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MODELING AND OPTIMIZATION OF MULTI-LAYER AGGREGATE PRODUCTION PLANNING

ABSTRACT

Aggregate production planning has attracted the attention of researchers for quite a long time now; and the continued researches depict the significance and scope for improvement in this arena. Here, a multi-product, multi-level and multi-period model has been formulated to identify the required aggregate plan for meeting the forecast demand, by regulating production rates, inventory, workforce, various production costs, and other controllable variables. Several new contributing factors, such as costs related to material handling, raw material inventory and worker training have been included in the objective function and constraint equations to make the model more realistic. A case study has been presented for a cosmetics and toiletries manufacturer in Bangladesh. Eventually, the problem has been solved using Genetic Algorithm and Particle Swarm Optimization approach. The solution illustrates that the model can be applied in a real world scenario to enhance productivity and profitability.

KEYWORDS | Aggregate production planning, inventory optimization, multi-period modeling, genetic algorithm, particle swarm optimization.

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INTRODUCTION

Aggregate production planning (APP) is a process that incorporates forecast of usually 3 months to 18 months, known as the medium range forecast. It focuses on the determination of production, inventory and workforce levels while meeting the fluctuating demands requirement. The planning horizon usually sets the next seasonal peak in demand as the target and assumes the physical resources of the firm deterministic and constant. Aggregating the information being processed becomes a must for a long planning horizon. Once the APP is established, constraints are imposed on the production process. Adhering to an APP model can help businesses operate in a leaner manner. It increases production rate significantly by maximizing the utilization of production equipment and allows for contingency measures so that firms can better accommodate the uncertainties in customer orders and production. That's why; it has always been of immense significance to formulate the APP model as realistic as possible.

Baykasoglu (2001) has presented APP as a midterm planning for capacity to regulate the production, workforce and inventory levels for a given set of constraints. A good number of practitioners and academia (Shi & Haase, 1996) has been carrying out intriguing researches on APP resulting different APP models with varying degree of sophistication in past few years. Holt, Modigliani, and Simon (1955) proposed the approach to solve APP model for the first time. Hanssmann and Hess (1960) developed linear programming model which was extended for multi-product and multi-stage production systems by Haehling (1970). Masud and Hwang (1980) introduced goal programming (GP), the step method and sequential multi-objective problem to solve APP problem. Jain and Palekar (2005) presented comparison among several heuristics by solving the aggregate production planning problem using the configuration-based formulation. Entezaminia, Heydari, and Rahmani (2016) proposed a multi objective APP model for a multi-period multi-site scenario considering green and reverse logistics. Al-e-hashem, Malekly, and Aryanezhad (2011) tackled a multi-period and multi-product APP model under uncertainty by applying LP-metrics method. Leung, Wu, and Lai (2017) presented a stochastic programming approach for addressing the uncertainty in a multi-site aggregate production planning.

Tsoulos (2009) presented Genetic Algorithm (GA) for constrained optimization model, whereas Bunnag and Sun (2005) presented a stochastic optimization method to solve constrained optimization problems over a compact search domain. Fahimnia, Luong, and Marian (2008) presented a methodology to model the Aggregate Production Planning problem, which is combinatorial in nature, when optimized with Genetic Algorithms. Konak, Coit, and Smith (2006) gave an overview and tutorial on genetic algorithm for multi-objective optimization. Eldos (2005) introduced a new topology independent scheme called the selective migration model in genetic algorithm. Ramezanian, Rahmani, and Barzinpour (2012) developed a mixed integer linear programming (MILP) addressing NP-hard class of APP, and implemented GA and tabu search for solving that problem. The mixed integer programming was implemented by Hung and Hu (1998) who considered maximizing revenue along with minimizing inventory and cost. Artificial intelligence approaches, sometimes including mathematical programming models have been used for solving APP models. Khalili-Damghani and Shahrokh (2014) solved a multi-objective multi-period multi-product APP problem using Fuzzy Goal Programming. The hybrid discrete event simulation (DES) and system dynamics (SD) methodology were introduced in the APP field by Jamalnia and Feili (2013).

Particle Swarm Optimization (PSO) has been applied to an array of applications which can generate good solutions with small calculation time and stable convergence. Eberhart and Kennedy (1995) introduced particle swarm methodology for optimization of nonlinear functions. Wang, Liu, Zeng, Li, and Li (2007) showed an opposition-based learning scheme to PSO (OPSO) along with a Cauchy mutation results in a better convergence. Lei (2008) applied a pareto archive particle swarm optimization for multi-objective job shop scheduling, whereas Chen (2011) introduced a two-layer particle swarm optimization (TLPSO) model. Later Wang, Sun, Li, Rahnamayan, and Pan (2013) modified the PSO algorithm by incorporating the idea of sub-particles. It produced a better search process than the general PSO.

However, the previous studies failed to incorporate some factors like costs related to material handling, raw material inventory and worker training; which undoubtedly shapes the APP model of a firm in a great way. So by considering the factors and constraints associated with these cost terms, the proposed APP model will become one step closer to the real scenario and will guide the firms in a more accurate fashion. And unlike many papers, instead of just minimizing the total production cost, this study has considered minimizing the total production loss as it also incorporates the effects of sales revenue.

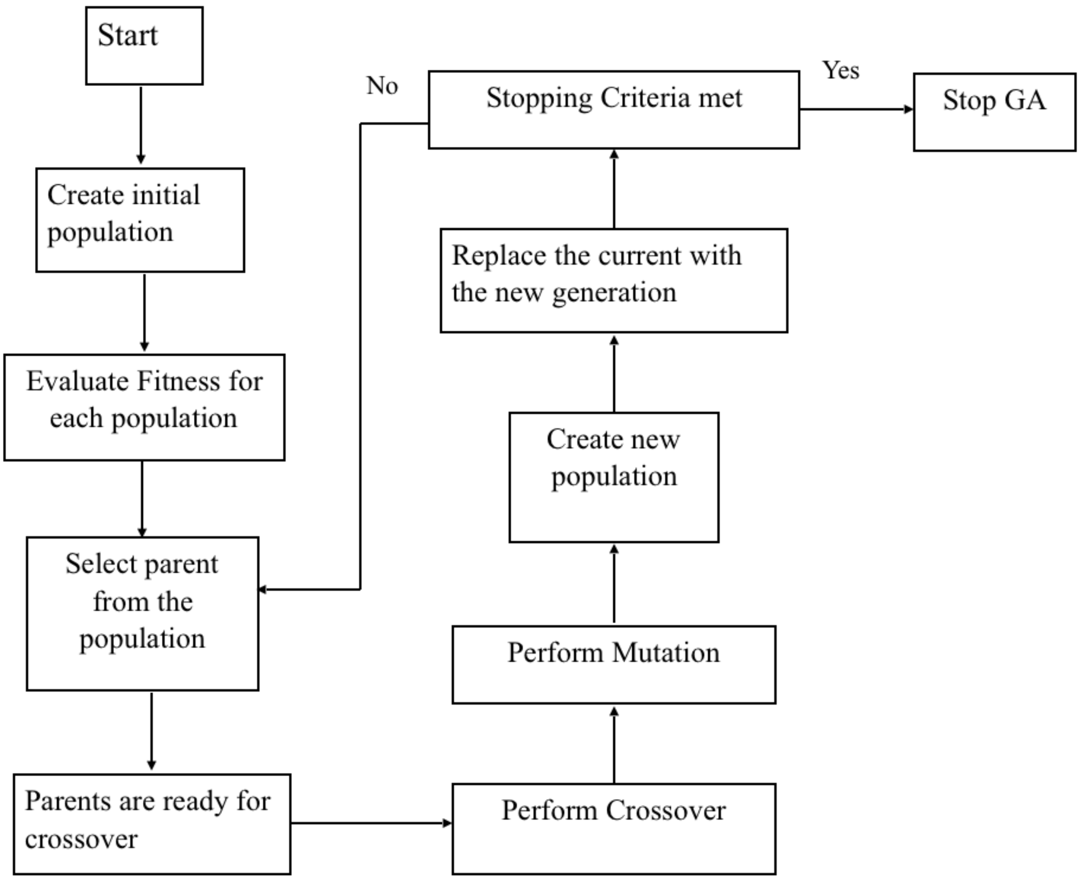
The rest of this paper is organized as follows. The proposed model is formulated and described in details with assumptions first. Then the model is implemented in a case study where GA and PSO are used. After presenting and explaining he results and findings, the paper concludes with some specific directions for future research in this arena.

THEORETICAL FRAMEWORK

Genetic Algorithm

A genetic algorithm is a problem solving method that uses genetics as its model of problem solving. It is a search technique to find approximate solutions to optimization and search problems. The basic of genetic algorithm is shown in Figure 1.

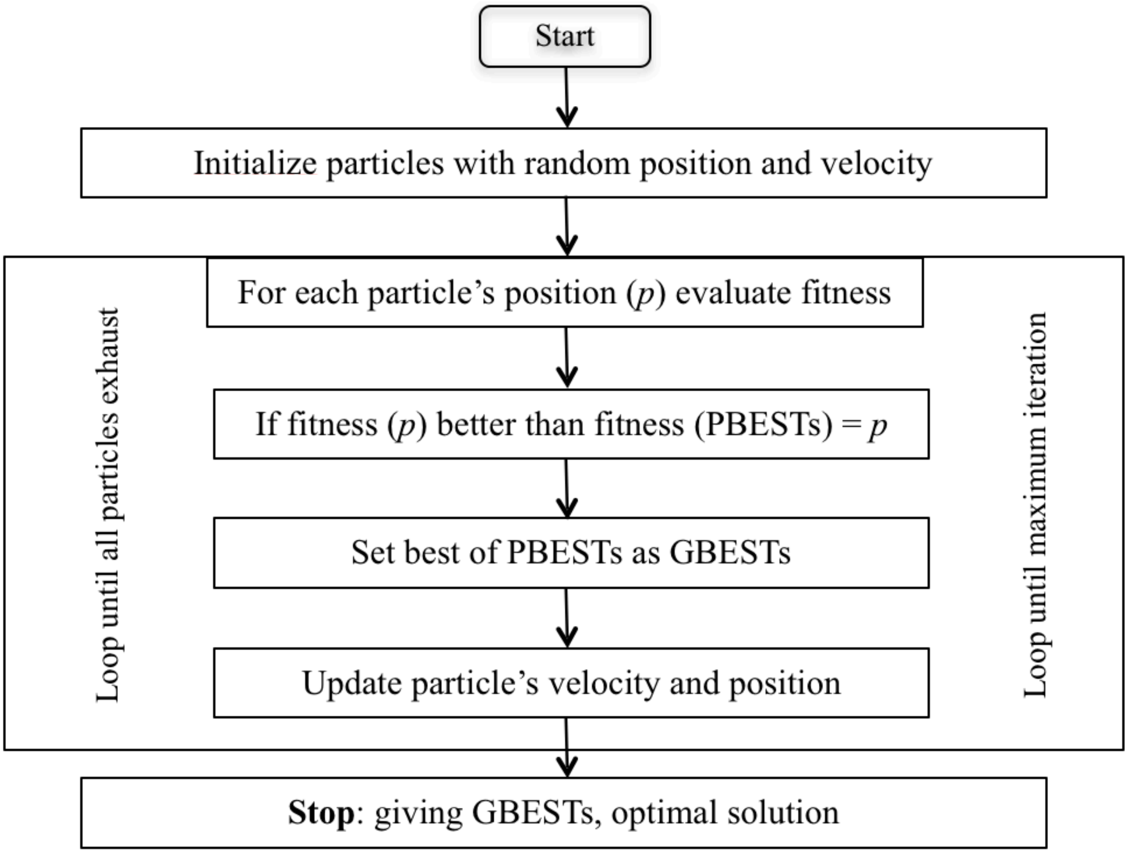
Figure 1: Outline of Genetic Algorithm



Particle Swarm Optimization (PSO) Algorithm

We have developed a PSO model for the relevant objective function and constraint equations, similar to the single objective GA model. The main purpose of this research work is to develop a fair comparison among these two models with the same set of considerations. The basic of PSO is illustrated in Figure 2.

Figure 2: Outline of PSO Algorithm



The APP Model Formulation

The mathematical model is based on the following assumptions:

1. Products are independent to each other, related to marketing and sales price.

2. All per unit costs and set up costs are considered constant for a given period.

3. Backorders are considered.

4. Shortage cost is not considered.

5. Hiring presumes an available supply of workers.

6. Backorder quantity of previous month is completed first in the current month and then the planned production of this month is commenced. So the production of backorder quantity is usually carried out in the regular production time.

7. The penalty of the backordered quantity for the j period is included in that months cost of Aggregate Production Planning.

8. Demand is continuous.

9. Workers hired in a certain period will not be laid off in the same period.

10. The manufacturer sets the wholesale price (while there is still uncertainty regarding demand), and the retailer orders product. The units are produced and delivered to the retailer.

11. The retailer takes delivery of ordered units when demand is still unknown and assumes ownership upon delivery.

12. Each worker is assigned for a particular line of product.

The following notations are used after reviewing the literature and considering practical situations:

P_{ijk} = Regular time production cost per unit of i^{th} (type of product) product in period j for k level (casual, temporary, permanent) workers (Tk./unit/minute)

a_{ijk} = Regular time quantity of i^{th} product in period j for k level workers (units)

α_{ijk} = Required time for regular time production per unit of i^{th} product in period j for k level workers (minutes)

O_{ijk}= Overtime production cost per unit of i^{th} product in period j for k level workers (Tk./unit/minute)

b_{ijk} = Overtime quantity of i^{th} product in period j for k level workers (units)

β_{ijk} = Required time for overtime production per unit of i^{th} product in period j for k level workers (minutes)

SC_{ij} = Subcontracting cost per unit of i^{th} product in period j (Tk./unit/minute)

d_{ij} = Subcontracting quantity of i^{th} product in period j (units)

γ_{ij} = Required time for production in subcontract per unit of i^{th} product in period j (minutes)

IR_{zj} = Inventory carrying cost per unit of z^{th} (type of raw material) raw material in period j (Tk./unit)

e_{zj} = Inventory level of z^{th} raw material in period j (units)

IF_{ij} = Inventory carrying cost per unit of i^{th} product in period j (Tk./unit)

f_{ij} = Inventory level of i^{th} product in period j (units)

B_{ij} = Backorder cost per unit of i^{th} product in period j (Tk./unit)

g_{ijk} = Backorder quantity of i^{th} product in period j for k level workers (units)

Y_{zj} = Material handling cost per unit of z^{th} raw material in period j (Tk./unit/minute)

r_{zj} = Material handling quantity of z^{th} raw material in period j (units)

π_{zj} = Material handling time per unit of z^{th} raw material in period j (minutes)

M_{ij} = Material handling cost per unit of i^{th} product in period j (Tk./unit/minute)

n_{ij} = Material handling quantity of i^{th} product in period j (units)

δ_{ij} = Material handling time per unit of i^{th} product in period j (minutes)

H_{ijk} = Hiring cost per labor of k level for i^{th} product in period j (Tk./labor)

h_{ijk} = No. of labor of k level hired for i^{th} product in period j (no. of labor)

F_{ijk} = Firing cost per labor of k level for i^{th} product in period j (Tk./labor)

l_{ijk} = No. of labor of k level fired for i^{th} product in period j (no. of labor)

T_{ijk} = Training cost per labor of k level for i^{th} product in period j (Tk./labor)

m_{ijk} = No. of labor of k level to be trained for i^{th} product in period j (no. of labor)

m_{ijkk} = No. of labor of k level to be trained to k' level for i^{th} product in period j (no. of labor)

S_{ij} = Sale price per unit of i^{th} product in period j (Tk./unit)

v_{ij} = Sale quantity of i^{th} product in period j (units)

ATR_{ijk} = Available time for regular production of i^{th} product in period j for k level workers (minutes)

ATO_{ijk} = Available time for overtime production of i^{th} product in period j for k level workers (minutes)

ATS_{ij} = Available time for subcontracting of i^{th} product in period j (minutes)

MU_{ijk} = Machine usage per unit of i^{th} product in period j for k level workers (machine-hours)

MMC_{ij} = Machine capacity for i^{th} product in period j (machine-hours)

WSR_{zj} = Warehouse space required for one unit of z^{th} raw material in period j (cubic feet)

WSR_{ij} = Warehouse space required for one unit of i^{th} product in period j (cubic feet)

$MWCR_j$ = Warehouse capacity for raw materials in period j (cubic feet)

$MWCF_j$ = Warehouse capacity for finished products in period j (cubic feet)

ν_k = Productivity of k level labor ($0 \leq \leq 1$)

SUP_{zj} = Quantity of z^{th} raw material in period j from suppliers (units)

μ_{zij} = Quantity of z^{th} raw material required for one unit of i^{th} product in period j (units)

L_{ijk} = No. of k level labor required for producing one unit of i^{th} product in period j

ω_j= Fraction of labor variation allowed in period j

The objective function includes production costs such as regular time production, overtime, subcontracts, inventory cost of raw materials and finished goods, backordering and material handling. The second portion of the objective function includes the cost of changing the labor levels, such as hiring, laying-off and training workers. Finally, the forecasted sales revenue has been deducted from these costs, and our objective is to minimize this difference. The factors that we have introduced in this objective function include segregating the raw materials and finished goods, material handling and training cost. We have tried to minimize the loss (i.e. maximizing the profit) by incorporating the sales revenue, while the other papers have tried to minimize the cost of production.

The objective function of the proposed model can be derived as follows:

Minimizing Total Loss = (Regular Time Production Cost) + (Overtime Production Cost) + (Subcontracting Cost) + (Inventory Cost of Raw Materials and Finished Goods) + (Backordering Cost) + (Material Handling Cost) + (Labor Hiring, Laying-off and Training Cost) – (Forecasted Sales Revenue)

Regular time production cost = $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[P_{ijk}a_{ijk}\alpha_{ijk}\right]$

This cost includes direct material, direct labor, manufacturing overhead, administrative and marketing or selling cost.

Overtime Production Cost = $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[O_{ijk}b_{ijk}\beta_{ijk}\right]$

Overtime Production Cost includes direct material, overtime labor, manufacturing overhead, administrative and marketing or selling cost.

Subcontracting Cost = $\sum_{i=1}^{I}\sum_{j=1}^{J}\left[SC_{ij}d_{ij}\gamma_{ij}\right]$

This cost includes the cost of materials provided by the manufacturer to the subcontractor, and the rate that will be charged for producing the products by the subcontractor.

Inventory Cost of Raw Materials and Finished Goods = $\sum_{z=1}^{Z}\sum_{j=1}^{J}\left[IR_{zj}e_{zj}\right]+\sum_{i=1}^{I}\sum_{j=1}^{J}\left[IF_{ij}f_{ij}\right]$

This cost includes holding or carrying cost and ordering cost. Holding cost includes insurance, depreciation, spoilage, breakage, warehousing costs (heat, light, rent, security) etc.

Backordering Cost = $\sum_{i=1}^{I}\sum_{j=1}^{J}\left[B_{ij}\sum_{k=1}^{K}\left[g_{ijk}\right]\right]+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[P_{ijk}g_{i(j-1)k}\alpha_{ijk}\right]$

This cost includes the penalty that the manufacturer has to pay for not being able to supply the product on time according to the demand and the cost of production in the current period to produce the backordered quantity of the previous period.

Material Handling Cost = $\sum_{z=1}^{Z}\sum_{j=1}^{J}\left[Y_{zj}r_{zj}\pi_{zj}\right]+\sum_{i=1}^{I}\sum_{j=1}^{J}\left[M_{ij}n_{ij}\delta_{ij}\right]$

This cost refers to the cost related to labor and equipment for loading, unloading, palletizing, depalletizing, unitizing, packaging, etc. for handling materials.

Labor Hiring, Firing and Training Cost = $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[H_{ijk}h_{ijk}+F_{ijk}l_{ijk}+T_{ijk}m_{ijk}\right]$

Hiring cost includes recruitment, screening and training. Quality may also suffer, whereas firing cost includes severance pay, the cost of readjusting workforce, lack of goodwill towards the farm on the part of fired workers, and loss of morale for remaining workers. Training cost includes the costs to bring new workers up to speed as well as training of the existing workers to increase their skill and expertise.

Forecasted Sales Revenue = $\sum_{i=1}^{I}\sum_{j=1}^{J}\left[S_{ij}v_{ij}\right]$

This includes the selling price that the manufacturer will charge to the customer and the forecasted demand.

So, the objective function can be expressed as follows:

$$\text{Min X} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[P_{ijk}a_{ijk}\alpha_{ijk} + O_{ijk}b_{ijk}\beta_{ijk} + P_{ijk}g_{i(j-1)k}\alpha_{ijk}\right] +$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\left[SC_{ij}d_{ij}\gamma_{ij} + IF_{ij}f_{ij} + B_{ij}\sum_{k=1}^{K}\left[g_{ijk}\right] + M_{ij}n_{ij}\delta_{ij}\right] +$$

$$\sum_{z=1}^{Z}\sum_{j=1}^{J}\left[IR_{zj}e_{zj} + Y_{zj}r_{zj}\pi_{zj}\right] + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left[H_{ijk}h_{ijk} + F_{ijk}l_{ijk} + T_{ijk}m_{ijk}\right] -$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\left[S_{ij}v_{ij}\right] \quad (1)$$

Where, X = Total loss

Functional Constraints:

Constraint Equations for Inventory:

$$f_{i(j-1)} + \sum_{k=1}^{K}\left[a_{ijk} + b_{ijk} - g_{ijk} + g_{i(j-1)k}\right] + d_{ij} - f_{ij} = v_{ij}$$

(2)

The forecasted demand v_{ij} consists of inventory level of finished goods of the previous period, as well as regular and overtime production, backorder and subcontracting. The backorder of previous period and the finished goods inventory of this period are then subsequently deducted to determine the forecasted sales quantity. Backorder of a previous period must be fulfilled in the next period.

$$e_{zj} \le e_{z(j-1)} + SUP_{zj} - \mu_{zij}\sum_{k=1}^{K}\left[a_{ijk} + b_{ijk} + g_{i(j-1)k}\right] \quad (3)$$

The raw materials available from the previous period plus the quantity received from suppliers in this period less the usage of raw materials for regular, overtime and backorder production in this period should be equal to the inventory at the end of this period.

Constraint Equations for Labor:

$$L_{i(j-1)k}\left[a_{i(j-1)k} + b_{i(j-1)k} + g_{i(j-2)k}\right] + h_{ijk} - l_{ijk} - L_{ijk}$$

$$\left[a_{ijk} + b_{ijk} + g_{i(j-1)k}\right] - m_{ijkk''} +$$

(4)

The number of labor at a certain level in this period is equal to the labor in the previous period plus the workers who were hired and from this the number of workers laid off is subtracted. Also the workers who were upgraded from a lower level are added and the workers who were transferred from this current level to a superior level are subtracted.

$$\sum_{i=1}^{I}\sum_{k=1}^{K}\left[h_{ijk} + l_{ijk}\right] \le \omega_{j-1}\sum_{i=1}^{I}\sum_{k=1}^{K}L_{i(j-1)k}\left[a_{i(j-1)k} + b_{i(j-1)k} + g_{i(j-2)k}\right]$$

(5)

The number of workers in the previous period determines how many people can be hired and laid off in the current period. This number should be less than or equal to a certain percentage of the labor level of the previous period, which will be determined by the company labor policy.

$$l_{ijk} + \sum_{k'=1}^{K} m_{ijkk''} \le L_{i(j-1)k}\left[a_{i(j-1)k} + b_{i(j-1)k} + g_{i(j-2)k}\right]$$

(6)

The number of workers who can be laid off or upgraded to a higher level in this period should be less than or equal to the number of workers in the previous period.

$$\sum_{k=1}^{K}\nu_k\left[ATR_{ijk} + ATO_{ijk}\right] \ge \sum_{k=1}^{K}\left[a_{ijk}\alpha_{ijk} + b_{ijk}\beta_{ijk} + g_{i(j-1)k}\alpha_{ijk}\right]$$

(7)

The number of labor hours available through regular and overtime must be greater than or equal to the time required for outputs at regular, overtime and backorder production.

Constraint Equations for Warehouse Capacity:

$$\sum_{z=1}^{Z}\left[WSR_{zj}e_{zj}\right] \le MWCR_j$$

(8)

This equation denotes that the space required for the inventory of raw materials should be less than or equal to the warehouse capacity of raw materials in each period.

$$\sum_{i=1}^{I}\left[WSF_{ij}f_{ij}\right] \leq MWCF_j \tag{9}$$

This equation denotes that the space required for the inventory of finished goods should be less than or equal to the warehouse capacity of finished goods in each period.

Constraint Equation for Machine Capacity:

$$\sum_{k=1}^{K} MU_{ijk}\left[a_{ijk} + b_{ijk} + g_{i(j-1)k}\right] \leq MMC_{ij} \tag{10}$$

This equation represents the limits of actual machine capacity. That is, the machine usage for regular, overtime and backorder production must be less than or equal to the machine capacity for a certain period.

Constraint Equation for Subcontracting:

$$d_{ij}\gamma_{ij} \leq ATS_{ij} \tag{11}$$

The time required for subcontracting in each period should be less than or equal to the time available at the subcontractors' facility.

Constraint Equations for Material Handling:

$$r_{zj} \leq SUP_{zj} + e_{z(j-1)} \tag{12}$$

This equation denotes that the quantity of raw materials handled in current period should be less than or equal to the amount of raw materials provided by suppliers in this period and inventory of raw materials in the previous period.

$$n_{ij} \leq a_{ijk} + b_{ijk} + g_{i(j-1)k} + f_{i(j-1)} \tag{13}$$

This equation denotes that the quantity of finished goods handled in current period should be less than or equal to the amount of goods produced in regular time and overtime in this period and inventory of finished goods in the previous period.

Non-negativity Constraints:

$$a_{ijk}, b_{ijk}, d_{ij}, e_{zj}, f_{ij}, g_{ijk}, n_{ij}, h_{ijk}, l_{ijk}, r_{zj}, m_{ijk} \geq 0 \text{ for all values of i, j, z and k} \tag{14}$$

MODEL IMPLEMENTATION

Case Description

Kohinoor Chemical Company (Bangladesh) Limited (KCCL) was used as a case study to demonstrate the practicality of the proposed methodology. This company was established in 1956. It is situated at Tejgaon Industrial Area, Dhaka. It is a pioneer manufacturing company in high quality beauty, toiletries and personal care products. A number of its brands such as Sandalina, Fast Wash, Genstar, Bactrol, Ice Cool and Fair & Care are renowned in Bangladesh. The brands Sandalina and Fast Wash have high demand in market, so they incur the most manufacturing resources and need to satisfy the customers within specified lead time. The major concentration of the study was focused on one Stock Keeping Unit (SKU) of each of the brands: 75-gram presentation of Sandalina soap (product 1) and 450 gram of Fast Wash (product 2). The planning horizon is 2 months long, namely September and October. Table 1, 2 and 3 summarize the information about products and raw materials for different periods and levels.

Table 1: Information about the Products, depending on the Period

Items	Product 1		Product 2	
	Period 1	Period 2	Period 1	Period 2
Forecasted Demand (units)	780000	760000	350000	360000
Subcontracting cost per unit (Tk./unit/min)	15.92	15.92	38.22	38.22
Required time for production in subcontract per unit (mins)	0.00011	0.00011	0.00025	0.00025
Inventory carrying cost per unit (Tk./unit)	0.16	0.16	0.382	0.382
Backorder cost per unit (Tk./unit)	1.2	1.2	2.6	2.6
Material handling cost per unit of finished product (Tk./unit/min)	0.477	0.477	1.15	1.15

(continue)

(conclusion)

Items	Product 1		Product 2	
	Period 1	Period 2	Period 1	Period 2
Material handling time per unit of finished product (mins)	0.0014	0.0014	0.002	0.002
Selling price per unit (Tk./unit)	24	24	52	52
Warehouse space required for one unit of finished product (cubic feet)	0.0068	0.0068	0.0246	0.0246
Machine capacity (machine hours)	630	630	420	420
Available time for subcontracting (mins)	210	210	210	210

Table 2: Information about the Products, depending on the Level

Items	Product 1						Product 2					
	Period 1			Period 2			Period 1			Period 2		
	Levels			Levels			Levels			Levels		
	1	2	3	1	2	3	1	2	3	1	2	3
Regular production cost (Tk./unit/min)	15.89	15.87	15.85	15.89	15.87	15.85	38.19	38.17	38.15	38.19	38.17	38.15
Regular time (mins)	0.007	0.0068	0.0066	0.007	0.0068	0.0066	0.01	0.098	0.096	0.01	0.098	0.096
Overtime production cost (Tk./unit/min)	20	19.5	19.2	20	19.5	19.2	49	48.7	48.3	49	48.7	48.3
Overtime (mins)	0.007	0.0068	0.0066	0.007	0.0068	0.0066	0.01	0.098	0.096	0.01	0.098	0.096
Hiring cost (Tk./labor)	5	0	0	5	0	0	5	0	0	5	0	0
Firing cost (Tk./labor)	100	120	150	100	120	150	100	120	150	100	120	150
Training cost (Tk./labor)	10	12	0	10	12	0	10	12	0	10	12	0
Number of labor	0.00094	0.00093	0.00092	0.00094	0.00093	0.00092	0.0013	0.0012	0.0011	0.0013	0.0012	0.0011
Number of labor to be trained	5	4	0	5	4	0	6	5	0	6	5	0
Labor productivity (%)	68	70	72	68	70	72	68	70	72	68	70	72
Available time for regular production (mins)	1800	1800	1800	1800	1800	1800	1200	1200	1200	1200	1200	1200
Available time for overtime (mins)	1800	1800	1800	1800	1800	1800	1200	1200	1200	1200	1200	1200
Machine usage (hours)	0	0	0.0001	0	0	0.0001	0	0	0.00023	0	0	0.00023

Table 3: Information about the Raw Materials

Items	Product 1				Product 2			
	Period 1		Period 2		Period 1		Period 2	
	RM 1	RM 2	RM 1	RM 2	RM 3	RM 4	RM 3	RM 4
Inventory Carrying cost per unit (Tk./unit)	0.00082	0.0142	0.00082	0.0142	0.00030	0.00010	0.00030	0.00010
Material handling cost of raw material per unit (Tk./unit/min)	2.46	42.7	2.46	42.7	0.92	0.31	0.92	0.31
Material handling time per unit (mins)	0.0014	0.0014	0.0014	0.0014	0.002	0.002	0.002	0.002
Quantity of raw materials from suppliers (gm)	292500000	4916667	292500000	4916667	333000000	204750000	333000000	204750000
Quantity of raw material per unit of product (gm)	73	1.3	73	1.3	167	103	167	103
Warehouse space for one unit of raw material (cubic feet)	0.0000542	0.000047	0.0000542	0.000047	0.000056	0.000035	0.000056	0.000035

Additional Information:

- Fraction of labor variation allowed according to labor union contracts and government regulations is 10%.
- Warehouse capacity for raw materials is 340 cubic feet.
- Warehouse capacity for finished products is 1000 cubic feet.

Genetic Algorithm Approach

The authors have used MATLAB computer software to solve the proposed model, using genetic algorithm approach for the KCCL case. Table 4 lists the values of the variables obtained by solving the model using GA by MATLAB.

Table 4(a): Calculated Multi-Product, Multi-Level and Multi-Period APP Plan

Items	Product 1						Product 2					
	Period 1			Period 2			Period 1			Period 2		
	Levels			Levels			Levels			Levels		
	1	2	3	1	2	3	1	2	3	1	2	3
Regular time quantity (units)	126667	126666	126666	84413	84413	84412	52000	52000	52000	50129	50130	50130
Overtime quantity (units)	86667	86668	86667	44413	44413	44412	34000	34000	34000	32130	32130	32130
Subcontracting quantity (units)	0			0			1			0		
Inventory level of finished product (units)	126762			20000			5610			5000		
Material handling quantity of finished product (units)	300000			300000			120000			120000		
No. of labor hired	0	0	0	0	0	1	0	0	0	0	1	0
No. of labor fired	0	0	0	0	0	1	0	0	0	0	0	0
No. of labor trained	0	0	0	2	0	2	0	0	0	0	0	1

Table 4(b): Calculated Multi-Product, Multi-Level and Multi-Period APP Plan

Items	RM 1		RM 2		RM 3		RM 4	
	P 1	P 2	P 1	P 2	P 1	P 2	P 1	P 2
Inventory level of raw material (units)	5000	5000	5000	5000	5000	5000	5000	5000
Material handling quantity of raw material (units)	3000000	500000	3000000	500000	3000000	2000000	3000000	2000000

Table 4(c): Calculated Multi-Product, Multi-Level and Multi-Period APP Plan

	Backorder Quantity (units)								
	Period 0			Period 1			Period 2		
	L 1	L 2	L 3	L 1	L 2	L 3	L 1	L 2	L 3
Product 1	86667	86666	86666	44413	44413	44413	1	0	1
Product 2	34000	34000	34000	32130	32130	32130	1	0	0

Table 5 illustrates the different GA parameters and options used to obtain the optimal value of the objective function. According to this calculation, the total profit for the two months taken into consideration comes to Tk. 35,47,000.

Table 5: Different GA Parameters and Options

GA Parameters	Options Used
Population Type	Double Vector
Population Size	20
Creation Function	Feasible Population
Fitness Scaling	Top
Selection Function	Roulette
Mutation Function	Adapt Feasible
Crossover Function	Heuristic
Migration	Both
Generations	60
Time Limit	Positive Infinity
Fitness Limit	Negative Infinity
Stall Time Limit	Positive Infinity
Iteration Needed to Complete	51

Particle Swarm Optimization Approach

Here in this research paper the authors proposed a particle swarm optimization model for solving this Aggregate Production Planning problem. Here for the initial run the cognitive coefficient C_1 is used as 0.5 and social coefficient C_2 is 1. A total of 20 particles are targeted and the stopping criterion is used as 100 loops or iterations. We have used MATLAB software for writing the program and solving the problem. For all the PSO variants the fitness value gives approximately similar values. It receives its minimum fitness or objective value Tk. 38,07,300 after 100 iterations. Table 5 illustrates the different PSO parameters and options used to obtain the optimal value of the objective function.

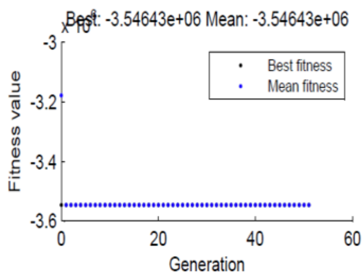
Table 6: Different PSO Algorithm Parameters and Options

PSO Parameters	Options Used
Population Size	20
Generations	100
Time Limit	Positive Infinity
Fitness Limit	Negative Infinity
Stall Time Limit	Positive Infinity
Stall Generations	50
Function Tolerance	1e-6
Constraint Tolerance	Negative Infinity

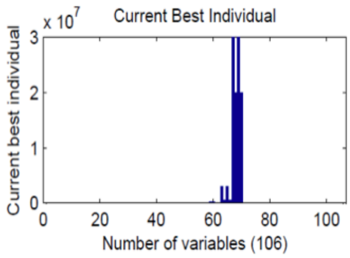
RESULTS AND FINDINGS

The solution developed by GA for the proposed single objective model is depicted in Figure-3.

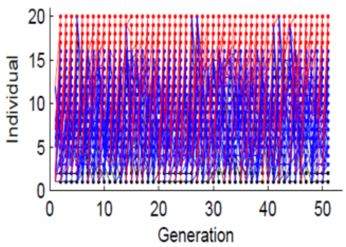
Figure 3: Solutions by Genetic Algorithm



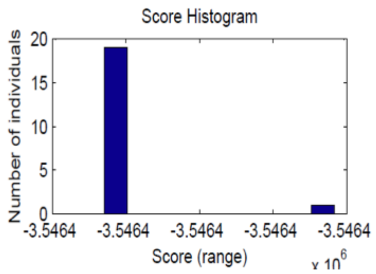
Function Values against Generation



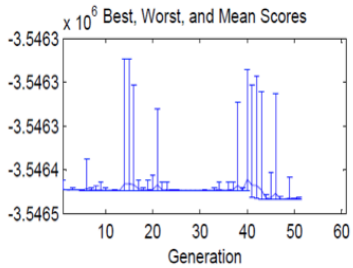
Best Fitness Function Values of



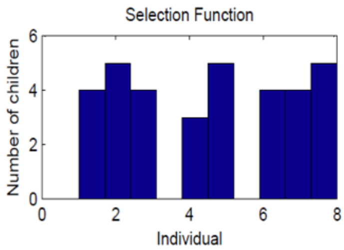
Genealogy of Individuals



Histogram of the Scores



Minimum, Maximum and Mean Fitness Function Values



Histogram of the Parents

Both the GA and PSO approaches yield different fitness function values each time the program is run. This is because the initial population selection and steps in further iterations are done at random by these algorithms. So we have executed each of the algorithms 20 times for our proposed model, and then deduced a mean value for evaluation. Table 7 depicts the heuristic optima in each run by both GA and PSO algorithms. The actual net profit of Kohinoor Chemical Company (Bangladesh) Limited (KCCL) for the two months considered was around 3600000. The mean from PSO is Tk. 3547000 and from GA is Tk. 3807300. So the output from the PSO is closer to the actual value than the GA. The PSO also shows better performance in terms of standard deviation and range which are mentioned in Table 7.

Table 7: Heuristic Optima of Individual Run by GA and PSO Algorithm

Run	Heuristic Optima (Total Net Profit for 2 Months in Taka)	
	GA	**PSO**
1	3811531	3504100
2	3504826	3345649
3	3604915	3491658
4	3962154	3764212
5	3809562	3564974
6	3807300	3561974
7	3665482	3547000
8	3596215	3549167
9	3789652	3546196
10	3965882	3491673
11	3995145	3469167
12	3896325	3556798
13	3812654	3594361
14	3807300	3600945
15	3647589	3675485
16	3998798	3546197
17	4095789	3534697
18	3807300	3534645
19	3759784	3534596
20	3807800	3526497
Mean (Tk.)	**3807300**	**3547000**
Standard Deviation (Tk.)	**151741.6059**	**81089.46**
Range (Tk.)	**590963**	**418563**

The percentage difference between the two values is calculated as follows:

$$\text{Percentage difference} = \frac{\text{Difference of GA and PSO mean values}}{\text{Average of GA and PSO mean values}} \text{ x } 100\%$$

$$= \frac{3807300 - 3547000}{0.5 \text{ x } (3807300 + 3547000)} \text{ x } 100\%$$

$$= 7.1\%$$

Since the percentage difference between the two values is quite close, this indicates that, for multiple runs both GA and PSO provide similar solutions. The difference in runtime is also negligible. This depicts the validity of our proposed model, as well as the case study used for the numerical analysis.

Several new contributing factors, such as costs related to material handling, raw material inventory and worker training have been included in the objective function and constraint equations to make the model more realistic. Without incorporating these factors, the models provide solution over Tk. 4000000 which is further from our actual value of Tk. 3600000. This fact supports the validation of the model as these costs are actually incurred in practical scenario for the industries and thus incorporating these costs allows KCCL to obtain a better solution. KCCL has already implemented this model and according to the response from the management of KCCL, they are obtaining more accurate and realistic solutions from this updated APP model.

CONCLUSION

Aggregate production planning (APP) is one of the most omnipresent but fluctuating problems in both the industry and academia. The battle to meet uncertain demands for different products in future as well as to decide hiring, firing, overtime, subcontract and carrying inventory level has always existed (Atiya et al., 2016). This research work presents a suitable approach for solving multi-product, multi-level and multi-period APP decision problems, with the forecast demand, related operating costs and capacity. The inclusion of variables such as material handling, labor training, raw material inventory, which have not been incorporated in other research works, has transformed the APP model to be more realistic. Finally, the PSO algorithm has been implemented in order to generate the optimal solution which is then again justified by implementing GA.

Future Recommendations

» Global optimum can be ensured by using a different fitness, crossover and migration functions, or utilizing different stopping criteria.

» Other than the factors that we have considered in this model, some other aspects can also be incorporated to enhance the accuracy of the model. These include shortage costs, availability of skilled workers, shortage of raw material supplies, etc.

» Cascade Rolling Horizon can be implemented with this model where the output of a certain number of period can be utilized as inputs for obtaining precise solutions for future periods.

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