Stochastic Make-to-Stock Inventory Deployment Problem: An Endosymbiotic Psychoclonal Algorithm Based Approach

Vikas Kumar[1], Prakash[1], M. K. Tiwari[2] and F. T. S. Chan[3+]

1 Department of Metallurgy and Materials Engineering, National Institute of Foundry and Forge Technology, Ranchi-834003, India

2 Department of Forge Technology, National Institute of Foundry and Forge Technology, Ranchi-834003, India

3 Department of Industrial and Manufacturing Systems Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong.

+ Communicating Author: ftschan@hkucc.hku.hk

Abstract

Integrated Steel Manufacturer (ISM) has no specific product. As, in any ISM they go on producing finished product from the ore. This enhances the uncertainty prevailing in the Integrated Steel Manufacturer (ISM) regarding the nature of finish product and significant demand by customers. In the present scenario where the low cost mini-mills are giving firm competition to ISM in terms of cost, this compels the ISM industry to target customers who want exotic products, and faster reliable deliveries. To meet the above objective, ISM are exploring the option of satisfying a portion of their demand by converting strategically placed products, this helps in increasing the variability of product produced by the ISM in short lead time. In this paper, authors have proposed a new hybrid evolutionary algorithm named Endosymbiotic-Psychoclonal (ESPC) to decide, what and how much to stock as a semi product in inventory. In the proposed theory, the ability of previously proposed psychoclonal algorithm to exploit the search space has been increased by making antibodies and antigen more cooperative interacting species. The efficacy of the proposed algorithm has been tested on randomly generated datasets and the results obtained are compared with other evolutionary algorithms such as Genetic Algorithm (GA) and Simulated Annealing (SA). The comparison of ESPC with GA and SA proves the superiority of the proposed algorithm both in terms of quality of the solution obtained and convergence time required to reach the optimal /near optimal value of the solution.

1. INTRODUCTION

In the present scenario manufacturing enterprises are in an environment where markets are frequently shifting, new technologies are continuously emerging and contenders are multiplying globally. This has enforced industries to build their strategies in a way to support global competitiveness, new product advancement and introduction, and swift market responsiveness (Shen and Norrie, 1999). Rapid advances in technology and changes in demand patterns to incorporate customized features in manufactured products, and the relatively shorter life cycle of manufactured goods has reallocated the emphasis of manufacturing strategy from mass production to small batch manufacturing and has enforced the industries to adopt Make-to-Order (MTO) strategy. However, in order to reduce lead times, some proportion of production is planned in advance in accordance with the forecast of orders. Order lead time are cited based on the estimated cycle time i.e. the gap between receiving requests and the earliest time the order can be delivered. This approach carries the risk that estimated orders may not materialize. Strategies based on delayed differentiation and component commonality tries to alleviate the risk by facilitating pooling of demand (Burman *et al.* 1998, and Brown *et al*. 2000).

In this competitive era, steel industry is one of the fast up-and-coming industries. Steel is a foremost essential raw material for the construction of engineering components, automobiles, buildings, household objects, and various end user products. In developing countries, steel industry is one of the pillars behind their economical growth. All the steps mandatory to convert the iron ore to the finished products are performed by these Integrated Steel Manufacturers (ISMs). Global competitiveness has enforced the hefty industries such as Integrated Steel Manufacturers (ISMs) to become more customized. Mini-mills are giving firm competition to these ISMs in the manufacture of Plain Carbon Steels as they benefit from the cost advantage and significantly shorter cycle times owing to the processing of steel scrap. In response to the pressure build up by the global competitiveness, ISMs have realized their potential in the manufacturing of ample assortment of high-quality customized products. The technology to produce exotic grades and to customize finishing operations has positioned the ISMs to respond to more customized finished products.

The infrastructure of ISMs permits them to make variety of products. Reliable deliveries of the customized product are required to be synchronized with the customized production schedules. These aspects have put great pressure on ISMs to increase the product variety and reduce the delivery lead time for a subset of their customers. Though, the necessity to have a large product variety and swift response time, places inconsistent demands on the production system.

The reduction of delivery lead times has pressurized the ISMs to alter from pure Make-to-Order (MTO) production mode to a hybrid MTO/Make-to-Stock mode (Ha, 1997). Preserving stocks of semi-finished products reduces the order accomplishment delay relative to the pure Make-to-order system. The semi-finished inventory is converted to finished product for the customers who agree to forfeit premium for it. The delivery through MTO mode, where production is not initiated until the customer order is received, continues for the other existing customers. As high degree of demand uncertainty exits in the market and the custom nature of the end product prevails, it is not economical to put the semi-finished inventory into stocks for all customers. As semi-finished inventory requires extra storage space, this puts extra burden of holding cost on the industry which is economically not viable. ISMs are facing the problem of finding an effective way to determine the position and amount of strategic inventory to hold. Inventory deployment came for rescue to industries in this regard.

The inventories used in ISMs are categorized in the form of slabs, band, coils, and finished products. The coils are prepared in two stages; (i) in the first stage the raw materials including iron ore, coke, and limestone are converted into band and (ii) in the second stage the surface and structure is modified as per the customer requirements on an order. In the schematic figure shown in Fig.1, the stages (stage from 1-3 represents the 1st phase operations & the stage 4 represents the finishing operations) of production of coils are shown. Out of the three categories slabs are very difficult to be differentiated in comparison to the finished products. The advantages of width and height modification by further operations associated with slabs enable them for the manufacturing of various types of finished product orders. Conversely band has slight flexibility where as the typical finished inventory has no flexibility i.e. it is applicable to a single customer.

<<Include figure 1>>

The cycle time can be reduced by appropriate positioning of the slabs during the various staging points. Closer the inventory is placed to the final product better is the reduction in cycle times and demand collection benefits, the converse is also true. For instance, the alternate inventory positioning at the slab and coil stage reduces the cycle time by about 50% and 75% respectively (Denton & Gupta, 2003). It can be also clarified as, by positioning the finished product into the stock for certain customer, the reduction in the cycle time is virtually zero if no stock outs are assumed

ISMs are susceptible to uncertainty which is a major factor affecting its inventory planning. Prominent causes of uncertainties such as extended cycle times, volatile scenario of the markets, supply uncertainty, shortage or excessive production of orders not only affect the planning but almost it damages the inventory planning. Due to tentative customer orders production, deviations from the actual orders lead to the shortage or extra inventory. Market volatilization for specialized steel products exist because of bullwhip effect, as they are at the start up of various supply chains. In a supply chain the increment in variability with the upstream travel of demand information is stated as bullwhip effect (see Lee *et al*., 1997 and Chen *et al.*, 2000). The effect is often identified with the simulation experiment, The Beer Game, which is used to demonstrate the effects of distorted information in the supply chain (which is the cause of the bullwhip effect, Kimbrough *et al.* 2002). The key driver of the bullwhip effect appears to be that the variability of the estimates or the forecasts of customer demand seems to amplify as the orders move up the supply chain from the customer, through retailers and wholesalers to the producer of the product or service (Carlsson *et al.* 2000). By the centralization of demand information, that is, providing each stage of the supply chain with complete information on customer demand, the bullwhip effect can be diminished.

In the production process, loss of yields at various points results in supply uncertainty. Sometimes it may happen that the slabs produced may not be of desired grade, but it can be distinguished only after the casting has been completed. At this instance it is almost impossible to re-adjust the supply plan in a short interval of time as the remaining slabs in the queue are already in the controlled production plan. Uncertainty in supply chain can also occur if slabs are purchased from the external sources and in this case the yield losses can be recognized after the received order does not matches with the specifications mentioned.

The paper is organized as follows. Section 2 deals with the related work. Section 3 deals with the model formulation starting with the problem description, leading to IDP problem formulation. Section 4 focuses on the background of the Endo-symbiotic Psychoclonal algorithm. Section 5 describes the proposed algorithm. Section 6 explains the numerical experiment and Section 7 concludes this paper.

2. Related work

In this article the problem of our interest is correlated to various dissimilar areas of research including in the field of random yield, multi product substitutable inventory, and stochastic fixed charge network flow problems.

The various literatures in the area of stochastic inventory deals with single-period problems, and with two product instances of the substitutable products problem. The single-period stochastic inventory models assume a two-stage decision process in which an initial inventory level is chosen (Birge *et al.* 1997), random supply and/or demand are observed, and inventory is subsequently allocated to demand e.g. newsvendor model (Porteus, 1990).

The assortment problem in which demand and yield are deterministic, deals with the problem of selecting the proper combinations to stock, and aims towards the minimization of the combined stocking and substitution costs. This problem has been studied by Pentico (1988). Multi-product inventory problem with downward substitution and random demand was first studied by Ignall and Veinott (1969), in which the main emphasis was given on the conditions of the myopic ordering policy in a multi-period setting. Sparling and Miltenburg (1998) presented a mixed model for U-line balancing problem. McGillivray and Silver (1978) and Parlar and Goyal (1984) presented the perfect yield analytical results for two-product problems. The solution methodology for the downward substitution of a two-stage stochastic linear programming formulation (2S-SLP) of large-scale multi-product problems was considered by Bassok *et al*. (2000). The two-product case with yield uncertainty was well thought-out by Gerchak *et al*. (1996).

Bitran and Dasu (1992) study heuristics for a lot sizing model and Hsu and Bassok (1999) present an efficient algorithm for 2S-SLP model that assumes a single lot size decision resulting in random yield of multiple products. The model proposed in this paper incorporates various characteristics of replacement models but also oversimplifies to cases other than downward substitution. The paper takes account of the uncertainties such as due to Bullwhip effect in which the variability of the estimates or the forecasts of customer demand seems to amplify as the orders move up the supply chain from the customer, through retailers and wholesalers to the producer of the product or service (Chen *et al*., 2000).

The uncertainties affecting the inventory planning has been well established in the proposed article. One frequently suggested strategy for reducing the magnitude of the bullwhip effect is to centralize demand information, i.e., to make customer demand information available to every stage of the supply chain. For example, Lee *et al.* (1997) suggest that "one remedy is to make demand data at a downstream site available to the upstream site". In perspective to the newsvendor type model, Shih (1980) illustrated that the cost impact of ignoring yield uncertainty can be nearly 5% of the total costs. Factors influencing yield randomness and related modeling approaches have been described by Yano and Lee (1995). Our model assumes stochastically proportional yield losses i.e. the number of good items in a lot is the product of a random yield rate with arbitrary distribution and the lot size and it is applicable to large-scale problems involving multiple products with substitution.

The multi-location inventory problem with transshipment between locations has been studied by Karmarkar (1979), Robinson (1990), and others. The work on Make-to-Stock (MTS) queues has been done by Buzacott and Shanthikumar (1993). The Genetic Algorithm optimization of inventory control system by has been studied by Disney *et al.* (2000). The problems of two-stage stochastic linear programming have been solved by specialized computational procedures developed by Wallace (1986). Our proposed model incorporates binary decision variables in the first stage decision process, which is the generalization of the work done by Wallace. The first stage decision corresponds to the selection of order type, design, and production-level decisions. The variables representing the supply and demand nodes define the second stage network-flow problem.

The studies related to the modeling of the problem that determine the optimal point of differentiation, subject to a service-level constraint (Garg and Tang, 1997; Lee and Tang, 1997; Lee and Billington, 1994; Lee, 1996; Graman and Magazine, 1998; Gupta and Benjaafar, 2004; Swaminathan and Tayur, (1998, 1999); Gupta and Denton, 2004), have been incorporated in our model. The aims of the authors are to confine the advantages of inventory pooling when order-up-to-level inventory models are used to elicit replenishment. The design features of the semi-finished product as decision variables are studied by only Swaminathan and Tayur (1998). The proposed model differs from it in that they have assumed the assembled products where as we are concerned about the semi-finished products. In steel industries the numbers of design choices are virtually infinite and there is much greater product customization. We have assumed general substitution as compared to the only downward substitution considered by Swaminathan and Tayur (1998). Swaminathan and Tayur (1998) considered model fixed costs where as we have considered inventory storage space constraints.

Our model can be classified as a stochastic fixed-charge-network flow problem (Nemhauser and Wolsey, 1999, Chapter II.6 for discussion of the deterministic versions of these problems). A dual-based procedure for the stochastic un-capacitated facility location problem has been studied by Louveaux and Peeters (1992). Laporte *et al.* (1994) study exact solution procedures for a location problem with stochastic demands in which facility capacities (inventory levels) are chosen a priori. Rao *et al.* (2000) studied a multi-product inventory model with downward substitution and fixed setup costs. Our model can be clearly distinguished from their work, as they assume perfect yield, no shortage constraints (rather, fixed setup costs), and take advantage of the downward substitution structure to propose simulation-based heuristics.

From the literature, it has been found that these methods used to determine semi-finished inventory are not very interactive and need much more computer memory to store the representations of the sequence. It is also known that although heuristics are generally quick, they are prone to get entrapped in local optima and thus do not always provide a true optimal solution.

These shortcomings of previously applied algorithms on inventory deployment problem motivated the authors to develop a Meta heuristic, which is capable of escaping local optima. To enable this, the authors have extended their previous approach of psychoclonal (Tiwari *et al.* 2005, Singh *et al.* 2005) by incorporating feature of reciprocal changes between the antibodies and antigens. The proposed algorithm termed as Endosymbiotic-Psychoclonal (ESPC) Algorithm, enjoys its flavor from Endosymbiotic algorithm (Margulis 1980) and Psychoclonal algorithm. The Endosymbiotic algorithm is based on the evolution process of eukaryotes from prokaryotes. An endosymbiont is an individual formed by the integration of two types of symbionts, in ESPC algorithm antigens (Ag's) an antibodies (Ab's) are modeled as symbionts and the toroid matrix formed by the series of reciprocal changes refer as endosymbiont. Psychoclonal algorithm in ESPC algorithm inherits its attributes from Maslow's need hierarchy theory and the Artificial Immune System (AIS) approach. There are different levels of needs arranged in a hierarchy, namely physiological needs, safety needs, growth needs, esteem needs, and self-actualization needs. Clonal selection explains the response of immune systems when a non-self antigenic pattern is recognized by antibodies. Characteristic features of immune systems are immune memory, hypermutation and receptor editing. In proposed algorithm antigens (Ag's) and antibodies (Ab's) are referred as symbionts, in engineering milieu, non-self antigens are constraints and antibodies are the candidate solutions. In this algorithm, the different levels of needs help in maintaining the feasibility of a solution and thus, preserve it in the immune memory for subsequent operation. Hypermutation is used to guide the algorithm towards local optima, and receptor editing helps it to escape and look for other solutions. This process continues till the self-actualization level and the best solution is attained. To prove the efficacy of the proposed algorithm intensive runs have been carried out on computer simulated dataset and the results obtained are compared with the GA and SA solutions.

3. MODEL FORMULATION

3.1 Problem Description

The model proposed in this paper deals with two types of decision-making processes for inventory deployment: (i) strategic planning decisions made on an infrequent basis (e.g. quarterly or biannually); and (ii) operational planning decisions made more frequently (e.g., weekly or monthly). We have considered the Inventory Deployment Problem (IDP).

IDP refers to the problem of determining the demand volume, customer's priorities and type of orders to be served in the Make-To-Stock (MTS) production mode on the basis of the given historical information. IDP also refers to the determination of the designs to be produced in the MTS mode to support the selected customer orders subject to a constraint on the total number of inventory designs that can be chosen based on known potentially large set of inventory. The orders that are not included in the MTS mode are served by Make-To-Order (MTO) production mode by default. The orders having insufficient planned production being planned to be served in the MTS mode are assumed to be satisfied by an alternate longer-cycle-time sourcing method (e.g., MTO production, outsourcing) and incur a shortage penalty. The fluctuations in demand leading to the surplus production volume, which remains unutilized is supposed to incur a penalty cost i.e. the opportunity cost of reserving production capacity.

Throughout the first planning stage i.e. the strategic planning phase, the ISM's objective is to select orders and inventory designs supporting consistent high-volume slab-to-order distribution at an aggregate level during horizon of the decision. In order to lessen the unfavorable consequences of supply and demand ambiguity the ISM fabricate the inventory of chosen designs thereafter. At this level of granularity, the complete planning era can be treated as a single period when accounting for the cost of supply-demand disparities. Thus, the proposed two stage stochastic linear programming model is such that demand and supply judgments across the strategic planning period are combined into a single second-stage period. The planning decisions of MTS orders are designed for the optimized production, in order to accomplish the aimed inventory levels on a monthly or weekly basis, if the variety of designs and their respective orders served by them are known.

In the MTS mode the operational scheduling period can be convincingly assumed to be independent for the couple of reasons. Primarily, due to extended cycle times for slab production, and high reliability of production efficiency on sequencing and scheduling of the bottleneck resource, deficiency in one period cannot be regained in the subsequent period without considerable cost. Subsequently, rescheduling to back till a missed order, results in domino effect, which may cause numerous delayed subsequent customer orders. Therefore, in order to overcome this, either rescheduling of the order within the

MTO mode is carried out or the order is completed from external sources i.e. by purchasing of on-hand slabs/coils at relatively higher cost. In addition, ISM's are equipped with sufficient capacity for finishing operations, leading to the shorter processing time for the customized finishing. This also refers to the reasonable assumption of decoupling of the planning decisions in different operational planning periods. In order to maintain the model refined regarding the aforementioned authenticity of steel production, we put forward a model that allocates a predetermined time-independent charge for each deficiency, and scarcity of Make-To-Stock items remaining within the same period (Carr *et al.* 2000). As per the proposed stochastic linear programming model, once the inventory-level (first-stage) decisions i.e. selection of the kind of order, design, and production-level designs are made, the supply and demand uncertainty is resolved and optimal allocation of slab inventory is made realizing the customer orders in a second-stage linear program.

3.2 IDP Model Formulation

The proposed IDP problem has the network structure resembling a bipartite graph. Vertices in the graph can be separated into a set of potential supply nodes, J={1,2,......,*m*}, representing the set of design choices, and a set of potential demand nodes, K={1,2,........,*l*}, representing the different order choices. As per the application rules the allowable allocations of supply and demand are represented by the edges between the supply and demand nodes. The additional notations used are shown below:

$C_j^e =$ per unit cost of having surplus inventory of design j;

$C_k^s =$ per unit cost of scarcity for order-type k;

$G_{jk} =$ supplementary revenue from cycle time reduction if design j is applied to order-type k;

$C_j^p =$ additional per unit cost of producing design j in the Make to Stock mode;

$d_j =$ binary decision variable representing the decision to stock design j;

$v_k =$ binary decision variable; $v_k = 1$ if order-type k is supplied from inventory, and 0 otherwise;

c = maximum number of permitted design choices;

W_j = production /procurement planned for design j;

O_{jk} = quantity of order-type k supplied by design j;

u_{jk} = incidence parameter; $u_{jk} = 1$ if design j can be applied to order k and 0 otherwise;

s_k = shortage for order-type k;

e_j = surplus production of design j;

Y_j = random yield rate for design j;

X_k = random demand for order-type k;

ε = random vector with yields, Y_j and demands, X_k, as components.

ξ and Ψ represents the set of positive integers and positive real numbers respectively. Similarly ψ represents the set of all real numbers, and A = {0, 1} is the binary set of variables. The domains of the problem parameter are: $c \in \xi, C_j^e \in \Psi, (C_k^s, G_{jk}, C_k^p, W_j, u_{jk}, s_k, e_j) \in \Psi, and (d_j, v_k) \in A.$, the random vector ε has support $\Theta \subseteq \Psi^{l+m}$, probability distribution P, and finite first moments, Ж.

Since IDP is formulated as two-stage stochastic integer program, the first stage corresponds to design and order choices, $d \in A^m$ and $v \in A^l$, and the planned production vector, $W \in \psi^m$. The production cost incurred during the first period is denoted as, $\sum_{j=1}^m C_j^p u_j$. The production cost in the second stage is $\sum_{j=1}^m C_j^e e_j$, for excess production and for production scarcities a cost $\sum_{k=1}^l C_k^s s_k$ is incurred.

The reduction in the cycle time due to matching designs with demand results in the total additional revenue equal to, $\sum_{j=1}^m \sum_{k=1}^l G_{jk} O_{jk}$. The complete problem, assuming a *risk-neutral* firm can be expressed as:

Max {F= $-C^p W + R(d, v, W)$}, … (1)

Subject to

$$\sum_{j=1}^m d_j \le c \quad , \qquad \dots (2)$$

$d \in A^m$, $v \in A^l$, W≥0 … (3)

Where $R(d,v,W,\varepsilon)$ is known as the recourse function. It is the expected additional revenue earned, net of any shortage/overage costs, acquiring from the inventory allocation decisions. In reality, $R(d,v,W) = E_{\varepsilon}[R(d,v,W,\varepsilon)]$, where $R(d,v,W,\varepsilon)$ is defined by:

$$R(d,v,W,\varepsilon) = \max \left\{ \sum_{j=1}^{m} \sum_{k=1}^{l} G_{jk} O_{jk} - \sum_{j=1}^{m} C_j^e E_j - \sum_{k=1}^{l} C_k^s s_k \right\} \qquad \dots (4)$$

Subject to

$$\sum_{k=1}^{l} u_{jk} O_{jk} + E_j = Y_j W_j \qquad \forall j, \qquad \dots (5)$$

$$\sum_{j}^{m} u_{jk} O_{jk} + s_k = X_k v_k, \qquad \forall k, \qquad \dots (6)$$

$$O_{jk} \le X_k d_j, \qquad \forall (j,k), \qquad \dots (7)$$

$$O_{jk} \ge 0, \qquad E_j \ge 0, \quad \forall (j,k). \qquad \dots (8)$$

Equation (1)-(3) representing the complete problem is feasible for any (d, W), due to positive linear basis provided by (e, s) in constraints (5)-(6), and the fact that $Y_j \ge 0, X_k \ge 0, \forall (j,k)$. In addition, randomness takes place only in the R.H.S. of constraints (5)-(8), and the coefficients of second stage are deterministic. The slab inventory is measured in tons and $O_{jk}s$ are treated as continuous variable. The total production in MTS mode accounts for less than the half of the ISMs capacity and as there are substantial production efficiencies associated with the high volume MTS mode, due to this reason, there is no upper bound on the variables W_j.

Some assumptions are assumed regarding the objective function coefficients such as non-negativity of the shortage costs. The insignificant revenues are such that if for some (j, k), $u_{jk} = 0$, then $G_{jk} = 0$ as well. In addition, $G_{jk} \ge \max\{-C_k^s - C_j^e, 0\}, \forall (j,k)$, i.e., it is never beneficial to select not to allocate accessible supply of design j to order k if $u_{jk} = 1$ for some j. The first stage procurement cost is assumed as $C_j^p + C_j^e > 0$, since otherwise it is insignificantly optimal to produce an infinite quantity of design j, and that for each design j, there is an order-type k such that $C_k^s + G_{jk} > C_j^p$, since otherwise it is optimal to bring to a halt producing design j completely.

At ISMs the available space in the slab yard is contributed for the storage of the slab inventory, hence for choosing a particular design no significant fixed cost is incurred. Equation (2) representing the storage cell constraint plays a role analogous to fixed costs, through the implied opportunity cost, linked with not selecting one of the other potential designs. Equation (5) and (7) implies that optimal production level $W_j^* = 0$, if $d_j = 0$ since otherwise $E_j > 0$ and needless surplus costs are incurred with no superfluous rewards. Constraints (6) and (7) implies that $v_k^* = 0$, if all d_j for which $u_{jk} = 1$ are zero.

4. BACKGROUND OF ESPC

As stated earlier, the proposed ESPC algorithm uses concepts derived from the natural processes of Endosymbiotic evolution, human psychology, and Artificial Immune System theory (Jerne, 1974). In this section, the salient features of the aforementioned theories are outlined.

4.1 Endosymbiotic Algorithm

The Endosymbiotic evolutionary algorithm was proposed by Kim *et al.* (2004). According to Kim *et al. a* symbiotic evolutionary algorithm is inspired by the biological coevolution that is a series of reciprocal changes in two or more cooperative interacting species. It maintains two or more populations (or species) that represent sub-problems. This means that an individual in a population becomes a partial solution to the entire problem. A complete solution to the entire problem is constructed by combining all the partial solutions, one from each of the populations.

The Endosymbiotic evolutionary algorithm (EEA) constructs and maintains a balancing population (Pop-B) and a sequencing population (Pop-S), like the existing symbiotic algorithm. Pop-B and Pop-S consists of symbionts that are the individuals representing work assignment to stations and model sequences, respectively. Each of the individuals becomes a partial solution to the problem being solved. EEA maintains another population Pop-BS that consists of endosymbionts. An endosymbiont is an individual formed by the integration of the two types of symbionts, so that it becomes an entire solution representing a combination of work assignment and model sequence. Indeed, Pop-BS represents the process of forming eukaryotes from prokaryotes.

There have been several variants to the symbiotic evolutionary algorithm, such as Ahmadjian *et al.* (1986), Potter (1997), Moriarty and Miikkulainen (1997), Kusumi *et al.* (1998), Watson *et al.* (1999), Mao *et al.* (2000), Kim *et al. (2000),* Tsujimura *et al.* (2001), Chang *et al.* (2002). The Endosymbiotic algorithm intends to replicate the natural process of Endosymbiotic evolution. The theory of Endosymbiotic algorithm was first proposed by Margulis (1980). The author provides an explanation for the evolution process of eukaryotes from prokaryotes in which the simple structured prokaryotes enter into a larger host prokaryote, and start living together in symbiosis and evolve to a eukaryote. Endosymbiotic Evolutionary Algorithm (EEA) incorporates an evolutionary strategy replicating the Endosymbiotic process embedded in an existing symbiotic evolutionary algorithm.

4.2 Background of Psychoclonal Algorithm

The psychoclonal algorithm (Tiwari *et al.* 2005*,* Singh *et al.* 2005*)* enjoys the flavour of *Maslow's need hierarchy theory* (Maier, 1965) and *Theory of clonal selection* (De Castero, L.N. and Zuben, 2002). *Maslow's need hierarchy theory* helps in constraints satisfaction by assessing the antibodies formed at each step. The clonal part helps in the somatic maturation of antibodies. In this section, the salient features of the aforementioned theories are outlined with proposed heuristic.

4.2.1 Maslow's need hierarchy theory

Human psychologists have always attempted to explain the nature of motivation in terms of the type of needs that people experience during their lifespan. The basic concept behind such a theory is that, people have certain fundamental needs and people are motivated to engage in behavior that will lead to satisfaction of their needs. Psychologists' claim that needs have a certain priority. As the more basic needs are satisfied, an entity seeks to satisfy higher needs. Abraham Maslow had given a framework that helps to explain the strength of certain needs, which is known as *Need Hierarchy Theory (*Maier, 1965*)*. The theory hypothesize that all people posses a set of five needs arranged in hierarchy, from most fundamental or basic survival need to the most sophisticated needs of self-actualization. According to this theory, one can move to upper strata of hierarchy if the lower levels of needs are satisfied. The five levels of needs, arranged in hierarchy and known as Maslow's Pyramid are shown in figure 2.

<<Include figure 2>>

4.2.2 Theory of clonal selection

Clone selection explains the response of the immune system, when a non-self antigenic pattern is recognized by a B-cell. When a non-self antigen above the threshold affinity is recognized by B-cell receptor, it is selected to proliferate and produces antibodies in high volume. Antigen (Ag) stimulates the B-cell to proliferate and mature into terminal Antibody (Ab) (non-dividing) secreting cells, known as plasma cells. Proliferation in the case of immune cells is an asexual, amitotic process. The cells divide themselves (no crossover) to generate clones. During reproduction, the B-cells progenies undergo a hypermutation process that together with the strong selective pressure, results in B-cells with an antigenic receptor presenting higher affinities than with the selective antigen. This process is known as the maturation of the immune response.

B-cells, in addition to proliferating and differentiating into plasma cells, can differentiate into long-lived B memory cells with a long-life span. These memory cells are pre-eminent in future responses to the same antigenic pattern, or a similar one. The aforementioned, process of clonal, proliferation, and affinity maturation is schematically shown in figure 3 (Castero *et al.* 2002*,* and Tiwari *et al*. 2005).

<<Include figure 3>>

5. PROPOSED ALGORITHM

5.1 Nomenclature:

Ab : Set of Antibodies available.

Ag : Set of Antigens available.

Ab_d : Set of the new Ab's that will replace R_c amount of the lower affinity Ab's from Ab.

$Ab_{k,n}$: *Ab's* from Ab with highest affinities.

Ag_m : Population of m Ag's.

R_k : Population of N_c clones generated from $Ab_{k,n}$.

R_k^* : The population after hypermutation.

BR^* : Best repertoire.

Â : Vector containing values of objective function g (.) as the affinity of all *Ab*'s

Â * : Vector containing values of antigenic affinity for matured clones. In relation to the antigen Ag_j.

N : The total number of antibodies

N_c : The total number of clones generated for each of the Ag's = $\sum_{i=1}^{n} R(\beta . N)$, i=*1,2,..n.*

R (.) : Operator that rounds its argument toward the closest integer.

β : Multiplying factor

POP_{ij} : Population set of constrained satisfied Ab's.

PAB_{ij} : Population of randomly generated *Ab's*.

PAG_{ij} : Population of randomly generated Ag's.

S : Number of bits in eukaryote.

Figure (4.) represents the flow of the Endosymbiotic-Psychoclonal Algorithm. The detail steps of the proposed algorithm are discussed below:

<<Include Figure 4>>

5.2 The Procedure

Need Level I:

Physiological needs: This refers to our most basic survival needs for food, water and shelter from the environment to permit our continued existence. In optimization, this corresponds to the generation of possible sequences based upon the problem environment.

For each cell; PAB_{ij} and PAG_{ij} has been generated randomly, PAB_{ij} is a 2D structure of toroid grid containing the generated set of Ab's. PAG_{ij} is also a 3x3 matrix of randomly generated constraints is Ag's. A set of eukaryotes with satisfied constraints are generated randomly or based on certain rules are stored in POP_{ij} matrix.

Need Level II:

Safety needs: The safety needs has to do with physical and physiological safety from external threats to our well-beings. An external threat in the engineering perspective corresponds to constraints imposed on the problem. This is where evolution of a particular entity or candidate solution is carried out.

Here, new Ab is produced by cooperation between PAB_{ij} and PAG_{ij}. Calculate the affinity vector (Â) of the generated Ab. Randomly select a population from POPij and compare it with newly generated Ab. If the Selected eukaryote *from* POP_{ij} *has* Â greater than that of generated *Ab* then it will update POP_{ij} toroidal matrix else algorithm will move to improve the quality of *Ab* by cloning and that of eukaryote by carrying out reciprocal changes in it.

Need level III:

Social needs: In engineering this refers to the selection of the candidate solution and the term social reflects the interaction between candidate solutions.

The selected antibody is cloned again by assigning cooperation between PAB_{ij} and PAG_{ij} and proportionally to the Â, generating a repertoire R_k of clones (higher the antigenic affinity, the higher the number of clones generated for each selected *Ab*).

Need level IV:

Growth needs: Here, candidate solutions diversify to extend the search-space. This movement towards local optima is the basic mechanism of every evolutionary technique e.g. crossover and mutation in GA.

Set R_k is submitted for hypermutation, inversely proportional to the vector affinity (Â), generating a population R_k^* of matured clones (the higher the affinity, the smaller the mutation rate). If the solution of R_k^* don't improve after fixed number of iteration (Reject is taken 2 in this report) then selected Ab is edited using receptor editing.

After satisfaction of need level IV, vector affinity (Â) of the matured clones R_k^* is evaluated and the best repertoire (BR^*) is passed through Need level III.

Need level V:

Self-actualisation needs: Self-actualization needs are unique and they can never be fully satisfied or fulfilled. This is very true for any optimization problem as we always concentrate on finding near optimal solution rather than the global-optima. According to theory, the more self-actualization needs are fulfilled, the stronger they become.

With the number of generation the solution quality of POP_{ij} goes on improving, when the solution quality stops improving, the algorithm is supposed to achieve self-actualisation needs. In ideal condition self-actualization is achieved at optimal solution. As mentioned above, this level becomes stronger and stronger after a number of generations. Thus, the process repeats till N=Ngen (maximum number of generation).

6. Numerical Experiment

It is tough to determine the capricious nature of customers therefore, to decide which order type for which design have to be kept in inventory and at what stage of its processing, to meet the customers demand at minimum tardiness is a complex decision making problem. In this study, the authors have proposed an ESPC algorithm to solve an inventory deployment problem. The dataset for different type of scenarios have been randomly generated using the information provided in Denton and Gupta (2004). The coefficients for additional revenues, shortage costs, and excess costs are all distributed as uniform (1, 4). Additional procurement costs C^P are assumed to be the same for all supply nodes and are fixed at one. The detail information regarding, demand for different order-type, yield rate for different design, Normal probability plot, and Histogram showing the deviation from the normality of the dataset can be obtain from www.geocities.com/gurukul007/inventorydata.pdf. The ESPC algorithm has been applied on the generated data. To initiate the working of the proposed algorithm, initial toroid matrix i.e. POP_{ij} matrix consisting of eukerates have been generated. In engineering milieu, the toroid matrix contains the feasible solution with all constraints satisfied. The eukerates of toroid matrix can be generated randomly or based on some rules. The toroid matrix is generated *i.e.* POP_{ij} matrix containing feasible solution with all constraints satisfied. PAG_{ij} matrix consists *Ag's*, in our case these are the constraints represented by Equation (2)-(8) in section 3. Then PAB_{ij} matrix is generated consisting of *Ab's* viz. candidate solution. The *Ag's* are attacked on *Ab's* randomly i.e. constraints are selected randomly and infeasible solutions are traced back into the feasible solution space based on the constraint represented by the *Ag*. As in considered problem, no penalty is involved that means each and every constraints need to be satisfied. But the order at which Ag's attack the same solution will affect the quality of solution of matured *Ab's* produced by the attack of Ag. An example of an antibody has been shown in Table (1) formed after the attack of *Ag's*. On the basis of *Ab* generation, the order-type has been secreted as shown in Table 2. The Vector affinities of the generated *Ab's* have been calculated using equation (1). The randomly selected *Ab* from PAB matrix has been compared with the eukerates selected from the toroid matrix represented by POP_{ij} matrix. If the vector affinity of selected antibody is greater then the solution selected from the toroid matrix then it will replace the solution else selected *Ab* is send for cloning carryout at need level III. The hypermutation is carried out on cloned *Ab*. The proposed algorithm has deterministic procedures for finding the rate of hypermutation, which is given as:

$$\sigma = \exp\left(-\delta * \hat{A}\right) \qquad \dots (13)$$

Where,

σ =Rate of hypermutation

δ =Control factor of decay

The hypermutation offers random changes in genes as with natural mutation. The difference lies in the terms of the degree of modification. After hypermutation, maturation is carried out by attacking the *Ag's* on the reproitires formed from cloning. Best matured reproitire has been compared with the eukerates, if the solution doesn't improve for a fixed number of iteration (In this research, reject is set to 2) the antibody is edited using receptor editing. The solution quality in the toroid matrix *i.e.* POP_{ij} improves with the number of iterations satisfying the self actualization needs of Ab's and eukerates.

For the problem, code has been generated in MATLAB 5.3 and the program is executed on IBM PC with Pentium CPU at 1.9GHz. The program for proposed ESPC algorithm is given on http://www.geocities.com/gurukul007/program/inventoryprg.pdf. The Endosymbiotic algorithm has been proposed by Margulis in 1980. In this paper, the authors have incorporated the merits of Endosymbiotic algorithm into the Psychoclonal algorithm and proposed a new Endosymbiotic Psychoclonal algorithm (ESPC). The ESPC algorithm has faster convergence than the GA (Genetic Algorithm) or SA (Simulated Annealing) based approaches. A prominent feature of the proposed algorithm is its ability to explore different areas of the solution space simultaneously, by breaking initial chromosomes into several populations, which enables it to take cut above the traditional GA's, where genes are blindly divided into two chromosomes. The diversity in the proposed algorithm is ensured by incorporating cooperation and co-evolution among the symbionts.

Endosymbiotic evolution, which is an extension of cooperative or symbiotic evolution, is yet another novel genetic approach that emulates the natural evolution of endosymbionts. An assay of the search strategy adopted by symbiotic evolution reveals that even though different populations cooperate, the distributed search over all the populations might hinder the convergence to good solutions. The proliferation of Endosymbiotic evolutionary algorithm has endowed the search strategy with an effective passage to get by the aforementioned situation. The subsistence of endosymbionts facilitates the exploitation along with the embedded parallel search that results in speedy convergence to better quality solutions. The result obtained by ESPC algorithm has been compared with Genetic Algorithm (GA) and Simulated Annealing (SA).The detailed result has been given in Table 3. While comparing the proposed ESPC algorithm with that of the GA and SA the crossover probability was set to be 0.6 and the mutation probability was set to 0.1. In SA the initial temperature was set to 200 and the final temperature was 7. From the table it can be seen that the tendency of SA to get entrap in local optima is very high and therefore the average solution quality of SA in most of the cases is less in comparison with ESPC and GA. The GA in most of the cases gives result near to that of ESPC but when the experimentation on convergence rate of both algorithms is done, it is found that GA got very slow convergence rate. The average number of generations required by GA to reach optimal / near optimal solution is 761 with standard deviation of 67 generations whereas, in ESPC the average number of generation required by algorithm to reach the optimal/near optimal solution is 264 with standard deviation of 32 generations. Thus, ESPC algorithm is around 288 times faster in converging toward the optimal / near optimal solution then GA.

7. Conclusion

In this article a problem pertaining to inventory deployment problem has been addressed using a new optimization approach named Endosymbiotic-Psychoclonal Algorithm. The performance of proposed endosymbiotic-psychoclonal has been tested on computer simulated dataset, the results obtained are found exemplary when the same has been compared with genetic algorithm (GA) and simulated annealing (SA). Tuning of various parameters of endosymbiotic-psychoclonal algorithm has been rigorously carried out and appropriate values have been selected after large number of trial runs.

The authors are testing the sensitivity of the proposed methodology towards different problems of production, planning and control. For future work a robust methodology need to be devised to tackle the large experimentation time required to tune the different parameters of Endosymbiotic Psychoclonal Algorithm.

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Table 1. An example of Antibody

1	0	1	0	0	0	1	1	0	1

Table 2. Represents Order-type assignment on design based on Ab generation

1	3	1	7	10	1	8	7	3	10	7	1	1	8	7	8	10	3	7	8

Table 3. **Numerical Results for randomly generated dataset**

K=25, U_j ~(0.8,1), $\forall j$ and D_k ~N(10,2)

F(P^a)	(c,n,m)	ESPC		GA		SA	
		AV	σ	AV	σ	AV	σ
U(0.1,0.3)	(5, 10, 20)	14.676	0.41	12.256	0.81	9.125	0.31
	(5, 10, 30)	0.929	1.88	0.9156	0.95	0.756	1.63
	(5, 20, 30)	7.234	0.59	6.584	0.48	6.452	0.62
	(5, 20, 40)	3.068	0.24	3.124	0.75	1.251	0.34
	(10, 20, 30)	0.864	0.35	0.758	0.25	0.565	0.76
	(10, 20, 40)	3.514	0.57	2.947	0.20	3.125	0.45
	(10, 30, 50)	4.505	2.14	3.210	1.23	2.265	0.65
U(0, 0.4)	(5, 10, 20)	10.266	0.35	10.256	0.23	9.303	0.53
	(5, 10, 30)	2.051	0.023	2.131	0.35	2.015	0.32
	(5, 20, 30)	10.567	2.54	9.154	3.15	9.532	0.14
	(5, 20, 40)	1.080	0.025	0.926	0.023	0.712	0.21
	(10, 20, 30)	4.135	0.11	3.589	0.15	4.021	1.05
	(10, 20, 40)	6.034	0.54	5.121	0.63	0.593	0.92
	(10, 30, 50)	4.838	0.47	4.568	0.83	3.978	0.35
U(10, 0.25)	(5, 10, 20)	9.035	0.515	9.142	0.61	8.691	0.61
	(5, 10, 30)	2.851	0.41	2.816	0.56	2.563	0.26
	(5, 20, 30)	2.237	0.64	1.915	0.34	1.654	0.25
	(5, 20, 40)	1.909	0.15	1.896	0.11	1.726	0.21
	(10, 20, 30)	7.420	0.24	7.670	0.68	6.840	1.27
	(10, 20, 40)	11.10	0.86	10.26	1.67	10.641	1.25
	(10, 30, 50)	0.135	0.002	0.054	0.004	0.03	0.002

AV: Average objective value; σ = Standard deviation; N = Normal Distribution; K= No. of scenarios, U = Uniform distribution; D = Demand; c = Maximum number of permitted design choices. n = set of design choices; m = set of different order choices, P^a = Probability.

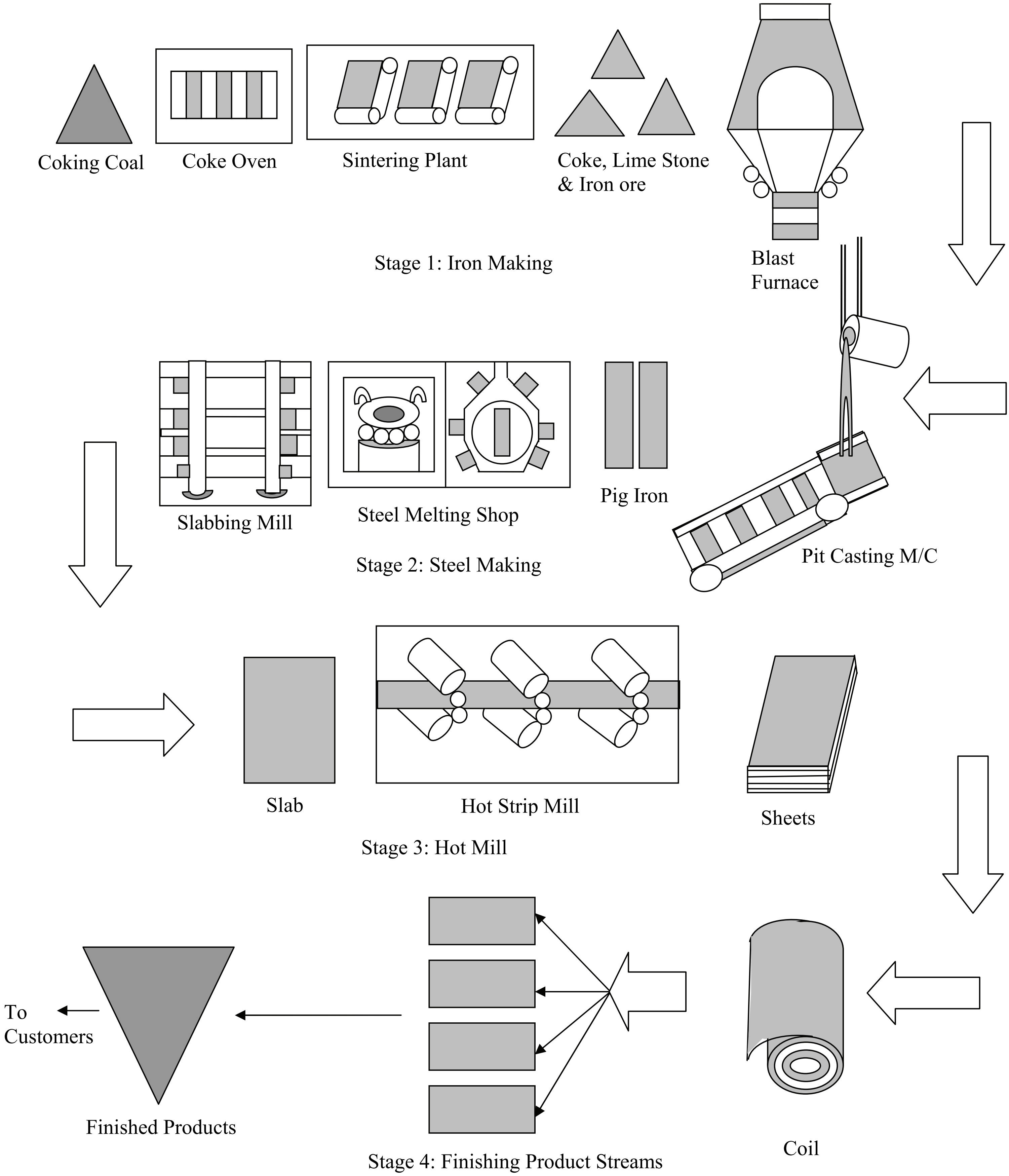

Fig.1. The process flow in an integrated steel mill

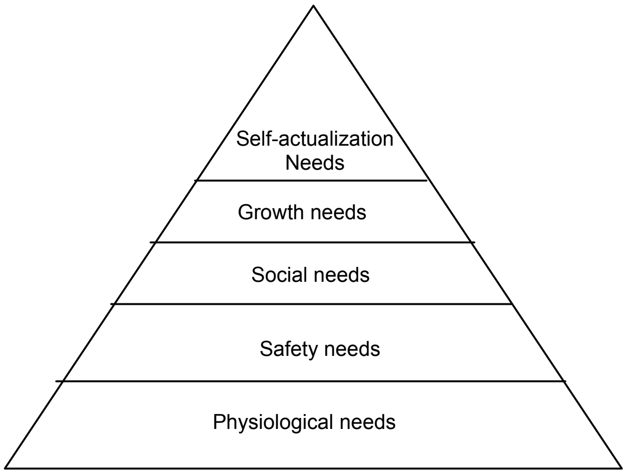

Figure 2. Maslow's Pyramid

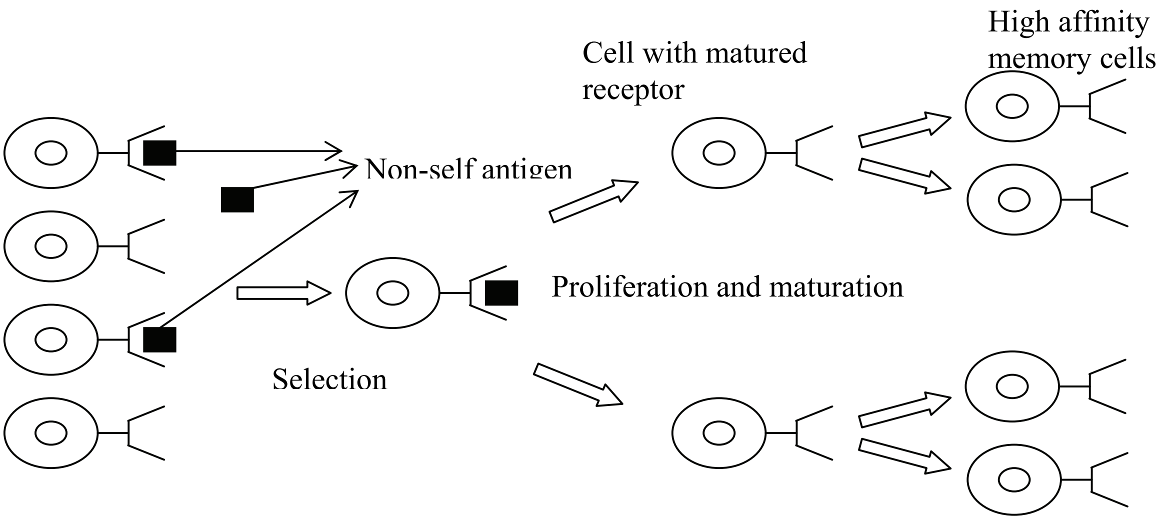

Figure 3. Process of Clonal selection, proliferation and affinity maturation

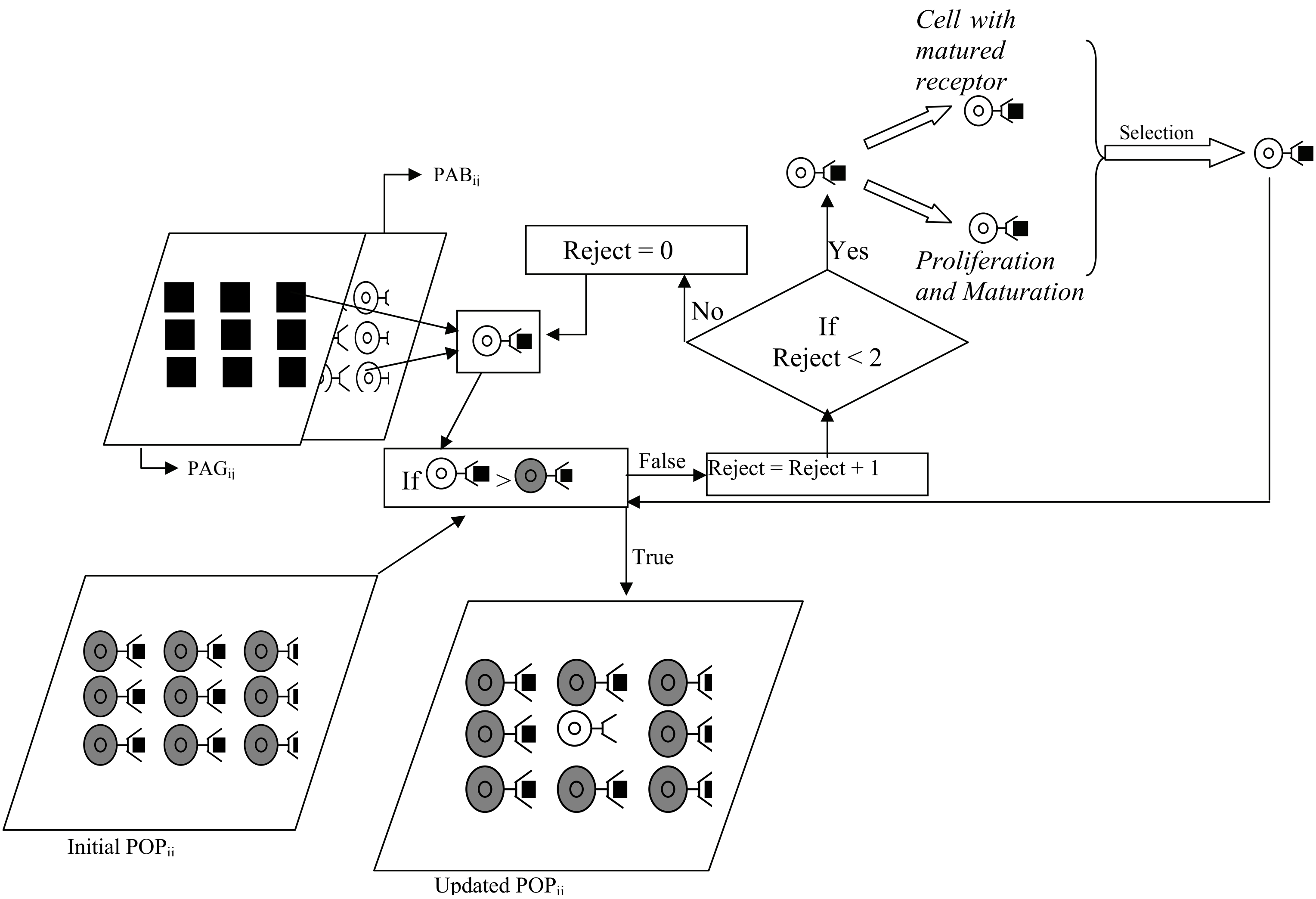

Figure 4. Flow diagram of Endosymbiotic -Psychoclonal algorithm