Intelligent Decision Making for New Product Development and Market Positioning Using Soft Computing

Soumya Banerjee[1], Ajith Abraham[2] and Crina Grosan[3]

[1]Dept. of Computer Application, Institute of Management Studies,
Dehradun, India
Email: soumyabanerjee@imsddun.com

[2]IITA Professorship Program, School of Computer Science and Engineering
Chung-Ang University, Seoul 156-756, Republic of Korea
Email: ajith.abraham@ieee.org
http://www.softcomputing.net

[3]Department of Computer Science, Faculty of Mathematics and Computer Science, Babes-Bolyai
University, Cluj-Napoca, Romania
E-mail: cgrosan@cs.ubbcluj.ro

Abstract: In any business organization, the project managers have to execute several critical decisions at each level according to the organizational hierarchy. New product and technology development and positioning encompasses most crucial activity for the existence of any concern in a competitive business model. The decisions involved in these processes are extremely uncertain and requires plenty of strategic interventions and proliferations. This paper proposes a novel method to address these issues with the implication of hybrid intelligent systems. Fuzzy inference systems have been used to model ambiguous conditions and ant colony optimization based intelligent multi-agents for searching the optimal combined strategy to meet the requirement. The well-blended model first try to focus on the objective of the business problem, then interprets using fuzzy linguistics, and finally initiate the ant-based search for finding the best suitable business strategy.

Keywords: New Product Development and Positioning, Fuzzy logic, Ant colony approach

1.0 Introduction

Development and forecasting a new product or technology that is still nascent in fabrication is often recognized as the key process of competition in a variety of markets. At present markets are generally perceived to be demanding, promising quality and higher performing product; in brief the cycle of such development must be optimized with a better certainty and cost efficacy. Therefore the decision maker must take certain criteria prior to kick off a new product/ technology life cycle, e.g. the requirement of end user, the strategies as well as technological opportunities, the existing resource of concern to optimize the structure of development phase. These issues also take care of the acceptance of the product / technology to the target population.

Considering the parameters of management science, the theme of the emerging product development is to translate an idea into tangible physical asset, which in turn decides the perfect product to develop and launch a substantial optimized investment and risk out in the middle.

All these criteria indicate that major decision issues behind the new product development or technology and is followed by a considerable amount of uncertainty. This usually diverts the decision makers to reach target performance. The uncertainty, vagueness, and ambiguity arise from manifold sources encompassing technical managerial and commercial fronts. It is accepted that minimization of uncertainty and optimizing the plan of development is the prime governing factor towards successful development of new product and effective positioning in market scenario.

Soft computing was first proposed by Zadeh [11] to construct new generation computationally intelligent hybrid systems consisting of neural networks, fuzzy inference system, approximate reasoning and derivative free optimization techniques. It is well known that the intelligent systems, which can provide human like expertise such as domain knowledge, uncertain reasoning, and adaptation to a noisy and time varying environment, are important in tackling practical computing problems. In contrast with conventional Artificial Intelligence (AI) techniques, which only deal with precision, certainty and rigor the guiding principle of hybrid systems is to exploit the tolerance for imprecision, uncertainty, low solution cost, robustness, partial truth to achieve tractability and better rapport with reality. In recent times the significant development of soft computing paradigm enables to contemplate such management decision-making problem in more intelligent and adaptive way. Fuzzy logic and fuzzy sets are quite effective for handling those imprecise conceptual phases of development or positioning of a product or technology. To some extent, hybrid intelligent approaches for problem solving are found more suitable to improve the quality of decision-making and strategy proliferation.

In this paper, the point of uncertainty from development till positioning a new product or technology has been envisaged and then uses hybrid intelligent techniques to explore the solution space and to make a final optimal decision.

1.1 Basic Definitions

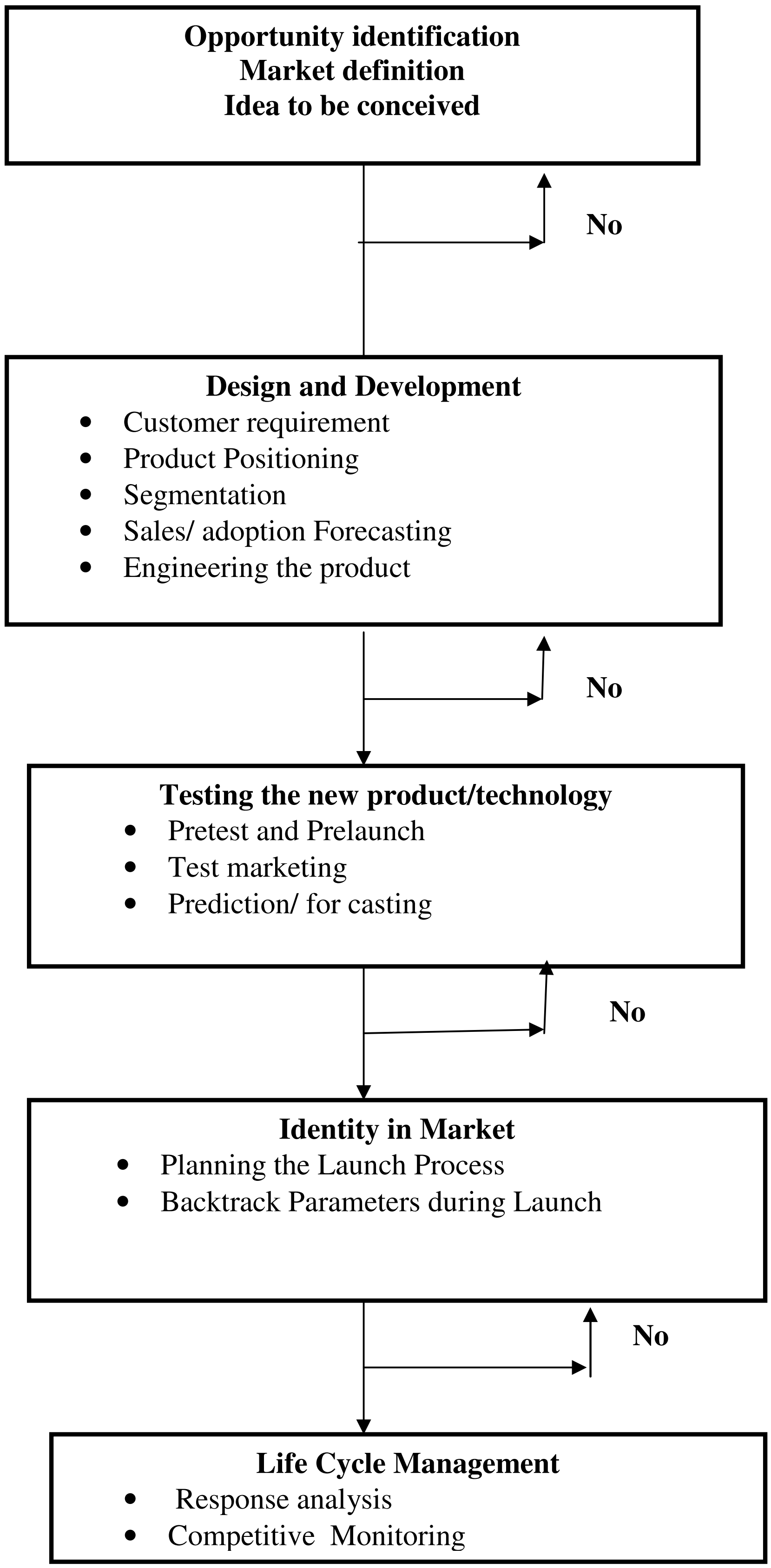
Development of a new product or technology can be defined as transformation of a market opportunity and asset of assumptions about product engineering into a salable product [1]. As it is already mentioned those entire enterprises become responsible with the interdisciplinary activities since from marketing skill, organizational behavior engineering throughput and to operational efficiency.

Investigating these broad factors in the enterprise categorizes the basic segregation of development phase into primary 4 phases as illustrated in Table 1.

Table 1. Basic segregation of development phase

Name of the phase	Description
• Conceptual phase	Basic proposition of product or technology
• Planning phase	Time versus activity scheduling
• Execution phase	The throughput of development strategy
• Completion	Positioning of the product in the real scenario.

The flow diagram can also be presented as follows [2]:



2.0 Imprecision and uncertainty in product development cycle

The product or technology development by nature is characterized by uncertainty which is fundamentally an information defect. The deviation of information (the difference between the amounts of information required to perform a particular task and the amount of information already provided) would produce uncertainty. Fox et al. ([3]) combines 3 dimensions of uncertainty as technical, market and process. They rate and categorize uncertainty along each dimension as being either low or high.

2.1 New product positioning

Bass model which has been widely used for explaining and predicting the time pattern of adoption of new products is represented as follows:

$$n(t) = p[N - N_{(t-1)} + \frac{q[N_{(t-1)}]}{N}[N - N_{(t-1)}] \qquad (1)$$

where:

$N_{(t-1)}$ represents the cumulative number of adoptions that have occurred until period t,

$n(t)$ represents the number of adoption of the product/technology occurring in period t,

p is the coefficient of innovation, capturing the intrinsic tendency of users (innovators to adopt as well as the effect of time invariant external influence),

Q is the coefficient of imitations or social contagion (word of mouth) of user or customers (imitators) capturing the extent to which the probability that one adopts, given that one has not done so yet, increase with the proportion of eventual adopters that has already adopted,

N represents the number of eventual adopters of the product/technology in the defined market.

The detailed description of the model can be found in [4] and [5].

This exhibits if the values of p, q and N would be guessed then the Bass model is well suited to forecast the adoption of new product in each period following the product information into the market.

The basic Bass model relies on several assumptions listed below:

- The diffusion process is binary (i.e. at any given time, a customer either adopts, or waits to adopt)
- There is a fixed maximum potential number of adopters (N).
- Eventually all N will adopt the product.
- There is no repeat purchase, or replacement purchase of the product.
- The impact of word-of-mouth (q) is independent of adoption time.
- The product diffuses independent of potential competing products (substitutes).
- Marketing strategies do not have any impact on the rate of diffusion (marketing aspects are not explicitly modeled).
- The contagion (word-of-mouth) effect is uniform, i.e. everyone in the population has the potential to influence everyone else in the same way.

3.0. Ant Colony Optimization

Ant Colony Optimization (ACO) is a meta-heuristic algorithm for solving combinatorial problems ([6], [7], [8] and [9]). In ACO, artificial ants construct a solution by building a path on a construction graph $G = (C, \alpha)$ where the elements of α (called connections) fully connect C (set of components). The artificial pheromone can be associated either to components (nodes) or connections (edges). The behavior of ant is specified by defining start states and termination conditions, construction rules, pheromone update rules and daemon actions. This has been exhaustively detailed in [10].

Each ant is initially positioned on a randomly chosen node of G and builds a solution by applying a probabilistic rule called as state transition rule. This probabilistic rule is biased by pheromone value so that the higher the pheromone on connection, the higher the probability it will be selected. In this paper, we formulate a support shell comprising fuzzy logic based *if-then* rules in conjunction with the ant colony optimization algorithm. The entire work envisages the product or the technology development from the embryo stage towards the positioning in the market using the proposed hybrid intelligent tool.

3.1 Contemplation of Problem with Ant Colony Optimization

New product adoption behavior in many markets can be represented using the formalism of graph theory. Each participants in the market (potential new product adopts) is a node in the graph network and the edges of the graph (network) and the edge of graph between the nodes serve to represent the nature of linkage between he market participants. Market is global place where the product/or technology has to be positioned is ideally a fully connected graph to the other (N-1) participants. There are several mathematical propositions related with various types of markets:

A graph G consists of a non empty set of elements called vertices and a list of unordered pairs of vertices called edges. The set of vertices of graph G is called the vertex set of G, denoted by $V(G)$ and the list of edges is called the edge list of G denoted by $E(G)$. The modifications in the development of later as hence primarily been in modeling the methods of communication among ants. Both strategic and tactical parameters in the new product development broadly depend on the assumption of the Bass model.

Now a fuzzy preference relation R on asset A is a fuzzy set on the product A x A such that $\mu_R : A \times A \rightarrow [0,1]$. Let $P(a, b) \in$ R be the fuzzy preferences relation between a and b where $a, b \in$ R be the fuzzy preference relation , $P(a, b) + P(b, a) = 1$. It is obvious that the higher value of $P(a, b)$ means stronger intensity. The fuzzy proposal between a and b for criterion i is obtained by a pair wise comparison $(g_i(a), g_i(b))$, which allows the linguistics performance of different market proposal of a new product and they are fuzzy numbers.

The related works have not revealed the methodology of how ant like agents makes the choice to traverse for the next iteration in the connected graph shown for the new product development and positioning. Ant system demonstrates good performance in solving problems that are combinatorial in nature. However this particular problem is simultaneously characterized by uncertainty and combinatorial in nature. Therefore classical ant colony could be modified to address these issues in new product or technology development and their respective positioning in the market. The basic modifications would be in the way of calculating transition probabilities where fuzzy logic is used. It is possible to deal with the uncertainty that would exist in complex combinatorial optimization problem by using fuzzy logic as separate modules within the ant system. The control strategy of ant can also be formulated in terms of numerous descriptive rules.

4.0 Experiments and results

Under new product development the following parameters have been taken into consideration:

i) Profitability

ii) Efficiency

iii) Strategic Values

iv) Business impact

v) Financial aspects

vi) Technical

vii) Managerial

viii) Personnel

Similarly, positioning of the new product demands the following parameters:

i) Diffusion process of product adoption

ii) Identification of repeat purchase or replacement purchase

iii) Estimation of volume of adopters.

iv) Ideal size of the volume of adopters = Potential Number of adopters.

v) The impact of word of mouth is independent of adoption time

vi) Presence of other contemporary product versus newly developed product.

vii) Influence of marketing strategies that don't have any impact on the rate of diffusion.

viii) The contagion (word of mouth) effect is uniform that is everyone in the population has the potential to influence everyone else in the same way.

In the experiments, we have 8 new product developments and positioning to be evaluated according to combinations of the 16 criteria mentioned above. The universe of discourse is a finite set of fuzzy numbers used to express an imprecise level of performance for each criterion. In the decision phase, we incorporate different linguistic terms "very high", "moderately poor" etc. The data values envisaged in the experiment are normally sited for the demonstration purpose for the proposed methodology. The empirical data can be given for a particular case study to be compatible with the concerned parameters. The model also interprets these linguistic terms as fuzzy number following the fuzzy preference relationship given below:

$$\frac{P(a,b) = D(a,b) + D(a \cap b, 0)}{D(a,0) + D(b,0)}, \qquad (2)$$

where $D(a,b)$ is the area where *a* dominates *b*, $D(a,0)$ the area of *a*, $D(b,0)$ the areas of *b*. As observed from (2), the fuzzy preference can be obtained using fuzzy membership functions. The linguistic terms used are *very high, fairly high, high, medium, slightly medium, moderately poor, fairly poor* and *poor*. Details are depicted in Table 2.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Profitability and Diffusion	**Very high, High**	**Medium, Moderately Poor**	**Very high, Medium**	**Fairly High, Medium**	**High, Fairly Poor**	**Fairly High, Slight Medium**	**Fairly Poor, Poor**	**Medium, Poor**
Efficiency and repeat purchase strategic values	FH M	M P	V H H	M F P	M P	F G M	F P P	M F P
Estimation of volume of adopters and business impact.	V H H	F H FP	V H M	F H M	H M	F H M	F P P	H F P
Financial and estimation of volume of adopters	H M	F H M	H F H	F H M	M F P	M FP	H FH	F H M
Technical solidity and product or technology	M F P	F P P	F H M	F H F P	F P P	H M	F P P	F H F P
Managerial and contagion Effect	V H H	F H P	F H M	F H M	M F P	H M	M F P	F P P
Personnel and word of mouth	F H F P	M FP	F H M	H M	F P P	V H H	F H M	F P P

Table 2. Fuzzy preference modeling and linguistic terms

Fuzzy preference relations to be formed for each combination of both criteria yields the values depicted in Tables 3-10.

Profitability

	1	2	3	4	5	6	7	8
1	0.51	1.0	0.67	0.95	0.87	0.95	1.00	1.00
2	0.00	0.50	0.13	0.18	0.34	0.18	0.64	0.56
3	o.32	0.87	0.50	0.63	0.65	0.63	0.97	0.88
4	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
5	0.13	0.66	0.35	0.44	0.50	0.44	0.75	0.69
6	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
7	0.00	0.36	0.03	0.05	0.25	0.05	0.50	0.44
8	0.00	0.44	0.13	0.17	0.30	0.17	0.56	0.50

Table 3. Profitability and diffusion process

Efficiency

Identification of repeat purchase or replacement purchase

	1	2	3	4	5	6	7	8
1	0.50	0.83	0.05	0.83	0.84	0.51	0.96	0.81
2	0.00	0.50	0.13	0.18	0.34	0.18	0.64	0.56
3	o.32	0.87	0.50	0.63	0.65	0.63	0.97	0.88
4	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
5	0.13	0.66	0.35	0.44	0.50	0.44	0.75	0.69
6	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
7	0.00	0.36	0.03	0.05	0.25	0.05	0.50	0.44
8	0.00	0.44	0.13	0.17	0.30	0.17	0.56	0.50

Table 4. Efficiency and identification of repeat purchase

	1	2	3	4	5	6	7	8
1	0.51	0.76	0.71	0.63	1.00	0.50	0.70	0.70
2	0.25	0.50	0.39	0.34	0.96	0.24	0.38	0.46
3	0.30	0.62	0.50	0.44	1.00	0.30	0.50	0.56
4	0.37	0.66	0.56	0.50	1.00	0.37	0.56	0.60
5	0.00	0.41	0.00	0.00	0.50	0.00	0.00	0.03
6	0.50	0.76	0.70	0.63	1.00	0.50	0.70	0.70
7	0.30	0.62	0.50	0.44	1.00	0.30	0.50	0.56
8	0.30	0.54	0.44	0.40	0.97	0.30	0.44	0.50

Table 5. Strategic Values and Estimation of volume of adopters

Ideal size of adopters+ influence of marketing strategy, independent of diffusion

	1	2	3	4	5	6	7	8
1	0.50	1.96	0.67	0.95	0.83	0.95	1.00	1.00
2	0.04	0.50	0.30	0.38	0.34	0.28	0.72	0.96
3	0.33	0.70	0.50	0.63	0.58	0.63	0.97	1.00
4	0.05	0.62	0.37	0.50	0.44	0.50	0.95	1.00
5	0.17	0.66	0.42	0.56	0.50	0.56	0.96	1.00
6	0.05	0.72	0.37	0.50	0.44	0.50	0.95	1.00
7	0.00	0.28	0.03	0.05	0.04	0.05	0.50	0.80
8	0.00	0.04	0.00	0.00	0.00	0.00	0.20	0.50

Table 6. Business impact and ideal size of adopters, influence of marketing strategy, independent of diffusion

Financial

Estimation of volume of adopters

	1	2	3	4	5	6	7	8
1	0.51	1.0	0.67	0.95	0.87	0.95	1.00	1.00
2	0.00	0.50	0.13	0.18	0.34	0.18	0.64	0.56
3	o.32	0.87	0.50	0.63	0.65	0.63	0.97	0.88
4	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
5	0.13	0.66	0.35	0.44	0.50	0.44	0.75	0.69
6	0.05	0.82	0.37	0.50	0.56	0.50	0.95	0.84
7	0.00	0.36	0.03	0.05	0.25	0.05	0.50	0.44
8	0.00	0.44	0.13	0.17	0.30	0.17	0.56	0.50

Table 7. Financial and estimation of volume of adopters

Presence of other contemporary product or technology

	1	2	3	4	5	6	7	8
1	0.51	0.64	0.67	0.95	0.87	0.95	1.00	1.00
2	0.36	0.50	0.13	0.18	0.34	0.18	0.64	0.56
3	0.82	0.95	0.50	0.63	0.65	0.63	0.97	0.88
4	0.63	0.72	0.37	0.50	0.56	0.50	0.95	0.84
5	0.37	0.50	0.35	0.44	0.50	0.44	0.75	0.69
6	0..84	0.95	0.37	0.50	0.56	0.50	0.95	0.84
7	0.37	0.50	0.03	0.05	0.25	0.05	0.50	0.44
8	0.63	0.72	0.13	0.17	0.30	0.17	0.56	0.50

Table 8. Technical solidity and presence of other contemporary product or technology

Managerial Input

	1	2	3	4	5	6	7	8
1	0.51	0.94	0.93	0.95	1.00	0.84	1.00	1.00
2	0.03	0.50	0.33	0.33	0.57	0.32	0.56	0.66
3	0.05	0.69	0.50	0.50	0.82	0.44	0.83	0.94
4	0.05	0.69	0.49	0.50	0.82	0.44	0.82	0.94
5	0.00	0.48	0.17	0.17	0.50	0.17	0.50	0.64
6	0.18	0.70	0.56	0.54	0.83	0.50	0.84	0.95
7	0.00	0.45	0.17	0.19	0.50	0.17	0.50	0.65
8	0.00	0.36	0.49	0.05	0.36	0.04	0.37	0.50

Table 9. Managerial input and contagion effect

	1	2	3	4	5	6	7	8
1	0.51	0.62	0.38	0.34	0.72	0.04	0.38	0.73
2	0.38	0.50	0.18	0.16	0.64	0.00	0.18	0.63
3	0.62	0.82	0.50	0.44	0.95	0.05	0.50	0.95
4	0.66	0.84	0.56	0.50	0.96	0.17	0.56	0.96
5	0.28	0.36	0.05	0.04	0.50	0.00	0.05	0.50
6	0.96	1.00.	0.94	0.83	1.00	0.50	0.95	1.00
7	0.62	0.82	0.50	0.44	0.94	0.05	0.50	0.95
8	0.28	0.36	0.05	0.04	0.50	0.00	0.05	0.50

Table 10. Personnel and word of mouth

4.1 Development of the proposed model

The work has considered that there exist *n* proposals for new product development and positioning in a concern satisfying *m* criteria and constraints. So, categorically, the experiment follows the below mentioned stages to build the complete decision making engine:

- Fuzzification of development and positioning process
- Representation of development and positioning factors in a dependency graph using bio-inspired agents (ants)
- Combined algorithm blending fuzzy logic and ant colony optimization
- Results or output stages

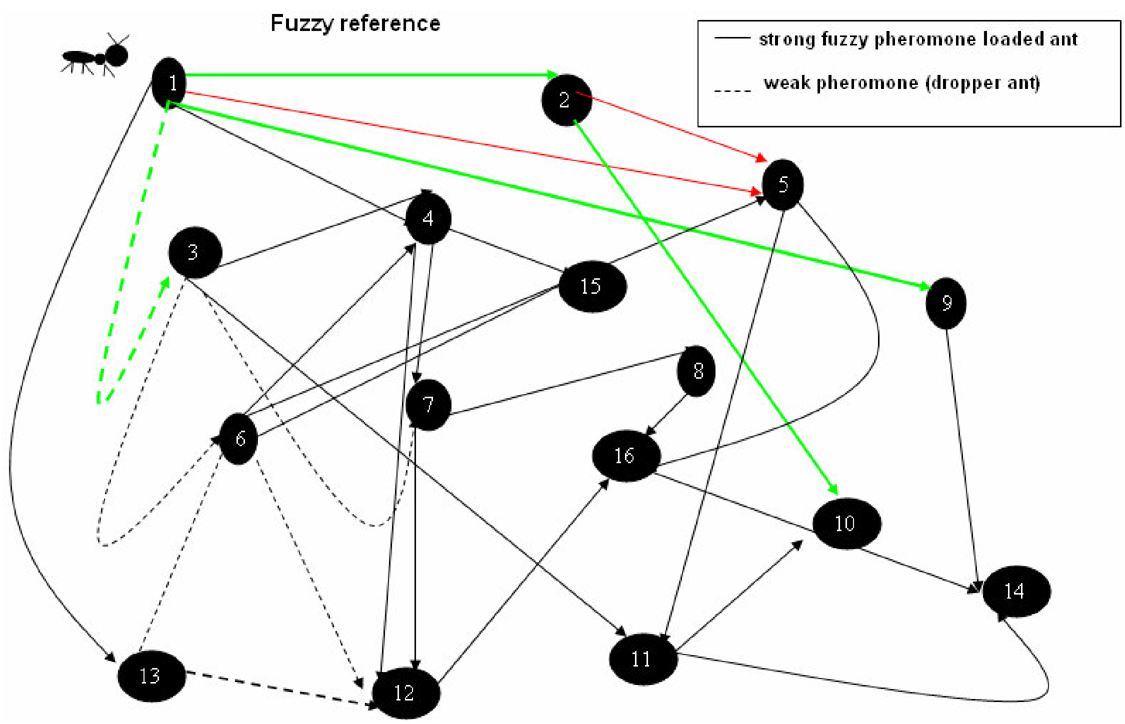


Figure 1. Strategic dependency network (graph)

Representation of development and positioning factors in a dependency graph with bio-inspired agents (ants):

Figure 1 illustrates the strategic dependency network. Let us assume that at the time point *t* ant *k* is positioned to find best possible and the maximum possible correlation between the dependency factors for new product development and positioning. It has to be mentioned that $J_i^k(t)$ denotes the set of nodes that ant *k* has not visited by the time *t* (the set of unvisited nodes in the cases of bigger instances of this problem) especially in the beginning of the search process; the number of nodes $\left|J_i^k(t)\right|$ in the set of unvisited nodes $J_i^k(t)$ could be large.

An ant based clustering algorithm is combined with the fuzzy classification algorithm. Few interesting works have been already demonstrated on combining fuzzy rules with ant based algorithms for optimization task. The proposed experiment also uses only one ant agent as multiple ants in a non parallel environment. We consider different types of behavioral soft ants.

In this model a certain stimulus and a response threshold value are associated with each assignment and real ant agent can perform. The movement of ant in this model is governed by α cut of fuzzy set. The fuzzy set (comprises of fuzzy number) is basically a dependency matrix with the probability that an ant starts performing a task with stimulus *s* and response threshold value θ which is given by:

$$T_n(s,\theta) = \frac{sn}{sn+\theta n},$$

where *n* is a positive integer. The ability of real ants to find shortest routes is mainly due to their depositing of pheromone as they travel; each ant probabilistically prefers to follow a direction rich in this chemical. The pheromone decays over time, resulting in much less pheromone on less popular paths. Given that over time the shortest route will have the higher rate of ant traversal, this path will be reinforced and the others diminished until all ants follow the same, shortest path (the “system" has converged to a single solution). It is also possible that if there are many equally short paths this situation can be handled by ACO as well. In this situation, the rates of ant traversal over the short paths will be roughly the same, resulting in these paths being maintained while others are ignored. Additionally, if a sudden change to the environment occurs (e.g. a large obstacle appears on the shortest path), the system responds to this and will eventually converge to a new solution. In general, an ACO algorithm can be applied to any combinatorial problem as far as it is possible to define:

- *Appropriate problem representation:* The problem must be described as a graph with a set of nodes and edges between nodes.
- *Heuristic desirability (η) of edges*: A suitable heuristic measure of the “goodness" of paths from one node to every other connected node in the graph (The best combination of strategy).
- *Construction of feasible solutions*: A mechanism must be in place whereby possible solutions are efficiently created.
- *Pheromone updating rule:* A suitable method of updating the pheromone levels on edges is required with a corresponding evaporation rule. Typical methods involve selecting the *n* best ants and updating the paths they chose.
- *Probabilistic transition rule*: The rule that determines the probability of an ant traversing from one node in the graph to the next. The feature selection task may be reformulated into an ACO-suitable problem. ACO requires a problem to be represented as a graph here nodes represent features, with the edges between them denoting the choice of the next feature. The search for the optimal feature subset is then an ant traversal through the graph where a minimum number of nodes are visited that satisfies the traversal stopping criterion.

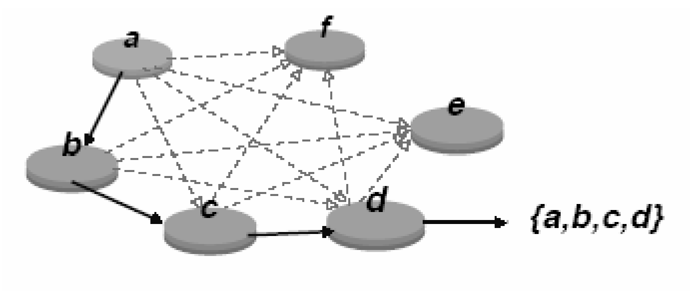


Figure 2. Graph showing explored nodes

Figure 2 illustrates this setup - the ant is currently at node *a* and has a choice of which feature to add next to its path (dotted lines). It chooses feature *b* next based on the transition rule, then *c* and then *d*. Upon arrival at *d*, the current subset *a; b; c* is determined to satisfy the traversal stopping criterion (e.g. a suitably high classification accuracy has been achieved with this subset). The ant terminates its traversal and outputs this feature subset as a candidate for data reduction. The heuristic desirability of traversal and edge pheromone levels are combined to form the so-called probabilistic transition rule, denoting the probability of an ant at feature *i* choosing to travel to feature *j* at time *t*:

$$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha.[\eta_{ij}]^\beta}{\sum_{l\in J_i^k}[\tau_{il}(t)]^\alpha.[\eta_{il}]^\beta} \tag{3}$$

where k is the number of ants, J_i^k the set of ant k's unvisited features, τ_{ij} is the heuristic desirability of choosing feature j when at feature and τ_{ij}(t) is the amount of virtual pheromone on edge ($i; j$). The choice of α and β is determined experimentally. Depending on how optimality is defined for the particular application, the pheromone may be updated accordingly. For instance, subset initially and "goodness" are two key factors so the pheromone update must be proportional to "goodness" and inversely proportional to size. There is also the possibility of allowing the removal of features here. If feature h has been selected already, an alternative transition rule may be applied to determine the probability of removing this attribute. However, this is an extension of the approach and is not necessary to perform feature selection. The overall process of the ACO feature selection is depicted in Figure 3.

The process begins by generating a number of ants, k, which are then placed randomly on the graph (i.e. each ant starts with one random feature). Alternatively, the number of ants to place on the graph may be set equal to the number of features within the data; each ant starts path construction at a different feature. From these initial positions, they traverse edges probabilistically until a traversal stopping criterion is satisfied. The resulting subsets are gathered and then evaluated. If an optimal subset has been found or the algorithm has executed a certain number of times, then the process halts and outputs the best feature subset encountered. If neither condition holds, then the pheromone is updated, a new set of ants are created and the process iterates once more.

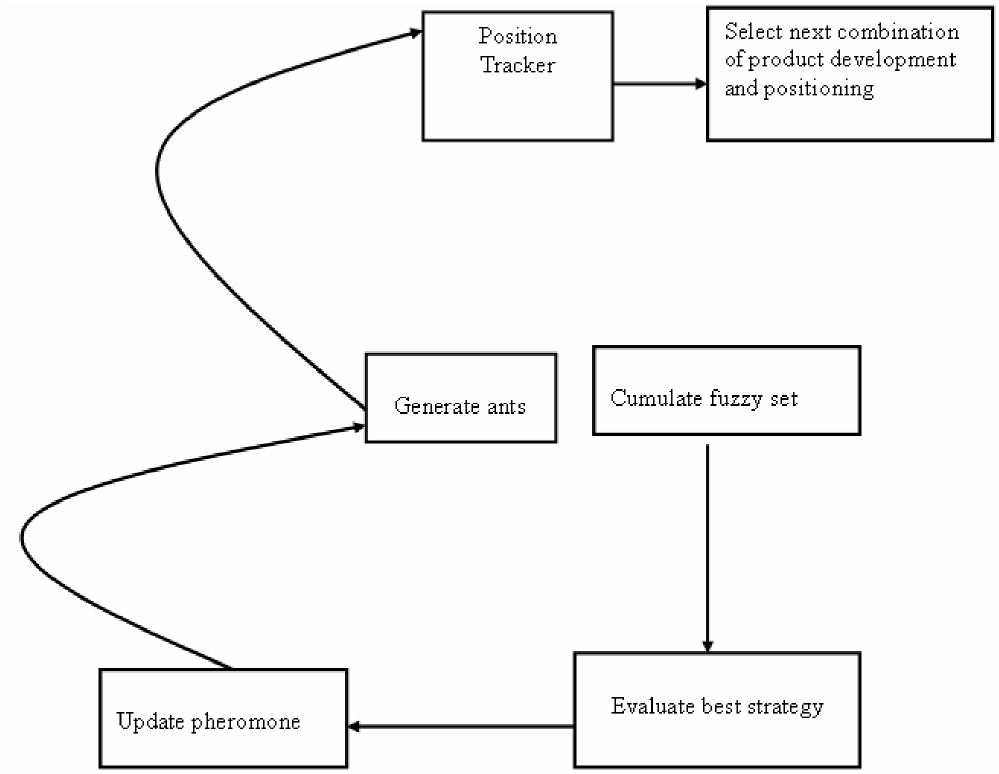


Figure 3. ACO feature selection

Picking up the strategic combination through ants based on fuzzy relation

When the ant is not carrying any strategy for traversing, it looks for possible strategy or combination of to pick up by looking at the eight neighboring cells around its current position. The object is basically the combination of new product development and positioning input. The heuristic for picking up a particular strategy depends on the number of combination of strategies in the heap. Three cases are considered: only one strategy, a heap of combined strategies and a heap of more than two strategies. If a single strategy is present then the ant has a fixed probability of picking it up. If there is a heap of two objects then with a probability the ant destroys the heap by picking a random strategy from the heap. In the third case the ant picks up the most dissimilar object from the heap if the dissimilarity is above a given threshold. The algorithm for picking up combination of strategy is given as follows:

```
Begin
    for every edge (i,j) of strategic network graph do
    τij (0) = τ0
    for k = 1 to m do /* m= different project proposal*/
      place ant k on a randomly  chosen node.
    End for
   Mark the 8 neighboring cells around the ant as "Unexplored Strategy    Combinations"
   /* refer fuzzy Linguistics   Table 1 */
    Repeat
         Consider the next unexplored cell around the ant
        If the cell is not empty then
            If the cell contains a single combination X, then
              the strategy X is picked up with a probability
           End If
           If the cell contains a heap of two strategies
           then the heap is destroyed by picking up a random strategy with a probability
           else
              If the cell contains a of H is removed only if remove heap H of more than 2
              strategies
              then the most dissimilar Strategy Label the NODE as "explored Strategy"
              End If
          End If
      Until all the neighboring cells have been explored or one strategy or combination is
      picked
 /* Body of Main Program*/
Begin
   Scatter the strategic parameters randomly on the board     /* Initialize Fig. 1 * /
  Initialize the ants with random position, and random direction
  for 1000 iterations do
    for each ant do
       Move the ant
```

if the ant is biasing towards a combination of strategy X ***then***

possibly drop the strategy X / Dropper Ant*/*

else

Possibly pick up a Strategy or combination X

Update pheromone trail by applying rules,

Apply online delayed pheromone update ($\tau, s^1, \ldots, s^k$)

/*Apply online delayed pheromone update ($\tau, s^1, \ldots, s^k$) *is used to store the track and edge details in tabu list with some pheromone update rule:*

$$\tau_j \leftarrow (1-\rho)\tau_j + \sum_{j=1}^{k} \Delta s^j \tau_j$$

$$\text{where } \Delta S^j \tau_j = \begin{cases} f(s^j) \text{ if } s^j \text{ contributes to } \tau_j, \\ 0 \text{ otherwise} \end{cases}$$

$\Delta S^j \tau_j$ *is the combination of a solution* s_j *to the update for pheromone value* τ_j *(k is the number of solution used for updating the Pheromones),* ρ *is the evaporation rate and f is a function which usually maps the quality of a solution to its inverse.*/*

Use the cluster centers obtained in step 3 to initialize cluster centers for the Fuzzy preference relation

Cluster the data using

Validate path (τ_{ij})

$S \leftarrow$ *Generate initial trace*

Initialize tabu lists($TL_1 \ldots\ldots TL_n$)

$K \leftarrow 0$

While *termination condition not met* ***do***

Allowed pheromone trace$(s,k) \leftarrow \{z \in N(s)\}$

No tabu condition is violated or at least one aspiration condition is satisfied.

$s \leftarrow$ *(s, allowed pheromone trace set (S,k))*

Update tabu list and detection condition of best strategy ( )

K ← K+1

end While

DetectBestStrategy( );

Repeat steps by considering each heap as a single Strategy

endif

endfor

endfor

5.0 Discussions

We have introduced the concept of tabu list, where for every session the list would like to store the pheromone trace or path, which is prone to proliferate. Here tabu ^{ij} (*t*) indicates the tabu list of ant (*i, j*). The list consists nodes in the strategic network that already has been visited nodes until the time *t* and the ant is forbidden to choose such node repeatedly. This is set to φ (not shown in the experiment), when the ant agent visit all nodes and completes its trip across the network. In our approach, the ant agent adopts the setting of parameter φ (*i,1*), where *l* is the degree of influence from the colony *l* (although we consider single ant for this work).

The absolute value of φ (*i,l*) indicates the degree of pheromone effect. The effect becomes stronger as the value increases and gets weaker when the value decreases. The hierarchical structure of decision criteria in the development of new product and positioning can be given as:

- Product attribute
- Platform attribute
- Technical attribute
- Personnel attribute
- Analytical attribute or competitive attribute.

In this example, we have considered 3 strategies to be evaluated under 5 main criteria (mentioned) and 20-25 other sub criteria for getting a strategic decision. To demonstrate the result of the fuzzy ant based algorithm we consider:

- Technical
- Managerial or business impact

- Word of mouth

	Strategy 1	Strategy 2	Strategy 3
Strategy 1	**(1.00,1.00,1.00)**	**(0.50,2.00,4.00)**	**(1.00,4.00,6.00)**
Strategy 2	**(0.25,0.50,2.00)**	**(1.00,1.00,1.00)**	**(0.25,3.00,7.00)**
Strategy 3	**(0.17,0.25,1.00)**	**(0.14,0.33,4.00)**	**(1.00,1.00,1.00)**

Table 11. Decision matrix obtained for technical

	Strategy 1	Strategy 2	Strategy 3
Strategy 1	**(1.00,1.00,1.00)**	**(1.00,2.00,3.00)**	**(0.25,2.00,3.00)**
Strategy 2	**(0.50,2.00,6.00)**	**(1.00,1.00,1.00)**	**(2.00,4.00,7.00)**
Strategy 3	**(0.33,2.00,6.00)**	**(2.00,5.00,9.00)**	**(1.00,1.00,1.00)**

Table 12. Decision matrix obtained for managerial or business impact

	Strategy 1	Strategy 2	Strategy 3
Strategy 1	**(1.00,1.00,1.00)**	**(0.50,2.00,4.00)**	**(1.00,4.00,6.00)**
Strategy 2	**(0.33,0.50,1.00)**	**(1.00,1.00,1.00)**	**(0.25,3.00,7.00)**
Strategy 3	**(0.33,0.25,1.00)**	**(0.14,0.33,4.00)**	**(1.00,1.00,1.00)**

Table 13. Decision matrix obtained for word of mouth

The decision matrices obtained are depicted in Tables 11-13. We have envisaged Analytic Hierarchy Process (AHP) to evaluate the decision matrices. A classical AHP based approach demands construction of comparison in which the relative importance among attribute is expressed as precise numbers on a standard scale (usually from 1 to 10).

Brief description of AHP:

Substantial works have been done on Analytic Hierarchy Process (AHP) [12][13]. AHP techniques requires decision makers to express their preferences for attributes using crisp number and calculates a weight vector that quantifies the level of importance of attributes. However, precise numbers fail to contain the subjectivity and vagueness in decision-making. This difficulty has been removed by using a fuzzy numbers as a superior means of representing pair wise comparisons in the AHP judgment matrix. Belton and Gear [14] have proposed the more revised approach of AHP. The method normalizes the relative performance measures of alternatives in terms of each criterion by dividing the values with the largest one.

7.0 Conclusions

New product and technology development and positioning encompasses most crucial activity for the existence of any concern in a competitive business model. The decisions involved in these processes are extremely uncertain and requires plenty of strategic interventions and proliferations. In this paper, we formulate a hybrid approach comprising fuzzy logic based *if-then* rules in conjunction with the ant colony optimization algorithm to optimize the decision making process. The entire work envisages the product or the technology development from the embryo stage towards the positioning in the market using the proposed hybrid intelligent tool. In brief, hybrid intelligent approaches for problem solving are found more suitable to improve the quality of decision-making and strategy proliferation. Although the work doesn't concentrate the comparisons of different methodologies vis-à-vis hybrid intelligent system as far as efficiency and complexity is concerned. The same can be considered as the future work.

References

1. Krishnan.V, and Ulrich.K.T, Product Development Decisions: A Review of the Literature, Management Science, 47(1), pp 1-21, 2001.
2. Urban.G.L, and Hauser.J.R,, Design and Marketing of New Product, Second Edition, Prentice-Hall Inc.,New Jersey, 1993.
3. Fox. J, Gann. R, et-al, Process Uncertainty: A New Dimensions FOR New Product Development, Engineering Management Journal, 10, pp 19-27, 1998.
4. Bass, Frank M., A New Product Growth Model for Consumer, Management Science, 16 (January), pp. 215-217, 1969.
5. Bass, Frank M., et-al, DIRECTV: A Case History of Forecasting Diffusion of a New Technology Prior to Product Launch, Interfaces, Special Issues on Marketing Engineering, Vol. 31, No. 03, part 2(May-June), p. S82-S93, 2001.
6. Dorigo.M. and L.M. Gambardella, Ant Colony System: A cooperative Learning Approach to the Traveling Salesman Problem, IEEE Transactions. Evolutionary Computation,1 :53-66, 1997.
7. Dorigo.M, Maniezzo. V and Colorni. A, Ant System: Optimization by a Colony of Cooperating Agents. IEEE Transactions. System. Man and Cybernetics, Part B, 26(1): pp. 29-41, 1996.
8. Garey. M.R, and Johnson. D. S, Computers and interact ability: A Guide to the Theory of NP Completeness, W.H. Freeman, 1979.
9. Lokketangen. A, Satisfied Ants, in ANTS 2000, 2000.
10. Dorigo.M and Caro.G.Di, The Ant Colony Optimization Meta-Heuristics in Corne D., M. Dorigo and F. Glover, Editors. New Ideas in optimization. London, UK: McGraw-Hill, pp. 11-32, 1999.

11. Zadeh LA, Roles of Soft Computing and Fuzzy Logic in the Conception, Design and Deployment of Information/Intelligent Systems, Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications, O. Kaynak, L.A. Zadeh, B. Turksen, I.J. Rudas (Eds.), pp1-9, 1998.
12. T. L. Saaty, The Analytic Hierarchic Process, McGraw-Hill International, New York, (1980)
13. T. L.Saaty, A Scaling Method for Priorities in Hierarchical Structures, Journal of Mathematical Psychology, 15, (1977), 234-281.
14. V. Belton and T. Gear, On a shortcoming of Saaty's method of analytic hierarchies, Omega, (1983), 228-230.