓		✓	✓	✓		✓																		
3	Attia et al. (2022)	✓	✓	✓				✓				✓														
4	Lahmar et al. (2022)	✓						✓									✓									
5	Liu and Yang (2021)	✓	✓	✓			✓	✓					✓													
6	Gómez-Rocha et al (2021)	✓		✓	✓	✓		✓			✓															
7	Tyas et al. (2021)	✓		✓	✓	✓		✓		✓		✓	✓								✓					
8	Yaghin et al. (2020)	✓	✓	✓				✓	✓					✓	✓											
9	Jang and Chung (2020)	✓		✓	✓	✓		✓			✓	✓	✓													
10	Ramyar et al. (2020)	✓		✓	✓	✓		✓																		
11	Rasmi et al. (2019)		✓	✓	✓	✓		✓		✓		✓	✓										✓	✓	✓	✓
12	Yuliastuti et al. (2019)	✓			✓	✓		✓				✓	✓													
13	Hahn and Brandenburg (2018)							✓			✓		✓									✓				
14	Mehdizadeh et al. (2018)	✓		✓	✓	✓		✓		✓						✓	✓			✓						
15	Entezaminia et al. (2017)	✓	✓	✓	✓	✓		✓	✓	✓			✓													
16	Jamalnia et al. (2017)	✓		✓				✓		✓								✓					✓			
17	Chakrabortty et al. (2015)	✓		✓	✓	✓		✓		✓		✓	✓													
18	Gholamian et al. (2015)	✓	✓	✓	✓	✓	✓	✓	✓	✓													✓			
19	Niknamfar et al. (2015)	✓						✓	✓					✓												
20	Rahmani et al. (2014)	✓		✓	✓	✓		✓		✓		✓	✓													
21	Madadi and Wong (2014)	✓	✓	✓			✓	✓		✓													✓			
22	Silva and Marins (2014)	✓	✓					✓	✓										✓							
23	Wang and Yeh, (2014)	✓		✓	✓	✓		✓			✓	✓	✓													
24	Aungkulanon et al. (2012)	✓		✓	✓	✓		✓					✓													
25	Mirzapour Al-e-Hashem et al. (2012)	✓	✓	✓	✓	✓	✓	✓	✓	✓													✓			
26	Ramezanian et al. (2012)	✓		✓	✓	✓		✓		✓		✓					✓									
27	Mirzapour Al-e-Hashem, Malekly et al. (2011)	✓	✓	✓	✓	✓	✓	✓	✓	✓													✓			
28	Mirzapour Al-e-Hashem, Baboli et al. (2011)	✓		✓	✓	✓	✓	✓	✓	✓																
29	Baykasoglu and Gocken (2010)	✓		✓									✓													
	Total	27	11	24	19	19	6	28	8	14	4	10	13	2	1	1	3	1	1	1	1	1	6	1	1	1

Table 4. Economic and social parameters based on objective functions in APP.

6. Results and Discussion

The results from the literature review are analyzed and discussed below.

	Number of studies	Percentage of studies
Deterministic	0	0
Non-deterministic:		
Stochastic	11	38 %
Fuzzy	11	38 %
Robust	7	24 %

Table 5. Summary of the APP models' representation methods

Table 5 shows that all the reviewed APP models are non-deterministic. This indicates that all the studies have included different uncertainties to improve their model's accuracy, and several approaches have been applied to deal with uncertainties. According to the results, stochastic and fuzzy models show the same percentage, which is 38% respectively, and robust models stand for only 24% of the studies. Both stochastic and fuzzy methods are the most common approaches to deal with uncertainties. This is because the stochastic technique requires the probability distributions of data to be determined, which is more accurate while fuzzy can deal with linguistic data representation in coping with uncertainties.

	Objective Function				
	Economic	Social	Socio-economic	Single	Multi
Number of studies	23	0	6	12	17
Percentage of studies	79%	0%	21%	41%	59%

Table 6. Summary of the APP objective functions.

Table 6 illustrates the number of reviewed APP studies with the categorization of single-objective and multi-objective. Based on the result, 41% of the APP studies, which is 12 out of 29 studies have applied a single objective which focuses on cost parameters while there are 17 studies with multiple objectives. Next, the APP studies have been analyzed based on the type of objective functions. From the table, the percentage of economic APP studies is the highest with 79%, followed by socio-economic APP studies with 21% while there is no APP study with a sole focus on social parameters. This shows that cost is the main aspect considered by the previous APP studies and researchers have introduced some social parameters to be combined with economic parameters.

Figures 4 and 5 show the parameters in the economic and social aspects respectively.

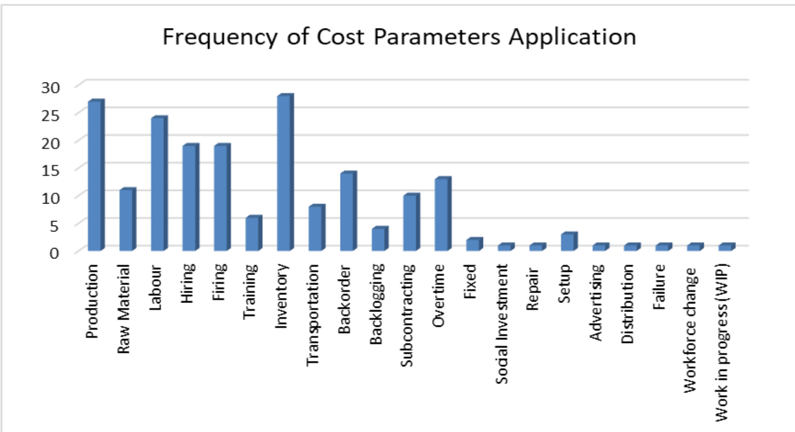

Figure 4. Frequency of cost parameters in APP

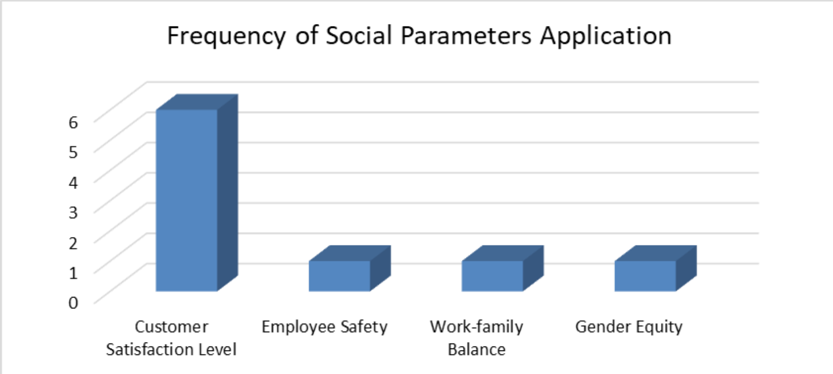

Figure 5. Frequency of social parameters in APP

From the literature, all APP studies have considered the economic parameters. Generally, APP costs can be categorized into several groups which are direct production cost (production, raw material, inventory, labor, hiring, firing, subcontracting, setup, workforce change, WIP), operational cost (transportation, backorder, backlogging distribution, advertising), quality and service cost (quality control, repair, service, failure), and financial and investment cost (fixed, social investment). However, previous APP studies have applied different sets of cost parameters in APP.

Based on Figure 4, inventory cost shows the highest application frequency of 28 and this illustrates that inventory management is the most important in the reviewed APP studies. The parameter with second highest frequency is the production cost (27), followed by the labor cost (24), firing cost (19), hiring cost (19), backorder cost (14), overtime cost (13), raw material cost (11), subcontracting cost (10), transportation cost (8), training cost (6), backlogging cost (4), setup cost (3), fixed cost (2), lastly, social investment cost, repair cost, advertising cost, distribution cost, failure cost, workforce change cost and work in progress (WIP) cost with only one study respectively. For social aspects, there are considerations from employee well-being (safety), social equity (gender equity and work-family balance) as well as customer-focused parameters (customer satisfaction level). Figure 5 shows the social parameters that have been applied in the reviewed APP studies. Among the social parameters, the most common one is customer satisfaction level with a frequency of 6, followed by employee safety, work-family balance, and gender equity, each with only one APP study. In short, the frequency of cost parameters application is much higher than that of social parameters. This shows that the previous APP studies have prioritized cost parameters over social aspects.

From the literature, the integration between cost and social parameters has been applied in several APP studies to achieve a more balanced focus for both aspects to improve organizational performance (Mirzapour Al-e-Hashem et al., 2012; Rasmi et al., 2019). More integration between both aspects is crucial as there could be a cross-parameter relation between certain cost and social parameters. One of the relations is between employee training cost and customer satisfaction level. It has been reported that there is a positive association between employee training cost and customer satisfaction (Hammad-Shah, Waseem-Shah & Gul, 2020). Comprehensive training should be provided to all the employees to enhance their performance, which will help them deliver better customer service to improve customer satisfaction. Similarly, well-trained employees will work autonomously, which also boosts customer satisfaction. It can be said that customer satisfaction increases when there is an investment in employee training. On the other hand, overtime cost is closely related to the social parameter of work-family balance. Overtime work is one aspect that causes employees' work-life balance to be imbalanced (Easya & Susanty, 2022). In other words, when the cost for workers' overtime increases, the work-family balance level decreases. This cross-parameter relation shows the importance of having an appropriate integration between both the cost and social parameters to achieve a better APP performance.

7. Future Research Directions

The findings of this systematic review highlight that there has been a greater emphasis on cost parameters relative to social parameters in APP. However, it is crucial to recognize the significance of social aspects in preventing human-centric issues. Besides the social parameters (customer satisfaction, work-family balance, employee safety, and gender equity) that have been introduced previously, ergonomics is another concern where it is indicated to improve work-life quality and increase work productivity (Abarqhouei & Nasab, 2011). In contrast, poor ergonomic design can result in fatigued workers leading to suboptimal performance and potential quality issues in production outputs. By implementing ergonomics principles such as promoting good posture, minimizing exertion, reducing unnecessary motions, and optimizing work heights and reaches, work productivity and efficiency can be enhanced. Moreover, addressing ergonomics concerns can foster greater employee engagement, subsequently reducing turnover and absenteeism rates and improving overall morale and commitment to an organization. Therefore, ergonomics issues are suggested to be considered in future APP studies.

Job security is also important to be prioritized in APP. Job security reduces anxiety about potential layoffs or job losses, allowing employees to focus on their tasks with greater concentration and dedication. When employees feel secure in their positions, they are more inclined to invest their time and energy into their work, knowing that their efforts contribute to long-term stability. Moreover, a sense of security fosters loyalty and commitment among employees, leading to increased engagement and productivity levels. A study by Alajlouni and Nawafleh (2018) identified a positive link between job security, job performance, and work productivity. It showed that employees who had little job security caused lower organizational productivity (Alajlouni & Nawafleh, 2018). To improve the job security of workers, the limits of hiring and firing levels could be fixed. By providing a stable environment where employees can thrive and grow, organizations can harness the full potential of their workforce, ultimately driving overall performance and success.

The literature shows that customers' and workers' aspects have been considered in APP, but community aspects have not been included. In this case, job opportunity is one of the social parameters from the community side. One of the issues in providing job opportunities is having collaborations between businesses and educational institutions. This can ensure that curricula meet industry needs and create pathways for internships and apprenticeships. Additionally, providing resources and support for startups and small businesses can stimulate job creation and innovation. Besides, more job opportunities could be provided for the local community to reduce the unemployment rate. Immergluck (2015) mentioned that local work is likely to have positive impacts on life quality and social capital. This contributes to the overall stability and resilience of the community, as a thriving job market attracts new residents and sustains existing ones, creating a virtuous cycle of prosperity. Overall, local employment opportunities not only strengthen the local economy but also enrich the fabric of the community and enhance its social vitality.

Other than that, by offering targeted training and education programs, individuals can acquire relevant skills aligned with market demands. By offering accessible training programs, communities empower their residents to acquire new skills or enhance existing ones, thereby increasing the pool of qualified workers available to local industries. This was indicated by Aljumah (2023) where there is a positive and significant relationship between job training and employment within the same company. Job training has a significant positive impact on employability, highlighting its contribution to employability development and enhancement and company performance improvement through the discovery and employment of talented and skilled employees. This, in turn, addresses skills gaps and shortages within the workforce, facilitating industry expansion and innovation.

The relationship between workers and family is another aspect to be considered. Several family issues can be raised if a worker frequently works overtime for a company while neglecting family matters. This is even worse when the workers spend their weekends or holidays in the workplace rather than having family time which would cause arguments among family members due to less communication. Additionally, extended hours at work can lead to fatigue and burnout, leaving employees with limited energy and availability for family commitments and activities. This is explained through an examination on the work-family conflict factor and the need for recovery from prolonged workplace fatigue (Jansen, Kant, Kristensen & Nijhuis, 2003). Moreover, unpredictable overtime schedules can disrupt family routines thus making it challenging to balance work and personal responsibilities. This imbalance can cause tension and stress within a family unit, leading to feelings of neglect or resentment.

On the other hand, community satisfaction level can also be included in APP. For instance, if a factory operates 24 hours daily, this will produce a certain nuisance level which can affect the resting hours of those residents who stay nearby. Sofer, Potchter, Gnaim and Gnaim (2012) indicated the significant levels of environmental nuisances in residential areas and factory operation activities that negatively affected the life quality of the local population. Besides, a factory's operations can cause serious traffic jam in the community, especially during the peak hours of people going to and for their workplace. The effect of traffic congestion was emphasized by Fattah, Morshed and Kafy (2022) as one of the major barriers to economic development, resulting in severe social and economic impacts such as extreme stress levels for employees, with a huge economic loss per day including delayed costs, fuel loss costs, and pollution costs.

The next direction is on the aspect of the model representation method in dealing with uncertainties in APP. To handle uncertainties in APP models, there are three methods which are fuzzy, stochastic, and robust. Based on the literature review, the robust method has the least application frequency in modeling APP. This could be due to the challenge of identifying different kinds of uncertain scenarios for the models compared to the fuzzy method where the data can be easily obtained through judgment from the respondents and the stochastic method where statistical analysis can be done to find out the probability distributions of the data. Hence, future APP studies could apply the robust method more extensively to cope with uncertainties by considering different kinds of scenarios.

At the same time, machine learning can be included in future APP studies. Machine learning can significantly enhance the APP process by improving forecast accuracy, and optimizing resource allocation. In this case, machine learning can be applied to predict future customer demands or production costings more accurately than traditional methods. To maintain customer loyalty and avoid excessive cost, companies need to have an efficient system for predicting customer demands without overstocking or understocking. In this respect, analytical methods like machine learning show great promise (Ali, Jayaraman, Azar & Maalouf, 2024). Other than that, Shoomal, Jahanbakht, Componation and Ozay (2024) emphasized the application of Internet of Things (IoT) for real-time tracking of production. The integration of IoT into production planning has the potential to address longstanding industry challenges, including enhancing efficiency, and resilience in APP.

Last but not least, previous studies have applied different kinds of metaheuristic techniques to solve complicated APP problems. So far, the most common ones are GA, TS, PSO, and HS. Future research could also apply other techniques from different metaheuristic groups such as Ant Colony Optimization (ACO) and Artificial Bees Colony (ABC) from the Swarm-based group; Simulated Annealing and Black Hole Algorithm (BHA) from the Physics-based group; Bat Algorithm (BA) and Cuckoo Search Algorithm (CSA) from the Nature-inspired group; Evolutionary Strategy (ES) and Differential Evolution (DE) from the Evolutionary group, and the Spotted Hyena Optimizer (SHO) and Gray Wolf Optimizer (GWO) from the Biogeographic-simulated group based on different conditions in APP (Abdel-Basset, Abdel-Fatah & Sangaiah, 2018).

8. Implications and Conclusions

This paper effectively synthesizes and contextualizes the previous studies in APP from the economic and social perspectives. It evaluates the studies and provides a new perspective on APP, as well as opening new avenues for future research. From this review, social parameters are found to be less frequently applied. Hence, researchers can go for a more detailed study specifically related to the social aspects of APP as well as introduce new social parameters in this area. On the other hand, this study assists managers in identifying the previous focus of APP from the year 2010 onwards and determining the parameters that have been applied. With this, managers can have a good reference about the future direction of APP by proposing new parameters to balance both the economic and social aspects in APP.

The previous APP models are grouped based on model representation methods, solution approaches, and objective functions. In terms of model representation, there are deterministic and non-deterministic models. No deterministic model has been developed in the reviewed APP studies while for non-deterministic models, the stochastic and fuzzy methods have a higher percentage of application to deal with uncertainties in APP. On the other hand, there are different approaches to solve APP models including the exact methods, software approaches, and heuristic/metaheuristic methods. In terms of objective functions, most of the reviewed APP studies have applied only a single objective function.

The outcome shows that there are 21 economic parameters and 4 social parameters that have been applied in the reviewed APP studies but only a few of them have used both the economic and social parameters. Cost parameters seem to be overweighed as compared to social parameters. It is arguably better to have a more balanced focus between both the cost and social parameters in APP. Based on the literature, the social parameters are still rarely utilized where customer satisfaction level is the most applied social parameter in APP. For the economic aspect, many cost parameters have been commonly applied in the reviewed APP studies and this shows that the focus on cost parameters in APP is sufficient.

This study provides managers and researchers with insights into the application of social and economic parameters in APP and motivates more research interest or attention to address the social aspects of APP. As a future recommendation, social aspects can be given more emphasis because workers, customers, and communities are the key beneficiaries of a production planning process. Future studies can extend the current APP models to incorporate social parameters such as community satisfaction level, etc.

Besides, there is no literature on the proposal of a standardized or general set of social and economic parameters that can be applied in APP and hence, this can be done in future research. The proposal of a standardized or general set of social and economic parameters for APP is pivotal in enhancing efficiency and efficacy of production operations. Such parameters provide a structured framework for decision-making, allowing businesses to anticipate and adapt to fluctuating market demands while considering socio-economic factors. By establishing common parameters in APP, managers can better account for variables like labor availability, wage rates, and economic conditions, fostering smoother coordination between production targets and societal needs. This standardization not only streamlines planning processes but also facilitates comparative analysis across industries and regions. Moreover, it lays a foundation for future research endeavors, enabling scholars to delve deeper into the interplay between economic dynamics, social factors, and production strategies, ultimately fostering innovation and resilience in the face of evolving market landscapes.

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