A multi-product and multi-period aggregate production plan: a case of automobile component manufacturing firm

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Abstract

Purpose – The study attempts to develop a multi-product multi-period (MPMP) aggregate production plan (APP) to fulfill the customers' demand in terms of throughput and lead time for achieving market competence.

Design/methodology/approach – This research proposes an integrated Fuzzy analytical hierarchy process (FAHP), multi-objective linear programming (MOLP), and simulation approach. Initially, FAHP is used to select the essential objectives a firm desires to achieve. Adopting the MOLP, an APP is formulated for the firm under study. Later, the simulation model of a firm is created in a discrete-event simulation (DES) software Arena© to evaluate the applicability of the proposed APP. A comparative analysis of the manufacturing performance levels (namely throughput, lead time, and resource utilization) achieved through the implication of an existing production plan and proposed APP is conducted further.

Findings – The findings from the study depict that the proposed MOLP-based APP can satisfy the customers' requirement (namely throughput and lead time) and improve the level of resource utilization compared with the firm's existing production plan.

Research limitations/implications – The proposed research facilitates researchers and practitioners to understand the process of developing MOLP-based MPMP APP and analyzing its applicability through simulation technique to be utilized for developing APP at their firm.

Originality/value – An integrated FAHP-MOLP-simulation framework is the novel contribution to the literature on production planning. It can be extended to solve strategic, tactical, and operational problems in different domains like service, healthcare, supply chain, logistics, and project management.

Keywords Aggregate production planning, Fuzzy AHP, Multi-objective linear programming, Simulation, Manufacturing performance

Paper type Research paper

1. Introduction

Production planning synergically arranges the manufacturing processes and resources to align them with the market needs. The rapid internationalization and the fierce competition within the manufacturing sector in the global market pose the incremental importance of production planning and control (Hassan Zadeh *et al.*, 2014). As a consequential response to the competition, a firm has to optimize its production activities to minimize the unproductive use of resources, such as space, machines material, and time. The optimal utilization of resources, minimal inventory levels for workflow balance, efficient production schedule for customer service levels, efficient supply chain network for low-cost production are essential ingredients of an accurately formulated production plan (Lohmer and Lasch, 2021; Miltenburg, 2005). However, the benefits of production planning may not be realized

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unless it is not done with systems level perspective. Thus, every firm tries to plan its manufacturing activities at different aggregation levels and operates with an intention to maximize profit and productivity by cutting down the overall cost of production and idle situations in a production system (Cheraghalikhani *et al.*, 2019; Miltenburg, 2008; Pan and Kleiner, 1995).

Aggregate production planning (APP) serves as the best solution to meet the forecasted demand with minimum production cost by balancing the existing capacity of the production system over a medium time horizon of 3–18 months (Brachmann and Kolisch, 2021; Buxey, 2005; Cheraghalikhani *et al.*, 2019; Pan and Kleiner, 1995; Pereira *et al.*, 2020). APP facilitates production planners to develop an effective production plan by utilizing the organization's resources, which helps to satisfy the expected demand of customers. A decision related to output rates, employment levels, back-orders and sub-contracting can be taken by planners using an aggregate production plan (Brachmann and Kolisch, 2021; Djordjevic *et al.*, 2019; Pan and Kleiner, 1995). APP considers one product or a family of similar products for formulating the planning model from an aggregated viewpoint (Brachmann and Kolisch, 2021; Cheraghalikhani *et al.*, 2019; Jamalnia and Soukhakian, 2009). Figure 1 demonstrates the conceptual model of APP. It highlights the different aspects, namely – characteristics, strategies adopted, decision options and objectives considered in APP formulation.

APP typically involves eight different types of objectives. The objectives are (1) Maximize customer service, (2) Minimize total production cost, (3) Minimize inventory investment, (4) Minimize changes in workforce levels, (5) Minimize changes in production rates, (6) Minimize total lead time, (7) Minimize subcontracting and (8) Maximize utilization of plant and equipment (Cheraghalikhani *et al.*, 2019; Pan and Kleiner, 1995). Selecting the most suitable objective functions plays a vital role while formulating an APP to gain production competence (Brachmann and Kolisch, 2021; Buxey, 1995; Cheraghalikhani *et al.*, 2019). Recently, Cheraghalikhani *et al.* (2019) contextualized that the implication of APP should be evaluated and validated to know whether the required manufacturing performance level is achieved or not? These theoretical arguments impose a strong need for developing a

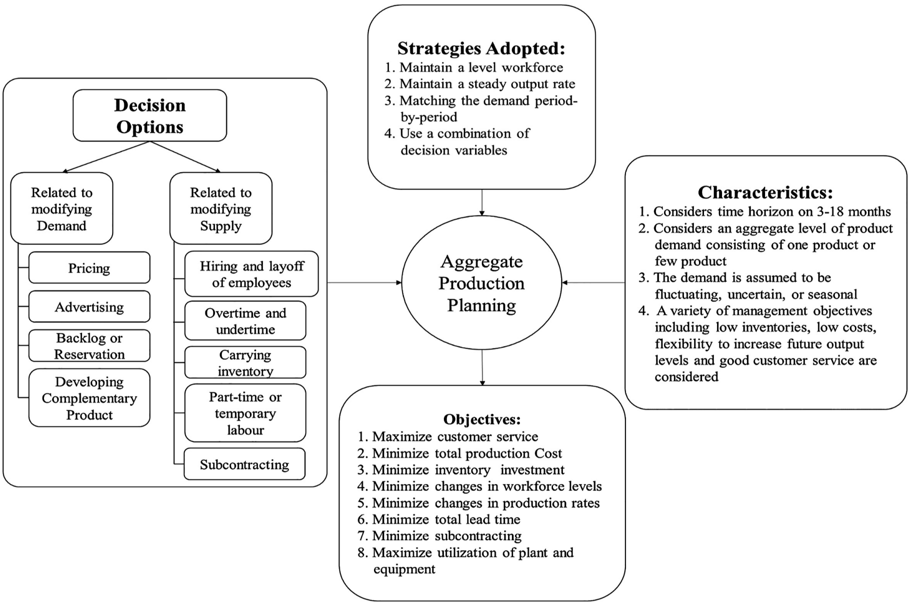


Figure 1.
The conceptual diagram of AP

framework that can facilitate selecting a suitable objective function for an APP, formulating an APP for a firm, and validating the implication of an APP for a firm. However, the present literature is sparse in fulfilling these needs.

Through the review of the extent literature (see section 2), critical research gaps are identified. Mostly scholars have made successful attempts to develop and formulate APP using various techniques (see Table 1). To the best of the authors' knowledge, minimal efforts are taken to develop a framework that aids in determining the critical objective functions while formulating an APP for a firm. The research on APP validation by analyzing its impact on manufacturing performances is scant (Cheraghalikhani *et al.*, 2019). Also, existing studies lack to determine and investigate the effectiveness of the proposed APP strategies. Further, there is a gap in literature considering the methodological lens. Mathematical optimization techniques are widely used in APP studies (see Table 1). In contrast, multi-criteria decision-making (MCDM) techniques are rarely adopted (Cheraghalikhani *et al.*, 2019). The present research work attempts to bridge these research gaps. The aim of this study builds a strong foundation for considering the following research questions (RQs):

RQ1. How to decide the essential objective functions the firm desires to achieve for APP?

RQ2. How to formulate and validate a multi-objective APP and analyze its impact on manufacturing performances?

To answer the RQs mentioned above, this study has formulated and validated an APP model using an integrated Fuzzy AHP – "Multi-objective linear programming (MOLP)" – Simulation method. Initially, using FAHP, the objectives most appropriate for a firm to achieve are selected. MOLP based mathematical model is formulated for solving the APP decision problem with forecasted demand, operating costs, and capacity as input variables. Furthermore, a simulation model of a real case is created to validate the applicability of LP formulation. The impact of the proposed APP on the manufacturing performances (namely throughput, lead time, and resource utilization) is evaluated through Simulation by comparing it with the firm's existing production plan for determining the effectiveness of the proposed APP.

The proposed FAHP-MOLP-Simulation framework not only assists managers in determining the suitable objective function for APP but also helps in formulating the APP and further evaluating its impact on manufacturing performances. This unique ability makes the present study different than the past studies presented in Table 1. The present study offers promising contributions to academia in the form of a novel integrated framework for formulating APP. At the same time, practitioners can get insights into the process of formulating APP in their firm to achieve the desired level of manufacturing performance effectively.

The remainder of the paper is organized as follows. The existing literature on APP is reviewed in Section 2. Section 3 illustrates the proposed integrated FAHP-MOLP-Simulation

Technique	Studies
Linear programming	Wang and Fang (2001), Liang (2007), Hanczar and Jakubiak (2011), Hahn and Brandenburg (2018), Rasmi *et al.* (2019)
Linear decision rule	Holt *et al.* (1955), Bushuev (2014)
Simulation	Tian *et al.* (2010), Jamalnia and Feili (2013), Mendoza *et al.* (2014)
Heuristic techniques	Liu *et al.* (2011), Mehdizadeh *et al.* (2018), Jones (1967), Jang and Chung (2020)
Goal programming	Jamalnia and Soukhakian (2009), Sadeghi *et al.* (2013), Leung *et al.* (2003)

Table 1. Techniques applied for formulating APP model

method for conducting the study. An industrial case is presented in Section 4 to demonstrate the application of the proposed framework for formulating APP at the firm under study. The results and findings of the proposed method are discussed in Section 5. Research implications of the current study are highlighted in Section 6. The concluding remarks drawn from the current research and the direction for conducting future studies are presented in Section 7.

2. Literature review

Recently, Dohale *et al.* (2021a) highlighted that a rightly configured and properly planned production function provides production competence to the firm, resulting in business success. Hence, production planning is considered as one of the critical infrastructural decisions in manufacturing (Dohale *et al.*, 2021b). Mula *et al.* (2006) categorized seven essential production planning decisions: material requirement planning, manufacturing resource planning, aggregate planning, inventory management, capacity planning, hierarchical production planning, and supply chain planning. APP is considered the critical production planning approach at the tactical level that strengthens the production systems by improving the production competence through manufacturing performance improvement (Pereira *et al.*, 2020). Thus, APP has attracted extensive attention from researchers and practitioners, resulting in considerable research since its inception in the 1950s (Buxey, 2005; Cheraghalikhani *et al.*, 2019). An appropriately formulated APP attempts to establish optimal production levels, lead times, resource utilization levels, and inventory and employment levels over a finite planning horizon to meet the total demand of the products comprising the same limited resources (Cheraghalikhani *et al.*, 2019). So, APP formulation has given the utmost importance in the literature (Cheraghalikhani *et al.*, 2019).

Nam and Logendran (1992) reviewed 140 journal articles and 14 books and enlisted different methods to develop the APP model. Some of the popular methods for developing APP are Linear Programming (LP), Goal Programming (GP), Linear Decision Rule (LDR), Simulation, Heuristics techniques, Management Coefficients Approach, and Simulation Search Procedures, etc. Table 1 enlisted the studies on the development of an APP using different techniques.

Pan and Kleiner (1995) explained the concept of Aggregate Production Planning and described the characteristics, decisions, strategies and techniques considered for developing an APP model. Buxey (1995) explored the discrepancy between theory and practicality in the application of APP using an empirical study by considering the examples of 30 firms. Masuds and Hwang (1980) have formulated a multi-product, multi-period aggregate production planning problem using multiple objective decision-making methods. In their study, authors have considered four objective functions: Maximization of contribution to profit and overhead while minimizing capital investment, back-orders, and changes in the workforce level. The constraints taken are related to three factors: labor balance, product balance, and production capacity balance. Mahdavi *et al.* (2012) established a mathematical model using a mixed-integer linear programming technique to formulate a multi-period multi-product (MPMP) production planning problem. The objective function considered by authors is to minimize total production cost, including production, storage, shortage, subcontracting costs, and costs associated with constraints like machine center capacities, material balance, inventory space, workforce, and linearization.

Jamalnia and Feili (2013) implemented a hybrid methodology using discrete event simulation (DES) and system dynamics (SD) techniques to simulate an APP problem. Hahn and Brandenburg (2018) developed an APP considering sustainable criteria for a chemical manufacturing firm using a multi-level deterministic linear programming model. Djordjevic *et al.* (2019) used a fuzzy linear programming model to develop an APP for automobile manufacturers. Cheraghalikhani *et al.* (2019) reviewed APP literature and identified the research gaps. Most of the studies are observed with the single-objective formulation. The literature on APP lacks integrating MCDM, machine learning, and simulation methods. Pereira *et al.* (2020) elaborated the essence of APP to fulfill the strategic plans of the business. Thus, the main objective of this study is to determine and investigate the effectiveness of the proposed APP strategies considering the total profit criterion. To this purpose, the present study developed an integrated FAHP-MOLP-simulation-based framework for formulating APP in multi-product multi-period (MPMP) conditions.

3. The method

The objective of the study is addressed using an integrated FAHP-MOLP-Simulation approach. The multi-objective linear programming technique is used to mathematically formulate the APP model with objective functions as – minimization of overall cost of production and lead time. Further, a simulation model of a firm is created to evaluate the impact of APP on manufacturing performance for determining the effectiveness of the APP model. The detailed research method is shown in Figure 2. The methodology comprises four stages:

Stage 1: Selecting the most suitable objective functions for formulating an APP using FAHP.

Stage 2: Formulating an APP problem using the MOLP model

Stage 3: Developing a simulation model of a case study under consideration for demonstrating the effectiveness of the LP model

Stage 4: Conducting a comparative analysis between the existing production plan and the proposed APP to evaluate the impact of APP on manufacturing performances

3.1 Stage 1: Objective function selection for APP using FAHP

AHP was conceived by renowned physicist Prof. Thomas L. Saaty in 1980 (Mardani *et al.*, 2015; Saaty, 1980). AHP is a most utilized multi-criteria decision-making (MCDM) technique. MCDM techniques are most suitable when the study aims to determine the appropriate alternatives (Dohale *et al.*, 2021c). MCDM based AHP conducts the pairwise comparison of decision criteria and develops priority weights using the popular integer-valued 1–9 AHP scale (Mardani *et al.*, 2015). The AHP model represents the problem in a hierarchy and divides it into sub-problems comprising criteria and sub-criteria (Bouzon *et al.*, 2016; Dohale *et al.*, 2021c). Although AHP received the general acceptability, decision-makers (DMs) may face difficulty in processing ambiguous information and results in subjective judgment due to the integer-valued crisp scale (Jakhar *et al.*, 2020; Liu *et al.*, 2020). Therefore, FAHP was developed to help DMs resemble reasoning and resolve uncertainty and vagueness (Dohale *et al.*, 2021g; Kannan *et al.*, 2013; Yadav and Sharma, 2015). These reasons lay a strong foundation for selecting the FAHP method in solving the real-world for making decisions. Various procedures are developed by the researchers for conducting the FAHP (Liu *et al.*, 2020). This paper applied Chang's extent analysis based FAHP method. This approach is simple and involves less computational time (Kumar and Garg, 2017; Salehi Heidari *et al.*, 2018). Thus, Chang's Extant analysis based FAHP is used to decide the most suitable objective functions for the APP in this research.

This study follows a five steps procedure of FAHP are described as:

(1) Identify the objectives for which pairwise comparison has to be done through literature review and validate them using experts' opinions

(2) Conduct a pairwise comparison of criteria considering decision-makers' perception and expertise individually using an AHP scale (1–9) shown in Table 2.

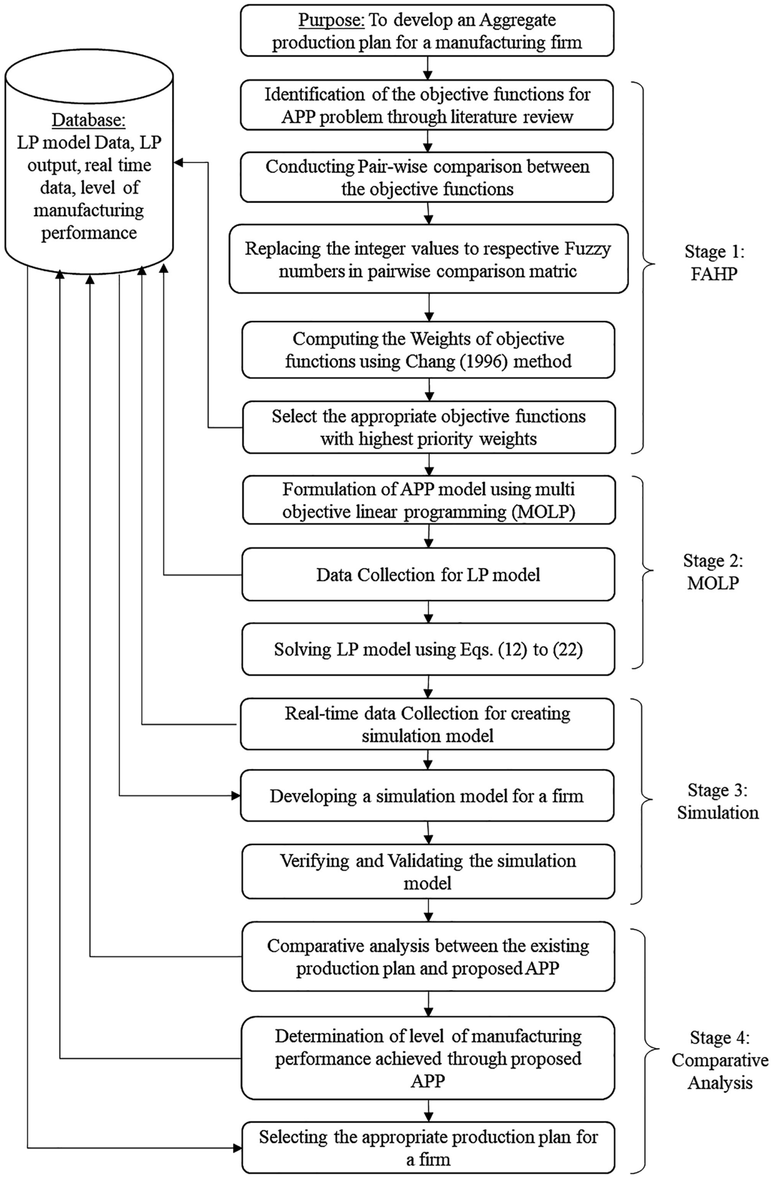


Figure 2.
Research method

(3) Calculate the consistency ratio (CR) of each pairwise comparison matrix using the guidelines given by Saaty (2008) to get surety of the appropriateness of the ratings given by DMs. If the CR value <0.1, the judgments are considered to be valid for weighing the criteria

(4) Transform the integer values in the pairwise comparison matrix to fuzzy numbers given in Table 2 and integrate all the DMs judgments using the geometric mean method (Hummel *et al.*, 2014; Kannan *et al.*, 2013)

Linguistic variable	Integer values	Fuzzy representation
Extremely strong	9	(9, 9, 9)
Intermediate	8	(7, 8, 9)
Very strong	7	(6, 7, 8)
Intermediate	6	(5, 6, 7)
Strong	5	(4, 5, 6)
Intermediate	4	(3, 4, 5)
Moderately strong	3	(2, 3, 4)
Intermediate	2	(1, 2, 3)
Equally strong	1	(1, 1, 1)

Table 2.
AHP 1–9 scale

$$P = (a,\ b,\ c)$$

$$K = 1,\ 2,\ \ldots,\ K\ (P\colon \textit{triangular fuzzy number},\ K\colon \textit{number of DMs}),$$

$$\text{where,}\quad a = (a_1 \times a_2 \times .. \times a_k)^{1/k},\quad b = (b_1 \times b_2 \times .. \times b_k)^{1/k},\quad c = (c_1 \times c_2 \times .. \times c_k)^{1/k}.$$

(5) Evaluate the priority weight of each criterion using the procedure proposed by Chang (1996) as given below.

The FAHP is presented as follows for determining the triangular fuzzy number weights.

(1) Consider the objective set $X = \{x_1, x_2,\ x_3,\ \ldots,\ x_n\}$, goal set $G = \{g_1,\ g_2, g_3,\ \ldots, g_n\}$, and $P^1_{gi},\ P^2_{gi},\ \ldots,\ P^m_{g_i}$ be p extent analysis value for every object, where $i = 1, 2,\ \ldots, n$. The triangular fuzzy numbers are $P^1_{gj},\ P^2_{gj},\ \ldots,\ P^j_{g_j}$, where $j = 1, 2,\ \ldots m$. Then the extent analysis for each goal is conducted.

The fuzzy synthetic extent value of i^{th} object for p goal is:

$$S_i = \sum_{j=1}^{p} P^j_{gi} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} P^j_{gi}\right]^{-1} \tag{1}$$

to acquire $\sum_{j=1}^{p} P^j_{g_j}$ the fuzzy addition operation of p extent analysis value is performed for a particular matrix $\sum_{j=1}^{p} P^j_{gi}$:

$$\sum_{j=1}^{p} P^j_{gi} = \left(\sum_{j=1}^{n} l_j,\ \sum_{j=1}^{n} m_j,\ \sum_{j=1}^{n} u_j\right) \tag{2}$$

Then the fuzzy addition operator- P^j_{gi} values are obtained to achieve $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} P^j_{gi}\right]^{-1}$ as:

$$\sum_{j=1}^{n}\sum_{j=1}^{m} P^j_{gi} = \left(\sum_{j=1}^{n} l_i,\ \sum_{j=1}^{n} m_i,\ \sum_{j=1}^{n} u_i\right) \tag{3}$$

The inverse of the vector is:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} P^j_{gi}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i},\ \frac{1}{\sum_{i=1}^{n} m_i},\ \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{4}$$

(2) After identifying S_i value, the degree of possibility of $P_2 = (l_2, m_2, u_2) \geq P_1 = (l_1, m_1, u_1)$ is calculated as:

$$V(P_2 \geq P_1) = sup_{y \geq x}\left[\min\left(\mu_{P_1}(x), \mu_{P_2}(y)\right]\right. \tag{5}$$

Representing equation (5) as

$$V(P_2 \geq P_1) = hgt(P_1 \cap P_2) = \left(\lambda_{P_2}(d) = \begin{cases} 1 & \text{if } m_2 \geq m_1, \\ 0 & \text{if } l_1 \geq u_2, \\ \dfrac{(l_1 - u_2)}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases}\right. \tag{6}$$

where, ordinate of the highest intersection point D between μ_{P_1} and μ_{P_2} is d.

Figure 3 shows the intersection between P_1 and P_2.

(3) The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $P_i (i = 1, 2, \ldots, k)$ can be defined by

$$\begin{aligned} V(P \geq P_1, P_2, \ldots, P_k) &= V[(P \geq P_1) \, and \times (P \geq P_1) \ldots and \, (P \geq P_k)] \\ &= min \; V(P \geq P_{ki}) \quad i = 1, 2, 3, \ldots, k \end{aligned} \tag{7}$$

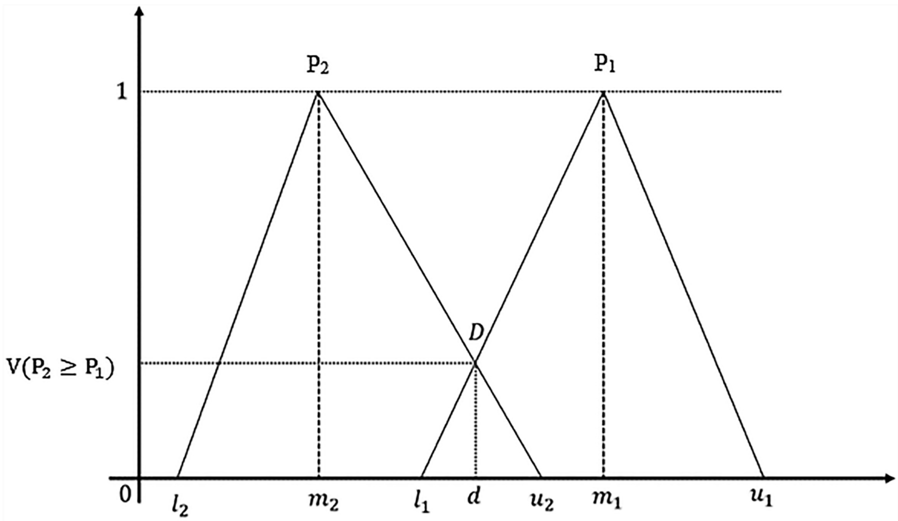
The assumption considered in calculating the weight vector is:

$$d'(M_i) = min \; \{V(S_i \geq S_k)\} \tag{8}$$

For $k = 1, 2, 3, \ldots, n; \; k \neq i$, the weight vector is

$$W' = \left\{d'(M_1), d'(M_2), \ldots, d'(M_n)\right\}^T \tag{9}$$

where $M_i = (i = 1, 2, 3, \ldots, n)$ *are n elements*.



Source(s): Chang (1996), Salehi Heidari *et al.* (2018)

Figure 3. Membership function (between P_1 and P_2)

(4) After doing normalization, the normalized weight is determined using the following equation:

$$W = \left\{ d(M_1), \, d(M_2), \ldots, \, d(M_n) \right\}^T \tag{10}$$

where W is a non-fuzzy number. The above steps are carried out for all judgment matrices to compute the priority weights developed on the normalized vector.

3.2 Stage 2: APP problem formulation using multi-objective linear programming

Linear programming (LP) is an optimization technique coined in 1947 during Second World War by Prof. George Dantzig for decision-making concerning the least cost adequate diet (Dantzig, 1998; Lewis, 2008; O'Connor and Robertson, 2003). Linear programming is a mathematical optimization technique comprising an objective function (Z) of either maximization or minimization type, subjected to linear constraints (Charnes and Cooper, 1961; Dantzig, 1998). The LP model, in general, can be expressed by Eq. (11) as:

$$\left.\begin{array}{l} \boldsymbol{Z} = \boldsymbol{a}_1\boldsymbol{x}_1 + \boldsymbol{a}_2\boldsymbol{x}_2 + \ldots + \boldsymbol{a}_n\boldsymbol{x}_n \\ \text{Subjected to,} \\ \boldsymbol{b}_{11}\boldsymbol{x}_1 + \boldsymbol{b}_{12}\boldsymbol{x}_2 + \ldots + \boldsymbol{b}_{1n}\boldsymbol{x}_3 \leq \boldsymbol{C}_1 \\ \boldsymbol{b}_{21}\boldsymbol{x}_1 + \boldsymbol{b}_{22}\boldsymbol{x}_2 + \ldots + \boldsymbol{b}_{2n}\boldsymbol{x}_3 \leq \boldsymbol{C}_2 \\ \boldsymbol{b}_{m1}\boldsymbol{x}_1 + \boldsymbol{b}_{m2}\boldsymbol{x}_2 + \ldots + \boldsymbol{b}_{mn}\boldsymbol{x}_3 \leq \boldsymbol{C}_m \end{array}\right\} \tag{11}$$

Linear programming (LP) is one of the most popular optimization techniques for determining the exact solution (Jacobs and Chase, 2018; Taha, 2017) for the given problem. The rationale behind selecting LP for formulating the APP in this study is due to its substantial advantages: (1) Linear programming enhances the quality of decisions and makes decision-making more objective for the user; (2) Linear programming aids in generating the best optimal solution for the problem under study; (3) Linear programming effectively formulates multi-objective and multi-dimensional problems to provide practical solutions (Dantzig, 1998; Gass, 2010; Jacobs and Chase, 2018; Lewis, 2008).

Linear programming method has received immense attention from researchers and practitioners. This, in turn, leads to a massive body of literature on applying the LP technique in the domains, such as – manufacturing, service, agriculture, supply chain, and project management, etc. Some of the applications of LP are discussed here. Coman and Ronen (2000) formulated a production outsourcing problem through LP to decide the products to outsource. Spitter *et al.* (2005) established a supply chain model for the supply chain operations planning problem considering the production dynamics. Kabak and Ülengin (2011) applied LP to solve a strategic resource planning decision of maximizing a firm's total profit by developing an optimal supply chain network design. LP and its extensions, namely, MILP, Fuzzy LP are widely used methodologies for modeling the supply chain risk mitigation and sustainable supply chain design and management problems (Ansari and Kant, 2017; Rajagopal *et al.*, 2017). In recent, Wu *et al.* (2020) adopted stochastics LP for addressing managerial accounting problems with business budgeting and planning to maximize total profit. Further, to get a detailed understanding of the LP method and its application in different domains, Gass (2010) is encouraged to refer.

An APP problem considered in this study is formulated using a multi-objective linear programming method. The objective functions taken are related to the minimization of the overall cost and lead time of production. Whereas the constraints applied to the problem are related to regular production hours, overtime production hours, subcontracting production hours, periodic demand, capacity of satisfying the maximum demand, and the limitation on the fluctuation of demand. The assumption, notations, and the complete model are explained as follows.

The basic assumptions considered while developing the model are: (1) the demand for i parts has already been forecasted for the T periods; (2) raw material availability is considered; (3) breakdowns are not considered in this model; (4) limited over-time is considered; (5) workers' absenteeism is not considered.

3.2.1 Notations used. The notations used in the formulation of the MOLP model are illustrated in Table 3.

3.2.2 Objective functions. Here in this study, based on the priority weights obtained through FAHP explained in section 4.2, the objective functions selected are related to minimization of the total production cost and the lead time for formulating an APP model.

The total cost is the sum of the different variable production costs incurred over the planning horizon T. Hence, the objective function related to the total cost minimization is given as:

f_1 – Minimization of Total Cost of Production

$$\boldsymbol{Min}.\ f_1 = \sum_{t=1}^{T} \sum_{p=1}^{P} \left(R_c^{p_i} R_t^{p_i} + E_c^{p_i} E_t^{p_i} + H_c^{p_i} H_t^{p_i} + K_c^{p_i} K_t^{p_i} + I_c^{p_i} I_t^{p_i} \right) \tag{12}$$

The total cost of production includes five components, as follows:

$\sum_{t=1}^{T} \sum_{p=1}^{P} (\boldsymbol{R_c^{p_i} R_t^{p_i}})$ are the total regular time production costs for parts i,

Notation	Description
$R_c^{p_i}$	The regular time production cost per labor-hour of ith part
$E_c^{p_i}$	The overtime production cost per labor-hour of ith part
$H_c^{p_i}$	The subcontractor production cost per labor-hour of ith part
$K_c^{p_i}$	The inventory holding cost per month of one labor-hour of work of ith part
$I_c^{p_i}$	The idle time cost per labor-hour of ith part
$D_c^{p_i}$	The penalty cost for delay per unit production hour of ith part
$R_t^{p_i}$	The regular time production hours scheduled in month t of ith part in period t
$E_t^{p_i}$	The overtime time production hours scheduled in month t of ith part in period t
$H_t^{p_i}$	The subcontractor time production hours scheduled in month t of ith part in period t
$K_t^{p_i}$	The number of working hours stored in inventory at the end of month t of ith part in period t
$I_t^{p_i}$	The number of idle time during regular production hours for ith part in period t
$W_t^{p_i}$	The expected demand in month t (hours of production) of ith part in period t
$M_t^{p_i}$	The highest demand the company should be able to satisfy in period t (hours of production) of ith part
MR_t^{Pi}	The maximum number of regular time hours in month t of ith part
ME_t^{pi}	The maximum number of overtime hours allotted in month t of ith part
MH_t^{pi}	The maximum number of subcontractor hours allotted in month t of ith part
$a_t^{p_i}$	The reduction in the number of production hours scheduled in month t compared to the number of production hours scheduled in month $t-1$ of ith part
$b_t^{p_i}$	The increase in the number of production hours scheduled in month t compared to the number of production hours scheduled in month t–1 of ith part
K_0	Initial inventory
T	The total number of months in the planning horizon
P	The total number of parts under consideration
p_i	ith part ($i = 1, \ldots, P$)

Table 3.
Notations used in MOLP model

$\sum_{t=1}^{T}\sum_{p=1}^{P}(\boldsymbol{E_c^{p_i}E_t^{p_i}})$ are the total overtime production costs for parts i,

$\sum_{t=1}^{T}\sum_{p=1}^{P}(\boldsymbol{H_c^{p_i}H_t^{p_i}})$ are the total subcontracting time costs for parts i,

$\sum_{t=1}^{T}\sum_{p=1}^{P}(\boldsymbol{K_c^{p_i}K_t^{p_i}})$ are the total inventory carrying costs for parts i,

$\sum_{t=1}^{T}\sum_{p=1}^{P}(\boldsymbol{I_c^{p_i}I_t^{p_i}})$ are the total idle time costs for parts i.

The second objective comprises the minimization of the lead time. The lead time is majorly driven by the regular production hours provided in a stipulated time. Thus, the lead time is taken as the function of the regular production hours. So, the objective function related to the minimization of lead time is given as:

f_2 – Minimization of Total Lead Time

$$\boldsymbol{Min}.\ f_2 = \sum_{t=1}^{T}\sum_{p=1}^{P}\left(R_t^{pi}\right) \tag{13}$$

3.2.3 Constraints. The model comprises four groups of constraints, namely, demand constraint, regular time constraint, overtime constraint, and subcontracting constraint.

(1) Demand Constraint:

$$K_{t-1}^{p_i} + R_t^{p_i} + H_t^{p_i} + E_t^{p_i} - K_t^{p_i} = W_t^{p_i} \tag{14}$$

$$K_{t-1}^{p_i} + R_t^{p_i} + H_t^{p_i} + E_t^{p_i} \geq M_t^{p_i} \tag{15}$$

where $\boldsymbol{W_t^{p_i}}$ denotes the imprecise expected demand of ith part in period t. The expected demand $\boldsymbol{W_t^{p_i}}$ cannot be exactly obtained in a dynamic market of real-world APP problems. The sum of regular time and overtime production hours, subcontractor time production hours, and the number of working hours stored in inventory should be equal to the market demand, as in Eq. (14). While Eq. (15) represents the limit of the highest demand of period t.

(2) Regular Time Constraint:

$$R_t^{p_i} + I_t^{p_i} = MR_t^{pi} \quad for\ t = 1,\ \ldots,\ T \tag{16}$$

where $\boldsymbol{MR_t^{pi}}$ denotes the imprecise maximum number of regular time hours of period t.

(3) Overtime production hours

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\left(E_t^{p_i}\right) \geq ME_t^{p_i} \quad for\ \ t = 1,\ \ldots,\ T \tag{17}$$

where $\boldsymbol{ME_t^{p_i}}$ represents the imprecise maximum number of overtime hours of period t.

(4) Subcontractor production hours

$$\sum_{t=1}^{T}\sum_{p=1}^{P}\left(H_t^{p_i}\right) \geq MH_t^{p_i} \quad for\ t = 1,\ \ldots,\ T \tag{18}$$

where $MH_t^{p_i}$ denotes the imprecise maximum number of subcontractor hours of period t.

$$R_t^{p_i} + H_t^{p_i} + E_t^{p_i} + a_t^{p_i} - b_t^{p_i} = R_{t-1}^{p_i} + H_{t-1}^{p_i} + E_{t-1}^{p_i} \quad \textbf{\textit{for}} \quad t = 2, \ldots, T \tag{19}$$

$$K_0^{p_i} = K_1^{p_i} = 0 \ , \ \ a_1 = 0 \ , \ \ b_1 = 0 \tag{20}$$

The initial inventory for Period-1 is taken as zero.

(5) An upper limit on Regular Time, overtime, and subcontracting production hours

$$0 \le R_t^{p_i} \le MR_t^{pi}, \quad 0 \le E_t^{p_i} \le ME_t^{pi}, \ 0 \le H_t^{p_i} \le MH_t^{pi} \ \textbf{\textit{for}} \ t = 1, \ldots, T \tag{21}$$

(6) Non-negativity constraints

$$a_1 \ge 0 \ , \ \ b_1 \ge 0 \ , \ \ I_t \ge 0 \quad for \quad t = 1, \ \ldots, T \tag{22}$$

$p_i = 1, \ldots, P \quad \forall$ equations.

3.3 Stage 3: Developing a simulation model of a case study

The third stage comprises the application of a simulation method. Simulation typically involves creating a virtual model of the existing process, service, or system (Banks *et al.*, 2005; Law and Kelton, 1991). Simulation is considered a reliable operations research tool for decision-making in the production and operations management domain concerning cost minimization, customer satisfaction, and retaining profits to maintain a firm's competitiveness (Junior *et al.*, 2019). An insightful prescriptive "what-if" analysis can be virtually conducted without disturbing the actual system using a simulation method (Banks *et al.*, 2005; Gabriel, 2017). Simulation also aids in validating the suggested solutions for the problem under study (Curry and Feldman, 2011). Due to these significant reasons, simulation is deployed in this study to determine the impact of the proposed APP strategy on manufacturing performances.

Simulation technique is extensively applied to solve the problems of the manufacturing and production systems, supply chain and logistics, construction and project management, business process modeling, healthcare, sustainability, and environment management, etc. (Banks *et al.*, 2005). This led to enormous literature on simulation, including the review articles highlighting the success stories of simulation applications (Jahangirian *et al.*, 2010; Junior *et al.*, 2019; Mourtzis *et al.*, 2014; Negahban and Smith, 2014; Oliveira *et al.*, 2019). Deshpande *et al.* (2007) benchmarked the performance measures of terminal operations of less-than-truckload (LTL) freight carriers using discrete event simulation. Jaipuria and Mahapatra (2015) used a system dynamics simulation method to analyze the impact of uncertainties in the lower to upper stream of the supply chain on the behavior of a make-to-stock manufacturing system. Simulation has been used along with other optimization techniques as well. For example, Dev *et al.* (2014) coupled the interpretive structural modeling (ISM) technique with discrete event simulation for reconfiguring the supply chain network to improve the performance. Prakash and Mohanty (2017) combined the data envelopment analysis (DEA) with the Monte Carlo simulation for aiding the selection of green cars. Linnéusson *et al.* (2020) utilize a hybrid simulation approach comprising system dynamics and discrete event simulation to support strategic maintenance decisions to enhance production performance.

A discrete event simulation (DES) is used in the present research to create an as-is model of a manufacturing firm under study. Banks *et al.* (2005) defined a DES as "the modeling of a system in which the state variable changes only at a discrete set of points in time." DES optimization consists of a set of commonly used tools and techniques by researchers and practitioners from industrial engineering domains for evaluating different solution settings to determine the optimal one that improves key performance indicators, such as – throughput, delivery lead time, service level, etc. (Gansterer *et al.*, 2014; Junior *et al.*, 2019). Numerous DES softwares are available recently to create a simulation model of a system under study. Amongst them, Arena© by Rockwell Simulation, due to its noteworthy benefits, is the most widely used DES software to create a replica of the existing system (Dias and Oliveira, 2016). Arena can model almost all kinds of problems, namely, stochastics, deterministic, discrete, and continuous. Arena offers *"flexibility and ease"* to create the model and re-edit it (Shawki *et al.*, 2015). Arena permits evaluating the existing system by creating an as-is model to conduct a comparative analysis between the different scenarios involving various system changes. Users can perform what-if analysis through Arena. What-if analysis aids in understanding the systems' behavior after incorporating critical modifications in the system (Dias and Oliveira, 2016; Dohale *et al.*, 2021f). Hence, the present study utilizes Arena© software to create a simulation model of a firm under study.

In this study, an integrated FAHP-MOLP-Simulation methodology is implemented in a real case to demonstrate its applicability. The case study is chosen as one of the methods in this research to explore an in-depth understanding and effectiveness of the proposed FAHP-MOLP-Simulation methodology on the manufacturing performance of a firm. A case study is a preferred approach when the objective is to answer "how" and "why" the events are occurring (Yin, 2018). Case studies are suitable in all kinds of research, namely, descriptive, exploratory, or explanatory. The present study being exploratory and inductive in nature, the use of a single case is preferred (Yin, 2018). Thus, firstly the objectives for formulating an APP are determined and selected using FAHP. Thereafter, an APP model is developed using the MOLP formulation using equations (12) to (22). Further, simulation experiments are conducted on the virtual model to test the APP given by MOLP for its effectiveness. The effectiveness of the LP-based APP is analyzed by evaluating its impact on manufacturing performances. Viswanadham and Narahari (1992) suggested different manufacturing performances, namely. Lead time, Work-In-Process, resource utilization, throughput, capacity, flexibility, and quality. However, in the present study, the impact of the proposed LP-based APP is evaluated on the manufacturing throughput, lead time, and resource utilization.

Further, a comparison between the manufacturing performances achieved through the firm's existing production plan and the proposed APP is carried out in a simulation environment. This is achieved by creating two different scenarios in the Arena simulation software. The first scenario highlights the level of manufacturing performances attained through the existing production plan of a firm. In the second scenario, the proposed APP is analyzed to evaluate the manufacturing performances gained through its implication. This, in turn, helps the production planner in decision-making related to the choice of the production plan for the firm under study.

4. The case

4.1 Case description

The practicality of the proposed hybrid LP-Simulation methodology is illustrated using a case example of ABC company. A pseudonym ABC is given to hide the identity of the firm under study. ABC is a Korean manufacturing firm located in Pune, India. The annual turnover of ABC firm is reported as ₹ 553 Million in 2018–2019. ABC manufactures the manifold assembly for ACs in cars. These manifolds help to transfer the conditioned air in the car. ABC produces the parts via a batch process. As the firms' business proliferates rapidly and thereby increasing market needs day by day, the firm faces difficulty meeting the quoted customer demand at a stated time. Thus, the firm faces a problem of delayed deliveries resulting in customer dissatisfaction. The initial discussion with the expert nominated by the management team, i.e. production manager of ABC firm, provided detailed insights into the problem and discussed the issues associated with improper production planning. This led to the development of a new production plan at an aggregate level.

The decision problem for ABC firm exemplified here aims to develop a FAHP-MOLP-Simulation based multi-product multi-period APP for minimizing total costs and lead time. The planning horizon of 6 months is taken here (i.e. Month 1, 2, . . ., 6). The model is applied to four different parts (Part 1, 2, 3, and 4). The preliminary data of the forecasted demand, inventory level, operating cost, and maximum labor and machine hours are collected from the industry expert. As the unit of analysis for the LP model is time (hours), the forecasted demand in terms of the number of units to be produced is converted to hours to produce them. The conversion of the units is demonstrated in Annexure. The forecasted demand for parts 1–4 for months 1–6 is given in Table 4.

The cost-related data provided by a firm (in monetary units) is:

$$\boldsymbol{R}_{\boldsymbol{c}}^{\boldsymbol{p}_i} = 30.00,\ \boldsymbol{E}_{\boldsymbol{c}}^{\boldsymbol{p}_i} = 45.00,\ \boldsymbol{H}_{\boldsymbol{c}}^{\boldsymbol{p}_i} = 50.00,\ \boldsymbol{K}_{\boldsymbol{c}}^{\boldsymbol{p}_i} = 10.00,\ \boldsymbol{I}_{\boldsymbol{c}}^{\boldsymbol{p}_i} = 15.00 \text{ for i} = 1, 2, 3, \text{and } 4$$

As per experts' suggestions, the highest demand the firm can satisfy, i.e. $\boldsymbol{M}_{\boldsymbol{t}}^{\boldsymbol{p}_i}$, is taken to be 50% more than the forecasted demand for all parts. The industry expert advised having the 4maximum total production cost per part type (i.e. part 1, part2, part 3, and part 4) no more than 40,000 monetary units and the lead time no more than 175 h.

4.2 FAHP for selecting objective functions to formulate APP

Using the five-stage procedure mentioned in Section 3.1, the FAHP procedure is conducted in this study. Initially, the most relevant objective functions considered in the APP are determined through a literature survey. It resulted in the identification of eight objective functions, namely, (1) Maximize customer service (Z1), (2) Minimize total production Cost (Z2), (3) Minimize inventory investment (Z3), (4) Minimize changes in workforce levels (Z4), (5) Minimize changes in production rates (Z5), (6) Minimize total lead time (Z6), (7) Minimize subcontracting (Z7), and (8) Maximize utilization of plant and equipment (Z8) (Cheraghalikhani *et al.*, 2019; Pan and Kleiner, 1995). Further, a pairwise comparison between the identified objective function is conducted using the integer value (1–9) scale of AHP utilizing a group decision-making procedure. The number of decision-makers (DMs) required for conducting a group decision making in AHP typically varies between 3 and 11 (Ahsan and Rahman, 2016). Thus, in this study, judgments of the three DMs nominated by the firm and having expertise in the domain of study are gathered. The consistency ratio (CR) of each pairwise comparison matrix is calculated. A sample pairwise comparison matrix of DM1 is shown in Table 5.

Using the guidelines given in Table 2, integer values in all the three pairwise comparison matrices are replaced with fuzzy numbers. In Table 6, a sample fuzzy pairwise comparison

Table 4.
Forecasted demand

Parts	Month-1 No. of Parts	Month-1 hrs	Month-2 No. of Parts	Month-2 hrs	Month-3 No. of Parts	Month-3 hrs	Month-4 No. of Parts	Month-4 hrs	Month-5 No. of Parts	Month-5 hrs	Month-6 No. of Parts	Month-6 hrs
Part 1	23,000	190	16,000	132	15,000	125	16,000	132	15,000	125	13,000	110
Part 2	23,000	202	16,000	140	15,000	132	16,000	140	15,000	132	13,000	115
Part 3	11,000	130	8,000	95	8,000	95	9,000	105	8,500	100	8,500	100
Part 4	11,000	115	8,000	85	8,000	85	9,000	95	8,500	90	8,500	90

matrix for DM1 is shown. The pairwise comparison and fuzzy pairwise comparison matrices by DM2 and DM3 are provided in Appendixes 1 and 2.

The fuzzy judgments of all three DMs are amalgamated using a geometric mean method (Hummel *et al.*, 2014; Kannan *et al.*, 2013). Further, using the extant analysis procedure for FAHP proposed by Chang (1996) given in equation (1) to (10), the final relative weights of all objectives are computed. The aggregated fuzzy pairwise comparison matrix, along with the calculated final relative weights, is shown in Appendix 3. Minimization of total production cost (Z2) and the minimization of lead time (Z6) received the highest weights of 0.3487 and 0.2603, respectively. Thus, these two objectives are considered for formulating the APP model for ABC firm, as outlined in Section 3.2. These two objective functions are then solved using the multi-objective linear programming formulation given in Section 3.2.2.

4.3 Solving procedure for the LP model

The detailed procedure for solving the APP problem for ABC firm using the proposed MOLP approach is discussed as follows.

Step 1: Formulate the MOLP model for an APP decision problem using Equations (12) to (22).

Step 2: Solve the objective functions associated with the constraints for each part using the solver of Lingo©18.0. Lingo is one of the most powerful and concise packages developed to solve mathematical optimization problems (ASADİ and DARABİ, 2015; Men and Yin, 2018). Lingo comprises an easy and complete guide that makes its user familiar with this software to a great extent. The models built by Lingo software are significantly easier to understand and maintain. Lingo can handle a large volume of data and briefly formulates and solves complex problems (Men and Yin, 2018). Further, Lingo can effectively solve linear, nonlinear, integer programming, and branch and bound problems (Amiri-Aref *et al.*, 2016; ASADİ and DARABİ, 2015). Due to these advantages, we utilized Lingo to solve the problem under study.

Step 3: The optimal solutions for the objective function are determined for each part and provided in Table 7. It is observed that the total production cost for each part type (Part 1, 2, 3, and 4) is in the allowable range (i.e. lesser than 40,000 monetary units). Whereas the lead time (R_t^{Pi}) for each part in each period is lesser than 175 h.

Step 4: Further, the validation of the solutions obtained from the LP model is carried out through a simulation model to evaluate the impact of the new APP on manufacturing performance.

Objectives	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8
Z1	1	1/9	1/5	1/7	1/6	1/8	1/2	1/2
Z2	9	1	7	4	5	2	8	6
Z3	5	1/7	1	1/3	2	1/4	2	4
Z4	7	1/4	3	1	4	1/3	6	7
Z5	6	1/5	1/2	1/4	1	1/6	3	5
Z6	8	1/2	4	3	6	1	7	5
Z7	2	1/8	1/2	1/6	1/3	1/7	1	3
Z8	2	1/6	1/4	1/7	1/5	1/5	1/3	1
							CR	0.078

Table 5. AHP Pairwise comparison by DM1

Table 6.
Fuzzy AHP pairwise comparison by DM1

Objectives	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8
Decision-Maker 1								
Z1	*(1, 1, 1)*	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/7, 1/6, 1/5)	(1/9, 1/8, 1/7)	(1/3, 1/2, 1)	(1/3, 1/2, 1)
Z2	(9, 9, 9)	*(1, 1, 1)*	(6, 7, 8)	(3, 4, 5)	(4, 5, 6)	(1, 2, 3)	(7, 8, 9)	(5, 6, 7)
Z3	(3, 4, 5)	(1/8, 1/7, 1/6)	*(1, 1, 1)*	(1/4, 1/3, 1/2)	(1, 2, 3)	(1/5, 1/4, 1/3)	(1, 2, 3)	(3, 4, 5)
Z4	(6, 7, 8)	(1/5, 1/4, 1/3)	(2, 3, 4)	*(1, 1, 1)*	(3, 4, 5)	(1/4, 1/3, 1/2)	(5, 6, 7)	(6, 7, 8)
Z5	(5, 6, 7)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1/5, 1/4, 1/3)	*(1, 1, 1)*	(1/7, 1/6, 1/5)	(2, 3, 4)	(4, 5, 6)
Z6	(7, 8, 9)	(1/3, 1/2, 1)	(3, 4, 5)	(2, 3, 4)	(5, 6, 7)	*(1, 1, 1)*	(6, 7, 8)	(4, 5, 6)
Z7	(1, 2, 3)	(1/9, 1/8, 1/7)	(1/3, 1/2, 1)	(1/7, 1/6, 1/5)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	*(1, 1, 1)*	(2, 3, 4)
Z8	(1, 2, 3)	(1/7, 1/6, 1/5)	(1/5, 1/4, 1/3)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	*(1, 1, 1)*

	Months	Production Hours Part 1											Total Cost of Production (in Monetary Units)
		$R_t^{p_1}$	$E_t^{p_1}$	$H_t^{p_1}$	$K_t^{p_1}$	$K_{t-1}^{p_1}$	$I_t^{p_1}$	$R_{t-1}^{p_1}$	$E_{t-1}^{p_1}$	$H_{t-1}^{p_1}$	$a_t^{p_1}$	$b_t^{p_1}$	
Part 1	Month 1	175	0	100	85	0	0	0	0	275	0	0	34,870
	Month 2	114	0	1	68	85	46	175	0	100	160	0	
	Month 3	122	0	0	65	68	53	114	0	1	0	7	
	Month 4	135	0	0	68	65	35	122	0	0	0	13	
	Month 5	122	0	0	65	68	53	135	0	0	13	0	
	Month 6	105	0	0	60	65	65	122	0	0	17	0	
		Production Hours Part 2											Total Cost of Production (in Monetary Units)
	Months	$R_t^{p_2}$	$E_t^{p_2}$	$H_t^{p_2}$	$K_t^{p_2}$	$K_{t-1}^{p_2}$	$I_t^{p_2}$	$R_{t-1}^{p_2}$	$E_{t-1}^{p_2}$	$H_{t-1}^{p_2}$	$a_t^{p_2}$	$b_t^{p_2}$	
Part 2	Month 1	175	50	75	98	0	0	0	0	300	0	0	36,789
	Month 2	112	0	0	70	98	48	175	50	75	188	0	
	Month 3	130	0	0	68	70	45	112	0	0	0	18	
	Month 4	142	0	0	70	68	28	130	0	0	0	12	
	Month 5	130	0	0	68	70	45	142	0	0	12	0	
	Month 6	102	0	0	55	68	68	130	0	0	28	0	
		Production Hours Part 3											Total Cost of Production (in Monetary Units)
	Months	$R_t^{p_3}$	$E_t^{p_3}$	$H_t^{p_3}$	$K_t^{p_3}$	$K_{t-1}^{p_3}$	I_t^{3}	$R_{t-1}^{p_3}$	$E_{t-1}^{p_3}$	$H_{t-1}^{p_3}$	$a_t^{p_3}$	$b_t^{p_3}$	
Part 3	Month 1	160	0	0	30	0	15	0	0	160	0	0	24,500
	Month 2	85	0	0	20	30	75	160	0	0	75	0	
	Month 3	95	0	0	20	20	80	85	0	0	0	10	
	Month 4	110	0	0	25	20	60	95	0	0	0	15	
	Month 5	95	0	0	20	25	80	110	0	0	15	0	
	Month 6	100	0	0	20	20	70	95	0	0	0	5	
		Production Hours Part 4											Total Cost of Production (in Monetary Units)
	Months	$R_t^{p_4}$	$E_t^{p_4}$	$H_t^{p_4}$	$K_t^{p_4}$	$K_{t-1}^{p_4}$	$I_t^{p_4}$	$R_{t-1}^{p_4}$	$E_{t-1}^{p_4}$	$H_{t-1}^{p_4}$	$a_t^{p_4}$	$b_t^{p_4}$	
Part 4	Month 1	170	0	0	55	0	5	0	0	170	0	0	25,280
	Month 2	80	0	0	50	55	80	170	0	0	90	0	
	Month 3	88	0	0	53	50	87	80	0	0	0	8	
	Month 4	87	0	0	45	53	83	88	0	0	1	0	
	Month 5	90	0	0	45	45	85	87	0	0	0	3	
	Month 6	90	0	0	45	45	80	90	0	0	0	0	

Table 7. MOLP results

4.4 Simulation model

A simulation model for ABC firm is created in ARENA© simulation software using real-time data related to the processing time of a resource required for producing each part, the number of parts to produce, and total run length, i.e. the time for running simulation. The sample data of processing time for Part-3 is provided in Table 8. The processing time (PT) data is collected using a stop-watch time study by observing the process. Ten readings of PT at a different time interval, in various shifts, have been taken to reduce the biases in the data (Kanawaty, 1992). Further, the average PT is calculated and taken as the input for the simulation model. The data related to the number of parts to be produced in a firm is retrieved from the solution obtained through the APP model solved in Section 3.2. The regular production time hours are equivalent to the production time of the firm for producing the products in the firm. Hence, the regular production time hours are converted to a number of parts, as shown in Table 9. The conversion of time to a unit of parts is described in Annexure. The data shown in Table 9 is then fed to simulation model. Figure 3 shows the simulation model for the ABC firm.

The aforementioned data is utilized to create the simulation model of ABC firm. The model shown in Figure 4 comprises three sections. The first section depicts part creation. In this section, all parts are created in arena simulation using the "part creation" tools. The information related to the parts, namely, part number, part name, sequence of operations, etc., is initialized in this section. The second section shows the shop-floor area of the ABC firm. All the processes required for producing the parts and inspection of the parts are created in this section. The last section is the dispatch section. All the parts that assure the quality got dispatched for packaging in this section.

After feeding the data, a test run of the simulation model is carried out. In the test run, the simulation model is verified and validated for determining whether the model replicates the behavior of the actual system or not? This helps to remove the discrepancies between the model and the actual system (Banks *et al.*, 2005). After a series of iterations and modifications, the simulation model created in this study fits well with the actual system.

The model is simulated for Month-1 comprising 25 days (excluding holidays) with one shift of 7 h each day. So, the total run length of Simulation is taken as 175 h. The total throughput demanded in Month-1 is 71,235, as shown in Table 9. A comparative analysis is carried out between the existing production plan and the proposed APP. Thus, two simulation scenarios are created to demonstrate the effectiveness of a new APP over the firm's existing production plan. The sample simulation result for Month-1 is shown in Tables 10 and 11. Table 10 consists of the results related to a number of parts that can be produced, i.e. throughput and the actual time required to produce the parts, i.e. lead time. The result

Table 8.
Sample processing time data for Part-3

Sr. No.	Process	Resource name	Processing Time (in Seconds) 1	2	3	4	5	6	7	8	9	10	Avg. PT
1	Process 1	Resource 13	22	38	28	24	21	21	35	20	23	21	25.3
2	Process 2	Resource 14	18	17	18	19	18	20	20	18	18	19	18.5
3	Process 3	Resource 15	13	13	13	14	16	13	14	13	13	15	13.7
4	Process 4	Resource 16	13	13	16	13	13	16	14	17	13	13	14.1
5	Process 5	Resource 17	27	27	24	29	28	29	26	26	29	25	27
6	Process 6	Resource 18	7	7	6	6	6	6	8	6	7	6	6.5
7	Process 7	Resource 19	23	21	21	26	19	20	23	19	18	19	20.9

Table 9.
Number of parts to produce month-wise

Months	Part 1 $R_t^{p_1}$	Part 1 No. of Parts	Part 2	Part 2 No. of Parts	Part 3 $R_t^{p_3}$	Part 3 No. of Parts	Part 4 $R_t^{p_4}$	Part 4 No. of Parts	Total number of parts to produce
Month 1	175	21,250	175	20,000	160	13,714	170	16,271	71,235
Month 2	114	13,843	112	12,800	85	7,286	80	7,657	50,200
Month 3	122	14,814	130	14,857	95	8,143	88	8,423	46,255
Month 4	135	16,393	142	16,229	110	9,429	87	8,327	50,378
Month 5	122	14,814	130	14,857	95	8,143	90	8,614	46,428
Month 6	105	12,750	102	11,657	100	8,571	90	8,614	41,592

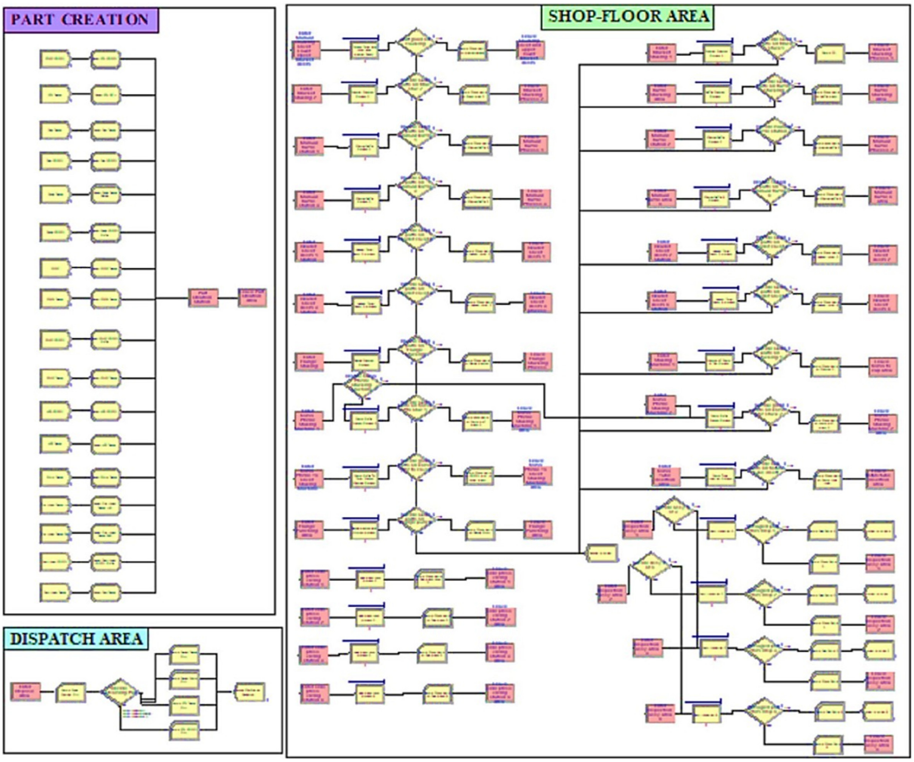


Figure 4.
Simulation model of ABC firm

Sr. No.	Scenarios	Scheduled run length (hrs.)	Actual time to produce the pats (Lead Time-Hrs)	Parts Produced					
				Part 1	Part 2	Part 3	Part 4	Total parts produced (Throughput)	Total parts demand
1	Scenario 1	175	175	13,734	12,905	12,401	14,735	53,775	71,235
2	Scenario 2	175	161	21,306	20,090	13,740	16,330	71,466	71,235

Table 10.
Simulation results for Month-1

related to resource utilization is provided in Table 11. The results from the simulation method are discussed in section 5.

5. Discussion

This section provides a brief interpretation and discussion about the results retrieved from a hybrid LP-Simulation methodology.

5.1 MOLP

The MOLP-based APP is developed to optimize the total production cost of a firm. The firm has set the level of the production cost to be lesser than 40,000 monetary units and lead time to be lesser than 175 h per part type. Figure 5 illustrates the comparative analysis of the results

Resource	Scenario 1	Scenario 2	Resource	Scenario 1	Scenario 2
Resource 1	0.6625	0.7024	Resource 14	0.7884	0.512
Resource 2	0.4421	0.7052	Resource 15	0.1325	0.5029
Resource 3	0.6569	0.7955	Resource 16	0.5805	0.5092
Resource 4	0.5207	0.7024	Resource 17	0.4488	0.5102
Resource 5	0.9998	0.5778	Resource 18	0.1533	0.5079
Resource 6	0.7196	0.7094	Resource 19	0.1214	0.6754
Resource 7	0.7721	0.6492	Resource 20	0.4065	0.6082
Resource 8	0.4826	0.7004	Resource 21	0.5105	0.6888
Resource 9	0.6113	0.7044	Resource 22	0.6493	0.6065
Resource 10	0.6327	0.7113	Resource 23	0.6857	0.6013
Resource 11	0.3538	0.6989	Resource 24	0.6879	0.6051
Resource 12	0.1135	0.6301	Resource 25	0.5192	0.5983
Resource 13	0.5368	0.5123	Resource 26	0.9997	0.689

Table 11.
Resource utilization

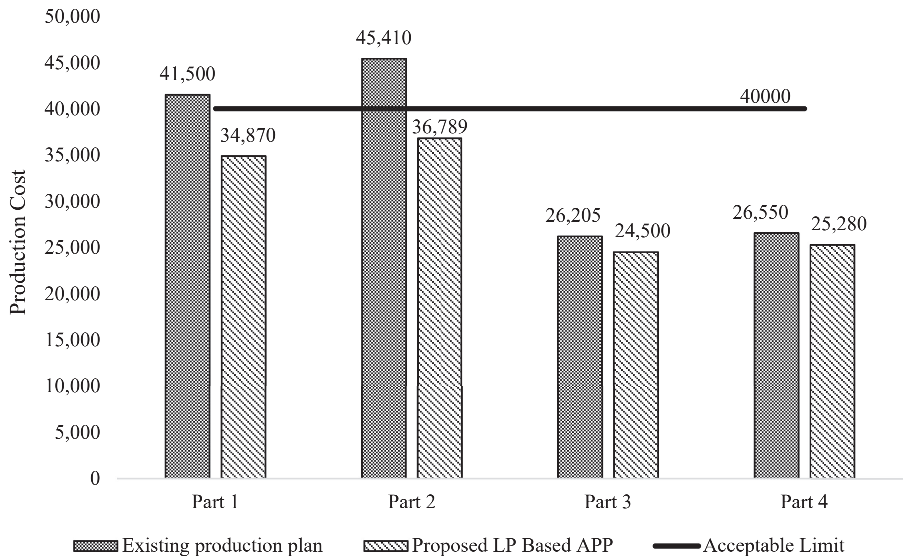


Figure 5.
Cost of production

achieved by deploying the firms' existing production plan and the proposed APP. It is seen from Figure 5 that the proposed APP helps to produce the forecasted demand at a lesser cost. Also, the production cost from the proposed APP is within the acceptable range of the firm.

5.2 Simulation

A sample simulation is provided in this study for Month-1. The lead time of 175 h and the required demand of each part shown in Table 9 are fed as an input in the model. The two simulation scenarios are created in this study. The first scenario shows the results of manufacturing performances achieved from the production plan over which the firm is currently working. Whereas scenario 2 illustrates the impact of proposed APP model on the manufacturing performances, namely, throughput, lead time, and resource utilization.

5.2.1 Scenario 1. This scenario illustrates the results generated from the simulation model after applying the traditional production plan the firm was using. It is seen from Table 10 that the required level of total parts demanded (71,235) in month-1 cannot be achieved through the existing production plan. The firm can only produce 53,775 quantities of parts. So, the customer's demand cannot be satisfied through the current production plan developed by using the firm's traditional planning technique. Further, analyzing the utilization of resources, it varies from 10% to 99.99% in scenario one, as shown in Table 11. However, the industry expert suggested that resource utilization should range between 40% and 85% for a smooth production flow based on his experience. Due to the uneven resource utilization, the presence of bottlenecks is observed. This further led to an increase in lead time.

5.2.2 Scenario 2. This scenario provides the results generated from the simulation model after applying the proposed APP. It is seen that for Month-1: 21,306 quantities of part 1, 20,090 quantities of part 2, 13,740 quantities of part 3, and 16,330 quantities of part 4 can be produced, thus satisfying the customers' demand for Month 1. Further, the total throughput needed, i.e. (71,235), can be achieved through the proposed APP. The resource utilization is improved in this scenario and ranges from 50% to 80%, as shown in Table 11. The results also depict that the actual lead time required for producing the demanded throughput is 161 h $\leq$ 175 h (the firm's threshold value for lead time). This signifies that by adopting the proposed APP, the firm can provide the required level of customers' demand within the stated time and thereby become delivery competent (Miltenburg, 2005; Ward *et al.*, 1998).

6. Research implications

The proposed research work provides significant implications to the theory on production planning and practical dimensions, as discussed below.

6.1 Theoretical contributions

Aggregate production planning involves a tactical planning process that combines all the strategic business plans, namely, profit improvement, inventory cut down, business scaling, etc., into a single mid-level plan. The APP plan manages the balance between demand and supply capabilities within production, finance, distribution, and procurement (Pereira *et al.*, 2020). APP effectively achieves manufacturing performances. Achieving manufacturing performances at the specified levels leads to fulfilling a firm's strategic manufacturing decisions and business goals (Dohale *et al.*, 2020, 2021b, d). Hence, a properly formulated APP guarantees a fit with the business goals at a strategic level (Cheraghalikhani *et al.*, 2019; Pereira *et al.*, 2020). Thus, it is essential to formulate a mathematical model for APP and validate it by determining the impact of the proposed APP on manufacturing performances.

This study helps to develop the optimal aggregate production plan using the proposed methodology to achieve the lowest-cost plan. This study provides a threefold theoretical contribution. At first, the present research work has identified and provided the list of objective functions considered for an APP model formulation. The integrated framework of FAHP-MOLP-Simulation is the novel contribution to the body of knowledge to form an APP model. FAHP is utilized to select the objective functions most desired by a firm to achieve. The MOLP model is adopted to develop an APP, while the simulation helps to validate its applicability through a real-life case. Thus, unlike other existing studies enlisted in Table 1, the current research bridges the gap of the validation of the APP model through simulation to evaluate its effectiveness.

6.2 Managerial implications

The current research has demonstrated the applicability of the integrated framework through a real-life case study of ABC firm. Thus, the current study provides notable implications for practitioners and policymakers. The proposed research provides three significant implications to the practitioners and policymakers. Firstly, policymakers or practitioners can adopt the proposed FAHP-MOLP-simulation formulation to develop the APP model in a wide range of industries. Secondly, the practitioners and policymakers can evaluate their existing production plan by deciding the most suitable objective functions using the proposed framework. Thirdly, simulation can be used to evaluate waiting time, work-in-process, resource utilization, and the status of inventory over time. The uncertainty within the production planning has gained enormous attention from the practitioners during the havocking conditions due to disruptive events (Dohale *et al.*, 2021e; Paul and Chowdhury, 2020). Thus, manufacturing managers and practitioners can utilize the proposed framework to decide appropriate objectives and develop a production plan for their firm. In the recent, Ambilkar *et al.* (2021) mentioned the complexity associated with the production planning of the product returns. Thus, the proposed three-stage approach can be used to develop a production plan for the returned products. Further, the proposed combinatorial FAHP-MOLP-Simulation framework is versatile and can be extended for decision making at the strategic, tactical, and operational levels to address the manufacturing and service operation problems.

7. Conclusion

Aggregate production planning aims to develop an efficient production plan to meet fluctuating future demand optimally using the organization's resources. An efficient APP reduces the total production costs by increasing resource utilization, leading to increased firms' competitiveness in the marketplace. Thus, the present study attempts to create a novel framework for developing the optimal aggregate production plan using an integrated approach of fuzzy AHP, multi-objective linear programming, and the simulation technique.

In this study, concerning RQ1, the FAHP is used to decide the objective functions a firm desires to achieve by quantifying the relative priority weights of objectives using a group decision-making technique. Three decision-makers have provided their judgments to conduct the pairwise comparison between the objective functions. Minimization of Total Cost (Z2) and Minimization of Lead Time (Z6) received the highest weights, 0.3487 and 0.2603, respectively. So, these are selected as the objective functions for the APP formulation. To answer RQ2, a MOLP model is formulated to develop an aggregate production plan. Further, a simulation method is adopted to validate the proposed APP model. The Simulation model helps to evaluate the applicability of the proposed APP formulated using MOLP without disrupting the firm's manufacturing setup. The impact of the existing production plan and the proposed APP on manufacturing performances like resource utilization, throughput, and lead-time are tested and evaluated in the analysis. To demonstrate the results, the model is simulated for Month-1. The proposed MOLP-based APP is observed to reduce the firm's total production cost and improve its throughput and lead time. These improvements will provide higher profit margins and a competitive advantage to a firm. Further, resource utilization is enhanced using the APP and lies within the range of 50%–80%. The feasible range for resource utilization suggested by the industry expert is 40%–85%. Thus, the proposed APP helps to maintain the utilization of resources in the acceptable range.

Recently, manufacturing firms across the world are facing unprecedented disruption due to COVID-19. The demand pattern of most of the products is collapsed (Dohale *et al.*, 2021e). Thus, it has been essential to have a formal framework to guide practitioners and policymakers in developing appropriate production planning at different aggregation levels. The proposed integrated framework can be a suitable solution for this issue. The proposed framework can assist the practitioners and policymakers in selecting the appropriate objective function, developing a production plan, and further evaluating the effectiveness of the new production plan by measuring its impact on manufacturing performances.

Like other optimization studies, the present research possesses certain limitations. The first limitation is related to the assumptions made while developing a MOLP formulation. The second limitation can be a selection of objective functions using experts' judgment. The involvement of experts may lead to subjectivity and biasness. The sample size of experts (three DMs) can further be increased to overcome this issue. As manufacturing consists of dynamism, multiple objectives can be considered to cope with the dynamic nature of the manufacturing, namely, minimization of inventory carrying cost, minimization of total labor cost, minimization of back-order cost, etc. Thus, future studies are encouraged to address these limitations.

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Annexure

The conversion of the number of parts into the number of production hours needed to produce them is carried out as follows:

The forecasted demand for Part 1 in month 1 is 23,000 quantities. Using the data collected from the shop floor, it is observed that 850 quantities of part 1 are produced in 7 h. Thus, 23,000 quantities will be produced nearly in 190 h.

$$\left(\frac{23{,}000 \times 7}{850} = 189.47 hrs. \approx 190 hrs.\right)$$

At the same time, 800 quantities of part 2 are produced in 7 h, thus the calculated production hours for producing 23,000 quantities of part 2 are 202 h.

$$\left(\frac{23{,}000 \times 7}{800} = 201.25 hrs. \approx 202 hrs.\right)$$

In this manner, the calculation for other parts is carried out.

(The same procedure is used for reconversion of the production hours to the number of parts.)

Appendix 1

Table A1.
Pairwise comparison matrix by DM2 and DM3

Objectives	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8
Decision-Maker 2								
Z1	*1*	1/8	1/4	1/6	1/5	1/7	1/3	1/2
Z2	8	*1*	7	4	6	2	8	9
Z3	4	1/7	*1*	1/3	2	1/6	4	5
Z4	6	1/4	3	*1*	5	1/4	5	7
Z5	5	1/6	1/2	1/5	*1*	1/6	4	5
Z6	7	1/2	6	4	6	*1*	8	6
Z7	3	1/8	1/4	1/5	1/4	1/8	*1*	3
Z8	2	1/9	1/5	1/7	1/5	1/6	1/3	*1*
							CR	0.097
Decision-Maker 3								
Z1	*1*	1/9	1/7	1/6	1/5	1/9	1/3	1/2
Z2	9	*1*	7	4	6	3	8	5
Z3	7	1/7	*1*	1/4	2	1/5	3	3
Z4	6	1/4	4	*1*	4	1/3	5	6
Z5	5	1/6	1/2	1/4	*1*	1/7	2	4
Z6	9	1/3	5	3	7	*1*	7	4
Z7	3	1/8	1/3	1/5	1/2	1/7	*1*	2
Z8	2	1/5	1/3	1/6	1/4	1/4	1/2	*1*
							CR	0.086

Appendix 2

Table A2. Fuzzy pairwise comparison matrix for DM2 and DM3

Objectives	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8
Decision-Maker 2								
Z1	*(1, 1, 1)*	(1/9, 1/8, 1/7)	(1/5, 1/4, 1/3)	(1/7, 1/6, 1/5)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)
Z2	(7, 8, 9)	*(1, 1, 1)*	(6, 7, 8)	(3, 4, 5)	(5, 6, 7)	(1, 2, 3)	(7, 8, 9)	(9, 9, 9)
Z3	(3, 4, 5)	(1/8, 1/7, 1/6)	*(1, 1, 1)*	1/3	(1, 2, 3)	1/6	(3, 4, 5)	(4, 5, 6)
Z4	(5, 6, 7)	(1/5, 1/4, 1/3)	(2, 3, 4)	*(1, 1, 1)*	(4, 5, 6)	(1/5, 1/4, 1/3)	(4, 5, 6)	(6, 7, 8)
Z5	(4, 5, 6)	(1/7, 1/6, 1/5)	(1/3, 1/2, 1)	(1/6, 1/5, 1/4)	*(1, 1, 1)*	(1/7, 1/6, 1/5)	(3, 4, 5)	(4, 5, 6)
Z6	(6, 7, 8)	(1/3, 1/2, 1)	(5, 6, 7)	(3, 4, 5)	(5, 6, 7)	*(1, 1, 1)*	(7, 8, 9)	(5, 6, 7)
Z7	(2, 3, 4)	(1/9, 1/8, 1/7)	(1/5, 1/4, 1/3)	(1/6, 1/5, 1/4)	(1/5, 1/4, 1/3)	(1/9, 1/8, 1/7)	*(1, 1, 1)*	(2, 3, 4)
Z8	(1, 2, 3)	(1/9, 1/9, 1/9)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/7, 1/6, 1/5)	(1/4, 1/3, 1/2)	*(1, 1, 1)*
Decision-Maker 3								
Z1	*(1, 1, 1)*	(1/9, 1/9, 1/9)	(1/8, 1/7, 1/6)	(1/7, 1/6, 1/5)	(1/6, 1/5, 1/4)	(1/9, 1/9, 1/9)	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)
Z2	(9, 9, 9)	*(1, 1, 1)*	(6, 7, 8)	(3, 4, 5)	(5, 6, 7)	(2, 3, 4)	(7, 8, 9)	(4, 5, 6)
Z3	(6, 7, 8)	(1/8, 1/7, 1/6)	*(1, 1, 1)*	(1/5, 1/4, 1/3)	(1, 2, 3)	(1/6, 1/5, 1/4)	(2, 3, 4)	(2, 3, 4)
Z4	(5, 6, 7)	(1/5, 1/4, 1/3)	(3, 4, 5)	*(1, 1, 1)*	(3, 4, 5)	(1/4, 1/3, 1/2)	(4, 5, 6)	(5, 6, 7)
Z5	(4, 5, 6)	(1/7, 1/6, 1/5)	(1/3, 1/2, 1)	(1/5, 1/4, 1/3)	*(1, 1, 1)*	(1/8, 1/7, 1/6)	(1, 2, 3)	(3, 4, 5)
Z6	(9, 9, 9)	(1/4, 1/3, 1/2)	(4, 5, 6)	(2, 3, 4)	(6, 7, 8)	*(1, 1, 1)*	(6, 7, 8)	(3, 4, 5)
Z7	(2, 3, 4)	(1/9, 1/8, 1/7)	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)	(1/3, 1/2, 1)	(1/8, 1/7, 1/6)	*(1, 1, 1)*	(1, 2, 3)
Z8	(1, 2, 3)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1/7, 1/6, 1/5)	(1/5, 1/4, 1/3)	(1/5, 1/4, 1/3)	(1/3, 1/2, 1)	*(1, 1, 1)*

Appendix 3

Table A3.
Aggregate fuzzy pairwise comparison matrix

Objectives	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Final Weights
Z1	*(1, 1, 1)*	(0.11, 0.11, 0.12)	(0.16, 0.19, 0.24)	(0.13, 0.15, 0.18)	(0.15, 0.18, 0.23)	(0.12, 0.13, 0.14)	(0.28, 0.38, 0.63)	(0.33, 0.50, 1)	0.0206
Z2	(8.28, 8.65, 9)	*(1, 1, 1)*	(6, 7, 8)	(3, 4, 5)	(4.64, 5.64, 6.64)	(1.26, 2.29, 3.30)	(7, 8, 9)	(5.65, 6.46, 7.23)	0.3487
Z3	(3.78, 4.82, 5.85)	(0.12, 0.14, 0.16)	*(1, 1, 1)*	(0.23, 0.30, 0.34)	(1, 2, 3)	(0.17, 0.20, 0.26)	(1.82, 2.88, 3.91)	(2.88, 3.91, 4.93)	0.0782
Z4	(5.31, 6.32, 7.32)	(0.20, 0.25, 0.33)	(2.28, 3.30, 4.30)	*(1, 1, 1)*	(3.30, 4.30, 5.31)	(0.23, 0.30, 0.44)	(4.31, 5.31, 6.32)	(5.65, 6.65, 7.65)	0.1579
Z5	(4.31, 5.31, 6.32)	(0.15, 0.17, 0.21)	(0.33, 0.5, 1)	(0.18, 0.23, 0.30)	*(1, 1, 1)*	(0.14, 0.16, 0.19)	(1.82, 2.88, 3.91)	(3.63, 4.64, 5.65)	0.0676
Z6	(7.23, 7.96, 8.65)	(0.30, 0.43, 0.79)	(3.91, 4.93, 5.94)	(2.28, 3.30, 4.30)	(5.31, 6.32, 7.32)	*(1, 1, 1)*	(6.32, 7.32, 8.32)	(3.91, 4.93, 5.94)	0.2603
Z7	(1.59, 2.62, 3.63)	(0.11, 0.12, 0.14)	(0.25, 0.34, 0.55)	(0.15, 0.18, 0.23)	(0.26, 0.35, 0.55)	(0.12, 0.14, 0.16)	*(1, 1, 1)*	(1.59, 2.62, 3.63)	0.0387
Z8	(1, 2, 3)	(0.13, 0.15, 0.17)	(0.20, 0.25, 0.34)	(0.13, 0.15, 0.17)	(0.18, 0.22, 0.28)	(0.17, 0.20, 0.26)	(0.28, 0.38, 0.63)	*(1, 1, 1)*	0.0279