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Sustainable Production-Inventory Model with Multi-Material, Quality Degradation, and Probabilistic Demand: From Bibliometric Analysis to A Robust Model

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ABSTRACT

An adequate sustainable production inventory model is expected to represent complex real-life cases involving fuel, emissions, and electricity costs as well as multi-materials, quality degradation, and probabilistic demand. Therefore, this study was conducted to develop this kind of model to determine the number of raw material shipments (m_j), production cycle time (T), and the number of finished goods delivered (n) to maximize the Expected Total Profit (ETP). The proposed model is based on a bibliometric literature analysis of the sustainable production-inventory problem which is visualized using the VOSviewer. Moreover, a sophisticated Harris-Hawks Optimization (HHO) algorithm was proposed to solve the problems identified in the sustainable production inventory model optimization. It is also important to note that three numerical cases were provided to evaluate the performance of the algorithm. The findings showed that the suggested HHO method outperforms the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in maximizing ETP and this means it is better for ETP optimization. It was also discovered from the sensitivity analysis that an increase in the rate of quality degradation (k) led to a reduction in both the ETP and T.

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1. INTRODUCTION

Sustainability is currently an important global issue and has promotes stakeholders to focus on increasing the economic, environmental, and social dimensions (Negri *et al.*, 2021). This requires implementing sustainable practices in industries to significantly reduce emissions, conserve resources (Mashud *et al.*, 2022; Taghikhah *et al.*, 2019), and solve social problems. The concept is being applied widely to supply chain activities and has been proven to be effective in improving company performance (Ho *et al.*, 2022; Shekarian *et al.*, 2022; Wang *et al.*, 2019). Meanwhile, it is important to note that procurement, production, and distribution decisions in supply chain systems can affect supply chain performance (Lu *et al.*, 2020; Maulana *et al.*, 2020).

This is the reason scholars have attempted to integrate inventory decisions into the supplier and manufacturing levels (Utama *et al.*, 2022a; Utama *et al.*, 2022b), internal manufacturing (Liu *et al.*, 2021), and manufacturing-customer relationship. One of the problems identified in integrated inventory is the production and procurement system which is popularly known as the Production Inventory model (Goyal & Deshmukh, 1992; Park, 1983). This led to the conduct of several relevant studies to solve this problem through the optimization of only the economic dimension. Therefore, there is a need to investigate the environmental and social dimensions.

Different forms of sustainable production inventory models have been proposed with most of the previous studies discovered to have focused on minimizing one indicator of the environmental aspect such as electricity costs (Gautam *et al.*, 2022), fuel consumption (Sarkar *et al.*, 2017; Utama *et al.*, 2022a; Wangsa & Wee, 2018), and emissions (Jaber *et al.*, 2013; Jauhari *et al.*, 2022; Ullah *et al.*, 2021).

Others also attempted to combine two indicators such as fuel consumption and emissions in developing a new model (Wangsa, 2017; Wangsa *et al.*, 2020). It was discovered that only Jauhari (2022) considered fuel, emissions, and electricity costs simultaneously. Moreover, it is also important to consider quality degradation in this model due to its existence in several industries including pharmaceutical (Silva-Aravena *et al.*, 2020), food (Ibrahim *et al.*, 2020; Lee *et al.*, 2015), and agro-industry (Liu *et al.*, 2018).

Most previous studies assumed that a single finished product requires a single raw material (SRM) (Bhattacharjee & Sen, 2022). This means their models cannot be applied to products requiring multiple raw materials (MRM). The studies also assumed that product demand is deterministic (Fiorotto *et al.*, 2021) without any consideration for stochastic demand.

Advanced metaheuristic procedures have been proposed to optimize production inventory models based on the rapid advances in computer technology. These include Particle Swarm Optimization (PSO) (Taleizadeh *et al.*, 2010) and Genetic Algorithms (GA) (Sadeghi *et al.*, 2011), as well as the integration of the two algorithms (Sadeghi *et al.*, 2013).

However, no study used the Harris-Hawks Optimization (HHO) algorithm to optimize the sustainable production inventory model problem. It was discovered that Heidari *et al.* (2019) only proposed the HHO algorithm by mimicking Harris Hawks' herd behavior in hunting prey.

The algorithm was reported to have good performance in optimizing scheduling (Utama & Widodo, 2021), forecasting (Chaudhuri & Alkan, 2022), energy (Dev *et al.*, 2022), and engineering field (Shehab *et al.*, 2022). This means it has the potential to solve the problems associated with the sustainable production inventory model.

Only a few studies considered fuel, emissions, and electricity cost indicators simultaneously in a sustainable production inventory model. It was discovered that none considered the multi-material, quality degradation, and probabilistic demand indicators and this is the primary motivation for this study.

The gaps in sustainable production inventory model research are also evident in the bibliometric literature analysis presented in section 2. Furthermore, HHO advanced algorithm was reported to have the potential to solve the problem of a sustainable production inventory model but it has not been applied for this purpose.

This study also proposes to apply the HHO algorithm in resolving problems associated with the model. Therefore, the Research Goals (RG) include (RG 1) developing a sustainable production inventory model that considers multi-materials, quality degradation, and probabilistic demands and (RG 2) applying the HHO algorithm to optimize the problems in the model.

This means the practical contributions involved include:

(i) the development of a new model of sustainable production inventory by considering multi-materials, quality degradation, and probabilistic demands; and

(ii) the application of the HHO algorithm as an optimization tool to solve the problems of sustainable production inventory model.

The structure of this paper is below: Section 2 provides a literature review and bibliometric analysis of the sustainable production inventory model. Section 3 describes the system's characteristics, assumptions, notations, and the proposed model on the sustainable production inventory model. The proposed algorithm for optimizing the sustainable production inventory model is presented in Section 4. Section 5 provides study data and procedures. Section 6 presents results and discussions. Finally, this article concludes with conclusions.

2. LITERATURE REVIEW AND BIBLIOMETRIC ANALYSIS

2.1. Bibliometric Analysis

This section presents the bibliometric problem of the sustainable production inventory model. The keywords used for this search are "Sustainable" and "Production" or "Inventory" and "Model". Fifty papers were collected from the Scopus database published in 2013-2022.

Figure 1 presents the development of article publications related to the sustainable production inventory model. This result shows that this topic started to be published in 2013. This topic increased dramatically from 2020-2022, and 17 papers were published in 2022.

Network Visualization of sustainable production inventory keywords based on VOSviewer is depicted in **Figure 2**. This result shows that 6 clusters were identified based on co-occurrence analysis. The main popularly used keywords are presented in cluster 1 (red color).

In this cluster, the main keywords are sustainable inventory model and its derivatives, such as sustainable economic production quantity (EPQ), controllable carbon emission, deteriorating, green technology, and shortage.

The second cluster (green color) includes a sustainable integrated inventory model, sustainable supply chain, controllable lead time, sustainable location, defective items, and stock levels that focus on the supply chain network.

The third cluster (blue) categorizes terms related to the economic order quantity, green inventory model, supply lead time uncertainty, and sustainable order quantity inventory model that focuses on the model for order quantity.

The fourth cluster in yellow is a group of sustainable production inventory model problems.

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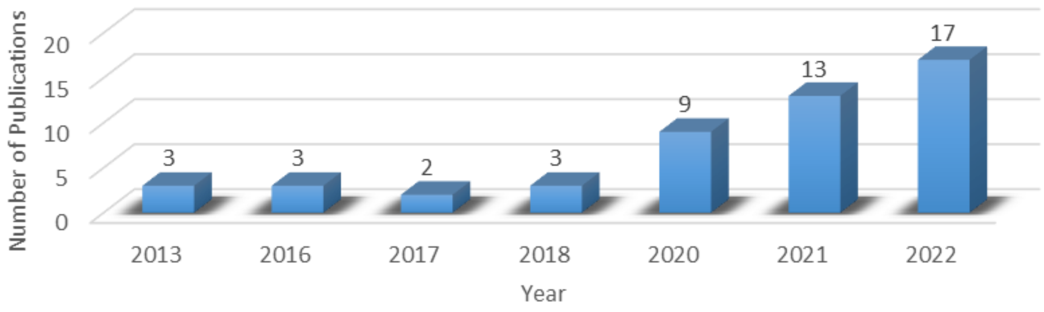

Figure 1. Development of article publications related to sustainable production inventory model.

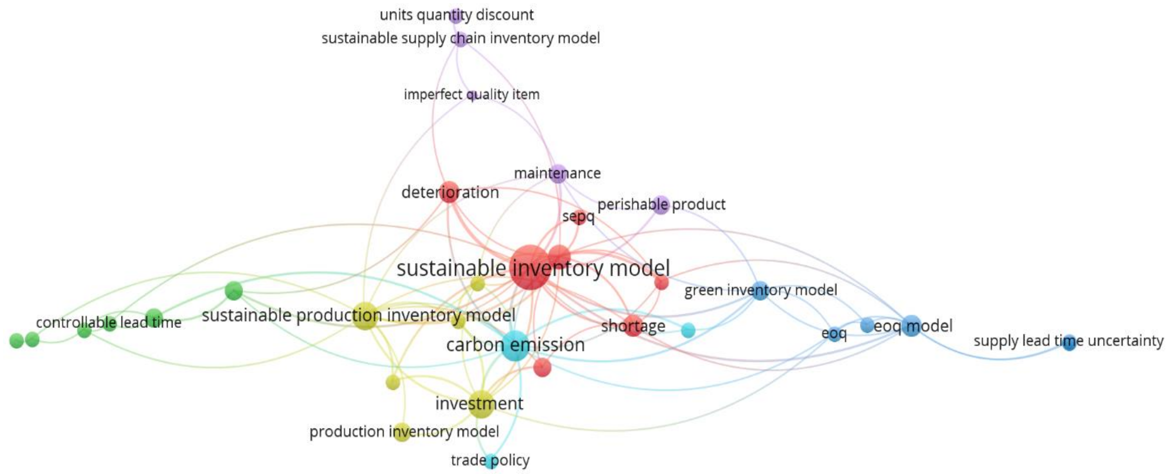

Figure 2. Network Visualization of sustainable production inventory keyword.

In this cluster, some related derivative keywords are investment, carbon emission, collaborative investment, preservation technology, and production inventory model. This cluster shows that the consideration of quality degradation, multi-raw materials, and stochastic demand are not discussed in previous studies. The fifth cluster (purple color) shows the cluster group of sustainable supply chain inventory models with qualities such as imperfect quality, perishable products, maintenance, and unit quantity discount. The last cluster in light blue is the green inventory management cluster with derivatives such as carbon emission and trade policy.

Finally, **Figure 3** analyzes co-occurrence by all keywords with an overlay visualization. The analysis results show that the most used keywords between 2021 and 2022 correspond to the green and yellow colors: carbon emission, sustainable production inventory model, defective items, and trade policy.

2.2. Content Analysis and Gaps

Based on the bibliometric analysis, Content Analysis, and Gaps model sustainable production inventory is explained in this section. Previous studies that have been conducted concerning the problems of the sustainable production inventory model are reviewed with a focus on the integration of production and inventory policies. It is pertinent to note that the procurement and production subsystems are interconnected in making decisions on raw material procurement and finished goods production. The model was initially proposed by Goyal (1977) and GoyalDeshmukh (1992) to minimize total costs.

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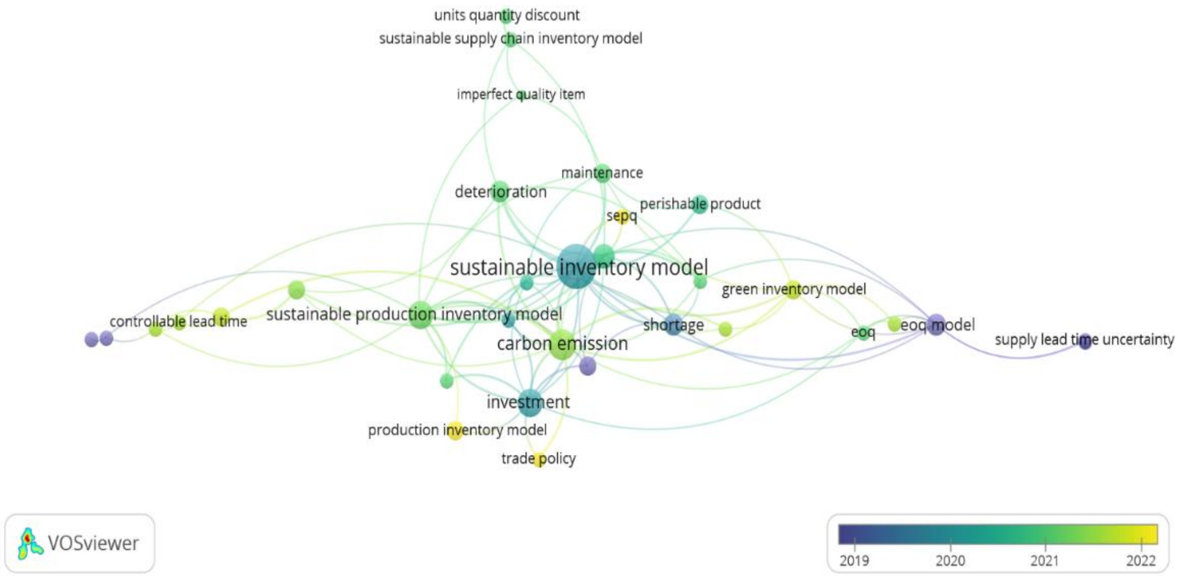

Figure 3. Analysis of representative terms on the subject over time.

Sustainability requires an integrated and collaborative approach in supply chain networks. It is also important to note that sustainable inventory management is one aspect of sustainable supply chain management (Becerra *et al.*, 2021) which is critical and recognized as corporate social and environmental responsibility (Pattnaik *et al.*, 2021). The previous studies that have been conducted on sustainable production inventory models are summarized in **Table 1**. It was discovered that most of these studies focused on the complexities of Single Raw Material (SRM), Single Stage Production (SSP), and Single Product (SP).

This means attention was generally on the development of economic and environmental models consisting of emission cost and fuel usage without consideration for the quality degradation in raw materials. It was also discovered that they mostly consider customer demand while deterministic and heuristic procedures are the popular methods applied to solve the problem.

There is no present study conducted on the sustainable production inventory model that considers multiple materials, quality degradation, and probabilistic demand. Therefore, this study was conducted to fill this gap by proposing a new model that considers these indicators. The HHO algorithm which is classified as a metaheuristic procedure was also proposed to optimize the problems associated with the sustainable production inventory model.

3. SYSTEM CHARACTERISTICS, ASSUMPTIONS, NOTATIONS, AND PROPOSED MODEL

3.1. System Characteristics

The proposed model was designed to address the shortcomings of earlier models. It can represent complex real cases due to the inclusion of the costs for fuel, emissions, electricity, multi-materials, quality degradation, and probabilistic demand in the model. Moreover, **Figure 4** shows the sustainable production inventory system which includes the raw material procurement, production, and distribution activities. The figure shows the process through which products are produced to meet the stochastic demands of buyers (D) using several raw materials (j) ordered from suppliers. It is pertinent to state the producers are required to order raw materials from suppliers m times for each raw material j (m_j).

Table 1. Literature Review on the sustainable production inventory model

Research	Complexity-Based Classification						Fuel cost	Tax emission	Electricity cost	Demand Characteristic	Quality Degradation	Optimization Tools
	SRM	MRM	SSP	MSP	SP	MP						
(Fiorotto *et al.*, 2021)	-	√	√	-	√	-	-	-	-	Deterministic	-	Exact
(Fang *et al.*, 2016)	-	√	√	-	√	-	-	-	-	Deterministic	-	Heuristic
(Budiman & Rau, 2021)	-	√	-	√	-	√	-	-	-	Stochastic	-	Heuristic
(Omar & Zulkipli, 2018)	√	-	√	-	√	-	-	-	-	Deterministic	-	Exact
(Karabağ & Tan, 2019)	√	-	√	-	√	-	-	-	-	Deterministic	-	Metaheuristic
(Khara *et al.*, 2020)	√	-	√	-	-	√	-	-	-	Deterministic	√	Heuristic
(Shafiee *et al.*, 2021)	-	√	√	-	-	√	-	√	-	Deterministic	√	Hybrid
(Jauhari *et al.*, 2022)	√	-	√	-	√	-	√	-	√	Stochastic	-	Heuristic
(Jauhari, 2022)	√	-	-	√	√	-	√	-	√	Stochastic	-	Heuristic
(Mashud *et al.*, 2022)	√	-	√	-	√	-	-	-	-	Deterministic	√	Heuristic
(Wangsa *et al.*, 2020)	√	-	√	-	√	-	√	-	-	Stochastic	-	Heuristic
(Gautam *et al.*, 2022)	√	-	√	-	√	-	-	-	√	Deterministic	-	Heuristic
(Bhattacharjee & Sen, 2022)	√	-	√	-	√	-	√	-	√	Deterministic	√	Heuristic
(Mishra *et al.*, 2020)	√	-	√	-	√	-	√	√	-	Deterministic	√	Heuristic
(Mashud *et al.*, 2022)	√	-	√	-	√	-	√	√	-	Deterministic	√	Heuristic
(De-la-Cruz-Márquez *et al.*, 2021)	√	-	√	-	√	-	-	√	-	Stochastic	-	Heuristic
This research (2022)	-	√	√	-	√	-	√	√	√	Stochastic	√	Metaheuristic

Where: Single Raw Material (SRM), Multi Raw Material (MRM), Single Stage Production (SSP), Multi-Stage Production (MSP), Single Product (SP), Multi Product (MP)

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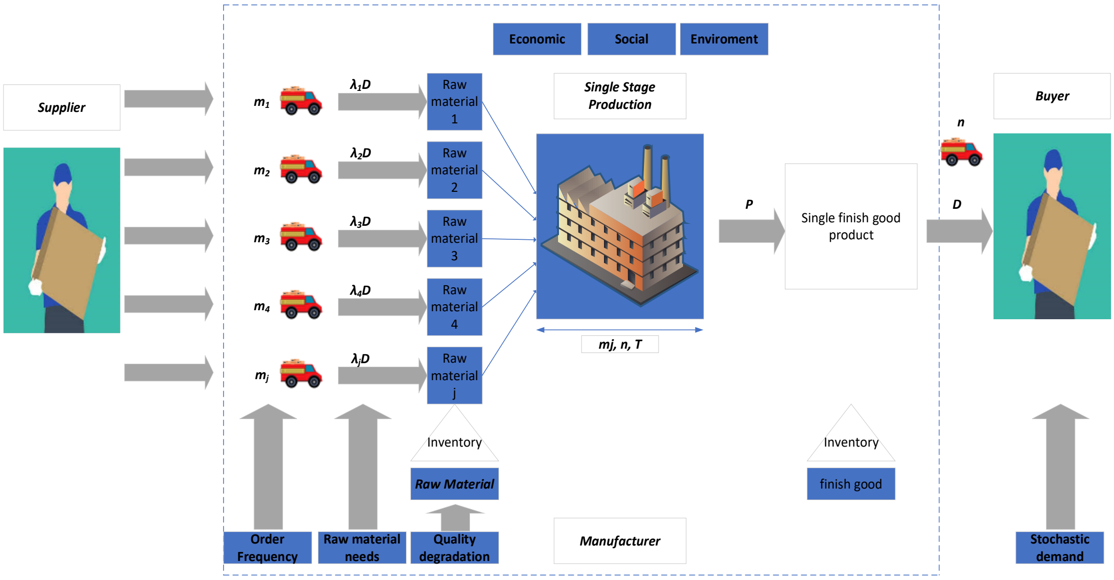

Figure 4. Characteristics of the sustainable production inventory model system.

The system has different requirements for each raw material to produce a finished product. This is indicated by the fact that each raw material j has a requirement coefficient λ (λ_j) to produce a food product. The system also considers the degradation of the quality of the raw materials over time to ensure appropriate optimization of those in the warehouse inventory.

Moreover, the system requires that the producers determine the production cycle (T), the finished goods to be sent to buyers in n times as well as each raw material to be ordered m times (m_j). The goods are produced at a production rate (P) which is more than the buyer demand (D).

3.2. Assumptions and Notations

The assumptions made in developing the mathematical models to represent the problem are stated as follows:

a) Demand for finished goods is probabilistic based on the normal distribution.

b) The finished good production rate exceeds the product demand rate $(P > D)$. This is to ensure all the demands are met.

c) Raw material j has the highest quality (Q_{max_j}) when it arrives in the warehouse for manufacturing.

d) Each raw material is adequate to meet production requirements. None of the raw materials is also expected to expire during the planning period because the producers have complete control over the procurement process.

e) There is no shortage of raw materials because suppliers can meet demands.

f) The buyer's request for a shortage of finished goods is permitted.

g) The quantity of raw materials ordered is not limited by vehicle capacity.

h) Vehicle capacity does not limit the number of finished good shipments.

The notation used in this model includes:

Index

j : index of raw materials $j = 1 \ldots N_r$

Parameters

P : production rate

D : finished good demand

N_r : number of raw materials

λ_j : the requirement of a finished good on j raw materials

q_{0_j} : order quantity of raw materials j

q_1 : finished good delivery quantity

k_j : rate of degradation quality of the j-th raw materials per unit of time

Q_{max_j} : maximum quality on j-th raw materials

Q_{min_j} : minimum quality on the j-th raw materials

$Q_j(t)$: quality remaining of the j-th raw materials in period t

$\Delta Q_j(t)$: quality degradation of the jth raw material until period t

τ_{max_j} : duration j-th raw materials can be stored

c_{loss_j} : loss costs quality of the j-th raw materials

c_{loss_p} : loss sales cost of finished goods

c_{sale} : finished goods selling price

c_{0_j} : purchasing cost of the j-th raw materials

c_1 : processing cost of the finished good

A_{0_j} : ordering cost of the j-th raw materials

$\mathrm{Tr_j}$: transportation costs for the j-th raw material

T_{pi} : finished good transportation costs

ar_j : fixed cost of transportation on the j-th raw material

$\mathrm{a_p}$: fixed costs of transportation of finished goods

$\mathrm{dr_j}$: distance of the j-th raw material supplier

$\mathrm{d_p}$: distance between the producer and the buyer

$KPLr_{\mathrm{j}}$: kilometers per litre for the j-th raw material procurement unload

$KPLr^*{}_{\mathrm{j}}$: kilometers per litre for the j-th raw material procurement full load

$\mathrm{KPL_p}$: kilometers per litre of unloading for delivery of finished goods

$\mathrm{KPL_p}^*$: kilometers per litre for the shipment of finished goods with a full load

$\beta_{\mathrm{r_j}}$: fuel cost for the shipment of the j-th raw material

β_{p} : fuel cost used to deliver the finished good

ρ_j : emissions for 1 litre of fuel in the j-th raw material shipment

ρ_p : emissions for 1 litre of fuel at product delivery

ρ_m : emissions for the production of each unit of product

ρs_m : emissions for production setups

ρi_m : emissions for finished goods inventory

$\rho 0_j$: emissions for the j-th raw material inventory

ε_{t} : emission tax per kg

ς_j : fixed social cost of procurement the j-th raw material per horizon

ς_{r_j} : social cost of procurement the j-th raw material per order

ς_{p} : social costs of delivering the finished good

ς_{fp} : social fixed costs of manufacturing

ς_{mp} : the social cost of manufacturing once produced

ς_{mi} : social costs of inventory finished goods

$\varsigma_{\mathrm{ir}_j}$: social cost of the j-th raw material inventory

ϵ_s : energy required for the production setup

ϵ_p : energy required to produce each unit

ϵ_i : energy required for storage of the finished good

$\epsilon 0_j$: energy required for the inventory of the j-th raw material

C_ϵ : energy tariff per kWh

K : safety factor

σ : standard deviation demands

SS : safety stock

EL : estimated cost of loss sales of finished goods

$f_s(K)$: probability density function of the normal distribution

$F_s(K)$: cumulative distribution function of the normal distribution

S : setup costs for processing the finished good

H_{0_j} : inventory costs for the j-th raw materials

H_1 : finished good inventory costs

I_{0_j} : average inventory for the j-th raw materials

I_1 : average finished good inventory

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L_j : total costs due to degradation of the quality of the j-th raw materials

TC_{0_j} : total cost of the j-th raw materials procurement system

ETC_1 : expected total cost of the finished good

ETP : expected total profit in the sustainable production Inventory system

Decision Variable

m_j : frequency shipment the j-th raw materials

T : production cycle time

n : delivery frequency of finished goods

3.3. The Proposed Model of Sustainable Production Inventory

The proposed model for sustainable production inventory problems associated with multi-raw materials and quality degradation is discussed in this section. It is important to note that the quality degradation of each raw material j was used to calculate the costs incurred by the company due to the reduction in quality. Therefore, a kinetic model function was used in this study to formulate the degradation of raw material quality in the inventory system (Rong *et al.*, 2011). It was assumed that the entire supply of raw materials j (q_{0_j}) was used for only production purposes (P) during the procurement cycle (T_p/m_j). It was also assumed at the beginning of the filling cycle that the raw material quality level j is the maximum level (Q_{max_j}). Moreover, the degradation rate formula at time t or $Q(t)$ is shown in Equation (1) and the quality loss for raw material j for production at time t is presented in Equation (2).

The raw material quality degradation was estimated by determining the maximum quality of j-th (Q_{max_j}), achieving minimum quality level (Q_{min_j}), and the j-th maximum duration (τ_{max_j}). Furthermore, Equation (3) indicates the model of the decline rate of raw material j quality in each period t. The linear relationship between the quality degradation j from period 0 (Q_{max_j}) to t is also modeled in Equation (4). The total cost quality reduction j ($L_j(m_j, T)$) during period t is indicated in Equation (5).

Figure 5 shows the system profile of the sustainable production inventory model designed for the problems investigated. It was discovered that there are two levels of inventory including the finished products and raw materials j. For finished products, the raw materials are processed in the amount of $\lambda_j P$ with a production time of T_p to meet the demand of buyers (D). Where λ_j indicates the j-th raw material needed to have a finished product. Moreover, the producers are required to ensure the production rate (P) is greater than demand (D) and the rate of raw material j needed for production is $\lambda_j P$. It is important to note that the proposed model estimates the number of finished products during the production cycle (T) to meet demand based on $q_1 = DT$ with $T_p = DT/P$. The finished products are also poured in batches (q_1) and sent to sales with the delivery frequency of n times. This makes it possible to estimate the cycle of finished product orders by sales using q_1/D. For the raw material inventory, producers obtain raw materials from suppliers with size q_{0_j} and procurement cycles $\frac{q_{0_j}}{\lambda_j D}$. These materials are subsequently sent to the producers with a delivery frequency of m_j times.

The demand for finished products (D) in this problem is stochastic based on the normal distribution and this means it can be estimated using the mean $D(T)$ and the standard deviation $\sigma\sqrt{T}$ during the period T. Moreover, the average inventory was estimated by calculating the average T-period inventory added with the safety stock (Jauhari *et al.*, 2021; Jauhari *et al.*, 2011). The safety stock formula in inventory is indicated in Equation (6). It is also possible for finished products to experience a loss of

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sales due to stochastic demand. These lost sales are estimated in period T using Equations (7) and (8) while the inventory for the finished products (I_1) and raw materials j (I_{0_j}) is modelled in Equations (9) and (10).

The proposed transportation model assumes that the vehicle departs to pick up raw materials with an empty load. Therefore, the model to procure raw materials from suppliers is presented in Equation (11) and the model to ship finished products is formulated in Equation (12). The costs related to raw material management are calculated in Equation (13) while the expected total cost of the finished product system $(TC_1(n,T))$ is presented in Equation (14). Moreover, the formula to determine the total revenue $(TR(n,T))$ in the system is indicated in Equation (15).

The Mixed-Integer Nonlinear Programming equation presented in Equation (16) is designed to predict the total revenue of the system under study with the constraints identified in Equations (17)-(19).

The Expected Total Profit (ETP) of the model is shown in Equation (16) with certain constraints required to be satisfied during optimization. First, the production level needs to meet all the demands in Equation (17). Second, the production cycle requirement in Equation (18) needs to be greater than 0. Third, the constraint in Equation (19) ensures the delivery frequency of raw materials j and finished products need to be an integer that is greater than 1. It is important to note that profit maximization was conducted through the simultaneous determination of the optimal decision variables including m_j, n, and T.

$$Q_j(t) = Q_{max_j} - k_j t \quad (1)$$

$$\Delta Q_j(t) = Q_{max_j} - Q_j(t) \quad (2)$$

$$k_j = \frac{Q_{max_j} - Q_{min_j}}{\tau_{max_j}} \quad (3)$$

$$\Delta Q_j(t) = k_j t \quad (4)$$

$$L_j(m_j, T) = c_{loss_j} \frac{m_j \lambda_j P}{T} \int_0^{\frac{\lambda_j DT}{m_j \lambda_j P}} \Delta Q_j(t)\, dt \quad (5)$$

$$SS = K\sigma\sqrt{T} \quad (6)$$

$$EL = \sigma\sqrt{T}\psi(K) \quad (7)$$

$$\psi(K) = (f_s(K) - K[1 - F_s(K)]) \quad (8)$$

$$I_1 = \frac{DT}{2n}\left(\frac{D}{P}(2-n) + (n-1)\right) + K\sigma\sqrt{T} \quad (9)$$

$$I_{0_j} = \frac{\lambda_j D^2 T}{2 m_j \lambda_j P} \quad (10)$$

$$T_{pi} = (\mathrm{a}_p + \varsigma_p) + \frac{d_p}{KPL_p} * (\beta_p + \rho * \varepsilon_t) + \frac{d_p}{KPL_p - \mathrm{KPL_p}^*} \frac{\mathrm{DT}}{n} (\beta_p + \rho_p * \varepsilon_t) \quad (11)$$

$$\mathrm{Tr_j} = (\mathrm{ar}_j + \varsigma_{\mathrm{r}_j}) + \frac{\mathrm{dr_j}}{KPLr_{\mathrm{j}}} (\beta_{\mathrm{r_j}} + \rho_j * \varepsilon_t) + \frac{\mathrm{dr_j}}{KPLr_{\mathrm{j}} - KPLr^*{}_{\mathrm{j}}} \frac{\lambda_j DT}{m_j} (\beta_{\mathrm{r_j}} + \rho_j * \varepsilon_t) \quad (12)$$

$$TC_0(m_j, T) = \sum_{j=1}^{N_r} \left(c_{0_j}\lambda_j D + \varsigma_j + (A_{0_j} + \mathrm{Tr_j})\frac{m_j}{T} + (H_{0_j} + \varsigma_{\mathrm{ir}_j} + \epsilon 0_j * C_\epsilon + \rho 0_j * \varepsilon_t) I_{0_j} + c_{loss_j} \frac{m_j \lambda_j P}{T} \int_0^{\frac{\lambda_j DT}{m_j \lambda_j P}} \Delta Q_j(t)\, dt \right) \quad (13)$$

$$ETC_1(n,T) = (c_1 + \epsilon_p * C_\epsilon + \rho_m * \varepsilon_t) * D + \varsigma_{\mathrm{fp}} + \frac{(S + \varsigma_{\mathrm{mp}} + \epsilon_s * C_\epsilon + \rho s_m * \varepsilon_t)}{T} + \frac{T_{pi} * n}{T} + (\varsigma_{\mathrm{mi}} + \epsilon_i * C_\epsilon + \rho i_m * \varepsilon_t + H_1) I_1 + EL^* c_{loss_p} \quad (14)$$

$$TR(n,T) = c_{sale} D \quad (15)$$

$$ETP(m_j, T, n) = TR(n,T) - \left(TC_0(m_j, T) + TC_1(n,T)\right) \quad (16)$$

$$P \geq D; \quad (17)$$

$$T > 0; \quad (18)$$

$$m_j, \quad n \quad \geq 1; \text{ and Integer} \quad (19)$$

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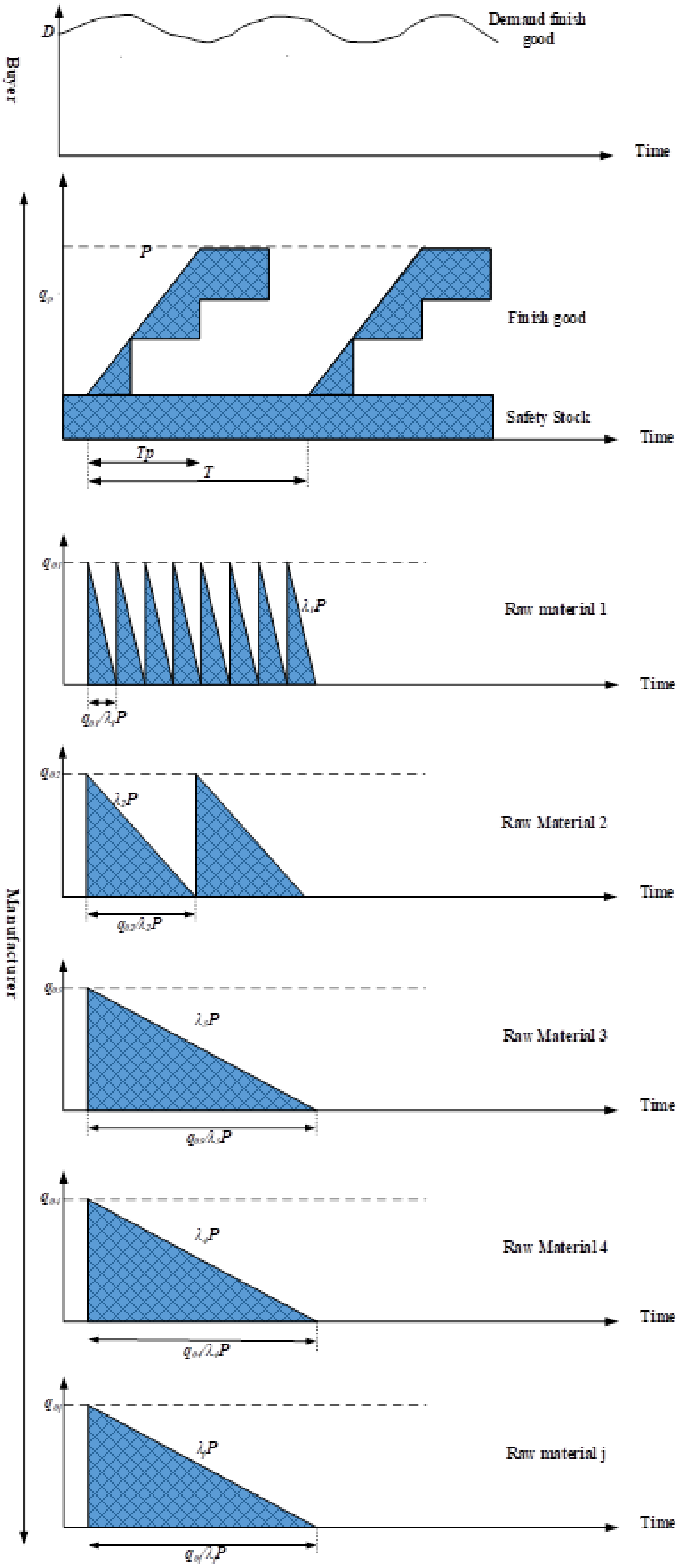

Figure 5. System profile of the sustainable production inventory model.

4. PROPOSED ALGORITHM

An HHO algorithm was proposed to optimize the objective function of the model problem through the application of the decision variables presented in Section 3.3. It is important to note that the number of decision variables can be calculated to solve the problem identified using $N_r + 2$. This means the number is determined based on the number of raw materials used to manufacture a product. Heidari *et al.* (2019) introduced the HHO algorithm with two main behaviors which include exploration and exploitation as shown in Algorithm 1. The exploration phase involves applying the Harris Hawks behavior to detect rabbit prey as expressed in Equation (20).

$X(Iter)$ represents the current position from Harris Hawks while $X(Iter+1)$ indicates its position in the next iteration. The rabbit's position is denoted by $X_{rabbit}(Iter)$ while r_1, r_2, r_3, and r_4 are all random numbers in the range (0,1). Moreover, the upper and lower limit variables are denoted as UB and LB, respectively. $X_{rand}(Iter)$ also simulates the Harris Hawks selected randomly from the current population while Equation (21) is used to calculate the average position of the current Harris Hawks population ($X_m(Iter)$). $X_i(Iter)$ calculates the location of each Harris Hawks in the current iteration and N is the total number of hawks. It was observed that the prey's energy (rabbit) decreases during the transition from exploration to exploitation as shown in Equation (22). The notation shows that $2E_0$ represents the rabbit's initial energy and E denotes the energy released by the prey depending on the maximum number of iterations (T).

It is pertinent to note that the Harris Hawks is exploring and experiencing exploitation when E_0≥1. The four strategies associated with Harris Hawks during the exploitation phase include soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with progressive rapid dives. The soft besiege behavior occurs when $r \geq 0.5$ and $|E| \geq 0.5$ as indicated in Equations (23) and (24). Moreover, the ΔX ($Iter$) shows the difference between the position vector of the rabbit and the current location in $Iter$ iteration with a value of $J = 2\,(1 - r_5)$ while r_5 describes the random numbers in the range (0,1).

The hard besiege strategy occurs when $r \geq 0$ and $|E| < 0$ as modeled in Equation (25). The soft besiege with progressive rapid dives occurs when $r < 0$ and $|E| \geq 0$ as presented in Equations (26)-(29). It is important to note that the levy flight function is denoted as LF, a random vector with size $1\ x\ D$ is represented by S, and the problem dimensions are described as D. The LF function can be estimated using Equation (28) where β is a constant of 1.5 while u and v are random values in the range (0.1). Hard besiege with progressive rapid dives occurs when $r < 0.5$ and $|E| < 0.5$ as modeled in Equation (30). Meanwhile, Y' and Z' values can be estimated using Equations (26) and (27).

5. STUDY DATA AND PROCEDURES

The data used to conduct the experiments include numerical examples from three different cases involving production problems that require small (Case 1), moderate (Case 2), and large numbers of raw material variations (Case 3). It is important to state that Case 1 focuses on the production problem requiring two raw materials, Case 2 involves five raw materials, and Case 3 uses ten raw materials.

$$X(Iter+1) = \begin{cases} X_{rand}(Iter) - r_1 |X_{rand}(Iter) - 2r_2 X(Iter)| & q \geq 0.5 \\ (X_{rabbit}(Iter) - X_m(Iter)) - r_3(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \quad (20)$$

$$X_m(Iter) = \frac{1}{N}\sum_{i=1}^{N} X_i(Iter) \quad (21)$$

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$$X(Iter+1) = \begin{cases} X_{rand}(Iter) - r_1|X_{rand}(Iter) - 2r_2X(Iter)| & q \geq 0.5 \\ (X_{rabbit}(Iter) - X_m(Iter)) - r_3(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \quad (20)$$

$$X_m(Iter) = \frac{1}{N}\sum_{i=1}^{N} X_i(Iter) \quad (21)$$

$$E = 2E_0\left(1 - \frac{Iter}{T}\right) \quad (22)$$

$$X(Iter+1) = \Delta X(Iter) - E|JX_{rabbit}(Iter) - X(Iter)| \quad (23)$$

$$\Delta X(Iter) = X_{rabbit}(Iter) - X(Iter) \quad (24)$$

$$X(Iter+1) = X_{rabbit}(Iter) - E|\Delta X(Iter)| \quad (25)$$

$$Y = X_{rabbit}(Iter) - E|JX_{rabbit}(Iter) - X(Iter)| \quad (26)$$

$$Z = Y + S\ x\ LF(D) \quad (27)$$

$$LF(x) = 0.01\ x\ \frac{u x \sigma}{|\nu|^{\frac{1}{\beta}}},\quad \sigma = \left(\frac{\Gamma(1+\beta) x \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) x\ \beta\ x\ 2(\frac{\beta-1}{2})}\right)^{\frac{1}{\beta}} \quad (28)$$

$$X(Iter+1) = \begin{cases} Y\ if\ F(Y) < F(X(Iter)) \\ Z\ if\ F(Z) < F(X(Iter)) \end{cases} \quad (29)$$

$$X(Iter+1) = \begin{cases} Y'\ if\ F(Y') < F(X(Iter)) \\ Z'\ if\ F(Z') < F(X(Iter)) \end{cases} \quad (30)$$

Algorithm 1. Pseudo-code of HHO algorithm

Inputs: The population size N and the maximum number of iterations
Outputs: The location of the rabbit and its fitness value
Initialize the random population Xi(i = 1,2,...,N)
while (stopping condition is not met) do
Calculate the fitness values of hawks = X^*
Set Xrabbit as the location of the rabbit (best location)
    for (each hawk (Xi)) do
    Update the initial energy E0 and jump strength J (E0=2rand()-1, J=2(1-rand())
    Update the E using Eq. (22))
    if (|E|≥ 1) then (phase of exploration)
        Update the location using Eq. (20)
    if (|E| < 1) then (phase of exploitation)
        if (r ≥0.5 and |E|≥ 0.5) then (Soft besiege Update the location vector using Eq. (23))
        else if (r ≥0.5 and |E| < 0.5) then (Hard besiege Update the location vector using Eq. (25))
        else if (r <0.5 and |E|≥ 0.5) then (Soft besiege with progressive rapid dives Update the location using Eq. (29)
        else if (r <0.5 and |E| < 0.5) then (Hard besiege with progressive rapid dives Update the location using Eq. (30)
    Evaluate the rabbit position
    Update rabbit position (X^*) if there is a better solution for the population
    $\boldsymbol{t = t + 1}$
Return Xrabbit

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Data for case 1 are P=10,500, D=8,500, N_r=2, λ_1= 4, λ_2=2, k_1=0.1, k_2=0.15, c_{loss_1}=2,000, c_{loss_2}=1,000, c_{loss_p}=140,000, C_{sale}=140,000, c_{0_1}=12,000, c_{0_2}=15,000, c_1= 125, A_{0_1}=125, A_{0_2}=100, ar_1=100, ar_2=100, a_p=700, dr_1=4, dr_2=6, d_p=10, $KPLr_1$=20, $KPLr_2$=20, $KPLr^*{}_1$=18, $KPLr^*{}_2$=18, $\mathrm{KPL_p}$=20, $\mathrm{KPL_p}^*$=18, β_{r_1}=1,000, β_{r_1}=1,000, β_p=1,000, ρ_1=1.5, ρ_2=1.2, ρ_p=1.75, ρ_m=5, ρs_m=50, ρi_m=1.25, $\rho 0_1$=1, $\rho 0_1$=1.5, ε_t=30, ς_1=25, ς_2=25, ς_{r_1}=25, ς_{r_2}=25, ς_p=50, ς_fp=1500, ς_mp= 70,000, ς_mi=250, $\varsigma_{\mathrm{ir}_1}$=15, $\varsigma_{\mathrm{ir}_2}$=15, ϵ_s=550, ϵ_p=15, ϵ_i=1, $\epsilon 0_1$=0.015, $\epsilon 0_2$=0.05, C_ϵ=1,444, K=1.645, σ=125, S=45,000, H_{0_1}=250, H_{0_2}=155, H_1=300.

Data for case 2 is presented as follows: P=9,500, D=7,400, N_r=5, λ_1=2, λ_2=0.1, λ_3=0.25, λ_4=0.1, λ_5=1, k_1=0.025, k_2=0.01, k_3=0.01, k_4=0, k_5=0, c_{loss_1}=200, c_{loss_2}=100, c_{loss_3}=200, c_{loss_4}=0, c_{loss_5}=0, c_{loss_p}=80,000, c_{sale}=75,000, c_{0_1}=8,000, c_{0_2}=1,300, c_{0_3}=3,400, c_{0_4}=500, c_{0_5}=500, c_1=100, A_{0_1}=50, A_{0_2}=50, A_{0_3}=50, A_{0_4}=50, A_{0_5}=50, ar_1=20, ar_2=20, ar_3=20, ar_4=5, ar_5=10, $\mathrm{a_p}$=5, dr_1=5, dr_2=2, dr_3=5, dr_4=7, dr_5=1, $\mathrm{d_p}$=5, $KPLr_1$=20, $KPLr_2$=20, $KPLr_3$=20, $KPLr_4$=20, $KPLr_5$=2, $KPLr^*{}_1$=19, $KPLr^*{}_2$=19, $KPLr^*{}_3$=19, $KPLr^*{}_4$=19, $KPLr^*{}_5$=19, $\mathrm{KPL_p}$=20, $\mathrm{KPL_p}^*$=18, β_{r_1}=1,000, β_{r_2}=1,000, β_{r_3}=1,000, β_{r_4}=1,000, β_{r_5}=1,000, β_p=1,000, ρ_1=0.5, ρ_2=0.2, ρ_3=0.02, ρ_4=0.001, ρ_5=0.001, ρ_p=0.0015, ρ_m=5, ρs_m= 1,000, ρi_m=1.25, $\rho 0_1$=0.5, $\rho 0_2$=0.5, $\rho 0_3$=0.5, $\rho 0_4$=0.2, $\rho 0_5$=1, ε_t=30, ς_1=10, ς_2=10, ς_3=10, ς_4=5, ς_5=5, ς_{r_1}=10, ς_{r_2}=10, ς_{r_3}=10, ς_{r_4}=50, ς_{r_5}=25, ς_p=10, ς_fp=1,000, ς_mp=500,000, ς_mi=100, $\varsigma_{\mathrm{ir}_1}$=25, $\varsigma_{\mathrm{ir}_2}$=25, $\varsigma_{\mathrm{ir}_3}$=25, $\varsigma_{\mathrm{ir}_4}$=125, $\varsigma_{\mathrm{ir}_5}$=100, ϵ_s=1,000, ϵ_p=20, ϵ_i=1, $\epsilon 0_1$=0.5, $\epsilon 0_2$=0.25, $\epsilon 0_3$=0.52, $\epsilon 0_4$=25, $\epsilon 0_5$=15, C_ϵ=1,444, K=1.645, σ=100, S=9,000,000, H_{0_1}=150, H_{0_2}=175, H_{0_3}=150, H_{0_4}=850, H_{0_5}=750, H_1=750.

Furthermore, data for case 3 are P=9,500, D=7,400, N_r=10, λ_1=2, λ_2=0.1, λ_3=0.25, λ_4=0.1, λ_5=1, λ_6=2, λ_7=0.1, λ_8=0.25, λ_9=0.1, λ_{10}=1, k_1=0.025, k_2=0.01, k_3=0.01, k_4=0, k_5=0, k_6=0.025, k_7=0.01, k_8=0.01, k_9=0, k_{10}=0, c_{loss_1}=200, c_{loss_2}=100, c_{loss_3}=200, c_{loss_4}=0, c_{loss_5}=0, c_{loss_6}=200, c_{loss_7}=100, c_{loss_8}=200, c_{loss_9}=0, $c_{loss_{10}}$=0, c_{loss_p}=150,000, c_{sale}=120,000, c_{0_1}=8,000, c_{0_2}=1,300, c_{0_3}=3,400, c_{0_4}=500, c_{0_5}=500, c_{0_6}=8,000, c_{0_7}=1,300, c_{0_8}=3,400, c_{0_9}=500, $c_{0_{10}}$=500, c_1=100, A_{0_1}=50, A_{0_2}=50, A_{0_3}=50, A_{0_4}=50, A_{0_5}=50, A_{0_6}=50, A_{0_7}=50, A_{0_8}=50, A_{0_9}=50, $A_{0_{10}}$=50, ar_1=20, ar_2=20, ar_3=20, ar_4=5, ar_5=10, ar_6=20, ar_7=20, ar_8=20, ar_9=5, ar_{10}=10, $\mathrm{a_p}$=5, dr_1=5, dr_2=2, dr_3=5, dr_4=7, dr_5=1, dr_6=5, dr_7=2, dr_8=5, dr_9=7, dr_{10}=1, $\mathrm{d_p}$=5, $KPLr_1$=20, $KPLr_2$=20, $KPLr_3$=20, $KPLr_4$=20, $KPLr_5$=20, $KPLr_6$=20, $KPLr_7$=20, $KPLr_8$=20, $KPLr_9$=20, $KPLr_{10}$=20, $KPLr^*{}_1$=19, $KPLr^*{}_2$=19, $KPLr^*{}_3$=19, $KPLr^*{}_4$=19, $KPLr^*{}_5$=19, $KPLr^*{}_6$=19, $KPLr^*{}_7$=19, $KPLr^*{}_8$=19, $KPLr^*{}_9$=19, $KPLr^*{}_{10}$=19, $\mathrm{KPL_p}$=20, $\mathrm{KPL_p}^*$=18, β_{r_1}=1,000, β_{r_2}=1,000, β_{r_3}=1,000, β_{r_4}=1,000, β_{r_5}=1,000, β_{r_6}=1,000, β_{r_7}=1,000, β_{r_8}=1,000, β_{r_9}=1,000, $\beta_{\mathrm{r}_{10}}$=1,000, β_p=1,000, ρ_1=0.5, ρ_2=0.2, ρ_3=0.02, ρ_4=0.001, ρ_5=0.001, ρ_6=0.5, ρ_7=0.2, ρ_8=0.02, ρ_9=0.001, ρ_{10}=0.001, ρ_p=0.0015, ρ_m=5, ρs_m= 1,000, ρi_m=1.25, $\rho 0_1$=0.5, $\rho 0_2$=0.5, $\rho 0_3$=0.5, $\rho 0_4$=0.2, $\rho 0_5$=1, $\rho 0_6$=0.5, $\rho 0_7$=0.5, $\rho 0_8$=0.5, $\rho 0_9$=0.2, $\rho 0_{10}$=1, ε_t=30, ς_1=10, ς_2=10, ς_3=10, ς_4=50, ς_5=25, ς_6=10, ς_7=10, ς_8=10, ς_9=50, ς_{10}=25, ς_{r_1}=10, ς_{r_2}=10, ς_{r_3}=10, ς_{r_4}=50, ς_{r_5}=25, ς_{r_6}=10, ς_{r_7}=10, ς_{r_8}=10, ς_{r_9}=50, $\varsigma_{\mathrm{r}_{10}}$=25, ς_p=10, ς_fp=1,000, ς_mp=500,000, ς_mi=100, $\varsigma_{\mathrm{ir}_1}$=25, $\varsigma_{\mathrm{ir}_2}$=25, $\varsigma_{\mathrm{ir}_3}$=25, $\varsigma_{\mathrm{ir}_4}$=125, $\varsigma_{\mathrm{ir}_5}$=100, $\varsigma_{\mathrm{ir}_6}$=25, $\varsigma_{\mathrm{ir}_7}$=25, $\varsigma_{\mathrm{ir}_8}$=25, $\varsigma_{\mathrm{ir}_9}$=125, $\varsigma_{\mathrm{ir}_{10}}$=100, ϵ_s=1,000, ϵ_p=20, ϵ_i=1, $\epsilon 0_1$=0.5, $\epsilon 0_2$=0.5, $\epsilon 0_3$=0.5, $\epsilon 0_4$=0.2, $\epsilon 0_5$=1, $\epsilon 0_6$=0.5, $\epsilon 0_7$=0.5, $\epsilon 0_8$=0.5, $\epsilon 0_9$=0.2, $\epsilon 0_{10}$=1, C_ϵ=1,444, K=1.645, σ= 100, S=9,000,000, H_{0_1}=150, H_{0_2}=175, H_{0_3}=150, H_{0_4}=850, H_{0_5}=750, H_{0_6}=150, H_{0_7}=175, H_8=150, H_{0_9}=850, $H_{0_{10}}$=750, H_1=750.

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The optimization experimental procedures conducted in this study with HHO used different population variations and iterations. Each case was optimized using three population variations which include the small, medium, and large iterations. A total of 100 populations and 100 iterations (Pop 100 x Iter 100) were used as small variations, 250 populations and 250 iterations (Pop 250 x Iter 250) for medium, as well as 500 populations and 500 iterations (Pop 500 x Iter 500) for large. Each experiment was run 30 times, thereby leading to 90 trials for each case and a total of 270 trials for the three cases.

The quality of the solution provided by the proposed algorithm was benchmarked using ETP and computation time with the GA and PSO algorithms. The parameters used to compare the algorithms were large populations and iterations which include Pop 500 x Iter 500. In the GA algorithm, a crossover probability of 0.8 and mutation of 0.8 was used while an inertia weight of 0.2 was applied in the PSO algorithm. It is important to state that all the algorithms were decoded on MATLAB R2018a on Windows 10 AMD A8 with x64-64 4GB RAM. Moreover, the ANOVA test was used to determine the quality of the solution based on ETP and the computation time to compare the proposed algorithm with the GA and PSO algorithms.

A sensitivity analysis was also conducted to examine the effect of changing variables on decision variables and the expectation of total profit. It was applied to Case 1 using the quality degradation rate (k), the standard deviation of demand (σ), and the safety factor (K) as variables. Each variable was changed with 10 different data and the results were recorded.

6. RESULTS AND DISCUSSION

6.1. Expected Total Profit (ETP) Optimization Using HHO

The proposed model was developed based on the complex real-world situation which involves incorporating costs of fuel, emissions, electricity, multi-materials, quality degradation, and probabilistic demand. It was applied to the aforementioned three cases. The ETP optimization using HHO based on trial variations is summarized in **Table 1**.

The experimental results showed that the experimental variations in Cases 1 and 2 are small (Pop 100 x Iter 100), medium (Pop 250 x Iter 250), and large (Pop 500 x Iter 500), and they all have the same solution. This means the problems associated with a small or medium number of raw materials produced the same ETP without any difference based on population variations and iterations.

However, the problems associated with a large number of raw materials in Case 3 showed that only the trials of medium variations and large variations produced similar and better ETP solutions compared to the population variation experiment and small iteration. This means the optimal solution for Case 3 was found in the population experiment as well as the medium and large iterations.

6.2. Computation Time on Problem-Solving with HHO

The results of the computation time required to solve the problems using HHO are presented in **Table 2** based on variations in trials and cases. It was discovered that an increase in the population and iterations led to an increment in the computation time needed to solve the HHO algorithm problems. The time was observed to reduce for smaller populations and iterations. The results from each case showed that the problems associated with a larger quantity of raw materials as indicated in Cases 1-3 necessitate an increase in computation time.

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Table 2. Computation time to solve problems using HHO (Second).

Cases	Results	Pop 100 x Iter 100	Pop 250 x Iter 250	Pop 500 x Iter 500
Case 1	Average	56	370	1,605
	Standard deviation	4.65	30.20	35.13
	Minimum	46	273	1,557
	Maximum	64	414	1,679
Case 2	Average	120	777	3,141
	Standard deviation	6.25	26.14	104.81
	Minimum	107	738	2,998
	Maximum	129	821	3,305
Case 3	Average	360	2,010	7,615
	Standard deviation	21	85.34	174.02
	Minimum	324	1,869	7,183
	Maximum	399	2,130	7,883

Table 3. Results of expected total profit optimization using HHO.

Cases	Results	Pop 100 x Iter 100	Pop 250 x Iter 250	Pop 500 x Iter 500
Case 1	Average	164,137,878	164,137,878	164,137,878
	Standard deviation	0.00	0.00	0.00
	Minimum	164,137,878	164,137,878	164,137,878
	Maximum	164,137,878	164,137,878	164,137,878
Case 2	Average	14,444,202	14,444,202	14,444,202
	Standard deviation	0.00	0.00	0.00
	Minimum	14,444,202	14,444,202	14,444,202
	Maximum	14,444,202	14,444,202	14,444,202
Case 3	Average	76,290,250	76,387,543	76,387,543
	Standard deviation	167,177	0.00	0.00
	Minimum	75,999,721	76,387,543	76,387,543
	Maximum	76,387,543	76,387,543	76,387,543

Tables 2 and **3** showed that the problems in Case 1 or 2 can be solved by varying population trials and small iterations (Pop 100 x Iter 100). This is reasonable because the small population and iteration experiments produced solutions considered to be as good as those classified as medium and large. They also have faster computation times than the other variations and iterations.

Medium population and iteration variations were also recommended to solve the problems in Case 3 because they produced similar ETP solutions with large variations and better than small variations. However, large variations require more computation time.

6.3. Algorithm Comparison

ETP and computation time for each algorithm were compared and presented in the Boxplot. The results for PSO and GA algorithms are listed in **Tables A7** and **A8** respectively in Appendix A. Moreover, **Figures 6-8** show a Boxplot of the ETP results for each algorithm in Cases 1–3. The solution provided to Cases 1 and 2 by the proposed HHO algorithm was observed to be as good as the PSO algorithm. However, the solution provided in Case 3 was found to be better.

These findings were further supported by the ANOVA test conducted on ETP as shown in **Tables 4** and **5** where the variance of the ETP value was found to be different (sig<0.05). It was discovered that HHO and

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PSO produced the same solution (sig>0.05) in Cases 1 and 2 as indicated in **Table 5**. However, HHO performed better than PSO in Case 3 as evidenced by a sig value <0.05. The ETP comparison results between HHO and GA also showed that the proposed model is superior in all cases.

Figures 9-11 show a Boxplot comparison of Cases 1-3 in terms of computation time and the PSO algorithm was observed to have outperformed the proposed HHO and GA algorithms. This was supported by the findings of the ANOVA test in **Tables 4** and **5** that the variance values of HHO, PSO, and GA algorithms differ. The computation time was discovered to be significantly different as indicated by the sig value <0.05. Meanwhile, the HHO algorithm produced a better ETP than PSO despite having a longer computation time.

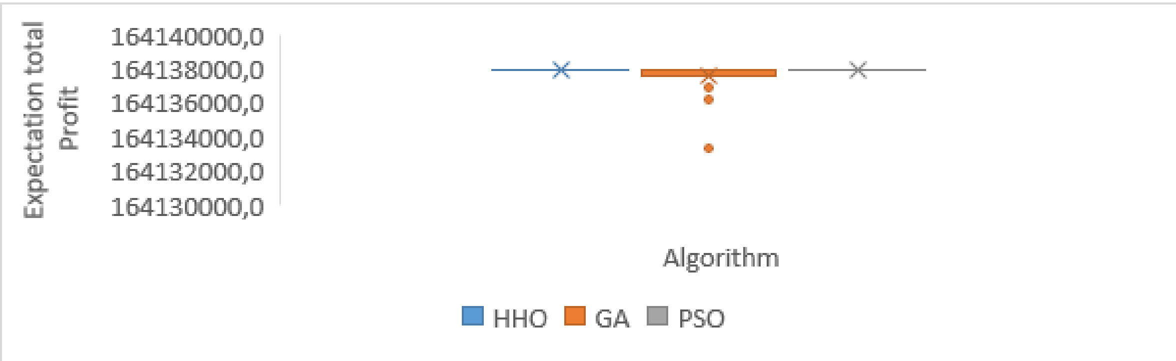

Figure 6. Boxplot of ETP results for each algorithm in Case 1.

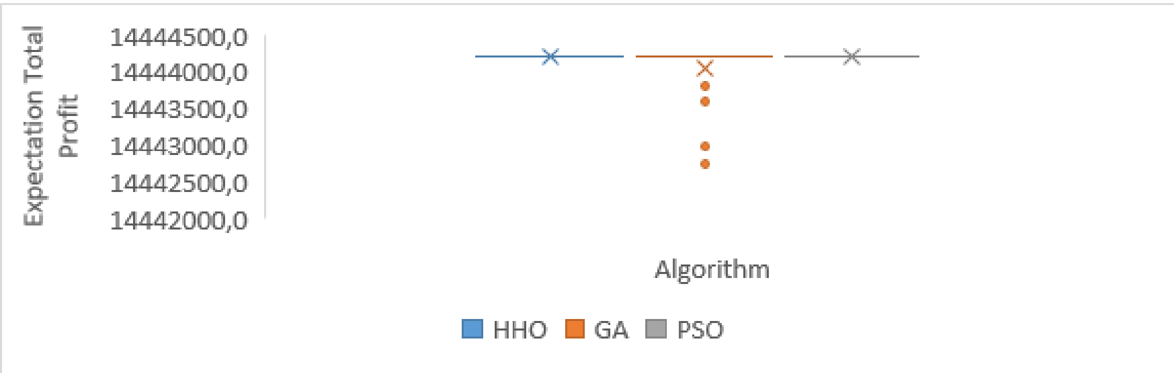

Figure 7. Boxplot of ETP results for each algorithm in Case 2.

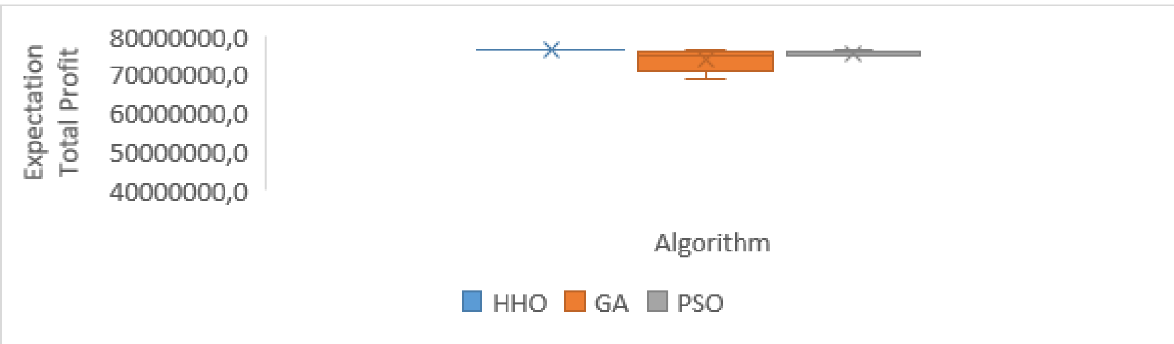

Figure 8. Boxplot of ETP results for each algorithm in Case 3.

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Table 4. The results of the ANOVA for the expected total profit (ETP) test and computation time in each Case.

Tests	Anova	Case 1	Case 2	Case 3
	Nilai F	4.823	5.703	24.551
ETP	Sig	0.010	0.005	0.000
	Nilai F	1325.044	1670.116	1276.111
Computation Time	Sig	0.000	0.000	0.000

Table 5. The results of the comparison of expected total profit (ETP) and computation time for each algorithm in each Case

Tests	Comparing	Sig Case 1	Sig Case 2	Sig Case 3
	HHO-GA	0.023	0.012	0.000
ETP	HHO-PSO	1.000	1.000	0.021
	PSO-GA	0.023	0.012	0.000
	HHO-GA	0.000	0.000	0.000
Computation Time	HHO-PSO	0.000	0.000	0.000
	PSO-GA	0.000	0.000	0.000

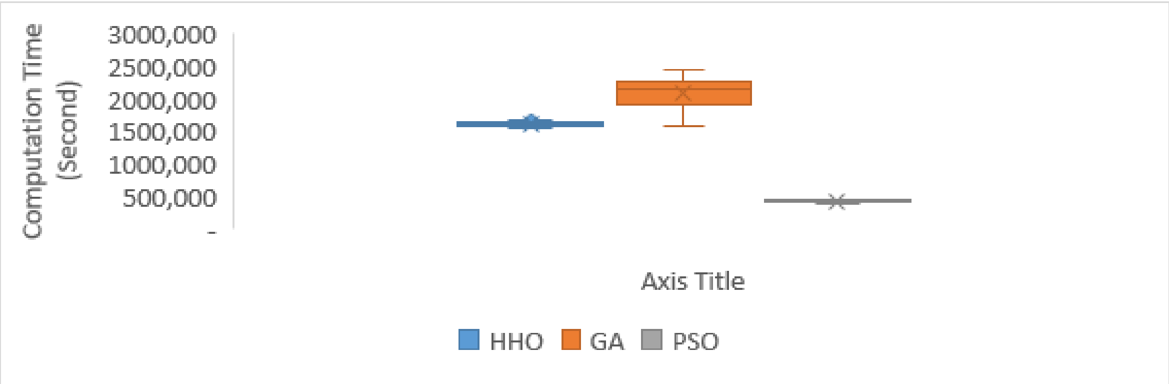

Figure 9. Boxplot of computation time for each algorithm in Case 1.

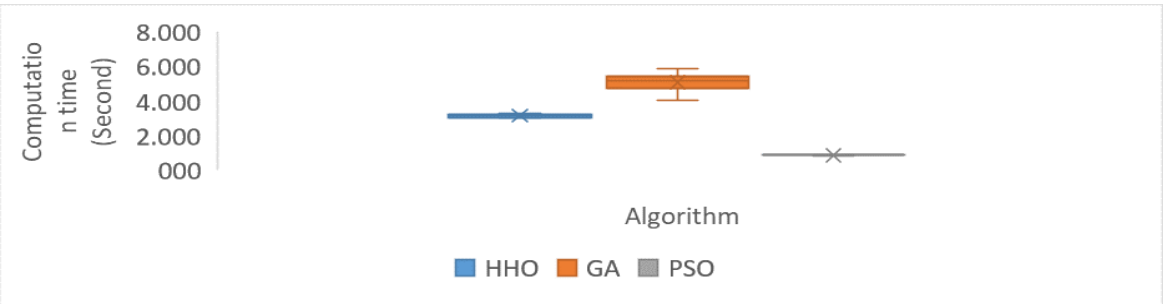

Figure 10. Boxplot of computation time for each algorithm in Case 2.

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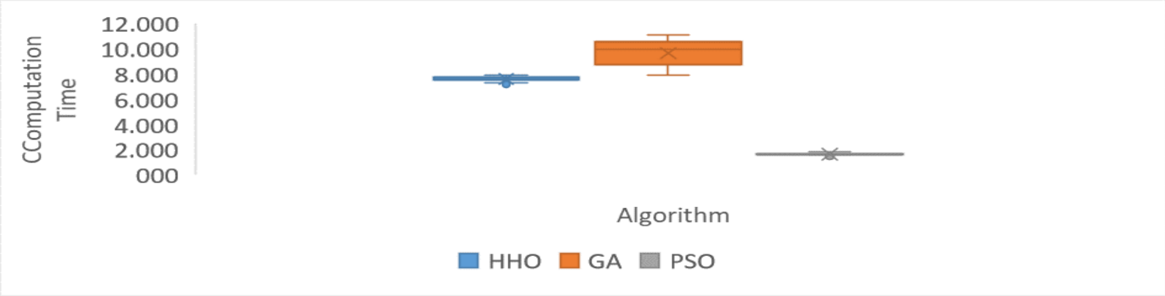

Figure 11. Boxplot of computation time for each algorithm in Case 3.

6.4. Sensitivity Analysis

The results of the sensitivity analysis conducted on the effect of changes in the rate of quality degradation (k), the standard deviation of demand (σ), and the safety factor (K) on the time of production cycle (T) and ETP are explained. **Figure 12** depicts the effect of k changes on T and ETP and it was discovered that an increase in the rate of quality degradation (k) led to an increment in ETP and T, and vice versa. Meanwhile, a change in the rate of decline in quality (k) did not affect the decision variables including the frequency of ordering raw materials (m_j) and delivery of finished products (n) as indicated by the value of 1 for both. The results further showed that an increase in the degradation rate (k) caused an increment in the frequency of ordering raw materials in one horizon. This is reasonable because an increase in the rate of quality degradation (k) is expected to cause a reduction in the raw material inventory j because of the increase in the frequency with which raw materials are ordered (m_j) and vice versa.

Figure 13 shows the effects of changes in the standard deviation of demand (σ) on T and ETP. The findings showed that an increase in the standard deviation of demand (σ) led to an increment in ETP and T, and vice versa. Meanwhile, the change in demand standard deviation (σ) has no effect on the decision variables associated with ordering raw materials (m_j) and shipping finished products (n).

The results also showed that a reduction in the standard deviation of demand (σ) led to a decrease in demand uncertainty which caused an ETP and T, and vice versa. This is reasonable because demand uncertainty usually increases with the standard deviation of demand (σ). A high uncertainty can cause decision-makers to increase safety stock and reduce T, thereby leading to high inventory costs and lower ETP, and vice versa.

It was discovered in **Figure 14** that an increase in the safety factor (K) also led to an increment in ETP and T, and vice versa. Meanwhile, the changes in the safety factor (K) did not affect the frequency of ordering raw materials (m_j) and delivering finished products (n).

The findings also indicated that an increase in the safety factor (K) increased the average finished product inventory, thereby, leading to a reduction in finished product lost sales (EL) and an enhancement in ETP and T. Meanwhile, a decrease in safety factor (K) caused a reduction in the average finished product inventory and this led to an increase in EL. As a result, ETP and T fell. This is considered reasonable because an increase in K enhances the risk of EL and vice versa.

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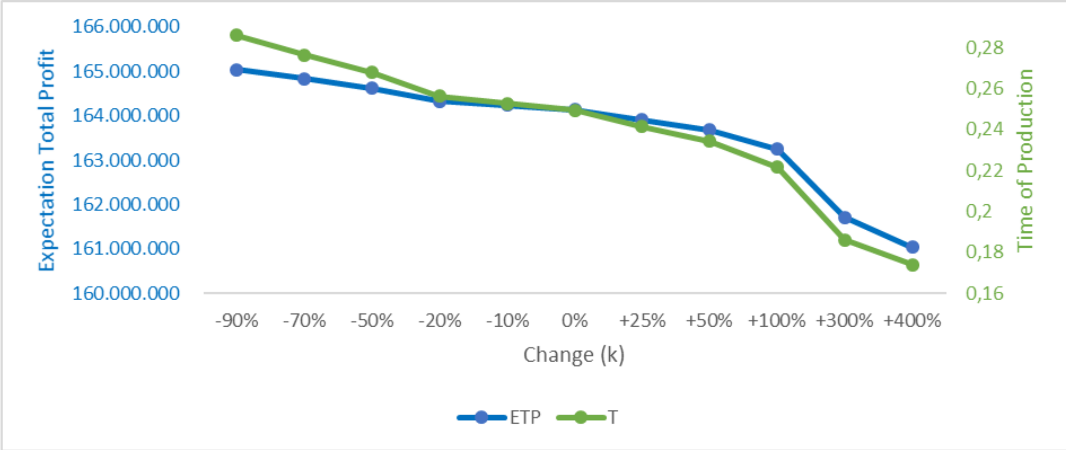

Figure 12. The effect of changing k on T and ETP.

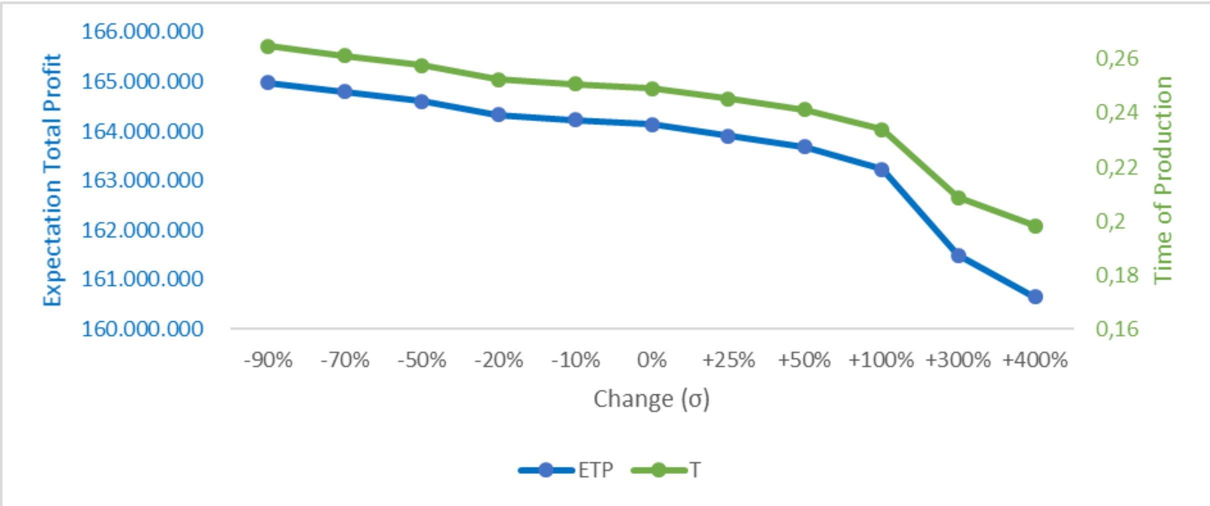

Figure 13. The effect of changing σ on T and ETP.

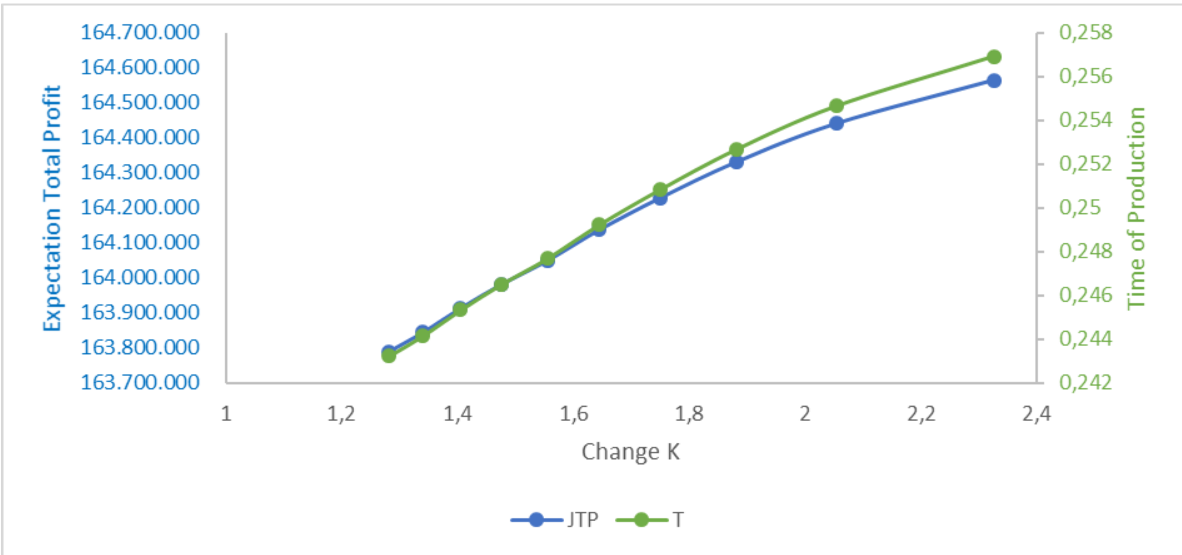

Figure 14. Effect of changes in K to T and ETP.

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6.5. Managerial Insight

The proposed model can be implemented in companies with a linear decline in raw material quality such as the agro, food, and pharmaceutical industries. Its implementation can assist managers and decision-makers determine production decisions, raw material procurement, and finished product delivery. Moreover, they can also benefit significantly from the findings related to ETP.

This study proposes the HHO procedure for optimizing the problem of the sustainable production inventory model. The proposed algorithm outperforms the GA and PSO algorithms. The findings suggested that managers and decision-makers use a population of 100 and iterations of 100 to solve problems involving raw materials numbers 2 (Case small) and 5 (Case medium). To solve problems with ten raw materials (Large Case), 250 populations and 250 iterations are recommended. The proposed algorithm can increase the company's ETP.

It was also indicated that the degradation of raw materials quality affects the company's ETP. This is observed from the fact that low-quality degradation can improve ETP. Therefore, managers and decision-makers are required to consider several factors such as humidity, temperature, and storage time. It has been indicated that perishable raw materials are extremely sensitive to changes in temperature and humidity (Mahmood *et al.*, 2019). This means proper management needs to be implemented in the storage areas to slow the decline in quality (k). There is also the need for strict and effective inventory management procedures such as the principle of a First-In First-Out (FIFO) inventory system. This method is useful in dealing with quality degradation issues caused by first processing first-come, first-served raw materials. It also has the potential to reduce warehouse storage time.

The study also showed that an increase in the standard deviation of demand (σ) reduced ETP. This means managers and decision-makers need to effectively manage demand at the sales level through Collaborative Planning, Forecasting, and Replenishment (CPFR). CPFR is a method of demand planning and fulfillment that improves the efficiency of manufacturing and supply chain businesses (Danese, 2006) (Panahifar *et al.*, 2015). It also can assist producers to obtain reliable demand data (Alptekin *et al.*, 2017).

An increase in the safety factor (K) was also observed to have the ability to raise ETP. Therefore, managers and decision-makers need to decide whether to use a high safety factor (K) when demand is uncertain to enhance the average inventory, but this can reduce the risk of EL and ETP.

7. CONCLUSION

This study proposed a sustainable production inventory model to maximize ETP with due consideration for fuel cost, emissions cost, electricity cost, multi-materials, quality degradation, and probabilistic demand which represent complex real-life cases. This is to ensure the limitations of previous models are resolved in the proposed model. Moreover, a new HHO procedure was also proposed to optimize the problems associated with the sustainable production inventory model. The findings showed that the proposed HHO algorithm was able to optimize the sustainable production inventory model problem. It also outperformed the GA and PSO algorithms in ETP but has a slower computation time than PSO.

The sensitivity analysis conducted also presented significant results such as the reduction in ETP and time of production cycle (T) due to the increase in the quality degradation rate. A similar trend was also recorded with the standard deviation of demand (σ) while an increase in the safety

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factor (K) was observed to have led to an increment in ETP and T.

The proposed study model has limitations that can be addressed in future investigations. These include the consideration of certain factors such as defective item production in the development of a new model in the future. The model also assumed the manufacturing process to be flawless with no product defects. In reality, errors in the manufacturing process can result in product defects. Therefore, further studies can be developed by considering the presence of defective items. There is also the need to account for the uncertainty of delivery lead time because the model designed in this study only considered demand even though the uncertainty for delivery lead time is more common in reality. It is recommended that the model is developed with due consideration for the uncertainty of the delivery lead time in future studies.

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