Amity Management Review
2010, Vol. 1, 13-20

Computational Business Intelligence Model for Marketing - Operations Interface

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Manufacturing and Marketing are the two functions of business process where harmony should be well managed in order to run successful business operations in any supply chain. It is extremely crucial to any business firm as the two functions assist and reinforce each other. Generally in a big house of manufacturing, these two functions have adverse and most of the time conflicting priorities that have to be dealt by management in an efficient manner. Developments of new business literature like Total Quality Management, Six Sigma, Just-in-Time, Supply Chain Management, etc. that focus on customer satisfaction make this interface more strategic in nature. Product and Process development, Marketing / Sales planning and Manufacturing planning decisions represent the areas where strategic decisions have to be made by joint decision of manufacturing and marketing departments (O'Leavy - Kelly and Flores, 2002). Again, certain marketing decisions like pricing, positioning and segmentation require overall understanding of the consequences of the operational issues (Karmarkar, 1996). Here, an attempt is made to highlight the issues and possible solutions of conflict between Manufacturing and Marketing departments by developing a mathematical model and using two stage batch production - inventory systems; popularly known as Partially Integrated Production Problem (Supriyo Roy, 2009). Considering the complexities of the model, for optimization we develop and analyze Soft Computing technologies that solve heuristically the objective function. This paper is organized as follows: in the first section, the theoretical framework of manufacturing - marketing interface is discussed. The remainder of the paper is dedicated to the conflicting areas of manufacturing and marketing departments, the ways to achieve integration between these two departments, the development and discussion of the mathematical modeling. The model is practical in nature and may be used as an add-on optimizer that co-ordinates distinct function with the aim of maximizing the profit function in any business house. The discussion, managerial implications and directions for future research conclude the paper.

Keywords: Marketing - Operations Conflict, Two stage Batch production -inventory system, Computational Intelligence, Cross functional Decision making

Manufacturing and marketing are the main functions of any business firm where harmony should be sustained in order to keep successful business operations. However, managing manufacturing / marketing interface is extremely crucial since the two functions assist and reinforce each other (Cheu & Chu, 2003). Therefore, these two functions have adverse and most of the time conflicting priorities that have to be dealt by management for integrative decision making.

In any conventional production system, all decisions regarding cross functional decision making are taken at a time by the decision maker. But, for a large manufacturing firm with multidimensional objective, this policy will not be implemented: they are to assist production and marketing decisions by considering all the factors. Marketing and Production department are interlinked, so the conflicts are inevitable. Marketing is considered as 'creation of consumer demand' whereas Operations is considered as 'fulfillment of consumer demand'. Here, marketing division first analyzes their strategy and take decisions regarding their products, forecast demand and volume of production. According to the target as fix-up by the marketing division, production department try to achieve that target in the best possible optimized way. Problem of this type in cross functional decision - making is termed as Partially Integrated Production and Marketing (PIPM) Problem.

Inventory models in concerned to PIPM have been proposed to deal with a variety of real life complex inventory problems. Inventory is an important resource in supply chains, serving many functions and taking many forms. But, like any resource it must be managed well if an organization is to remain competitive. High level of inventory 'hide' problems while lower inventory 'exposes' problems. The challenge in inventory control, is not only to pare inventory to the bone to reduce costs or to have plenty around to satisfy all demand, but to have the right amount available to achieve the competitive priorities for the business most efficiently. Inventory models considering the effect of demand and incorporating the marketing

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decisions are highlighted by many researchers (Abad, 1994; Bhunia & Maiti, 1994; Bhunia et al. 2009; Goyal & Gunasekaran, 1995). Refer to research areas in PIPM model; one may refer to the work of Lee and Kim (1993).

Most of the researchers have used traditional optimization techniques for solving production - inventory / supply chain problems. The traditional methods of optimization and search do not fare well over a broad spectrum of problem domains. Traditional techniques are not efficient when the practical search space is too large. Numerous constraints and number of passes make the production / supply chain problem more and more complicated. Traditional optimization techniques like geometric programming, dynamic programming, and quadratic programming found it hard to solve these problems and they are inclined to obtain a 'local' optimal solution.

To overcome these limitations, there has been a growing interest in optimization algorithms and methods: popularly termed as Computational Intelligence. Recently, this type of methods, such as Genetic Algorithms, Simulated Annealing, Particle Swarm, Tabu Search etc. have been used by the researchers for parameter optimization, classification and learning in a wide range of applications of integrated managerial decision making problems. According to Goldberg (1989), Davis (1991), and Sakawa (2002) Genetic algorithms are adaptive computational procedures which are modeled as the mechanics of natural genetic systems. They express their abilities by efficiently exploiting the historical information to speculate on new offspring with expected improved performance. Genetic Algorithm (Holland, 1975) is different from traditional optimizations in the following ways:

- Works with a coding of the parameter set and not the parameters themselves.
- Searches from a population of points and not limited to a single point.
- Uses information of fitness function and not derivatives or other auxiliary knowledge.
- Uses probabilistic transition rules rather than deterministic rules.

In each iteration, three basic genetic operations i.e., selection, crossover and mutation are performed. In the recent year, a number of researchers have contributed their work and try to implement this methodology in several implicational fields like Traveling salesman problems by Forrest (1993), Scheduling problem by Davis (1991), and many more. But, till now only a very few researchers have applied this in the field of marketing - production integrated control model. Extensive research work in this field refers to Sarkar and Khan (1999), Sarkar and Newton (2002), Sarkar & Yao (2003), Roy et al. (2005), Roy et al. (2008), etc.

Mathematical Model Formulation

In this paper, we consider a manufacturing firm's production system that procures raw materials from suppliers in a lot and after a series of batch production operation it transformed into a finished product. Taking jointly the production and purchasing as components of a single integrated system, we determine the optimum production lot size of a product and the ordering quantities of associated raw materials together by minimizing the total cost of the system.

Assumptions & Notations

We develop a mathematical model of the problem. First, a general model is developed by considering both supplier of raw material and buyer of finished products. Using this model we develop an optimal ordering policy for procurement of raw materials and the manufacturing batch size to minimize the total cost for meeting equal shipments of the finished products at fixed intervals to the buyers (Roy Supriyo 2009).

For this, we consider a manufacturing production system that procures raw materials from suppliers in a lot and after a series of batch production system it turns into finished product. It is a common practice to evaluate separately the Economic Lot Sizes for manufacturing a product and purchasing raw materials. However, when the raw materials are used in production and their ordering quantities are dependent on the batch quantity of the product it comes under the importance of not to isolate the problem of economic purchase of raw materials from economic batch quantity.

In raw material inventory situation of any organization, normally the raw materials are consumed only at a given rate during the production up time of the batch and not throughout the total period of cycle. Keeping in mind for the benefit of the firm, management takes the following principles:

1. Ordering policy of the raw materials can either be based on its
   - Economic Order Quantity (EOQ) or
   - On the requirement of the raw material in a lot of Economic Production Quantity

2. Optimum purchasing - production policy should be determined by considering the system as a whole and not by treating its components individually.

The finished product supply policy may be continuous or periodic. Based on the supply pattern of raw material, it can be classified as follows:

- Ordering quantity of raw material is equal to the raw material required for one lot of a product.
- Ordering quantity of raw material is equal to the raw material required for multiple lots of the product.
- Multiple order of a raw material for one lot of product to be manufactured.

The goal of the management is to determine the optimum batch size of the product and the ordering quantities of raw materials that minimizes the overall cost of the system. In this area, research works of Sarkar, Karim & Haque (1995), Sarkar and Parija (1994), etc. are worth-mentioning. Sarkar and Khan (1999) developed an optimal batch size for a production system operating under periodic delivery policy. In their model formulation of option - II (Case - A & Case - B), the integer variables are relaxed as continuous variable and developed an expression using different floating-point parameters. Taking the lower and upper integral values of the integer variables, they solved their problems. But, this method does not guarantee for finding the optimality of the problem. The said problem should be solved by mixed integer programming methodology for non - linear programming.

In this paper, we develop an elitist real - coded Genetic Algorithm for mixed integer non - linear programming to investigate the effects of partially integrated production and marketing policy of a profit making firm and also to determine jointly the optimal policy for procurement of raw materials and the manufacturing batch size. Here, the demand rate is assumed to be a function of the marketing cost and selling price of the product. The selling price is determined by a mark - up over the production cost which is a generalized cost function dependent on the several factors like raw material cost, labor charges, production rate and other factors of the manufacturing system. The production rate is finite and is considered to be a decision variable. The model has been formulated for different feasible cases under various scenarios based on the supply pattern of the raw materials and the delivery policy of the product. In each feasible case with different scenarios, constrained maximization problem for marketing division and constrained minimization problem for production division have been developed separately.

Notations

The following notations are used in developing our proposed model.

P_p : Production rate which is taken as decision variable

D_p : Demand rate (unit / year)

Q_p : Production lot size

H_p : Annual inventory holding cost (Rs / unit / year)

A_p : Setup cost for the product (Rs / set-up)

r_1 : Quantity of a raw material required in producing one unit of the product (particular raw material i; $i = 1$)

D_1 : Demand of raw material (particular) for the product in a year, $D_1 = r_1.D_p$

Q_1 : Ordering quantity of raw material (particular i; $i = 1$)

A_1 : Ordering cost of a raw material (particular, i; $i = 1$)

H_1 : Annual inventory holding cost for raw material (particular, i; $i = 1$)

P_{r1} : Price of raw material (particular, i; $i = 1$)

Q_1^* : Optimum ordering quantity of raw material (particular, i; $i = 1$)

x : Shipment quantity to customer at a regular interval (units / shipment)

L : Time between successive shipments, $= (x/D_p)$

T : Cycle time measured in year $=(Q_p/D_p)$

m : Number of full shipments during the cycle time $= T/L$

t_s : Production time in a cycle

Assumptions

1. Only one raw material is used in this proposed production-inventory system.
2. The unit production cost $f(P_p)$ is dependent on raw material cost, labors charges and production rate of the product and is expressed as

$$f(P_p) = P_{r_1} + \frac{L}{P_p^{\beta}} + k_1 P_p^{\gamma}$$

P_{r1}, L, k_1 are non-negative real number. Here, P_{r1} be the raw material costs (for particular item i, $i=1$) and L be the labor cost to produce one unit of Product.

3. Demand rate D_p ($P_p > D_p$) is a function of selling price S_p and marketing cost M per unit production. It takes the form:

$D_p(M, S_p) = M^{\alpha}(a-bS_p)$, where a, b being constant

$S_p = \lambda_p f(P_p)$; λ_p is the mark - up rate.

4. Shortages are not allowed.
5. Time horizon is infinite.
6. Delivery of final product start functioning until the whole lot is finished.
7. Supply of raw materials will be in lots; is a decision variable.
8. Supply policy of finished product is assumed to be continuous.
9. Lot-sizes are assumed to be integers.

Based on the supply pattern of the raw material our proposed model can be classified in the following possible scenarios:

Scenario - I: One lot of each raw material will be required for one lot of production.

Scenario- II: One lot of each raw material will be required for multiple lots of production

Scenario - III: Multiple lots of each raw material will be required for one lot of production

Delivery policy of the product can be classified as follows:

(a) Periodic Supply

Whole lot in single installment (Case - A)

Whole lot in multiple installments (Case - B)

(b) Continuous Supply (Case-C)

In Case - A, the whole production lot will be delivered in one shipment or distributed to one customer or among different wholesalers / customers at a time. In Case - B, the whole production lot will be delivered in multiple shipments to one customer or distributed among different wholesalers / customers. However, in Case - C, the product will be delivered or sold continuously from the beginning of the production.

Here, we discuss Scenario - I and Scenario - II separately. But it is very important to note that, Case - B of Scenario - I and Case - C of Scenario - II are not feasible. Marketing division determines the selling price of the final product to the customer based on several expenditure and demand or production volume of that product. Therefore, our objective is to maximize the marketing profit Z_p per unit time. The profit will be determined in the following manner:

Profit = [Revenue] - [Marketing Cost] - [Production Cost]

Hence the problem of marketing department is to maximize the marketing profit.

Max. $$Z_p(M, P_p) = S_p D_p - M.D_p - f(P_p) D_p$$

(1) subject to the condition that $P_p > D_p$

We denote this problem as *marketing sub - problem*. Here, the profit function is a function of two continuous variables M, the marketing expenditure per unit product and P_p , the production rate per unit time. This problem is common to all the feasible cases of different scenarios. Now, we shall find out the average cost of all the feasible cases for different scenarios.

Scenario - I: Case - A

In this case, the ordering quantity of raw material is equal to the requirement of the raw material for a batch of the production system. The raw material that is replenished at the beginning of a production cycle will be fully consumed at the end of this production run.

The problem of production department is to minimize the production cost. In this case, the average cost of the system *(i=1)* is equal to the sum of set up cost of the finished product, inventory holding cost of the finished product, ordering cost and inventory costs for raw material.

$$Z_c = \frac{(A_p D_p)}{Q_p} + \frac{H_p(Q_p D_p)}{2P_p} + \frac{(A_1 D_1)}{Q_1} + \frac{H_1(Q_1 D_p)}{2P_p}$$

(2) Based on the demand determined from the problem (1) production division enquires about how much amount to be produced and how much time the production will be continued so that the Z_c obtained from (2) is minimized.

Hence the sub-problem of production division is to minimize the production cost is as follows

$$Z_c = \frac{(A_p D_p)}{Q_p} + \frac{H_p(Q_p D_p)}{2P_p} + \frac{(A_1 D_1)}{Q_1} + \frac{H_1(Q_1 D_p)}{2P_p}$$

(3) subject to $Q_p > 0\ t_s > 0$

Therefore, **NET PROFIT** of the system is given by $Z = Z_p - Z_c$

Problem (1) and (3) can be solved by using any traditional optimization method or any soft computing method in Computational Intelligence platform.

Scenario - I: Case - C

In this case, the production sub problem is given by

$$Z_c = \frac{A_p D_p}{Q_p} + \frac{H_p t_s (P - D)}{2} + \frac{A_1 D_1}{Q_1} + \frac{H_1 Q_1 D_p}{2P_p}$$

(4) subject to $Q_p > 0$ and $t_s > 0$

Therefore, **NET PROFIT** of the system is given by

$Z = Z_p - Z_c$

Problem (1) and (4) can be solved by using any traditional optimization or any soft computing method under Computational Intelligence platform.

Scenario - II: Case - A

In this case, the production sub problem is given by

Minimize

$$Z_c = \frac{A_p D_p}{Q_p} + \frac{(n+1)}{2Q_p} - \frac{Q_p t_s}{2T} + \frac{A_1 D_1}{Q} + \frac{r_1 Q_p H_1}{2}\left(\frac{D_p}{P_p} + n - 1\right)$$

(5) subject to $Q_p > 0$ and $t_s > 0$

The **NET PROFIT** of the system is given by

$Z = Z_p - Z_c$

Problem (1) and (5) can be solved by using any traditional optimization or any soft computing method under Computational Intelligence platform.

Scenario - II: Case - B

In this case, the production sub problem is given by

$$Z_c = \frac{D_p}{Q_p}(A_p + A_1) + [\tfrac{1}{2} Q_p (\frac{D_p}{P_p} + 1) - \tfrac{x}{2}] H_p + \frac{Q_1 t_s}{2T}$$

(6) $x = \frac{Q_p}{m}$, m = number of full shipment during the cycle time $= \frac{T}{L}$

subject to $Q_p > 0$ and $t_s > 0$

The **NET PROFIT** of the system is given by

$Z = Z_p - Z_c$

Problem (1) and (6) can be solved by using any traditional optimization or any soft computing method under Computational Intelligence platform.

Now, we shall develop the algorithms for determining the optimal value of M and P_p with the average profit for marketing division of the proposed production inventory system by a real coded Genetic Algorithm for solving constrained maximization problem involving two continuous variables. But for minimization problem, we develop Simulated Annealing that can be used within a standard GA by starting with a relatively high rate of mutation and decreasing it over time along a given schedule. Here, we develop SA for constrained minimization involving either one continuous variable or one continuous and one discrete variable. Here, we develop SA within GA and try to implement this in our proposed model by showing numerical example.

Computational Intelligence Approach

Genetic Algorithm

We develop GA for solving constrained maximization problem involving two continuous variables. For this development of GA, refer to our earlier work (Roy et. al. 2008). But for minimization problem, this is the first time we try to develop Simulated Annealing that can be used within a standard GA by starting with a relatively high rate of mutation and decreasing it over time along a given schedule. Our problem is highly integrative/ stochastic; so high rate of mutation is feasible.

Simulated annealing (SA) is a related global optimization technique that traverses the search space by testing random mutations on an individual solution (Ingber, 1989). A mutation that lowers fitness is accepted probabilistically based on the difference in fitness and a decreasing temperature parameter. SA has a "cooling mechanism" (referred to as the 'temperature') which initially allows moves to less fit solutions. The effect of cooling on the simulation of annealing is that the probability of following an unfavorable move is reduced. This initially allows the search to move away from local optima in which the search might be trapped. When minimizing, the objective function is usually referred to as a 'cost function'; but for maximizing, it is usually referred to as 'fitness function'. In SA parlance, one pinpoints of seeking the lowest energy instead of the maximum fitness. SA can be developed / used within a standard GA (SAGA) by starting with a relatively high rate of mutation and decreasing it over time along a given schedule. It is interesting to investigate whether SA can be applied efficiently and effectively within GA in production-inventory problems. Active research work in this area is highly necessary.

Stepwise Procedure of Simulated Annealing

From an initial solution, SA repeatedly generates a neighbor of the current solution and transfers to it according to some strategy with the aim of improving the objective function value. During this process, SA has the possibility to visit worse neighbors in order to escape from local optima. Specifically, a parameter, called temperature T is used to control the possibility of moving to a worse neighbor solution. The algorithm, starting from a high temperature, repeatedly decreases the temperature in a strategic manner (called cooling schedule) until the temperature is low enough or some other stooping criteria is satisfied. Algorithm accepts all "good" moves and some of the "bad" moves according to the Metropolis probability, defined by exp $(-\delta/T)$ where δ is the decrease in the objective function value. Further, for running simulated annealing, one of the prime tasks is to define a suitable neighborhood function so that this generation function guarantees every feasible solution within the search space. We then fix an initial solution and there are also many control parameters that need to be set-up (e.g., initial temperature, cooling ratio, and a stopping criterion). In our present optimization problem, the proposed algorithm works as follows:

Define an objective function f, and a set of heuristics H.

Define a cooling schedule: starting temperature $ts > 0$, a temperature reduction function Φ, a number of iterations for each temperature *ntemp*, and termination criterion.

Select an initial solution s_0;

Repeat

Randomly select a heuristic $h \in H$;

iteration_count = 0;

Repeat

iteration_count ++;

applying h to s_0, get a new solution s_1;

$\delta = f(s_1) - f(s_0)$

if ($\delta \geq 0$) then $s_0 = s_1$;

else

generate a random x uniformly in the range (0, 1);

if $x < \exp(\delta / T)$ then $s_0 = s_1$;

Until iteration_count = *ntemp;*

Set $t = \Phi(t)$;

Until the stopping criteria = true

Performance of simulated annealing in performing an optimization problem is based on the following criterion:

Initial Solution: Generated uniformly at random within a user defined range.

Initial Temperature: This was generated by using the following procedure: (a) generate specific number of solution at random; (b) find the solutions with the two optimized cost; and (c) initial temperature was set at twice the difference between the two optimized costs. In each run, initial temperature is allowed to be adjusted by the user.

Cooling Schedule: In the developmental phase of our proposed algorithm, we use different types of cooling schedule to find the global optimum. Popular use of this type is as T = ξ * T where ξ is a parameter that may be adjusted by the user. Optimal setting of ξ is highly problem-dependent robust in nature. The common practice to search a near-optimal ξ is to start with a relatively smaller value and then gradually turns it to a large value close to 1.0 (say 0.98 / 0.99). This trial-and-error process is very tedious. The second type of cooling schedule which one may use is: $T = T/(1+\theta T)$; where, θ is the parameter adjusted by the user and is strictly problem dependent. Again, there is no universally optimal θ which is best for all problems; it is strictly problem dependent. In our analysis, we go on by using first type of cooling schedule.

Stopping Criterion: Inner loop criterion was fixed by the user with the number of iterations for which the temperature T remains fixed. The outer loop criterion was determined by the maximum number of iterations set by user and also the lowest temperature. This implies that algorithm of simulated annealing stops when its temperature is below this lowest value.

Numerical Illustration

To illustrate our inventory model, let us consider a hypothetical system with the following values of parameters. As there is no real-world data available due to commercial confidentially and neither is there any benchmark data available from the literature, the values considered here are feasible in the proposed system. All algorithms were coded in Microsoft Visual C++ latest version and all experiments were run on a PC Pentium IV. All algorithms started from a solution produced by a greedy heuristic and allowed fairly computation time for a better comparison.

$P_{rl} = 40,\ L = 1000,\ a = 1000,\ b = 0.5,\ \alpha = 0.1,\ \beta = 1.5,\ \gamma = 0.5,\ k_l = 0.2,\ \lambda = 1.25,\ A_p = 500,\ A_l = 1000,\ h_p = 10.5,\ h_l = 7.0,\ r_l = 1.0,\ x = 500,\ M = 1.0376$

For the above parametric values, the sub problem (constrained maximization problem) of marketing department and the sub problem (constrained minimization problem) of production department are solved by real coded elitist GA and SA respectively. In 20 runs, the best -found results are shown in Table -1

Result of marketing division (Maximization)

P_p 1488.8701, $Z_p = 10610.06$, $D_p = 973.7565$, $f(P_p) = 47.7346$, $S_p = 59.6682$

Result of production division (Minimization)

Option - I/Case - A (Minimization)

$[Popsize = 200, Maxgen = 200, Q_p = (450{,}600)]$

$Q_p = 527.27,\ Z_c = 5123.30$

Option - I/Case - C (Minimization)

$[Popsize = 200, Maxgen = 200, Q_p = (550{,}600)]$

$Q_p = 567.23,\ Z_c = 4692.59$

Option - II/Case - A (Minimization)

$[n(lower) = 1, upper = 20]$

$Q_p = 324.67,\ Z_c = 9234.67$

Option - II/Case - B (Minimization)

$[n(lower) = 1, upper = 20]$

$Q_p = 719.12, Z_c = 3124.98$

Table - 1: Best found solutions for different options

Scenario	I		II	
Case	Case - A	Case – C	Case –A	Case - B
Z_p	10610.06	10610.06	10610.06	10610.06
Z_c	5123.30	4692.59	9234.67	3124.98
Z	5486.76	5917.47	1375.39	7485.08
M	1.0376	1.0376	1.0376	1.0376
P_p	1488.8701	1488.8701	1488.8701	1488.8701
$f(P_p)$	47.7346	47.7346	47.7346	47.7346
S_p	59.6682	59.6682	59.6682	59.6682
D_p	973.7565	973.7565	973.7565	973.7565
Q_p	527.27	567.23	324.67	719.12
N	-	-	1	1

It is interesting to highlight that SA within GA in minimization problem comes with a different result than by using only GA (net profit is automatically changes) - indicates the efficacy of using hybridization over direct GA (Roy Supriyo 2009) . This is significant in the light of using hybridization over direct method. Here it should be noted that, though the above table presents the relatively 'Best' solutions found for the various feasible cases, but a table of mean or mode performance may give a better idea of the algorithms overall performance ....sensitivity analysis is envisaged for further study.

Conclusion

Latest manufacturing technologies enhance cross-functional interaction between marketing and operation. In spite of increasingly emphasizing on the aspect of end user's demand, many production-inventory decision-making processes do not take into account only the dynamic nature of the marketer. Here, an attempt has been made to bridge the gap between marketing and operations, with the objective of developing mathematical model that can act as an optimizer in an add-on advanced planning system within an enterprise. Basic idea of this research is the integration of work on determining production and raw material batch sizes under different ordering and delivery assumptions for heuristically evaluating the two-stage batch production problem. Integrated unit production cost function is formulated by considering the various cost factors. Proposed model is developed simultaneously by formulating constrained maximization problem for marketing division and minimization problem for production/operation division. Considering the complexities for highly non-linear optimization problem, a Computational Intelligence approach is successfully developed and implemented. Interestingly, this is our first attempt to develop SA within GA (Hybridization) for integrated production problem. For further research, this proposed model may further be developed by using other advanced Hybridization methods like GA-PSO or ACO-PSO. The model is practical in nature and may be used as an add-on optimizer that co-ordinates distinct function with an aim of maximizing the profit function in any organization.

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