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Implementation of Particle Swarm Intelligence Within Inventory Control for an Electrical Industry: A Case Study

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ABSTRACT

Optimal inventory management is a major issue in many companies and may impact their productivity and profitability. Our research targets an electrical energy facility in Iraq to find optimal quantities and inventory costs that reduce total inventory costs, including ordering, holding, transportation, and inspection. The research compares classical particle swarm optimization (CPSO) with modified particle swarm optimization (MPSO). The artificial neural network analyzes the relationship between input and output to form a cost function. The MPSO technique produced better cost savings than CPSO or traditional methods (EOQ). The traditional economic order quantity management system produced total costs of $7,486,304.80, but CPSO cut them to $5,414,100 while MPSO lowered them to $2,418,000 when controlling 20 electrical items. The results show that MPSO achieves better than traditional methods and CPSO in lowering expenses and improving inventory handling. Sensitivity analyses are carried out on some important parameters, and the changes in the objective function are investigated. Finally, the experimental results verify MSPO's good performance.

Keywords: Artificial neural network, Economic order quantity, Hybrid algorithm, Inventory control, Particle swarm optimization.

1. INTRODUCTION

Inventory management is essential to operational effectiveness because it makes forecasting, acquiring, and maintaining ideal stock levels possible, directly affecting profitability and customer satisfaction **(Praveen et al., 2020)**. Maintaining the effectiveness and profitability of a business's operations depends on effective inventory management and control, which has grown in importance as a management function. Therefore, several investigations tried to create models that might be utilized to limit the amounts of excess stock and lower the costs associated with them without sacrificing customer demands or operational effectiveness **(Aldhaheri, 2019)**. In an inventory control challenge,

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the two primary decisions that impact demand are a) when to buy (by creating a purchase order) and b) how much to buy (by determining the lot size) **(Zipkin, 2000)**. One approach most frequently used to determine the ideal level of raw material inventories required by a business to sustain steady operations at an economical cost is the Economic Order Quantity (EOQ) technique. This method is popular because it is simple and can give businesses the best results. This is demonstrated by the Economic Order Quantity (EOQ) method, which calculates the most appropriate time (reorder point) to make a repurchase quantity the most efficient inventory for the business. **(Abdullah et al., 2020)**

Most of the real-world problems in various scientific and technical fields can be represented as optimization problems **(Stanovov et al., 2022)**. The process of choosing the most effective or efficient option from a set of possibilities to maximize or minimize one or more functions is termed mathematical optimization **(Maciel et al., 2020)**. Metaheuristic algorithms may be classified based on either physical laws, swarm intelligence, human inspiration, or evolution principles. **(Morales-Castañeda et al., 2021)** noted that "optimization strategies are grouped according to basic concepts about physical and biological algorithms. It also comprises a genetic algorithm (GA), Harmony Search Algorithm (HAS), Particle Swarm Optimization (PSO), bacterium foraging optimization (BFO), cuckoo search algorithm (CSA), bee colony algorithm (BCA), ant colony optimization (ACO), and firefly algorithm (FA). The first group comprises biology-inspired algorithms **(Ramli et al., 2015)**

Swarm intelligence-based algorithms are more effective in iterations and computing effort than other techniques because of their parametric modification and control **(Gad, 2022)**. Kennedy and Eberhart introduced Particle Swarm Optimization (PSO) in 1995 as an optimization method based on flocks of birds, schools of fish, and even human social behavior. PSO is currently regarded as one of the top swarm intelligence-based algorithms **(Eberhart and Kennedy, 1995; Kennedy and Eberhart, 1995)**. Its simplicity, low parameter count, global optimal search capabilities, and convergence rate have drawn the interest of scholars during the past 10 years **(Morales-Castañeda et al., 2023)**. When PSO is modified appropriately, it may effectively control the balance between exploration and exploitation **(Jain et al., 2022; Shami et al., 2022)**.

The exploitation phase concentrates on possible locations, whereas the particles in the exploration phase cover a larger area in space. Because of the benefits above make it an appropriate choice for optimizing real-world optimization issues **(Morales-Castañeda et al., 2023)**. PSO has some limitations, including the potential to produce poor solutions due to inaccurate control parameter selection and local minimum stockiness **(Miao et al., 2021)**. Numerous research studies have tried to enhance the conventional PSO algorithm using various techniques. Weight enhancement has been shown to enhance the searching capability of PSO **(Karunanithi et al., 2023)**, such as updating the formula of velocity for particle promotion in the direction of optimal solutions **(Singhai, 2020)**, merging with other optimization methods by adding a dynamic mutation method from GA to PSO improves its convergence performance and optimization efficiency **(Zhang et al., 2022)**. A nonlinear programming model is formulated to optimize inventory control and spare part supply decisions to minimize overall cost. An improved dynamic migrating particle swarm optimization self-adaptive approach has been proposed. It needs to avoid premature convergence, and its capacity for local exploitation must balance with the PSO capacity of global exploration **(Guo et al., 2022)**. To overcome these deficiencies and devise an improved capability of PSO to solve complex optimization problems.

An adaptive strategy-based modified PSO termed MPSO is presented **(Liu et al., 2020)**. Numerous attempts have been undertaken to address the shortcomings of optimization algorithms. Combining two or more separate algorithms is a common technique for improved performance **(Miao and Wang, 2019)**. Many researchers have proposed Artificial Neural Networks (ANNs) to simulate the relationship between input and output using artificial neural networks (ANNs) **(Hussien and Al-Shammari, 2021)**. Choosing incorrect parameter values during MPSO optimization will produce unsatisfactory results or slow the process. The approach faces an early solution (premature convergence) problem most severely in industrial applications with strong non-linearity and multiple solution spaces. MPSO's performance drops when its processing needs grow too high, particularly in sectors with limited resources. Adding MPSO needs special technical work to connect everything properly. The system requires accurate data feeds to work properly when it receives information.

The system requires spending money plus training staff members to work properly with the algorithm. The main problem in this research is the higher inventory costs. A high inventory cost burdens the electricity facility and may lead to a shortage or excess storage quantities, also considered a problem. This research aims to minimize the total inventory cost of an electrical power facility in Iraq for twenty electrical products because the facility faces a higher inventory cost problem. In this study, the inventory parameters were optimized, and the overall inventory cost was reduced using an ANN-based PSO approach, which involves optimization within inventory control by applying a hybrid particle swarm algorithm (ANN-PSO). A modified MPSO is applied to optimize the total inventory cost. In this work, we use ANN to link inputs and outputs. This is combined with classical particle swarm optimization (CPSO) to form a hybrid algorithm (ANN-PSO) and another hybrid modified particle swarm optimization (ANN-MPSO) ANN type is Feed Forward-Back propagation (FF-BP).

2. METHODOLOGY

The electric power company was selected as a case study in Baghdad, Iraq, is the site of the present research. The electricity company is regulated by service. Twenty products are considered in this case study. The company is seeking to minimize total inventory costs. **Fig. 1** to clarify the research methodology.

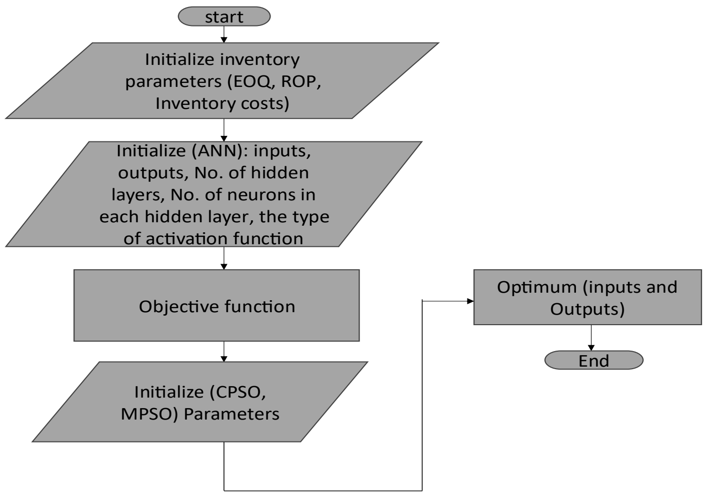

Figure 1. Flow chart of the research process.

2.1 Economic Order Quantity (EOQ)

Data were collected for twenty electrical products and spare parts from the inventory of the General Directorate of Transmission and Distribution of Electricity in Iraq, which served as a case study. This data included product sales, inspection costs, unit prices, and annual demand. The Economic Order Quantity (EOQ) model helps reduce stock-outs and optimize order quantities while minimizing total costs for each product. The optimal scenario occurs when the holding and ordering costs equal the required order quantity **(Gonzalez and González, 2010)**. The following mathematical model calculates the twenty products' cost estimates and economic order quantities.

2.1.1 EOQ Mathematical Model

Initially, when calculating the EOQ, it is necessary to find the incoming costs through the following assumptions:

1. Fixed order cost C_f= purchase quantity*unit cost price ($/unit)
2. The purchase cost per unit is constant throughout the year.
3. Holding cost assumed = 10% **(AK and Raut, 2020)**.
4. Unit price for each product.
5. Demand (D) per year.
6. Lead time is constant and known = 30 days.
7. Number of working days per year =250 days
8. Inspection cost(C_{insp}).
9. Transportation cost(C_T) was calculated using Eq. (1) **(Al-Ashhab, 2022)**:

C_T was calculated through Eq. (1)

$$C_T = \sum(\text{Nswti. } TCswi\, .Dswi\,) + \sum(\,Nwsti\,.\,TCwsi\,.Dwsi\,) \quad (1)$$

Where:
N_{swti}: Number of deliveries per year from supplier to warehouse (units).
N_{wsti}: Number of deliveries per year from the warehouse to the station (units).
TC_{swi}: Total cost for transported per kilometer ($/Km) from supplier to warehouse
TC_{wsi}: Total cost to transported per kilometer ($/Km) from the warehouse to the station.
D_{swi}: Distance from the supplier to the warehouse (km).
D_{wsi}: Distance from the warehouse to the station (km).
i: Number of products.

Table 1 illustrates the parameters included for C_T.

Table 1. Parameters of transportation cost (C_T)

Parameters	Value
$\boldsymbol{N_{swti}}$	(3) time a year
$\boldsymbol{N_{wsti}}$	times a year
$\boldsymbol{TC_{swi}}$	10 $/km
$\boldsymbol{TC_{wsi}}$	58.8 $/km
$\boldsymbol{D_{swi}}$	536.5 km
$\boldsymbol{D_{wsi}}$	30 km
$\boldsymbol{i}$	20 products

The data of products entering the company's warehouses, including inspection costs, unit prices, annual demand, times orders, and lead time, is analyzed by applying EOQ through Eq. (2) **(Aziz and Yunus, 2023)**.

$$\text{EOQ} = \sqrt{\frac{\boldsymbol{2*D*S}}{\boldsymbol{i*C}}} = \sqrt{\frac{2*D*(C_f+C_T+C_{insp.})}{i*C}} \quad (2)$$

Where:
D = Annual demand.
i =Inventory percentage or unit stock holding cost per item per year assumed to be 10% per annum.
C = Price per unit.
H = cost of holding per unit,
S = total Ordering cost of product independent of Q.
C_f = Fixed order cost,
C_T = Transportation cost,
$C_{insp.}$ = Inspection cost.

The Holding Costs (H) were calculated using Eq. (3), where:

$$\text{Holding Costs (H)} = i * C \quad (3)$$

$$\text{Annual holding Cost (HC)} = \frac{Q}{2} \cdot H \quad (4)$$

$$\text{Annual ordering Cost (OC)} = \frac{D}{Q} \cdot S \quad (5)$$

Number of orders (n*) = $\frac{D}{Q}$ **(Fithri et al., 2019)** (6)

Q is the EOQ order quantity.
Based on (**Kehinde Busola et al., 2020)**, the calculated Reorder point (ROP) is by using the following equation:

$$\text{(ROP)} = \left(\frac{Annual\ demand}{no.of\ working\ day\ in\ a\ year}\right) \cdot Lead\ \ Time \quad (7)$$

2.1.2 Total Inventory Cost

A primary objective in inventory management is to minimize total inventory costs. The total cost is determined by summing the most significant inventory costs, which include purchase, ordering, and carrying (holding) inventory costs. The purchase cost is incurred when acquiring the inventory. Therefore, the total inventory costs (TIC) can be calculated as follows:

$$\text{(TIC)} = \frac{D}{Q} \cdot S + \frac{Q}{2} \cdot H \quad (8)$$

Table 2 represents these cost calculations and the EOQ, ROP, and inventory Cost. The electrical company provided the collected data, which included unit cost per unit demand per year, distances between locations for transmission, lead time, annual quantity, and unit prices. This data was organized for twenty products to calculate each product's transportation cost, Economic Order Quantity (EOQ), Reorder Point (ROP), and n*. The CT is calculated based on Eq. (1) and the information in **Table 1.**

After applying Eq. (2), **Table 2** indicates that the EOQ method generates a higher total inventory cost of $7,486,304.80, where the calculation of total cost based on Eq. (8) The calculations for EOQ yielded equal holding costs Eqs. (3 and 4) and order costs Eq. (5)**,** as the EOQ aims to determine the optimal order quantity by minimizing holding and ordering costs. As shown in Eq. (7)**,** the ROP indicates that an order should be placed when the product quantity falls below a specified level, as detailed in **Table 2.**

Table 2. EOQ, ROP, and inventory cost

Products	**1**	**2**	**3**	**4**	**5**
Times orders	1	1	1	1	1
Demand/year	6	28	40	20	52
Quantity	18	29	57	23	50
Unit cost price ($)	125844.89	329997.14	6228.75	273574.31	328289
Holding cost	10%	10%	10%	10%	10%
Fixed order cost ($)	2265208.02	9569917.06	355038.75	6292209.13	16414450
transport cost ($)	592.7	367.9	187.1	463.9	213.4
Inspection cost ($)	1404.5	871.7	443.5	1099.1	505.6
Lead time(days)	30	30	30	30	30
EOQ	46.49	127.4	213.7	95.9	228
R O P	0.7	3.3	4.8	2.4	6.2
Optimal orders n*	0.1	0.2	0.1	0.2	0.2
Holding cost ($)	292565.9	2102816.2	66563.8	1312179.2	3743152.4
Ordering cost ($)	292565.9	2102816.2	66563.8	1312179.2	3743152.4
Total cost ($)	585131.8	4205632.4	133127.6	2624358.4	7486304.8

Table 2. EOQ, ROP, and Inventory cost (Continue)

Products	**6**	**7**	**8**	**9**	**10**
Times orders	1	1	1	1	1
Demand/year	18	84	10	51	24
Quantity	17	73	44	33	23
Unit cost price ($)	47798.46	47798.46	26332	5480	4973
Holding cost	10%	10%	10%	10%	10%
Fixed order cost ($)	812573.82	3489287.57	1158608	180840	114379
Transport cost ($)	627.6	146.1	242.5	323.3	463.9
Inspection cost ($)	1487.1	346.3	574.5	766.1	1099.1
Lead time(days)	30	30	30	30	30
EOQ	78.3	350.2	93.8	184	105.7
R O P	2.1	10	1.2	6.1	2.8
Optimal orders n*	0.2	0.2	0.1	0.2	0.2
Holding cost ($)	187207.8	837010	123551.5	504210	26303.9
Ordering cost ($)	187207.8	837010	123551.5	504210	26303.9
Total cost ($)	374415.6	1674020	247103	100842	52607.8

Table 2. EOQ, ROP, and inventory cost (continue)

Products	11	12	13	14	15
Times orders	1	1	1	1	1
Demand/year	8	23	47	14	53
Quantity	26	72	73	22	53
Unit cost price ($)	29611	5424.5	10841	1207	678
Holding cost	10%	10%	10%	10%	10%
Fixed order cost ($)	769886	390564	791393	26554	35934
Transport cost ($)	410.3	148.1	146.1	485	201.3
Inspection cost ($)	972.3	351	346.3	1149	477.0
Lead time(days)	30	30	30	30	30
EOQ	64.5	182.1	262	80.8	239.2
R O P	0.9	2.7	5.6	1.6	6.3
Optimal orders n*	0.1	0.1	0.1	0.1	0.2
Holding cost ($)	95578.3	49391.4	142036.4	4880.1	8110.5
Ordering cost ($)	95578.3	49391.2	142036.4	4880.1	8110.3
Total cost ($)	191156.6	98782.8	284072.8	9760.2	16220.6

Table 2. EOQ, ROP, and Inventory Cost (Continue)

Products	16	17	18	19	20
Times orders	1	1	1	1	1
Demand/year	67	75	110	225	112
Quantity	75	85	104	248	153
Unit cost price ($)	6330	60132.22	226.01	135	115.99
Holding cost	10%	10%	10%	10%	10%
Fixed order cost ($)	474750	5111238.7	23505.04	33480	17746.4
Transport cost ($)	142.2	125.5	102.5	43.0	69.7
Inspection cost ($)	337.0	297.4	243.0	101.9	165.2
Lead time(days)	30	30	30	30	30
EOQ	317.1	357	481.8	1058.6	589.2
R O P	8	9	13.2	27	13.4
Optimal orders n*	0.2	0.2	0.2	0.2	0.1
Holding cost ($)	100386.6	1073619.2	5444.9	7146.1	3417.5
Ordering cost ($)	100386.6	1073619.2	5444.9	7146.1	3417.5
Total cost ($)	200773.2	2147238.4	10889.8	14292.2	6835

By effectively implementing the EOQ method, the electrical company could achieve significant cost savings while aiming to reduce total inventory costs. The results were then optimized using a hybrid algorithm (ANN-PSO) and a modified PSO and compared with the classical PSO and EOQ calculations.

2.2 Classical Particle Swarm Optimization (CPSO)

The social behavior of flocking birds inspires particle swarm optimization (PSO), which can be described as an algorithm based on social psychology. Unlike genetic algorithms (GA), PSO does not rely on crossover and mutation. Instead, it is a population-based optimization technique that begins with a population of random solutions and identifies optimal solutions by updating successive generations **(Vanneschi and Silva, 2023)**. Eberhart and Kennedy developed the PSO evolutionary computing method in 1995 **(Kennedy and Eberhart, 1995)**. An Artificial Neural Network (ANN) models the relationship between input and output to determine the cost function (objective function). The ANN is a computational model inspired by the human brain **(Mahmoud and Fattah, 2023)**. A neural network is a distributed model that processes information across many interconnected nodes or neurons, similar to how the human brain operates. This allows for complex problem-solving and pattern recognition**(Patel et al., 2022)**. Due to their architecture, ANNs can learn from examples, similar to human learning, by modifying their connections in response to incoming signals **(Devkar and Sharma, 2023)**.

The human brain has a remarkable capacity to identify hazy, confusing, and partial facts and information and to make independent conclusions. ANN tries to mimic a typical neuron's structure and functions. A single output (a synapse via an axon) and several inputs (bifurcations) make up a neuron. Determining the activity of other neurons is the role of neuron function, where the input layer serves as a receiver for input values in an ANN design. Layers of input and output are separated by a hidden layer, a collection of neurons. These strata may be found in one or more locations. The activation function utilized is either the step function or the ramp function. The Back Propagation (BP) algorithm is the most widely used technique for implementing neural networks (NNs). At this step, the weights and layers are modified in response to the difference between the target and acquired outputs **(Al-Waily et al., 2020; Al Saffar et al., 2023)**. The BP method propagates layers of hidden output to the output layer, where the output is estimated, as shown in **Fig. 2**. This output matches what is needed for a certain input **(Abdolrasol et al., 2021)**. Feed-forward propagation in backward ANNs has become known for its simple design, in which data flows from input to output in a single path. Because of this, it is simpler to use and understand. These ANNs can simulate complex interactions between inputs and outputs. This is especially helpful in situations like inventory cost-minimizing, where there may be complex relationships between several factors that are difficult for traditional methods to determine. The backpropagation algorithm allows for efficient training of the network by adjusting weights based on the error of the target output compared to the expected result. This adaptability is crucial for optimizing the ANN's performance and minimizing total inventory costs, as it can learn from past errors and improve over time. ANN is used in conjunction with optimization techniques like PSO. The ability of the Feed-Forward Back Propagation ANN to provide a good fit for optimization makes it a suitable choice for this research, as it can effectively link inputs and outputs to form an objective function that the optimization algorithm can minimize. Applying swarm intelligence to neural networks is an attempt to enhance the training and optimization processes, especially when dealing with complex, high-dimensional search spaces.

Many studies on the combination of swarm intelligence techniques, such as particle swarm optimization (PSO) and artificial neural networks (ANN), have been conducted in several ways. However, as mentioned in this study, the particular method of employing modification within PSO could be a unique addition to this sector. The use of ANN to link the inputs and the output to form the cost function to minimize total inventory cost by transmitting to the PSO algorithm. Although this PSO and ANN combination for cost minimization is not entirely novel, the particular approach and improvements suggested in this study could provide new insights or improvements.

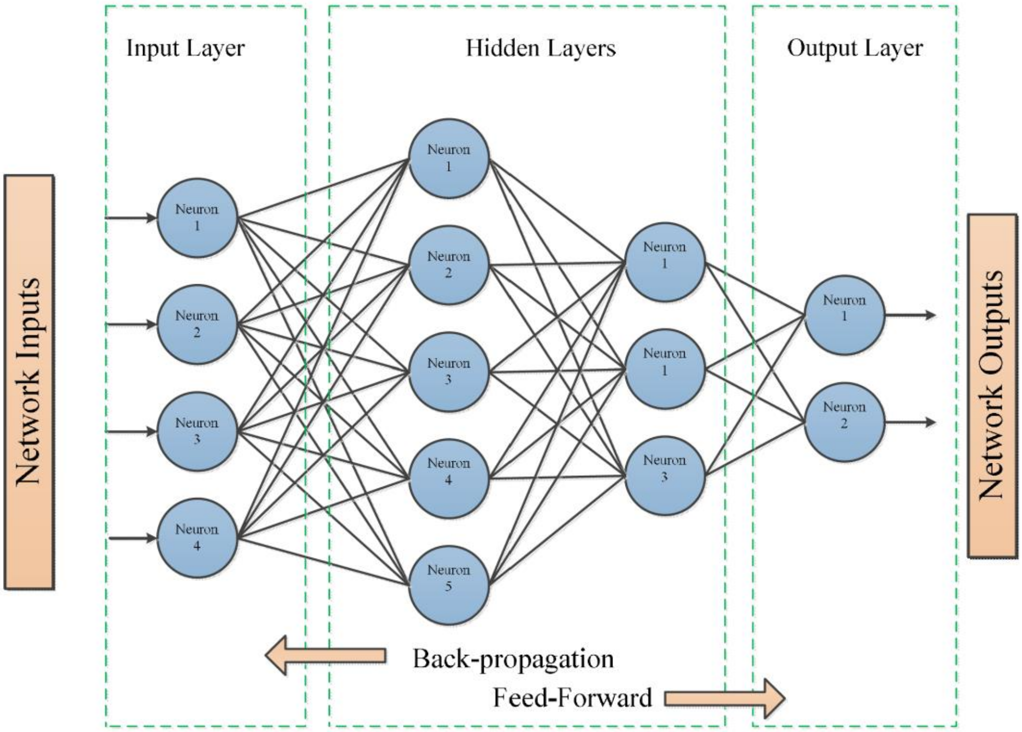

Figure 2. ANN architectures. **(Abdolrasol et al., 2021)**

This study considers twelve inputs: annual demand, unit cost price, fixed order cost, transportation cost, inspection cost, ROP, the optimal number of orders, lead time, EOQ, quantity, holding cost, and ordering cost. These inputs are fed into an ANN with the total cost as the output. The feed-forward network uses a backpropagation structure with two hidden layers. The first hidden layer is trained using the bipolar continuous activation function (tansig), as shown in Eq. (9)**,** while the second layer employs a pure linear activation function, represented in Eq. (10)**.** The fundamental mathematical equations for both activation functions are provided.

$$f_{net} = \frac{2}{1+\exp\,(-\lambda_{net})} - 1 \qquad \lambda > 0 \tag{9}$$

$$f_{net} = net\ (\,w^t . x_i) \tag{10}$$

Where w^t is the weight of inputs and x_i is the input.
To complete the optimization and identify the optimal input with the minimum output, the trained values from the ANN were submitted to both the PSO and modified PSO algorithms. **Figs. 3** and **4** depict the structure and performance of the ANN, while **Fig. 5** presents its training performance using the mean square error (MSE) metric.

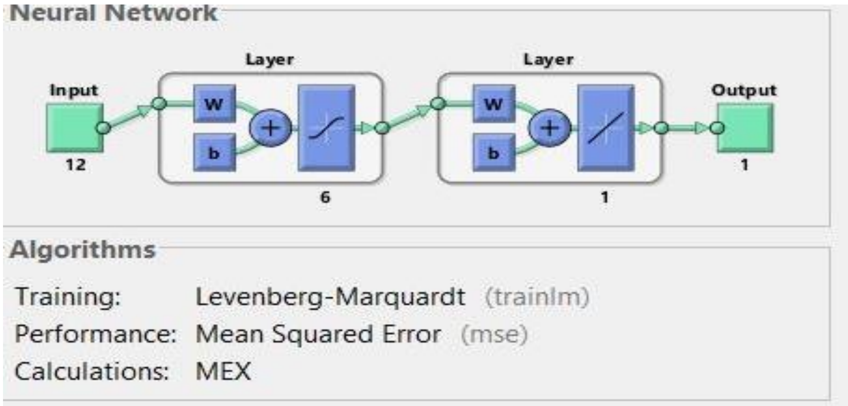

Figure 3. Structure of ANN.

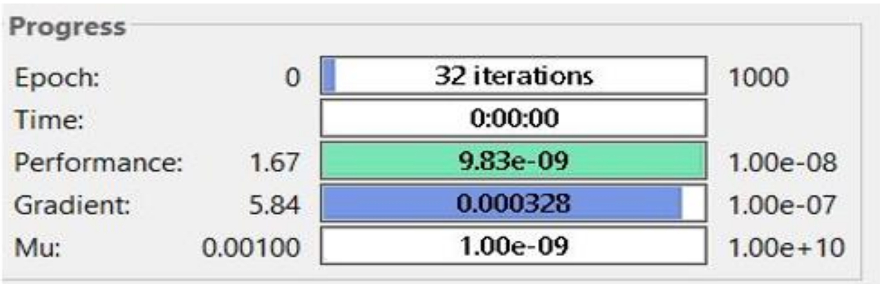

Figure 4. Performance of ANN.

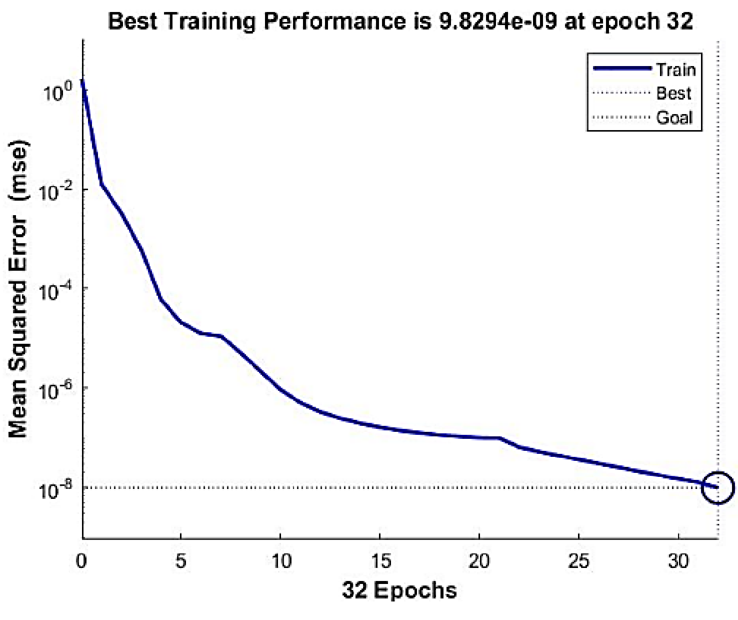

Figure 5. Training of ANN.

The optimal linear regression that links the targets and outputs was displayed to generate the regression plot. It illustrates how effectively the neural network's objective can adapt to variations in output **(Mahmoud and Fattah, 2023)**. The regression diagram is shown in **Fig. 6.** Measured from zero (no correlation at all) to one (perfect correlation), measures how well the neural network's objective can track variations in the output.

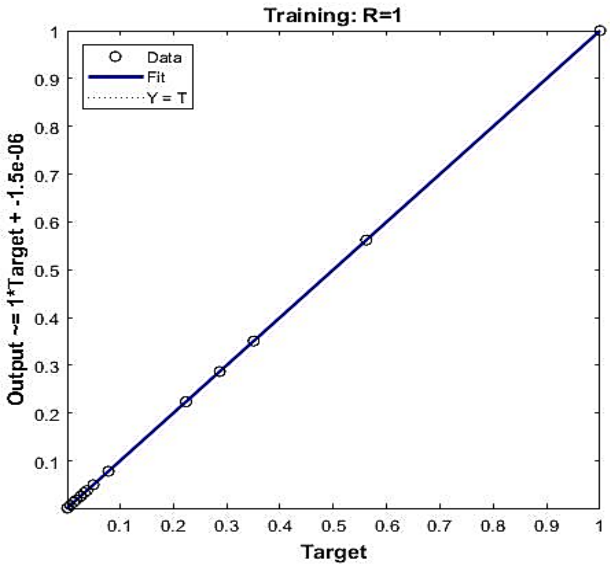

Figure 6. Regression plot of the ANN.

The following formula was used to update the particle's position and velocity **(Tang and Meng, 2024)**.

$$V_{(t+1)} = w.V_{(t)} + C_1.r_1.\left(P_{best} - X_{(t)}\right) + C_2.r_2.(G_{best} - X_{(t)} \quad (11)$$

$$X_{(t+1)} = X_{(t)} + V_{(t+1)} \quad (12)$$

where $X_{(t)}$ is the particle's position at the current iteration t, $V_{(t)}$ is the particle's velocity at iteration t, $P_{best}$is the particle's individual best position and G_{best} is the group's global best position. Acceleration coefficients are denoted by C_1, C_2, r_1, and r_2 are random numbers [0-1].

In a classical PSO, inertia was treated as a constant, and its value was determined by setting it with other constants in **Table 3**. The performance of PSO is highly sensitive to its parameters, such as the acceleration coefficients and the inertia weight. It is crucial for balancing the exploration and exploitation of the search space. Poorly chosen parameters can lead to ineffective search behavior, causing either slow or premature convergence.

Table 3. Parameters of classical PSO

Parameter	Value
No. of iteration	100
Inertia (w)	0.98
C1	2
C2	2
r_1, r_2	[0-1]
Swarm Size	30
Dimensional space	12

2.3 A Hybrid Modified Optimization MPSO

In this work, the MPSO will enhance particle exploration (finding new locations) and exploitation (refining existing high-quality areas) by adjusting the weight during each iteration. As the process advances, reducing the weight increases the likelihood that the particles will focus on the best solutions discovered, based on **(He and Huang, 2012)** equation:

$$w_t = w_{min} + \frac{T-t}{T-1}(w_{max} - w_{min}) \tag{13}$$

In this context, w_t represents the inertia weight at the current iteration, w_{min} is the minimum weight value (limiting particles' influence based on prior experiences), and w_{max} is the maximum weight value (restricting the effect of previous experiences). T refers to the total number of iterations, indicating the duration of the particles' movement and search for the optimal solution. In contrast, t denotes the current iteration, where the values are shown in **Table 4.**

Table 4. Parameters of modified MPSO

Parameter	Value
Overall number of iterations	100
W max	2
W min	1
C1	2
C2	2
$\mathbf{r_1, r_2}$	[0-1]
Swarm Size	30
Dimensional Space	12

3. SENSITIVITY ANALYSIS

It is a technique used to determine the impact of changes in input variables on the final outcomes of the model. The goal is to measure the sensitivity of the results (such as total cost or the economic quantity) to changes in different factors (such as demand or holding costs). The variables that can change within the system and are believed to significantly impact the outcomes are selected. In this case, the key variables are: (1) Demand varies between 160 to 230 in fixed units, and (2) Holding Cost Rate varies between 5% and 14%.

4. RESULTS AND DISCUSSION

This research uses data on the inventory of twenty products collected from the General Directorate for Transmission and Distribution of Electrical Power in Iraq as a case study. Initially, EOQ, inventory costs, and ROP calculations were performed for these twenty electrical products. The analysis revealed that the total inventory cost for all twenty products reached approximately $7,486,304.80. To solve the problem of minimizing the total inventory cost, twelve parameters (inputs) were considered for optimization: annual demand, purchased quantity, lead time, transportation cost, inspection cost, holding cost, ordering cost, fixed order cost, unit price, EOQ, ROP, and n*. These twelve parameters were inputs for the ANN network, classical PSO, and modified PSO, with total cost as the output. The ANN networks were then applied to perform the cost function for both the modified and classical PSO. While the PSO results showed strong convergence, they were more costly overall compared to the modified PSO. The total cost from the modified PSO, based on **(He and Huang, 2012)** equation, was lower than the total cost from both the classical PSO and EOQ calculations, indicating better performance. Due to the inertia being continuously adjusted during each iteration until the optimal swarm was achieved, as shown in **Table 5,** compare the hybrid classical PSO and the hybrid modified PSO after applying the above modified PSO.

Table 5. Comparison between the hybrid CPSO and the hybrid MPSO

parameters	The result of the parameter(min-max)	CPSO	MPSO
Demand per year (unit)	(6-225)	197.123	99.042
Unit cost price ($)	(115.9-329997.14)	217345.342	29876.505
Fixed order cost ($)	(17746.4-16414450)	12452619.844	818652.970
Transport Cost ($)	(43-627.6)	567.026	275.702
Inspection cost ($)	(101.9-1487.1)	1411.539	873.067
EOQ	(46.9-1058.6)	978.220	212.034
ROP	(0.7-27)	24.461	16.782
n*	(0.1-0.2)	0.186	0.122
Holding cost ($)	(3417.5-3743152.4)	2879498.344	1623815.404
Ordering cost ($)	(3417.5-3743152.4)	2879498.344	1623815.404
Lead time(days)	(30-30)	30	30
Quantity(unit)	(17-248)	198.604	91.099

The modified PSO resulted in a total cost of $2,418,000, compared to $7,486,304.80 for EOQ and $5,414,100 for PSO, as shown in **Table 6.**

Table 6. Result of optimum value of total cost.

Total cost ($)	CPSO	Modified PSO
7486304.8 $	5.4141e+06= (5414100$)	2.4180e+06= (2418000$)

Through its combined MPSO-ANN system, this research delivers better inventory management that outperforms classical methods with enhanced cost benefits and reliable performance. The approach uses a Modified Particle Swarm Optimization (MPSO) method to automatically control the weight factor to balance exploring and exploiting optimum solutions. The study connects ANN technology with MPSO to help improve decision-making through better cost evaluation and optimization results. ANN is used to link between inventory inputs and output (total inventory cost). As shown in **Fig. 7**, the modified PSO demonstrates superior performance, with faster convergence between the number of iterations and the objective function. While **Fig. 8** shows the change in the objective function (total inventory cost) with the number of iterations.

The researchers apply the methods to actual electrical power sector data by optimizing 20 product inventories. This research shows that its models perform well under different parameter conditions and tests their impact on total cost and EOQ optimization results. Our sensitivity tests help us understand how model parameter changes affect the overall cost and the EOQ value. This research focuses on electrical energy sector needs and applies the technique that handles specific problems with higher costs, changing customer demand patterns. This research introduces this industry exclusively so businesses like it can apply the results immediately. Our study goes beyond classic inventory systems by creating and testing a hybrid MPSO-ANN model that shows better results with actual industry data while providing improved cost savings and effective performance against existing methods. The study compares three methods: The research analyzes the approaches of Economic Order Quantity (EOQ), Classical Particle Swarm Optimization (CPSO), and Modified Particle Swarm

Optimization (MPSO). Determining the economic order quantity, EOQ helps companies reduce total inventory costs while managing their ordering and holding expenses. This method works best when demand stays stable and lead times stay the same because of its basic design. This solution struggles to work with unpredictable real-life demands and costs. Through its swarm behavior, CPSO shows improved performance in finding optimal solutions for challenging optimization problems. CPSO shows weak performance with early stopping patterns and an imbalance between exploration and exploitation. MPSO improves CPSO by automatically changing inertia weights across iterations to reach a perfect balance between exploration and exploitation. It preserves particle variety during optimization and automatically adjusts to changing industrial settings with different requirements. Our findings demonstrate how the methods save substantial amounts by lowering total inventory expenses were MPSO delivers $2,418,000 in total inventory costs, representing a 67% savings over EOQ and a 55% savings compared to CPSO. MPSO provides better cost savings plus dynamic performance while joining with ANN technology and works across many situations. The method shows better inventory cost savings than EOQ and CPSO, making it more useful for practical applications with changing market conditions, as shown in **Table 7.**

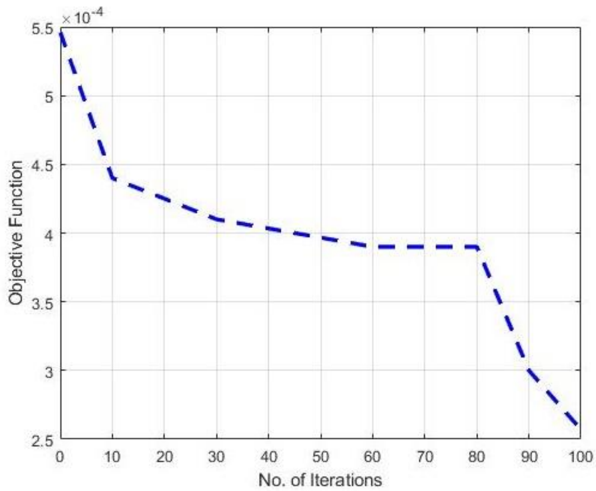

Figure 7. The convergence of modified PSO

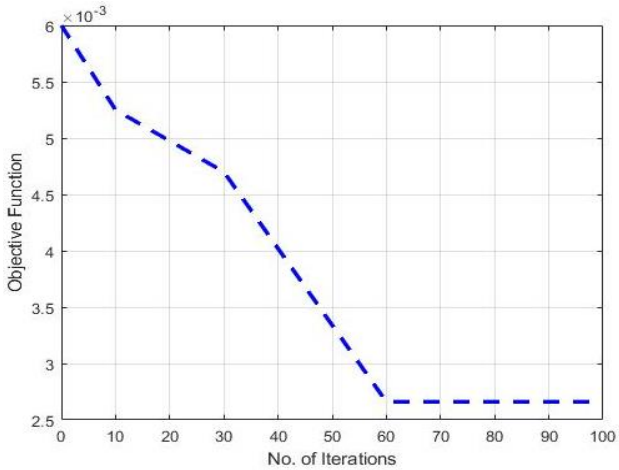

Figure 8. The convergence of Classical PSO.

Table 7. Summary of the Comparison.

Method	Cost ($)	Strengths	Weaknesses
EOQ	7,486,304.80	Simple, easy to implement	Inflexible, assumes fixed demand and costs
CPSO	5,414,100.00	Handles non-linear problems, adaptable	Premature convergence, static parameters
MPSO (Proposed)	2,418,000.00	Dynamic, robust, integrates with ANN	Slightly higher computational complexity

To evaluate the algorithm, we conducted a comparative analysis using data from **(Pang et al., 2019)** and researcher **(Gonzalez and González, 2010)**. The aim of validation is to ensure that the algorithms employed are accurate, reliable, and provide acceptable results by comparing these research findings with other experimental results. Two real case studies in inventory control in different industries is solved to validate the proposed algorithm MPSO. After applying the total inventory cost result for both researchers through the hybrid modified PSO, the comparison is shown in **Tables 8 and 9.** The hybrid-modified PSO effectively minimizes the total inventory cost and parameters. The results show excellent validations of this research in minimizing total cost, The comparison between data demonstrates the superiority of MPSO in performance and reliability. The results suggest that MPSO is a highly effective approach for inventory problems where the cost saving of **(Gonzalez and González, 2010)** is ~ 66.99%, and for **(Pang et al., 2019)** with cost-saving ~ 69.8%, while for the proposed study~67% cost saving. After applying the sensitivity analysis, **Table 10** shows the result.

Table 8. Results of validation for the parameters.

Parameters with EOQ calculations	(Gonzalez and González, 2010)	(Pang et al., 2019)	Proposed MPSO (This study)
Demand(units)	From (8.6 -1667.4) to 864.9713	From (442.99-551332.89) to 11864	From (6-225) to 99.042
Unit cost price ($)	From (0.17-280.07) to 126.1363	From (0.81-85.58) to 5.67	From (115.9-329997.14) to 29876.505
Fixed order cost ($)	From (12.19 -304.71) to 106.9074	From (12846.71-446579.6) to 115.047	From ((17746.4-16414450) 818652.970
Lead time(days)	From (4-14) to 4.6896	From (15-25) to 18.902	From (30-30) to 30
EOQ	From (5.7-1070) to 728.3822	From (162.84-35298.9) to 14903.06	From (46.9-1058.6) to 212.034
ROP	From (0.2-45.9) to 31.8502	From (78.46-82972.2) to 22704.461	From (0.7-27) to 16.782
Number of orders n*	From (0.8-2.9) to 1.1745	From (2.72-15.62) to 3.592	From (0.1-0.2) to 0.122
Holding cost ($)	From (16.48-474.83) to 392.2809	From (1025.31-15529.89) to 4055.660	From (3417.5-3743152.4) to 1623815.404
Ordering cost ($)	From (16.48-474.83) to 342.6963	From (1025.31-15529.89) to 4055.660	From (3417.5-3743152.4) to 1623815.404

Table 9. The result of the validation for the total cost.

Results of references	Total cost before applying MPSO	With MPSO (Proposed)
(Gonzalez and González, 2010).	949.65$	313.4366$
(Pang et al., 2019)	465639.38$	140278.601$
Proposed	7486304.8 $	2418000$

Table 10. Sensitivity analysis results

Demand	Holding Cost rate	EOQ	Total Cost
160.0	0.05	178.89	894.43
160.0	0.06	163.3	979.8
160.0	0.07	151.19	1058.3
160.0	0.08	141.42	1131.37
160.0	0.09	133.33	1200.0
160.0	0.1	126.49	1264.91
160.0	0.11	120.6	1326.65
160.0	0.12	115.47	1385.64
160.0	0.13	110.94	1442.22
160.0	0.14	106.9	1496.66
170.0	0.05	184.39	921.95
170.0	0.06	168.33	1009.95
170.0	0.07	155.84	1090.87
170.0	0.08	145.77	1166.19
170.0	0.09	137.44	1236.93
170.0	0.1	130.38	1303.84
170.0	0.11	124.32	1367.48
170.0	0.12	119.02	1428.29
170.0	0.13	114.35	1486.61
170.0	0.14	110.19	1542.72
180.0	0.05	189.74	948.68
180.0	0.06	173.21	1039.23
180.0	0.07	160.36	1122.5
180.0	0.08	150.0	1200.0
180.0	0.09	141.42	1272.79
180.0	0.1	134.16	1341.64
180.0	0.11	127.92	1407.12
180.0	0.12	122.47	1469.69
180.0	0.13	117.67	1529.71
180.0	0.14	113.39	1587.45
190.0	0.05	194.94	974.68
190.0	0.06	177.95	1067.71
190.0	0.07	164.75	1153.26
190.0	0.08	154.11	1232.88
190.0	0.09	145.3	1307.67
190.0	0.1	137.84	1378.4
190.0	0.11	131.43	1445.68
190.0	0.12	125.83	1509.97
190.0	0.13	120.89	1571.62
190.0	0.14	116.5	1630.95
200.0	0.05	200.0	1000.0

200.0	0.06	182.57	1095.45
200.0	0.07	169.03	1183.22
200.0	0.08	158.11	1264.91
200.0	0.09	149.07	1341.64
200.0	0.1	141.42	1414.21
200.0	0.11	134.84	1483.24
200.0	0.12	129.1	1549.19
200.0	0.13	124.03	1612.45
200.0	0.14	119.52	1673.32
210.0	0.05	204.94	1024.7
210.0	0.06	187.08	1122.5
210.0	0.07	173.21	1212.44
210.0	0.08	162.02	1296.15
210.0	0.09	152.75	1374.77
210.0	0.1	144.91	1449.14
210.0	0.11	138.17	1519.87
210.0	0.12	132.29	1587.45
210.0	0.13	127.1	1652.27
210.0	0.14	122.47	1714.64
220.0	0.05	209.76	1048.81
220.0	0.06	191.49	1148.91
220.0	0.07	177.28	1240.97
220.0	0.08	165.83	1326.65
220.0	0.09	156.35	1407.12
220.0	0.1	148.32	1483.24
220.0	0.11	141.42	1555.63
220.0	0.12	135.4	1624.81
220.0	0.13	130.09	1691.15
220.0	0.14	125.36	1754.99
230.0	0.05	214.48	1072.38
230.0	0.06	195.79	1174.73
230.0	0.07	181.27	1268.86
230.0	0.08	169.56	1356.47
230.0	0.09	159.86	1438.75
230.0	0.1	151.66	1516.58
230.0	0.11	144.6	1590.6
230.0	0.12	138.44	1661.32
230.0	0.13	133.01	1729.16
230.0	0.14	128.17	1794.44

The fixed settings for the simulation runs previously shown in **Table 2** were subjected to a sensitivity analysis. Only the holding cost and the demand were altered. All other parameters remained unchanged. When demand increases from 160 to 230 (a gradual increase of 10), the Total Cost increases significantly. Also, when the holding cost rate increases from 5% to 14%, the Total Cost increases, but differently. The table displays the key variables and their impact on the Total Cost as the analysis output. The sensitivity analysis results have been shared in **Table 10** and visualized through two plots. **Fig. 9** shows how the total inventory cost changes with varying demand levels for holding cost rates. Moreover, **Fig. 10** illustrates the relationship between EOQ and holding cost rates for different demand levels. When the holding cost increases, the EOQ reduces while the total cost increases. These figures can guide adjustments to inventory policies under varying conditions.

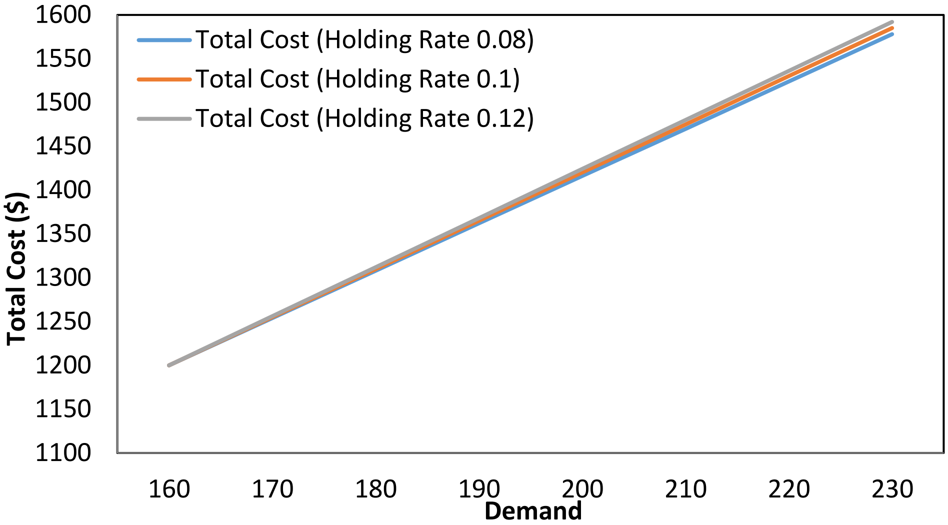

Figure 9. Total Cost vs Demand for different Holding Cost rates

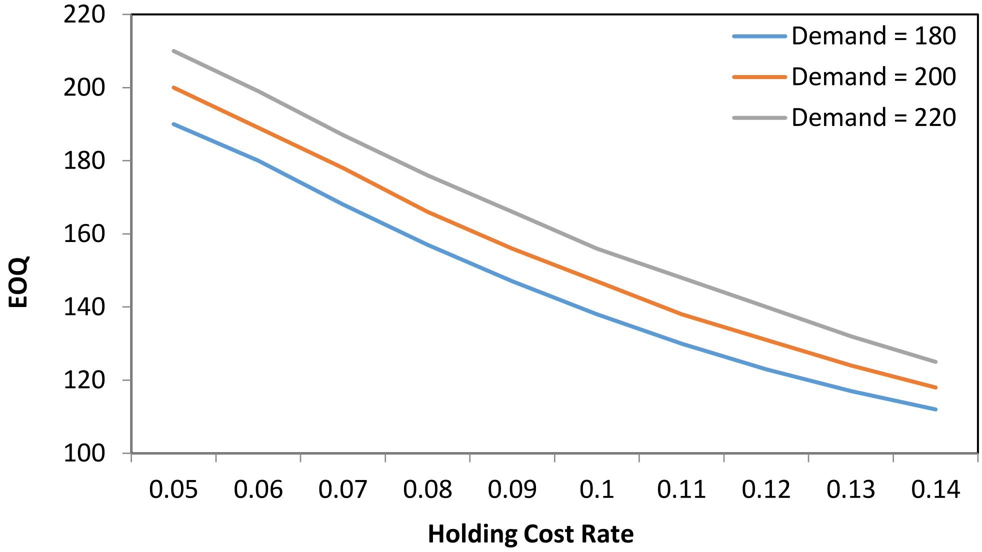

Figure 10. EOQ vs Holding Cost Rate

5. CONCLUSIONS

This research presents a hybrid algorithm that combines Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO). Using the PSO approach, the modification method effectively applies the inertia adjustment equation during each solution update. The findings clearly compare the results of the classical CPSO and the modified MPSO. The MPSO-ANN algorithm demonstrates improved convergence and achieves better total inventory cost outcomes compared to both classical PSO and EOQ calculations. Implementing modified PSO can lead to substantial cost savings in inventory management, and the findings highlight the effectiveness of modified algorithms in minimizing inventory costs for electrical products. It can be applied to industries facing similar inventory challenges, as seen in other studies

emphasizing the importance of effective inventory control models. The electrical facility should be using this hybrid model to enhance their system instead of depending on Excel, which could help them reduce the total cost. The MPSO algorithm is recommended for use in solving inventory optimization problems in the electrical industry. Minimizing inventory costs directly reduces operational expenses. By optimizing inventory management, electrical facilities can reduce the need for excessive storage space, lower holding costs, and minimize losses due to obsolete or overstocked parts. This leads to improved profitability for the business. The findings of this research can offer the industry significant cost-saving opportunities. The performance of PSO is highly sensitive to its parameters, such as the cognitive and social coefficients and the inertia weight. Poorly chosen parameters can lead to ineffective search behavior, causing slow or premature convergence.
Some recommendations for future work are to extend the intelligent order management system to incorporate dynamic pricing strategies based on real-time market conditions and customer demand signals by using other artificial intelligence algorithms and involve demand forecasting to eliminate the variability in the demand for the future. The model (PSO-ANN) should aim for the usual forecast and target series fitness. The model may automatically decide the forecasting targets, such as the actual rate, percentage of changes, etc. The model should use a trading strategy to recommend the trading rules based on the expectation of returns and risk. In my opinion, for future work, the best solution would not be an optimization model but a compromise solution. Such a solution could be, for example, a model that allows calculating a level of stock by a given level of customer service and then calculating the total costs, which will be effective in future work.

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Credit Authorship Contribution Statement

Ayat Deah Hamdan: Writing – review & editing, Writing – original draft. Iman Q. Al Saffar: Review & editing, Validation, Methodology and Supervising.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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تنفيذ ذكاء خوارزمية سرب الطيور في السيطرة على الخزين في قطاع المواد الكهربائية: دراسة حالة

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قسم الهندسة الميكانيكية، كلية الهندسة، جامعة بغداد، بغداد، العراق.

الخلاصة

إدارة المخزون المثلى هي قضية مهمة في العديد من الشركات وقد تؤثر على إنتاجيتها وربحيتها. يستهدف بحثنا منشأة للطاقة الكهربائية في العراق للعثور على الكميات المثلى وتكاليف المخزون التي تقلل من إجمالي تكلفة المخزون بما في ذلك التوريد، والتخزين، والنقل، والتفتيش. يقارن البحث بين تحسين سرب الجسيمات التقليدي (CPSO) وتحسين سرب الجسيمات المعدل (MPSO).يتم استخدام الشبكة العصبية الاصطناعية لربط العلاقة بين المدخلات والمخرجات لتشكيل دالة تكلفة. أنتجت استراتيجية MPSO توفيرًا أفضل في التكاليف مقارنةً بكل من CPSO أو الطرق التقليدية .(EOQ) أنتج نظام كمية الطلب الاقتصادية التقليدي تكاليف إجمالية قدرها 7486304,8 دولارًا، ولكن CPSO خفضها إلى 5414100 دولار، بينما خفضتها MPSOإلى 2418000 دولار عند التحكم في 20 عنصرًا كهربائيًا. تظهر النتيجة أن MPSO يحقق نتائج أفضل من الطرق التقليدية و CPSOعندما يتعلق الأمر بتخفيض كلف الخزين. تم إجراء تحليل الحساسية لبعض المدخلات المهمة، وتم التحقيق في التغيرات في دالة الهدف. أخيرًا، تم حل دراستين حالتين في السيطرة على المخزون في صناعات مختلفة للتحقق من صحة الخوارزمية المقترحة والنتائج التجريبية.

الكلمات المفتاحية: الشبكة العصبية الاصطناعية، كمية الطلب الاقتصادية، الخوارزمية الهجينة، التحكم في المخزون، خوارزمية سرب الطيور.