Inventory control problem using Metaheuristic Techniques: Application to Two Warehouse Inventory Model

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Abstract

Inventory management necessitates striking a balance between the benefits of having stockpiles of items, which allow you to meet client requests, and the expenses of carrying inventory. Methods for managing inventories are essential, and by using these methods, most businesses may greatly cut their expenditures related to the flow of goods. In today's marketplaces, firms must efficiently manage their supply chains to preserve market contributions and increase profits. Inventory control in the most effective manner is a critical component of supply chain control. When dealing with inventory control concerns, strategic decisions must be taken, such as the ordering times and the product order quantities. These choices can either reduce overall costs or increase total earnings. Because of the considerable costs correlated with preserving inventory and the fact that it degrades over time, it is generally not economically practical for a company to keep a large inventory on its business premises for an extended time. On the other hand, keeping a limited inventory is not profitable because it increases the risk of running out of stock at the point of sale during periods of high demand for the commodities being sold. According to the outcomes, excellent inventory management is necessary to ensure that the firm is conducted in the most cost-effective manner possible. This study's author used the Multi-objective Particle Swarm Optimization (MOPSO) and the Firefly algorithms to adhere to the EOQ inventory model. As part of his evaluation of inventory costs, the author of this paper performed a comparison analysis. As a result, the author determined that the APSO algorithm outperformed the Firefly approach in performance.

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1. Introduction

Traditional inventory models have been constructed with the concept that an item's lifetime is never-ending throughout the stock-in period, according to the existing body of work on inventory control theory [1]. This can be observed in the current corpus of art. This signifies that an item's utility does not change during the stock-in period and can be fully utilized to meet future demand. Due to the influence of deterioration, this assumption is only sometimes correct for various regularly used physical goods, such as wheat, rice, or any other form of food grains, vegetables, or fruits. Some of these products are faulty in some way, whether via damage, degradation, or the effect of other factors. Because of excellent inventory management, there are some cases where damaged units may constitute a partial loss. These products can be sold at a price lower than the cost of purchasing them. As a result, the deterioration effect is a critical component of inventory control theory [2]. When it comes to highly perishable commodities, the loss resulting from the degradation effect can be prevented or reduced if backlogged demand is addressed and purchases can be made inexpensively. As a result, finding a suitable trade-off for these items is a challenging task, and it is only natural that much attention has been dedicated to difficulties of this sort in inventory research literature.

The level of responsiveness maintained by a supply chain is directly related to the amount of inventory kept on hand [3]. (i) Inventory increases supply by ensuring that products are available when customers need them. Inventories serve this critical function. (ii) Using economies of scale in production and distribution to reduce costs. (iii) Contribute to the competitive establishment plan. If an establishment's competitive plan necessitates responsiveness, the company can improve its responsiveness by warehousing a considerable amount of merchandise close to its clients. On the other hand, a corporation can use its inventory to increase its efficiency by reducing its stock through centralized stocking. [4].

We consume a variety of meals throughout the day to satisfy our hunger. Some of us may choose rice as our primary source of nutrition, but others may favor wheat in various cuisines. Vegetables are sometimes readily available when we order them; however, they may be purchased at a higher cost than during typical availability periods. But have we ever thought about where the wheat, veggies, and rice paddies used in these cuisines come from? We are all aware that these cereal grains are not produced throughout the year, yet we must consume them regularly because they are essential to survival. The question now is how long farmers can provide us with these. We've been persuaded to believe they store food grains securely and distribute them as needed.

The necessity to carefully preserve some food grains derives from being produced at specific times of the year and in specific geographical locations. We may retain a certain quantity in our houses for personal consumption, such as 4-5 kilograms of pulses or 20-50 kilograms of wheat or rice, and after a given time, we will need to repurchase it from elsewhere (shops). As a result, there are many sites or stores where these items are stored in large volumes properly and systematically to offer us the desired things when we want them. To carry out our daily tasks, we need a range of resources. We may purchase large quantities of some of these products and store them in our homes.

Similarly, businesses require various products to function, but some commodities are only sometimes readily available. On the other hand, they need such things all year and cannot function without them. Because coal is a raw material, an energy power plant (known as a thermal plant) uses coal all year to create electricity. Because coal is unavailable everywhere and must be brought from a specific location, which takes time, the power plant must store it for the entire year to use when needed. Because energy generation is a continuous process, the producer is always in high need of coal. As a result, raw materials and completed products (such as energy) require storage space. Storage necessitates the availability of adequate space since it requires making the necessary arrangements to preserve goods from the time they are made or purchased until they are used. This type of storage is known as "warehousing" when worked on a maximum scale and in a prescribed manner. The Identify Quality of Inventory Model Drivers is depicted in Figure 1.

Figure I: Iinventory Management Strategies

Inventory-related costs:

(i) Procurement expenses are the dollars needed to buy a product or service.

(ii) The ordering cost is a fixed cost associated with the ordering method of purchasing things.

(iii) Holding costs are the costs associated with stocking the commodity.

(iv) To be considered a fair cost, the deficit must equal the penalty for running out of products.

A good inventory management principle is just-in-time (JIT) or zero inventory [5]. According to this theory, manufacturing operations should deliver whatever material is required while ensuring 100% supply protection without maintaining inventory. Due to the reason contributing domain which is often just-in-case (JIC), lead times in most production environments are highly unpredictable. It is vital to keep some inventory on hand in case of supply variations [6]. A firm will charge an inventory cost for a Just in Case supply management system as an added incentive. This research is an expansion of [7], which offers a variety of swarm intelligence inventory control strategies. By focusing on commodity demand and item prices, these approaches try to lower development costs. This study expands on such systems. This essay looks at efficiency and compares two methods for improving inventory management. One way for modeling inventory management in the manufacturing process is known as Multi-objective Particle Swarm Optimisation (MOPSO), while the other is known as the Firefly Algorithm (FFA).

2. Background works

Several nature-inspired metaheuristic methods are introduced so that they can improve problem-solving methods across increasingly huge search spaces. PSO is a metaheuristic method that helps with the problem of global optimization. [8] This algorithm was created by observing the social behavior of fish schools and bird flocks. Since then, many academics have employed this technique to overcome challenges with inventory-based optimization. To solve an optimization problem with a single objective, PSO does not need to be updated; however, modifications are required to handle an optimization problem with several conflicting goals. At the start of 2000, [9] introduced a breakthrough new approach named MOPSO. This is a multi-objective PSO formulation with constraints. Intending to fulfill the consumer's expected minimal cost, the most realistic-world inventory difficulties can be recast as a problem of multi-objective optimization. This ensures that the customer's requested minimum cost is met. [10] PSO is a robust meta-heuristic algorithm that, due to its capacity to tackle these problems successfully, gives outstanding efficiency in a wide range of optimization situations. [11, 12] State that the authors employed MOPSO to find a solution for a multi-period, multi-item inventory planning model with a fixed budget and well-known deterministic demand. Asset management demands several important decisions, one of which is storage space allocation. This is owing to the desire to store more goods and the demand for more significant storage space, which presents a cost-inconvenient reason. [13] To lower total storage space and overall inventory costs, researchers examined an inventory optimization issue to identify a Pareto optimum solution at different time intervals. The model response variable and parameter level were modified using the Taguchi approach. This is done since both proposed approaches are sensitive to parameter values.

This technique also has the advantage of offering a nearly optimum answer. The authors of the article [14] proposed three distinct models of inventory control challenges. The three models under consideration are the stochastic single-product model, the deterministic single-product model, and the deterministic multi-product model. The provided models might be solved using the Emperor Penguins Colony (EPC) metaheuristic technique due to the difficulty of their sophisticated computations. This method falls under the category of soft computing. A fresh metaheuristic algorithm called EPC ought to be used further for the inventory management issue. The outcomes of using the suggested method with the models are distinguished from those of the nine renowned and cutting-edge metaheuristic algorithms used in this research. To rationalize the introduced EPC, the cost and timeline characteristics are assessed. Statistical analysis is used to find significant differences in data provided by multiple algorithms. The data show that the suggested algorithm for the inventory control models supplied provides superior solutions at a lower cost and with a lower percentage of overall CPU utilization than alternative methods. As previously said, effective supply chains are critical for firms in today's highly competitive marketplaces. Ensuring that the supply chain operates properly will maintain its market share and boost its profitability. Inventory control that is effective and efficient is a fundamental component of supply chain management [15].

This research aims to identify the optimal number of commodity orders to place throughout various time periods to reduce inventory maintenance costs, including those associated with ordering, storing, and purchasing products. Here are three NP-hardness models. As a consequence, the EPC method was used to test and assess the quality of the nearly ideal solution. This study's main contribution is the application of the EPC algorithm to inventory control mathematical models to reduce the amount of computer effort needed. It also compares the EPC method to the other nine metaheuristic algorithms. In order to solve the given models, the revised EPC technique is offered as a revolutionary soft computing strategy. The deterministic single-product model, the deterministic multi-product model, and the stochastic single-product model are the three models that are discussed here.

3. Materials and methods

The algorithm's way of applying to the models provided as a using soft computing is described in the following. The issue specification, which might be either a deterministic single-product or a deterministic multi-product, serves as the foundation for the model's initial construction. The model's fitness function is then built from the ground up. After the algorithm's population has been produced, its position and cost are calculated using the model and the fitness function. Following the start-up step, the algorithm's main loop will optimize and record the best solutions. Figure 2 shows a high-level summary of the algorithm's application to the models discussed in this paper. The same systematic process utilized to apply the algorithm to the problem was also used to apply multiple metaheuristics. The multi-objective Particle Swarm Optimisation (MOPSO) and the Firefly algorithm (FFA) are employed in this work. These are the two methods.

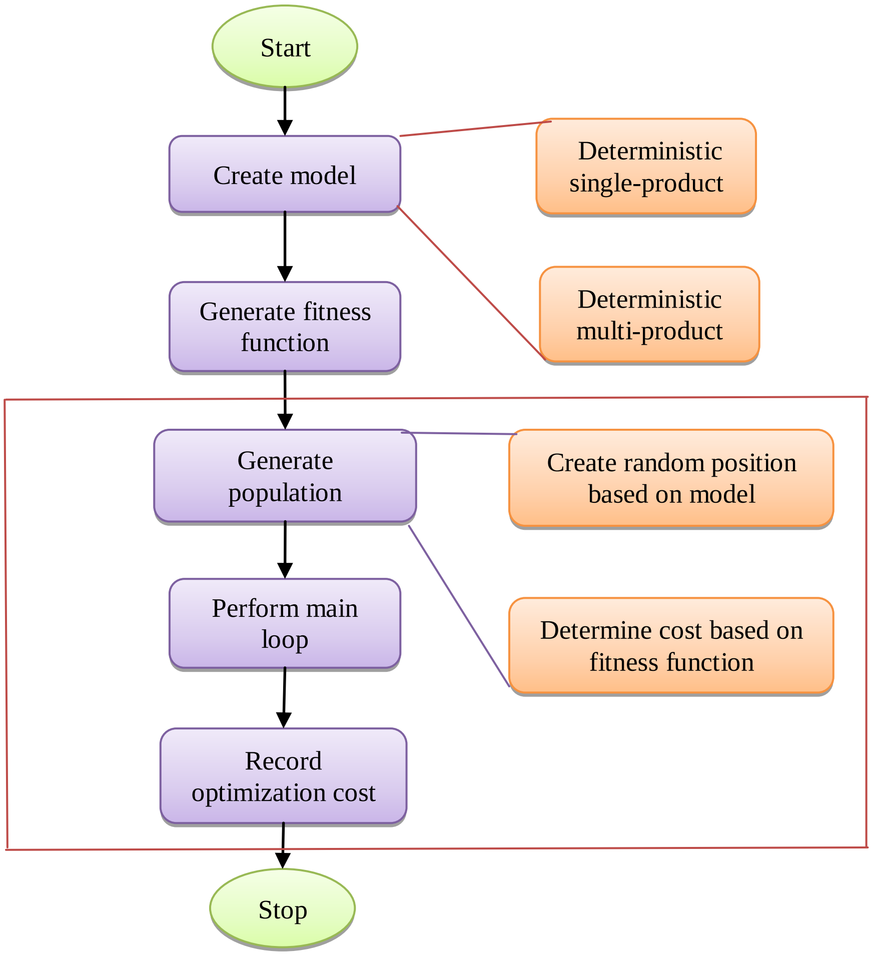

Figure 2: Representation scheme of soft computing approach

Objective Functions

Total inventory cost, which may be computed as Total Inventory Cost = Total Demand Cost + Total Transportation Cost, is the first objective function in this model.

Firefly algorithm

The firefly algorithm (FA) is one instance of an algorithm built from nature-inspired computing. It can determine the optimal solution for the entire world [19]. The primary idea of the Firefly algorithm is accomplished by combining two variables: the quantity of light available and the degree of firefly attraction. The objective function, f(x), which may be a minimization or maximization function, is more likely to be connected to the intensity of a firefly's light. On the other side, the attractiveness, β, between fireflies is connected with the distance between two fireflies, where β is based on the change in distance.

Step 1: involves randomly generating the initial population of fireflies, which is denoted by x_i (i= 1, 2,..., n), and using the objective function $f(x_i)$ to determine the light intensity at each x_i.

Step 2: is to define the light absorption coefficient, denoted by.

Step 3: While time is less than the maximum generation.

Step 4. **for**i = 1 to N (N each firefly)

Step 5: **for**j = 1 to N

Step6: **If**$\left(I_i < I_j\right)\left\{X^i = X^i + \beta_0 exp^{\left(-\gamma r_{ij}^2\right)}.\left(X^i - X^j\right) + \alpha\varepsilon_i\right\}$

Step7: $\beta = \beta_0 exp^{\left(-\gamma r_{ij}^2\right)}$

Step 8 will involve evaluating any new solutions and adjusting the amount of light.

Step9: finish **for**i

Step10: **end for**j

Step 11: Rank the fireflies and determine which one now has the title of best global g*.

Step12: **end while**

The Proposed Algorithm

In this study, we apply a multi-objective particle swarm optimization (MOPSO) technique, a modified version of the PSO algorithm. The simplicity of this strategy serves as a motivator for its use. It is straightforward to implement and can manage multiple objectives that are at odds with one another.

Multi Objective Particle Swarm Optimization (MOPSO)

PSO must be changed in order to successfully address the multi-objective optimization conundrum. Finding the Pareto Front of answers rather of a single global "best" option constitutes the first step. Then, all non-dominated solutions discovered during the iterative process must be stored in an archive of non-dominated responses.

Swarm Initialization

Each particle's velocity in the swarm is expressed by a vector named vi(t), which occupies the same space as the other vectors. Xi denotes the position vector of particle I, a component of the search space X in that xi(t) is equivalent to X. Here, t is the time index that separates discrete time steps from the method's iteration count. Every particle reaches its best via interactions and learning from others, symbolized by pi(t), the local best solution. The symbol g(t), the global best solution, stands for the best experience that every member of the swarm has to offer.

Mathematical model of motion

The particle i's initial position is represented by $x_i(t)$, while its velocity is denoted by$v_i(t)$. Particles progress first towards their bests, then towards the global bests, acquiring an updated position denoted by $x_i(t+1)$. V_i(t) is the velocity obtained by adding the beginning vector to the end vector. As a result, the position formula is as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

$$v_i(t+1) = wv_i(t) + C_1(p_i(t) - x_i(t)) + C_2(g_i(t) - x_i(t))$$

The PSO equation is standardized using a more straightforward method, which is:

$$v_i(t+1) = wv_i(t) + C_1 r_1\left(x_{pbesti} - x_i(t)\right) + C_2 r_1\left(x_{gbesti}(t) - x_i(t)\right)$$

where,

w = inertia coefficient

C_1, C_2 = acceleration coefficients r_1, $r_2 \in (0,1)$

The following is the pseudocode for the MOPSO (Mousavi et al., 2014) algorithm.

for*i* = 1 to Pop initialize position (*i*) initialize velocity (*i*)

if position (*i*) and velocity (*i*) be a feasible candidate solution penalty = 0

else penalty = a positive number end if

end for

w = [0.4, 0.9]

do while Iter <= Gen

for*j* = 1 to Pop

Calculate the particle's new speed. Calculate the particle's new location *p*best (iter) = min (*p*best(*i*))

end for

*g*best (iter) = min (*gbest*)

$w = w_{max} - ((w_{max} - w_{min})$/iter_max) × iter

While adjusting the particle end's location and speed

Pseudocode 1: Pseudocode of MOPSO algorithm

4. Results and Discussion

Cost-Benefit analysis at farmer's level

The cost-benefit analysis for red chili production in Northern Telangana at various agricultural productivity is shown in Table 1. The rising production costs are primarily due to greater amounts of input elements such as labor, seed, pesticide, and fertilizer, but they are also partly due to an increase in postharvest losses. Overall, the storage supply will result in financial gains for the farmers. (That is, the large, medium, and small farmers). The entire investigation is being performed in Indian Rupees.

Table 1: Summary of farmers' cost-benefit analyses under the existing supply chain's functioning without enough storage and under a hypothetical situation with enough storage

Costs	Large-scale Farms (LSF)		Medium-scale Farm (MSF)		Small-scale (SS)	
	Without storage	With storage	Without storage	With storage	Without storage	With storage
[A] Fixed cost	7,438,000	8,538,000	2,586,395	2,866,395	44,633	59,633
[B] Variable Cost	7,570,363	3,867,463	1,783,461	1,043,891	44,700	29,380
Total Cost	15,008,363	12,405,463	4,369,856	3,910,286	89,333	89,013
[C]Total Revenue	27,004,500	30,762,900	10,502,218	11,255,288	176,461	192,981
[D] Profit/Loss [C-B]	19,434,138	26,895,43	8,718,757	10,211,39	131,761	163,601
Breakeven Point (yr.) [A/D]	0.38	0.31	0.30	0.29	0.33	0.36

If we look at Table 1, we'll note that the amount of fixed expenses each farmer in the hypothetical scenario is expected to pay has increased due to the storage facility investment. It makes no difference whether or not storage facilities are provided; this is always the case. However, in the hypothetical case where storage facilities are provided, the variable costs and money earned by reducing losses and selling the tomato were sufficient to increase profit for all farmer groups. As a result, the cost-benefit analysis showed a significant drop in post-harvest losses (the estimated 80% decrease in all post-harvest losses), leading to a cost reduction and revenue increase matched to an imagined situation in which appropriate storages were available in the supply chain. This was brought about by a marked decrease in post-harvest losses.

All of the fictitious storage facilities produced higher profit and revenue with a somewhat lower breakeven point, despite the fact that the storage facilities utilized by the different kinds of farms differed (Figure 3). Breakeven levels for large (0.4 to 0.3 years) and medium (0.3 to 0.28) farmers were slightly lower than expected. Regardless, the breakeven analysis found that the return on investment achieved by small-scale farms from storage facility investments is roughly similar to that of farms without storage facilities. Regardless, the cost of cold storage in 2020 was determined using data acquired from various districts in Northern Telangana as part of the cost-benefit analysis's plethora of possible outcomes. It is believed that the pricing will be around 40,000 Indian rupees.

To calculate the optimal output and distribution within warehouses and outlets, the following assumption must be made:

1. There is no lag time.

2. The rate of deterioration that is affected by the passage of time is considered.

3. The deficit is permitted to persist.

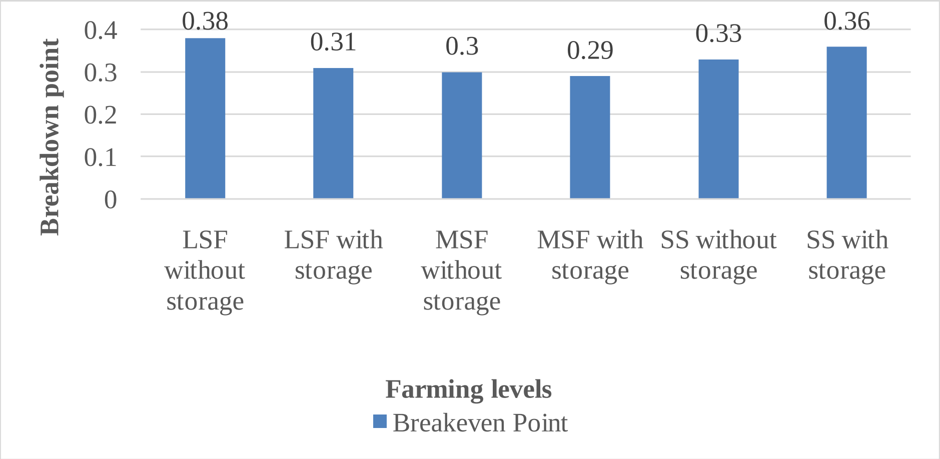

Figure 3: A comparison of farmers' breakeven points between the existing supply chain operation, which does not involve storage, and a hypothetical one that does.

Consider the following possibilities, each with the scaling parameter N set to the values shown:

On the integer grid, between 1 and N, these institutions may be located at different locations along the x and y axes. w+1 sites are necessary for independent locations. To preserve geographically distinct areas. Consider that s are equal to 0.05 and 0.1, respectively. The manufacturers create goods that are subsequently sold. Every commodity is required to have a retail store. The criterion is the amount that can be sold at a particular time. The demand that the necessary volumes be produced and delivered is met, implying that the capabilities of each warehouse have limits.

The amount of product turnover, represented by the variable rotation (p), is less than the quantity of merchandise transferred from the warehouse to the supermarket's retail location. Assume there is a single warehouse that feeds all of the outlets. One of the difficulties is determining how to assign inexpensive delivery units to various warehouses.

Costs: The cost of transporting the goods from the cold storage of the warehouse to the distribution center depends on how far away the manufacturers that make every material are from the distribution center. The following formula should be used to determine the transport costs of the commodity p if the distance between installations (a, b) and the transport expenses (tcost) surpass that distance.

Distances (a, b) times cost (p) are subtracted.

In this case, the gap is also thought to represent the radius L1, which means the grid distance. This section contains the whole comparison of two things x and y.

Optimization Problem

A distribution timeline for the commodity (food grain), a list of sites, specifications, and capacity limits, and a supply plan from warehouses (cold storage) to outlets were provided. Each retail outlet must source from only one warehouse to obtain all its merchandise. These sums must be assured to meet demand while lowering total expenses.

Variables for the Optimization Problem

The control variables are binary variables having a value of 1 if the warehouse is w, and they are used to alter optimization. Reduce tcost + decoct is the goal.

The two variables x and y are linear in the goal and restriction functions. Due to its restriction to integer numbers, the issue is a mixed integer linear program (MILP).

Constraint 1	Capacity of Warehouse
Constraint 2	Fulfilled Demand
Constraint 3	$y(s,w) = 1\ y(s)$ (each sales outlet associates to one warehouse)
Constraint 4	$x(p,f,w)\ \geq 0$ (non-negative production)
Constraint 5	$y(s,w)\epsilon\{0,1\}(binaryy)$

The target function of minimizing the overall cost as much as feasible is considered during the execution of both the MOPSO and the Firefly algorithms. The original Firefly method requires approximately two iterations to arrive at the best answer, whereas the MOPSO approach requires only one iteration. As shown in Figures 4 and 7, the proposed MOPSO algorithm has a high rate of convergence, which gives it an advantage over the firefly approach.

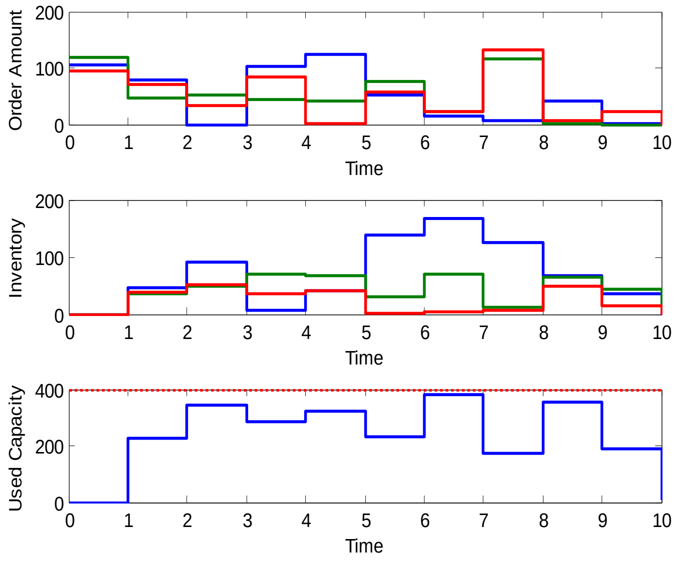

Figure 4: MOPSO for used capacity, order amount and Inventory w.r.t time

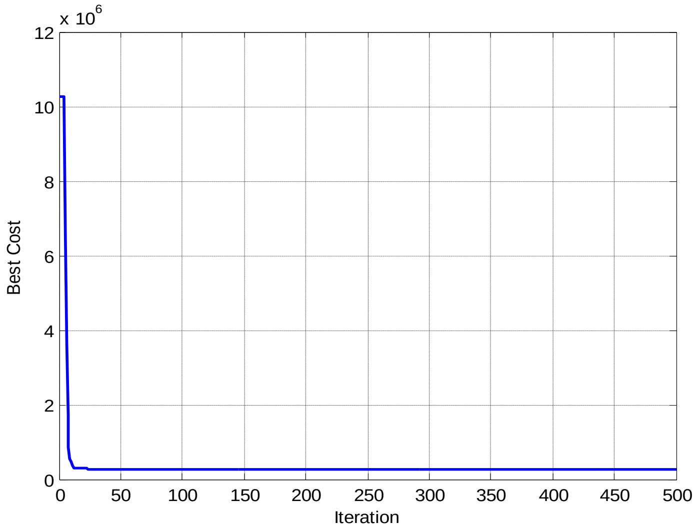

Figure 5: MOPSO best cost w.r.t number of iterations

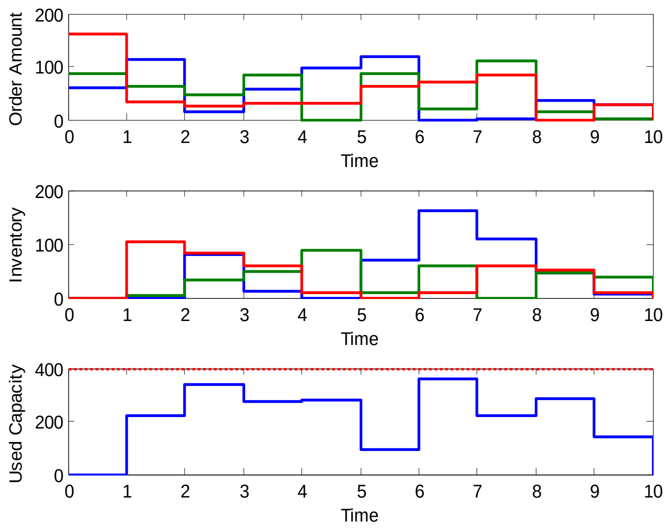

Figure 6: FFA for used capacity, order amount and Inventory w.r.t time

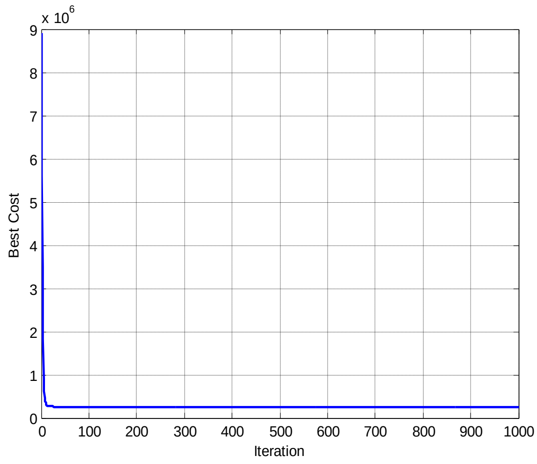

Figure 7: FFA best cost w.r.t number of iterations

5. Conclusion

Many material possessions deteriorate due to various factors such as dryness, damage ability, perishability, etc. As a result, any inventory system decisions should consider the effects of these natural occurrences. When the impact of deterioration on a product is substantial, finding a solution to balance the costs of holding, deterioration, and back ordering might be challenging. The employment of approaches from the field of soft computing allows for solving complex problems. The tactics used in this approach are designed to supply the most beneficial solution in the shortest amount of time. Inventory management is the most challenging difficulty that may be managed and streamlined using soft computing technologies. This is the conclusion after applying the assumptions included in this model. The

MOPSO method optimizes costs, and the results are compared to those produced by the Firefly algorithm.

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