Economic Analysis of Public Priced IoT Based Traceability System in Perishable Food Supply Chain

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Abstract

Worldwide food contamination crises and their consequence on health and monetary losses inflated public concerns, putting food supply chain under pressure to assure quality and safety. When short shelf life food products go through post-harvest process, it becomes difficult to isolate contamination source. Consequently, supplier claims to produce good quality food, meanwhile it reaches to consumer's contaminations occurs in transit, which results in financial and reputation loss. Hence, food traceability is highly important to combat losses and maintain quality as expected. Internet of things (IoT) has potential to improve performance of logistic through traceability. Despite all the advantages, it imposes a mere cost on supply chain players. However, they can consider it as an opportunity to raise consumer fidelity when quality sensitive consumers are ready to bear additional cost. So this system termed as public priced traceability. Further, implementation of proposed traceability raises the question of investment decision that who will bear the implementation cost. To address the question a game theory approach applied. Mathematical model is developed for individual supplier, retailer and centralized investment. Numerical study revealed that in centralized investment model is the most profitable option, although selling price and information sensing price is higher than other models.

Keywords

Internet of Things (IoT), Traceability System, Supply chain optimization and Game Theory.

1. Introduction

Defects in manufacturing and functionality are now a concern to consumers. Such defects have led to product recalls, such as those of smart phones (CNN 2016) and medical devices (Ball et al. 2018). Contrasting other supply networks, the perishable food supply chain is more difficult due to improved quality assurance, effective information transmission, and handling requirements (Tsang et al. 2020). The food supply chain is further broken down into a number of phases. Supplier assesses product quality at each step of harvest. In this case, all of the supplier's efforts to produce a high-quality product result in financial losses if the environment parameters (temperature, pressure, and humidity) of the final product are not monitored during the logistics process. The demand of consumers for quality food is triggered by the numerous food scandals. The scandals with disastrous consequences are, milk contamination with melamine (Xiu and Klein 2010) and horse meat scandal in 2013 (Behnke and Janssen 2020). Consumers place the highest level of hygiene expectations on food, but the supply chain has been plagued by quality scandals and hygiene violations. As a result, people are becoming more sensitive about the quality of the products they purchase as well as their origin and delivery conditions, even though these facilities are more expensive. Consumers in China are reportedly willing to pay more for pork traceability, according to a recent survey (Wu et al. 2016). As a result, consumers are crucial in motivating participants in the supply chain to fund the traceability system. Such a system of traceability is known as a public priced system.

Consumers' desire to validate the accuracy and provenance of data is growing quickly. As a result, supply chain participants must build an effective traceability system for the accurate distribution of information if they want to earn the trust of end consumers. An effective traceability system captures and transmits collected data in real-time at each node (Huang et al. 2012; Dai et al. 2015; Zhang et al. 2015). Over time, a number of technologies have developed that could track the products to differing degrees. Time temperature indicators (TTI), radio frequency identification (RFID), barcode scanners, and other classic technologies are among the most important. These systems can detect origin and environment parameters automatically (Wang and Li 2012). However, this lack of real-time access to information prevents buyers from having an easy tracking of their purchases. Organizations are therefore looking for an effective and scalable approach to solve the issues. The emerging trend, the Internet of Things (IoT), offers the ability to track and retrieve food quality information in real-time (Yan 2017; Tang and Veelenturf 2019; Yang et al. 2019).

Despite the benefits of an IoT-based traceability system, a transparent supply chain comes at an additional expense to its supply chain members. Hence, the question arises that who will be the main investor in the traceability system when consumers and all other participants in the supply chain reap benefit from it? The question is addressed in the following manner. A single supplier-retailer supply chain is treated using a game theoretic technique. In this study, we built a mathematical model that took into account the scenarios of individual and centralized investments. The overall supply chain profit for each scenario was then compared.

2. Literature Review

The challenge of handling perishable goods with a limited shelf life and the importance of traceability systems in the supply chain to guarantee the delivery of high-quality goods to consumers are the only area covered in the literature section. Monitoring product quality and automation is a traceability system attribute that significantly affects the cost of installation. Some of the more developed agro-industries with shared members' interests embraced ICT on their own and acknowledged its critical contribution to raising market value. However, due to high investment costs to embracing new digital technologies, small-to-medium businesses (SMEs) still operate manually or semi-automatically (Yan 2017). Therefore, resistance to change and high investment costs are important barriers to the uniform distribution of automatic traceability systems to various scales of organizations.

Dessureault et al. (2006) studied the firm traceability economics of dairy product companies in Canada. To evaluate the system's costs and advantages, they conducted a survey. It appears to be the first empirical study in the field of traceability economics. This research was expanded by Rasende-Filho and Hurley (2012) to confirm whether traceability lessens crisis consequences. They assumed that the defect was limited to a supplier's raw materials and defined traceability as the likelihood to isolate the issue. The authors developed a principal-agent model based on incentive contract notions, where incentives are paid based on the traceability system's accuracy and food safety. Saak (2016) focuses on the decision made by supply chain enterprises to adopt a traceability system while taking reputational and upstream and downstream moral hazard into account. Gautam et al. (2017) examined the traceability of the kiwi fruit supply chain. Using a multi-objective integer non-linear programming paradigm, transportation and liability costs are reduced on the occurrence of contamination. With the removal of intermediary, food supply chains can reduce the cost compared to traditional supply chain (Iansiti and Lakhani 2017; Hoffman et al. 2018).

Emerging technologies in the traceable food supply chain include IoT, machine learning, block chain, and data mining, among others. Alfian et al. (2017) proposed an RFID-based e-pedigree traceability system employing Wireless Sensor Network (WSN) to capture environmental parameters while tracking the location of the product. Hasan et al. (2019) conducted research on the significance of shipment tracking in logistics. According to research, IoT may be used to monitor environmental factors, and block chain can be used to automate payments and levy fines when violations occur. To increase the effectiveness of the traceability system, Alfian et al. (2020) suggested an integrated RFID and machine learning model to determine the direction of tagged goods. Aiello et al. (2015) conducted research on the use of RFID traceability in the supply chain for perishable goods. In order to maximize supply chain profit and achieve the ideal granularity level, a stochastic mathematical model was devised. Zhang et al. (2017) discussed the difficulties in managing the perishable supply chain built on real-time data tracked by IoT technology due to the high rate of degradation and cross-regional transportation. Pal and Kant (2019) suggested a methodical, layered, hierarchical paradigm based on architecture. This layered model takes into account the IoT's implementation along with the delivery of perishable commodities. To control the shelf life of perishable goods in an online store Tsang et al. (2019) presented an Internet-based approach. A quality deterioration model that combines IoT and fuzzy logic is used. The deployment of IoT to lower degradation costs and improve quality was the main focus of Yang et al. (2019).

3. The Model

In this study, we take into account a supply chain in a single supplier-retailer setup, where the supplier distributes food products through the store after delivering them to the retailer with sensor tags already attached to each product. Understanding and identifying the dominant player who will carry the investment when consumers are willing to pay more is the main objective.

3.1 Assumptions and Notation

The following assumptions are set for the development of the model.
The supplier's production costs are unaffected by the product's level of quality improvement. Monitoring environmental variables to prevent product degradation is referred to as the quality improvement level (Ghosh and Shah 2015).
Retailer transfers the information sensing pricing accurately collected from customers to suppliers without charging extra to customers. Suppliers can charge information-sensing prices to retailers based on the number of units sold through the point of sale (POS) (Table 1).
The lead time is assumed to be zero (Bhaskaran and Krishnan 2009; Chen et al. 2015).
The demand function for a food product is deterministic, continuous, price and quality sensitive. It is assumed as, $D = a - bp + \gamma\zeta - \beta p_s$, where $p = w(1+r)$, (Zhang et al. 2015; Zhu et al. 2017).

Table 1. Notation

Symbol	Description
a	Market Potential
b	Price Sensitivity to consumer demand
γ	Consumer sensitivity to IoT level investment to track quality
β	Consumer Sensitivity to information sensing price
r	Retailer's Margin
c_{IoT}	Coefficient of implementation cost associated with IoT investment
c_p	Cost of product
c_s	Cost of Sensor
w	Supplier's Wholesale Price
$\prod_*$	Profit where {$* \longrightarrow$ Supplier/Retailer/Centralized}
w'	It is the total sum of wholesale price and information sensing price
p'	It is the total sum of selling price and information sensing price
Decision Variables	
p	Retailer's Selling Price
p_s	Information sensing price of the product
ζ	IoT investment index, to measure consumers sensitivity towards quality improvement level

3.2. Model development

Three different mathematical models are developed such as, supplier alone bears the Investment, retailer alone bears Investment and both bear the investment in a centralized model. We have considered IoT implementation cost as $c_{IoT}\zeta^2$ in each of the models, where c_{IoT} is the IoT investment parameter (infrastructure cost) and ζ is the quality improvement level. Several other literature have considered similar quadratic assumption (Ghosh, and Shah 2015; Zhu 2017).

3.2.1 Model 1: supplier alone bears the Investment

In this model we assume that supplier alone bears the IoT investment cost. The decision-maker for QIL is the supplier. The selling price of the products in the target market is decided by the retailer. The retailer transfers the wholesale price along with the information sensing price to the supplier. The profit functions of retailer and the supplier are presented below.

$$\prod_s = (a - bp + \gamma\zeta - \beta p_s)(w' - c_s - c_p) - c_{IoT}\zeta^2 \quad (1)$$

$$\Pi_r = (a - bp + \gamma\zeta - \beta p_s)(p' - w') \tag{2}$$

$$p' = p + p_s,\ w' = w + p_s$$

First order solution is given by (proof in Appendix A).

$$\frac{\partial \Pi_r}{\partial p} = 0 \qquad p(p_s, \zeta) = \frac{a - p_s\beta + \gamma\zeta}{2b} \tag{3}$$

We substitute the response function p in Π_s, the simultaneous solution using first order condition is given by

$$p_s^* = \frac{\begin{array}{c}4abc_{IoT} - 4abrc_{IoT} + 4ac_{IoT}\beta - 4bc_{IoT}c_s\beta - 4brc_{IoT}c_s\beta - 4bc_{IoT}c_p\beta \\ -4brc_{IoT}c_p\beta + bc_s\gamma^2 + brc_s\gamma^2 + bc_p\gamma^2 + brc_p\gamma^2\end{array}}{8bc_{IoT}\beta + 8brc_{IoT}\beta^2 - 4c_{IoT}\beta^2 - b\gamma^2 - br\gamma^2} \tag{4}$$

And $$\zeta^* = -\frac{ab\gamma + abr\gamma - bc_s\beta\gamma - brc_s\beta\gamma - 2bc_p\beta\gamma - 2brc_p\beta\gamma}{-8bc_{IoT}\beta - 8brc_{IoT}\beta + c_{IoT}\beta^2 + b\gamma^2 + br\gamma^2} \tag{5}$$

Again substituting values of p_s^* and ζ^* in p, we get $$p^* = \frac{4(1+r)c_{IoT}\beta(a - (c_s + c_p)\beta)}{-4c_{IoT}\beta^2 + b(1+r)^2(8c_{IoT}\beta - \gamma^2)} \tag{6}$$

3.2.2 Model 2: The retailer alone bears the investment

In this model we assume that the retailer invests in IoT based traceability system. The retailer takes the decision of QIL. Further the retailer uses the information sensing price from the consumers as the incentive. The profit functions of retailer and the supplier are presented below.

$$\Pi_s = (a - bp + \gamma\zeta - \beta p_s)(w - c_p) \tag{7}$$

$$\Pi_r = (a - bp + \gamma\zeta - \beta p_s)(p' - w - c_s) - c_{IoT}\zeta^2 \tag{8}$$

Π_r is concave function with respect to p and ζ (shown in Appendix B). The simultaneous solution using first order condition is given by

$$p = \frac{-2(1+r)c_{IoT} + rc_{IoT}(-ar + b(1+r)(p_s - c_s) + rp_s\beta - r\gamma(-p_s\gamma - rp_s\gamma + c_s\gamma + rc_s\gamma)}{-4br(1+r)c_{IoT} + r^2\gamma^2} \tag{9}$$

$$\zeta = \frac{(ar + bp_s + brp_s - bc_s - rp_s\beta)\gamma}{4bc_{IoT} + 4brc_{IoT} - r\gamma^2} \tag{10}$$

Putting the values of p and ζ in Π_s and solved for p_s.

Π_s is concave in p_s (Appendix B). The condition of first order gives

$$p_s^* = \frac{\begin{array}{c}-r^2\beta\gamma(-a\gamma + bc_p\gamma + brc_p\gamma) - (-2b^2(1+r)^2(c_s - rc_p) + ar^2\beta - br^2 \\ (1+r)c_p\beta)(4bc_{IoT} + 4brc_{IoT} - \gamma^2)\end{array}}{r^2\beta^2\gamma^2 - (b + br - r\beta)(4bc_{IoT} + 4brc_{IoT} - \gamma^2)} \tag{11}$$

Putting the optimal value of p_s^* in p and ζ, we get the following expressions.

$$p^* = \frac{(1+r)(b^2(1+r)^2 c_{IoT} c_p - 2rc_{IoT}(c_s + rc_p)\beta^2 + 2ac_{IoT}(b + br + r\beta) - 2b(1+r)^2(2c_{IoT}c_s\beta + c_p\gamma^2))}{4b^2(1+r)^2 c_{IoT} - 4r^2 c_{IoT}\beta^2 - b(1+r)\gamma^2} \quad (12)$$

$$\zeta^* = -\frac{(ab + br - b^2c_p - 4b^2rc_p - b^2r^2c_p - bc_s\beta - 4brc_s\beta + brc_p\beta + br^2c_p\beta)\gamma}{-4b^2c_{IoT} - 8b^2rc_{IoT} - 4b^2r^2c_{IoT} + 4r^2c_{IoT}\beta^2 + b\gamma^2 + br\gamma^2} \quad (13)$$

3.2.3. Model 3: Centralized investment model

In this model, we assume that the supplier and the retailer as a single decision-maker take the decision of selling price, QIL and information sensing price, maximizing total profit of supply chain. Both supplier and the retailer take the incentive collected from consumers. Profit of the supplier and retailer is presented as below.

$$\prod_C = (a - bp + \gamma\zeta - \beta p_s)(p' - c_s - c_p) - c_{IoT}\zeta^2 \quad (14)$$

$\prod_C$ is concave in p_s and ζ (refer Appendix C). The simultaneous solution using first order condition is given by following:

$$p_s = -\frac{-2ac_{IoT} + 2bpc_{IoT} + 2pc_{IoT}\beta - 2c_{IoT}c_s\beta - 2c_{IoT}c_p\beta - p\gamma^2 + c_s\gamma^2 + c_p\gamma^2}{4c_{IoT}\beta - \gamma^2} \quad (15)$$

$$\zeta = -\frac{-a\gamma + bp\gamma - p\beta\gamma + c_s\beta\gamma + c_p\beta\gamma}{4c_{IoT}\beta - \gamma^2} \quad (16)$$

Putting the p_s and ζ in equation 14, $\prod_C$ is concave in p (Appendix C) and the condition of first order gives

$$p^* = \frac{c_{IoT}((c_s + c_p)\beta(5b + 3\beta) + a(3b + 5\beta)) - 2(a + b(c_s + c_p)\gamma^2}{4b^2c_{IoT} + 10bc_{IoT}\beta + 4c_{IoT}\beta^2 - 4b\gamma^2} \quad (17)$$

Putting the optimal value of p^* in equation 15 and 16 we get

$$p_s^* = \frac{(a - b(c_s + c_p))(2bc_{IoT} - c_{IoT}\beta + 2\gamma^2)}{4b^2c_{IoT} + 10bc_{IoT}\beta + 4c_{IoT}\beta^2 - 4b\gamma^2} \quad (18)$$

$$\zeta^* = \frac{2(a - b(c_s + c_p))(b + \beta)\gamma}{4b^2c_{IoT} + 10bc_{IoT}\beta + 4c_{IoT}\beta^2 - 4b\gamma^2} \quad (19)$$

4. Numerical Analysis

To demonstrate the model, numerical analysis is carried out in this section. The values taken for the parameters are $a = 1500,\ b = 50,\ c_p = 7,\ c_s = 3,\ r = 0.2,\ \gamma = 45,\ \beta = 35,\ c_{IoT} = 40$ (Ghosh, and Shah, 2015; Aiello, Enea, and Muriana, 2015). Most of the parameter values are considered from the past studies and a few are assumed.

Table 2. Optimal results in different investment bearing models

	p_s	ζ	p	$\prod_r$	$\prod_s$	$\prod_{sc}$
Model 1	3.39	4.22	16.02	2056.2	4486.48	6542.68
Model 2	2.20	3.65	14.52	868.79	3861.15	4729.94
Model 3	7.46	8.58	18.37	_	_	8239.73

The result in Table 2 demonstrates that, compared to all other models, the centralized investment model is the most profitable for the whole supply chain, although the price of QIL and information sensing is higher in the centralized approach than in all other alternatives. It shows that people who value quality are willing to pay more for it. Higher the retailer and supplier investment in QIL is influenced by increased information sensing prices, which improves demand and boosts sales. Additionally, in the absence of such incentives, investment bearer maintains lower QIL, which lowers demand and lowers overall supply chain profit. The centralized approach is the best option for investment, according to the aforementioned result.

5. Sensitivity Analysis and Managerial Insights

This analysis is carried out to study the impact of various parameters on results. The effect of consumer sensitivity towards information sensing price (β) is analyzed. On the overall supply chain profit, the effect of customer sensitivity to information sensing pricing (β) is investigated. Figure 1 shows that profit in all models remains constant until a certain value, after which it starts to decline. Profit therefore remains constant for a certain value in different models, after which it drops, as customer sensitivity to information sensing price increases. The supply chain participants may find great value in putting this result into practice. Consumers spend additional price after the selling price of a product in order to obtain high-quality food that is still fresh, but after a certain price point they become reluctant to pay.

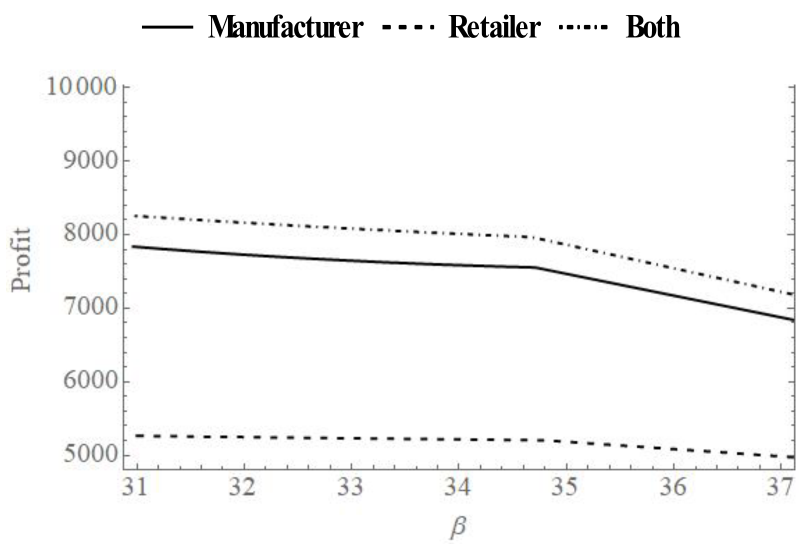

Figure 1. Total supply chain profit vs β

6. Conclusion

A pioneering initiative by supply chain participants to implement an advanced technology-based traceability system to increase supply chain transparency is being studied in this paper. IoT is a cutting-edge technology that can address the visibility gap in the complex food supply chain, boost productivity, and satisfy consumers. Consumers and supply chain participants will benefit more from the extensive implementation of IoT in traceability. We developed mathematical models that took into account (i) investment made by the supplier, (ii) investment made by the retailer, and (iii) centralized investment. Our study offers useful insights for the practical implementation of IoT-based traceability systems. When supply chain members invest in centralized models, both suppliers and retailers will be the leading players from an investment bearing standpoint. Additionally, the results show that, despite selling price and information sensing price being higher than other models, the centralized model has the highest total supply chain profit.

Additionally, profit remains constant as consumer sensitivity to price-sensing information increases up to a certain point. Total profit remains the same with an increase in sensing price up to that threshold value since quality-sensitive buyers can tolerate higher costs up to a certain extent.

This study shares certain shortcomings with previous published material, which suggests areas for future investigation. Deterministic additive linear demand ignores the cost of uncertainty. We have taken into account such deterministic demands while examining how IoT applications have an impact on the outcomes. Future research will extend this deterministic demand assumption to stochastic demand to evaluate the effects it has on the outcomes. Second, monopoly setup was assumed in the traceable supply chain model, but in reality, supply networks are significantly more intricate than this.

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APPENDIX

APPENDIX A:

$\prod_r = (a - bp + \gamma\zeta - \beta p_s)(p' - w')$ Where, $p' = p + p_s$, $w' = w + p_s$

$$\frac{\partial \prod_r}{\partial p} = 0$$

(A.1)
$$p(p_s, \zeta) = \frac{a - p_s\beta + \gamma\zeta}{2b}$$

$$\frac{\partial^2 \prod_r}{\partial p^2} = -2b(\frac{r}{1+r}) < 0$$

$$H(p_s, \zeta) = \begin{bmatrix} \frac{\partial^2 \prod_r}{\partial {p_s}^2} & \frac{\partial^2 \prod_r}{\partial p_s \partial \zeta} \\ \frac{\partial^2 \prod_r}{\partial \zeta \partial p_s} & \frac{\partial^2 \prod_r}{\partial \zeta^2} \end{bmatrix}$$

$$H(p_s, \zeta) = \begin{bmatrix} -\beta(1 - \frac{\beta}{2b(1+\mathrm{r})}) & \frac{(b + br - \beta)\gamma}{2b(1+\mathrm{r})} \\ \frac{(b + br - \beta)\gamma}{2b(1+\mathrm{r})} & -2c_{IoT} + \frac{\gamma^2}{2b(1+\mathrm{r})} \end{bmatrix} \quad \text{(A.2)}$$

Since $H(p_s, \zeta) > 0$ and principal diagonals are negative, so the objective function is concave in nature.

APPENDIX B:

$$H(p,\zeta)=\begin{bmatrix}\frac{\partial^2 \prod_r}{\partial p^2} & \frac{\partial^2 \prod_r}{\partial p \partial \zeta} \\ \frac{\partial^2 \prod_r}{\partial \zeta \partial p} & \frac{\partial^2 \prod_r}{\partial \zeta^2}\end{bmatrix}$$

$$H(p,\zeta)=\begin{bmatrix}-2b(\frac{r}{1+r}) & \frac{r\gamma}{1+r} \\ \frac{r\gamma}{1+r} & -2c_{IoT}\end{bmatrix} \tag{B.1}$$

Since $H(p,\zeta)>0$ and principal diagonals are negative, so the objective function is concave in nature.

$$\frac{\partial^2 \prod_s}{\partial p_s^{\ 2}}=\frac{-((2c_{IoT}(b+br-r\beta)(b+br+r\beta)}{r^2(4b(1+r)c_{IoT}-r\gamma^2)} \tag{B.2}$$

Hence $\frac{\partial^2 \prod_s}{\partial p_s^{\ 2}}<0$ (B.3)

Hence $\prod_s$ is concave in nature.

APPENDIX C:

$$H(p_s,\zeta)=\begin{bmatrix}\frac{\partial^2 \prod_C}{\partial p_s^{\ 2}} & \frac{\partial^2 \prod_C}{\partial p_s \partial \zeta} \\ \frac{\partial^2 \prod_C}{\partial \zeta \partial p_s} & \frac{\partial^2 \prod_C}{\partial \zeta^2}\end{bmatrix}$$

$$H(p_s,\zeta)=\begin{bmatrix}-2\beta & 0 \\ 0 & -2c_{IoT}\end{bmatrix} \tag{C.1}$$

Since $H(p_s,\zeta)>0$ and principal diagonals are negative, so the objective function is concave in nature.

Biographies

Ms Aishwarya Dash is graduated in Mechanical Engineering from IGIT Sarang, Odisha in 2015. Earned his post-graduation in Industrial Engineering & Management from CET, BBSR in 2017, Continuing PhD in IIT Kharagpur. Her area of Interest lies in supply chain management, digital technology, logistics and inventory management. Her interests are development of novel mathematical/ analytical models capturing the real-life situation to draw meaningful managerial insights.

Prof. S. P. Sarmah obtained his Ph.D. degree from IIT Kharagpur, India and currently working as a professor in the Department of Industrial Systems Engineering at IIT Kharagpur. Prior to teaching, he worked in industry for nearly four years. Prof. Sarmah's present research areas are supply chain coordination, supply chain risk management, reverse logistics, production planning and control, inventory management, and project management. He is currently associated with four projects with Computerization of NLC, E-business Center of Excellence, Intelligent Decision Support System in online auctions and Sustainable Agricultural Logistics. He currently guides nine PhD scholars and many Bachelor's and Master's Students. He has published papers in leading international journals such as European Journal of Operational Research, International Journal of Production Economics, Mathematical and Computer Modeling: International Journal, Transportation Research Part E, and cited by researchers in the field. He is also a reviewer of many international journals. Apart from teaching and research, Prof.

Sarmah is actively engaged with industry consultancy projects and conducted short courses for academia and industry personnel.

Prof. Manoj Kumar Tiwari (FNAE, FNASc, FIIIE, FIISE, and FIETI) is Director, National Institute of Industrial Engineering (NITIE) Mumbai from November 2019. He was a Professor with Higher Academic Grade (HAG) in the Department of Industrial and Systems Engineering at Indian Institute of Technology, Kharagpur and currently on lien for five years. As a researcher, he is working in the domain of Manufacturing System and Supply Chain Management. His research and teaching interests are in modeling the Manufacturing Processes and Operations analysis in Supply Chain Networks. Optimization, Simulation and Computational Intelligence are the main techniques adopted by Prof. Tiwari to automate the decision support system for complex and large-scale problems in Manufacturing and Logistics System. His research interests have been supported by several industries, national and international research funding agencies. He has published more than 325 papers (H Index, Google Scholar – 67 and Scopus-51) in the International Journals of repute and he has been rated as Rank 1 among top 100 individual researchers across the world who had published research articles in International Journal of Production Research (Taylor amp; Francis) during the time period 1985-2010 (International Journal of Production Research, Volume 51, Issue 23-24, 2013). He is also mentioned as Top leading author in the domain of Supply Chain Analytical Techniques by Journal of Computer amp; Industrial Engineering (Volume 137, 2019). He is the recipient of "Most Influential Researcher Award" in the domain of Operations and Supply Chain Management.