



Internet of things for perishable inventory management systems: an application and managerial insights for micro, small and medium enterprises

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Abstract

Micro, Small, and Medium Enterprises (MSMEs) operating in the food retailing sector encounter two main concerns with respect to their perishable inventory management system, i.e., the product's shelf life and investment in warehouse monitoring systems. New technologies like the Internet of Things (IoT), automated inventory control platforms, and automatic storage and retrieval systems offer effective solutions to these issues. However, MSMEs are reluctant to adopt these technologies due to their prior perception of higher implementation costs and the expected benefits. The present study aims to optimize IoT implementation in MSMEs' inventory management systems and to provide tangible proof of its feasibility and usefulness. In so doing, we propose a mathematical model and analyze the impact of IoT through two case studies. The model provides a cost–benefit analysis of IoT investments that aim to increase products' shelf life. We adopted the fractional program method, solved by particle swarm optimization on MATLAB software. The findings demonstrate the positive correlation between adopting IoT and reduced inventory costs supporting IoT deployment for improved perishability performance in MSMEs. The study offers several insights and practical guidelines in considering IoT deployment in MSMEs.

Keywords MSME · Inventory management · Internet of Things · Perishable · Warehousing

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1 Introduction

The dynamic behavior of customers, cut-throat competition, rapid growth in technology, and globalization have all imposed critical challenges on maintaining acceptable quality and optimal inventory levels in retail industries and warehouse sectors (Gupta et al., 2020). For practitioners, monitoring and control aspects of warehouse management are vital tasks that include analyzing various parameters such as enzymes, micro-organisms, temperature, and humidity which constitute serious challenges when managing perishable items (Bakker et al., 2012; Gupta et al., 2020; Pérez et al., 2019). In recent years, issues concerning the management and warehousing of perishable items have gained increased interest among researchers and practitioners (Gupta et al., 2020; Tiwari et al., 2017). Perishable items are characterized by shorter shelf life and require meticulous warehousing and management systems to avoid spoilage, maintain their availability, and ensure revenue generation for the whole business (Gupta et al., 2020; Patel & Gor, 2019). Perishable warehouse and inventory management systems concern several items (e.g., storage of pharmaceuticals, fruit, vegetables, grains, and volatile liquids).

Previous studies have argued that most food companies, particularly Micro, Small, and Medium Enterprises (MSMEs), view higher perishability rates as the main reason for declining revenue generation (Kamble et al., 2020b; Zhu et al., 2021). MSMEs face enormous financial and organizational challenges in warehouse facility management (Belhadi et al., 2018), involving significant national economic losses. According to Yang et al. (2019), 30% of perishable items handled by MSMEs deteriorate due to improper handling and lack of facilities (e.g., China loses 43 billion US\$ per year). In the context of MSMEs, deterioration is a widespread phenomenon in perishable items, leading to wastage of around 20% of all food production (Li et al., 2019). In a developing country like India, improper maintenance of perishable items by MSMEs led to annual losses of 40%, at a value of over 14 billion US\$ a year. The main causes of such losses in MSMEs are poor storage systems, outdated storage facilities, improper handling of units, poor collaboration, and lack of infrastructure (Sharon et al., 2014). Sharon et al. (2014) found that inadequate and outdated warehouse facilities in MSMEs generated 6% of post-harvest losses. Insufficient storage and non-optimized handling depend on various factors like lack of communication, lack of logistic facilities, and inadequate strategies between supply chain partners.

To maintain product quality and the smooth flow of inventories, the public and private sectors have introduced many initiatives to develop warehouse facilities via high-tech infrastructures. For instance, the National Horticulture Mission (NHM), India, estimates that over US\$ 8.5 billion was invested in the warehouse sector, and 101 high-tech cold storage projects were approved in 2019. The recent literature has extensively recommended adopting advanced technologies such as the internet of things (IoT) for perishable inventory management (Čolaković et al., 2020; Kamble et al., 2018b; Moeuf et al., 2018; Pundir et al., 2019a; Salunkhe & Nerkar, 2017). According to Kamble et al. (2019), IoT substantially improves the product picking process, communication between processes and reduces product spoilage. It thus appears that IoT has great potential to help food-related MSMEs to control food product quality, reduce waste by enhancing food shelf life, manage operating conditions equipment, and reduce energy consumption (Kamble et al., 2018b, 2020b).

Despite the vast potential of IoT in the food retail supply chain (Kamble et al., 2019; Pundir et al., 2019b; Sharon et al., 2014), the adoption of IoT for perishable or Non-Instantaneous Deteriorating Items (NIDIs) inventory management is still in the nascent stage, especially for MSMEs (Hansen & Bøgh, 2021). Many financial, organizational, and technical challenges

hinder IoT investment in MSMEs (Hansen & Bøgh, 2021; Huang et al., 2020; Kamble et al., 2018b). A study by Kamble et al. (2019), for instance, argued that the apparent lack of successful IoT initiatives is mainly due to the perception of high operating and implementation costs. However, no validation studies are available in the present literature. Hence, there is an urgent need to conduct additional studies to validate the benefits of IoT and convince MSME managers/owners. The current research focuses on IoT implementation in MSMEs in the NIDIs context. A mathematical model with IoT investment for profit maximization in a single warehouse environment is developed and validated using a case study.

The remainder of the paper is organized as follows. Section 2 presents a literature review on our study's three main topics, i.e., IoT, MSMEs, and perishable items warehousing. Section 3 illustrates the IoT-based model for perishable items inventory management in the context of MSMEs. Section 4 presents the model formulation, while Sect. 5 demonstrates the model's application and offers insights for discussion and implications. Finally, Sect. 6 concludes the paper with the limitations and the future research agenda.

2 Literature background

2.1 Internet of things implementation in MSMEs

IoT refers to an object-space connected network wherein real-time communication between physical and cyber systems is established. It includes several information and communication-based technologies such as computers, mobile technologies, smart sensors, and analytics platforms (Hansen & Bøgh, 2021; Moeuf et al., 2018). IoT is based on mutual intelligent relationship formation through sensing, information processing, and networking among objects with minimum human intervention.

The implications of IoT are not well developed among MSMEs, and very few successful cases are available in the literature. This means that MSMEs' real benefits and the requirements for implementing IoT are not fully known (Moeuf et al., 2018). Theoretically, several studies have asserted that IoT might be extremely useful for smaller companies. For instance, (Moeuf et al., 2018) found that 90% of experts agreed that IoT is a crucial Industry 4.0 technology that MSMEs should leverage to generate exploitable data. Hansen and Bøgh (2021) posit that IoT would shape the future of operation management in MSMEs and has considerable potential to ensure their survival and competitiveness. This is further supported by Shin (2017), who stated that IoT is a crucial enabler for MSME innovation. However, the practical implementations of IoT in the MSME context are lacking in the literature. According to Hansen and Bøgh (2021), MSMEs owners and managers are reluctant to invest in IoT as they are unaware of its usefulness. Moeuf et al. (2018) and Shin (2017) called for more studies to provide empirical evidence on the potential of IoT in the context of MSMEs.

2.2 IoT implementation and investment in warehouse management of perishable items

By 2025, IoT smart objects are expected to reach 212 billion entities, generating more interest from researchers and practitioners (Salunkhe & Nerkar, 2017). In recent years, research on the smart warehouse, logistics, and automation has gained considerable traction, with most studies driven by customer-centric approaches. As automation plays a crucial role in item

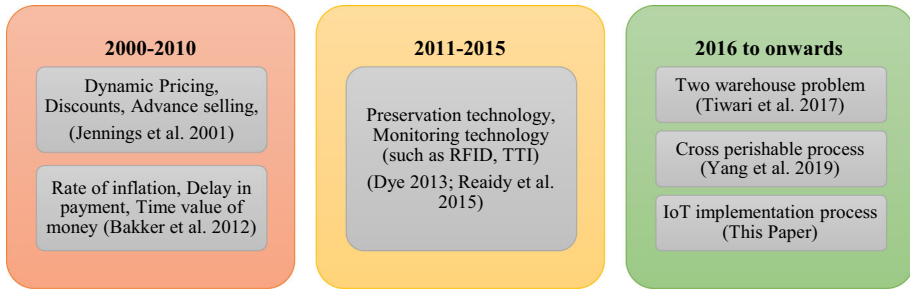


Fig. 1 Progress in the literature of perishable inventory

selection at retail outlets, developing novel IoT implementation strategies in the warehouse is also gaining interest (Kamble et al., 2018a).

Advances in research on IoT have evolved significantly since 2011, successfully fulfilling Industry 4.0 (Kamble et al., 2020b). The growth of MSMEs is central to warehousing, given the nature of business (Mogale et al., 2020). Hansen and Bøgh (2021) confirmed that MSMEs struggle to adopt advanced technologies due to a lack of resources, knowledge, dedicated strategies, and practical research implications.

Recently, Kumar et al. (2021) provided a comprehensive literature review on warehouse management systems through a systematic evolutionary method that considered peer-reviewed articles published between 1990 and 2019. They identified three clusters based on warehouse management themes, sub-themes, and topics. The first cluster (1990–2000) shows that the preliminary studies were published on operation strategy (planning, policy, and warehouse location/size) and warehouse operations (reception, storage, picking, and shipping), while the second cluster (2000–2010) reveals that the primary focus in this period was resource management and infrastructure design (location-allocation/ reallocation, layout design, safety, and ergonomics). The third cluster (2010–2020) focuses on integrating technologies and equipment (sub-theme: technology implementation, automation, control, equipment configuration) and performance evaluation. Concerning the existing literature, Fig. 1 provides information on the chronological development of automation and emerging practices in the targeted area.

The literature is relatively scarce regarding the warehouse management of perishable items (i.e., NIDIs) for MSMEs. Bakker et al. (2012) discussed various critical NIDI issues that included discount models, the concept of shortages and back-ordering, single item and multi-item inventory control systems, multi-warehouse theory, the need for advanced technologies for deteriorating inventory, multi-echelon inventory control, the concept of inflation, the time value of money, and permissible delays in payment. Bakker et al. (2012) enhanced the literature by including warehouse and profit aspects. New parameters later evolved in the modeling like inventory policy (FIFO, LIFO), customer service levels, promotions or budget constraints, waste or shrinkage, returns, advances in technology, and product strategy.

At the same time, COVID-19 has shown the need for an advanced warehousing system that is self-sustainable and operational (Kumar et al., 2021).

Table 1 presents the application and other aspects of advancement in inventory management, warehousing, and MSMEs. However, the intervention of new technologies such as IoT and blockchain-related issues have not been discussed extensively (Fig. 2).

Not every aspect of the NIDI model can be categorized without the concept of demand and deterioration. Perishable inventory management typically follows price-dependent demand

Table 1 Development in literature in inventory management, warehousing, and MSMEs

Field of Research	Objective function	Technology used	Methodology	Application areas	Implications	Utility	References
Inventory Management	Cross perishability	Smart things	Experimental	Perishable items	IoT increases the real-time visibility	Improved transparency	Yang et al. (2019)
	Monitoring and control system	RFID tags	Conceptual	Warehouse	Multi-Stage Supply Chain	Improved last-mile delivery	Čolaković et al. (2020)
	Optimal ordering quantity	Smart things	Longitudinal	Green food	Reducing Inventory misplacement	Real-time stock count	Mogale et al. (2020)
	Minimization of cost	price-dependent strategy	Analytical	Preservation technology	Shelf Inventory Control Policies	Reducing investment	Li et al. (2019)
	Customer service level	Smart things	Conceptual	Warehouse	Effectiveness of RFID	Reducing bottom line	Kumar et al. (2021)
Warehousing	Security measures	Smart things RFID tags	Correlational	Three dimensional space	Optimization of ordering time. Ordering Time savings in the order of 81 to 99%	Data synchronization	Hervet-Escobar et al. (2017)
	Storage capacity	Cloud of Things	Conceptual	Warehouse Monitoring System	Processing time savings	Real-time Product tracking	Čolaković et al. (2020)
	To meet consumption requirement	Smart things and Bottom-up approach	Conceptual	Warehousing environment	Collaborative warehousing environment	Information transparency	Ready et al. (2015)

Table 1 (continued)

Field of Research	Objective function	Technology used	Methodology	Application areas	Implications	Utility	References
MSME's	Process automation	Smart things	Conceptual	Production	Smart management	Fraud Prevention and Safety	Kamble et al. (2018b); Pundir et al. (2019b)
	Budget constraints	Smart things and multi-agents	Analytical	Storage	System reliability and safety aspects	Optimizing operations	Huang et al. (2020)
	Implication of IoT	Empirical investigation	Conceptual	Smart MSMEs	Interconnections between technologies	Predictive maintenance	Kamble et al., (2018a, 2018b); Hansen and Bøgh (2021)
	Sustainable performance	Empirical investigation	Conceptual	Smart manufacturing systems	Sustainability	Higher employee productivity	Hansen and Bøgh (2021)
	Greener performance	Lean	Conceptual	Production	Smart management	Customer engagement	Belhadi et al. (2018)
	IoT deployment	Exploratory	Individual interviews and case study	seamless integration of entities	The link between disruptive and open IoT attributes	Identifying new markets	Shin (2017)

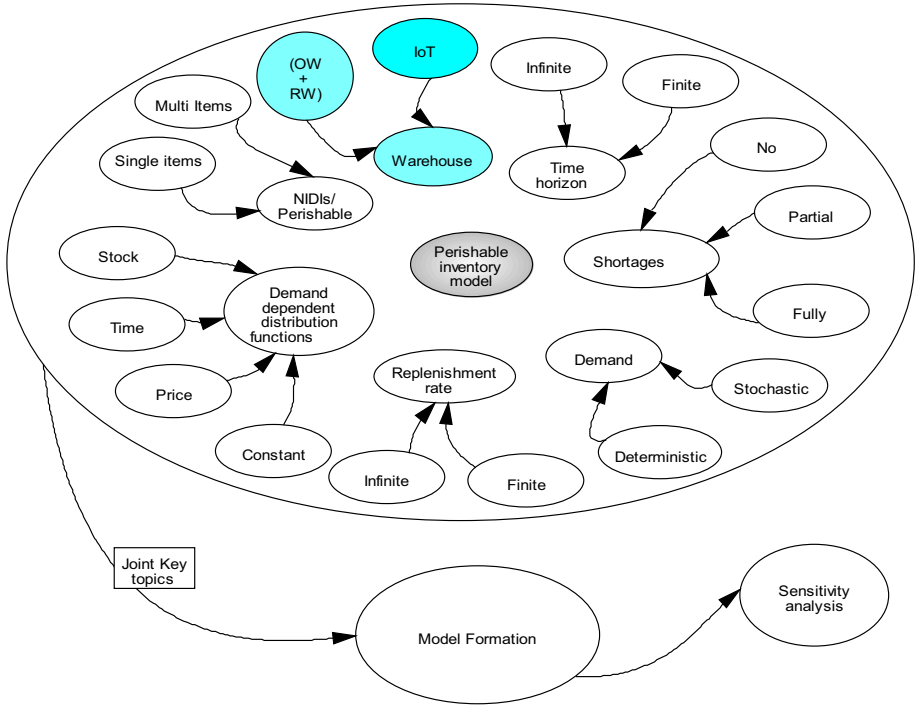


Fig. 2 IoT integration in the warehouse sector for a perishable inventory model

as these commodities are not unique. Customers, therefore, switch to alternative items if prices increase. Bakker et al. (2012) stated that an item’s price is a key factor that encourages customers to buy more items. They also showed that price-dependent demand is more realistic in the current business environment as lot size and retailer price are mutually interdependent. Tiwari et al. (2017) studied the impact of price-dependent demand on replenishment strategies with attractive price discounts under the first-in-first-out (FIFO) dispatch policy; seasonal products are generally based on a price-dependent demand function.

Chakraborty et al. (2020) proposed two static models showing that dynamic pricing can effectively increase overall profit, developing a price-dependent demand-based model with the time value of money. Li et al. (2019) considered price-dependent demand to explore the possibility of a preservation technology for blackberries, predicting the deterioration period of the items. Pérez et al. (2019) studied stock-dependent demand using a discounted cash flow approach for inflationary conditions. The present study focuses on a perishable inventory management system for MSMEs, thereby contributing to their strategies and implications.

3 IoT-based model for NIDI inventory management in the context of MSMEs

According to Čolaković et al. (2020), a typical IoT network includes four essential layers. The first layer is a *sensing layer* that includes different types of ‘things’ like RFID tags, sensors, and actuators. Second, the *networking layer* enables the flow of information through

the wired or wireless network. Third, the *service layer* connects the application by a middle-ware technology. Finally, the *interface layer* displays information to retailers and promotes interaction with the system.

In our study, the service and interface layers are together referred to as application and networking layers.

3.1 Framework for sensing layer

The design and implementation of sensing layers are crucial for IoT implementation, combined with hardware such as the RFID tag, sensors, and actuators that sense and monitor the physical systems and collect the data (Kamble et al., 2019). Yang et al. (2019) used a network of wireless sensors to collect and transmit information about temperature, humidity, the physical position of items, etc., in real-time to create a smart management system. The general type of sensor includes a temperature sensor, a humidity sensor, and a gas sensor. An actuator is a device that organizes a system and performs actions in an IoT system (Salunkhe & Nerkar, 2017). Embedded systems are generally controllers that detect an electrical function with real-time processes (Čolaković et al., 2020; Modh et al., 2015; Salunkhe & Nerkar, 2017; Yang et al., 2019).

3.1.1 Protocols

A protocol is a standard set of rules that allow electronic devices to communicate with each other. The protocols decide the data transmission mode, and commands are based on Bluetooth, RFID, Zing bee, or BLE technology (Čolaković et al., 2020).

3.2 Framework for networking layer

3.2.1 Gateway

A gateway is a part of networking hardware used in communication networks that permit data to flow from one node to another. Gateways are distinct from routers or switches in that they communicate using more than one protocol (Salunkhe & Nerkar, 2017). Some available gateways include LTE Cellular Gateways, Ethernet Gateways, Cellular Gateway, Wireless sensor adapters, and Modbus Gateway.

3.2.2 Connectivity

Connectivity processes enable the device to communicate from the server and include 3G/4G/5G, Wi-Fi, and White space spectrum.

3.2.3 Connection management platform (CMP)

CMP is an integral part of the networking layer, mainly responsible for connecting the sensing & application and the management layers. The connection management platform includes connectivity analyses and monitoring.

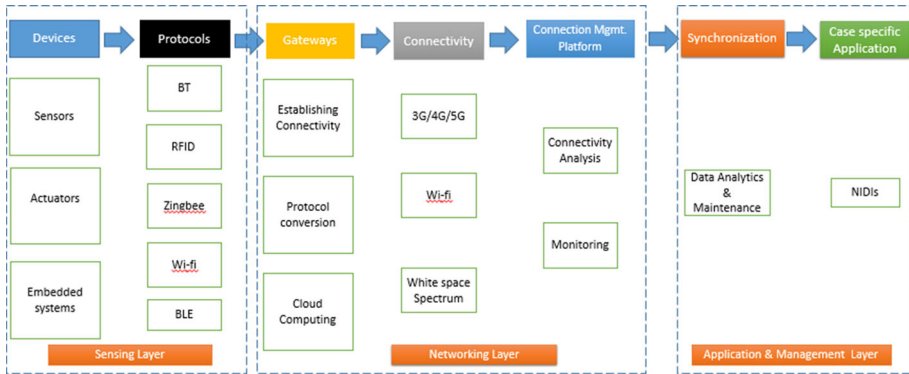


Fig. 3 Technological framework for IoT implementation in the warehouse system

3.3 Framework for application and management layer

After successfully implementing the sensing and networking layers, the application and management layer provides the much-required human–machine interface. This layer predicts how much effort is required in the warehouse to maintain an optimal inventory level. The framework is based on the synchronization process, data analytics, and maintenance concepts.

Nunes (2008) defined the perishability index (PI) of each perishable item on which the operating conditions are determined. The perishability index helps the warehouse operation to retain the appropriate temperature and humidity for a specific type of inventory. Based on the discussion in the previous sections, we put forward an IoT implementation framework for the retailer’s warehouse (See Fig. 3).

4 Model formulation

4.1 Notations and assumptions

4.1.1 Notations

The following notations were used in the model.

Notation	Details
<i>Decision variables</i>	
φ	Amount of IoT investment to reduce spoilage rate
$m(\varphi)$	Reduced deterioration rate (Proportion to IoT implementation condition), $0 \leq m(\varphi) \leq 1$
T	Duration of one cycle
T^{n*}	Duration of n cycle
t_1	A point at which stock in the warehouse is zero
<i>Known parameters</i>	
D	Demand rate (per unit time)

Notation	Details
c_h	Holding cost of the item in the retailer's warehouse (per unit/time)
c	Purchasing cost per unit item
$p(> c)$	Retail price per unit item
c_l	Cost of lost sales (₹ /unit)
c_s	Shortage cost per unit time
θ	Rate of deterioration (fix rate)
R	Replenishment cost per order in the single-warehouse system
<i>Dependent parameters</i>	
H_s	The overall cost imposed on the sensing layer
H_{gs}	Investment cost on gas sensors
H_{ts}	Investment cost on temp. sensors
H_{hs}	Investment cost on humidity sensors
H_a	Investment cost on actuators
H_e	Investment cost on embedded system
H_p	Investment cost on protocol setup
H_n	The overall cost imposed on the networking layer
H_g	Investment cost on Gateways
H_c	Investment cost on connectivity
H_{cm}	Investment cost on Connection Mgmt
H_{am}	The overall cost imposed on the application and management layer
H_{sy}	Investment cost on synchronization of the system
H_{hi}	Hidden infrastructure cost
x	A point at which random deterioration being started with limit, a random variable over (l, u) with Probability Density function $f(\cdot)$ and Cumulative distribution function $F(\cdot)$
<i>Functions</i>	
$I_1(t)$	(Case 1) Stock level during no backlogged
$I_2(t)$	Stock level during the backlogged condition in case 1
$I_3(t)$	Level of inventory during case 2
$TP(t_1, T, \varphi)$	Total profit function

4.1.2 Assumptions

The following assumptions are made.

- (i) Lead time is zero and constant market demand (Tiwari et al., 2017).
- (ii) At period $[0, x]$, there is no deterioration; then the product starts deteriorating at a rate of θ , where X is the random deterioration start time (Yang et al., 2019).
- (iii) During the cycle, there is no repair or replacement of spoiled items (Chakraborty et al., 2020; Patel & Gor, 2019).
- (iv) Yang et al. (2019) and Li et al. (2019) developed a mathematical model to implement preservation technologies in inventory management systems. Their model considers preservation cost as a variable. In our model, the total investment cost function is φ , for IoT implementation, and includes the implementation costs related to sensing,

networking, and application and management layers. Hence, $m(\varphi)$ is a continuous, concave, increasing function of the retailer's capital investment φ . Through $m(0) = 0$ and $\lim_{\varphi \rightarrow \infty} m(\varphi) = 1$. Hence, we assume $m'(\varphi) > 0$, which shows that IoT investment is beneficial, and $m''(\varphi) < 0$, to represent the return of the IoT implementation cost.

- (v) We followed the assumption of Pérez et al. (2019) according to which demand is partially backlogged, where decreasing function $\beta(y)$ (i.e., $\beta'(y) < 0$) represents a fraction of partially back-ordered demand. According to Dye (2013), it shows the time duration for the next replenishment cycle which satisfies the condition $0 \leq \beta(y) \leq 1$ with $\beta(0) = 1$ for all y . According to Patel and Gor (2019), the value of y decides whether shortages are either lost or wholly backlogged.
- vi. We considered infinite replenishment to reduce complexity (Chakraborty et al., 2020; Gupta et al., 2020).
- vii. Preservation technologies are functional (Li et al., 2019).

We assume that the spoilage of an item starts from any random stage in time x . Consequently, we considered two special cases:

- Case 1: The product starts deteriorating before the inventory level reaches zero (see Fig. 4).
- Case 2: The inventory level reaches zero before deterioration starts (see Fig. 5).

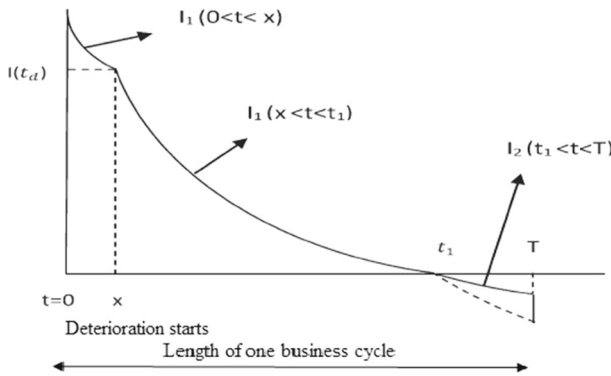


Fig. 4 Inventory level when $x < t_1$

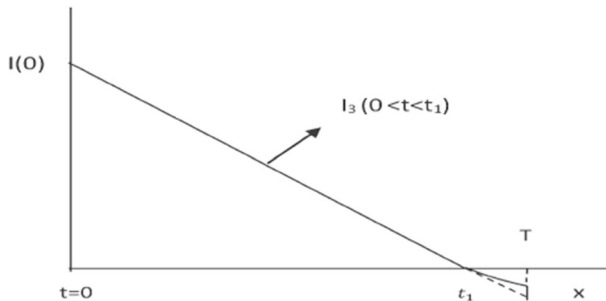


Fig. 5 Graphical representation of the stock when $(x > t_1)$

Profit functions for cases 1 and 2 are calculated separately and drive the expected average profit from the conditions. We used similar values in both cases in the solution approach, so the model is formulated only once.

The total Investment cost of IoT = Overall cost incurred of sensing layer + Overall cost incurred of networking layer + Overall cost incurred of application and maintenance layer + Hidden implementation cost.

The overall cost of sensing layer = Investment cost of gas sensors + Investment cost of temperature sensors + Investment cost of humidity sensors + Investment cost of actuators + Investment cost of the embedded system + Investment cost of protocol setup.

$$H_s = (H_{gs} + H_{ts} + H_h + H_a + H_e + H_p) \quad (1)$$

The total cost incurred of the networking layer = Investment cost of Gateways + Investment cost of Connectivity + Investment cost of connection management.

$$H_n = H_g + H_c + H_{Cm} \quad (2)$$

The overall cost imposed on the application and management layer = investment cost of synchronization + Hidden infrastructure cost.

$$H_{am} = H_{sy} + H_{hi} \quad (3)$$

Therefore, the total investment cost of IoT is given by Eq. 4, where the limit $i = 1$ to n defines the number of setups.

$$\varphi = \left(\sum_{i=1}^n H_s + \sum_{i=1}^n H_n + \sum_{i=1}^n H_{am} \right) \quad (4)$$

4.1.3 Case 1: $x \leq t_1$

In case 1, we discussed the change in stock level with zero shortage. The literature review suggests that most previous research assumes a specific period in which no-spoilage occurs since, without any monitoring technology like IoT, standalone preservation mechanisms cannot predict a product's remaining shelf life. For example, a cold storage refrigeration system retains the freshness of perishable items but cannot precisely predict the point at which the product starts deteriorating (Yang et al., 2019). Shin (2017) argues that IoT helps to monitor and prevent perishable food from spoilage. Recently Yang et al. (2019) conducted an experimental study on a real-time shelf life estimation with IoT by kinetic food quality models. Technically, it is well proven that IoT can monitor and control aspects of warehouse management systems and offers managers new opportunities and benefits (Čolaković et al., 2020).

To identify the managerial implications of IoT implementation, we selected one business cycle, as shown in Fig. 4. For the analysis, it is more useful to consider a random point from which deterioration will start. We also examined how the implementation of IoT plays a role in optimal inventory level decisions with the variance in the deterioration occurrence over time. In Fig. 4, we represent the length of the business cycle on the x-axis and the warehouse inventory level on the y-axis; the condition $I_1(0 < t < x)$ shows the level of inventory before deterioration starts. After a specific period at a certain point, x deterioration begins over the condition $I_1(x < t < t_1)$. The proposed IoT-governed preservation mechanism is implemented in the second interval ($x \leq t \leq t_1$) and we investigated whether IoT investment is beneficial for a retailer or not with function $m'(\varphi) > 0$, along with the decision of the IoT

investment return with condition $m''(\varphi) < 0$. The condition $I_2(t_1 < t < T)$ depicts the level of inventory during the shortage period.

The differential equation represents the change in stock level during the no shortage period.

$$\frac{dI_1(t)}{dt} = -D; \text{ When } 0 \leq t \leq x \tag{5}$$

For the second interval,

$$\frac{dI_1(t)}{dt} = -D - \{1 - m(\varphi)\}\theta I_1(t); \text{ When } x \leq t \leq t_1 \tag{6}$$

Solving the above equation under the boundary condition $I_1 = 0$,

$$I_1(t) = D(x - t) + \frac{D}{\theta(1 - m)} \left[e^{\theta(1-m)(t_1-x)} - 1 \right]; 0 \leq t \leq x \tag{7}$$

For the second interval,

$$\frac{D}{\theta(1 - m)} \left[e^{\theta(1-m)(t_1-x)} - 1 \right]; \text{ Where } x \leq t \leq t_1 \tag{8}$$

The overall inventory holding cost during the period $(0, t_1)$ is given by

$$\begin{aligned} c_h \int_0^{t_1} I_1(t) dt &= c_h \int_0^x I_1(t) dt + c_h \int_x^{t_1} I_1(t) dt = \frac{Dc_h x^2}{2} \\ &+ \frac{Dc_h}{\theta(1 - m)} \left[e^{\theta(1-m)(t_1-x)} \left\{ x + \frac{1}{\theta(1 - m)} \right\} - \left\{ t_1 + \frac{1}{\theta(1 - m)} \right\} \right] \end{aligned} \tag{9}$$

The costs incurred during the backlogged period $[t_1, T]$ and $(T - t)$ is queue time for customers who seek the item at the time t ($t_1 \leq t \leq T$) and waiting for the product till the next replenishment is receive in the warehouse. Therefore, the demand which will be backlogged is a fraction of $\beta(T - t)$ and the rest is zero.

The change in stock level during $[t_1, T]$ shortage period is expressed by-

$$\frac{dI_2(t)}{dt} = -D\beta(T - t); \text{ When } t_1 \leq t \leq T \tag{10}$$

Solving the equation at $I_2(t_1) = 0$,

$$I_2(t) = -D \int_{t_1}^t \beta(T - y) dy; \text{ When } t_1 \leq t \leq T \tag{11}$$

The overall backlogged cost during shortage for the entire period is $Dc_s \int_{t_1}^T (T - t)\beta(T - t)dt$ and the total lost sales cost is $c_1 D \int_{t_1}^T [1 - \beta(T - t)]dt$, while

the total amount of back-ordered and sales quantity is represented by $D \int_{t_1}^T \beta(T - t)dt$, $Dt_1 + D \int_{t_1}^T \beta(T - t)dt$, respectively.

The total output volume is $I_1(0)$ with the back-ordered quantity is:

$$Dx + \frac{D}{\theta(1-m)} \left[e^{(1-m)(t_1-x)} - 1 \right] + D \int_{t_1}^T \beta(T-t) dt \quad (12)$$

The overall investment in IoT for the period $[0, T]$ is $T\varphi$.

4.1.4 Case 2: $t_1 < x$

In this case, we have considered the entire inventory ($I_3(0 \leq t \leq t_1)$) consumed before the deterioration starts. The inventory consumption pattern is shown in Fig. 5. For both, the cases expected average profit function is calculated separately.

The variation in the stock level is given by Eq. (13).

$$\frac{dI_3(t)}{dt} = -D; 0 \leq t \leq t_1 \quad (13)$$

Applying the condition $I_3(t_1) = 0$, we obtain Eq. (14)

$$I_3(t) = D(t_1 - t); 0 \leq t \leq t_1 \quad (14)$$

At a specific period holding cost is given by Eq. (15)

$$c_h \int_0^{t_1} I_3(t) dt = \frac{c_h D t_1^2}{2} \quad (15)$$

The overall output or quantity of production in the present situation is given by Eq. (16).

$$D t_1 + D \int_{t_1}^T \beta(T-t) dt \quad (16)$$

If the shortage and cost of lost sales are not dependent on x they all are identically similar to Case 1. Therefore, the average expected profit is given by Eq. (17).

$$\nabla(t_1, T, \varphi) = \frac{TP(t_1, T, \varphi)}{T} \quad (17)$$

where

$$\begin{aligned}
 P(t_1, T, \varphi) &= Dpt_1 \\
 &\quad - \int_{l}^{t_1} \left[\frac{Dx^2c_h}{2} + cDx + \frac{Dc_h}{\theta(1-m)} \left\{ e^{\theta(1-m)(t_1-x)} \times \left(x + \frac{1}{\theta(1-m)} \right) - \left(t_1 + \frac{1}{\theta(1-m)} \right) \right\} \right. \\
 &\quad \left. + \frac{cD}{\theta(1-m)} e^{\theta(1-m)(t_1-x)} \right] f(x) dx - \int_{t_1}^u \left[cDt_1 + \frac{Dc_h t_1^2}{2} \right] f(x) dx - K - \varphi T \\
 &\quad + (p - c) D \int_{t_1}^T \beta(T - t) dt - c_1 D \\
 &\quad \times \int_{t_1}^T \{1 - \beta(T - t)\} - c_s D \int_{t_1}^T (T - t) \beta(T - t) dt
 \end{aligned}$$

For simplification, we have used the approximation method shown in Eq. (18).

$$e^{\theta(1-m)(t_1-x)} \approx 1 + \theta(1-m)(t_1-x) + \frac{\theta^2}{2}(1-m)^2(t_1-x)^2 \tag{18}$$

We get

$$\begin{aligned}
 TP(t_1, T, \varphi) &= Dpt_1 - \int_{l}^{t_1} \left[\frac{Dx^2c_h}{2} + cDx + Dc_h \left\{ (t_1 - x)x + \frac{\theta(1-m)(t_1-x)^2}{2} + \frac{(t_1-x)^2}{2} \right\} \right. \\
 &\quad \left. + cD \left\{ (t_1 - x) + \frac{\theta(1-m)(t_1-x)^2}{2} \right\} \right] f(x) dx \\
 &\quad - \int_{t_1}^u \left[cDt_1 + \frac{Dc_h t_1^2}{2} \right] f(x) dx - K - \varphi T + (p - c) D \int_{t_1}^T \beta(T - t) dt - c_1 D \\
 &\quad \times \int_{t_1}^T \{1 - \beta(T - t)\} - c_s D \int_{t_1}^T (T - t) \beta(T - t) dt
 \end{aligned} \tag{19}$$

4.1.5 Solution methodology

The objective of this study is to maximize profit through IoT implementation. The profit function is given by Eq. (17). This type of problem is called a fractional program (FP). We begin by considering the definition of the fractional program.

Definition If the objective function is the ratio of two non-linear functions, then the optimization often presented by programming is called fractional programming (Dubey et al., 2020; Vandana et al., 2018).

Let us consider function $q(x)$, which is the ratio of $f(x)$ and $g(x)$, that helps to solve the concavity of the average profit function. This concavity relates to the rate of change of a function's derivative, which belongs to set $S = \{x \in X : c_h(x) \leq 0\}$ where $g(x)$ is positive on X , then in non-linear programming, it will satisfy the $\sup\{q(x) : x \in S\}$. Here \sup means supremum or large set. So, $f(x) \geq 0$ is concave function and $g(x) > 0$ and $h(x) > 0$ are convex functions (Cambini & Martein, 2009).

$$q(x) = \frac{f(x)}{g(x)} \quad (20)$$

We adopted the standard procedure of Cambini and Martein (2009) to solve the fractional programming problem.

Proposition 4.1 *If we perform fractional programming and consider both $g(x)$ and $f(x)$ are solved through concave fractional programming, the selective function $q(x)$ will be pseudo concave on set S . This condition accrues as one of them ($f(x)$ or $g(x)$) is strictly pseudo-convex, and the other is strictly pseudo concave.*

Proposition 4.2 *Concave fractional programming provides a set of local maximums. Thus, there will be one global maximum in the set. In this case, we used Karush–Kuhn–Tucker conditions and assume that the value of $f(x)$ is strictly concave or $g(x)$ is strictly convex. Karush–Kuhn–Tucker (KKT) is used for non-linear functions in differentiable concave functions for profit maximization.*

Note: KKT solves the first derivative test for non-linear programming.

To prove the proposition, we need to show that the total profit function $TP(t_1, T, \varphi)$ is concave.

As $g(x) = x$; where all the values of x show convexity.

Solving Eq. 19, we got

$$\frac{\partial TP}{\partial T} = D\beta(T - t_1)[p - c + c_1 - c_s(T - t_1)] - c_l D - \varphi \quad (21)$$

$$\begin{aligned} \frac{\partial TP}{\partial t_1} &= Dp - \int_l^{t_1} [Dc_h \{t_1 + \theta(1 - m)x(t_1 - x)\} + cD \{1 + \theta(1 - m)(t_1 - x)\}] f(x) dx \\ &\quad - (p - c) D\beta(T - t_1) \\ &\quad - \int_{t_1}^u (cD + Dc_h t_1) f(x) dx - \varphi + c_l D \{1 - \beta(T - t_1)\} + c_s D(T - t_1) \\ \frac{\partial TP}{\partial t_1} &= D[p + c_l - c - c_h t_1] - [p + c_l - c - c_s(T - t_1)\beta(T - t_1)] \\ &\quad - \theta(1 - m) D \int_l^{t_1} \{c_h x(t_1 - x) + c(t_1 - x)\} f(x) dx \end{aligned} \quad (22)$$

and

$$\frac{\partial TP}{\partial \varphi} = \frac{D\theta m'(\varphi)}{2} \int_l^{t_1} [c_h x(t_1 - x)^2 + c(t_1 - x)^2] f(x) dx - T \quad (23)$$

The following proposition establishes the concavity of $TP(t_1, T, \varphi)$ for one business cycle with a backlog.

Proposition 4.3 At any value of φ , the profit function $TP(t_1, T, \varphi)$ is indeed concave w.r.t. the length of one business cycle time (T) and t_1 , so that $[(p - c) + c_l - c_s(T - t_1)] > 0$; for all the values of T and t_1 yields.

Proof For any given φ , the second-order partial derivatives of Eq. (21).

$$\frac{\partial^2 TP}{\partial T^2} = -c_s D\beta(T - t_1) + [p - c + c_l - c_s(T - t_1)] \times \beta' D(T - t_1) \tag{24}$$

and

$$\frac{\partial^2 TP}{\partial t_1 \partial T} = c_s D\beta(T - t_1) - [p - c + c_l - c_s(T - t_1)]\beta' D(T - t_1) = -\frac{\partial^2 TP}{\partial T^2} \tag{25}$$

Differentiating Eq. (22) w.r.t. t_1

$$\frac{\partial^2 TP}{\partial t_1^2} = -\theta(1 - m)D \int_l^{t_1} (c_h x + c) f(x) dx - Dc_h + \frac{\partial^2 TP}{\partial T^2} \tag{26}$$

The term $\frac{\partial^2 TP}{\partial T^2} < 0$, because $[p - c + c_l - c_s(T - t_1)] > 0$ and $\beta'(T - t_1) < 0$. Now according to the definition $g'(x) > 0$ and $0 \leq m(\varphi) < 1$ solution will follow $\frac{\partial^2 TP}{\partial t_1^2} < 0$ (Li et al., 2019).

The Hessian matrix or Hessian is a square matrix of second-order partial derivatives of a scalar-valued function or scalar field, which describes the local curvature of a function of many variables (Li et al., 2019).

$$|H| = \begin{bmatrix} \frac{\partial^2 TP}{\partial T^2} & \frac{\partial^2 TP}{\partial t_1 \partial T} \\ \frac{\partial^2 TP}{\partial t_1 \partial T} & \frac{\partial^2 TP}{\partial t_1^2} \end{bmatrix} \tag{27}$$

$$|H| = \frac{\partial^2 TP}{\partial T^2} \times \frac{\partial^2 TP}{\partial t_1^2} - \left(\frac{\partial^2 TP}{\partial t_1 \partial T} \right)^2 \tag{28}$$

Putting the value from Eqs. 25 and 26 in Eq. 28.

$$\det(H) = -[c_s D\beta(T - t_1) - \beta' D(T - t_1)(p - c + c_l - c_s(T - t_1))] \times \left[-\theta(1 - m)D \int_l^{t_1} (c_h x + c) f(x) dx - Dc_h + \frac{\partial^2 TP}{\partial T^2} \right] - \left[\frac{\partial^2 TP}{\partial T^2} \right]^2$$

Li et al. (2019) proposed and proved the lemma on concavity for Hessian matrix solution, according to that if $\frac{\partial^2 TP}{\partial t_1 \partial T} = \frac{\partial^2 TP}{\partial T \partial t_1}, \frac{\partial^2 TP}{\partial T^2} < 0$ and $\frac{\partial^2 TP}{\partial t_1^2} < 0$ then total profit function $TP(t_1, T, \varphi)$ is strictly concave and average profit function i.e. $\nabla(t_1, T, \varphi) = \frac{TP(t_1, T, \varphi)}{T}$ will be strictly pseudo-concave which is the complete proof of the proposition.

Proposition 4.4 Investment in IoT is always profitable for the warehouse in MSMEs because it decreases the length of the shortage period, increases the inventory level in the warehouse, and the ratio between (t_1/T) i.e., optimal service level improves with the implementation of IoT.

Proof As per the assumptions, $T - t_1$ is the length in which the warehouse stock level is zero, and $(0, t_1)$ is the operating period in the cycle $[0, T]$.

$$\frac{\partial \nabla}{\partial T}(t_1, T, \varphi) = 0 \quad (29)$$

and

$$\frac{\partial \nabla}{\partial t_1}(t_1, T, \varphi) = 0 \quad (30)$$

Simplifying Eq. (17), we get,

$$\nabla(t_1, T, \varphi) = D\beta(T - t_1)[p - c + c_l + c_s(T - t_1)] - c_l D - \varphi \quad (31)$$

And

$$\begin{aligned} & (p - c + c_l)[1 - \beta(T - t_1)] + c_s(T - T_1)\beta(T - t_1) + c \\ &= \int_l^{t_1} [c_h \{t_1 + \theta(1 - m)x(t_1 - x)\} + c \{1 + \theta(1 - m)(t_1 - x)\}] f(x) dx \\ & \quad + \int_{t_1}^u (c + c_h t_1) f(x) dx \end{aligned} \quad (32)$$

Hence, we can say that cycle time (T) and deterioration starting point (t_1) is the function of IoT investment cost (φ). By implicit differentiation w.r.t. φ we get,

$$\frac{a_1}{T} = \{[p - c + c_l + c_s(T - t_1)]\beta'(T - t_1) - c_s\beta(T - t_1)\} \times \left(\frac{dT}{d\varphi} - \frac{dt_1}{d\varphi}\right) \quad (33)$$

$$a_2 T = a_1 + [a_3 + a_4] T \frac{dt_1}{d\varphi} \quad (34)$$

where

$$a_1 = \frac{\theta m'(\varphi)}{2} \int_l^{t_1} (t_1 - x)^2 (c_h x + c) f(x) dx > 0,$$

$$a_2 = \theta m'(\varphi) \int_l^{t_1} (t_1 - x) (c_h x + c) f(x) dx > 0,$$

$$a_3 = \int_l^{t_1} \{\theta(1 - m)(c_h x + c) + 1\} f(x) dx > 0,$$

and

$$a_4 = \int_{t_1}^u c_h f(x) dx > 0.$$

Solving Eq. (33) and (34), we can get

$$\frac{dt_1}{d\varphi} = \frac{a_2 T - a_1}{[a_3 + a_4] T} \quad (35)$$

and

$$\frac{dT}{d\varphi} - \frac{dt_1}{d\varphi} = -\frac{a_1}{T\{c_s\beta(T - t_1) - [p - c + c_l + c_s(T - t_1)]\beta'(T - t_1)\}} \tag{36}$$

Further

$$a_2T = a_1 > 0; \text{ since } T - \frac{t_1 - x}{2} = T - \frac{t_1}{2} + \frac{x}{2} > 0 \tag{37}$$

As $T > t_1$, $\frac{dt_1}{d\varphi} > 0$, Therefore, the IInd part of the proposition is proved.

$$a_1 > 0; [p - c + c_l + (T - t_1)] > 0 \tag{38}$$

Proposition 4.3 and $\beta(T - t_1)$ is a decreasing function.

$$\beta'(T - t_1) < 0 \tag{39}$$

$$\frac{dT}{d\varphi} - \frac{dt_1}{d\varphi} < 0 \tag{40}$$

To prove the Ist part of the proposition, we differentiate $\frac{t_1}{T}$ w.r.t. φ ,

$$\frac{d}{d\varphi} \left(\frac{t_1}{T} \right) = \frac{1}{T^2} \left(\frac{dt_1}{d\varphi} T - \frac{dT}{d\varphi} t_1 \right) > \frac{t_1}{T^2} \left(\frac{dt_1}{d\varphi} - \frac{dT}{d\varphi} \right) > 0 \tag{41}$$

The above results indicate that the service level is directly proportional to φ , so the proposition is entirely true and well-proofed.

Proposition 4.5 Small retailers always try to limit the stock out period. Therefore, the implementation of monitoring and control techniques such as IoT is essential. High investment in IoT implementation is required to optimize the decision variables so that stock in time gets elongated and helps the retailer reduce spoilage and mitigate the extra cost of IoT implementation.

Proposition 4.6 For any given φ , the overall profit per unit time, has a unique global maximum, The profit function $TP(t_1, T, \varphi_{n+1})$ w.r.t. φ_{n+1} .

$$\frac{\partial^2 TP}{\partial (\varphi_{n+1})^2} = \frac{m''(\varphi_{n+1})D\theta}{2} \int_l^{t_1} [c_h x(t_1 - x)^2 + c(t_1 - x)^2] f(x) dx, 0 \tag{42}$$

where $m''(\varphi_{n+1}) < 0$., To optimize and solve the profit function (t_1, T, φ_{n+1}) , we required a special algorithm due to the non-linear feature of the problem(Dubey et al., 2020; Dye, 2013; Vandana et al., 2018). We have followed the solution approach of Tiwari et al. (2017), who state that analytical methods fail to solve a highly complex problem and require high computational work and analytics. Particle swarm optimization algorithm (PSO) has been used broadly to obtain feasible solutions based on the food-searching activities of birds (Mogale et al., 2020; Tiwari et al., 2017). We have adopted the PSO technique with a continuous iteration process due to its broader acceptance and applicability in perishable inventory management literature.

Proposition 4.7 For any value of IoT implementation cost (φ) distributed over time, the overall profit per unit time for a specific time horizon, say $n = 4\text{years}$, has a unique global maximum. Hence, the overall implementation cost is distributed in a span of four years.

Table 2 Model formulation for investment distributed in 4 years using amortization and depreciation

Period (Years)	0	1	2	3	4
hIoT facilities depreciation	Z = percentage of depreciation (0.15 < z > 0.40)	Zφ	Zφ	Zφ	Zφ
Profit term		Year 1	Year 2	Year 3	Year 4
Assets	φ	φ ₁ = φ - Zφ	φ ₂ = φ ₁ - Zφ	φ ₃ = φ ₂ - Zφ	φ ₄ = φ ₃ - Zφ
Profit term	Estimated years (4)n > 0	n - 1	n - 2	n - 3	n - 4

Regardless of their implementation costs, the investment in IoT systems has a specific financial and economic lifespan. There are various methods to calculate equipment's economic lifespan, such as the decline balance method, straight-line method, and production units. According to cost accounting standard-16 (CAS-16) which is issued by the council of the institute of cost accountants of India- "Amortization is the systematic allocation of the depreciable amount of an intangible asset over its useful life" (ICMAI, 2017). According to CBDT (Central Board of Direct Taxation), notification clarifies that with effect from April 1, 2017, the depreciation rate will range from 15 to 40 for plant and machinery and 40% for computer items (Income tax India, 2019). Our model has used the straight-line method for depreciation calculation (Jennings et al., 2001).

We know that $\varphi = \text{Total capital investment in IoT implementation}$.

According to the law of depreciation and amortization, we can split the implementation cost over the n years and profit from the implementation in $P_1 = n$.

$$\text{Depreciation} = \frac{\text{Overall capital cost of Implementation}}{\text{life span}} \quad (43)$$

The overall profit is calculated in Eq. 19 for only cycle 1. To see the long-term effect and tangible benefits of IoT implementation, we have assumed eight replenishment cycles for four years, i.e., each year, two replenishments. Hence, the implementation cost is split into four years (Table 2).

Where $z = \text{depreciation rate}$ and $\varphi_1, \varphi_2, \varphi_3, \varphi_4$ represents the change in the values of φ for a four-year term, respectively.

5 Computational results

5.1 Numerical illustration and analysis

To illustrate our proposed models, we solved one numerical example involving a small food company. We used PSO run on MATLAB on a 1.80 GHz Intel Core i5 with 8 GB of memory RAM computer to solve the problem (Obradovic et al., 2021).

To illustrate the model, we assumed the following values:

Replenishment cost per order $K = ₹ 120$ per order, Retail price = ₹ 35/per unit, Cost of purchase of item = ₹ 20 per unit, Inventory holding cost $c_h = ₹ 3$ per unit/ unit time, Goodwill

cost $c_s = ₹ 4$ /per unit/per year, Fixed demand per unit time $D = 1000$, $t_d = 0:0417$, $W = 101$, $c_l = ₹ 5$ /per unit, $\theta = 0.2$, Rate of Backlog is assumed to be $\beta(x) = e^{-x}$. The uniform distributed deterioration rate was $U \sim (0.024, 0.076)$ with a standard deviation of 0.013. The reduced deterioration rate is $m(\varphi) = 1 - e^{-a\varphi}$ with simulation coefficient $a = 0.02$, depending on the percentage change in deterioration rate regarding capital expenditure in IoT implementation.

The Probability density function (PDF) is given by Eq. (44).

$$f(x) = \frac{3x^2}{(u^3 - l^3)}, \text{ where } l = 0.03 \leq x \leq u = 0.08 \quad (44)$$

5.2 Sensitivity analysis

To explain the robustness of the proposed IoT implementation model in the warehouse and to analyze the impact of the parameters on the desired optimal solution, we performed the sensitivity analysis by changing the model's operating parameter values within the range of $-30\text{--}30\%$.

The prior literature argues that one of the most common problems faced by agri-food manufacturing MSMEs worldwide is poor inventory management of perishable items (Zhu et al., 2021), affecting the profit of smaller companies and threatening their survival. Our study thus draws meaningful insights for MSME managers/owners seeking efficient inventory management using IoT.

To maximize profit (∇^*) inventory managers in MSMEs always try to maintain warehouse stock levels to avoid shortages of items by implementing advanced monitoring and control technology that regulates the preservation of items. The IoT implementation decision is adjusted so that overall profit and other decision variables are not affected. Higher inventory holding costs push small agri-food retailers to decrease their stock level. Thus, a shorter cycle reduces investment in IoT (Fig. 6 a, b). The observation from Table 3 and Fig. 6c shows that an increment in the inventory-holding cost and a reduction in the IoT implementation cost counter one another so that the overall profit is constant.

Table 3 shows that when the deterioration rate is high, retailers spend more on IoT investment. On the other hand, Fig. 7 proves that cycle time remains unchanged with high investments. Therefore, managers in small agri-food retailers should increase the order size to enhance their profit and invest in technology. As the product cost is directly proportional to the order level, it directly affects the stock in any given period. If the item's price is high, then the preservation and monitoring technology investment is higher to reduce the deterioration rate. Table 3 shows that the value of the cycle length and the inventory level strongly depends on the value of the simulation coefficient (a). The lower value of the simulation coefficient indicates an insignificant impact of IoT investment on spoilage rate (Fig. 8).

According to Fig. 9, service level (t_1/T) increases as an increment in standard deviation. Table 4 depicts an increase in total profit after IoT implementation, but it is insignificant as we deployed the overall IoT implementation cost in one cycle. Earlier studies suggest that when the implementation cost is relatively high and imposes long-term benefits over time, the lifecycle costing depends on the price distribution over a certain period and can be calculated through the amortization and depreciation concept (Moon & Phillips 2021). To this end, we integrated the concept of amortization and depreciation and built proposition 4.7. Although we initially developed our model for just one cycle (T), it was extended by n number of cycles (T^{n*}) and the results are shown in Table 5.

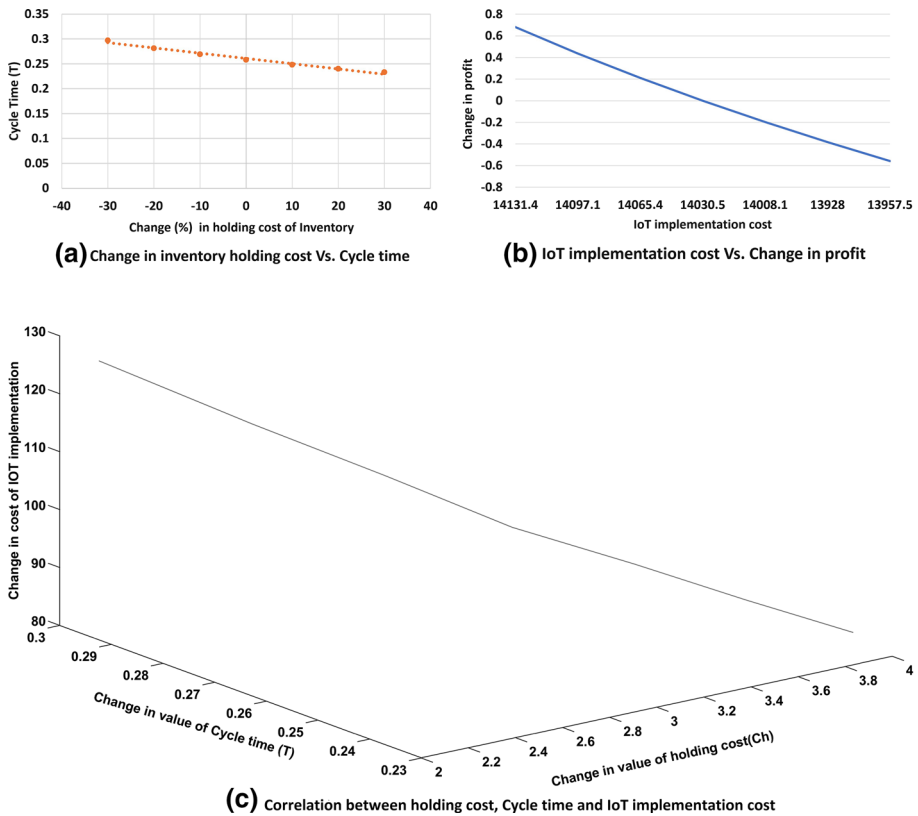


Fig. 6 Effect of change in the parameter of inventory holding cost on the variables

The findings show that investment in IoT is likely to be beneficial for small retailers in warehouse management.

5.3 Theoretical contributions and implications of the study

Our study investigated the usefulness of IoT implementation in managing warehouses and the inventory of perishable items, especially for MSMEs. We first formulated a practical IoT-based inventory model in retail operations that emphasized the investment cost, which is of utmost importance for MSMEs. We then examined the profitability and impact of IoT investment on inventory management of perishable items. Our findings suggest that a higher holding cost pushes inventory managers in MSMEs to decrease inventory levels, which eventually leads to a shorter cycle length. These benefits lead to increased product shelf-life, demanding more investments in IoT-based preservation technologies. Therefore, low stock-in period and IoT implementation are also reduced due to the short cycle length and longer product shelf-life, requiring more investment in preservation technology and IoT.

On the other hand, a higher deterioration rate prompts managers in MSMEs to invest more in advanced monitoring and preservation technology to maintain their warehouse inventory levels. To alleviate the effect of items' goodwill cost, managers are advised to spend more

Table 3 Sensitivity analysis of critical parameters for a single cycle

Parameter	Change (%)	Value	t_1	T	φ	∇^*	Change in profit (%)
a	- 30	0.014	0.201	0.240	106.2	13,998.2	- 0.268
	- 20	0.016	0.215	0.250	103.1	14,013.5	- 0.0785
	- 10	0.018	0.218	0.255	102.2	14,024.7	- 0.0654
	0	0.02	0.221	0.258	101	14,030.5	0
	10	0.21	0.224	0.261	100.4	14,045.7	0.0712
	20	0.024	0.225	0.265	99.9	14,055	0.1297
	30	0.26	0.231	0.268	96.67	14,062	0.1838
c	- 30	14	0.226	0.26	89.5	20,040.5	42.783
	- 20	16	0.225	0.257	94.85	18,036.8	28.513
	- 10	18	0.223	0.257	99.24	16,036	14.252
	0	20	0.221	0.258	101	14,030.5	0
	10	22	0.219	0.259	105.39	12,036.7	- 14.243
	20	24	0.217	0.26	107.57	10,039	- 28.476
	30	26	0.213	0.262	108.66	8043.11	- 42.696
p	- 30	24.5	0.202	0.267	85.872	3582.06	- 74.479
	- 20	28	0.211	0.263	94.04	7060.68	- 49.695
	- 10	31.5	0.217	0.26	99.22	10,546.2	- 24.862
	0	35	0.221	0.258	101	14,030.5	0
	10	38.5	0.225	0.257	105.46	17,527.9	24.88
	20	42	0.227	0.256	107.49	21,021.7	49.772
	30	45.5	0.229	0.255	109.1	24,516.7	74.673
c_h	- 30	2.1	0.265	0.297	125.8	14,131.4	0.6811
	- 20	2.4	0.248	0.281	117.502	14,097.1	0.4367
	- 10	2.7	0.234	0.269	109.884	14,065.4	0.2109
	0	3	0.221	0.258	101	14,030.5	0
	10	3.3	0.21	0.248	96.188	14,008.1	0.1974
	20	3.6	0.2	0.24	89.938	13,928	0.3833
	30	3.9	0.192	0.233	84.005	13,957.5	0.5579
θ	- 30	0.014	0.221	0.258	84.978	14,053.6	0.1268
	- 20	0.016	0.221	0.258	91.655	14,046.9	0.0791
	- 10	0.018	0.221	0.258	97.544	14,041	0.037
	0	0.02	0.221	0.258	101	14,030.5	0
	10	0.022	0.221	0.258	107.578	14,031	- 0.341
	20	0.024	0.221	0.258	111.929	14,026.7	- 0.065
	30	0.026	0.221	0.258	115.931	14,022.7	- 0.921
c_l	- 30	3.5	0.219	0.258	101.416	14,039.9	0.0291
	- 20	4	0.22	0.258	101.7	14,038.4	0.018
	- 10	4.5	0.221	0.258	101.8	14,037.1	0.0091

Table 3 (continued)

Parameter	Change (%)	Value	t_1	T	φ	∇^*	Change in profit (%)
c_s	0	5	0.222	0.258	101	14,030.5	0
	10	5.5	0.221	0.257	102.23	14,029.5	-0.009
	20	6	0.221	0.257	103.6	14,029.3	-0.0178
	30	6.5	0.222	0.257	104.415	14,028.1	-0.026
	-30	2.8	0.219	0.258	101.15	14,039	0.0227
	-20	3.2	0.22	0.258	101.165	14,037.9	0.014
	-10	3.6	0.22	0.258	101.813	14,036.8	0.0071
	0	4	0.221	0.258	101	14,030.5	0
	10	4.4	0.221	0.258	102.813	14,028.6	-0.007
	20	4.8	0.221	0.257	103.15	14,025.5	-0.0143
	30	5.2	0.222	0.257	103.476	14,024.8	-0.0274

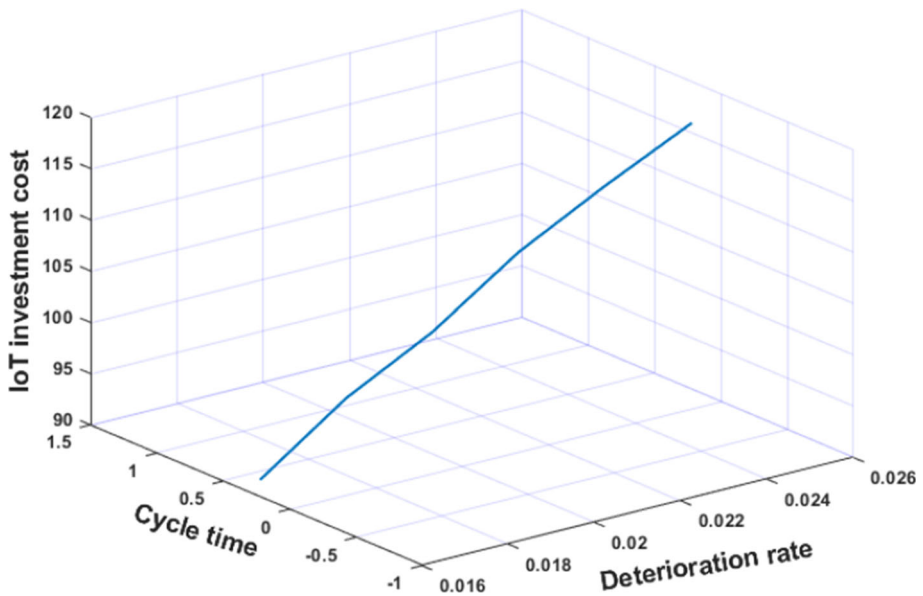


Fig. 7 Graph between change in IoT investment vs. cycle time vs. change in deceleration rate

on advanced technology to support the stock-in period. We also observed that a higher value of simulation coefficient 'a' increases shelf life and reduces shortages. Thus, the threshold value of 'a' decides the level of the IoT investment in the warehouse. Our study presents meaningful implications from both a theoretical and a practical perspective.

At the theoretical level, our study is among the first to open the debate on the applicability of IoT in the specific context of MSMEs operating in a critical sector such as food retailing. Indeed, the application of digital technologies such as IoT has long been unsuitable in the context of MSMEs given the many constraints hindering these companies from implementing

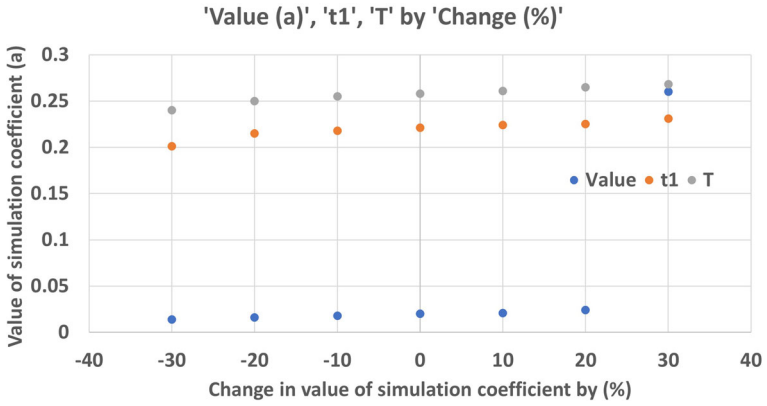


Fig. 8 Value of simulation coefficient (a) over 't1', 'T' by Change (%)

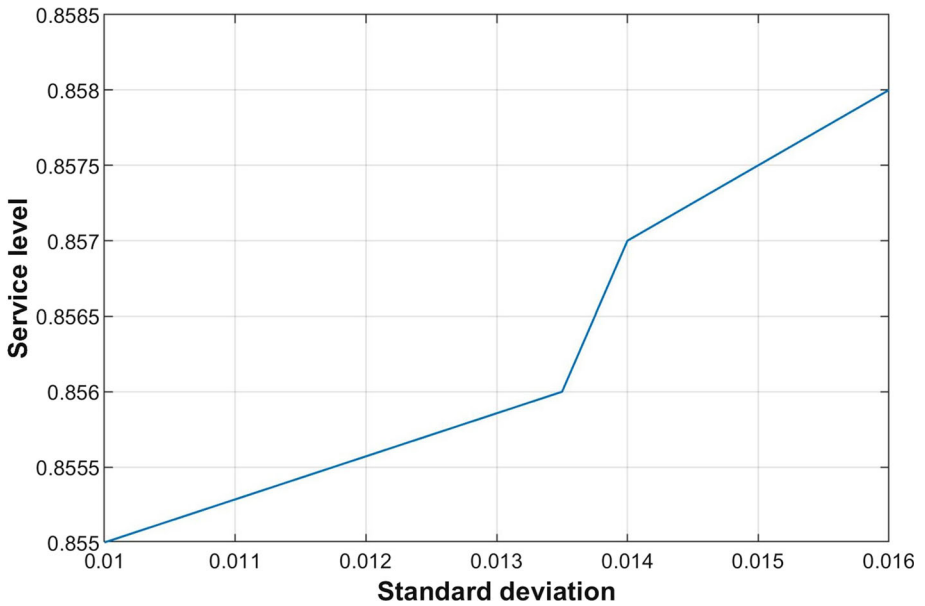


Fig. 9 Service level Vs. standard deviation

Table 4 Result of the model for one cycle

Effect of IoT implementation	ϕ^*	t_1^*	T^*	∇^*
With IoT implementation	101	0.221	0.2586	14,055.8
Without IoT implementation	0	0.133	0.1978	13,975.6

Table 5 Maximum expected profit for the four years of the span

Effect of IoT implementation	**	t_1^*	T^{n*}	∇^*
Year 1	25	0.221	0.2586	28,111.6
Year 2	25	0.221	0.2586	41,166.5
Year 3	25	0.221	0.2586	60,221.5
Year 4	25	0.221	0.2586	74,276.1

and leveraging digital capabilities (Kamble et al., 2018a, 2020b). Our study asserts that, just like large corporations, MSMEs could implement and benefit from IoT. Hence, scholars and researchers could build upon our findings to explore this topic. On the other hand, we use a novel problem formulation for IoT application in warehouse management (Kamble et al., 2020a) which could be highly useful for researchers seeking to explore and resolve item perishability in warehousing management.

At the managerial level, two critical implications of our study advance the understanding of MSME owners and managers on the relationship between IoT and perishable items inventory management in the context of MSME retailers. First, our study provides practical proof of the feasibility and usefulness of IoT in managing perishable items in the context of small companies. MSME owners/managers need to understand that IoT investment is beneficial, even though it may be costly at the beginning of the implementation process. They should therefore deploy a long-term vision to leverage IoT implementation efficiently. Second, managers of perishable item warehousing need to be aware that preserving high levels of stocks from perishing requires increased investment in new monitoring and control technologies such as IoT. Hence, the implementation of IoT should be regarded as a strategic initiative for its profitability and growth management. It is true that MSMEs, especially in the food supply chain, struggle with the high cost of warehousing and inventory management. However, the implementation of IoT should not be seen as an additional investment but rather as a solution that can drastically reduce the high cost of inventories. Accordingly, we believe this study will help managers better understand how to leverage IoT to solve item perishability in MSMEs.

6 Conclusion and future research

The advancement in automated monitoring and control technologies in warehouses has led to new opportunities and challenges for retailers in implementing and maintaining their warehouses' perishable inventories. However, automated monitoring and control technology such as IoT seems more profitable for MSMEs in the retailing sector. To address this issue, we formulated and analyzed IoT implementation costs in the retailer warehouse. The study aimed to investigate the impact of IoT on existing operating parameters (holding cost, selling cost, deterioration rate, shortage cost, goodwill cost, unit purchase cost) and how it can increase the overall profit of retailers by reducing spoilage.

To this end and to examine the feasibility of IoT implementation strategies, we developed two cases (case 1; $x \leq t_1$ and case 2; $t_1 < x$) and compared their results, which show that IoT implementation increases retailers' profit margin. With the help of a sensitivity analysis, we also observed that the simulation coefficient, deterioration rate, and selling price significantly impacts profit. Since IoT implementation is a significant budgetary investment,

the overall implementation cost can be divided over time. We also looked at a scenario where the implementation cost is divided over a certain timespan, including amortization and depreciation in the model. Our analysis suggests that retailers could gain more profit in upcoming cycles. We analyzed this notion with the help of a digital example.

However, we also need to specify certain technical limitations of our model. First, we only focused on retailer benefits. It would be interesting to analyze the effect of IoT under the impact of demand-dependent carbon emissions. Second, as is frequent in the prior literature, we only considered deterministic demand rates with zero lead time. Our analysis could be extended by adding more realistic conditions such as delays in product availability, non-zero lead time, carbon emission sensitivity demand, and return on investment (ROI).

Moreover, IoT and other technology cannot be implemented on a large scale without government support, conducive policies, and stakeholders' cooperation. Further, the factor related to cross perishability is also an essential variable in IoT implementation, which requires more explorative studies in the future. Finally, modeling the payback period of IoT investment could be a relevant and insightful addition to this study.

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