Nat. Volatiles & Essent. Oils, 2021; 8(4): 15676-15691

Comparison Of Adaptive Particle Swarm Optimization And Firefly Algorithm For Analysing Inventory Cost: Application To Two Warehouse Inventory Model

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Abstract

In the past , a lot of study has been investigated in the field of resource management and control. Inventory management and control system is essentially concerned with demand and supply chain concerns. There are essentially various stock levels, such as raw components, finished goods, etc. Maintaining a high amount of inventory for a long period in the premises of a business company is typically not profitable for a business due to high keeping costs and degradation. However, holding a small amount of inventory is also not profitable, as it creates a problem of stock-out during high demand for goods at the point of sale. As a result, proper inventory management is needed to operate the company perfectly from an economic point of view. In the present study ,author has implemented two algorithm in accordance to EOQ inventory model i.e. Adaptive Particle Swarm Optimization(APSO) and Firefly algorithm. In this research author has done a comparative analysis for examine cost of inventories. In result author has found that APSO gave better performance as compare to Firefly algorithm.

Key Words: EOQ, APSO, Firefly.

1.Introduction

Study of inventory control is the focus of nearly all industrial operations. Inventories are nothing but resources processed, preparing for processing, or undergoing processing. An observation of virtually every business balance sheet shows, for example, that a large portion of its inventory contains raw material inventories, parts and subassemblies and finished products during manufacturing. Inventories of raw materials provide a reliable supply of output input. In-process inventories mitigate the consequences of a plant's fluctuations in output rates and also protect against process failures. Variety and fast distribution of the commodity are the main marketing factors. A broad inventory demands less replenishment and, due to economies of scale, can decrease ordering costs. The presence of an inventory indicates a temporary difference in supply and demand for two operations. An inventory is an amount of material stored for sale or production. Inventory control for tangible commodities, materials or other components for all sectors of the economy such as business, manufacturing, agriculture, defense etc., is part and parcel of a logistics framework. An inventory may be required in an economy that is perfectly predictable to benefit from the economic features of a specific technology or to coordinate or monitor the development process in order to follow changing trends of demand. Inventories are used as a buffer against stock-up losses when uncertainties are present.

A policy on inventories is a series of decision-making regimes that decide "when and how much." The goal function in an inventory dilemma can take different forms. Typically this means minimizing the expense or enhancing the benefit function.

Inventory related costs:

I) Costs of procurement are the purchase costs of an object device.

(ii) Cost of ordering is a fixed cost of purchasing products by ordering.

(iii) Holding costs are the expense of keeping the product (or holding).

(iv) The cost of the shortage shall be the cost of the penalty for running out of stock.

Just-in-time (JIT) or null inventory mechanism is a perfect inventory management principle whereby manufacturing processes will supply whatever material is needed and 100% supply protection as required without maintaining an inventory (Vrat , 2014)There is considerable uncertainty in lead times in most production situations, since the supply environment is probably just-in-case (JIC), and is generally for the automotive sector. As a buffer to contend with supply volatility, inventory should be retained. (Monden, 2011). Inventory is the premium charged to a Just in Case supply management by a company. This study is an expansion of (Simi c et al., 2018)(Simi c et. Al., 2019), which introduces numerous swarm intelligence approaches of inventory control, but limits development costs depending on commodity demand and the price of goods to minimization. This paper provides a new analysis efficiency focused on a study of the two methods used to improve inventory management. One of the approaches used is Adaptive Particle Swarm Optimization (APSO) and the 2nd is Firefly Algorithm (FFA) for modeling inventory management in the production method.

2. Review of Literature

With aid of effective preparation and control, cost savings and value maximization of the inventory of raw materials can also be ensured. For a long time, the simulation of this inventory control management had been a research concern among industrial engineers. (Agrell , 1995) suggested an inventory management issue multi-criteria system in which IDEM was used to assess batch size and stock protection. A single complex, multi-item inventory management model was proposed by (Dolgui & Ould-Louly, 2001) to calculate the average cost of keeping and determine probabilities with leadtime uncertainty.

(Ertogral , 2008), including transport costs dependent on the Lagrangian rule, solved the issue of multi-item single source picking. (Lee & Kang ,2008) developed a commodity inventory control model for many periods. First, their paradigm was derived for one object and then applied to many items. Related to evaluating many components, the researchers have taken an interest in multi-objective models.

(Roy & Maiti, 1998) implemented multi-purpose stock models of decaying products to increase benefit and reduce wasting costs in a smooth setting. But it didn't recognize any scarcity

(Pasandideh et al. , 2013) studied a bi-target economic issue in output quantity of damaged products conceived as a multi-target nonlinear model of programming with the purpose of finding the order amounts of the commodity in order to reduce overall inventory costs and the necessary warehouse space.
(Mousavi et al. , 2014), together with these goals, established a multi-item multi-purpose stock management model for known-deterministic budgetary requirements. The stock model for fad deteriorating at the end of the defined time was 1st examined by Whitin (1957). Most of scholars have seen their inventory models deteriorate constantly in the past. (Ghare et al., 1963). initially developed an economic order quantity stock model of continuously growing demand and a persistent decline in the final plan horizon .
(Krishnaraj et al. , 2012) have found a scarce stock model. The inventory model is known as a time-dependent keeping model for (Sharma et al. , 2012) and (Amutha et al. , 2013,b) The demands on one object is supposed to be continuous in the classical EOQ (Economic Order Quantity) model developed in 1915. Stock models of constant demand values are used by researchers (Misra RB, 1975),), (Shah Y.K ,1977), (Raafat , 1991) (Ritchie ,1984). The inventory model for products with various constant rates for degrading demand has been developed by (Singh et al. , 2012).
A multifaceted inventory routing issue with continuous demand rates was created by (Zhong et al. ,2012).A inventory model with a degradation rate and constant demand from Weibull was proposed by (Mishra , 2012). A model inventory for continuing demand was developed by (Amutha et al., 2013a) under the allowable time for payment. (Tripathy, 2013) has further developed a model of inventory with a range of demand rates and prices. (Kumar et. al., 2013) have established a general model for inventorying weibull goods that are declining with persistent demand influenced by partial time-based backlog and decline.
A single quadratic demand inventory problem has been developed by (Bhandari et al., 2000). For (Weibull, Tripathy et al., 2010) developed a model of stockpiling for quadratic demand products, with allowable payment delays. (Begum et al., 2010) also established a concept of inventory order standard for items that are quadratically complicated. The inventory practice was investigated for perishable goods with a model of quadratic demand, under which period depended on depreciation (Misra et al. 2012).
(Panda et al. , 2012) also examined ongoing weakening regulation of quadratic demand-rate capital. An inventory model for quadratic request and partial retrieval degradation of items was also developed by (Begum et al. , 2010). For publications that decrease in quadratic demand, (Kaur et al. , 2012) established the order inventory development system. A three-echelon convergence supply chain storage model for quadratic and efficient demand peretible items and two parameter depreciation have been developed by (Trivedi et al. , 2013).
(Singh et al, 2013) have provided a model of economic order quantity for the degrading product, subject to permissible payment delays and with time-based quadratic demand and vector worsening. A model inventory has been evaluated of the quadrant requirement, continuous degradation and the importance of rescue in 2014 (Venkateswarlu et al., 2014). (Venkateswarlu et al. , 2014).
For non- instantial degrading products with stock-related and partial backlogging, Wu et al. (2005) found optimum refill strategy. (Ouyang et al. , 2006), for non-instantly decaying goods and allowable payment waits, found a fitting inventory model. The missing data of (Ouyang et al., 2006) has been completed by (Chung , 2008). The economic order quantity model for non- immediate degrading products with allowable time-to-payment was suggested by (Geetha et al. , 2009).

(Chang et al., 2010) suggested the optimum refill policy for non-instantly declining inventory-based supplies. (Chang et al., 2010) model from two dimensions expanded by (Soni, 2013I) the rate of demand as a multivariable price and inventory level function and (ii) the permitted delay of payment. Furthermore, by treating the sale of the inventories as rescues and all potential recovery periods, (Soni, 2013) has been expanded further to cover less than the time of the non-deterioration.

In terms of allowable late payment delays, (Goyal, 1985) was the first person to suggest a model of the economic order quantity. (Aggarwal et al., 1995) The model for decaying products has been applied to (Goyal ,1985) model. . (Aggarwal et al., 1995) The model was further broadened to cover shortages by (Jamal et al., 1997). Under the authorisation for a time period of payments depredating the amount, (Chung et al. , 2005) established an Optimum Inventory Strategy The economic order quantity model for non- immediate degrading products with allowable time-to-payment was suggested by (Geetha et al. , 2009).

The model of economic quantities was first developed by (Buzacott , 1975) in light of the influence of inflation. (Datta et al. ,1991) analyzed inflation and the money's time value effects at the level of production and scarcity based on linear time. (Hariga et al. , 1996) treated the model of inflationary batch sizing as optimum time vector.

In view of the inflation effect and monetary value, the model of quantity of the economic order for improving/degrading goods with time-different patterns in demand was considered (Moon , 2005). An inflation inventory model for the deterioration of stock-based items with partial backlog shortages has been established (Yang et al., 2010). (Singh, 2011) considered a model of economic order quantity for goods with linear inflation demand and permissible payment latency. A stock-based demand inflation-induced stock model was built with an allowable payment delay (Singh et al., 2014). The inventory model has been developed for non-instantaneous publications with partial backlogging (Ghoreishi et al. , 2015).

The research (Sustrov a , 2016) provides an efficient investigation into the modeling and prediction of artificial neural networks in the fields of stock management, especially the issue of lot-sizing. In the study, many forms of neural networks are generated and evaluated for the most effective design of neural networks.

For a sequential supply chain, demand frequency and lead period are implemented and developed into an optimized inventory forecasting model that minimizes the total costs incurred, including procurement, inventory keeping, packaging and transport. Duan and Ventura, 2019) introduces the MILP formulation to solve this multi-period, multi-supplier and multistage issue with the predetermined market for a single commodity.

A variety of nature-inspired metaheuristic algorithms have been proposed to refine the solution by searching in large search spaces. PSO is one of the metaheuristic algorithms used to solve the global optimization problem. (Kennedy and Eberhart , 1997)(Guan et. al.,2019) developed this algorithm by studying the social behavior of birds or fish flocks. Since then, several researchers have been experimenting with this algorithm to solve inventory based optimization problems. PSO is sufficient to solve a single objective optimization problem, but a change is necessary to solve a problem consisting of multiple competing objectives. At the beginning of 2000, (Coello & Lechuga , 2002) suggested a new method called MOPSO which was a constrained multi-objective formulation of PSO. In order to meet the customer's desired minimum cost or budget requirement, much of the real-life inventory challenge may be recast into a multi-objective optimization dilemma. PSO is an effective meta-heuristic algorithm that achieves outstanding efficiency in a wide range of optimization problems(Parouha and Verma ,2021).(Tsou , 2008) built such a model and applied MOPSO to create the Pareto front of non-dominated solutions and sorted them using order preference methodology close to the ideal solution (TOPSIS) according to the preference of decision makers. (Mousavi et al., (2014) (Chanet. Al., 2020) used MOPSO to address a multi-item multi-period inventory planning model of known deterministic demand under a small budget. Storage space is another essential decision that comes with asset control as the decision to retain more inventory and storage space needs provide a cost-contradictory objective. (Tavana, 2016) analyzed an inventory optimization problem with the goal of finding Pareto an optimal solution at various times and at the same time minimizing total inventory costs as well as total storage capacity. As both of these proposed algorithms are very sensitive to parameters, the Taguchi approach was used in this model to change the parameter level and the response variable of the model. This approach also has the advantage of having a near-optimal solution.

2.1 Research gap

Thus, it is convenient to overcome the limitations of traditional methods .From above review of literature it is clear that firefly algorithm has not used of optimization . So in this study we have implemented APSO algorithm and Firefly algorithm for optimization and then compare their result for approaching minimize cost of inventories.

3. Mathematical Model Formulation

3.1 Objective Functions

Total inventory cost is the 1st objective function of this model which can be obtained as

Total Inventory Cost = Total Demand Cost + Total Transportation Cost

3.2 The Proposed Work

There are two types of algorithm used in this research.

1) Adaptive Particle swarm optimization (APSO).

2) Firefly algorithm.

1) Adaptive Particle Swarm Optimization (APSO)

Initial position of the particle i is x_i^t. In the search space particles interact with each other and after learning their position, particles increase their velocity,v_i^t to find the best solution for the problem. Local best solution orp_i^t is the personal best position for each article which is obtained by updating the position byx_i^{t+1} and end vector has an velocity of v_i^{t+1} .

Among the representatives of the swarm denoted by g(t) as the best global approach, there is a common experience of the best. Therefore, the equation is –

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \boldsymbol{v}_i^{t+1}$$

$$v_i^{t+1} = \mathrm{w}v_i^t + \mathrm{C}_1(p_i^t - x_i^t) + \mathrm{C}_2(\mathrm{g}^t - x_i^t)$$

$$v_i^{t+1} = \mathrm{w}v_i^t + \mathrm{C}_1\mathrm{r}_1\left(x_{p\ best}^t - x_i^t\right) + \mathrm{C}_2(\mathrm{x}_{\mathrm{gbest}}^t - x_i^t)$$

Step 1: Initialization. A random population of individuals $\{x_i\}$, $i \in [1,N]$
Each individual's n-element velocity vector $\{v_i\}$, $i \in [1,N]$
The best-so-far position of each individuals: $b_i \leftarrow x_i$, $i \in [1,N]$
Neighborhood size $\sigma < N$; $nPop = 150$; Pop. Size; Max.
velocity, v_{max}; $MaxIt = 1000$; Max. Num. of Iter. $\omega = 1$;
Inertia weight
c1 = 2; Personal Learning Coefficient; c2 = 2; Global Learning
Coefficient.

Step 2: While (the termination criteria is not satisfied) **or** ($MaxIt = 1000$)

Step 3: for *each* individual x_i, $i \in [1,N]$
$H_i \leftarrow \{\sigma$ nearest neighbors of $x_i\}$
$h_i \leftarrow \arg\min_x \{f(x) : x \in H_i\}$
Generate a random matrix $r_p(k) \sim U<0, 1>$ for $k \in [1, N]$
Generate a random matrix $r_g(k) \sim U<0, 1>$ for $k \in [1, N]$
$v_i(k+1) \leftarrow \omega v_i(k) + c_1 r_p(b_i - x_i(k)) + c_2 r_g(h_i(k) - x_i(k))$
if $|v_i(k+1)| > v_{max}$ ***then***
$v_i(k+1) \leftarrow v_i(k)\, v_{max} / |v_i(k)|$
end if
$x_i(k+1) \leftarrow x_i(k) + v_i(k)$
$b_i \leftarrow \text{argmin}\{f(x_i(k)), f(b_i)\}$
end for *i* Next individual

Step 4: end while Next generation

Step 5: *Post-processing the results and visualization;*

End.

Find new solutions and update light intensity.
end for *l*
end for *i*
Rank the fireflies , find the optimal solution.

Step 4 : If the stopping criteria is met then output the results, otherwise go to step 3.

Figure 1: Steps of APSO algorithm.

2) Firefly algorithm

Another intelligent swarm-inspired algorithm implemented by (Yang, 2009) is the Firefly Algorithm (FFA) .The origin of the FFA is imitated by the true actions of fireflies, as its appellation suggests. This producing light is known as a means of contact between fireflies and also as a lure for beasts. Therefore, the FFA mathematical formulation, representing fireflies' motions, is based on the lights produced and their intensity. In this scenario, smaller, random fireflies are attracted to light flames. The lighter is moved from hereafter, the less bright. With distance the attraction and pressure decline. The brightness of a firefly reflects the consistency of the solutions. Firefly shifts at random if there is no lighter firefly visible. FFA has been developed to solve major problems(Atabaki, et. Al.,2019). The following equation sums up a firefly's progress into a lighter firefly j for a specific iteration (t+1):

$$x_i^{t+1} = x_i^t + \beta_0 e^{\gamma r_{i,j}^2}\left(x_i^t - x_j^t\right) + \alpha\left(rand - \frac{1}{2}\right)$$

Where the attraction effect is shown by $\beta_0 e^{\gamma r_{i,j}^2}\left(x_i^t - x_j^t\right)$ and $\alpha\left(rand - \frac{1}{2}\right)$ signifies the randomization concept in which α is the coefficient of randomization; β0 applies to the strength of the light in distance r 5 0, and for the majority of instances it is equal to 1; The difference b/W any two fireflies I and j, respectively, situated at xi and xj, is the Cartesian distance, that is

$$,r_{i,j} = \sqrt{\sum_{k=1}^{d} x_{i,j} - x_{j,k}}$$

The fittest one is retained after all the gestures are made by the fireflies. The moving method is iterated until it satisfies a termination condition.

Step 1 : Initialization

- Initialize pop size using $x = x_{\min} + (x_{\max} - x_{\min})*rand$, where $x_{\min} = -0.5$ and $x_{\max} = 0.5$, *i.e.* generate randomly n fireflies where in each firefly represents a job schedule.
- Generate processing times $hr(\tilde{p}_j)$, due dates $gm(\tilde{d}_j)$, early/tardy penalties.
- Set FA parameters $\gamma = 0.1$, $\beta_0 = 1$, $\alpha = 0.5$
- Define the objective function $f(x)$, $x = (x_1, x_2, ..., x_d)^T$

Step 2 : Calculate light intensities, light intensity of firefly I_i at x_i is determined by the value of objective function $f(x_i)$.

Step 3 : for each iteration (1, ...,Max It) do:

for $i = 1 : n$

for $l = 1 : n$

If $I_i < I_l$ move firefly i towards firefly l

end if ,obtain attractiveness ,which varies with distance r

Find new solutions and update light intensity.

end for l

end for i

Rank the fireflies , find the optimal solution.

Step 4 : If the stopping criteria is met then output the results, otherwise go to step 3.

Figure 2: Steps of Firefly algorithm.

4. Result and discussion

The presumption to be considered is: To define optimum levels of output and distribution within warehouses and outlets:

1. Lead time is zero
2. The time-dependent deterioration rate is considered
3. The shortage is permitted.

Assume that for the scaling parameter N a certain value applies:

$$wN2\ storage\ facilities$$

$sN2outlets\ for\ distribution$

These facilities are in the x and y directions at various integer grid points between 1 and N. To have separate sites, w+1 is required. In order to have separated sites. Take $N = 20$ and s=0,05 and s=0,1, respectively.P goods from the factories are made.

$P = 20\ take.Take\ P = 20.$

A retail outlet d is required for each commodity $p\ (s, p)$. The criteria is the quantity which can be sold over time. The need to produce and deliver the necessity amounts is fulfilled, suggesting that each warehouse has limitations in capability (w).

The quantity of product p moved from warehouse w to supermarket outlet is less than rotation (p) while rotation(p) is the p product's turnover amount.

Assume that all outlets are provided from just one warehouse. Part of the challenge is how to map units of cheap delivery to warehouses.

Costs: The expense of shipping the goods from the warehouse to the delivery center depends on how far the factories from each material are situated. If dist (a,b), as long as the transport costs tcost(p) is beyond the gap between installations (a) and (b), transport costs of the commodity p shall be:

$Removal\ of\ dist(a,b) * tcost(p).$

The gap is also regarded as the radius L1, in the present case the grid distance. This is the full comparison between x and y.

Optimization Problem

Provided a collection of locations and limitations on specifications and capacity, a product delivery schedule from warehouses to outlets .These sums must be guaranteed to meet demand and mitigate overall costs. Each sales outlet is also required from exactly one warehouse to obtain all its goods.

Variables for the Optimization Problem

In order to adjust optimization, the control variables are $y(s, w) = a$ binary variable with the value of 1 if the warehouse w.

The aim is to reduce

$$Tcost + Dcost$$

The constraints are:

Capacity of Warehouse
Fulfilled Demand.
$y(s,w) = 1\ y(s)$ (*each sales outlet associates to one warehouse*).
$x(p,f,w) \geq 0$ (*nonnegative production*).
$y(s,w) \epsilon \{0,1\}$ (*binary y*).

In the target and restriction functions, the variables x and y are linear. The problem is a mixed-integer linear program, since it is limited to integer values (MILP).

Generate a Random Problem: Facility Locations

Set the values N, f, w and s and find the facility.

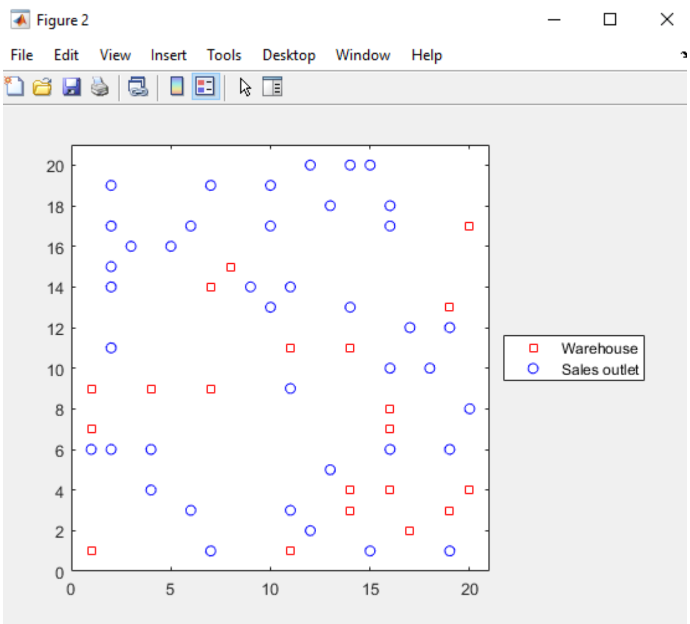

Figure:1 Facility locations

Generate Random Capacities, Costs, and Demands

$P = 20;$ % 20 *products*
% *Production potential for and commodity between* 500 *and* 1500
$pcap = 1000 * rand(P) + 400;$

% Capacity for each commodity or warehouse between P*400 and P*800
$wcap = P * 500 * rand(W,1) + P * 500;$
% Rate of product turnover for each product from 1 to 3
$turn = 2 * rand(1,P) + 1;$
% The cost of product transport for each product per distance from 5 to 10
$tcost = 5 * rand(1,P) + 5;$
% Product market demand for each 200 to 500 sales outlets
$d = 200 * rand(S,P) + 200;$

Integer Variables and Bound Constraints

The integer variable is length (obj1) + 1 up to the end.
$intcon = P * W + 1: len(obj);$
Len(obj1) + 1 to end also extends the upper limits.
$lowerbound = zeros(len(obj,1));$
$upperbound = \inf(len(obj,1));$
$upperbound(P * W + 1{:}end) = 1;$

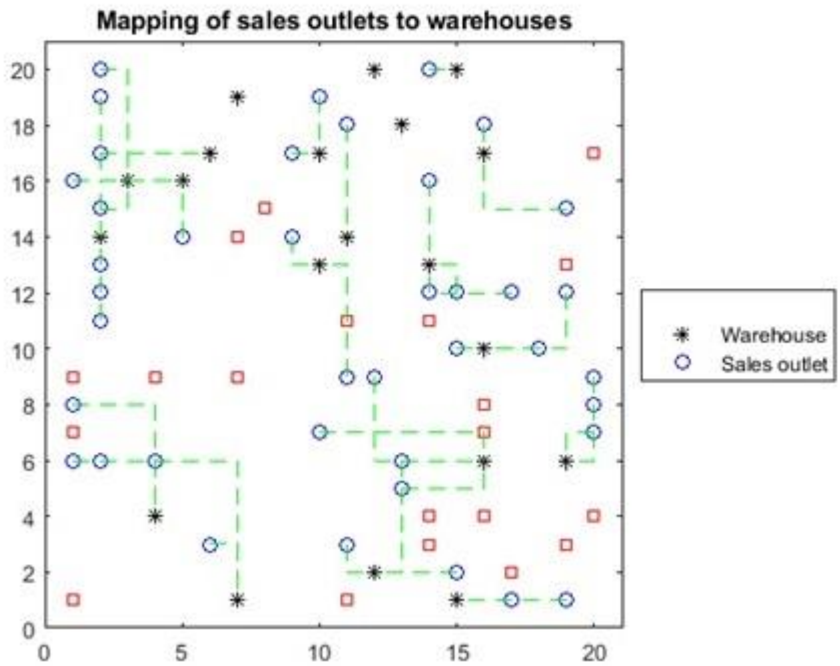

Figure: 2 Mapping of warehouse distribution outlets

The unused warehouses are the black * without green lines. The minimization of the total cost is considered as a goal function during the execution of the APSO and the Firefly algorithm. The APSO algorithm takes fewer iterations while the original firefly algorithm requires approximately two iterations in order to achieve the optimal solution. Compared with the firefly approach the proposed APSO algorithm also achieve a high rate of convergence. As a result, the results in figures 3, 4, 5 and 6 indicate the dominant optimality and convergence superiority of the APSO algorithm over the Firefly algorithm.

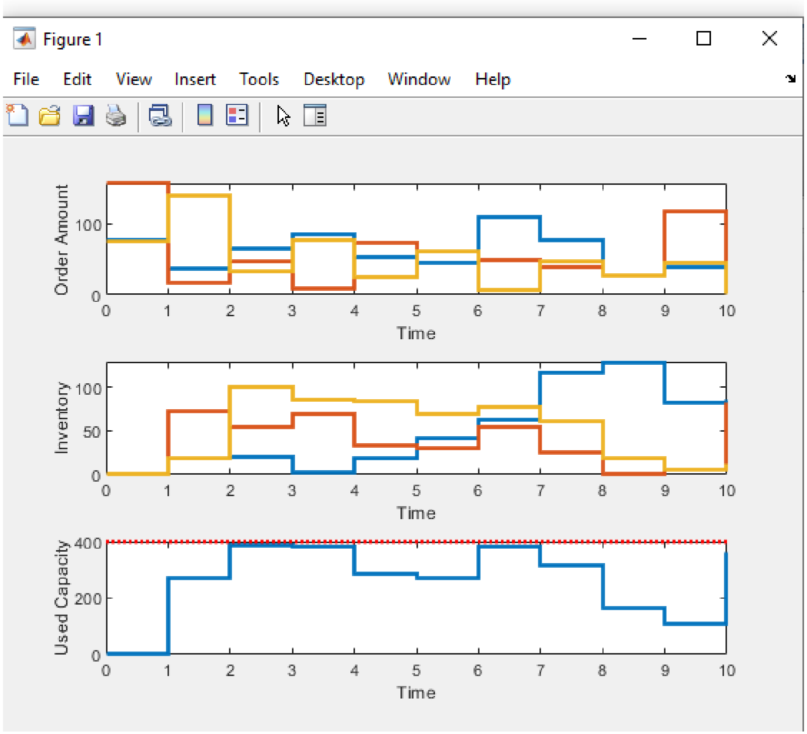

Figure: 3APSO for used capacity, Inventory and order amount w.r.t time

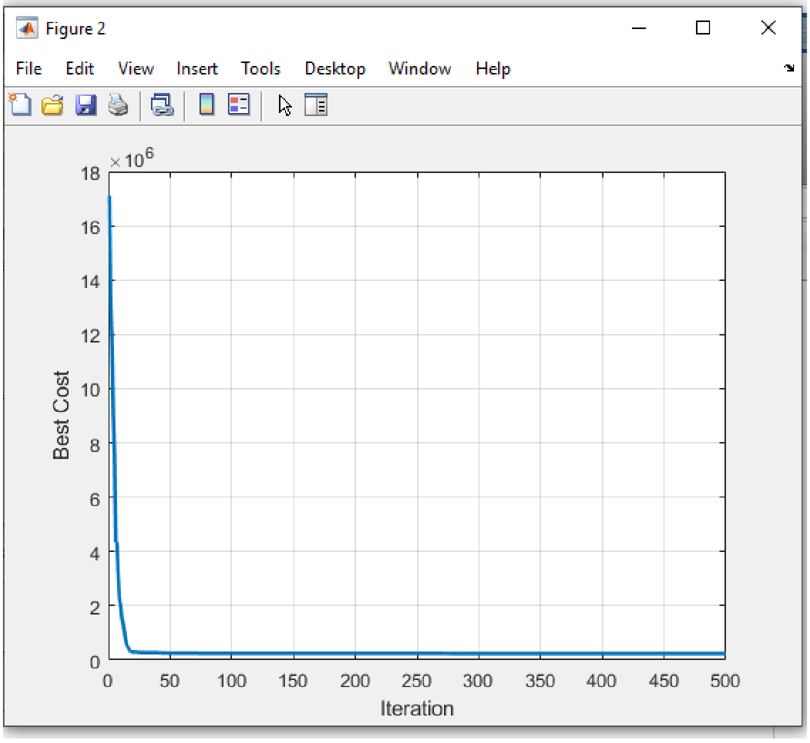

Figure: 4 Cost optimization with APSO

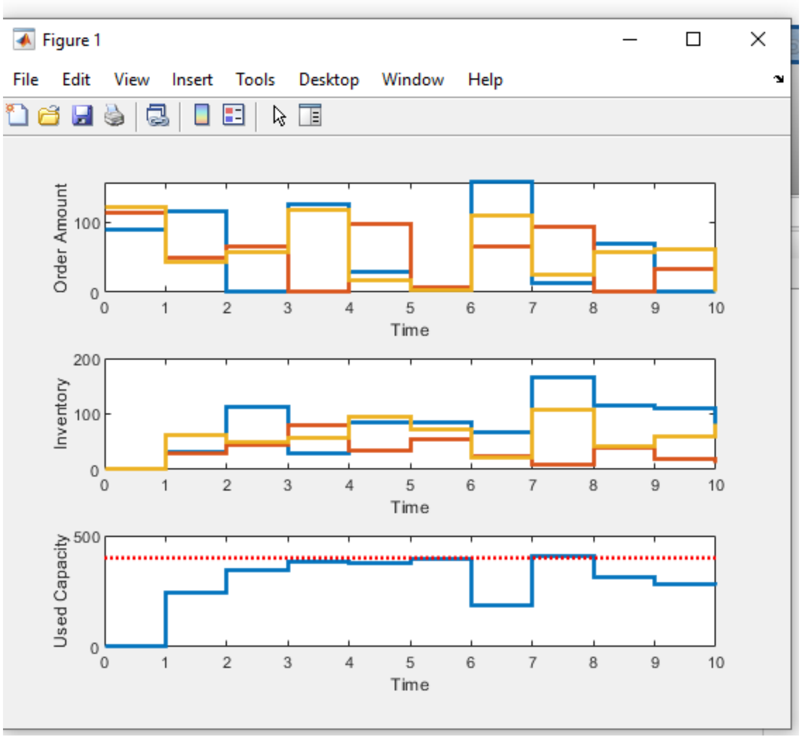

Figure: 5 Firefly for used capacity, Inventory and order amount w.r.t time

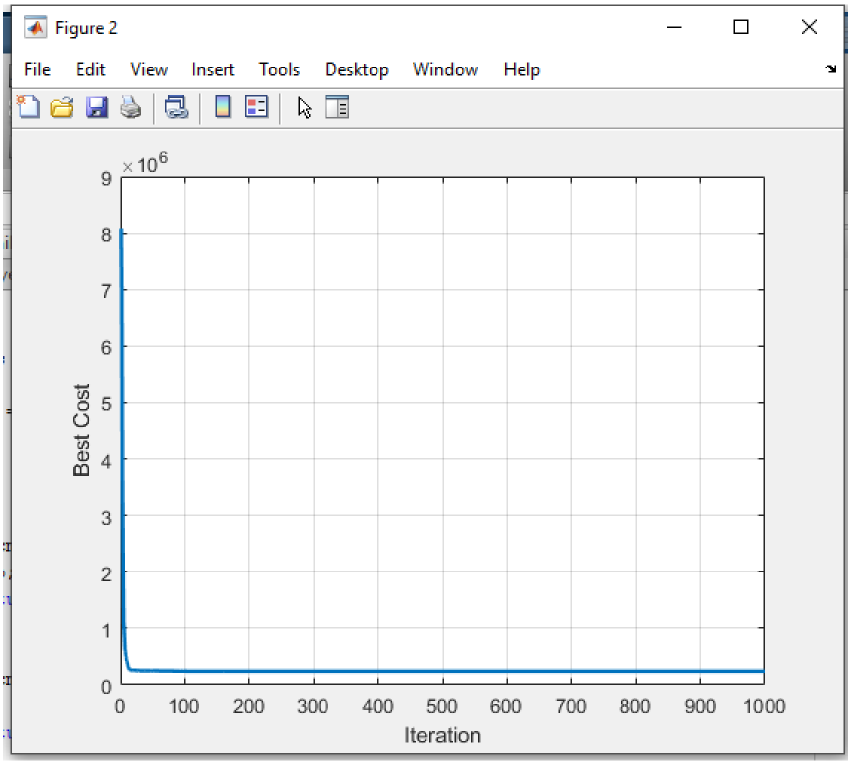

Figure: 6 Cost optimization with Firefly algorithm

5.CONCLUSION

Due to a scarcity of assets and environmental suspicions, inventory management has become a region of great importance for the improvement of productivity. The study attempted to contribute to understanding the application of inventory management strategies for worsening inflation shortage items that are closer to reality. An ECONOMIC ORDER QUANTITY model has been developed for decaying items with power demand, partial backlogging and inflation. We concluded that the lifetime of deteriorating items and inflation rate increases, increasing the initial level of inventory, but reducing the total average inventory cost with partially permissible shortages. With the help of assumptions in this model, we conclude that when consumer goods in the market are affected by stock levels under inflation, time discounts and partially backlogged shortages, the optimal replenishment policy is more valuable. Adaptive PSO algorithm is used for cost optimization and compares the results with firefly algorithm.

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