SOLVING AN AGGREGATE PRODUCTION PLANNING PROBLEM BY FUZZY BASED GENETIC ALGORITHM (FBGA) APPROACH

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ABSTRACT

This paper work demonstrated an interactive Fuzzy Based Genetic Algorithm (FBGA) approach for solving a two products & two periods aggregate production planning (APP) with some vulnerable managerial constraints like imprecise demands, variable manufacturing costs etc. This proposed approach used the strategy of simultaneously minimizing the most possible value, the most pessimistic value & also most optimistic value of the imprecise total costs in lieu of some strong resource constraints. Another important purpose of this study is to derive & observe the variations along with the scope of the imprecise total cost, maximizing the possibility of obtaining lower total costs and also minimizing the risk of obtaining higher total costs. Here the authors employed different unique genetic algorithm parameters scrupulously for solving nondeterministic polynomials problems like APP problems. For reinforcing & accelerating the decision making for the decision maker a case study was considered in a Ready Made garment company in Bangladesh. Consequently, the proposed FBGA approach yields an efficient APP compromise solution and could be efficient for large scale problems.

KEYWORDS

Multi-objective optimization, Fuzzy Logic, Genetic Algorithm, Aggregate Production Planning

1. INTRODUCTION

Customer demand enters into the production system as units of products. However, production has to be planned as hours of machining and worker hours. In recent era since modernization grasp all kinds of traditional thinking as well as modern manufacturing practices. Obsolescence is the burning issue which takes only a tiny period for any consumer goods. Product life cycles are being shortened with an alarming rate which results unpredicted customer demand. For any supply chain profitability it is mandatory to maintain a balance between supply chain responsiveness & supply chain efficiency. For achieving strategic fit a manufacturing firm bears

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some important roles while acting as a member in any particular multi-echelon supply chain network. The outburst of all these is that the demands are becoming imprecise. So the ultimate goal for any manufacturing firm is to maintain a reach aggregate production planning which encompasses all levels of production costs, inventory costs, sub ordering costs & hiring costs. The primary output of the aggregate planning process is a master schedule, which describes the number of units to be produced during each period and the work force levels required by that period.

Aggregate production planning has lured a significant academic researchers & practitioners because of its immense importance. Shorten product life cycle in market & fickle customer perceptions push the researchers to choose this broad area to research (Shi and Haase, 1996). Since the relevant information regarding customer demands are imprecise in nature by using deterministic models bear suboptimal results. By Using fuzzy models such drawback could be terminated (Aliev, 2007). APP problems exaggeratedly imply constraint optimization and since the objective function bears some uncertainty so constrained optimization is must there. Along with fuzzy approach genetic approach also enticed a lot of researchers. Constrained optimizations are often being solved by different direct & indirect approaches. Among indirect approaches genetic approach is mostly lucrative because of its consistent & optimized results (Ioannis, 2009). Genetic algorithm is furnished with different genetic parameters like crossover, mutation, selection functions etc and different researchers used different combinations to solve constrained & unconstrained optimization problems (Bunnag & Sun, 2005). Not only the constrained optimization problem but also Pareto optimizations problems becoming a common field of research (Cai & Wang, 2006). Here the concerned multi-objective problem is also a constrained problem which encompasses all the relevant operating costs, production costs etc. These problems have long attracted the attention of researchers using traditional techniques of optimization and search as well as Genetic algorithms (Schaffer, 1985). Yeh and Chuang (2011) used multi-objective genetic algorithm for partner selection in green supply chain problems. Mixed integer linear programming approach, auxiliary multi-objective problems all utilized substantives results for multi period & multi product aggregate production planning problems (Ramezanian, 2012). Due to NP-hard class of APP, implementation of genetic algorithm and Tabu search are also very common in modern literature for solving these APP problems.

Throughout the review it is obvious that there already have been a long evolution phase past for Genetic algorithms as well as fuzzy logic for solving APP problems. Yet the researchers obstinately keep on this & they got newer dimension. Here the authors maintain their optimism while reviewing all the literatures since there have a lot of space for future contributions. Here the authors considered multiple objectives for multi period & multi product APP problem. But the distinction lies in the followed approach. Since the present situation of demand patterns as well as manufacturer's capacity are changing every day the authors used the imprecise values with a fuzzy triangular membership functions. Again the authors used three distinct scenarios simultaneously with different genetic algorithm options for solving multiple objectives of fuzzy linear programming models including escalating factors. This work develops a novel interactive FBGA approach considering escalating factors as well. The proposed approach used the genetic algorithm options first for solving imprecise multiple objectives & then they are being fuzzified to get optimal solution regarding decision maker's satisfaction. The rest of this paper is organized as follows: Section 2 describes the problem, details the assumptions, and formulates the problem. Section 2 also focused on the parameters of Auxiliary Multiple Objectives Fuzzy Linear Programming (MOFLP) approach, crisp formulation for solving that model & the ways of solving. The following section 3 outlined the FBGA model for the APP case and considered parameters for solving that approach. In section 4 some discussions is placed on a detailed case study which was performed from Comfit Composite Knit Limited (CCKL) for justifying the feasibility of the proposed FBGA approach which is followed by the results & findings in section 5. Conclusions are finally drawn in Section 6.

2. PROBLEM FORMULATION

2.1 Problem description & notation

Here in this paper the authors assumed that any particular company manufactures N types of products to satisfy the market demand over a planning horizon T. Generally, the environmental coefficients and related parameters are uncertain in a medium time horizon. Therefore, the forecast demand, related operating costs, and labor and machine capacity are imprecise over the planning horizon. Assigning a set of crisp values for the environmental coefficients and related parameters is inappropriate for dealing with such ambiguous APP decision problems. This APP problem focuses on developing an interactive Fuzzy Based Genetic Algorithm (FBGA) approach to determine the optimum aggregate plan for meeting forecast demand by adjusting regular and overtime production rates, inventory levels, labor levels, subcontracting and backordering rates, and other controllable variables. In addition of that some important assumptions are that the values of all concerned parameters are constant throughout the concerning periods. The forecasted demand over a particular period can be either satisfied or backordered, but the backorder must be fulfilled in the next period.

The authors employed the following notations for formulating the APP problem which predominantly akin in different literatures (R. C. Wang & T.F. Liang, 2004; Masud and Hwang, 1980; Wang and Fang, 2001).

D_{nt} Forecasted demand for nth product in period t (units)
a_{nt} Regular time production cost per unit for nth product in period t (Tk./unit)
Q_{nt} Regular time production for nth product in period t (units)
i_a Escalating factor for regular time production cost (%)
b_{nt} Overtime production cost per unit for nth product in period t (Tk./unit)
O_{nt} Overtime production for nth product in period t (units)
i_b Escalating factor for overtime production cost (%)
c_{nt} Subcontracting cost per unit of nth product in period t (Tk./unit)
S_{nt} Subcontracting volume for nth product in period t (units)
i_c Escalating factor for subcontract cost (%)
d_{nt} Inventory carrying cost per unit of nth product in period t (Tk./unit)
I_{nt} Inventory level in period t for nth product (units)
i_d Escalating factor for inventory carrying cost (%)
e_{nt} Backorder cost per unit of nth product in period t (Tk./unit)
B_{nt} Backorder level for nth product in period t (unit)
i_e Escalating factor for backorder cost (%)
K_t Hiring Cost for one worker in period t (Tk./man-hour)
H_t Worker hired in period t (man-hour)
m_t Layoff cost for one worker in period t (Tk./man-hour)

F_t Workers laid off in period t (man-hour)
i_f Escalating factor for hire and layoff cost (%)
i_{nt} Hours of labor per unit of nth product in period t (man-hour/unit)
r_{nt} Hours of machine usage per unit of nth product in period t (machine-hour/unit)
V_{nt} Warehouse spaces per unit of nth product in period t (ft^2/unit)
W_{tmax} Maximum labor level available in period t (man-hour)
M_{tmax} Maximum machine capacity available in period t (machine-hour)
V_{tmax} Maximum warehouse space available in period t (ft^2)

2.2 Fuzzy Based Genetic Algorithm (FBGA) Model

2.2.1 Multi-Objective functions

Most practical decisions made to solve APP problems usually consider total costs. Here the authors targeted three objective functions for which was solved by the proposed Fuzzy Based Genetic Algorithm (FBGA). First one selected is total costs as objective function (Masud and Hwang, 1980; Saad, 1982; Wang and Fang, 2001). The total costs are the sum of the production costs and the costs of changes in labor levels over the planning horizon T. Accordingly, the objective function of the proposed model is as follows:

$$\boldsymbol{Min\ Z} = \sum_{n=1}^{N}\sum_{t=1}^{T}[a_{nt}\,Q_{nt}(1+i_a)^t + b_{nt}O_{nt}(1+i_b)^t + c_{nt}S_{nt}(1+i_c)^t + d_{nt}I_{nt}(1+i_d)^t + e_{nt}B_{nt}(1+i_e)^t] + \sum_{t=1}^{T}(K_tH_t + m_tF_t)\left(1+i_f\right)^t \qquad (\mathbf{1})$$

Here the first five terms are used to calculate production costs. The production costs include five components-regular time production, overtime, and subcontracts, carrying inventory and backordering cost. The later portion specifies the costs of change in labor levels, including the costs of hiring and lay off workers. Escalating factors were also included for each of the cost categories.

2.2.2 Constraints

Constraints on carrying inventory:

$$I_{n(t-1)} - B_{n(t-1)} + Q_{nt} + O_{nt} + S_{nt} - I_{nt} + B_{nt} = \breve{D}_{nt} \quad for\ \forall n, \forall t \qquad (\mathbf{2})$$

Where, $\widehat{D}_{nt}$ denotes the imprecise forecast demand of the nth product in period t. In real-world APP decision problems, the forecast demand $\widehat{D}_{nt}$ cannot be obtained precisely in a dynamic market. The sum of regular and overtime production, inventory levels, and subcontracting and backorder levels essentially should equal the market demand, as in first constraint Equation. Demand over a particular period can be either met or backordered, but a backorder must be fulfilled in the subsequent period.

Constraints on Labor levels:

$$\sum_{n=1}^{N} i_{n(t-1)}\left(Q_{n(t-1)} + O_{n(t-1)}\right) + H_t - F_t - \sum_{n=1}^{N} i_{nt}\left(Q_{nt} + O_{nt}\right) = 0 \quad for\ \forall t \tag{3}$$

$$\sum_{n=1}^{N} i_{nt}\left(Q_{nt} + O_{nt}\right) \leq W_{tmax} \quad for\ \forall t \tag{4}$$

Here in the fourth constraint equation represents a set of constraints in which the labor levels in period t equal the labor levels in period t-1 plus new hires less layoffs in period t. Actual labor levels cannot exceed the maximum available labor levels in each period, as in fifth equation. Maximum available labor levels are imprecise, owing to uncertain labor market demand and supply.

Constraints on Machine capacity & Warehouse space:

$$\sum_{n=1}^{N} \hat{r}_{nt}\left(O_{nt} + Q_{nt}\right) \leq \widehat{M}_{tmax} \ \ for\ \forall t \tag{5}$$

$$\textstyle\sum_{n=1}^{N} V_{nt} I_{nt} \leq V_{tmax} \ \ for\ \forall t \tag{6}$$

Here $\hat{r}_{nt}$ and $\widehat{M}_{tmax}$ denote the imprecise hours of machine usage per unit of the nth product and the imprecise maximum available machine capacity in period t, respectively. Above two equations represent the limits of actual machine and warehouse capacity in each period. Non-negativity Constraints on decision variables are:

$$Q_{nt}, O_{nt}, S_{nt}, I_{nt}, B_{nt}, H_t, F_t \geq 0 \ \ for\ \forall n, \forall t \tag{7}$$

2.3 Model Development

2.3.1 Model the imprecise data with triangular possibility distribution

This study assumes the decision maker (DM) to have already adopted the pattern of triangular possibility distribution for all imprecise coefficients. Fig. 1 presents the triangular possibility distribution of imprecise number$\tilde{a}_{nt} = \left(a_{nt}^{p}, a_{nt}^{m}, a_{nt}^{o}\right)$. In practice, a DM can construct the triangular possibility distribution of $\tilde{a}_{nt}$ based on the three prominent data, such as the most pessimistic value (a_{nt}^{p}), the most possible value (a_{nt}^{m}) and finally the most optimistic value (a_{nt}^{o}).

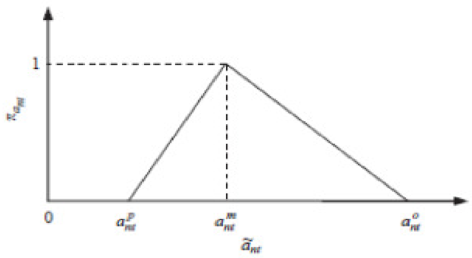

Fig 1: The triangular possibility distribution of $\tilde{a}_{nt}$

$$\begin{aligned}
\tilde{a}_{nt} &= (a_{nt}^{p}, a_{nt}^{m}, a_{nt}^{o})\ \forall n, \forall t,\\
\tilde{b}_{nt} &= (b_{nt}^{p}, b_{nt}^{m}, b_{nt}^{o})\ \forall n, \forall t,\\
\tilde{c}_{nt} &= (c_{nt}^{p}, c_{nt}^{m}, c_{nt}^{o})\ \forall n, \forall t,\\
\tilde{d}_{nt} &= (d_{nt}^{p}, d_{nt}^{m}, d_{nt}^{o})\ \forall n, \forall t,\\
\tilde{e}_{nt} &= (e_{nt}^{p}, e_{nt}^{m}, e_{nt}^{o})\ \forall n, \forall t,\\
\tilde{k}_{t} &= (k_{t}^{p}, k_{t}^{m}, k_{t}^{o})\ \forall t,\\
\tilde{m}_{t} &= (m_{t}^{p}, m_{t}^{m}, m_{t}^{o})\ \forall t,\\
\tilde{r}_{nt} &= (r_{nt}^{p}, r_{nt}^{m}, r_{nt}^{o})\ \forall n, \forall t\\
\tilde{D}_{nt} &= (D_{nt}^{p}, D_{nt}^{m}, D_{nt}^{o})\ \forall n, \forall t\\
\tilde{W}_{tmax} &= (W_{tmax}^{p}, W_{tmax}^{m}, W_{tmax}^{o})\ \forall t,\\
\tilde{M}_{tmax} &= (M_{tmax}^{p}, M_{tmax}^{m}, M_{tmax}^{o})\ \forall t,
\end{aligned}$$

Fig 2: The Imprecise data with triangular possibility distributions

2.4 An Auxiliary Multiple Objective Fuzzy Linear Programming (MOFLP) Model

2.4.1 Strategy for solving the imprecise objective function

The imprecise objective function of the FBGA model in the previous section has a triangular possibility distribution. Geometrically, this imprecise objective is fully defined by three prominent points (z^p, 0) (z^m, 1) and (z^o, 0). Because of the vertical coordinates of the prominent points being fixed at either 1 or 0, the three horizontal coordinates are the only considerations. Consequently, solving the imprecise objective requires minimizing z^p; z^m; and z^o simultaneously. That is, the proposed approach simultaneously involves minimizing the most possible value of the imprecise total costs, z^m, the most pessimistic value, z^p & also most optimistic value (z^o) of the imprecise total costs. Which indirectly satisfied the objectives of maximizing the possibility of obtaining lower total costs, (z^m _ z^p), and minimizing the risk of obtaining higher total costs, (z^o _ z^m). The last two objectives actually are relative measures from z^m, the most possible value of the imprecise total costs. Hence necessitates an auxiliary multiple objective fuzzy linear programming model for solving the objective functions first. Fig. 3 depicts the ways minimizing the unpredictable objective functions.

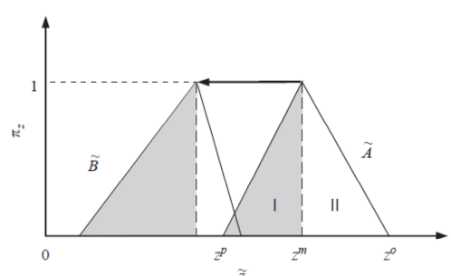

Fig 3: The Strategy to minimize the total costs

As indicated in Fig. 3, possibility distribution $\tilde{B}$ is preferred to possibility distribution $\tilde{A}$. This result is presented below for three new crisp objective functions.

$$Min\ Z_1 = Z^m = \sum_{n=1}^{N}\sum_{t=1}^{T}[a_{nt}^m Q_{nt}(1+i_a)^t + b_{nt}^m O_{nt}(1+i_b)^t + c_{nt}^m S_{nt}(1+i_c)^t + d_{nt}^m I_{nt}(1+i_d)^t + e_{nt}^m B_{nt}(1+i_e)^t] + \sum_{t=1}^{T}(k_t^m H_t + m_t^m F_t)(1+i_f)^t \quad (8)$$

$$Min\ Z_2 = Z^p = \sum_{n=1}^{N}\sum_{t=1}^{T}[a_{nt}^p Q_{nt}(1+i_a)^t + b_{nt}^p O_{nt}(1+i_b)^t + c_{nt}^p S_{nt}(1+i_c)^t + d_{nt}^p I_{nt}(1+i_d)^t + e_{nt}^p B_{nt}(1+i_e)^t] + \sum_{t=1}^{T}(k_t^p H_t + m_t^p F_t)(1+i_f)^t \quad (9)$$

$$Min\ Z_3 = Z^o = \sum_{n=1}^{N}\sum_{t=1}^{T}[a_{nt}^o Q_{nt}(1+i_a)^t + b_{nt}^o O_{nt}(1+i_b)^t + c_{nt}^o S_{nt}(1+i_c)^t + d_{nt}^o I_{nt}(1+i_d)^t + e_{nt}^o B_{nt}(1+i_e)^t] + \sum_{t=1}^{T}(k_t^o H_t + m_t^o F_t)(1+i_f)^t \quad (10)$$

2.4.2 Crisp formulation

Recalling Eq. (2) of the FBGA model the author considered the situation in which available resource (the right hand side), D_{nt}, is imprecise and has triangular possibility distributions with the most possible and least possible values. In real-world APP decision problems, the decision maker can estimate a possible interval for imprecise demand based on experience and knowledge. The main problem is obtaining a crisp representative number for the imprecise demand. This work adopts the weighted average method proposed by Lai and Hwang (1992) to convert D_{nt} into a crisp number. If the minimum acceptable possibility, β, is given, then the auxiliary crisp equality constraints can be presented as follows:

$$I_{n(t-1)} - B_{n(t-1)} + Q_{nt} + O_{nt} + S_{nt} - I_{nt} + B_{nt} = w_1 D_{nt,\beta}^p + w_2 D_{nt,\beta}^m + w_3 D_{nt,\beta}^o \quad \forall n, \forall t \quad (11)$$

Where $w_1+w_2+w_3 = 1$, w_1, w_2, w_3 denote the weights of the most pessimistic, most possible and most optimistic value of the imprecise demand, respectively. The weights w_1, w_2 and w_3 can be determined subjectively by the experience and knowledge of the DM. Similarly, if the minimum acceptable possibility, β, is given, then the auxiliary crisp inequality constraints on Eq. (4) can be presented as follows:

$$\sum_{n=1}^{N} i_{nt}(Q_{nt} + O_{nt}) \le w_1 W_{tmax,\beta}^p + w_2 W_{tmax,\beta}^m + w_3 W_{tmax,\beta}^o \quad \forall t \quad (12)$$

To solve the imprecise right-hand sides in Eq. (11) and (12), this work applies the concept of the most likely values proposed by Lai and Hwang's (1992) approach, assuming w_2 = 4/6 and w_1 = w3= 1/6. The reason for using the most likely values here is that the most possible values usually are the most important ones, and thus should be assigned more weights. Moreover, to solve Eq. (5) with imprecise technological coefficient ($\tilde{r}_{nt}$) and available resources $\tilde{M}_{tmax}$, the approach proposed here converted these imprecise inequality constraints into a crisp one using the fuzzy ranking concept (Tanaka et al., 1984; Lai and Hwang, 1992). Consequently, the auxiliary inequality constraints on Eq. (5) can be presented as follows:

$$\sum_{n=1}^{N} r_{nt,\beta}^{p}\,(Q_{nt}+O_{nt}) \le M_{tmax,\beta}^{p} \quad \forall t \tag{13}$$

$$\sum_{n=1}^{N} r_{nt,\beta}^{m}\,(Q_{nt}+O_{nt}) \le M_{tmax,\beta}^{m} \quad \forall t \tag{14}$$

$$\sum_{n=1}^{N} r_{nt,\beta}^{0}\,(Q_{nt}+O_{nt}) \le M_{tmax,\beta}^{0} \quad \forall t \tag{15}$$

2.5 Solving the auxiliary MOFLP problem

Furthermore, the auxiliary MOLP problem can be converted into an equivalent single-goal LP problem using the fuzzy decision-making of Bellman and Zadeh (1970) and Zimmermann's fuzzy programming method (1978). The positive ideal solutions (PIS) and negative ideal solutions (NIS) of the three objective functions can be specified as follows, respectively (Hwang and Yoon, 1981; Lai and Hwang, 1992).

$z_1^{PIS} = \text{Min } Z^m, \qquad z^1{}_{NIS} = \text{Max } Z^m$ **(16a)**

$z_2^{PIS} = \text{Max } (Z^m\text{-}Z^o), \qquad z_2^{NIS} = \text{Min } (Z^m\text{-}Z^o)$ **(16b)**

$z_3^{PIS} = \text{Min } (Z^o\text{-}Z^m), \qquad z_3^{NIS} = \text{Max } (Z^o - Z^m)$ **(16c)**

For each objective function, the corresponding linear membership function is defined by

$$f_1(z_{f1}) = \begin{cases} 1, & z_{f1} < z_1^{PIS} \\ \dfrac{z_1^{NIS} - z_{f1}}{z_1^{NIS} - z_1^{PIS}}, & z_1^{PIS} \le z_{f1} \le z_1^{NIS} \\ o, & z_{f1} > z_1^{NIS} \end{cases} \tag{17}$$

$$f_2(z_{f2}) = \begin{cases} 1, & z_{f2} < z_2^{PIS} \\ \dfrac{z_{f2-}\, z_2^{NIS}}{z_2^{PIS} - z_2^{NIS}}, & z_2^{NIS} \le z_{f2} \le z_2^{PIS} \\ o, & z_{f2} > z_2^{NIS} \end{cases} \tag{18}$$

$$f_3(z_{f3}) = \begin{cases} 1, & z_{f3} < z_3^{PIS} \\ \dfrac{z_3^{NIS} - z_{f3}}{z_3^{NIS} - z_3^{PIS}}, & z_3^{PIS} \le z_{f3} \le z_3^{NIS} \\ o, & z_{f3} > z_3^{NIS} \end{cases} \quad \textbf{(19)}$$

Here Z_{f1}, Z_{f2} and Z_{f3} are the fuzzified objective function values for determining the corresponding linear membership function. Hence to mention that the total cost is imprecise & has a triangular possibility distribution. So, $Z^{-} = (z_{f1} - z_{f2},\ z_{f1},\ z_{f1} + z_{f3}) \equiv (Z_1, Z_2, Z_3)$. Using the fuzzy decision-making of Bellman and Zadeh (1970) and Zimmermann's (1978) fuzzy programming method, the complete equivalent single-goal LP model for solving the APP decision problem can be formulated as follows:

Max L

Subject to,

$$L \le f_i(z_{fi}), \qquad i = 1,2,3$$

$$I_{n(t-1)} - B_{n(t-1)} + Q_{nt} + O_{nt} + S_{nt} - I_{nt} + B_{nt} = w_1 D^{p}_{nt,\beta} + w_2 D^{m}_{nt,\beta} + w_3 D^{o}_{nt,\beta} \quad \forall n, \forall t$$

$$\sum_{n=1}^{N} i_{n(t-1)} \left(Q_{n(t-1)} + O_{n(t-1)}\right) + H_t - F_t - \sum_{n=1}^{N} i_{nt} \left(Q_{nt} + O_{nt}\right) = 0 \qquad \forall t,$$

$$\sum_{n=1}^{N} i_{nt}(Q_{nt} + O_{nt}) \le w_1 W^{p}_{tmax,\beta} + w_2 W^{m}_{tmax,\beta} + w_3 W^{o}_{tmax,\beta} \qquad \forall t,$$

$$\sum_{n=1}^{N} r^{p}_{nt,\beta} \left(Q_{nt} + O_{nt}\right) \le M^{p}_{tmax,\beta} \quad \forall t,$$

$$\sum_{n=1}^{N} r^{m}_{nt,\beta} \left(Q_{nt} + O_{nt}\right) \le M^{m}_{tmax,\beta} \quad \forall t,$$

$$\sum_{n=1}^{N} r^{0}_{nt,\beta} \left(Q_{nt} + O_{nt}\right) \le M^{0}_{tmax,\beta} \quad \forall t,$$

$$\sum_{n=1}^{N} V_{nt} I_{nt} \le V_{tmax} \qquad \forall t,$$

$$0 \le L \le 1$$

$$Q_{nt}, O_{nt}, S_{nt}, I_{nt}, B_{nt}, H_t, F_t \ge 0 \qquad \forall n, \forall t$$

3. OUTLINE OF THE BASIC FBGA MODEL

The algorithm of the proposed FBGA approach for solving the APP decision problem is as follows.
Step 1: Formulate the FBGA model for the multiproduct APP decision problem considering escalating factors on all imprecise parameters.

Step 2: Model the imprecise coefficients ($\tilde{a}_{nt}$, $\tilde{b}_{nt}$, $\tilde{c}_{nt}$, $\tilde{d}_{nt}$, $\tilde{e}_{nt}$, $\tilde{k}_{t}$, $\tilde{m}_{t}$, $\tilde{r}_{nt}$) and right-hand sides ($\tilde{D}_{nt}$, $\tilde{W}_{t}$, $\tilde{M}_{t}$) using triangular possibility distributions.

Step 3: Develop three new crisp objective functions of the auxiliary MOLP problem.

Step 4: Given the minimum acceptable possibility, β, convert the imprecise constraints into crisp ones using the weighted average method or the fuzzy ranking concept.

Step 5(i): For solving the imprecise multiple objective functions using Genetic Algorithm first of all generate random population of *n* chromosomes
Step 5(ii): Evaluate simultaneously the Multiple fitness Z_i of each chromosome x in the population
Step 5(iii): Create a new population by repeating four steps (Selection, Crossover, Mutation and Acceptation) until the new population are complete.
Step 5(iv): Use new generated population for a further run
Step 5(v): If the stopping condition is satisfied, stop, and return the best solution in current population
Step 5(vi): If the stopping condition is not satisfied then go to step 2 & follow loop.

Step 6: After getting imprecise multiple objective functions, specify the linear membership functions for them, and then convert the auxiliary MOLP problem into an equivalent FLP model using the fuzzy decisions of Bellman and Zadeh (1970) and Zimmermann's (1978) fuzzy programming method.

Step 6: Solve and modify the model interactively. If the DM is not satisfied with the initial solution, then the model must be modified until a satisfactory solution is found.

3.1 Fuzzy Based Genetic Algorithm (FBGA) Model Parameters

The mechanics of a simple genetic algorithm are surprisingly simple, involving nothing more complex than copying strings and swapping partial strings. A simple genetic algorithm that yields good results in many practical problems is composed of three operators. Those are Reproduction, Crossover & Mutation. Crossover options specify how the genetic algorithm combines two individuals, or parents, to form a crossover child for the next generation. Here the authors choose five different crossover options for five scenarios. Here the authors employed three kinds og crossover and those are scattered crossover in which if p1 and p2 are the parents such as p1 = [a b c d e f g h] and p2 = [1 2 3 4 5 6 7 8] and the binary vector is [1 1 0 0 1 0 0 0], then the function returns the following child1 = [a b 3 4 e 6 7 8]. Second crossover was the intermediate crossover function and the final one was arithmetic crossover where random weighting factors were considered. Then another genetic algorithm parameter is the mutations which specify how the genetic algorithm makes small random changes in the individuals in the population to create mutation children. Here the authors use Constraint dependent mutation & Adapt feasible mutation options. Another important term is creation function. Creation function creates the initial population for genetic algorithm. Here the authors choose feasible population & constraint dependent creation functions. Next parameter is selection function where the authors used only tournament selection option for tournament size 2 & 4.

4. MODEL IMPLEMENTATION

4.1 Case description

The Comfit Composite Knit Limited is the sister concern of Youth Group, which is one of the pioneer company of Ready Made Garments (RMG) sector in Bangladesh. This company readily produced knit ware items among them some are fancy & some are expensive. The jacket items as well as cardigan items are most expensive and most time & cost incurring manufacturing items. So it needs a lot of precise observations & perfect manufacturing practices to catch up the market & satisfy the buyers within specified lead time. Since they are the most expensive items, major concentration was on one particular style of hooded jacket (Product 1) & another special type of ladies cardigan (Product 2).

The APP decision problem for CCKL's Knit garments manufacturing plant presented here focuses on developing an interactive Genetic Algorithm approach for minimizing total costs. The planning horizon is 2 months long, including May and June. The model includes two types of knit ware items, namely the hooded jacket (Product 1) and special type of ladies cardigan (Product 2). According to the preliminary environmental information, Tables 1 & 2 summarizes the forecast demand, related operating cost, and capacity data used in the CCKL case. Other relevant data are as follows.

I. Initial inventory in period 1 is 500 units of product 1 and 200 units of product 2. End inventory in period 2 is 400 units of product 1and 300 units of product 2.
II. Initial labor level is 225 man-hours. The costs associated with hiring and layoffs are Tk. (20, 22, 25) and Tk. (6, 8, 10) per worker per hour, respectively.
III. Hours of labor per unit for any periods are fixed to 0.033 man-hours for product 1 and 0.05 man hours for product 2. Hours of machine usage per unit for each of the two planning periods are (0.09, 0.1, 0.11) machine-hours for product 1 and (0.07, 0.08, 0.09) machine-hours for product 2. Warehouse spaces required per unit are 1 square feet for product 1 and 1.5 square feet for product 2.
IV. The expected escalating factor in each of the costs categories are 1%.

Table 1 Forecasted demand, maximum labor, machine and warehouse capacity data

Item (Units)	Period	
	1	2
$\tilde{D}_{1t}$ (pieces)	(1200, 1400, 1500)	(2750,3000, 3200)
$\tilde{D}_{2t}$ (pieces)	(1400, 1600, 1800)	(700, 800, 1000)
$\tilde{W}_{tmax}$ (man-hours)	(180, 225, 250)	(180, 225, 250)
$\tilde{M}_{tmax}$ (machine-	(360, 400, 430)	(450, 500, 540)
V_{tmax} (ft2)	1000	1000

Table 2 Related Operating cost data for the CCKL case

Product	**a_{nt} (tk./unit)**	**b_{nt} (tk./unit)**	**c_{nt} (tk./unit)**	**d_{nt} (tk./unit)**	**e_{nt} (tk./unit)**
1	(20, 22, 25)	(38, 40, 44)	(25, 27, 30)	(3, 3.5, 4)	(40, 42, 44)
2	(18, 20, 22)	(36, 40, 42)	(28, 30, 32)	(3.5, 4, 4.5)	(45, 47, 50)

The PIS of the three new objective functions is (Tk.130, 000, Tk.20, 000, Tk.10, 000) and the NIS is (Tk.240, 000, Tk.10, 000, Tk.50, 000). The corresponding linear membership function of the three new objective functions can be defined according to Equations. (17) to (19). The authors used MATLAB computer software to solve the proposed Fuzzy Based Genetic Algorithm (FBGA) approach for the CCKL case. Total Three runs were implemented considering three scenarios with different FBGA parameters shown in Table 3. Table 4 lists the multiple objective values for three FBGA runs through MATLAB. Finally Since from Table 4 it is clear that the least cost is achieved in the third scenario so in Table 6 lists the entire initial APP plan for the CCKL case based on the present information for that third scenario. Here the initial total cost is imprecise and has a triangular possibility distribution of (Tk.2,17,238, Tk.2,35,087, Tk.2,56,457) for the third FBGA run, and overall degree of Decision Maker's satisfaction with multiple goal values is 0.79. Moreover, the DM may try to modify the results interactively by adjusting the linear membership functions and related model parameters until a satisfactory solution is obtained.

Table 3 Different Genetic Algorithm options used for three scenarios

FBGA Parameters/ Options	**Scenario 1**	**Scenario 2**	**Scenario 3**
Population Type	Double	Double	Double
Population Size	360	360	360
Creation Function	Constraint dependent	Feasible Population	Constraint dependent
Mutation	Constraint dependent	Constraint dependent	Adapt Feasible
Crossover	Intermediate	Scattered	Arithmetic
Migration (Fraction)	Forward (0.2)	Forward (0.2)	Both (0.5)
Reproduction (Fraction)	Crossover (0.8)	Crossover (0.8)	Crossover (0.5)
Selection (Size)	Tournament (2)	Tournament (2)	Tournament (4)
Distance Measure Function	Crowding	Crowding	Crowding
Pareto Front Pop. Fraction	0.35	0.35	0.35
Iteration needed to complete	107 Generations	116 Generations	136 Generations

Table 4 Imprecise Objective Function values for different scenarios

Imprecise Objectives	**Scenario 1**	**Scenario 2**	**Scenario 3**	**PIS**	**NIS**
Z_1	2,17,272.30	2,17,273	2,17,238.30	1,30,000	2,40,000
Z_2	2,35,121.88	2,35,123.37	2,35,086.98	20,000	10,000
Z_3	2,56,493	2,56,497.16	2,56,457	10,000	50,000
Total Cost(Tk.)	7,08,886.20	7,08,893.55	**7,08,782.32**		

Table 5 Fuzzified objective values & other values for the APP plan of CCKL case

Fuzzified Objectives	z_{f1}	z_{f2}	z_{f3}	$f_1(z_{f1})$	$f_2 z_{f2})$	$f_3(z_{f3})$	**L**	**Minimum Total Cost ($\tilde{Z}$)**
Scenario 1	2,35,120.9	17,848.6	21,372.2	0.044	0.78	0.72	0.79	Tk. (217238, 235086,256457)
Scenario 2	2,35,123.6	17,850.3	21,373.8	0.044	0.79	0.71		
Scenario 3	2,35,087	17,848.6	21,370	0.044	0.79	0.72		

Table 6 Initial multi-product & multi-period APP plan for the CCKL case (**Third Scenario**)

Items (Product 1)	**Period**		**Items (Product 2)**	**Period**	
	1	**2**		**1**	**2**
Q_{1t} (Units)	544	1026	Q_{2t} (Units)	664	454
O_{1t} (Units)	544	1010	O_{2t} (Units)	670	454
S_{1t} (Units)	186	333	S_{2t} (Units)	85	95
I_{1t} (Units)	446	524	I_{2t} (Units)	160	212
B_{1t} (Units)	5	582	B_{2t} (Units)	140	94
H_t (man-hours)	102.65	173.40	F_t (man-hours)	0	163.49

5. RESULTS & FINDINGS

The APP decision problem presented in the CCKL case was solved using the crisp ordinary Fuzzy Linear Programming (FLP) model, as summarized in Table 7. Consequently, the optimal value when applying FLP to minimize the total costs was Tk. 2, 35,087. In contrast with the proposed FBGA approach, the improved results were Tk. (217238, 235087, and 256457) for the third scenario. These figures indicate that the FBGA solutions are an efficient compromise solution, compared to the optimal goal value obtained by the FLP model. Thereafter, an improved APP plan is obtained by the proposed FBGA approach under an acceptable degree of DM satisfaction in a fuzzy environment. From the initial results and linear membership function values, it is revealed that the changes in the PIS and NIS of the objective functions, influences the objective and L values. These findings imply that the DM must specify an appropriate set of PIS and NIS of the objective functions for making APP decisions, to effectively seek the right linear membership function for each objective function. Finally, the proposed FBGA approach is the most practical for solving APP decision problems and can generate better decisions than other models. The proposed FBGA approach outputs more wide-ranging decision information than other models. The proposed FBGA approach focuses on the multi-periods and multi-products (product family) problems in an APP decision making process.

Table 7 Comparison of solutions between FLP & Proposed Approach

Item	FLP model	The proposed FBGA approach
Objective function	Min Z	Max L
L (DM's overall degree of satisfaction)	100%	79% (can be more after changing membership functions)
Z (Total costs)	Tk.2, 35,087	(Tk. 2,17,238, Tk.2,35,087, Tk.2,56,457)

The proposed approach also provides information on alternative strategies for overtime, subcontracting, inventory, backorders, and hiring and layoffs workers, in response to variations in forecast demand. Additionally, the proposed model considers the actual limitations in labor, machine, and warehouse capacity.

6. CONCLUSIONS

This work presents a novel interactive FBGA approach for solving multi product and multi period APP decision problems with the forecasted demands, related operating costs, and capacity. The proposed FBGA approach not only provides more computational efficiency and more flexible doctrines, but also supports possibilistic decision-making in an uncertain environment. This proposed FBGA approach also can helps to determine optimum solution even it is NP (nondeterministic polynomial) hard problems. Different Genetic Algorithm options have been considered in this APP problem which could make an impression for the future researchers to choose the suitable combination for solving multiple objective problems. Consequently, the proposed approach is expected to be suitable for making real world APP decisions.

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