Evaluating the Transparency Capability of Smart Manufacturing Systems

Abstract: Transparency encompasses the potential to monitor operations instantaneously so that required corrective actions can be taken as needed. Transparency entails the ability to track processes in real-time, enhance the visibility of the operations, and require a seamless network for improved communication for smart manufacturing systems. However, there is a lack of proper metrics to assess the transparency of smart manufacturing environments. This paper contributes to the assessment of transparency by proposing a metric for its evaluation. In doing so, we found that the assessment of transparency takes the quantification of traceability into account. Hence, a step-in assessment is conducted by initially developing a mathematical model for traceability, followed by a model for transparency. The model is validated by analysing the sensitivity and applicability through simulation-based experimentation. The results demonstrate the level of traceability followed by transparency with the implementation of smart manufacturing systems. A point of inflexion that determines the variability in the offerings of traceability at a given set of inputs was found. This is one of the few works that focus on the development of a metric for quantifying transparency through the traceability of smart manufacturing systems. Furthermore, it investigates the behaviour by analyzing the sensitivity of the model through simulation-based approaches, which is a unique addition to the realm of the smart manufacturing literature. Managers can refer to this study's findings to design the deployment of smart manufacturing systems with informative trade-offs to maintain their required traceability and transparency capabilities.

Keywords: Transparency, Traceability, Smart Manufacturing, Sensitivity, Simulation-based experimentation.

1. Introduction

The pandemic has had a detrimental impact on global GDP, reducing it by approximately 4.8%, which has put pressure on global factories and supply chains (Chaudhary et al., 2020; Kumar et al., 2020). The emergence of the COVID-19 pandemic has increased the demand for highly resilient, agile, transparent, and customized systems, which can be met through the implementation of smart manufacturing systems (Pansare & Yadav, 2022). The pandemic has significantly impacted manufacturing operations, leading to labour shortages, unplanned downtime, increased processing times, low utilization rates of resources, and lower productivity (Ardolino et al., 2022). This influence has had a disruptive effect on the value chain, affecting the performance and efficiency of the system. The deployment of emerging technologies through smart manufacturing systems will develop capabilities such as increased resilience, transparency, and agility, which will help mitigate the effects of COVID-19 disruptions to a significant extent (Parhi, Kumar, et al., 2023). For illustration, smart manufacturing enhances the real-time monitoring of downtime operations in a factory, which can help in the early detection of faults and proactive control of the system with reduced human intervention. So, the global pandemic has expedited the need to adopt smart manufacturing systems by identifying areas for technology implementation with limited investment (Bhatia & Diaz-Elsayed, 2023; Jena & Patel, 2022). Moreover, there is an evident requirement for an agile business environment due to the changing market demands for cost-effective customized product offerings (Hoeppe, 2018; Parhi, Joshi, et al., 2023). This has led to the development of an integrated manufacturing environment capable of responding to changing circumstances, resulting in smart manufacturing (Ghobakhloo, 2020; Tortorella et al., 2022). A fully digitized manufacturing environment can lead to 30% faster and 25% more efficient production, ultimately increasing productivity by 20% and generating a 1% revenue uplift (Rüßmann et al., 2015).

Additionally, the deployment of smart manufacturing systems is expected to contribute to a global market boost of approximately 12.4% by 2025. It has been observed that there is a 28% increase in the adoption rate of technologies facilitating global digital transformations (MarketsandMarkets, 2020). The digital transformation of the manufacturing ecosystem enables the real-time acquisition of data from the shop floor and enhances the prediction of system downtime (Castelo-Branco et al., 2023; Hettiarachchi et al., 2022). This is accomplished through the use of technologies such as the Internet of Things (IoT) and Cyber-Physical Systems (CPS), resulting in increased transparency of the value chain (Mittal et al., 2020). In a smart manufacturing environment, transparency applications visualize systems using real-time data and offer suggestions for corrective measures as needed (Xu et al., 2018). In the context of smart manufacturing, transparency refers to the ability to track processes in real-time for efficient and effective control (Agrawal et al., 2021; Sudhir et al., 2023). For example, transparency plays a critical role in monitoring machine health conditions and taking corrective actions during anomalies to ensure effective control (Yang et al., 2019). Transparency also plays a crucial role in quality control applications (Agrawal et al., 2021; Bhatia & Diaz-Elsayed, 2023). One application of transparency is the use of sensor-based inspection systems to identify any defects in a product. The inspection system can be reconfigured to accommodate changes made to the product, resulting in dynamic testing, and thereby enhancing the quality rate of the systems. The transparency of smart manufacturing systems augments the capability to monitor equipment performance in real-time, thereby enhancing performance rates. Additionally, proper tracking of machines enables easy detection of operational downtime, facilitating effective production planning to improve system utilization rates. During downtime, transparent systems can identify faults and take corrective actions. Thus, transparency focuses on proper monitoring and estimating the overall equipment effectiveness (OEE) through evaluation of quality rate, performance and utilization of the smart manufacturing system in real-time (Parhi, Joshi, et al., 2023). Monitoring OEE through transparency provides insights into the operational performance of the manufacturing system and improve the efficiency of the smart manufacturing operations. Manufacturing transparency facilitates real-time monitoring of smart manufacturing systems and captures a history of actions, which can be referred to for predicting future disruptions and enabling proactive control (Mittal et al., 2018).

Transparency is a core differentiating aspect of smart manufacturing systems (Parhi et al., 2022; Shashi et al., 2019). Moreover, transparency is a crucial dimension to consider when upgrading to smart manufacturing systems (Bibby & Dehe, 2018; Brad et al., 2018; Kusiak, 2018). A survey on smart manufacturing adoption factors reveals that transparency is an essential requirement and a prerequisite for embracing digital transformation (Parhi et al., 2022; Raut et al., 2021). However, manufacturing firms face several challenges in implementing transparency in their operational processes due to the absence of relevant metrics (Bhatia & Diaz-Elsayed, 2023; Mittal et al., 2018). Quantifying transparency presents a challenging task due to the subjectivity inherent in the metrics involved. Transparency revolves around the levels of visibility and traceability, which, due to their abstract nature, are difficult to assess mathematically (Parhi, Joshi, et al., 2023). Consequently, there is currently a scarcity of literature in the operations management domain that focuses on quantitatively assessing manufacturing transparency. Nevertheless, evaluating transparency is important as it represents a critical barrier to the adoption of smart manufacturing in firms (Jena & Patel, 2022). The measurement of transparency will enable managers to assess the level of operational offerings of smart manufacturing systems, which can be further improved as needed. It can also serve as a tool for estimating the maturity of smart manufacturing adoption. Assessing transparency in the manufacturing context will enable visualization and evaluation of performance parameters. This facilitates early detection, proactive responses, and resilient control to avoid and manage disruptions caused by the COVID-19 pandemic (Parhi, Kumar, et al., 2023). Achieving this involves tracking process parameters in real-time, and sharing information on critical Key Performance Indicators (KPIs), thereby enhancing the monitoring of downtime, human resource requirements, and resource utilization through effective production planning based on historical data. Thus, it significantly mitigates the impacts of the pandemic. Furthermore, transparency plays a fundamental role in influencing the performance of smart manufacturing supply chains (Centobelli et al., 2022). Therefore, industry experts convincingly recommend the need to determine transparency mathematically. However, transparency cannot be directly measured as it involves tracking and tracing operations, which involves traceability (Parhi, Joshi, et al., 2023; Sunny et al., 2020). Thus, the assessment of transparency requires quantification of traceability in smart manufacturing operations (Hader et al., 2022; Sunny et al., 2020). Traceability refers to the ability to identify, monitor, and locate products, and process parameters in the smart manufacturing system and communicate them through the network (Hader et al., 2022).

Transparency, *measured through traceability*, in smart manufacturing systems involves the visibility of the system via continuous real-time monitoring of process parameters and communication through decision-making platforms. Traceability embodies the identification, and monitoring ability of the system, which leads to the development of a potential for the system to track, communicate, and make robust decisions. For instance, the deployment of transparency gives rise to the capability to track anomalies through monitoring based on traceability capability, communicate it through the network and take necessary actions proactively. Hence, transparency consists of the detection ability, communication, and presentation which enables its estimates to quantify the potential of smart manufacturing systems to trace an object in real-time, communicate it through the network, and make informed decisions. This will assist in benchmarking with competing firms deploying smart manufacturing systems (Li et al., 2018). The assessment of transparency is also essential for evaluating the overall performance of smart manufacturing systems (Parhi, Joshi, et al., 2023). Transparency assessment involves understanding the level of visibility, monitorability, and communication within the system, and finding ways to improve them. Therefore, there is an urgent need to establish mathematical expressions for transparency capabilities. However, the literature is silent on these issues, making it essential to establish expressions for transparency (Karadgi et al., 2021). Studies conducted by Sunny, Undralla and Pillai (2020) and Kuhn and Franke (2021) also emphasize the need to establish a quantitative metric to evaluate transparency for smart manufacturing systems. Some studies conducted by Liu et al., (2024); Montecchi et al., (2021) and Zelbst et al., (2020) have discussed the quantification of transparency, but their perspective is limited to logistics and supply chains. However, to date, no research work has demonstrated the quantification of transparency for smart manufacturing systems. Given this knowledge gap, this paper contributes to the field by addressing the following research questions.

- How can the transparency of smart manufacturing systems be measured?
- What can be the behaviour of a transparency assessment model?

Currently, many aspects of smart manufacturing systems are still in their infancy, and organizations are facing challenges in deploying these systems due to their complexities and the substantial capital investments required (Kamble et al., 2018; Karadayi-Usta, 2020). However, it is crucial to understand the functionalities of smart manufacturing capabilities to enable a phased deployment with limited investment. One fundamental capability that deserves attention is transparency. This study presents one of the initial attempts to develop a mathematical model for smart manufacturing transparency. The assessment of transparency will benefit managers by providing them with a metric to quantify the digital transformation ecosystem, guiding them to improve capability through the proper use of technology and expanding it with limited investment. The novelty of our research is discussed next. Researchers have given negligible attention to the development of a mathematical model that captures the level of transparency. To date, there is not any approach that focuses on the quantification and assessment of manufacturing transparency. We have developed a unique metric and a new mathematical model to quantify transparency for smart manufacturing systems, representing an innovative addition to the realm of transparency assessment in the smart manufacturing domain. Our research attempts to articulate the model for transparency and provide recommendations based on the findings. While the best approach to test the model would be to use real-life data, unfortunately, such data is not yet available in open-source platforms. Therefore, we have created a simulation environment to generate artificial data for investigating the functionality of the model under different scenarios. This approach forms a unique method to evaluate the transparency model based on simulation studies and derive implications for managerial reference. The simulation environment has been built based on input from industry professionals associated with smart manufacturing capabilities.

The manuscript is structured as follows: Section 2 provides a brief theoretical background on smart manufacturing concepts, transparency, and traceability. Section 3 discusses the adopted methodology and defines the problems related to traceability and transparency. In Section 4, the results of the study are examined for various scenarios. Section 5 discusses the research implications, and finally, the conclusions are outlined in Section 6.

2. Theoretical Background

The smart manufacturing system represents the epitome of digital transformations on the factory floor, emphasizing integration across manufacturing assets, communication, resilience, and transparency of systems (Bhatia & Diaz-Elsayed, 2023; Prinz et al., 2019). Transparency is a critical aspect of the smart manufacturing system as it enhances real-time monitoring capabilities, enabling the development of other essential capabilities such as intelligence, resilience, and flexibility (Alguliyev et al., 2018; Lee et al., 2019). For example, transparency in smart manufacturing systems allows for real-time visibility of products, enabling the identification of defective parts or anomalies that can be traced, leading to necessary corrective actions as required (Abualsauod, 2023). One application of transparency is the monitoring of process parameters using IoT-based sensors and the estimation of the overall equipment effectiveness (OEE) in real-time (Li, 2018; Moktadir et al., 2018; Prinz et al., 2019). System transparency facilitates the real-time acquisition of data, often referred to as big data, which is then subjected to analytics algorithms to derive actionable insights (Luo et al., 2019; Raut et al., 2021). The choice of analytics depends on the type of data, application, and observations, emphasizing the importance of integration and ubiquitous connectivity in achieving real-time monitoring, traceability of parameters, and transparency in business operations (Kim et al., 2015; Prinz et al., 2019; Sung, 2018).

Despite the benefits realized through transparency, it remains a significant barrier to the adoption of smart manufacturing systems (Bhatia & Diaz-Elsayed, 2023). This is often due to challenges faced by firms, such as a lack of qualified manpower, improper formulation of digital strategies, and incorrect choices in technology implementation (Jena & Patel, 2022). Therefore, it is crucial to make appropriate technology choices and gain a comprehensive understanding of the key aspects of transparency before its implementation. System transparency, as a paramount requirement of smart manufacturing systems, warrants a thorough and exhaustive description, which will be illustrated in the following sections.

2.1. Transparency of Smart Manufacturing Systems

Transparency accelerates the real-time monitoring of manufacturing process parameters, leading to accurate performance estimation and increased productivity (He et al., 2023). Transparency sets smart manufacturing systems apart from conventional systems, enabling them to facilitate cost-effective and timely customization. For instance, real-time monitorability, which provides visibility into the smart manufacturing infrastructure, can detect customer requirements, and communicate the necessary details to make process alterations that meet the demand. This can be achieved through contemporary practices like additive manufacturing (Kumar et al., 2023), allowing for the production of complex customer-centric products at reduced time and cost. Another technology that can lead smart manufacturing systems towards a safe, secure, and transparent ecosystem is the use of blockchain technology. Blockchain facilitates the verification of nodes, enabling secure transactions across assets and data sharing through a decentralized database, resulting in traceable and visible processes, thus enhancing process transparency (Alazab & Alhyari, 2024). Applications of blockchain technology provide a sense of mutual trust and credible coordination, expediting better monitorability and interoperability, and extending its use to food, logistics, and manufacturing supply chains (Liu et al., 2024). The use of blockchain technology enhances information sharing throughout the manufacturing value chain by collecting, processing, and sharing data, resulting in the development of a responsive and resilient manufacturing ecosystem (Montecchi et al., 2021; Song & Zhu, 2022). Such capabilities give manufacturers a competitive edge and are facilitated through system transparency.

System transparency, however, relies on the level of visibility into the processes, which is analyzed through traceability (Azevedo et al., 2023). Traceability refers to the system's potential to trace and detect functional parameters and act accordingly (Agrawal et al., 2021; Sunny et al., 2020). It involves tracking and tracing a product from initiation to its endpoint, enabling process visibility, monitoring, and detection, ultimately contributing to achieving transparency in manufacturing systems (Agrawal et al., 2021; Centobelli et al., 2022). Achieving traceability and transparency requires the deployment of technologies such as IoT, digital twins, and CPS (Kuhn & Franke, 2021). IoT is responsible for acquiring real-time data from the shop floor resources of the smart factory, while digital twin showcases the behaviour of process parameters in a virtualized interface, and CPS facilitates the visualization of value chain processes, monitors key performance indicators (KPIs), and estimates performance parameters based on acquired data (Hader et al., 2022; Parhi, Kumar, et al., 2023). For example, the running time of a drilling machine is monitored using IoT, with the data communicated and visualized through a digital twin, allowing tracking of running time and downtime in a CPS. Subsequently, necessary decisions are made for efficient control. The adoption of digital transformation technologies such as IoT, CPS, digital twin, and blockchain enhances supply chain transparency in the manufacturing sector, fostering responsive and efficient value chains in the Industry 4.0 environment (Hamdy, 2024; Zelbst et al., 2020). Supply chain transparency in the Industry 4.0 environment emphasizes visibility and providing accurate information for various processes at the right place and time through the application of digital technologies (Zelbst et al., 2020). Industry 4.0 transparency primarily focuses on deploying visualization at the business and enterprise level to achieve stakeholders' and business needs alongside core factory operations (Parhi et al., 2022). Transparency encompasses the adoption of digital technologies, knowledge integration, traceability to articulate process visibility, resilience for managing risks, sustainability, and organizational governance for efficient decision-making (Montecchi et al., 2021). Greater transparency leads to end-to-end digital integration of the value chain, resulting in improved visibility, enhanced productivity, and improved supply chain performance (Centobelli et al., 2022; Kandarkar & Ravi, 2024; Karadgi et al., 2021). However, along with significant benefits, transparency also poses certain limitations. The enhanced transparency of the system augments information monitoring, communication, and data sharing capabilities, thus leading to interoperability; however, such systems are prone to cyber-attacks and data leakage (Parhi et al., 2021). Hence, the application of transparency requires the use of relevant cybersecurity protocols to prevent data espionage, theft, and encrypt manufacturing operations to ensure secure process coordination (Liu et al., 2024; Parhi, Kumar, et al., 2023). Data overload is another challenge faced by transparent systems, which can be managed by ensuring the use of edge-based storage tactics to encourage localized storage necessary for developing a distributed facility for smart manufacturing operations (Gilchrist, 2016).

Transparency capabilities, such as monitoring and detection, enhance the visualization of KPIs, ensuring better control over manufacturing process parameters and enabling proactive decision-making. Therefore, managers should prioritize technologies that enable better monitoring and detection of processes (Singh et al., 2023). The development of a transparency model is a strategic decision for deploying smart manufacturing systems and finds wide applicability in detecting process parameters for efficient production planning applications (Parhi, Kumar, et al., 2023). While achieving transparency is a significant requirement for smart manufacturing systems, the assessment of transparency remains a gap in the current literature. Quantifying transparency would enable managers to identify ways to improve and make informed choices for effective implementation (Parhi, Joshi, et al., 2023). Current studies focus on broader aspects to assess transparency and emphasize supply chain aspects, supplier perspectives, and sustainability levels (Kandarkar & Ravi, 2024; Montecchi et al., 2021; Morgan et al., 2021). Certain empirical studies in the field of supplier transparency (For E.g. Morgan et al., 2018) and supply chain transparency (For E.g. Zelbst et al., 2020) attempted to measure transparency, but their approach was limited to a holistic perspective. They considered transparency as a behaviour and discussed items related to this behaviour. This type of transparency assessment is more qualitative. However, quantitative assessment of transparency for manufacturing operations, considering its fundamental nature and applications, is yet to be addressed. In this research, we compute the traceability and transparency quantitatively for smart manufacturing systems due to their fundamental importance in deploying digital transformation. Following a detailed discussion on smart manufacturing fundamentals and transparency, the next section outlines the methodology adopted for a comprehensive analysis.

3. Methodology

Our research adopts a simulation-based approach to assess the transparency of smart manufacturing systems. We have chosen this approach because smart manufacturing is currently in a nascent phase, with many capabilities yet to be implemented (Kamble et al., 2018; Parhi et al., 2022). The significance of using simulation-based methods lies in promoting evaluative thinking and contemplating the influence of various scenarios on the problem efficiently (Raychaudhuri, 2008). The application of simulation studies aids in observing the behaviour of the model within a virtual environment and identifying threshold points for decision-making. Consequently, the application of a scenario-based simulation approach holds great significance for this type of problem due to the scarcity of available data. Obtaining real-time data for such systems is also challenging. Therefore, transparency values are estimated based on randomly generated values for the input variables, allowing us to observe the effects of changes in these variables on the output. Additionally, the use of random data enables the distribution of potential outcomes, aiding in understanding the sensitivity of the model (Gentle, 2003). The detailed flow of our research methodology is illustrated in Figure 1. Initially, we investigated the elements that contribute to the transparency of smart manufacturing systems, as described in Section 3.1. Our findings revealed that traceability is a significant element of transparency, necessitating its assessment as a precursor to evaluating transparency. Subsequently, we developed a mathematical model for assessing traceability. This model considers critical aspects of traceability and provides a means for quantifying them (details are provided in Section 3.1). The mathematical model for traceability includes expressions for its quantification, as well as a set of constraints formulated based on the type of variables and situations used for assessment.

To ensure the correctness of the mathematical model for traceability, we conducted a thorough examination for potential errors. Once the model was confirmed to be correct, we performed pilot data testing to validate its effectiveness. Pilot data testing involves generating a small sample of input data to obtain output values that satisfy all given constraints. Through pilot testing of the model, we ensure that a small sample of data is generated and used to evaluate the behaviour of the variables for traceability. Once the model runs successfully, satisfying all required constraints using pilot data, it is validated for mathematical correctness and further consideration. Subsequently, we designed simulation experiments by creating different scenarios. Random data is generated for the inputs, and the probabilities of the outputs are computed for each scenario. The detailed steps followed for running simulations of traceability are summarized in the next section.

- Initially, the scenarios are taken for the different instances of the inputs for traceability,
- For each scenario, the various input values are considered. Considering inputs, the values of M, i.e., the maximum number of interactions considered acceptable are kept constant for a scenario, and the various values of N_I (number of interactions) are generated. Further, depending on the values of N_I, the values of P $(portability)$are generated. The details of the input notations are given in section 3.1.
- The values of the R $(reachability\ index)$ are determined for the subsequent values of M and N_I.

- Similarly, keeping in view the values of R, the corresponding values of P are generated.
- The same process is continued for the different scenarios to compute the distribution of traceability.
- Plot the distribution in a graph.

Finally, the simulation findings are summarized in a graph, which is further interpreted. The subsequent step involves developing a mathematical expression to estimate transparency based on traceability. Following that, pilot testing of the data is conducted to validate the model in a similar manner as done for traceability. Similar to traceability, the transparency model is validated for mathematical acceptability by satisfying all constraints using pilot data. This is followed by developing scenarios and computing the outputs for different scenarios to determine the value of transparency. Ultimately, the findings are summarized, and the results are interpreted. The steps involved in the simulation study for transparency are summarized next.

- Each scenario considers a particular value of the $\zeta\ i.e., loss\ parameter.$
- For a given value of ζ, the generation of different values for the parameters, i.e., $M = \{1,3,5,8,10\}$ is done, and the values of transparency are estimated for different scenarios. Only five values of $M\ i.e., M = \{1,3,5,8,10\}$ are considered to restrict the simulation readings to limited scenarios.
- The values of transparency are determined for the subsequent values of traceability.
- The same process is continued for the different cases of each scenario and for all scenarios to compute the distribution of transparency.
- Plot the distribution in a graph.

The advantage of the simulation methodology is generating multiple scenarios and observing the study findings based on the results. Hence, multiple data points can be monitored, and the performance between the values of the inputs is examined. The application of the simulations take into consideration the problem from versatile scenarios and the threshold limit is determined. The limit can serve as a critical benchmark for designing smart manufacturing systems from the perspective of the attainment of a decent level of capabilities. Nevertheless, the study limitations consider certain assumptions in place for conducting simulation studies and operating in a virtual environment (refer to section 3.1.2.). This type of approach is initial work in the realm of smart manufacturing, which considers the quantification of critical digital transformation metrics, analyses their behaviour, and derives inferences from results. The next section summarizes the details of the mathematical model used for the computation of transparency.

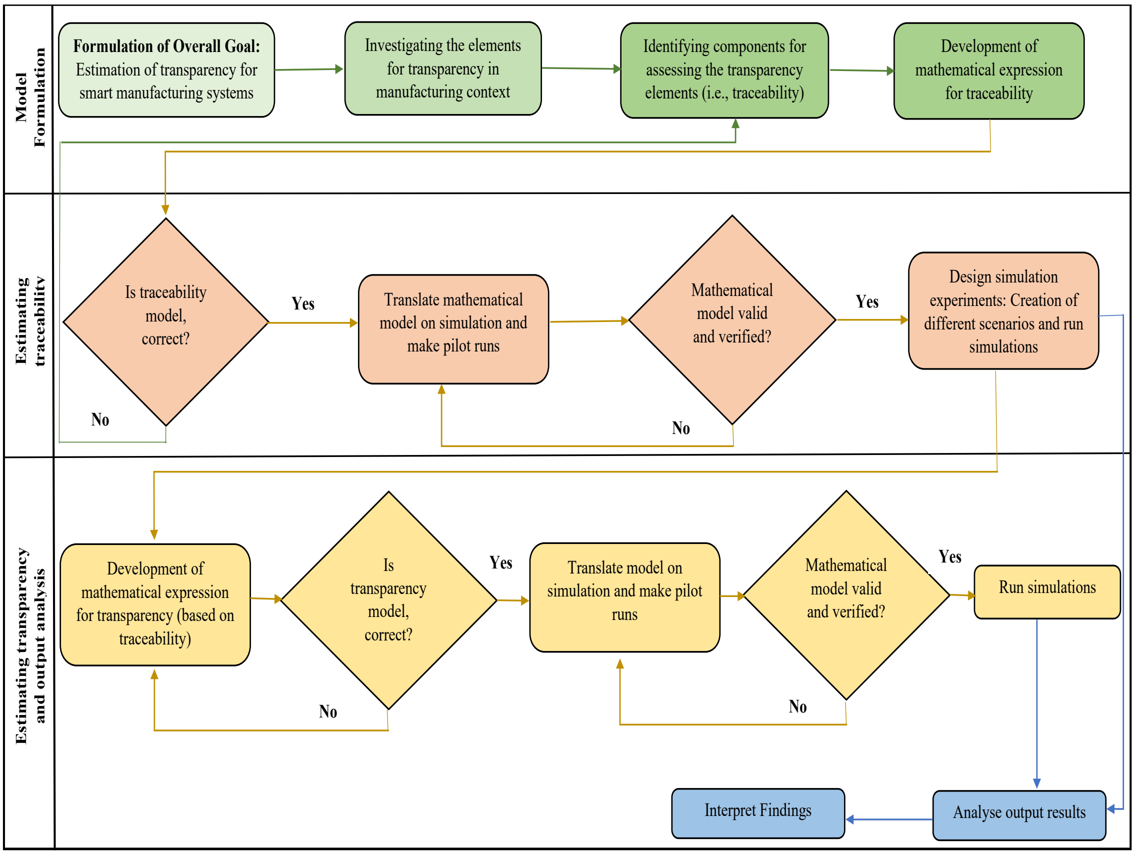


Figure 1 Flow diagram of research methodology

3.1. Problem Formulation and Modelling

In this section, we carry out problem formulation and present the mathematical model for transparency in smart manufacturing systems. Estimating transparency in these systems relies on the development of mathematical formulations. To date, no literature has successfully provided a potential metric for quantifying transparency in smart manufacturing contexts. Current research on transparency is primarily limited to qualitative assessment and is focused on its subjective nature (Kandarkar & Ravi, 2024; Morgan et al., 2018; Parhi, Joshi, et al., 2023). Quantifying transparency considering the evaluation of multiple variables based on their fundamental nature is what needs to be addressed and is the focus of our research. Our research offers advantages over other approaches in that we have developed a mathematical model to assess the transparency of smart manufacturing systems by considering vital aspects of capability and suggesting proper ways to evaluate, improve, and build upon it. The model's applicability will be easier for practitioners due to the use of inherent estimates for smart manufacturing transparency, which are easily adoptable and replicable. Transparency, owing to its subjective nature, was challenging to compute and simulate directly, so we have considered the basic nature of the capability and the concept it entails for estimation. Therefore, it is crucial to understand the definition of the variables that contribute to the assessment of smart manufacturing transparency. The definition of these variables is summarized below.

Definition 1. (*Transparency*). In the context of smart manufacturing, a system can be considered transparent if it exhibits an enhanced level of visibility. The level of visibility in smart manufacturing situations refers to the accessibility of the system to product-related, production-related, and customer-related information without any delay (Sunny et al., 2020). The delay time represents the duration taken by the manufacturing system to provide the requested information (related to product, production, or customers). The lower the delay, the higher the transparency. The delay time can be understood through the traceability of the system. The level of visibility and communication indicates the traceability of smart manufacturing systems. For instance, transparency in machine maintenance systems indicates the level at which the fault-causing elements responsible for downtime are monitored and communicated to the system, based on which decisions are made. The easier it is to visualize the process and communicate with the system, the better the traceability will be, leading to improved transparency. Greater traceability leads to higher transparency, establishing a directly proportional relationship as shown in $Eq\ (1)$.

$$Transparency \propto Traceability \tag{1}$$

Definition 2. (*Traceability*). Smart manufacturing systems possess the ability to identify, examine, and provide evidence of various details such as the location, process parameters, and production status of products on the shop floor. This information is then communicated through the network (Agrawal et al., 2021; Parhi, Joshi, et al., 2023). Hence, the significance of traceability lies in its assessment of the functionalities that make a manufacturing system transparent (Azevedo et al., 2023). As previously discussed, transparency cannot be directly measured and is assessed as a function of traceability. Thus, traceability serves as a potential measure for evaluating the level of transparency.

Traceability requires certain capabilities within smart manufacturing systems, such as the ability to detect observations in processes (referred to as reachability $- Re$) and the ability to transfer information from one asset to another (referred to as portability $- P$) (Brad et al., 2018; Spagnuelo et al., 2020). In this study, we measure the traceability of the smart manufacturing infrastructure using Re and P as indicators. Traceability ensures the capability to detect observations and communicate them over the network infrastructure (Azevedo et al., 2023). To assess traceability, the network infrastructure must be robust and easily reachable, with fewer interactions, and the structuredness of the data should be high. The traceability primarily depends on the capability of the network infrastructure and the communication system. The stronger the communication infrastructure, the better the information transfer, leading to an improved software interface for monitoring. For instance, traceability in machine maintenance systems indicates how easily, with fewer efforts (*in terms of time, money, and skills*), the anomaly-causing element responsible for downtime is detected and communicated to the system in less time. The reason for using the argmax function to estimate traceability is the significance of visibility or data structuredness to ensure smooth monitorability. The expression for traceability is shown in $Eq\ (2)$.

$$Traceability\ = argmax\,\{\,Re, P\,\} \tag{2}$$

Definition 3. (*Reachability*). Denoted as Re and is measured as the capability of the system to detect any observation of the processes. It assesses the visibility aspect of traceability. Re is assessed in terms of the interactions performed by the operator to reach a particular observation. Reachability (Re) is measured as the potential to detect an observation. Re is expressed in terms of the interactions (such as clicking, sliding, and browsing) performed by the user to reach a particular observation (Spagnuelo et al., 2020). The lesser the interaction the better the value of Re. For example, when monitoring the runtime of a production line during a shift, the operator should require fewer interactions such as clicks or slides to reach an exact value of any observation in the system. The fewer the interactions, the better the reachability, thereby ensuring sound visibility of the system. The expression of Re is expressed in $Eq.\ (3)$. Where N_I is denoted as the number of interactions performed to reach an observation and M refers to the maximum interaction deemed acceptable for a system. The value of M is considered less for a continuous type of production environment where the monitorability should be considered with lesser delay and can be considered a bit higher for a discrete manufacturing environment viz. job shop or batch production system. Table 1 shows the situations, which demonstrate that variation of the reachability at different values of N_I and M. It is observed that when $N_I \leq M$; Re is, maximum i.e., 1 because the current interactions is lesser than maximum acceptable limit which makes the system better visible. Contrary, when $N_I > M$, value decreases due to underperformance of the system to not provide enough visibility and making more interactions than acceptable limits. In such instances, the managers should try to improve the visibility potential of the system by reducing the interactions and enhancing monitorability.

$$Re = \begin{cases} 1, \ if \ 0 \leq \ N_I \ \leq M \\ e^{1-\frac{N_I}{M}}, \ if \ N_I > M \end{cases} \tag{3}$$

Table 1 Reachability situations

Cases	**Situation**	$\boldsymbol{Re}$
Case I	$N_I = M$	1
Case II	$N_I \ > M$	Between 0 but less than 1
Case III	$N_I \ < M$	1

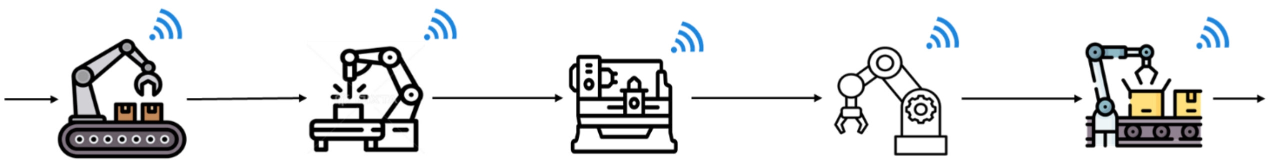
Definition 4. (*Portability*). Denoted as P and is defined through the scale to determine the degree of structuredness of data in the manufacturing system. The portability (P) of a manufacturing resource ensures the ability of the system to transfer information from one asset in the network to another. The ratings for the expression of portability are given between 0 to 1, which is in line with the thoughts expressed by (Berners-Lee, 2009). The P ratings also depend on the cybersecurity protocols followed by the network to ensure smooth and secure communication for data transmission. A safer network entails a lower chance of data espionage, thus resulting in greater information availability. P enables gauging the network infrastructure and ensuring greater traceability and transparency of the smart manufacturing systems. P indicates the strength of the network infrastructure and the expression is indicated in $Eq.$ $(4a \ to \ 4f)$. The Re and P indices are used to determine the traceability of the manufacturing system. In doing so, we found a point of inflexion that acts as a reference point for the practitioners to effectively design and operate the system to have a permissible reading of traceability.

$$P = \begin{cases} 0, unavailability \ of \ information & (4a) \\ 0.2, open \ format \ information & (4b) \\ 0.4, information \ in \ the \ form \ of \ structured \ data & (4c) \\ 0.6, information \ availability \ in \ non-propreitary \ format & (4d) \\ 0.8, \ information \ through \ URI & (4e) \\ 1, \ information \ availability \ through \ linked \ data & (4f) \end{cases}$$

Definition 5. (*Point of Inflexion*). Denoted as P_I, it is defined as the threshold limit at which a greater variability and stepwise augmentation in the value of traceability are observed at increasing values of R and P respectively. The expression for P_I is shown in $Eq.$ (5).

$$P_I = \max\ (Traceability) \tag{5}$$

The above formulation and concepts are explained by taking a sample situation for the problem comprising 5 machines connected seamlessly through one another using IoT systems as shown in Figure 2. From the figure, two scenarios are taken i.e. I (with significant manual intervention) and II (with less human intervention). As shown in scenario I, the utilization of the machine will be less i.e., 0.6 due to lesser autonomy and greater human intervention. As a result, the values of Re and P will determine the values of traceability and transparency respectively. Similarly in scenario II, due to lesser human intervention, the machine utilization will be high as the value of the traceability and transparency makes the system smarter and more autonomous.



Scenarios	Utilization	N_I	M	Re	P	$Traceability$	$Transparency$
Scenario I (*With significant intervention*)	0.6	8	6	0.71	0.2	0.75	0.6 (with ζ = 20)
Scenario II (*With less intervention*)	0.8	2	3	1	1	1	0.9 (with ζ = 10)

Figure 2 A Sample Situation

A detailed explanation of the concepts discussed will be explained in a subsequent section. The problem description for traceability is shown next.

3.1.1. Problem Description

Traceability is a potential measure for assessing the level of visibility and communicating it through the network of the smart manufacturing system. Traceability accomplishes this action through the capabilities of reachability and portability. Considering Re as stated in $eq.$ (3), it is difficult to reflect the expression owing to the computational complexities involved in the process. Hence, we have expressed Re in terms of reachability index (R) which is computed as $\frac{M}{N_I}$ for the sake of simplicity in the computation of traceability. In doing so, we can successfully run simulation models and obtain accurate results for traceability by estimating the $argmax$ values, which would otherwise be difficult. Additionally, the use of ratios considers both the variables of reachability indices and provides comprehensive consideration for traceability assessment. The computation of traceability is accomplished based on the revised mathematical expression as discussed in the $Eq.$ (6). However, there need to be certain assumptions considered for the computation prior to the formulation of the model. The detailed assumptions are mentioned in section 3.1.2.

$$Traceability = argmax \{ R, P \} \tag{6}$$

3.1.2. Assumptions

To process the mathematical model, certain assumptions need to be addressed initially, as summarized in this section. Firstly, it is assumed that the system under consideration is end-to-end connected, encompassing various manufacturing assets and computational control platforms. The problem environment taken into account is assumed to cover all aspects of smart manufacturing systems. So, the model is assumed to be in an organizational environment that has deployed smart manufacturing systems to a significant extent, serving as a takeaway for managers seeking to reference our research for the execution of transparency. Secondly, the network infrastructure used for integration is assumed to be robust and reliable to facilitate efficient and seamless communication. The communication infrastructure should be robust enough to facilitate continuous communication and information exchange. Finally, the use of standard communication protocols is assumed to ensure proper and universal communication across various platforms within the organization. This ensures swift and efficient communication, resulting in significant values of portability and reachability. Managers aiming to implement transparency and traceability should ensure the use of standard protocols to facilitate proper data communication between different servers and hosts, enabling integration. These assumptions may limit the applicability of our proposed model, considering the level of deployment of smart manufacturing systems. However, it remains quite relevant to the current manufacturing landscape by offering potential directions to managers in their upgrade efforts. Additionally, existing legacy systems can consider embracing transparency capabilities by incorporating the insights provided in our proposed models and deploying them effectively.

3.1.3. Notations

i: $1, \ldots\ldots, m$ $(no\ of\ smart\ manufacturing\ assets)$

$R_i\ (R)$: $Reachability\ index\ for\ 'i'\ manufacturing\ asset$

$P_i(P)$: $Portability\ for\ 'i'\ manufacturing\ asset$

$N_{I_i}(N_I)$: $No\ of\ interactions\ the\ operator\ performs\ to\ reach\ the\ required\ observation\ 'i'$

$manufacturing\ asset.$

$M_i\ (M_i)$: $Maximum\ number\ of\ interactions\ considered\ acceptable\ for\ 'i'\ manufacturing$

$asset.$

3.1.4. The proposed model

Traceability for $'i'$ manufacturing asset where $i = \{1, \ldots\ldots, m\}$ and $'m'$ is the total manufacturing asset is represented as:

$$Traceability = \sum_{i=1}^{m} argmax \{R_i, P_i\} \tag{7}$$

$s.t.$

$$0 \leq P_i \leq 1 \quad \forall\, i = 1, \ldots., m \tag{8}$$

$$0 \leq N_{I_i} \quad \forall\, i = 1, \ldots., m \tag{9}$$

$0 \leq M_i \qquad \forall\, i = 1, \ldots., m$ (10)

N_{I_i}, M_i $are\ integers \quad \forall\, i = 1, \ldots., m$ (11)

$Eq.$ (7) shows the expression of traceability for 'i' manufacturing asset in a system. $Eq.$ (8) describes the portability range for 'i' manufacturing assets. As already discussed, the value of the portability will vary from 0 to 1 with various readings showing different interpretations as shown in $Eq.$ (4). $Eq.$ (9) and (10) shows that the reachability index parameters for 'i' manufacturing asset are positive values and cannot be negative in readings. Finally, $Eq.$ (11) shows that the reachability index parameters are integers.

3.2. Problem description for transparency

Transparency describes the visibility and traceability of the manufacturing processes and related information. Thus, transparency is related to traceability to ensure the proper network infrastructure and communication system augments the monitoring ability of the manufacturing system. The more the strength of the network infrastructure, the better the visibility and monitoring capability hence greater transparency. For example, to monitor defective products on the production line, technologies such as IoT can be used to trace the faulty parts, ensuring better visibility. The process of communicating defect information to the system is referred to as transparency. It can be stated that the transparency of a smart manufacturing system is directly proportional to traceability as shown in $Eq.$ (1). However, due to certain delays or losses in the network, the level of visibility for the smart manufacturing system represented as transparency also gets affected. Hence, the transparency of the smart manufacturing system is equated as a function of traceability with certain loss parameters (ζ). The loss parameter occurs in the network due to jitter and transmission losses. Transparency focuses on the visibility capability, explained through the data interchangeability rate, i.e., the amount of data successfully interchanged to enable successful monitorability and availability. For example, the information bits delivered in packets for transferring real-time data of tool wear rate from the machine to the centralized control system may experience certain missed values or communication delays due to transmission loss. This transmission loss is represented by the loss parameter (ζ), explaining the delay time and incompleteness in data due to network losses (Gilchrist, 2016). As explained previously, traceability entails the visibility level of the smart manufacturing system, emphasizing the monitoring capability of the system. Hence, transparency is related to traceability based on the amount of successful data communication and information exchanges that have taken place in the smart manufacturing system. The augmentation in the level of traceability, explained through the successful data interchange, mentioned as $(1 - \zeta)$, gives transparency. The detailed expression for transparency is discussed in $Eq.$ (12). The advantage of the proposed transparency model is that it considers the fundamental nature, i.e., visibility and communication, for quantitative assessment, which was absent in previous models. In $Eq.$ (12), $(1 - \zeta)$ can be referred to as a constant of proportionality, and transparency is the level of visibility estimated as an interchangeable data rate. This is because the higher the rate of interchangeability of data, the better the system visibility.

The value of transparency always varies between 0 to 1. This is because transparency shows the rate of successful transactions made over in the network.

$$Transparency = (1 - \zeta) \times Traceability \tag{12}$$

3.2.1. Notations

i: $1, \ldots\ldots, m$ $(no\ of\ machines\ and\ systems)$

$\zeta_i(\zeta)$: $loss\ parameters\ for\ 'i'\ manufacturing\ asset$

$Traceability_i$: $Traceability\ for\ 'i'\ manufacturing\ asset$

3.2.2. The proposed model for transparency

Transparency for $'i'$ manufacturing asset where $i = \{1, \ldots\ldots, m\}$ and $'m'$ is the total manufacturing asset is represented as:

$$Transparency = \sum_{i=1}^{m} (1 - \zeta_i) \times Traceability_i \tag{13}$$

$s.t.$

$$0 \leq Traceability_i \leq 1 \quad \forall\, i = 1, \ldots., m \tag{14}$$

$$0 \leq \zeta_i \leq 1 \quad \forall\, i = 1, \ldots., m \tag{15}$$

$Eq.(13)$, shows the expression of transparency for 'i' manufacturing asset. $Eq.(14)$, shows that the traceability of 'i' manufacturing asset value varies between 0 to 1. The value of 'i' varies from $1\ to\ m$, where 'm' is the total number of manufacturing assets in the system taken under consideration. The expression for traceability and transparency will be limited to only those manufacturing assets that possess the capability to monitor, track, and communicate real-time information or are actively involved in core processing operations. $Eq.(15)$, establishes the notion that the value of the loss parameter (ζ_i) for 'i' manufacturing asset always varies between 0 to 1. It is because the ζ_i is the measure of loss in communication due to resistance and other issues, which values are better if they are 0, and worst if nearer to 1. If the value of $\zeta_i = 1$, it means that the transparency offering of the smart manufacturing asset is 0, which needs to be visited for future improvement. The more improvements made in the communication infrastructure of the manufacturing asset, the value of ζ_i keeps on deducing. The limitation of the proposed mathematical model and the simulation results (discussed in Section 4) for traceability and transparency is that it is grounded on assumptions that restrict the applicability of the model to systems with significant monitoring, communication, and visibility capabilities. However, considering the barriers faced by manufacturing systems related to adoption costs, technology infrastructure, implementation issues, etc., the applicability of the model may be challenging. Therefore, managers can seek guidance from various smart manufacturing implementation strategies and design deployments effectively prior to model testing (Jena & Patel, 2023; Parhi et al., 2021). The next section discusses the results of the problem and outlines the discussions.

4. Computational results

This section analyses the model discussed in section 3.1. and 3.2. respectively. Smart manufacturing is currently in its nascent stages, due to which the deployment is limited and fragmented to certain parts of the value chain. Hence, it is difficult to get real-time data for traceability and transparency because of which we have used Monte Carlo simulation for our model. The significance of Monte Carlo simulation lies in its ability to generate random input data and investigate its impact on the outputs. The significance of using random data lies in its ability to create a range of possibilities and outcomes, resulting in more accurate outputs that are complex and difficult to derive with real-time data (Gentle, 2003). This benefit allows the use of random data to serve the purpose of Monte Carlo simulation for conducting *what-if* analyses of the model (Raychaudhuri, 2008). Additionally, Monte Carlo simulation is used to predict future outcomes based on mathematical relationships between process parameters for different types of input data under diverse scenarios. In our specific problem, we generate random input data for the components that define traceability and estimate its impact on the output, which is traceability itself. We consider different values of Portability and Reachability to analyze the traceability of the system. The results are analyzed by examining the relationships between portability and traceability; reachability, and traceability, as well as considering both indicators in relation to traceability simultaneously. Simulating these indicators and analyzing their effects on traceability is crucial to understanding the role played by different dimensions of the network infrastructure in smart manufacturing systems. By assessing the effects of reachability and portability, we can determine the different values of traceability and establish threshold limits for achieving desirable levels of traceability while reducing variations in capability observations. The same process is adopted for estimating transparency. Using a simulation-based experimentation approach for traceability and transparency allows for analyzing the sensitivity and applicability of the mathematical model. Managers can utilize mathematical expressions and simulations to determine the level at which they need to design the system in order to maximize the benefits of smart manufacturing capabilities and enhance overall outputs. The application of the simulation approach will also assist decision-makers in finding references to observe the behaviour of different parameters for assessing traceability and transparency, which can be a critical takeaway for smart manufacturing deployment and execution. However, the drawback of this approach lies in the restriction of model usage in a real-time environment, which could be further explored through potential case studies.

4.1. Simulation parameter settings for traceability

Let us simulate the value of traceability for the different values of the unit variables. We have taken $i = 1$ for conducting the analysis of $eq. (7)$ and $eq. (13)$. The simulations for different scenarios of the corresponding values of M at different values of N_I and P. We have computed reachability in our study based on the concept of reachability index, which can be denoted as the fraction of M and N_I. The reachability index shows the corresponding values of M and N_I for a given value of reachability (R). The simulation focuses on a generation of different scenarios for the parameter M. The scenarios with different values of M are generated. Only five values of M $i.e., M = \{1,3,5,8,10\}$ are considered to restrict the simulation readings to limited scenarios. The reason for considering these numerous scenarios relates to the various possible instances that can arise in a generic system, providing a holistic perspective on the problem under consideration. The inclusion of these scenarios encompasses all the pertinent factors required for decision-making, considering the research objectives.

We have run simulations for each scenario 100 to 500 times to reach different values of traceability. It is done to study the variations in different variables and how traceability behaves over a period. However, only significant, and viable data points are considered for the analysis. For instance, it is practically not viable to have 50 interactions to reach an observation (N_I) in a system. If it is so, then the system might be at fault, or certain maintenance needs to be done. Hence, only selected points are shown in the sample solution table for ease of simplicity. The details of the simulations are summarized in Table 2.

Table 2 Summary of the scenarios for traceability

Scenario #	**No of simulations**	**Number of Instances Evaluated for N_I and P**	M
Scenario I	500	10	1
Scenario II	500	10	3
Scenario III	500	10	5
Scenario IV	500	10	8
Scenario V	500	10	10

The details are shown in graphs (refer to Figure 3) for portability and reachability index expressed in terms of $M/_{N_I}$. As the value of M is less, there is a reduced variability observed in the values of traceability with changing values of portability and reachability index. It is because with lesser interaction on the part of the user with the system to reach observation, the network infrastructure is sound, and the monitorability of the system is very high; hence lesser variabilities can be observed in the traceability.

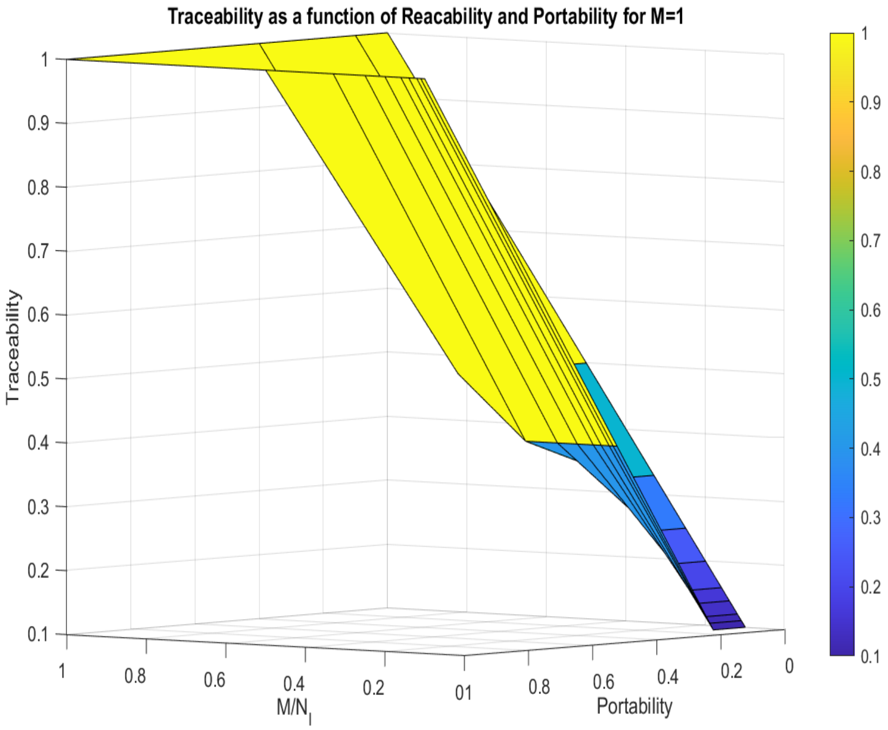


Figure 3 Traceability as a function of reachability and portability for $M = 1$

The details are shown in graphs (refer to Figure 4) for portability and reachability index expressed in terms of $M/_{N_I}$. As the value of M has slightly increased, there is an enhancement in variabilities observed in the values of traceability with changing values of portability and reachability index. It is because with slightly increasing interaction to reach an observation, the monitorability of the system decreases due to the lesser performance of the reachability index and portability of the system; hence increased variabilities can be observed in the values of traceability.

***Interpretation of M values*:** For the M value to be less, significant improvements and investments must be made in the network infrastructure to ensure higher converging portability *(P)* to observe a significant improvement in the traceability of the smart manufacturing system. The more significant the improvement in digital transformation infrastructure is there, the lesser will be the value of M.

***Interpretation of Point of Inflexion (P_I)*:** In this research, interestingly, we provide the Point of Inflexion (P_I), which guides the level of effect of one on another, i.e., R and P on traceability (refer to Figure 4). Traceability and transparency require infrastructure support and ubiquitous connectivity, which will incur significant investments. However, in order to do a trade-off between the level of transparency & traceability and the cost involved, the P_I acts as a guide to determine the extent of investment to optimize the resources. From Figure 4, it can be observed that the P_I under consideration portability and reachability index together to assess traceability is 0.2. It can be interpreted that after the values of P_I (0.2 for current scenario of $\mathrm{M} = 3$) the traceability value of the manufacturing system increases stepwise; hence, the system's variabilities are also enhanced. The managers deploying the smart manufacturing systems must look to the traceability of the system above P_I to observe a stepwise increase in the values of traceability for given values of the reachability index ($M/_{N_I}$) and P.

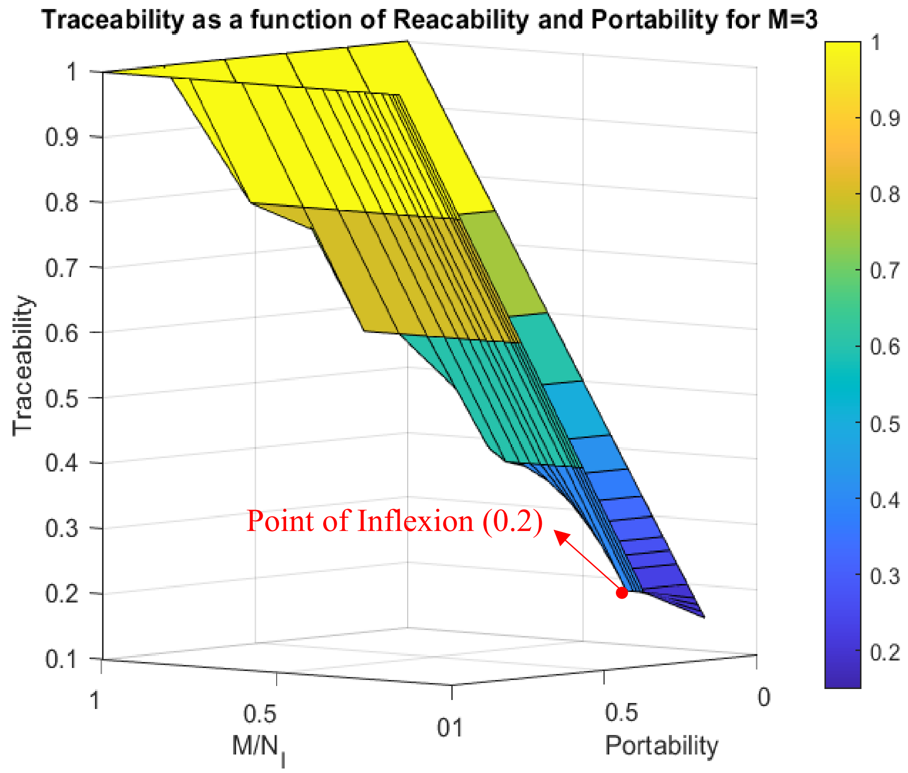


Figure 4 Traceability as a function of reachability and portability for $M = 3$

The detailed distribution for scenario 3 is shown in the graph (refer to Figure 5) for the portability and reachability index expressed in terms of $M/_{N_I}$. As the value of M has increased significantly, there is a greater enhancement in variabilities observed in the values of traceability with changing values of portability and reachability index. It can also be noted that with increasing values of M, the number of simulations to reach a higher value increases, which means the data sample becomes more distributed. It is because, as the number of interactions enhances due to the lower performance of the network, it requires greater efforts and time for the system to reach a higher value of traceability.

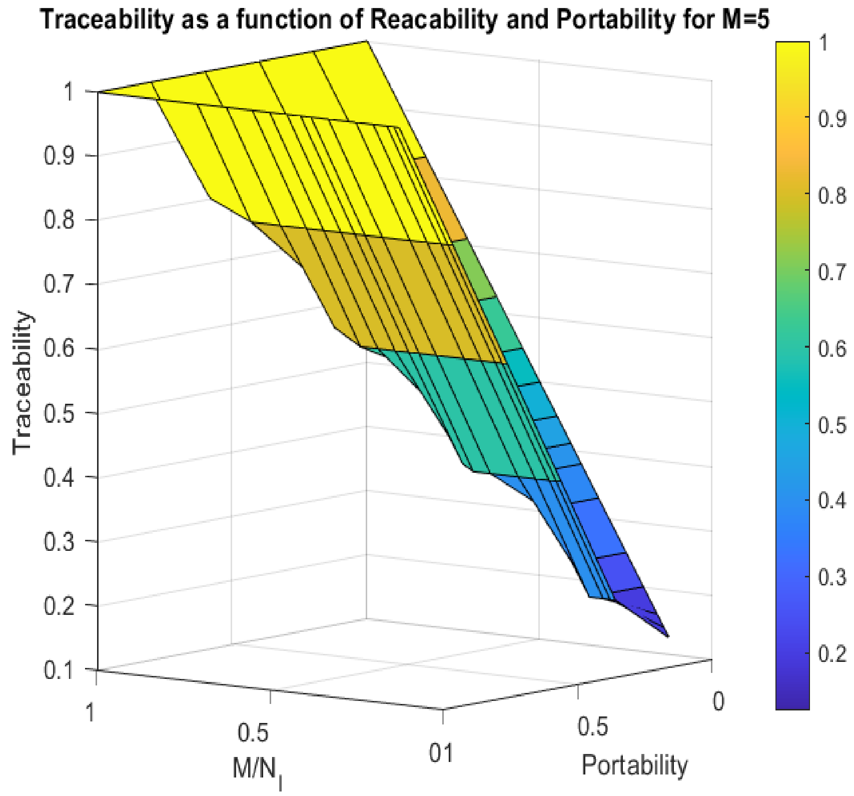


Figure 5 Traceability as a function of reachability and portability for $M = 5$

Now, considering higher values of M are studied. The details are shown in Figures 6 and 7 for portability and reachability index expressed in terms of M/N_I. As the value of M has increased drastically, there is an augmentation in variabilities observed in the values of traceability with changing values of portability and reachability index.

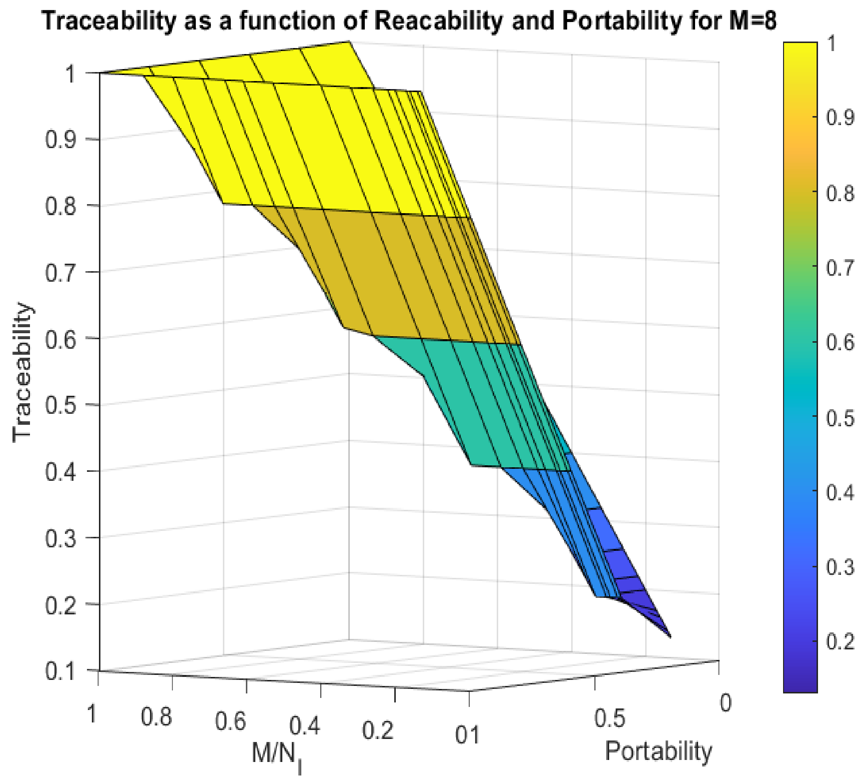


Figure 6 Traceability as a function of reachability and portability for $M = 8$

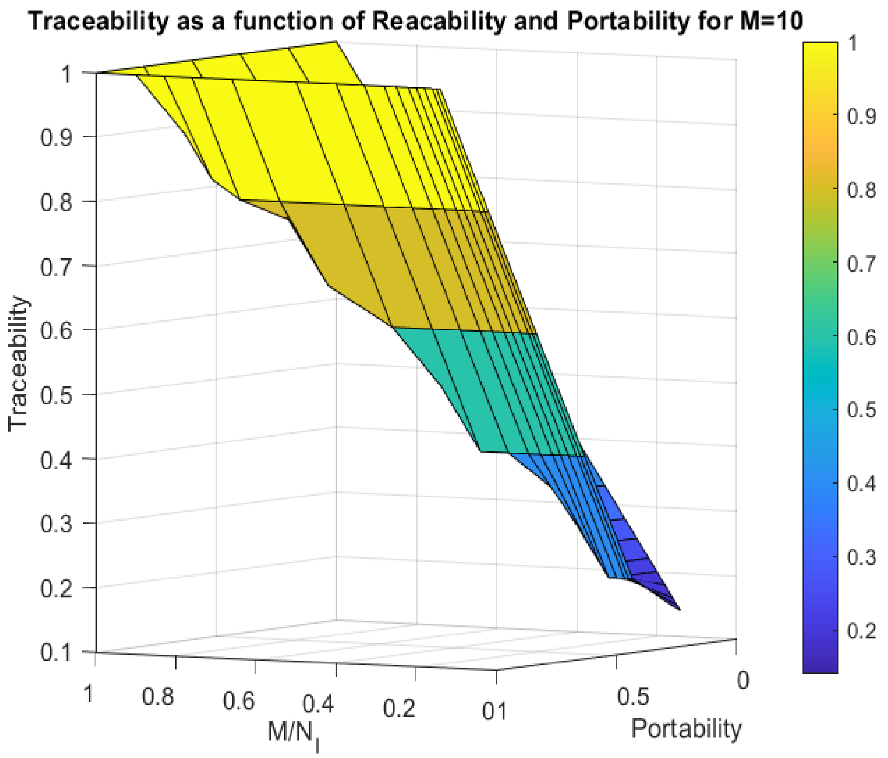


Figure 7 Traceability as a function of reachability and portability for $M = 10$

The simulation results are shown in Figure 8, and Figure 9 plots for reachability index expressed in terms of $M/_{N_I}$ and portability. As the value of M has risen significantly, there is an increase in variabilities observed in the values of traceability with changing values of portability and reachability index. Also, the distributions of the simulations to reach a maximum value of traceability have also increased. It can be noted that with significant variations in the different parameters, there are no remarkable changes in the traceability values. It changes at more values of reachability index (R) and P due to higher values of M.

After analysing the combined effect of P and R, we observe the individual effects of each indicator on the values of traceability. Figure 8 summarizes reachability in different scenarios (i.e., values of M). From the figure, it is explicit that as the value of M increases, the variability of traceability also increases for different values of reachability. Considering all the values of M in combination, it is observed that at the value of 0.2 for reachability, the variability of traceability is observed for different M. So, the 0.2 can be known as a Point of Inflexion *(P_I)*. The organization should at least choose to stay near or above the inflexion point to achieve an acceptable value of traceability. As the value of M increases, the no of interactions required to achieve the inflexion point is also enhanced. An acceptable value of M should be between 3 to 4 to avoid greater variabilities and distribution of traceability for a given smart manufacturing system, as observed from the results of the simulations. From the portability vs. traceability graph (Figure 9), the value of M increases with enhancing portability value, and greater variability in the value of traceability is observed. The traceability varies with portability in a stepwise increasing manner, i.e., at a constant value of portability, a significant increase in traceability can be observed. At the value of 0.2, i.e., Point of Inflexion (P_I), the enhancement in the value of traceability is observed, making the system more accessible. In other words, after the point of inflexion, the traceability value of the manufacturing system increases stepwise. Consequently, it can be inferred that irrespective of the consideration of., R, and P either in isolation or combination (using a 3d graph) with the traceability of the system, the P_I is 0.2 for the system. The managers must try to keep the traceability of the system above the P_I to experience a significant improvement in the values of traceability for smart manufacturing systems.

As the value of M increases, the difference between the value of M/N_{I} and portability decreases, i.e., at a lesser change in the value of M/N_{I} and P, the enhancement in the value of traceability is observed. The traceability function is sensitive toward changes in the values of M/N_I and P. Nevertheless, with the enhancement in the value of portability, a greater change is observed in traceability compared to the value of M/N_I. Hence, traceability is more sensitive to portability. It can be interpreted that the more the ease of the availability of information, the more the traceability of the system. The determination of traceability through portability and reachability is undertaken for a single manufacturing asset. However, for $'m'$ assets present in the smart manufacturing system, traceability can be estimated and summed to find the system's overall value.

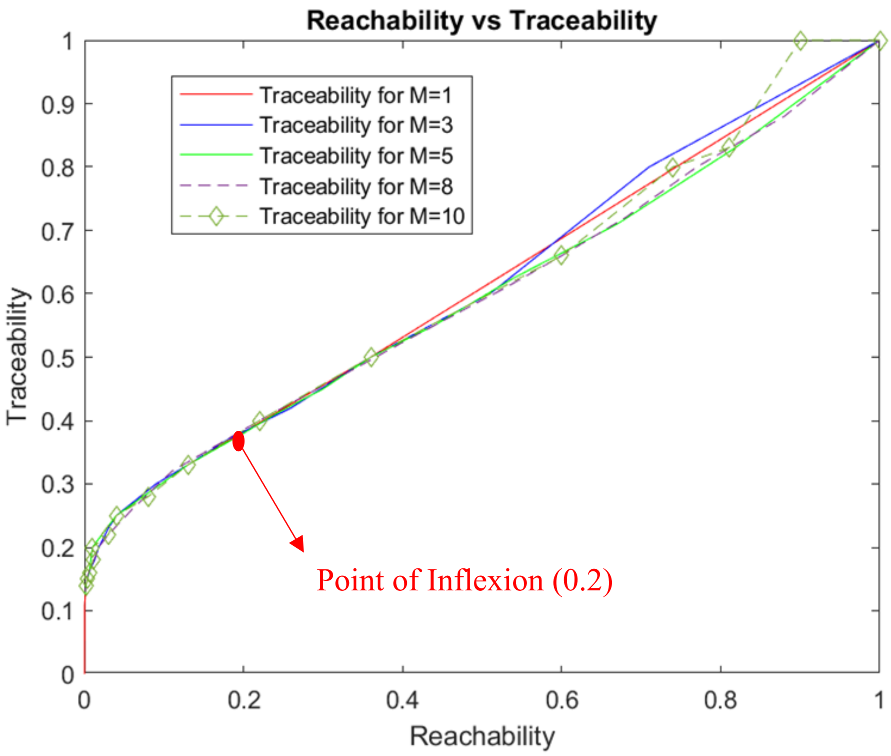


Figure 8 Reachability and traceability for different values of *M*

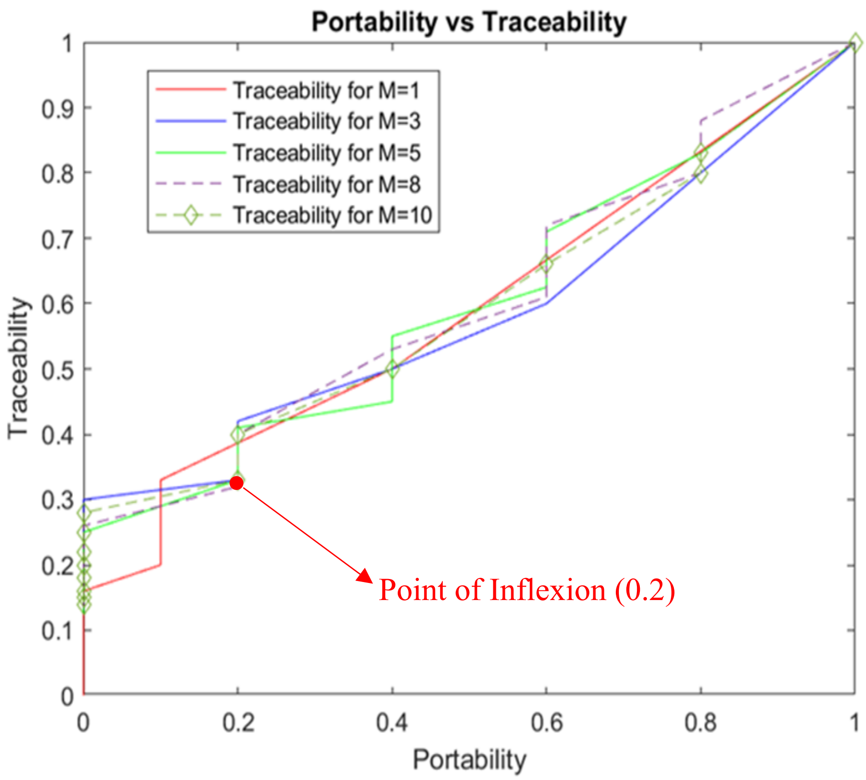


Figure 9 Portability and traceability for different values of *M*

4.2. Simulation parameter settings for transparency

The values of traceability are estimated for the different values of M for the system. The same simulation procedure is followed as that for traceability (*see Section 4.1*). Then the various values of ζ are considered for evaluation of transparency. Simulating transparency for different values of M and traceability for a given ζ is to analyze the effect of M and ζ on the system's transparency as referred to in $eq. (13)$. To accomplish the respective goal, we have undertaken a simulations-based approach, in which the random data are generated, and the probability of the output is assessed. The different cases of the loss parameter value ($\zeta = 1\%, 5\%, 10\%, 15\%, 20\%, and\ 25\%$) are considered for carrying out the simulations. The details of the simulation scenarios are summarized in Table 3.

Table 3 Summary of the scenarios for transparency

Scenario #	**No of simulations**	**Number of Instances Evaluated for Traceability**	ζ	M
Scenario I	500	10	1	1,3,5,8,10
Scenario II	500	10	5	1,3,5,8,10
Scenario III	500	10	10	1,3,5,8,10
Scenario IV	500	10	15	1,3,5,8,10
Scenario V	500	10	20	1,3,5,8,10
Scenario VI	500	10	25	1,3,5,8,10

The transparency capability of the businesses as a function of traceability can be analysed by simulating various M values for different scenarios at a given ζ. We have run simulations for different scenarios 100 to 500 times each to reach different values of traceability and transparency. It is done to study the variations in different variables and how the transparency behaves over a period. However, only significant, and viable data points are considered for carrying out the analysis. Figure 10 shows the analysis of the transparency (for different ζ and at various M) with the traceability estimates. From the traceability vs. transparency graph, with the increasing value of M, there is no change in the slope of the curve. However, with the enhancement in the value of M, the transparency increases with greater distributed points, and more simulation readings are required to reach the maximum value. The enhancement in the value of M shows the greater data distribution to reach a higher value of transparency. It might be because the more the value of M, the more the number of interactions required to reach the maximum traceability; hence more time and effort are required to reach greater visibility, because of which the distribution of transparency readings increases. The managers should keep an optimum reading of M to reach the maximum value of transparency in less time. It will augment the reactiveness of the smart manufacturing systems for any change in readings of the assets, thus improving visibility and monitorability for the smart manufacturing system.

Nevertheless, with the enhancement in the value of ζ, the transparency value decreases with growing traceability. It is observed that as the value of ζ increases, the slope of the transparency curve decreases. This implies that a small increment in traceability will not result in a significant improvement in transparency reading at higher ζ values. In summary, as the value of ζ increases, more deviation in transparency is observed. This is because, with the enhancement in the value of ζ, the network infrastructure's ability to facilitate communication also decreases due to increased resistance. As a result, despite excellent monitorability (which enhances traceability), the information cannot be communicated seamlessly over the network, reducing the transparency of the processes (Gilchrist, 2016). Managers and practitioners deploying smart manufacturing systems must strive to reduce the value of ζ, i.e., the loss parameter, to achieve greater transparency. This can be achieved by improving the communication infrastructure and simplifying the system's monitorability to enhance the traceability of the system. The ζ (loss parameter) can be reduced by enhancing the quality of network infrastructure and lowering losses caused due to jitter and transmission. It will enhance the seamless communicability amongst the manufacturing assets leading to greater transparency and control of the businesses. Making appropriate choices in selecting network infrastructure, the hardware used for communication, and communication protocols that can be standard or proprietary based are significant to enhance the information transfer over each transaction and attain a decent level of system transparency in manufacturing systems. Therefore, transparency also decreases proportionally. Determining transparency based on traceability is undertaken for a single manufacturing asset in our research. However, using this approach, the managers can estimate the transparency findings for all the manufacturing assets, which can be summed to compute the overall value of transparency for the system.

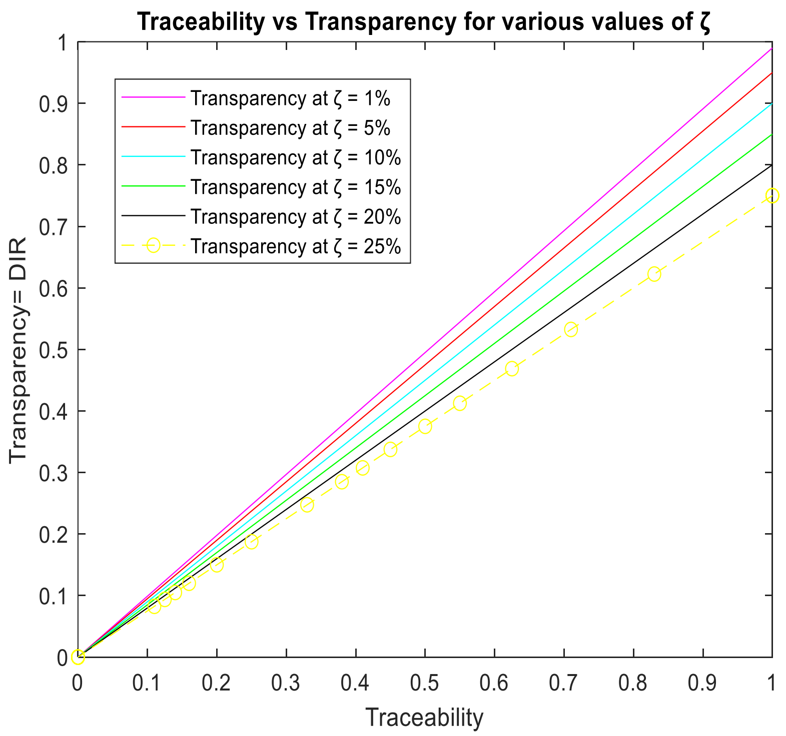


Figure 10 Traceability vs. Transparency Curve

5. Discussion

This section discusses the implications derived from the research findings. Organizations strive to deploy smart manufacturing systems, but they often face challenges in making the right choices regarding technologies, executing capabilities, and optimizing asset utilization to enhance performance and gain a competitive advantage. The primary objective for these organizations is to implement smart manufacturing in a way that maximizes productivity while minimizing investments. This can be achieved if managers and decision-makers develop a process that focuses on critical capabilities such as resilience, transparency, and flexibility, which in turn contribute to the competitive priorities of the business and improve overall performance. The main focus of this study is to determine transparency for smart manufacturing firms by developing a mathematical model conducting simulation-based experimentation studies, and then discussing the results to facilitate efficient decision-making. Our study holds value in several aspects. The key takeaways from this study are discussed from both theoretical and practical perspectives, providing valuable insights for researchers and practitioners alike. The findings of this study combine methodological rigor in quantifying the transparency alongside simulating its findings and with practical relevance through providing recommendations for smart manufacturing design contributing towards advancements of theory and practice.

5.1. Theoretical Implications

Smart manufacturing systems are characterized by radical transformations in processes, leading to modifications in structural and infrastructural decisions (Parhi et al., 2021). Structural decisions focus on making alterations in fundamental aspects such as sourcing, process technology, and facilities based on the type and nature of the equipment in the firm (Miltenburg, 2005). The deployment of smart manufacturing systems introduces transparency capabilities that impact sourcing by enhancing suppliers' visibility within the factory's supply chain (Upadhyay et al., 2023). Transparency also enables real-time monitoring of processes and production parameters, allowing for improvements as needed. Additionally, transparency empowers equipment to sense, detect, and understand potential flaws, making them intelligent and enhancing equipment outputs and productivity (Bueno et al., 2020). Infrastructural decisions, such as human resources potential, are also improved through transparency capabilities by enabling real-time monitoring of performance and suggesting necessary improvements. Smart manufacturing transparency monitors process flow and traces system performance in real-time, aiding in the identification of potential bottlenecks and downtime, thus improving production planning functions (Parhi et al., 2021). Furthermore, transparency alters the organization structure and controls by decentralizing the transparent system and focusing on localized decision-making for smart manufacturing systems. As a result, transparency capabilities have a profound impact on decision areas within production systems, unlocking their potential for performance improvement. Therefore, managers implementing smart manufacturing should possess the ability to assess the transparency of the production system, enabling them to modify strategic decisions and gain a competitive advantage.

Transparency is a critical capability, necessitating its assessment in this study. The focus of this research is to develop a metric for assessing transparency and conduct empirical studies through simulation-based experimentation to evaluate variations in transparency under different sets of inputs. The results of this research address the assessment and analysis of transparency capabilities in smart manufacturing systems, filling a gap in the existing literature (Karadgi et al., 2021). Additionally, the analysis of transparency contributes to the evaluation of traceability, making it a significant addition to the realm of smart manufacturing literature. Researchers can refer to our study findings to analyze changes in transparency under specific sets of inputs. The traceability curve can also serve as a reference point for practitioners deploying smart manufacturing systems to achieve better productivity with limited investments. The theoretical implications of this study are summarized in the following pointers, which will be discussed next.

5.1.1. Quantification of Transparency

The study develops a mathematical model for transparency, which is a fundamental capability in smart manufacturing. The development of this model demonstrates a structured approach to measuring a crucial metric for digital transformation. It serves as a reference point for managers, enabling them to make informed choices regarding various transparency components, enhance their offerings, and make suitable decisions. The evaluation approach and simulation for transparency contribute to the conceptualization of a model which is a sizable addition to smart manufacturing literature. The assessment of transparency also involves quantifying traceability, which allows us to establish a metric for measuring the level of visibility in the smart manufacturing system. By focusing on the relevant elements of traceability, the visibility offerings of the smart manufacturing infrastructure can be improved, enabling benchmarking against competitors. The assessment of smart manufacturing transparency assists managers and consultants in identifying critical areas of focus for their organizations to realize the benefits of digital transformations and benchmark their performance against competing organizations.

For academics, this study holds significant value as it serves as a crucial reference for evaluating transparency and its components. Such evaluation can aid in designing a smart manufacturing strategy by initially focusing on the elements that have a predominant impact on transparency and making substantial investments in that direction. This should be followed by executing the strategy through informed choices in smart manufacturing technologies and empowering the digital transformation infrastructure to enhance this fundamental capability. As needs evolve, the focus can then be shifted to other capabilities. Academicians can study the fundamental capabilities and design a smart manufacturing strategy by considering their influence on manufacturing decisions and outputs. Additionally, the models proposed and analyzed for assessing traceability and transparency can be extended to supply chains by incorporating sustainability factors. The expressions for traceability and transparency can be useful for estimating the visibility and monitorability of product flows in the value chain, providing necessary recommendations for their sensitivity. This research provides insights into the key factors that shape transparency and offers guidance on incorporating it effectively into the broader framework of smart manufacturing strategies.

5.2. Practical Implications

The main contribution of the research that focuses on the development of a metric to assess the transparency offerings of smart manufacturing systems is a critical requirement for managers embracing digital transformation (Parhi, Joshi, et al., 2023). The managers can refer to the findings of the study and design the deployment of smart manufacturing systems to realize better productivity at a limited capital. For instance, the proposed model for transparency assessment can be used to evaluate the monitorability of a specific smart manufacturing facility for various manufacturing processes, such as product tracking, defect monitoring, supervising production parameters behaviour, and production planning applications. Beyond manufacturing applications, transparency can also be crucial for managing marketing and customer relationships. Furthermore, transparency applications can prove vital for supplier management, allowing vendors to track operations flow in the factory and synchronize their functions with the customers' value chain. The critical implications for the managers are summarized next.

5.2.1. Design of smart manufacturing systems

The application of the simulation-based experimentation approach demonstrates a reference model to optimize the transparency offerings of the firm using simulation approaches. The use of metrics to quantify traceability and transparency aids managers in establishing a reference point for designing the deployment of smart manufacturing systems. While managers aspire to deploy smart manufacturing systems, they encounter significant technical, financial, and organizational barriers during the transition. Our findings can guide managers to focus on critical variables and make appropriate choices among technologies, even with limited investment, for the effective execution of smart manufacturing transparency. The researchers in the domain can refer to the study findings to assess the sensitivity and applicability of the smart manufacturing offerings towards changing inputs. Interestingly, we found a point of inflexion (P_I) for traceability values. P_I shows a threshold limit of the offerings of the manufacturing firm, that needs to be followed by the decision-maker to augment the offerings of the firm and attain maximum benefits. The decision-makers can refer to P_I values and try to make sure to design the system by considering that the minimum threshold limit of traceability should be maintained for a firm to at least realize the benefits of digital transformation. Hence, the threshold limit acts as a reference point for the managers and practitioners to adequately implement them by finding an efficient and effective way of operationalization. The decision support system for smart manufacturing transparency is summarized in Figure 11. The decision support system shows the adjustments that need to be made in the system to enable effective decision-making. Initially, the input data and process parameters are fed into the system, it is followed by real-time monitoring of the processes. The process flow is monitored for tracking for evaluations of the indicators for traceability and transparency assessment. The point of inflexion is identified for the process and monitored. In case of deviations, the necessary corrective actions are taken for improvement in the processes and to manage the parameters. Moving forward the visualization of outputs takes place and necessary feedback is taken for any improvement in the processes resulting in better functionality of the system. The decision is used, and based on it the inputs are improved which resulted in an optimized value of the traceability and transparency offerings of the smart manufacturing systems. The DSS shows the way the transparency assessment and evaluation of transparency help in identifying the ways the improvements are made in the outputs.

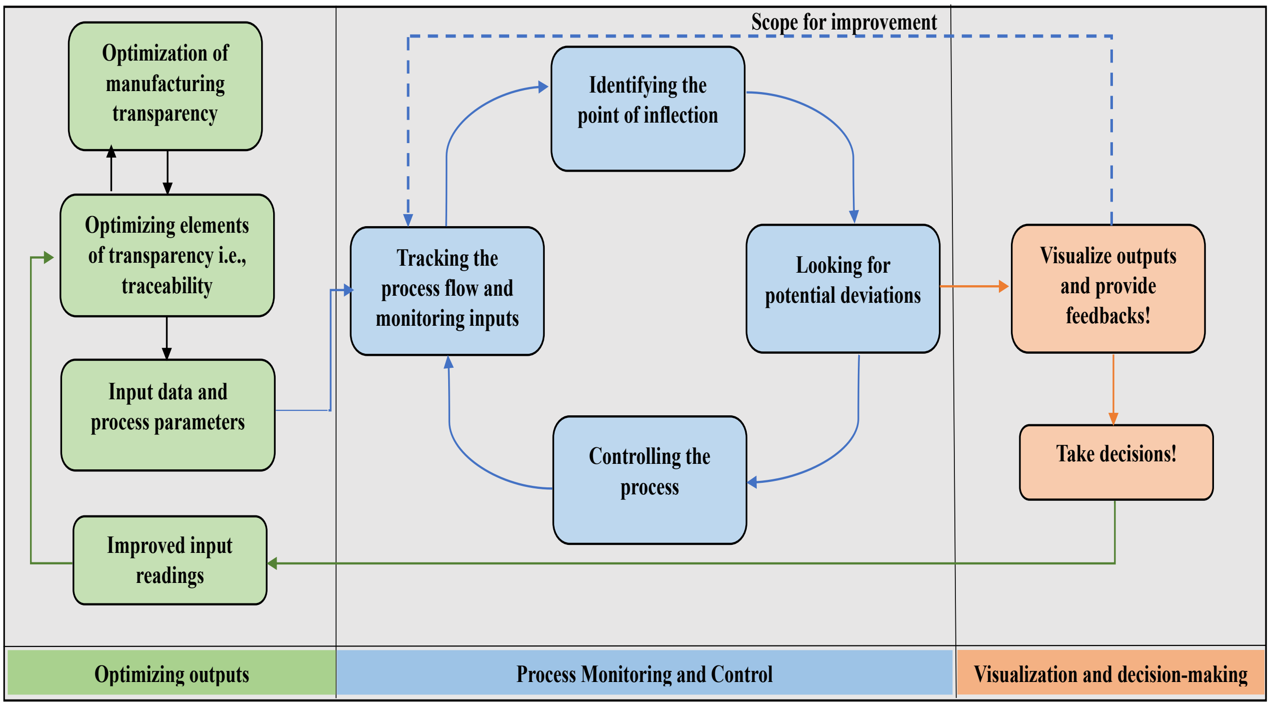


Figure 11 Decision support system for smart manufacturing transparency

5.2.2. Differentiation from conventional systems

The determination of transparency as a fundamental capability focuses on the differentiating factors that set smart manufacturing apart from conventional systems. System transparency enhances real-time monitoring and control capabilities of manufacturing processes, which are not present in conventional settings. During pandemic situations, transparency plays a crucial role in tracking the manufacturing of essential goods such as PPEs and ventilators, allowing proactive decisions to be made in managing potential disruptions. Consequently, it is essential to quantify this capability to enable decision-makers to assess their current level of offerings and make critical improvements as necessary. Ultimately, the outcomes of this study provide guidance for managers to prioritize the implementation of traceability and transparency as fundamental requirements for smart manufacturing deployment. By concentrating on the mathematical model and effectively managing the given constraints, managers can ensure efficient and smooth real-time execution. The findings of the study provide an assessment model (currently absent in the literature), and simulation studies to analyze sensitivity and create virtual scenarios to test applicability, all of which have implications for practitioners and academics in smart manufacturing. Individuals planning to adopt or who have already deployed smart manufacturing systems can learn from our research to design, deploy, and effectively execute smart manufacturing transparency, yielding significant benefits. Nevertheless, the limitation of case-based testing in this work can be further addressed.

6. Conclusions

The deployment of smart manufacturing focuses on integrating technologies to transform the capabilities of existing manufacturing environments, with an emphasis on integration, intelligence, and agility, all within a limited investment. Among the various smart manufacturing capabilities, transparency is fundamental. This is because smart manufacturing systems are designed to monitor real-time information, process data, and make decisions for improved control, thereby increasing the visibility of processes and facilitating innovation and enhanced performance. Therefore, it is essential to develop models to assess and control the transparency of smart manufacturing systems. These models will enable managers to gauge the potential of smart manufacturing transparency and benchmark against competing firms.

Our paper aims to develop models for assessing the transparency of smart manufacturing systems. We outline the elements contributing to transparency and identify traceability as a critical component. Initially, we develop a model for quantifying traceability and evaluate its correctness and validity. Subsequently, we develop a model for transparency based on traceability. We conduct simulation-based experiments on the traceability and transparency models to analyze the behaviour and understand its behaviour through sensitivity and applicability. The results reveal a point of inflexion for traceability, which acts as a threshold for attaining smoother capability readings with reduced variability. The point of inflexion acts as a reference point for managers to effectively implement transparency in smart manufacturing processes, thereby improving performance. These research findings contribute to the field by providing a potential measurement system for assessing manufacturing transparency capability and demonstrating sensitivity through simulation-based experimentation. Practitioners can utilize these findings to design smart manufacturing deployments and focus on critical areas that significantly influence system performance. However, empirical validation of the work based on a real-time case-based investigation still needs to be addressed. Future work will involve validating these findings through case studies and exploring qualitative and quantitative approaches for other smart manufacturing capabilities, such as intelligence and resilience while identifying areas that require further investigation. Researchers can conduct experiments to test the proposed model of smart manufacturing transparency in various types of production environments, from job shops to continuous setups, and observe the behaviour of the capability across different configurations, deriving potential implications from it. Additionally, significant statistical tests, such as the two-sample t-test, can be conducted to observe differences in simulation results across different production environments.

Author contributions

XXX

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The authors report there are no competing interests to declare.

Data Availability Statement

The data that support the findings of this study are available from the authors upon reasonable request.

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