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Logistic Management in the Supply Chain Market Using Bio-Inspired Models With IoT Assistance

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ABSTRACT

The internet of things (IoT) is a modern generation of internet-associated embedded information and communication technology in an online environment to incorporate logistics and supply chain processes seamlessly. Automation in inventory monitoring, product control, storage, customer relationships, fleet tracking, etc. is a common issue faced by firms suggesting alternatives to the various problems. In this study, IoT-assisted bio-inspired framework (IoT-BIF) has been proposed for effective logistics management and supply chain processes. IoT with bio-inspired model sensors can track products via different supply chain units to address under-stocking and over-stocking issues. This modern technology allows the connection of numerous objects by gathering real-time data and sharing it; the resulting data can help automated decision-making in industries. The experimental results show that the proposed IoT-BIF method reduces the cost, memory utilization, average running time compared to other popular methods.

KEYWORDS

Bio-Inspired Models, IoT, Logistic Management, Supply Chain

1. INTRODUCTION

Internet of Things (IoT) has been built to improve today's means of connectivity. At the moment, the Internet is a network tool that users need computers to access (Wang J, et al. (2021), Tabassum M, et al. (2021), Rana M, et al. (2021)). IoT tries to get people connecting through the Internet and to have objects or computers. Much such information can be shared through the Internet and new ways of Internet communications: things about people and things are created (Sankayya M, et al. (2021)). Integrated sensor devices allow information to be exchanged across a single framework, generating a common operational image for creative applications.The seamless sensing, data analytics, and information representation using cutting-edge all-round sensing and cloud computing accomplish it (Sennan S, et al. (2020), Sreekantha D K, et al. (2021), Jan M A, et al. (2020)). IoT includes different applications such as agriculture (Lv Z, et al. (2020)), hospitals (Gao Q, et al. (2020)), transportation (Manogaran G, et al. (2020)), infrastructure (Saeed R. H, (2021)) etc. While times have improved with the advent of technology, the principal aim is to make machine knowledge sensitive without human involvement. The radical emergence from the modern Internet into a network of linked

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objects resulted in gathering information, communicating with the environment (control/ command), and further delivering information transfer, analytics, applications and messaging services through established internet protocols (Gupta D, et al. (2021), Su J, et al. (2021), Tayal A, et al. (2020), Ali Z & Mahmood T (2020)).

Another type of IoT applications preferred by major high-tech firms is Industrial IoT (IIoT) (Hu S, et al. (2020)). It has improved IIoT's acceptance, provided that computers are better able to handle complex tasks like data processing and communication than human beings. The core building blocks in the concept of an IoT are big data analytics, machine-to-machine connectivity, machine learning and deep learning algorithms (Orjuela K G, et al. (2021), Zhou Z, et al. (2021)). The above data allow businesses to identify problems more efficiently and fix them, which results in a net saving of money and time. In a production business, it is possible to use IIoT to effectively regulate and run the supply chain, conduct quality management and assurance, and minimize overall energy consumption (Rejeb A, et al. (2021)). The logistics and supply chain management (LSCM) comprises an integration activity between a network of facilities that procure, transform, and deliver products to customers using a distribution system. LSCM often consists of integration activities. IoT brings logistics andsupplies chain interactions to a new level to communicate and collaborate independently between items as they are processed in a warehouse or transferred between multiple supply chain organizations (Hussain S, et al. (2021), Cakir M, et al. (2021)). Such emerging capabilities create enormous resources to solve LSCM problems more efficiently.

IoT technology offers visibility, mobility and adaptability to fulfil different LSCM specifications in the supply chain. To this end, physical hardware, such as Automated Data Recognition and Capture (ADRC) technology, with RFID tags (radio frequency identification tags), sensor tags, or telematics modules are available for physical interface applications (Praveen K V & Prathap P J (2021), Rani P, et al. (2021)). These hardware devices then acquire intelligent features, including identity, location, communication, sensing or logical functions that enable creative supply chain management (SCM) under IoT services. The usability and management ability of bio-based algorithms for logistic domains build solutions and optimization leftovers into a historical analysis area (Khalaf O I, et al. (2020)). Bio-inspired models (BIMs) have been used for problem-solving using biological principles-based computer models. Bio-inspired models are generally used as a philosophical approach and are not used in a research area or various related programming fields (Manogaran G & Alazab M (2020)). BIM concentrates less on high-speed tailored algorithms and concentrates more on tractability and durability. Biological computation frequently depends on and builds on unregulated deep learning rules through organizations (Detorakis G, et al. (2018)). For efficient logistical management and supply chain processes, IoT-assisted Bio-Inspired Framework (IoT-BIF) has been therefore proposed. To fix understocking or overstocking problems, IoT can detect goods with organic model sensors using various supply chain equipment. The state-of-the-art technology facilitates various products by capturing and exchanging real-time data, which will simplify industrial decisions.

The bio-inspired computing approach has proven to produce excellent wireless and supply chain network contexts in information transmission. Therefore, for better logistics management and supply chain activities, the IoT-assisted biologically-inspired framework (IoT-BIF) was presented in this study. IoT can monitor items using various supply chain units using bio-inspired model sensors to resolve under-stock and over-stock problems. This current technology enables various things to be connected by collecting and exchanging data in real-time. The generated data may aid automate decisions.

The rest of the paper includes the literature study reports, follows the research proposal discussion in detail, simulation analysis and observations, and concludes with endnotes and the future scope.

2. LITERATURE STUDY REPORTS

This section explains some various existing logistic and supply chain management frameworks. The following frameworks can give basic ideologies behind the research formulation.

Müller M, et al. (2019) proposed a framework named Hybrid IoT-based Decentralized Application for Logistics and Supply Chain Management (HIDALS) and recommended that providing high-value parcels should confirm reciprocal transfer between companies through a shared repository in supply chain and logistic distributors. They offered more advanced grain and holistic effects of tracking than existing theories of distributed ledgers and intelligent sensors.

To ensure an effective fruit classification, product range and distribution model for the required delivery, packaging selection, stock optimization, cost savings, improved revenue and benefit and consumer lots, Khumaidi A, et al. (2020) proposed developing the technologies and computational integration into a market method known as the Smart System for Fruit Packinghouse Management (SPHM). The proposed Smart Logistic System, the Smart Indexing System, the Smart Packing System, and the Smart Storage System consist of four sub-systems.

In supply chain management, Abdel-Basset M, et al. (2018) used the Internet of Things (IoT) by developing an intelligent and stable SCM system (ISSCM). For manufacturers and administrators, they prepared a web platform. They monitored goods movement via radio frequency identification (RFID) technologies at each supply chain management point. They suggested a system combined with the analytical hierarchy process for neutrosophic decision making trial and evaluation laboratory (N-DEMATEL) methodology.

Verdouw C N, et al. (2018) presented an IoT-based reference architecture for agri-food provider networks (IoT-RAAFN). Their referenced architecture provided a hybrid approach integrating IoT and cloud device technologies. Their model aimed to provide affordable, customized solutions by hiring the European future Internet programme technology facilitators and encouraging the re-use of domain-specific features.

The revolutionary HYBRID Bio-Inspired Algorithm (HYBRID-BA) was introduced by Domanal S G, al. (2017) to prepare activities and control resourcesessential role in the cloud computing world. The virtual machines' tasks were effectively assigned using a Modified Particle Swarm Optimization algorithm. The suggested HYBRID Bio-Inspired algorithm (Modified PSO+Modified CSO) was then allotted / control of resources (CPU and Memory), as required by the tasks.

Zhang X, et al. (2013) introduced a novel bio-inspired approach to overcome the logistics selection process (BIA-LSP). In comparison, the duration and length of the road were taken into account. The solution suggested resolved the efficiency in its optional solutions should better be used. The efficacy of the proposed approach was measured by a case study. The outcome indicated that the suggested approach could perform better in solving routes to control emergency logistics.

The new location model for the hub, focused on transport costs, was proposed by Sachan R K & Kushwaha D S (2020) and applied to the proposed model's optimal solution, an anti-predatory nature-inspired algorithm (APNIA) given an optimum solution in respective to the warehouse and data centrenetwork and the respective overall cost for logistics. The real-time Warehouse Setup Problem (WSP) interrogated from ten various locations in Kanpur City, India, was experimentally tested. From the logistics company's point of view, they showed that their suggested Truck Transportation Cost-based Model (TTCM) gave around two to ten percent precise logistics total costs.

Alkan, B et al. (2021) The argument was made that operational efficiency is limited, and decision-making is hindered, and the supply chain network is disruptive. This article's major objective is to examine the architectural trade in the modular supply chain network between complexity and modularity. In this context, we create and apply to assembly supply chains and logistics an information-entropic complexities model. This methodology identifies the complexity of the system modules and the effect of the network topological composition as a mix of the complexity intrinsically involved.

Toorajipour, R., et al. (2021) In this research, artificial intelligence (AI) in the management of the supply chain (SCM) is systematically examined in the current literature. This study aims to identify present and possible AI methodologies that can improve the research and practise of SCM to tackle the existing scientific gap in AI in SCM. There were also detected gaps in the literature that must be addressed by scientific investigation. In particular, four aspects have been addressed:

(2) SCM prospective AI strategies for use in SCM; (3) existing SCM Subfields enhanced by the AI; and (4) the AI model subfields.

The bio-inspired computational model has demonstrated the best performance in wireless communication and networking conditions for supply chains. Thus, the research suggests an efficient logistics management and supply chain systems, IoT assisted the Bio-Inspired Framework (IoT-BIF). IoT module in the proposed frameworkcan track goods through different supply chain units with biologically inspired model sensors to solve under-stocking and overstocking problems. This new technology makes it possible to link multiple items by capturing and exchanging real-time data, leading to automatic industry decisions.

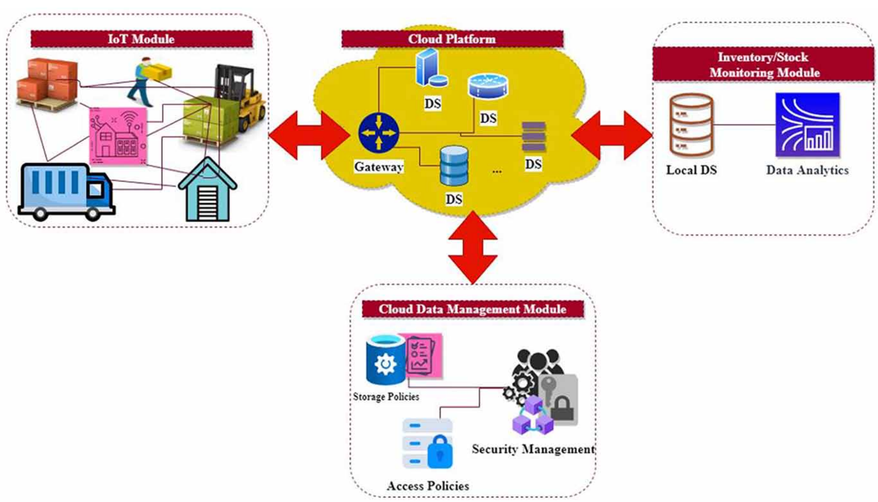
3. RESEARCH METHODOLOGY

The entire research model design has been categorized into several modules, including the IoT module, Cloud Data Management (CDM) module, and Inventory/Stock Monitoring module. The following explains the proposed IoT-BIFunder these modules.

Figure 1 defines the basic architecture of the proposed framework for logistic management in the supply chain network included the three major modules of signal/data processing and analytics. The first module, the IoT module, consists of a wireless sensor network connected through the Internet or WiFi channel. Radio Frequency Identification (RFID) Sensors, Sensor-enabled store vehicles, Customer service delivery vehicles with IoT sensors comes under this module. These sensors gather data and store it in their local database or other datastores. The sensor data are kept in the cloud platform to enables anytime-anywhere accessibility to supply chain service provider, administrators and customers. The cloud data management module handles various storage policies and access policies.

In this module, the cloud data security system manages the security of stored data, intermediate data, and processed results in the cloud platform. This module uses blockchain technology for securing the logistics and supply chain network.The third module, the inventory/stock monitoring module, performs the tracking of goods and services concerning its overstocking and understocking information. The inventory task scheduling has been discussed in this module using the bio-inspired technology named Enhanced Ant Colony Optimization (ACO) algorithm. The local datastore in this module access and stores the necessary information for the task scheduling and keeps the intermediate data in it. The cloud platform virtually interconnects these three modules to make an

Figure 1. IoT-BIF Framework for Logistic Management



intelligent supply chain network. The gateway unit in the cloud platform allows the sensor module to transmit the sensored information to the various datastores in it. The following subsections describe the detailed configuration steps and statistical explanations on the modules, as mentioned above in the proposed IoT-BIF.

IoT Module

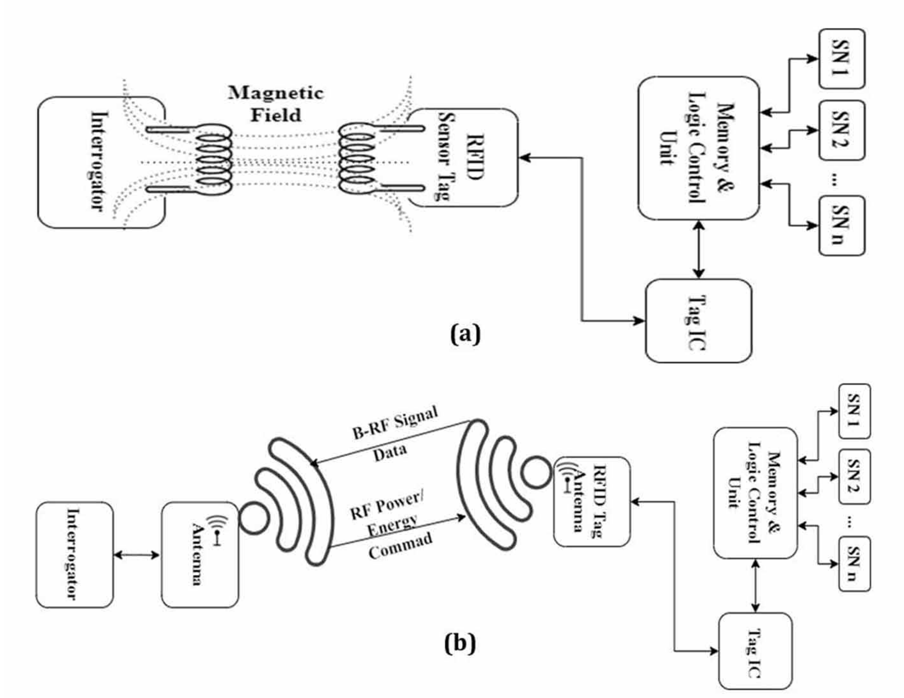
The RFID signal places a significant role in IoT based logistic management for supply chain networks. This section describes the technical configuration of RFID sensors from its fundamental design implementation.While the RFID tag chip has an Integrated (IC) circuit regulated via RF energy, it is possible to theoretically incorporate components with sensing capabilities into RFID tags to be simultaneously recognized and sensed. Ultimately, the combination of RFID tags with sensing parts can provide wireless efficient, contactless and visible sensing ability.RFID sensors acquire RF energy with aHigh Frequency (HF) antenna or Ultra-High Frequency (UHF) antenna from an interrogator. It then triggers the RFID chip on the RFID tag and returns the Identification (ID) Number /Code number into an interrogator.The ID code uniquely identifies an ‘item.’ The item feature refers to its identity stored and modified in a database in real-time to satisfy the various applications’ needs.Therefore, RFID sensors’ computation tagged items/objects areno longer limited and fixed to particular locations due to the RFID interrogator’s extensive coverage and versatility. As the selected RFID sensors can sometimes be entirely passive, changing the RFID sensors battery with traditional wireless sensor nodes is unnecessary. It is, therefore, possible to versatile and realistic the information sensing protocol for RFID sensors and broadens its applications to a wider spectrum.The proposed model implements high-frequency RFID sensor devices (HF-RFID) and ultra high-frequency RFID sensors (UHF-RFID). Proposed technological development and computer integration into the market system known as the Smart System for fruit bag management to secure a successful fruit classification, product range and distribution model for required delivery, packaging selection, stock optimization, price savings, improvement in revenue and advantages and consumer plots (SPHM). Four subsystems are consisting of the proposed Smart Logistic System, the Smart Indexing System, the Smart Packaging System and the Smart Storage System.

HF-RFID sensor module implements the Inductive coupling structure, and the UHF-RFID uses the respective antennas and wavelength carrier signal, as shown in figure 2a and 2b.Sensor devices with HF-RFID technology send and accept all power/energy and information with an inductor-capacitance module that can be accomplished the inductive link by an alternating magnetic field between the coil antennas in the interrogator and the tag. A resonant tank with an inductive capacitor generates the alternating magnetic field. The operative mode is different from the HF RFID system of the RFID sensor unit, having an RF transmission path, a UHF interrogator, an RFID sensor and tag module, the configuration of which is shown in Figure 2b. A UHF-RFID sensor system acts as a radar rear dispersal. The propagation efficiencies are calculated by key parameters, such as radiation power, antenna gain and receiving antennas, the wavelength and distance of the transmitter signal and receiver antennas.The following illustrates the mathematical model of the HF-RFID sensor and then UHF-RFID:

$$RF = \frac{1}{2 * \pi * \sqrt{L_a * C_a}} = \frac{1}{2 * \pi * \sqrt{L_b * C_b}} \tag{1}$$

Equation computes the resonance frequency $\left(RF\right)$ of the RFID sensor device, where $L_a and C_a$ represents the inductance and the capacitance of the resonant tank, resonance to the frequency F_s. The F_s measures the frequency of the RF source in the interrogator in the inductor coupling model. The $L_b and C_b$ reflects the tag antenna, which constitutes the receiver working at the same frequency:

Figure 2. RFID Sensor Configuration (a) HF-RFID; (b) UHF-RFID



$$V_I = -\frac{d\left(\phi'\right)}{dt} = -\frac{d\left(\psi'\right)}{dt} = -M_b \frac{d\left(\int S.dA\right)}{dt} = -M_b \frac{d}{dt}\left[\int\left(\frac{\varsigma_0 * I_a * r^2 * M_a}{2*\left(r^2+d^2\right)} * \cos\theta\right).dA\right] \tag{2}$$

The inductive voltage represented by V_I on the RFID tag antenna is measured using equation 2. This voltage is directly proportional to the rate of change of magnetic flux $\left(\phi'\right)$ through the coils of the inductive capacitance resonant tank in the RFID sensors. The ψ' denotes the magnetic flux of individual coils wounded in it. The parameters M_a and M_a are the number of windings of the coils in the resonant tank (tag) and the respective interrogator in the HF-RFID sensors. The variable ς_0 represents the initial constant factor. The S and A denote the inductance strength and the area of the magnetic coils in the RFID sensor placed with an angle θ. $\int\left(\frac{\varsigma_0 * I_a * r^2 * M_a}{2*\left(r^2+d^2\right)^{3/2}} * \cos\theta\right).dA$ measures the strength of the magnetic induction with current detected in the resonant tank (I_a). The remaining variables r and d represent the radius of the winding coils in the interrogator and the distance between the two coils, respectively. The inventory/stock monitoring module provides cloud data centre, cloud storage, cloud computing and intelligent services for intelligent manufacturing lines. The terminal clients receive sturdy, high-quality service with computer equipment and huge storage systems able to transmit, measure, and store massive amounts of information from terminal pieces of equipment through the management control centre. The monitoring module for the inventory/stock seeks to maintain sufficient supply throughout the whole operational area, with lower logistical costs and better quality of service:

$$V_I^{'} = -\left(\frac{\varsigma_0 * r^2 * M_a * M_b * A}{2 * \left(r^2 + d^2\right)^{\frac{3}{2}}} \right) * \frac{d\left(I_a\right)}{dt} = -C_{mi} * \frac{d\left(I_a\right)}{dt} \tag{3a}$$

$$C_{mi} = \left(\frac{\varsigma_0 * r^2 * M_a * M_b * A}{2 * \left(r^2 + d^2\right)^{\frac{3}{2}}} \right) \tag{3b}$$

Equation 3a gives the alternative expression for the inductance voltage (V_I) and expressed as $V_I^{'}$. This equation considers the mutual induction coefficient C_{mi} , as seen in equation 3b, when $\theta = 0^o$.

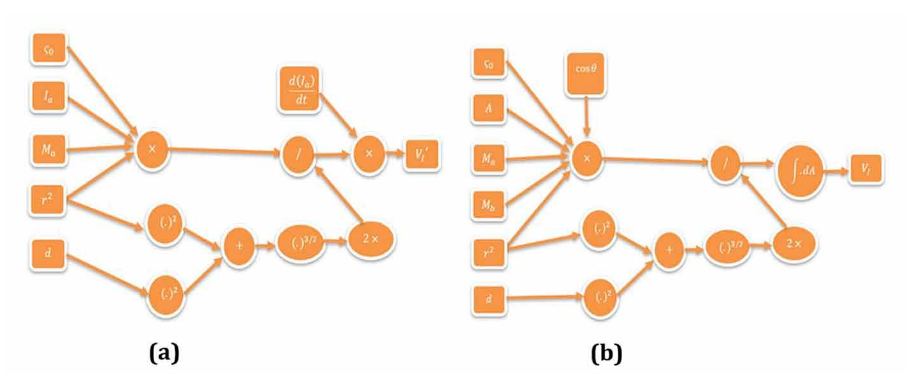
Figures 3a and 3b display the power received and the two antennas' key parameters and their relationship. The process diagram for Equation 2 is shown in Figure 2a, while Equation 3 is seen in Figure 2b. With rectifier and controller circuits, the RFID chip and sensor module will collect and transmit data.

Furthermore, the UHF-RFID sensors' fundamental structure illustrated in figure 2b demonstrates the transmission of the power signal and data between interrogator and RFID tag. The following section gives some significant formulas and descriptions:

$$\left. \begin{array}{l} P_D = \dfrac{T_P * T_G}{4 * \pi * D^2} \\ E_d = \dfrac{\lambda^2 * R_G}{4 * \pi} \end{array} \right\} \tag{4}$$

$$R_P = P_D * E_d = T_P * T_G * R_G \frac{\lambda^2}{\left(4 * \pi * D\right)^2} \tag{5}$$

Figure 3. Inductive Voltage (a) when $\theta = 0^o$; (b) when $\theta \neq 0^o$



Equation 4 identifies the power density and the effective dimension of the RFID tag's receiving antenna from the interrogator module. The RFID sensor tag is used as a passive interface to conduct the interrogator's sensing and transmission processes.In equation 4, the variable P_D which is the power density of RF energy at the distance D of the interrogatorantenna has been represented. In the equations mentioned above, the mathematical relationship of RF transmission has been clearly understood.Thus, equation 5 resulted in the reception power R_P, which measures the product of power density and effective dimension at the receiving antenna of the RFID tag. The transmission power and transmission gain are directly proportional to the power density and can be denoted, as $T_P \, and \, T_G$, respectively. Effective dimension of the receiving tags' antenna denoted by E_d, is directly proportional to R_G and λ. The variable R_G is the reception gain at the receiving antenna at the RFID tag, and λ is the RF carrier signals' wavelength:

$$\left.\begin{aligned} P_r &= P_D * \rho = \frac{T_P * T_G}{4 * \pi * D^2} * \rho \\ P_D^I &= \frac{P_r}{4 * \pi * D^2} = \frac{T_P * T_G * \rho}{\left(4 * \pi\right)^2 * D^4} \\ E_d^I &= \frac{\lambda^2 * R_G^I}{4 * \pi} \end{aligned}\right\} \tag{6}$$

$$R_P^I = P_D^I * E_d^I = \frac{T_P * T_G * \rho * R_G^I * \lambda^2}{\left(4 * \pi\right)^3 * D^4} \tag{7}$$

In direct proportion to the tags' Radar cross-section, the RF-power reflections are given. The P_r power reflected with the RFID tag denoted in equation 6 derives the P_D^I, the power density reflected at the interrogator, as seen in the above equation. R_G^I denotes the gain of the interrogator antenna. The variable E_d^I thus determines the effective dimension of the receiving antenna at the interrogator. Finally, equation 7 determine the UHF-RFID power reflection at the interrogator by taking the product of $P_D^I \, and \, E_d^I$, as similar to equation 5.The tag's information is conveyed to the interrogator by modelling the waves represented by the carrier RF, including the RFID tag ID and RFID sensor information. The antenna gain, distance between antennas and radar cross-section of the tag are apparently key parameters in deciding the measurements in the resultant RFID sensor distance and performance.

The terminal clients receive sturdy, high-quality service with computer equipment and huge storage systems able to transmit, measure, and store massive amounts of information from terminal pieces of equipment through the management control centre. The monitoring module for the inventory/stock seeks to maintain sufficient supply throughout the whole operational area, with lower logistical costs and better quality of service. Service quality and distribution systems' costs are the major elements determining the location of delivery centres and the range of distribution networks.

Cloud Data Management Module

The cloud data management module includes several policies for securing the machine to machine communication and machine to human communication. The data sensed from the RFID sensor preprocess to fit them for storing it in the required format fro various logistics management tasks, including product tracking, inventory management, transportation and delivery, etc. This module uses access policies and storage policies for cloud users or administrators who have participated in the supply chain network's logistic management. The proposed IoT-BIF concentrates on the security-related design configurations for the sensor data management in the cloud platform. Sensor data is stored in the cloud as though stored in a locker, where the cloud storeroom plays access control. The data are encrypted, and the cloud service typically has a decryption key that administers the privileges to access the data by each consumer. In private, confidential data, such as corporate records or, more broadly, personal data, this is a vital concern. It is very difficult for sensitive information kept by an organization exchanged among employees or business associates. It can be resolved conveniently by only encrypting the data before sending it to the cloud/safe.Several architectures have solved this problem, which functions on two confidence assessment and predictive encryption policies. The proposed approach uses the general and standard policies for cloud storage and access. Furthermore, this system integrates the emerging technology for security management in the SCM named the hybridized model that the analytic hierarchy process integrated decision making trial and evaluation laboratory (DMTEL)inspired by the literature study (29).

The remaining residues left in the environment cause the next procedure to be carried out by the same or different party. It employs a chemical compound called pheromone, which works as a signal that human beings of the same race may feel and utilise to maintain the swarm. Once a food source is identified, the ants return to the nest and establish to share information.

The basic security criteria for the proposed IoT-BIF is discussed in the Cloud data management module. The parameters for protection are often multi-dimensional, nuanced, ambiguous and contradictory. Thus, this neutrosophy-based hybridized security model (HSM) successfully solves several aspects of uncertainty. HSM is used to assume interrelationships between causes and consequences between criteria. The HSM in IoT-BIF is used for measuring the weight of protective needs in the cloud platform.

This HSM generally begins with choosing the most experienced administrators for evaluating storage and access related security policies and criteria. This HSM structure then determines the various goals and the basic criteria in the DMTEL, which are termed cause and effects. Following this, the DMTEL four class scale, including Non-Influential (NI), Influential (I), High-Influential (HI) and Very-High Influential (VHI). Each of these scales represents them with a triangular neutrosophic number in the form, as shown below:

Table 1 describes the neutrosophic values for the given classes. The N-Values can be defined as the triangular values for each class, which effectively handles the vague, uncertain, inconsistent, and incomplete information. Each value in the triangular number consists of the member functions such as falsity, truth, and indeterminacy, as expressed in follows:

$$f_{\tilde{x}}\left(a\right)=\begin{cases} \text{œ}_{\tilde{x}} & a=q \\ \dfrac{q-a+\text{œ}_{\tilde{x}}\left(a-p\right)}{q-p} & p\le a\le q \\ \dfrac{a-q+\text{œ}_{\tilde{x}}\left(r-a\right)}{r-p} & q\le a\le r \\ 1 & \text{Otherwise} \end{cases} \tag{8}$$

Equation 8 determines the falsity membership function $f_{\tilde{x}}\left(a\right)$ of the input criteria or factor a, where $\tilde{x}$ be the triangular neutrosophic number set represented by $\tilde{x}=\left\langle p,q,r\right\rangle$ constrained under $M_{\tilde{x}}$. The $M_{\tilde{x}}$ gives the minimum possible degree of falsity membership function or relation.

Table 1. Scales and their values by HSM

SCALE	RANK	N-VALES
NI	1	$\langle 0,0,0 \rangle = \tilde{1}$
I	2	$\langle 0,1,2 \rangle = \tilde{2}$
HI	3	$\langle 1,2,3 \rangle = \tilde{3}$
VHI	4	$\langle 2,3,4 \rangle = \tilde{4}$

*N-Value: Neutrosophic Value

The falsity membership relation thus estimates the degree of non-significance. The set values p, q, r gives the possible values that depict the fuzzy event, which are minimum, average and maximum, respectively.

Generally, this HSM starts by hiring the best-experienced managers to assess security rules and criteria for storage and access. Then the different aims and key criteria in the DMTEL, called cause and effect, are determined by this HSM framework. Then the DMTEL four classes, including Non-influence (NI), Non-influence (I), High-influence (HI) (VHI). Each of these scales expresses them as indicated below with a triangular neutrosophic number:

$$t_{\tilde{x}}\left(a\right) = \begin{cases} \mathrm{N}_{\tilde{x}} & \mathrm{a{=}q} \\ \dfrac{q - a + \mathrm{N}_{\tilde{x}}\left(a - p\right)}{q - p} & p \leq a \leq q \\ \dfrac{a - q + \mathrm{N}_{\tilde{x}}\left(r - a\right)}{r - p} & q \leq a \leq r \\ 1 & \text{Otherwise} \end{cases} \tag{9}$$

Similar to Equation 8, equation9 determines the truth membership function $f_{\tilde{x}}\left(a\right)$ of the input criteria or factor a, where $\tilde{x}$ be the triangular neutrosophic number set represented by $\tilde{x} = \left\langle p, q, r \right\rangle$ constrained under $N_{\tilde{x}}$. The $N_{\tilde{x}}$ gives the maximum possible degree of truth membership function or relation. The truth membership relation can be referred to as the degree of significance:

$$id_{\tilde{x}}\left(a\right) = \begin{cases} \mathrm{O}_{\tilde{x}} & a = q \\ \dfrac{q - a + \mathrm{O}_{\tilde{x}}\left(a - p\right)}{q - p} & p \leq a \leq q \\ \dfrac{a - q + \mathrm{O}_{\tilde{x}}\left(r - a\right)}{r - p} & q \leq a \leq r \\ 1 & \text{Otherwise} \end{cases} \tag{11}$$

Indeterminacy membership function $id_{\tilde{x}}\left(a\right)$ reflects the neutral\unknown fact regarding the given criteria a, as expressed in equation 11. The neutrosophic value for this membership function thus set under the constraint $O_{\tilde{x}}$, which is the minimum possible degree of indeterminacy membership function or relation. The experts do experimental and mathematical research based on their expertise in the identification of criterion principles. As the parameters are always ambiguous, complexity and indefinite, those using strictly flexible sets and neutrosophic numbers are challenging to portray. The fuzzy-neutrosophic combined set thereby discusses those conditions where every membership value is connected to the roles of falsity, indeterminacy, and truth. The degree of inclusion of these fuzzy membership grades determines the degree of involvement:

$$F_s\left(\tilde{x}\right) = \left|\left(N_{\tilde{x}} - O_{\tilde{x}} - M_{\tilde{x}}\right) + \frac{p+q+r}{3}\right| \tag{12}$$

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{j1} & \cdots & x_{jk} \end{bmatrix} \tag{13}$$

After determining the perfect scale factors, the HSM finds the average matrix or direct relation matrix. This matrix forms by averaging the experts' matrices and then transforms it into the crisp value of $\tilde{x}$ and denoted by simply x. This crisp value transformation depends on the score function, as shown in equation 12. The $F_s\left(\tilde{x}\right)$ can thus be defined as the score function. Since this score function tends to transform the neutrosophic value into te crisp value, the $\left|.\right|$ operator gives the magnitude value. From the individual crisp values, the direct relation by taking average has been computed using equation 13 and resulted in the matrix X. In matrix X of $m \times m$, x_{jk} determines the degree to whichcriterion j effect criterion k:

$$A_N = A * C = \frac{A}{\max\limits_{j} 1 \le j \le m} \sum_{k=1}^{m} x_{jk} \tag{14a}$$

where:

$$C = \frac{1}{\max\limits_{j} 1 \le j \le m} \sum_{k=1}^{m} x_{jk} \tag{14b}$$

Then, HSM measures the normalized value of the direct relation matrix using equation 14a and 14b. Then verify the accuracy of the matrices that experts produced in the previous step. For the estimation of accuracy ratios, we used super judgement tools. The accuracy ratio is below 0.1. And ultimately, the weight of the parameters should be determined to assign them a priority.

Inventory/Stock Monitoring Module

The inventory/stock monitoring module connects to the cloud data centre, cloud storage, cloud computing and smarts for smart production lines. Computing equipment and large storage equipment capable of transmitting, measuring and stocking large volumes of information from terminal pieces of equipment through the management control centre provides terminal customers with a robust, high-quality operation.The inventory/stock monitoring module aims to ensure sufficient supply across the scope of operation with the decreased logistical expense and a higher quality of service. The positioning of delivery centres and the variety of distribution networks are the main factors influencing the quality of service and distribution system costs. The location and path selection of the fulfilment centre can be configured thoroughly to maximize the distribution method.

The inventory/stock monitoring module provides cloud data centre, cloud storage, cloud computing and intelligent services for intelligent manufacturing lines. The terminal clients receive sturdy, high-quality service with computer equipment as well as huge storage systems able to transmit, measure, and store massive amounts of information from terminal pieces of equipment through the management control centre. The monitoring module for the inventory/stock seeks to maintain sufficient supply throughout the whole operational area, with lower logistical costs and better quality of service.

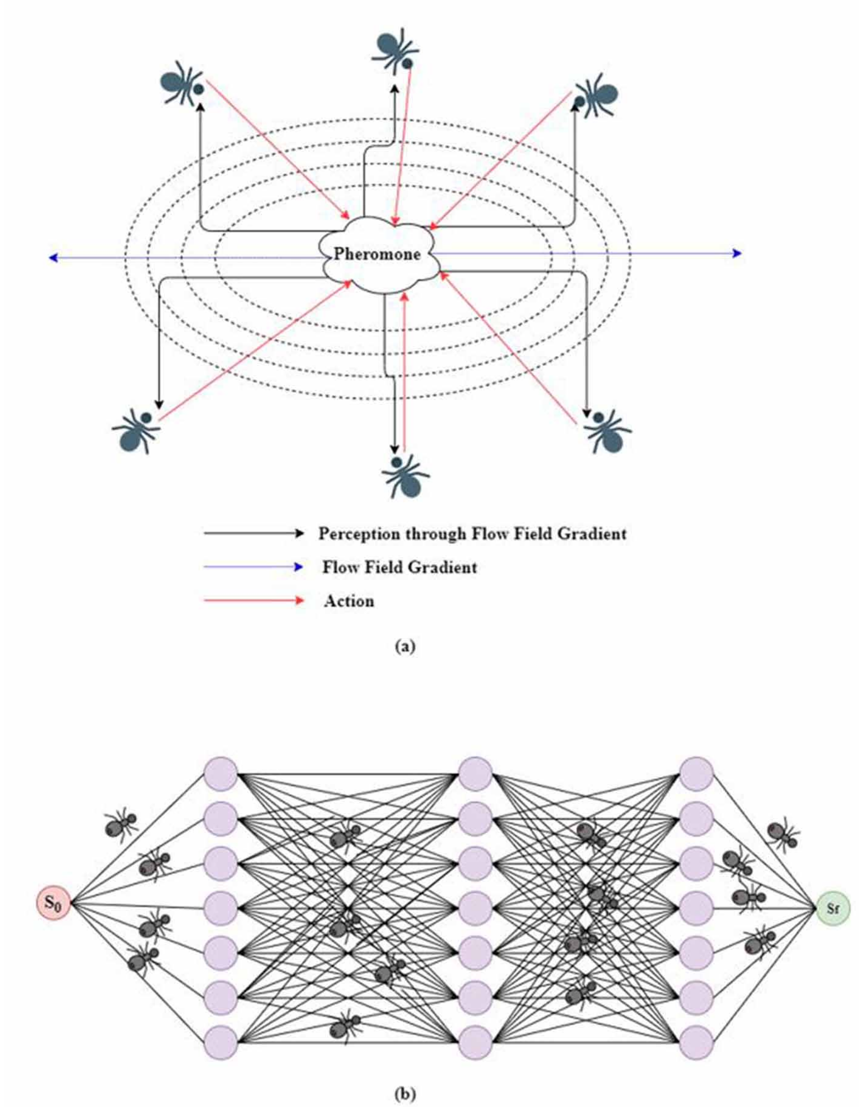
The ant colony algorithm performs the optimization of the distribution routes in the supplychain network. Ants interact using an indirect communication system known as the stigmergy, meaning symbol or mark, and ergon, i.e., work or motion, as shown in Figure 4a. The residue left behind in the environment triggers the execution by the same or separate party of the following operation. The ants use a chemical agent called pheromone, which functions as a signal sensed and used by humans of the same race to support the swarm, including guidance when searching for food sources. Once they have found a food source, ants return to the nest and set up an information-sharing pheromone route. Thus the ants can reach out their food sources, even among any complicated routes, as shown in figure 4b, where S_0 is the initial position and the S_f gives the final position (where the food source left out). Many other food-giving ants will feel the trace/odour transmitted by pheromones and lay a trail that reinforces current pheromones. The normal evaporation mechanism is included in the deposited pheromones, which decreases the strength of the smells; the decrease is directly proportional to the time passed from the nest to the source of food. The stronger the odour, the shorter the distance was. When several aunts go to the same food source, several travels to the same source will occur. This trail of more extreme pheromones provides the perfect solution. The following gives anenhanced ACO algorithm design:

$$n = \sum_{j=0}^{m-1} s_j\left(t\right) \tag{15a}$$

$$E_{jk} = \frac{1}{D_{jk}} \tag{15b}$$

The ACO method is quite close to the popular Travel Salesman Problem (TSP). The TSP situation with $m = 0,1,\ldots,m-1$, denoting a city number, illustrates the ant colony algorithm model. The number of ants in the ant colony should be n, and the variable $s_j\left(t\right)$ indicates the sum of ants in city j at that time t, as expressed in equation 15a. The D_{jk}, where $j,k=1,2,\ldots,m$ indicates the distance from city j to city k .The heuristic information E_{jk}, as measured using equation 15b generally transferred from city j to city k :

Figure 4. Idea Behind ACO; (a) Pheromone Deposition Structure (b) Optimized Path Distribution



$$p_{jk}^{i}\left(t\right)=\begin{cases}\dfrac{I_{jk}^{H}\left(t\right)*E_{jk}^{H'}\left(t\right)*r_{jk}\left(t\right)}{\sum_{j\in a}I_{jk}^{H}\left(t\right)*E_{jk}^{H'}\left(t\right)*r_{jk}\left(t\right)}; & for\ \ all\ \ j\\ 0; & Otherwise\end{cases} \tag{16}$$

The likelihood of i^{th} ant from the current route to the selection for a neighbouring path is determined by the pheromone $I_{jk}^{H}\left(t\right)$ and heuristic knowledge $E_{jk}^{H'}$ are put on the starting node to move, where H and H' are the weight of the pheromone and heuristic information. The probability of the path change is further increased to prevent the risk of premature trapping of the colony optimization algorithm at the local optimum. Consequently, the Path Transformation Probability

Formula is governed by a regulating factor $r_{jk}\left(t\right)$, as seen in equation 16. As the number of iterations increases, this factor helps to pick the ant of the little knot's pheromone and escape any pheromones of the kernels. The a is the node-set that is allowed to the i^{th} ant:

$$I_{jk}\left(t+1\right)=\left(1-\partial\right)*I_{jk}\left(t\right)+\sum_{1=1}^{\mu}\Delta I_{jk}\left(t\right) \tag{17a}$$

$$\Delta I_{jk}\left(t\right)=\begin{cases}\frac{C}{D_{jk}^{i}};N_{jk} & \text{is selected by i}^{\text{th}}\text{ ant at time t}\\ 0; & \text{Otherwise}\end{cases} \tag{17b}$$

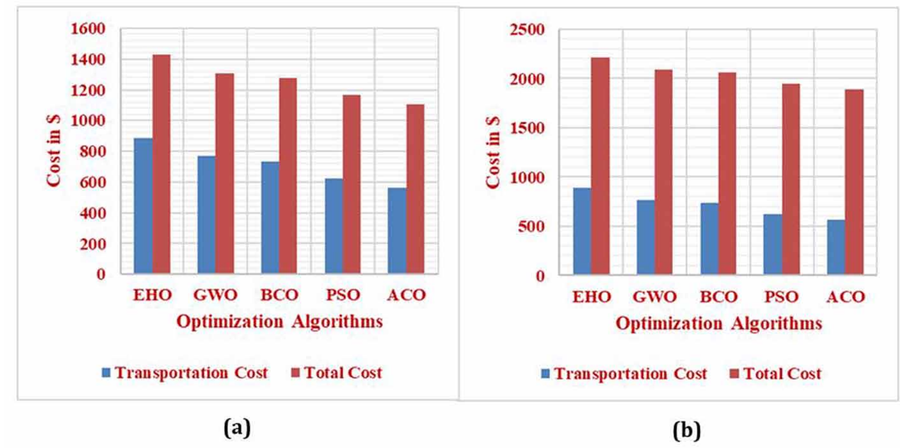
The pheromone of the current position N_{jk} should be updated after the ant j^{th} has a preferred distribution point (selected node) N_{jk}, as the modification of the pheromone increases the convergence speed and precision of the ant colony optimization algorithm. The upgraded form for the local pheromone is given in (17a)derived from (17b). The pheromone volatility coefficient ∂ is used to find the pheromone residual coefficient by $1-\partial$. For equation 17b, $\Delta I_{jk}\left(t\right)$ represents the existing pheromone of the ant i at time t for the current position N_{jk}. The C denotes the constant value that controls the pheromone value. The variable D_{jk}^{i} is the pathlength of the i^{th} ant travelled till in its search for food.

4. SIMULATION ANALYSIS AND OBSERVATIONS

The simulation analysis section includes the evaluation results of the proposed IoT-MIF and compared them with existing logistics and supply chain management frameworks included in the literature survey. The entire research was evaluated in two ways. The first case was evaluated the performance of the bio-inspired algorithms in the proposed framework and suggested the ant colony optimization algorithm for the same among many other algorithms, including Particle Swarm Optimization (PSO), Elephant Herding Optimization (EHO), Bee Colony Optimization(BCO), and Grey Wolf Optimization (GWO). Case 2 analyzed the overall performance of the proposed IoT-MIF related to the existing model, including HIDALS, SPHM, IoT-RAAFN, HYBRID-BA, BIA-LSP, and APNIA. The first four models concentrated on IoT and Cloud Management, whereas the last three was concentrated on the bio-inspired algorithm integration into logistics management in the supply chain market. The entire research was simulated using MATLAB 2020a, installed in the serverwith Dual Processors Intel Xeon E5-2600 v4/v3 CPU, Expandable Memory of 1TB DDR4 supported by 16TB SATA HDD or 8TB SATA SSD. Case I evaluation considers the two orders (Order 1 with production Cost of \$1300, Order 2 with the production cost of \$540) and evaluates the transportation cost, memory utilization, and the average running time.

Figure 5 includes the evaluation result obtained for the transportation cost in the supply network considers with the two orders (Order 1 with production Cost of \$1300, Order 2 with the production cost of \$540). The two evaluation results in the lowest transportation cost and, thus, the given orders' overall cost. The ACO algorithm enabled inventory/stock monitoring module of the proposed IoT-BIF can assure the least cost logistic management in the supply chain network. This metrics totally depends

Figure 5. Cost Metrix Evaluation for (a) Order 1 (b) Order 2



on the inventory distribution with optimal distance or path. The computed results of the optimization algorithm are thus evaluated in memory utilization and the average running time.

The ACO Algorithm enables the proposed IoT-BIF inventory/stocking module to manage the supply chain with minimal cost logistics. This depends on the distribution of the merchandise at an ideal distance or path. Throughout the memory and average operating period the calculated outcome of the optimization procedure is assessed based on root mean square deviations as shown in figure 5.

The optimization algorithms' memory utilization was evaluated to analyze the capacity requirement for the real-time implementation of the proposed IoT-BIF model with optimized inventory/stock monitoring by ensuring efficient service distribution. Figure 6 illustrates the obtained memory allocation and utilization of the proposed optimization algorithm compared to other algorithms. Both the trails have resulted in the minimum memory utilization in mbs.

Figure 7 explains the average running time evaluation of the path optimization by the various algorithms for distribution of the accepted two orders as described above. This evaluation was executed for the two trails. The results obtained for trail 1 were evaluated and traced in figure 7a, whereas trail 2

Figure 6. Memory Utilization (a) Trail 1 (b) Trail 2

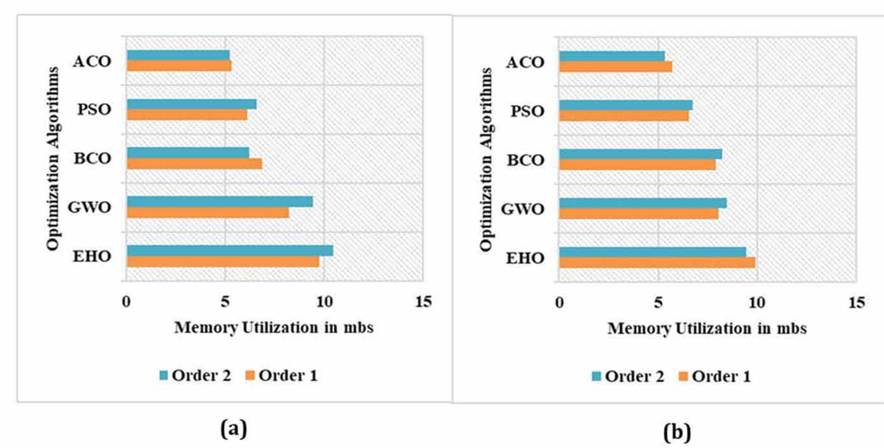
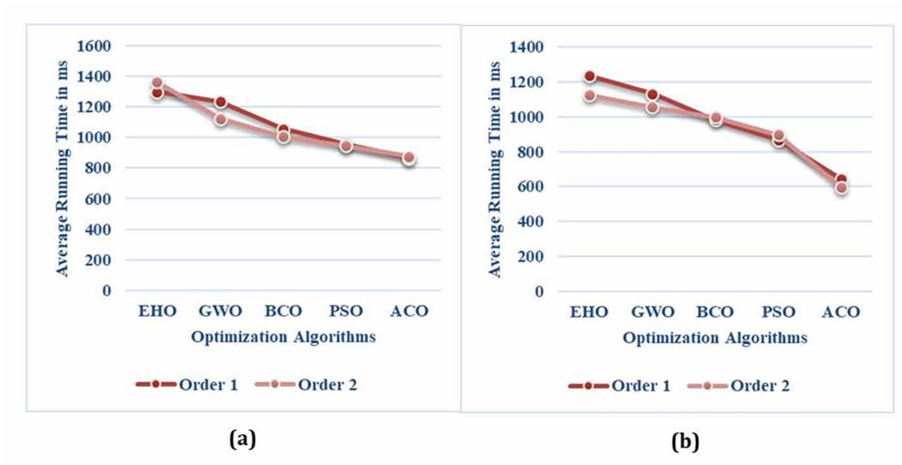


Figure 7. Average Running Time (a) Trail 1 (b) Trail 2



are plotted in figure 7b. These above results can ensure that the ACO algorithms take the least amount of running time for the ratio of about 33.64%, with the largest running time by the EHO algorithm.

The network lifetime of the proposed framework determines the efficiency of the IoT sensor communication and processing. Figure 8a evaluates the network lifetime of the proposed IoT-BIF compared to existing models without integrating the bio-inspired algorithms. In contrast, figure 8b included the comparative results of the existing models with the bio-inspired algorithms and the proposed framework. The above figure concluded that the increase in the number of nodes decreases the network lifetime. Even though the proposed IoT-BIF showed the highest lifetime of about 24% higher than the lowest one. For the logistic management in a supply chain network with bio-inspired algorithms, the network lifetime gives the best.

Figure 9 reports the energy consumption level evaluation. Energy consumption is one of the major evaluation criteria for any IoT based frameworks or model. Thus, this study identified the proposed model's energy consumption level compared with the existing supply chain management

Figure 8. Network Lifetime (a) Without Bio-inspired Algorithm (b) With Bio-Inspired Algorithm

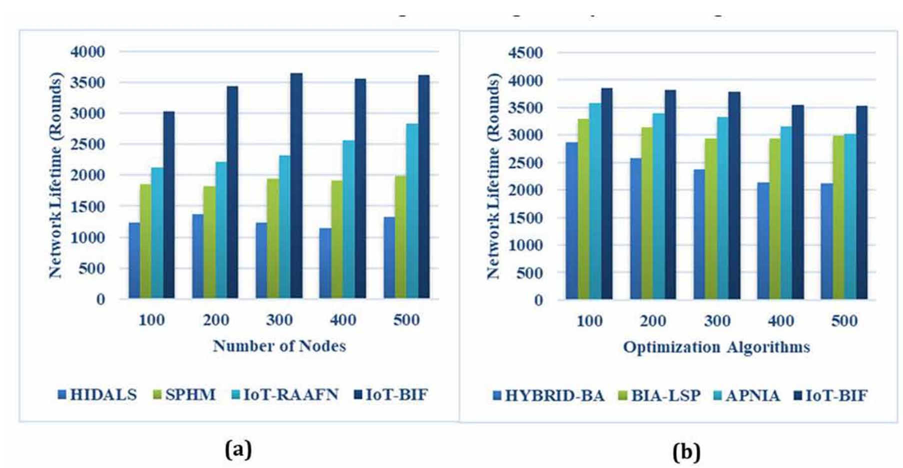
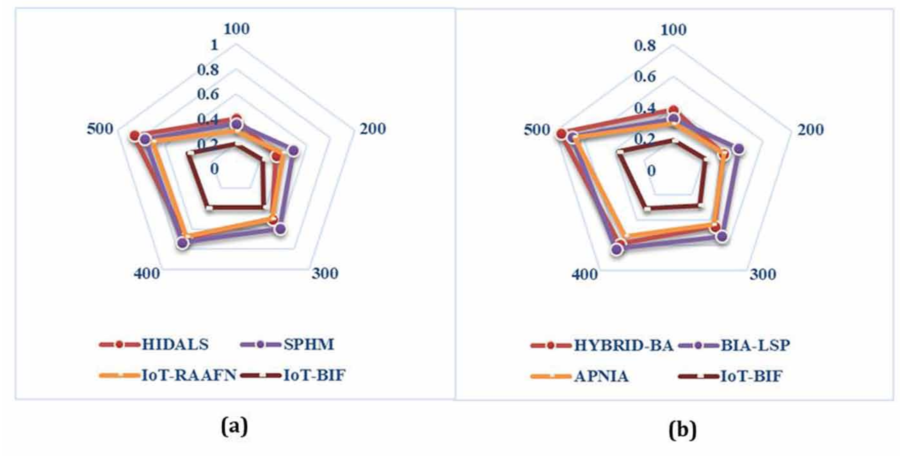


Figure 9. Energy Consumption (a) Without Bio-inspired Algorithm (b) With Bio-inspired Algorithm



model integrated with the IoT module and not with bio-inspired algorithms, as seen in figure 9a. This figure showed the lowest energy consumption for IoT-BIF of about 0.315 at the mean. Figure 9b demonstrates the obtained results of energy consumption while implementing the given models incorporating bio-inspired algorithms. Both the results suggest the proposed model with the bio-inspired algorithm for real-time implementation with the lowest energy consumption and the highest network lifetime.

5. CONCLUSION AND THE FUTURE SCOPE

For efficient logistics management and supplies chain processes, IoT-assisted Bio-Inspired System (IoT-BIF) was proposed in this report. IoT sensors (RFID) monitored goods through various supply chain units, using the ACO technique, to cope with under- and over-stocking problems and the distribution path optimization. This new technology facilitated the interaction of several objects by capturing and exchanging real-time data, which could help simplify industry decision-making. The test results indicated that the proposed IoT-BIF approach decreases costs, memory usage and average time relative to other common approaches.The suggested template further assessed its IoT connectivity performance, contributing to the highest network life and energy usage. In the future, the integration of the CNN model for improved supply chain management has been planned.

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