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Design and development of automobile assembly model using federated artificial intelligence with smart contract

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ABSTRACT
With smart sensors and embedded drivers, today's automotive industry has taken a giant leap in emerging technologies like *Machine learning, Artificial intelligence, and* the *Internet of things* and started to build data-driven decision-making strategies to compete in global smart manufacturing. This paper proposes a novel design framework that uses *Federated learning-Artificial intelligence (FAI)* for decision-making and *Smart Contract (SC)* policies for process execution and control in a completely automated smart automobile manufacturing industry. The proposed design introduces a novel element called *Trust Threshold Limit (TTL)* that helps moderate the excess usage of embedded equipment, tools, energy, and cost functions, limiting wastages in the manufacturing processes. This research highlights the use cases of AI in decentralised *Blockchain* with smart contracts, the company's trading policies, and its advantages for effectively handling market risk assessments during socio-economic crisis. The developed model supported by real-time cases incorporated cost functions, delivery time and energy evaluations. Results spotlight the use of FAI in decision accuracy for the developed smart contract-based *Automobile Assembly Model (AAM),* thereby qualitatively limiting the threshold level of cost, energy and other control functions in procurement assembly and manufacturing. Customisation and graphical user interface with cloud integration are some challenges of this model.

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Artificial intelligence; blockchain; federated machine learning; original equipment manufacturer; smart contract

1. Introduction

Digital transformation and technology adoption tend to enhance the quality and quantity of assembly, distribution, and manufacturing in a fully automated smart manufacturing enterprise (Manimuthu et al. 2021). All these technology-driven approaches require smart infrastructure and customised business plans with market strategies to boost the production line-ups, thereby enhancing their manufacturing capabilities (Jain, Shao, and Shin 2017). Smart manufacturing involves domain-related technology adoptions that target an achievable decision in the manufacturing ecosystem (Elverum and Welo 2016). Some smart technologies that are actively used in today's modern and fully automated industries include *Artificial Intelligence, Bigdata, Blockchain, Robotics, and Machine Learning* (Koh, Dolgui, and Sarkis 2020; Singh, Rathore, and Park 2020).

These technologies assist in collecting, processing, and assembly to polishing, fitting, and distributing data to the commercial and industrial markets. Smart sensors, electronic controller units, actuators, and embedded software are critical in handling the generated data resources from individual equipment and processes. Industries widely use *artificial intelligence* and *machine learning* mainly for data processing and analysis, and decision making (O'Leary 2013), whereas *big data* and the *Internet of Things* (IoT) for decision analytics and data collection, respectively. Data-driven decision-making provides solid evidence in improving productivity and enhancing the manufacturing and assembly processes, thereby helps in monetary gain and accountability in real-time (Theorin et al. 2017). Many convolutional methodologies of today's industrial practices are getting a smarter transformation due to these technological advancements and digital adoption, in particular the increasingly prominent role of blockchain, artificial intelligence and machine learning (Liao et al. 2017; Xu, Xu, and Li 2018; Dolgui et al. 2020; Koh, Orzes, and Jia 2019; Pournader et al. 2020; Koh, Dolgui, and Sarkis 2020). All the processes are fully automated, sophisticated software tools and cus-

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tomised control methodologies help industries achieve efficiency (Gupta et al. 2020).

Based on the infrastructure and manufacturing capacity, technologies can be incubated and handled effectively during every transformation stage available in the assembly and testing process(Manimuthu and Ramadoss 2019). Rather than investing in machinery and goods, industries focus more on technology adoption. It helps them mitigate the market risks that directly affect their profits in a competitive industrial environment (Khan and Byun 2020). Besides, skilled labour and smart infrastructure design prove that digital adoption can make technology-oriented process enhancements profitable, forecasting the market trends and investment capabilities. Such transformation plays a critical role in enhancing sustainability and quality assurance besides trust management in the production and manufacturing processes(Yu Zhang and Wen 2017).

Besides, contractual formalities and guaranteed return of investment using smart control and operational strategies help industries sustain global markets. Apart from market risk, the small and medium enterprises (SMEs) concentrate more on curtailing the production and manufacturing cost and energy consumption. Such environments involve consistent investment plans and flexible return policies with suppliers and developers. Now the focus is on leveraging *smart contracts (SCs),* a self-executing decentralised blockchain-based procurement mechanism towards data transparency. It helps monitor and control third-party interventions, hidden brokerages, real-time consumption, and unauthorised activities (Wang et al. 2019; De Giovanni 2020). Thus, from procurement to design and from processing to control, all the critical elements involved in supply chains need to be closely monitored before deploying and testing the latest digital technologies relying on a data-driven and collaborative model (Xu and Dang 2020). This cooperative mode allows sharing the datasets from a centralised data repository, often referred to as a *federated learning system*, which handles product movement, energy consumption, and other real-time data through embedded systems (Treleaven, Brown, and Yang 2017; Zheng et al. 2020). However, the deliberation on its (*federated system)* relevance to practice is still at the nascent stage though it leaves scope for diversified objectives.

Against this background, this study recognises a few research gaps to explore the integration of manufacturing processes with smart systems at process and module levels. First, the current models do not consider threshold levels for key parameters such as energy consumption and individual component/module manufacturing costs. Under market eventualities, these values will assist the industries in predicting and projecting their target production and manufacturing procedures not to be any loss to initial investments of sectors. Second, to our best knowledge, the literature lacks a deliberation on integrating smart contracts for controlling parameters such as energy and cost values of different components, especially for complex environments such as automobile manufacturing, which warrants the assistance of smart-decision framework. Third, the literature remains far from reporting the application of *federated learning systems* in a real-time manufacturing systems perspective, though the domain receives some focus only in recent times (Lu et al. 2020; Pokhrel and Choi 2020). To address these gaps, the study proposes the research question: *How to design and deploy Federated Learning-Artificial intelligence (FAI) assisted smart decision-making system for automobile manufacturing environments?*

The main objective of this *federated learning model* is to introduce a nominal range called *Trust Threshold Limit* (TTL) that helps the system sustain any business process/method with minimum freedom from excess usage in terms of energy and cost without facing losses. Our work defines TTL as a maximum limit that industrial processes use to minimise process losses. It provides the functional entity value, including the permitted level of purchase and energy usage compared with their maximum risk through the smart-decision framework. All these available attributes are modelled and deployed in the developed design, unique to production industries.

The study is a pioneering one for the automotive manufacturing industry in multiple aspects. First, it deliberates how the smart contract is involved in the control, execution, and legalisation of manufacturing and distribution of spare parts and components required for the automobile manufacturing process (Magazzeni, McBurney, and Nash 2017). Second, the study deliberates the effectiveness of using machine learning, especially *federated learning,* for computing suitable TTL values for each tool, method, and component in manufacturing environments. Third, the study developed an AI-enabled *Automobile Assembly Model* (AAM) that stresses the need and importance of IoT and ML-based data-driven decision-making. Thus, it offers a perspective on the role of negotiable entities such as *smart contracts* in processing real-time purchase and demand information (Yuanyu Zhang et al. 2019). Use cases of AAM include analyzing the productivity and distribution when SC and TTL are in place. Critical elements like energy, cost function, time, and productivity are remarkably improved using AAM as a reference framework in the industry.

The remainder of this paper is organised as follows. Section 2 reviews the recent literature on blockchain and smart manufacturing processes. Section 3 discusses model components and control parameters. Section 4 explains the modelling and design methodologies. Experimental study and use case analysis are shown in section 5. Next, section 6 elaborates the simulation and experimental analysis. Section 7 discusses the findings, and Section 8 deliberates both theoretical and managerial implications. Finally, Section 9 concludes with limitations and future scope.

2. Literature background

The review process adopted a systematic exercise by retrieving the relevant publications from different repositories through the following search strings: (TITLE-ABS-KEY (blockchain) OR TITLE-ABS-KEY (smart AND contracts) OR TITLE-ABS-KEY (federated AND artificial AND intelligence) OR TITLE-ABS-KEY (machine AND learning) OR TITLE-ABS-KEY (artificial AND intelligence) AND TITLE-ABS-KEY (automotive AND assembly) OR TITLE-ABS-KEY (automobile AND assembly)) AND (LIMIT-TO (DOCTYPE, 'ar') OR LIMIT-TO (DOCTYPE, 're')) AND (LIMIT-TO (LANGUAGE, 'English')) AND (LIMIT-TO (SRCTYPE, 'j')). The below sub-sections summarise the recent literature around blockchain, artificial intelligence in manufacturing, and federated learning systems.

2.1. Blockchain in manufacturing

Manufacturers are actively involved in developing and deploying blockchain in their industrial practices due to many functional aspects: operations control, risk management, active process control, and additive manufacturing supply chain(Macrinici, Cartofeanu, and Gao 2018). These factors help them gain more visibility in market risk and obtain asset tracking availability throughout their market venture capitalisation of investments in real-time. It can influence the design, control, process, assessment, and delivery of products at both ends of the industry. With global supply-demand forecasting, auditing the control strategies and cost function are critically important, thereby fostering customers' trust and market sustainability(Allam and Dhunny 2019). All these key scaling factors will adversely affect the system performance (Yuanyu Zhang et al. 2019). Some of the industrial impacts of using blockchain include *supply-chain monitoring, data-driven decision making, asset tracking, control, process management, trust validation, quality and quantity assurance, market risk forecasting, energy and cost management, policy formation, and risk management.* Thus, from procurement to delivery, all the raw materials to finished goods can be mapped and modelled using suitable policy-based blockchain applications. The application allows manufacturers to track their product movements and traceability on the supply of goods and equipment among companies, vendors, and suppliers (Gonçalves et al. 2021). Risk accessibility, especially on large-scale production and manufacturing with suitable network and blockchain aided supply help ease the system-centric smart automation environment (Manimuthu et al. 2019; Manimuthu and Dharshini 2021; Mohanta et al. 2020)). SC and market policy aims to showcase component and finished product-wide deliverables. Industries also encourage legitimate and legally available SC, especially for risk-prone industries (Baryannis et al. 2019). Thus, companies need to functionally incubate, implement and plan suitable infrastructure design in manufacturing and supply chains to effectively utilise the blockchain in investment, retail, export-import, and pre-and post-processing of raw materials in real-time (Min 2010).

Enterprise resource management and control system strategies need to have long upgrades. In few cases, these strategies require infrastructure and automation investments to utilise the blockchain primitives in their workplace efficiently. As a nascent technology, blockchain with other smart technologies needs to be effectively handled and efficiently used in today's modern manufacturing industries. The reliable and smart manufacturing process requires a focus on product reception to supply (Manimuthu et al. 2021). Customer markets need to be studied to ensure a sustainable market index in the growing global trade environment. According to agile and smart manufacturing companies' market valuation and customer index, reliable and quality assured product delivery between manufacturers and consumers is very narrow. This gap requires substantial steps that warrant long-term business trend forecasting and market investments (Manimuthu et al. 2021).

Blockchain has proven potential in influencing manufacturing and supply chain practices. Critical elements such as energy consumption, cost, processing, and control strategies are integrated towards sustaining the product supply under the required specifications. Policy formulation, government regulations, and legal advisories become part of industrial practices; blockchain with operational and trade policies help in guiding and proliferating these regulatory gaps (Andoni et al. 2019). Recently, Venkatesh et al. (2020) propose a blockchain environment to track the social sustainability dimension of manufacturing industries. Thus, the objectives of supply chain transparency, effective management of technologies, and deploying smart innovation tools together offer a win-win situation to all participating industries of a blockchain-enabled automation environment. In addition to the supply-chain practices and operations, fostering the state-of-the-art design that helps to get maximum potential with available resources becomes instrumental (Ivanov, Sokolov, and Dolgui 2014; Saberi et al. 2019). Summing up all the critical elements for the design, a novel smart and comprehensive operations and business model is developed.

2.2. AI in automotive industries

Processing capabilities and error detection/identification are a few critical elements in the smart manufacturing industries. A highly reliable smart system needs to be deployed for automated and completely robotic control units in assembly, control, and movements (Min 2010; Yuanyu Zhang et al. 2019; Fenwick and Vermeulen 2019; Cioffi et al. 2020). Due to the enormous range of data computing and fast processing capabilities, AI is being implemented in industries and other smart technologies (Refer to Table 1). A wide range of customised AI algorithms is readily available in the market to do various operations such that algorithms can mimic the actions and processing techniques performed by labours. Thus, transforming the workplace with manual process into a robust and customisable AI-driven operation tends to prove their betterment in areas like pre-and post-processing, control and application delivery, and other supply chain practices in real-time(Allam and Dhunny 2019; Kolvart, Poola, and Rull 2016; Singh, Rathore, and Park 2020).

As a core component for Industry 4.0 and smart IoT systems, AI never stops enhancing the business model where it helps to transform the industry to compete in the global market (Omohundro 2014; Parunak 1996; Wang et al. 2018). Thus, in today's business model, industries aim to incorporate AI in their designs and offer smart solutions to data-driven decision-making procedures. Due to the advent of developing smart technologies, the transformation of sectors to adopt industrial 4.0 and industrial IoT standards is getting linear growth. Production, control, processing, and manufacturing are vital areas that get boosted with these smart techniques of operations (Rane and Narvel 2021). AI provides an independent and stand-alone solution to numerous inventory

Table 1. Studies related to emerging technology from the automotive industry.

S.no	Authors & Year	Domain	Focus	Methods	Applications
1	Gonçalves et al. (2021)	Automotive Industry	Decision-Making	Multivariate approach	Forecasting Assembly process
2	Guo and Ryan (2021)	Auto Assembly Line	Risk-Averse Optimisation	Mixed-Integer Programming	Large Vehicles Assembly
3	Kong et al. 2021	Mobility Services	Decision-Making	Bloom Filter	Driver Performance Evaluation
4	Mishra, Mahanty, and Thakkar (2021)	Automotive Industry	Servitisation	Graph-Theoretic Approach	Quality Concerns
5	Loading et al. (2021)	Automotive Industry	Judgment Analysis	Discrete Event Simulation	Manufacturing systems
6	Raj Kumar Reddy et al. 2021	Automotive Industry	State Of the Art	Clustering Analysis	Vuca World
7	Shahbazi and Byun 2021	Automotive Industry	Data Analytics	Hybrid Prediction Models	Smart Manufacturing
8	Alavian et al. (2020)	Automotive Industry	Continuous Improvement	Industry 4.0	Production Systems
9	Dutta et al. 2020	Blockchain Technology	State Of the Art	Literature Review	Business Visibility
10	Gupta et al. 2020	Autonomous Vehicle	State Of the Art	Literature Review	Cybersecurity
11	Hadian et al. (2020)	Automotive Industry	Decision-Making	Vikor – MCDM	Outsourcing
12	Jabbar et al. 2020	Automotive Industry	Decentralized Platform	Internet Of Vehicles	Vehicle Communication
13	Kim, Jung, and Hu 2020	Automotive Industry	Smart Contracts	Deep Learning	Dashcam Application
14	Xia et al. 2020	Vehicle Technology	Blockchain Transactions	Bayesian Game	Electronic Trading
15	Xu and Dang (2020)	Automotive Industry	Causal Analysis	Digital Cause & effect Diagram	Knowledge Management
16	Copeland et al. 2019	Vehicle Sourcing	Edge Communication	Network Function Virtualization	Essential Services
17	Samarakoon et al. (2020)	Automotive Industry	Decision-Making	Federated Learning	Vehicular communications
18	Sharma, Kumar, and Park 2019	Automotive Industry	Distributed Framework	Node Selection Algorithm	Smart City
19	Erfurth and Bendul (2018)	Automotive Industry	Manufacturing networks	Cross Case Study	Global Manufacturing
20	Kumar et al. (2018)	Integrated Planning	Production control	Modeling And Simulation	Production Scheduling
21	Sharma, Kumar, and Park (2019)	Vehicle Technology	Distributed framework	Blockchain	Smart Environment
22	Jain, Shao, and Shin (2017)	Automotive Industry	Data Analytics	Performance Analysis	Process Modelling
23	Wei et al. (2017)	Auto Part Manufacturer	Optimization Algorithm	Support Vector Machines	Manufacturing Process Quality
24	Keivanpour, Ait-Kadi, and Mascle (2017)	Automotive Industry	Decision-Making	Fuzzy Logic	End-Of-Life Vehicle
25	Theorin et al. (2017)	Agile Manufacturing	Information Systems	Event-Driven Architecture	Manufacturing Systems
26	Elverum and Welo (2016)	Automotive Industry	Innovation Management	New Product Development	Rapid Prototyping
27	Gupta and Vardhan (2016)	Automotive Industry	Equipment Effectiveness	Production Cost	Equipment effectiveness
28	Lacerda, Xambre, and Alvelos (2016)	Automotive Industry	Continuous Improvement	Value-Stream Mapping	Component Manufacturing

Note: MCDM – Multi-criteria decision making.

and supply-chain problems existing within the industrial environment. All these fully automated frameworks run with the help of customised AI-IoT algorithms with potential risk assessment features. Thus, manufacturing and supply chain industries are constantly looking for these robust and customisable smart innovations to be adopted in their workplace (Bhamra, Dani, and Burnard 2011; Gupta et al. 2020; Macrinici, Cartofeanu, and Gao 2018; Singh, Rathore, and Park 2020).

2.3. Federated learning

The collaborative learning mode of machine learning helps iteratively train vast amounts of data from each of the embedded sensors and devices installed inside every manufacturing equipment. Data from the vendors, suppliers, and stockholders are collected and processed before transferring to the following sections for further operations. IoT plays a significant role in the instant delivery of accumulated data from the devices. Such data have critically been used in training to obtain functional insights on different goods and commodities in real-time. One of the key factors that assist in designing and modelling accumulated sensory data is standard console built-up, where data can be stored as packets with timestamps (O'Leary 2013). Thus, centralised federated learning is performed whenever the data is obtained using IoT-enabled smart sensors that tend to get accumulated on an arbitrary basis and logged based on a specific customised AI algorithm. The majority of reported studies were conceptualised and developed using conventional techniques and approaches. The review confirms that the literature remains far from using a *federated-learning system* in manufacturing to improve efficiency, even though there is a growing interest in recent times. This provides an opportunity to study the application of FAI as a smart decision-making framework in an automotive assembly process. Apart from the consummate design and planning features, using federated models provides lot of managerial insights for effective operations and business practices in real-time. Some of the obsoleted models exiting in current practices can be easily tuned, restructure or replaced using the learning models. A detailed literature studies about design elements, decision models and operation support entities are tabulated (Table 1) to give broader insights AI, and Blockchain in industrial use cases.

3. Model design background and key parameters

Federated Learning with AI (FAI) algorithms helps in bringing different steps of algorithms and codes along with sensory data in a single window for *Grouping- > Processing- > Analysis- > Interpretation- > Mapping- > Modelling- > Training- > Feature Extraction- > Decision Making*. Data are stored after all these processes in a local data repository or data centre (based on industry infrastructure and data generated).

In the developed FAI model, regression methods are used a few data processing sections for data normalisation and probability on error identification/rectification during sampling and training. This training model depends on few critical parameters as follows:

(1) Batch size or Repository sampling values (B)
(2) Number of data entries/iteration (D)
(3) Total number of nodes or components (N)
(4) Deployed FAI models (M)
(5) Training range (R)
(6) Data sampling rate (S)

Depending on the data obtained from vendors, suppliers, and stocks, values are modelled and trained. If datasets are generated from a single period, sampling rate needs are assigned for training and processing to a separate FAI model. In such cases, training values must be correlated and normalised to avoid sampling errors affecting the overall outcome for a particular component in the system model(Gupta et al. 2020; Treleaven, Brown, and Yang 2017; Zheng et al. 2020). Thus, to avoid such discrepancies at the output, further modelling is done using batch processing. Each batch consists of components of the same type obtained from multiple vendors at the same frequency for processing. Each of the tools and features is identified and grouped with specific identification (ID) numbers. Consider an item 'A' obtained from vendor 'X' at a time 't'. Then following notations are provided by the user to retrieve a particular A at any time instance 't_i'.

(1) Total number of components from particular vendor $= \sum X = X1+X2+\ldots..+Xn$
(2) Total number of samples recorded at the time 't' $= Y$
(3) Number of clients involved in the same process $= Z$
(4) Training dataset value for X at any time 't' $= W(R, B)$ where W is the weight of a particular dataset.
(5) Error accumulated during training $= E$

Thus, during the training and while applying FAI,

$$\text{Tested sampling rate for component X} = \sum_{t=1}^{n} \frac{Y(Z)}{W(Rn, Bn)} + \frac{E}{W(Rn, Bn)} + S' \quad (1)$$

Where $$S' = \sum_{t=1}^{n}\left[\frac{S}{B+N}+\frac{D}{S}\right] \tag{2}$$

Samples tested correction and modelling using FAI at time 't' is obtained using the equation (1). Similarly, the dataset for all the components is modelled and stored in a shared data repository. This data repository can be revoked using their unique packet identifier (PID). Thus, using suitable PID and sampling test results, the correct proportion of tools and components from processing to production can be revoked from the storage. These capabilities are provided with every section until the final product is delivered to the clients(Parunak 1996; Allam and Dhunny 2019;). Apart from the information handling and data processing, FAI helps to handle the stock comparison and pricing values. This helps monitor volatile market share and commodity pricing options of components or raw materials subjected to market investment risk and economic crisis. Thus, their cost of production, usage, wastages, and energy involved in utilising them are critically modelled and planned at each section (O'Leary 2013; Wang et al. 2018).

3.1. AI and Smart contract

Algorithms and learning methodologies involved in smart manufacturing entities vary with time. Thus, this basic featurization endorses the *smart contract* (SC) usage that extends the production process visibility to engineer and train the functions and standard operating procedures. SC is framed between the suppliers and the manufacturers (mutual agreement) on the risk of raw materials, processing, testing, and validation of goods(Baryannis et al. 2019; Magazzeni, McBurney, and Nash 2017; Min 2010). SC has provisions to include the insurance schemes available for the assembly, inventory, and product delivery. Since the entire operation is handled using FAI and SC, the arbitration of data obtained from all the market shareholders is modelled for effective management in real-time. Some of the segments that involve SC in the production and manufacturing in the industry include:

(1) Raw Materials
(2) Financing and Stock valuation
(3) Insurance and market risk
(4) Delivery and Transportation

All these four SCs are actively enabled during the manufacturing and assembly process. AI models help find suitable negotiation factors for cost, energy, market risk by predicting and forecasting the feasibility of SC policies before the commencement of works in the industries. Both regulatory and technical policies can be bundled together using SC as FAI helps in foreseeing the risk factors in prediction, planning, procurement, purchase, manufacturing, assembly, and delivery(Cioffi et al. 2020; Khan and Byun 2020). Thus, to validate this blockchain during the loading, unloading, and distribution of components and tools in and out of the industry and to study SC's limitations, functionalities, and features, FAI helps manage the potential risk in the manufacturing process. Data with the least possible error values help fetch the desired benefits of utilising AI and SC in the workplace. A new normalisation phenomenon is introduced in the manufacturing process to cut off accumulated errors, and data mismatch from obtained datasheets to processed data (Nofer et al. 2017; Sayeed, Marco-Gisbert, and Caira 2020). This method is data-centric, and normalisation helps mitigate the system's accumulated data errors without affecting the policy to a greater extent. This novel error limiting factor is called *Trust Threshold Limit* (TTL).

3.2. Trust Threshold Limit (TTL)

TTL refers to the maximum limit that any goods and components involved in assembly, manufacturing, and delivery can be experimentally utilised with minimum wastage or losses. Thus, as the name indicates, TTL sets the threshold limit for all the tools and devices actively participating in product delivery. SC depends on the permitted TTL limit for each entry in the data socket, exceeding which the chance of loss in the product market is high. With TTL value, the responsibility of the policy-maker and FAI function is to optimise the scaling factor for the component within that particular limit(Mohanta et al. 2020; Sayeed, Marco-Gisbert, and Caira 2020; Yu Zhang and Wen 2017; Yuanyu Zhang et al. 2019). The novel decision aid model and the threshold limit values helps the operations, production and logistics in their purchase, procurement, distribution, and delivery. Apart from the normal supply-chain and logistics operations (Ivanov et al. 2016, 2019), the developed state-of-the-art TTL values helps the existing business model to incubate them for better component and product movements in their real-time industrial environment.

Example: Consider equation (1) where testing samples for product X are obtained by FAI and weights of X. When it comes to TTL, the maximum limit value needs to be obtained using the same weights and data distribution. Thus TTL (X) can be modelled as follows:

$$TTL(X) = \sum_{t=1}^{n}\frac{W(R,B)}{Y} + \sum_{t=1}^{n}\frac{E}{(B+D) * \frac{1}{R+Z} * X'} \tag{3}$$

$$\text{Where} \quad X' = \frac{1}{\frac{B}{D} + R} + \sum \frac{X}{W(R,B)} + Z * W(R,B) / \sum X + E \tag{4}$$

For a manufacturing and production unit to operate with full potential both in terms of benefits from supply and process/procurement/purchase, equations 3 and 4 will significantly help. Design testing and analysis fall under the same umbrella of TTL. Timestamp and component ID are used as a reference entity to model the FAI at different sections with other industrial procedures (Min 2010; Nofer et al. 2017).

4. Methods

The model framework is structured under four stages of sequential processes, as shown in Figure 1. The process gets started with data collection, followed by data normalisation. The processed data is tested and analyzed using suitable testing and validation methods (support vector machine learning). All these segmented and normalised datasets are then modelled and trained using FAI for decision-making and validation in real-time. SC is provided with the market risk knowledge and resource utilisation metrics during all the stages of data accumulation, processing, and control, thereby ensuring the market standards for better product delivery. Policymakers and standard decision-making units critically evaluate the outcomes at every stage. Finally, the end product is delivered with the same features to the consumer market(Gupta et al. 2020; Min 2010).

4.1. Stage 1: Data collection and classification

The entire process of product design and delivery relies solely on the accuracy of data gathered from each of the available components in the system. Discrete datasets from each supplier, vendor, and stockholder are actively collected along with their market risk policy to frame their suitable SC. As these data are entirely obtained from the IoT-enabled smart sensors, these data require a lot of pre-and post-processing functions to be performed. Information about manufacturing, warranty, composition, maker's policy, structural details are logged and

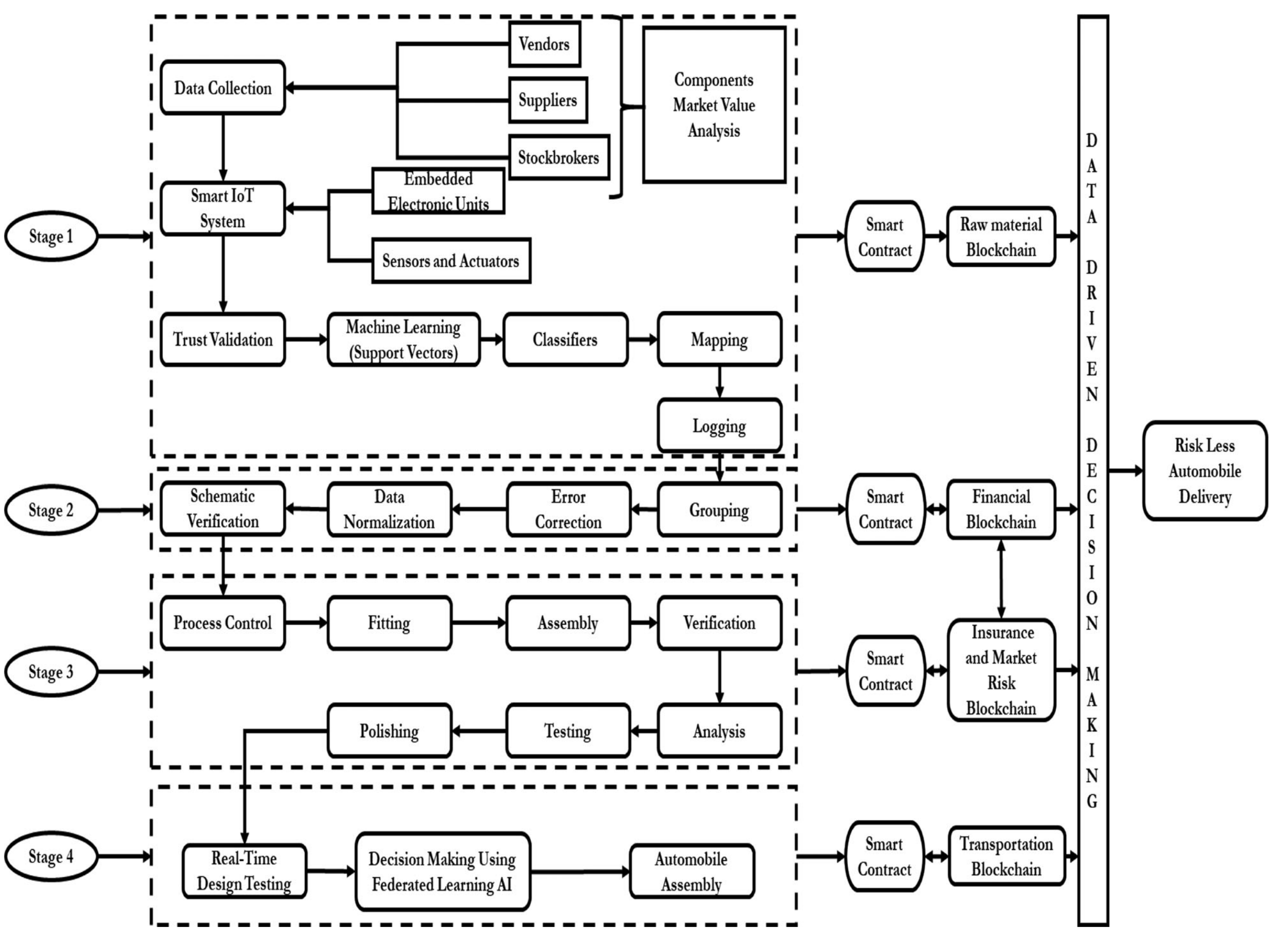

Figure 1. Research Flow.

modleled during the collection process. Sensors, actuators, and other embedded electronic equipment collect the data and efficiently hand them to the central data repository for further processing and analysis. After the data collection, the accumulated data are modelled and mapped with their unique ID. The equipment data are stored in their respective local data repositories for long-term referencing and policy formulation. These data are then retrieved for the 1st stage of processing, called *Trust validation*. The data obtained and stored from the suppliers and stockholders are cross-referenced and verified to prove confidence and originality regarding measurements, validity, defects, or other deformities. If any flaws are identified during this stage of trust validation, SC will immediately help manufacturers raise a replacement or refund the stocks. This blockchain feature needs to be mentioned at the time of policy formation. This can be materialised and followed as a standard defect identification and originality check of goods and commodities covered under the same risk assessment policy(Khan and Byun 2020). In addition to the existing literature (Ivanov, Sokolov, and Dolgui 2014, 2019), the impact of engaging smart technologies are explained in detail with the help of AI and blockchain. This sheds lights for new research and design perspectives of altering the industrial design for performance enhancement and monetary benefits.

The datasets are modelled using the *support vector machine learning model (SVML) in the post-trust-validation phase*. During this unsupervised ML training, the dataset is provided with classifiers where each classifier offers the information on the source of goods, timestamp, and purchase details. All these data are modelled and mapped under SC group policy intended to avoid the market risk practice. Depending on the supplier's datasheets and procedures, the manufacturer has the freedom to plan additional policies if the system's performance predicts a better ratio than expected during the policy formation(Mohanta et al. 2020; Yu Zhang and Wen 2017).

Each support vector is identified and mapped with their classifiers and logged in the same database for each reference and identification. All the mapped dataset is logged in a customised database for easy and smooth identification and utilisation. During the end-product delivery, these classifiers and the support vectors are invoked from the system database for final checking and clearance. In case of any contradiction to the proposed details, S and FAI values, will be cross-checked and modified as per the risk assessment SC in the system (Magazzeni, McBurney, and Nash 2017; Yuanyu Zhang et al. 2019).

4.2. Stage 2: Grouping and normalisation

All the logged data and support vectors are moved to the next section of data normalisation. The data with errors are identified and removed/correlated with the next least possible error values required for processing the tools. Thus, error rectification is completely done during this process of data normalisation. In some worst-case scenarios, if the schematic of a particular component consecutively fails to meet the expectations, then the financial blockchain is invoked using the SC. One of the most prominent examples of today's automotive world for such financial SC and their smart policy is recalling *Honda Model* cars due to their faulty airbags. Under such circumstances, group policies are shared between all the involved parties, from suppliers to manufacturers. Due to these unexpected circumstances, the loss incurred is equally shared by all the commodity vendors and companies (Sayeed, Marco-Gisbert, and Caira 2020; Zheng et al. 2020). If the defect is identified in the product (Airbag as in Honda cars), then the faulty product id is revoked from the database for vendor identification. If the vendor SC is not assigned under such financial blockchain, then the company is entirely liable for the incidents. If SC is derived in favour of the manufacturer, then the vendors will take the whole responsibility and address the incidents with compensation or replacement of the entire automobile itself. Thus, data error normalisation and schematic verification play a major role in training and SC formation.

4.3. Stage 3: Control, verification, and analysis

Two of the critical stages in the manufacturing and assembly in the fully automated smart manufacturing industry are verification and analysis. In this stage, the component datasets are evaluated for fixing their TTL range. This range plays a significant role in *energy usage, supply-demand management, cost, and flawless product delivery*. Normalised data obtained after verifying the schematics is shared with the assembly and verification section. TTL of the component is set before starting the process (Magazzeni, McBurney, and Nash 2017; Yu Zhang and Wen 2017). Once the process is initiated, TTL for that tool is picked from the data model for fitting and assembly. During the assembly and fitting schemes, the dataset is verified for TTL; thereby, the reference limit for the whole processing mechanism solely depends on the limit set by TTL. In this system driven control and processing, all the accumulated datasets are going through series of processes as follows:

(1) Fitting
(2) Assembly
(3) Verification
(4) Analysis
(5) Testing
(6) Polishing under the same TTL value from the SVML training used for deriving SC.

All the SC under this stage is assigned under the insurance and market risk blockchain category. SC associated with insurance blockchain helps the retail business ventures to take part in the investment procedures, thereby helps in boosting their market share and business development processes (Yuanyu Zhang et al. 2019). Market liability is insured, and the IoT devices closely monitor the actions performed at each section. As the data generated from embedded devices are a continuous process, classifiers and the support vectors are assigned instantly irrespective of the functionality and operations performed at different stages of the assembly and delivery process.

If any mismatch occurs during the production and delivery stages, the dataset is retrieved from the local database, and their TTL is critically examined with their support vectors. Thus, errors are eliminated. Comparing with the existing industrial setup, engaging smart technologies will give maximum insights about the crucial designs and process automation. Joining up with the available resources, the operations and control schemes can be modelled for maximum benefits. For every stage of product design and fitting, the SC can be provided with suitable regulatory primitives, thereby bringing all the datasets under a single database (Zheng et al. 2020). Insurance companies offer higher flexibility in share exchanges for policymaking and production strategy analysis subjected to market risk and investment returns. For investment returns, the predicted performance by the FAI schemes holds a high hand in the market demand with a better supply chain ratio. At the same time, all the involved third-party vendors and suppliers try to seek more capital investors. To ensure assured returns from the entitled policies, commonly available risk factors include:

(1) Raw material cost
(2) Supply-demand ratio
(3) Goods quality
(4) Delivery time
(5) Economic crisis
(6) Market credibility

Thus, this stage involves a high risk-high return if the expected product reaches the target audience within the stipulated time. Thereby effectively balances operational credibility in real-time(O'Leary 2013; Wang et al. 2018). Working performance and service satisfaction from the end-users play a vital role in framing and fixing the SC once the product is available for usage. A Timeline for the next bulk production relies entirely on the target audience's satisfactory report analysis, which takes time to obtain in real-time.

4.4. Stage 4: Decision making, FAI, and product dispatch

The next critical and most crucial stage of AAM design is the decision-making by which the real-time testing is evaluated. Data obtained from this stage is used as a reference for all SC forms considered a baseline scheme for identifying the TTL values. The convolutional data processing method offers more error functions than the FAI scheme (Giancaspro 2017; Macrinici, Cartofeanu, and Gao 2018). Apart from the analysis and training, the SC and training datasets are arbitrarily cross-referenced for smooth data interpretation and model evaluation. From the study, key findings include market valuation for each product, cost and distribution quantity to individual shareholders, profit-loss margin and transportation and insurance coverage, quantity, and quality of goods delivery, etc. By doing this model evaluation using TTL and FAI, the decision can be obtained for the AAM design that includes energy usage, cost, and components quantity(Allam and Dhunny 2019).

5. Case study

Implementation of the developed model in a smart industrial environment helps to understand the benefits of using TTL and FAI in real-time. As the company can incubate the necessary blockchain techniques, the infrastructure requirement has diversified requirements. The operations and control scheme of the developed AAM are thoroughly evaluated in real-time. Implementing the SC in the workplace without halting the operations in the industry is quite challenging, but the time taken to implement is significantly less than any other existing conventional models.

5.1. Company background

Small and Medium Enterprises (SMEs) are actively involved in emerging the latest technologies in their working strategies. One such SME is situated in Europe, where it assembles various automotive parts manufactured across the globe. They have an automated assembly, distribution, and small-scale manufacturing unit (locally develop few components). As a new commercialisation strategy in 2020, they started implementing the SC Blockchain technique in their vehicle assembly and distribution process. Initially, they tested the scheme for their domestic warehouse operations, which assembles embedded components essential for product delivery, as their concentration was only on transportation blockchain. Step-by-step, they have expanded their market to neighbouring countries like Malaysia, India, and few others (Baryannis et al. 2019; Yuanyu Zhang et al. 2019). Since the company is about eight years old, the global response index for testing and emerging new techniques in their design is quite challenging in the beginning. However, their initiative is relatively new to the commercial vehicle market. Due to confidentiality and workplace design ethics, the company name is kept anonymously as XYZ company. The company's goal is to deliver commercial trucks to various customers across the world. The company aims to implement AI models, IoT, and other ML techniques are driven decision-making. There are three stages in the vehicle assembly and delivery process. Each stage involves new technologies and standards AI methodologies that aim to bring a solid result-oriented profitable design. The developed design helps the company compete effectively in the local and global market for the long term.

The other objective of implementing SC and AI is to provide a hassle-free and risk-less automobile delivery environment that facilitates desirable profit. This leads to less impact due to socio-economic crises or any other strategies from existing competitors. The trucks assembled from this factory vary from 10–18 wheels, and each truck goes through the same assembling stages using AI and Blockchain(Nofer et al. 2017). Stage 1 consists of component classification and analysis. Data are modelled and associated with the *Raw Material Blockchain*. Stage 2 comprises embedded equipment and machinery data that helps in the investigation, grouping, and classification of data. This section is closely associated with financial and insurance blockchain. The final stage in the design of AAM for XZY company is the final assembly of the product, where all the sections and stages are involved in achieving the desired outcome. In this stage, 3, TTL, and SC help finalise the FAI values by which the company stakeholders will plan and execute their business plans in real-time.

The vehicle design has many smart embedded components. Thus their working conditions, testing, and field assembly values need to be processed and modelled (Yuanyu Zhang et al. 2019). Depending on the industrial standards, market needs, and commercial value, the quality and quantity of tools, software, and devices are mapped and installed. Figure 2 exhibits details of commercial vehicles assembled in the plant. The vehicle consists of much electronic equipment that acts as embedded agents and assists the IoT system in data collection, distribution,, and storage.

5.2. Business case

Component procurement, vendor selection, equipment identification and market valuations, and the best commercial value for the product are critical zones focused in the design. Data collection, processing, and analysis based on various factors like *energy usage, product loss/damages, and cost of production* are critically considered in the modelling, evaluation, and implementation of them in the workplace. Implementing the AAM helps to improve productivity, competitive market pricing for the

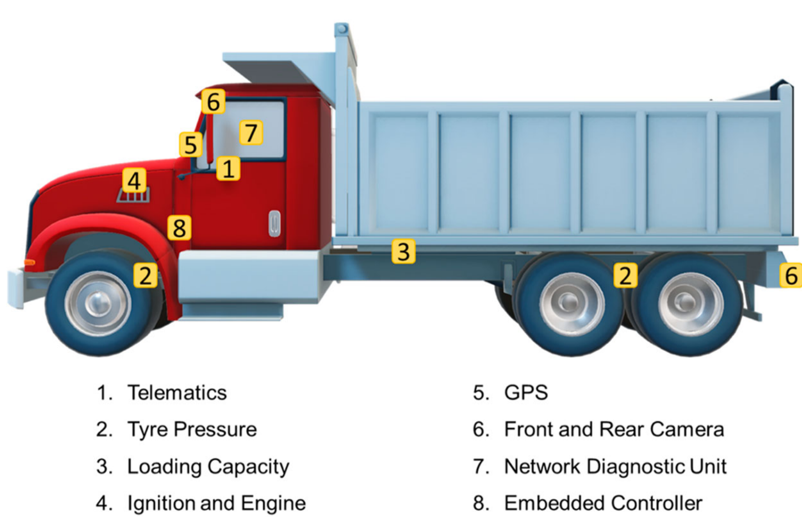

Figure 2. Components involved in Industry Grade Commercial Truck.

vehicle delivered, and security for all the investors. Further investigation includes 1. Component classification based on loading and unloading time and market cost. 2. Analyse the pricing values from all the vendors, suppliers, and stockholders. 3. It assists in arranging the components with their respective logistic sections. 4. Processing and evaluating the datasheets received from all the component delivery members. 5. Identify the component's originality, insurance policy, and smart contract details for practical usage at different sections in the XYZ company. This helps effective utilisation of IoT devices and smart components on the manufacturing floor. Data collected are transferred to different processing and control zones for interpretation, classification, and analysis. For this purpose, AAM uses support vector machine learning and classifiers.

Thus, data are modelled, mapped, and processed based on industrial requirements and product's commercial standards in real-time. Required data statistics are immediately processed and modelled using FAI to obtain the TTL value for any individual component involved in the system design. Stock availability, component usage metrics, energy consumption at the workplace, and cost of production are modelled individually in the AAM design. Thus, the final product assembly and delivery involves a lot of complex data processing and training mechanism that assures better market value for the vehicle without any losses in per capita investment for each investor. As all the schemes modelling are done through a smart contract, the AAM framework requires stage-by-stage data processing that uses IoT, machine learning models that significantly assist in curtailing losses at various stages of the assembly process. Table 2 shows the project charter carried out for AAM design and deployment in the XYZ company.

Table 2. Project charter.

Business Case: Statistical modelling and efficient cost reduction and energy consumption in stages like loading, transportation, procurement, production, and assembly. Sensor-based embedded application processes are fully automated. Modelling and design evaluation is done using R programming. Industry-grade simulation software helps to derive the required values and thresh limits for each component involved in the design. Market procurement with minimum gain margin will provide better scaling values when all the components are modelled using the same procedures. This helps reduce the stock pricing and market valuation by attracting many investors without the risk of the vehicle's monetary loss and commercial value.
Problem Statement: Implementing cost-effective procurement, processing, and product delivery strategy using FAI and SC. Effectively utilise IoT and Machine Learning functions for data collection, analysis, estimation, and performance evaluation in a fully automated assembly and delivery unit in the automobile industry.
Goal Statement: Minimising excess resource utilisation, cost, and energy in all the critical areas covered under the smart contract. Introducing a novel performance measurement index helps the industry maintain a permitted level of profit-safe margin during purchase and holdings called Trust Threshold Level (TTL).
Team Requirement: Since the industry is fully automated, only 6–10 skilled labourers are sufficient to assist the devices, data processing centres, and robotic platforms. Skillset includes troubleshooting in embedded software tools, design testing, and high-level experience handling machine learning algorithms and R models.
Period: 13 months (Full Time) Jan 2020 to Feb 2021 for implementation, modelling, testing, and deployment of developed AAM in the workplace with fully established FAI-TTL assistance with Smart Contract.
Equipment used: Sensors, Actuators, Electronic Controller Units, Near Field Communication Devices, RFID (Radio Frequency Identification) tags, and IoT enabled smart Transceiver units.
Software and Data Repository used: Local Data storage and processing unit, Automotive Grade Design software like MATLAB and R modelling tool.

5.3. Data collection and vector classification

In this design stage, goods, software, tools, and components from all the parties are unloaded and verified for their originality and standards in real-time. All stock values, component lists and specifications are labelled, tagged, and received at the unloading section. Stocklist, storage requirements, processing features, marking details like time and validity of the contract are mapped and stored with their respective suppliers (Guo and Ryan 2021). This stage uses a unique identifier for easy recovery in case of loss, damage, or faulty components. Data about the suppliers are kept confidential throughout the process as the SC policy will give additional safety and security details from the manufacturer. Cross functional embedded equipment can be combined together for data collection and processing. Energy reading is obtained from a coordinated and modelled central controlling unit where all the federated models are deployed for processing and calculation in real-time.

Once the details about the tools, components, and other miscellaneous elements involved in the design, assembly, and production process are received, they were labelled, and tagged for easy classification, identification, and storage. The stocks are stored in the local repository, and the same is modelled using Support vector ML. In this process, each vendor ID is mapped and logged with their devices and tools. This information is categorised and provided as samples for the ML model for training and feature extraction purposes. Once their detailed analysis is obtained, the stockpile is provided with classifiers. The stockpile and their unique component ID can be invoked and identified at any stage of their requirement in real-time. For this analysis and categorisation, AAM uses R packages, and the dataset is analyzed for feature extraction using automotive software tools (Manimuthu et al. 2021). Key findings from this stage include:

(1) Fault identification
(2) Component Classification
(3) Mapping of tools and Devices with their suppliers

(4) Product policy identification
(5) Stocks and Storage range and capacity index
(6) Market cost and Energy consumed during Unloading and storage in dedicated facilities

From this stage, the raw materials are assigned and model with their specific SC type based on company requirement, market trend, and investors interest. Some primary SC types include *Smart Legal contract, Decentralized Autonomous Organization (DAO) contract, Application logic Contract (ALC)*. In this AAM, components are categorised in the production process using only two SC: Smart Legal and ALC(Parunak 1996).

5.4. Smart legal contract (SLC)

One of the commonly used blockchain elements where all the elements, tools, and software investors and stakeholders are legally merged under one common agreement says profit or loss needs to be shared legally under accepted terms and conditions. This SC covers software, tools, and hardware, and the industry's data centre for future references. Trust among all involved parties is ensured using SC. Market reliability, stock value predictions, and product commercial value evaluations are accountable and shared by all the investors using SLC. Easily accessible machine-level SC assists in tying the consumer market with industries without any external brokerages. Energy wastages calculation uses a digital IoT environment. Most SMEs use this blockchain in their product procurement, delivery, and market stock analysis.

5.5. Application logic contract (ALC)

SC assists in using IoT devices for data collection, processing, analysis, and decision-making in automobile assembly and delivery. Most of the tools and methods used in the AAM involve many application-specific IoT devices, support vectors, classifiers, and federated learning models. ALC helps bridge gaps in programming tools, system design software, and industrial standards for assembly and production processes. ALC applies to design and modelling. All the active components, irrespective of manufacturers and process, can be brought under a common umbrella of SC without additional policy formation. Many investors agree to get involved in the logical contract without scrutinising their design and development details. Since XYZ company comes under SME in Europe, the implementation and design process is much more flexible while using ALC as one of the SC.

5.6. Spare parts inspection and trust validation

The pivotal stage is to classify different tools and components from manufacturers. During this stage, market valuation and the component's purchase cost are critically studied. Forecasted market value is quoted as the best market index during their training in real-time. All the datasets are trained and modelled using their unique ID and training vector classifiers. Database that holds the record about multiple components of the exact specifications using SC procedures. Their label and time tags are uniquely modelled, trained, and stored under their unique classifiers and support vectors (Zheng et al. 2020).

Once the automotive elements are classified based on different datasheets, market values and usages are modelled and trained using their support vectors and classifiers. This helps identify and eliminate the data errors and accumulated processing errors during data reception and storage by different IoT devices installed at different critical industrial zones. Data play a critical role in TTL limit identification for every industry-grade tool and embedded component. Datasets with errors are processed separately rather than training with other error-free datasets. Further data normalisation shows the datacentric ability of ML in processing the information among different sections of the industry(Pokhrel and Choi 2020).

After classification and modelling, the components are mapped with their respective section based on usage requirements in the assembly process. In this stage, errors accumulated during the dataset training and evaluation are updated, and new entries are stored. Sections involved in the XYZ company use this mapped dataset and their normalised values for smooth and easy identification of components from multiple manufacturers. This classification is based on their market valuation and stock listings as well. Grouping and logging take place once the trained values are available at respective data loggers. Irrespective of time, cost, and energy usage, all the elements are logged and categorised using their classifiers and support vectors in this stage. Since the next stage of vehicle design requires tools and components based on timing and assembly, these logged data are clustered together (Manimuthu et al. 2021).

5.7. Product design and schematic verification

As all the datasets required for component assembly and product structuring are readily available, the SC policy is checked before starting this process. During the process, almost all the assembly operations will be completed, and only the delivery of the final product will remain in the industry. Before starting this process, product

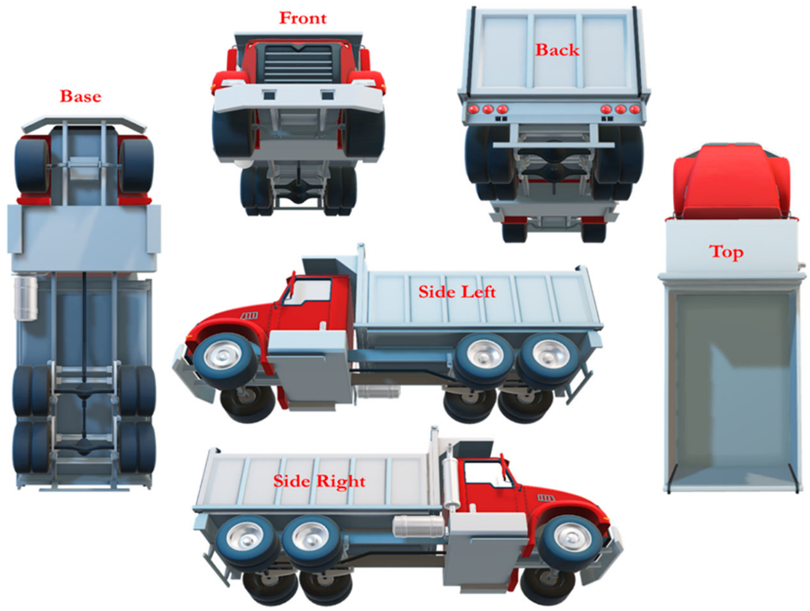

Figure 3. Rendered Schematic Viewpoint for the Heavy-Duty Commercial Vehicle.

schematics, as shown in Figure 3, are critically analyzed and evaluated deeply to come with the process initiation. The schematics include the components assembly with reference to the different viewpoints. The references are shared with all the divisions and the sections for their correct fitting and design verification in detail. Cross-sectional views help the design process more compact as the tools are categorised according to their requirements. Robots take care of the assembly process using the embedded software, and R models help in data visualisation. Once verified and approved, this stage of production and assembly cannot be intervened by any of the embedded devices in the middle(Singh, Rathore, and Park 2020). Only the emergency halt operation can be performed. Steps and processes involved in this stage include:

(1) Fitting
(2) Assembly
(3) Polishing
(4) Testing
(5) Analysis
(6) Verification

In each section, ML values, trained classifiers elements, and the permitted storage level are recorded; So that there will not be any excess values in any sections. This helps to secure the system from any loss due to excess storage cost, and energy required to process and store the values. The product design schematics with all viewpoints, as shown in Figure 3, are kept readily available for usage and shared as a key reference to assemble every individual component (O'Leary 2013). In contrast to the existing business models and industrial setup, the developed design uses smart technologies, AI and smart contract to assess and manage all the error prone zone in the business and industrial operations.

5.8. Product delivery

After assembling the product, the usages are updated with their ID and TTL values in real-time. In this stage, data obtained from the sensors and embedded devices are modelled and trained using FAI. Component's classifiers and support vectors are correlated for their usage and threshold limits in real-time. Once the process is initiated, data obtained are relatively normalised and mapped in parallel with their SC before getting transported to the final product delivery section(Gonçalves et al. 2021).

Data about the components and tools, embedded software, and smart sensors are cross verified for their market utility, licenses, and delivery cost with their intended consumers or vendors for commercial stocking. Fault identification at this stage is crucial as the entire schematics of the system need to be reworked and revamped based on the TTL values. FAI training is again performed to restore the system, just as every process involving the faulty component. The component is replaced completely. If the fault is identified during assembly or production, the entire items delivered during that time-stamped stage and product classifiers are separated from the rest of the sections. This helps secure the production without being affected much by the fault at different stages during mass production(Min 2010).

Further, with TTL, the market pricing is carefully identified and evaluated to get the best pricing value during the final product delivery – SCs help bring quality and quantity during the distribution of vehicles in the commercial market. Stakeholders and investors, participating venture capitals are provided with the vehicle standardisation schemes and method of designs and explained about the TTL and their performance in developing customer-centric smart vehicle design with an assured profit margin to all the investors and participating agencies in real-time in terms of market share, stocks and commodity and consumers commercial market trust(Cioffi et al. 2020).

6. Design simulation and experimental analysis

Model development, simulation, and software-based programming include three levels of data extraction and modelling, as shown in Figure 4. In all the stages, feature extraction, error identification, rectification, model processing, and data training are performed continuously using SVML and FAI. The modelling scheme involves SC and TTL to ensure the proper commercial pricing to design and the required number of assembly and product design components.

6.1. Level 1: Data normalisation and feature extraction

R packages and industry-grade smart system software are used in bringing the full features available from every

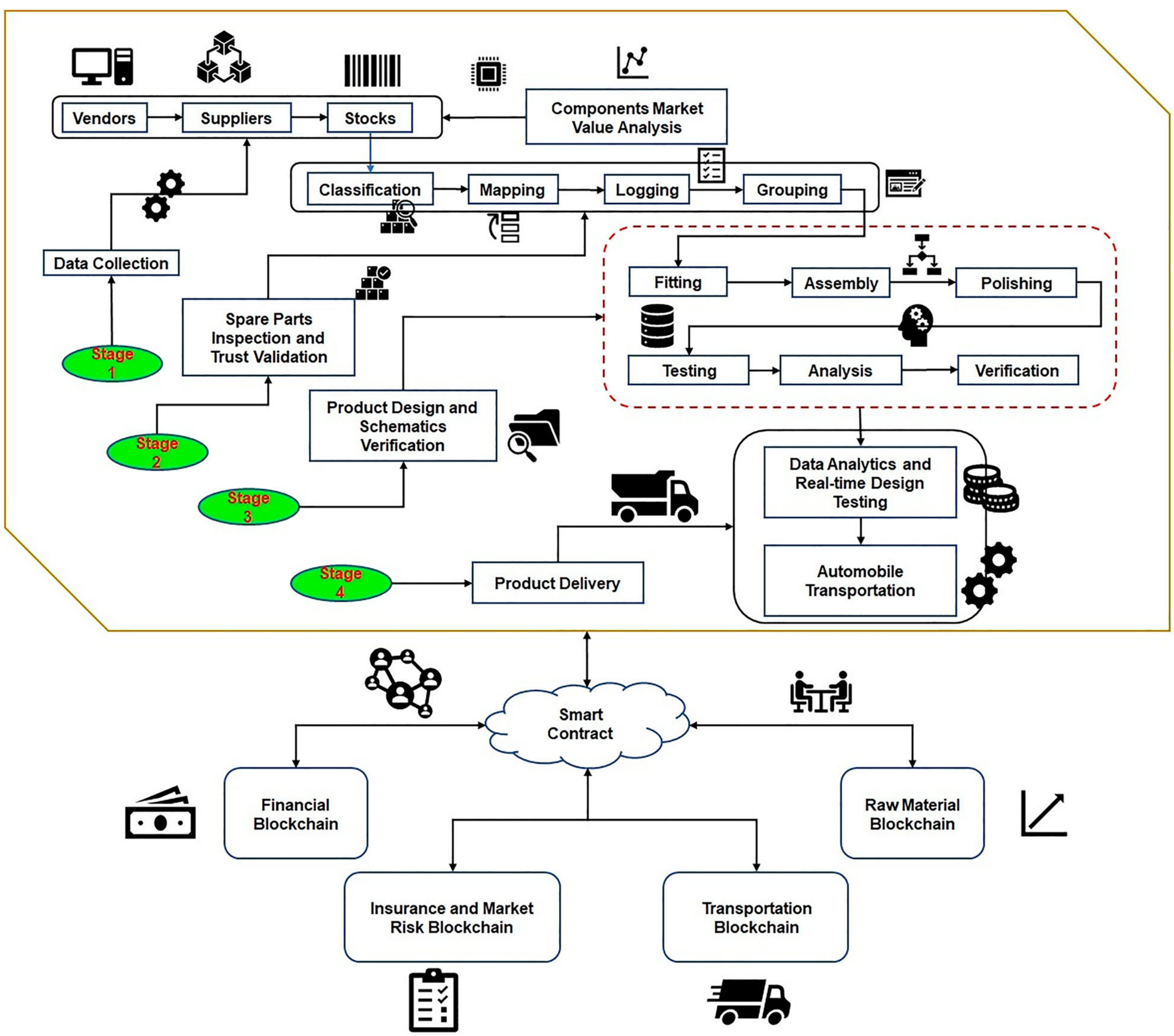

Figure 4. Automobile Assembly Model (AAM) using TTL, FAI, and Smart Contract Blockchain.

component involved in the design. Training and evaluation include *stock lists, pricing values, and manufacturer support* for smooth testing, loading, unloading, and information extraction. The process involves fact sheets and design information obtained from original vendors and suppliers. This information is retrieved and modelled using SVML, and classifiers are provided to each section for smooth identification(Nofer et al. 2017). Each component is mapped and logged onto a local database for easy pick and place into different sections involved in the process. Investors and stakeholders are advised about the market price.

6.2. Level 2: Trust Threshold Limit identification and modelling

One of the critical levels of design and testing is function evaluation and vector characterisation of components for identifying their TTL values in the system. This TTL references *consumption, wastages, energy usage, and cost function* involved in the commercial vehicle assembly and distribution process. With TTL, the loss margin is greatly improved, and the stock pricing is kept on the desired limit by all the involved component vendors. Support vectors and the federated training values are modelled and smoothly channelised for best throughput as the limit is set during the initialisation process. Table 3 shows the impact of using TTL and SC in analyzing the risk index in the commercial market. Before implementing FAI, the use case of SC is not completely achieved in the design as suitable infrastructure is not viably available. Based on the contracts and mutual agreements, the purchase and string values go through their applicable SC. Thereby the unwanted storing cost and the risk involved in storing are significantly reduced. It is not mandatory to pay additional costs, and energy wastages for maintenance are nullified completely. Thus, this implementation directly reduces the risk involved in handling all forms of products movements. If the SC is not implemented, the policymakers have the freedom to implement additional maintenance charges along with storage and delivery cost. Almost *1.5%* of the risk index is improved using TTL and FAI while setting the FAI margin as *1.27%* during the purchase and installation of ECU alone. Then the same process is done for every individual component. The overall gain margin using FAI in the design includes a whopping *26.46%* overall gain throughout the entire process. However, this whole FAI margin will not be reflected the same at the end of product design and delivery as the market share is prorated and has its stock and investment fluctuations(Giancaspro 2017). The procedure is followed in the SME for almost ten months unlike any other existing models, which may normally be implemented only for few months before deploying on a large-scale industrial environment. Now it is fully operational and exporting vehicles overseas with a solid profitability range of in the body and commercial division split-up alone for each investor based on their investment percentages apart from market gain and fluctuations in real-time.

6.3. Level 3: Federated learning AI and smart contract

The installation, procurement, purchase, and product delivery process is subject to the cost and energy usages apart from market investments and stock prices. The training and evaluation of data and component's specifications are based on their original suppliers (Fenwick and Vermeulen 2019; Yuanyu Zhang et al. 2019).

The *smart contract* involved in the design includes the insurance policies that attempt to protect and secure the initial investments made during the production and delivery process. In this SME, only two insurance policies are incubated in the design process. *1. Pure Holding Type and 2. Intermediate Holding type*.

6.4. Pure holding type

Companies that participate in component investments and market share alone without product design and component pricing come under this category. These investment companies hold a significant share in the SC, and the commercial market's profit margin is also very high.

Table 3. Raw materials implemented with FAI training percentage and valuation index.

Elements	License (In Years)	License Grade	Units	Smart Contract (SC) Type	Risk Index (%) (Before FAI)	FAI Margin	Risk Index (%) (After FAI)
ECU	2	Industrial	25	ALC	14	1.27	9.8
Embedded Controller	1	Retail	50	ALC	25	2.14	17.5
Sensors	1.5	Vendor	120	Smart Legal	27	4.21	18.9
Actuators	1	Vendor	100	Smart Legal	30	5.31	21
Conveyors	3	Industrial	12	ALC	15	2.89	10.5
Data Stack	5	Retail	5	ALC	10	3.47	9.5
Logger	2	Retail	10	Smart Legal	5	4.01	3.75
Debugger	1	Vendor	10	Smart Legal	5	3.16	3.5

6.5. Intermediate holding type

As the name suggests, instead of investing and acquiring a significant stake in the company, these companies will invest along with other retail investors in terms of cost, energy, and component purchases. The main advantage of this type of holding is high return in the short term, but it also involves heightened risk due to market fluctuations. Companies in this category tend to be proactive in commercialising the automobile as soon as the product reaches the commercial market for consumer utility in real-time. Table 4 shows the insurance type and the SC values for each critical component with many vendors and suppliers. In addition to these components and tools, many other products are available in the vehicle where the gross margin is shared between many local investors.

From table 4, it can be observed that the gross margin gain for each component raised to an average of 1.5–2.3 percent irrespective of their SC and Insurance holding type. Thus, TTL and FAI help companies get better investment returns and market sustainability for the long term.

Similarly, the TTL tends to limit all the company's share value based on their market trends and commercial market fluctuations in real-time irrespective of the share contributions these companies have in the vehicle design, development, and commercialisation. As shown in Table 5, companies from A-G supplies different embedded components, and the conveyors are purchased from companies X to Z in the local market. Due to the randomness of investments and stock prices, the valuation of each company is closely monitored and fed to the FAI for their best training attributes. Hence, with these values, the best market price for each of the essential elements is obtained. Based on this, TTL is developed as iterations for the next consecutive progression of matrices for the same companies.

In this process of training and evaluation of goods and services, SC involved in the design helps to get better pricing values from the commercial market by identifying, analyzing, and estimating the pricing of goods and commodities. It also the product movement from and to the company and commercial market respectively in real-time.

The tariff rate, along with their market valuation, are identified, modelled, and evaluated based on delivery speed, charges/item, and market capitalisation(SC; and Enterprise value). Many vendors have their delivery agencies for loading and unloading goods and commodities. Thus, TTL and FAI help identify the best pricing agency for delivery and transportation in the commercial market. Table 6 shows the delivery agency list and their enterprise valuations like market cap, enterprise value, and delivery charges before and after implementing FAI and TTL in the workplace.

Similarly, the performance index is evaluated for the dealers based on the revenue and gross sales. These data must be submitted as per the company policy and SC blockchain for insurance, maintenance, and market share calculation in real-time. Thus, all the agencies and dealers produce their total retail and commercial revenue data for FAI training and analysis. This helps to study and identify potential issues or threats or quality index and improve cost margin gain regarding distribution and

Table 4. Insurance type and gross margin % of different components in AAM design.

Elements	Insurance Holding Type	Smart Contract (SC) Type	SC Rate (%) (Before FAI)	Gross Margin (%) (Before FAI)	SC Rate (%) (After FAI)	Gross Margin (%) (After FAI)
Conveyor	Pure	ALC	2.23	4.20	4.68	6.59
Data Stack	Intermediate	ALC	3.01	5.32	7.21	8.32
ECU	Intermediate	Smart Legal	2.86	3.26	4.19	3.53
Sensors	Immediate	Smart Legal	4.33	5.32	10.35	9.81
Battery	Pure	Smart Legal	4.53	4.82	9.83	7.09
Software	Pure	ALC	2.87	2.94	3.80	3.61

Table 5. Companies market valuations for each critical component in AAM design.

			Companies (Market Fluctuation %)							
Elements	A	B	C	D	E	F	G	X	Y	Z
ECU	4.011	6.12	3.51	9.6	15.28	17.79	6.402			
Embedded Controller	6.19	4.29	5.35	7.29	4.69	8.29	4.69			
Sensors	3.67	4.67	3.14	8.21	4.36	7.26	3.03			
Actuators	5.158	5.146	5.173	5.193	5.103	6.09	5.049			
Conveyors	-	-	-	-	-	-	-	11.93	10.29	9.143
Data Stack	5.21	6.21	5.179	4.29	9.21	7.29	6.73			
Logger	4.019	9.27	7.95	7.63	6.72	6.1	4.03			
Debugger	5.753	6.017	6.32	5.236	4.93	5.017	6.73			

Note: Values highlighted in Red gives the best market valuation for a particular component using FAI and TTL.

Table 6. Transportation tracking with delivery rate of all dealers in AAM design.

Dealer ID	Delivery Charges (%)	Delivery Rate (Before FAI)	Market Cap (%)	Enterprise Value (%)	Delivery Charges (%) (After FAI)	Delivery Rate (After FAI)
IN263	12.23	23.86	131.53	168.75	5.22	21.15
IN753	16.23	15.93	95.89	123.02	−16.68	13.22
IN632	17.30	14.40	89.28	114.55	−21.64	11.68
IN895	14.23	19.27	110.58	141.87	−6.67	16.56
IN412	9.21	20.31	110.76	142.11	7.44	17.60
IN724	11.04	21.42	118.15	151.59	4.54	18.71
IN244	19.23	20.15	119.96	153.91	−17.86	17.43
IN893	10.25	19.33	106.88	137.13	3.37	16.61
IN710	10.86	22.36	122.66	157.38	6.38	19.65
IN837	9.31	18.40	101.29	129.96	4.31	15.68
IN720	8.39	19.38	105.29	135.08	8.09	16.67
IN207	19.34	22.36	131.14	168.25	−14.81	19.65
IN663	14.30	23.64	132.50	169.99	−0.28	20.93
IN743	17.29	20.93	121.94	156.45	−11.83	18.22
IN552	13.70	19.30	110.20	141.39	−5.30	16.59
IN349	14.93	19.76	113.73	145.92	−7.68	17.05
IN735	15.73	24.36	137.53	176.45	−2.79	21.65
IN753	13.29	23.18	129.19	165.75	1.55	20.47
IN823	14.37	22.31	125.92	161.55	−2.46	19.60
IN634	14.20	21.34	120.90	155.11	−3.49	18.63
IN900	11.36	22.56	124.16	159.30	5.44	19.85
IN209	10.30	22.79	124.25	159.41	8.44	20.08
IN760	8.24	19.39	105.19	134.95	8.50	16.68
IN860	11.80	21.29	118.25	151.71	2.43	18.58

Note: Negative Value indicates gross margin exceeds the desired limit (Outperforms in Market Valuation).

Table 7. Dealers revenue and gross sale improvisation using FAI, TTL, and SC during AAM design.

Dealer ID	Gross Sales (Margin %) (Before FAI)	Revenue (%) (Before FAI)	Gross Sales (Margin %)(After FAI)	Revenue (%)(After FAI)
IN263	14.06	7.56	16.08	10.29
IN753	11.90	13.26	13.92	15.98
IN632	11.57	17.02	13.58	19.75
IN895	12.72	5.77	14.74	8.49
IN412	11.73	8.56	13.75	11.29
IN724	12.71	5.80	14.73	8.53
IN244	14.50	16.05	16.51	18.77
IN893	11.62	3.62	13.63	6.35
IN710	13.05	8.24	15.07	10.96
IN837	10.97	4.29	12.98	7.02
IN720	11.11	8.91	13.13	11.63
IN207	15.45	14.27	17.46	16.99
IN663	14.55	1.35	16.57	4.08
IN743	14.28	11.03	16.29	13.76
IN552	12.58	4.56	14.60	7.29
IN349	13.12	6.87	15.14	9.59
IN735	15.26	4.44	17.27	7.16
IN753	14.08	0.10	16.09	2.83
IN823	14.02	3.29	16.04	6.02
IN634	13.57	3.81	15.59	6.53
IN900	13.28	7.27	15.29	10.00
IN209	13.07	10.71	15.08	13.44
IN760	11.08	9.36	13.09	12.08
IN860	12.87	3.40	14.89	6.13

market limitations. Table 7 shows the similar gross margin gain achieved by the dealers and commercial distribution agencies after implementing FAI and TTL in their operating procedures. Advancing further from the existing design (Ivanov et al. 2016), all the participating agents are provided with their stock movement details and pricing values. This includes wastages, flaws and defects in their goods and services.

Table 8. Energy evaluation during AAM design, testing, and evaluation.

Category	Gross Margin % (Before FAI)	Energy Consumed/ Day (%)	Gross Margin % (After FAI)	Energy Consumed/ Day (%)
Loading	6.346	7.631	11.1055	6.1048
Polishing	3.21	12.78	5.6175	10.224
Assembly	6.27	15.364	10.9725	12.2912
Fitting	4.95	16.37	8.6625	13.096
Organizing	5.071	12.71	8.87425	10.168
Tunning	4.32	20.3	7.56	16.24
Testing	9.22	20.13	16.135	16.104
Control	13.432	15.019	23.506	12.0152
Unloading	11.432	8.31	20.006	6.648
Total Energy		128.614		96.2432

Apart from the cost and component distribution, it is very much possible for the TTL to identify and analyze the energy consumed per product. Thus, Table 8 shows the reduction in energy consumption after implementing TTL and FAI in the intelligent industrial unit. It is estimated and recorded from unloading at the warehouse throughout different production and assembly stages. Thus, the loading, unloading, transportation, assembly, fitting, and polishing costs, along with analysis and design schematic verification costs, are identified, recorded, and processed. The processed value is applied with FAI and SC policies for getting final market evaluation and stock prices/unit of energy consumed in the industrial process(Ivanov, Sokolov, and Dolgui 2014, 2019). Figure 5 depicts the performance before and after implementing TTL in the workplace. The tabulated results are visually represented in figure 5 to compile and

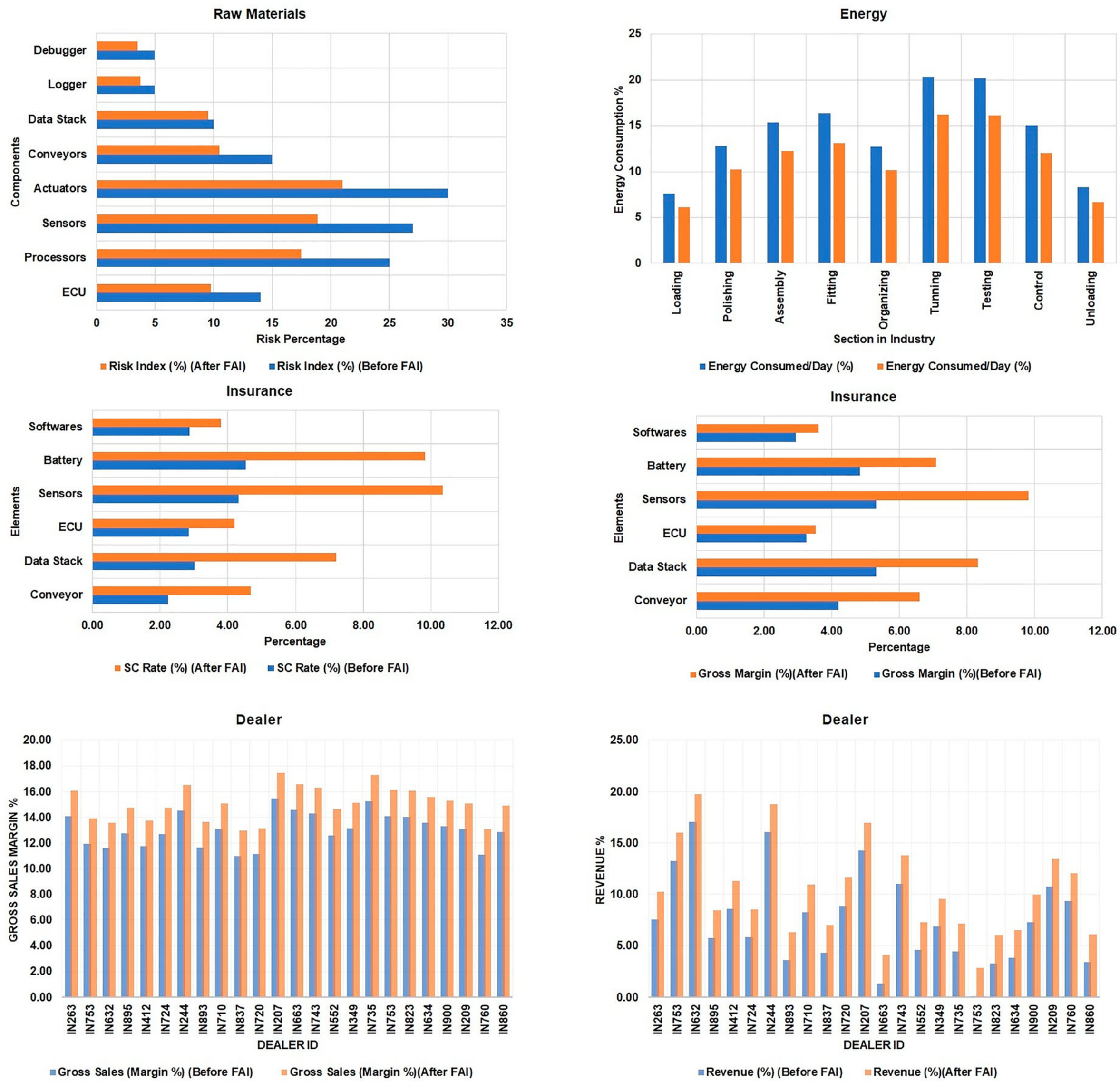

Figure 5. Data visualisation and results comparison (before & after implementing TTL & FAI).

show the use case of TTL and the effect of using FAI and SC in the design process. Apart from the cost and energy, the interest rate, delivery charges, and SC's policies help the industry achieve better performance and improved productivity in real-time.

7. Discussions of findings

The study has designed and developed an *Automobile Assembly Model* (AAM) concentrating on industrial-grade commercial vehicle design. This study practically implemented and evaluated the developed design using real-time data analytics and machine learning models to process, train, and test developed AAM. Before explaining the key findings, the study has opened doors for emerging technologies like *IoT, AI*, and *SmartContract Blockchain* into the commercial vehicle industry practices. Various studies on *Blockchain, AI, and IoT* have detailed their usage from the industry perspective (Singh, Rathore, and Park 2020; Yuanyu Zhang et al. 2019). They also triggered the point that combining multiple technologies with data analytics tends to solve many real-time problems in the industrial environment over many decades. *Quality and performance valuation, design analytics, and productivity enhancement* constitute several possible sustainability solutions to withstand in any global industrial market. In addition to the additive manufacturing and process automations, the use of SC and IoT helps the industrial environment and active participants to obtain a detailed market response curated with the existing business practices.

Data modelling, computational algorithm design, simulation, and schematic formations were again a big hurdle due to prevailing trust issues between stakeholders and investors. As the SC helps bridge this trust issue by policy formation and legal assistance, all the investors tend to have hassle-free investment plans in real-time. This design includes multiple procedures in terms of purchase, delivery, utility, and distribution. All the data are modelled using *SVML,* and *Federated Learning ML techniques* as the data are effectively captured by the embedded IoT in the industry. Developed AAM shows the use cases of ML and IoT in fixing, evaluating, and processing all forms of data irrespective of sources without any deviation from their programmed functions. The programmed model uses a customised R programming scheme, and simulations are done using company-owned industry-grade licensing software. Thus, unbiased data is fed to the training, testing, and evaluation model at all assembly stages in real-time.

Irrespective of industry, these methodologies can be implemented with a few minor customisations. Many industries, including leather, textile, biogas, fuel cells, and two-wheelers, can incubate these methods in their practices to achieve profitability in the short term. They maintain ongoing modifications include curtailing the cost of productivity and minimise energy consumption during their production procedures. In some other cases, these techniques were exclusively used in identifying the flaws, damages, and defects in the components, tools, and product design. This aims to attain sustainability without losing the market margin gain within the calculated time frame. Recent reviews show that the fault identification and testing scheme evaluation can be made based on industry standards and company policy, whereas in AAM, all the investors need to abide by the SC policy. This method of testing and evaluation includes all forms of cost, energy consumption, and market fluctuations. This confirms an eco-friendly market share dividend among all the participating agencies as per their investment percentage and profit margin obtained during product delivery.

Qualitative evaluation of every deliverable plays a significant role in design, development, and product assembly. Many techniques other than ML includes fuzzy logic; the neural network can explore SMEs based on their production cost and infrastructure capabilities. Prediction analytics and modelling with these techniques aim to offer better performance without considering any market investments. Thus, ultimately, improved production cost, commercial value gain, and market valuation become void in these industries. In some worst cases, the decision model lags in providing the required results as the dataset may not be sufficient to provide result-oriented decisions in real-time. Thus, flexible and robust infrastructure capable of emerging smart technologies in industrial practice is required in the automated industrial setup. The discussion made from the literature and practical industrial white papers shows the importance of decision-making models and flexible data processing metrics. This helps industries to improve resilience against fluctuating global market. Accordingly, the policy makers and regulatory management authorities will get a clear understanding of the business process and manage the operations with open information, transparency and visibility. This includes operations, logistics, distribution and transportation.

The present AAM uses four form factors that act as pillars in the design, development, and successful testing of the design scheme. It includes smart technologies and industrial standardizations. Form factors include 1 – data *from Stock, suppliers, and vendors, 2. Smart Contract Policies, 3. Trust Threshold Level for each element involved in the production process, 4. SVML and FAI* for performance comparison, modelling, and analysis at various stages of design. In addition to these critical form factors, other methods used in training and processing data and stages include *classification, assembly, fitting, polishing, testing, analysis, assembly, grouping, logging, and schematic verification.*

Data shared between different stages with the ML algorithms will extract the features and help in decision making. SC comes into the picture when the devices or equipment are observed of any faults or damages or malfunction during any stage of the assembly until the product is delivered into the commercial market.

As this process is technically considered stable, the market fluctuation always prevails while fixing the products' cost and commercial value. Thus, in this AAM, *a novel estimation technique called TTL is implemented in the design itself.* Through this estimation scheme, all the products are modelled based on their *cost, energy usage, market value, and profit margin* of utilising them in the design. TTL has the following features that have helped the XYZ company to have a commercial profit margin of *13 percent within 60 days* of their commercial vehicle sales. Feature includes:

(1) Data modelling and component analysis (Vendors, suppliers, stocks)
(2) Loading, Unloading, distribution, and usage valuation cost
(3) Consumer satisfactory index
(4) Market valuation and SC legal policies
(5) Sale valuation and investors profit margin
(6) Storages and stock listing data

(7) Stock purchase valuation comparison
(8) Market pricing vs. Purchase pricing analytics

These data help fine-tune each component's threshold value after their potential utility during the assembly and delivery process. AAM with TTL in the industries uses a margin variation function with a maximum deviation of *2.3-3.2 percent.* TTL derived from the production and assembly process involves market investments and company stock shares that are openly available for any kind of investors. It helps them to take part in legal policy with smart contract blockchain.

Data is modelled and distributed among various sections for cross-referencing, stocking, and complex computation purposes.

8. Implications

The design and research analysis offer significant contributions in operations and supply chain, specifically automotive assembly processes.

8.1. Theoretical contributions

First, the study provides a use case of machine learning models and smart IoT devices and bridges two indigenous methodologies that contribute to productivity improvement(O'Leary 2013; Yuanyu Zhang et al. 2019). When compared with the existing industrial practices, these smart techniques notably promote the stock value in the commercial market. *Timing, data analytics, fault identification, and systematic assembly process* were made throughout the production and product delivery process. Targeting the commercial vehicle distribution market, SMEs focus more on reducing the losses from purchasing and procuring raw materials. The process is continued till the final product is delivered. *Second*, the study provides procedural guidance to create a smart industrial ecosystem that involves AI-enabled smart sensors and machine learning practices(Manimuthu et al. 2021) for the best market valuations to each commodity. As the design involves stock pricing and energy consumption factors, all these data are modelled with their respective normalisation values obtained during *training, analysis, and estimation*. In this way, the marginal error accumulated at every stage of data processing is significantly improved.

Third, this is the first study that emphasizes the FAI and its role in the product assembly industry. The deliberations in managing the product complex system and support vectors for data normalisation helps to find the best fit values for design and testing. Fourth, it discusses cost-saving functions in the available industrial practices focusing on their internal costing features and functions. The developed AAM tried to integrate all forms of functions, procedures, values, and specifications of every tool and commodity. Further, the TTL value helps identify and process every component's functional attribute with detailed identification, analysis, and market utility. Thus, it indirectly facilitates the firm to get more visibility and position itself in the competitive commercial vehicle market. Besides, FAI and TTL designed and implemented are unique and novel where both relatively bring sustainable industrial practices and solutions that any industry can quickly adapt in their workplace. The model developed, solutions provided, and dataset training functionalities are entirely customisable based on the industry requirement and infrastructure support. It will significantly contribute to all forms of supply chain practices and operations management with assured safety. Finally, the secured smart contract usages act as a backup to meet any legal grounds in real-time.

8.2. Practical implications

The study has notable managerial contributions. The design provides use cases to the SMEs and large-scale industries irrespective of their domain. First, it supports the incubation and use of smart IoT devices in industrial processes through real-time data collection and processing using machine learning algorithms. Here data act as a critical resource in consecutive processing stages in the IoT-enabled smart assembly unit. *Grouping, vectorisation, feature extraction, and data analysis* involve both *SVML and Federated learning* at different stages. They all help leverage the information about the tools, software, components, and devices in the assembly process.

Secondly, in the developed design, a novel element called *Trust Threshold Limit* is used in all areas of data training under the *Federated Artificial Intelligence (FAI)* integrated framework. It supports the industrial automation and analytics that can be realistically modelled using the emerging smart techniques. Limit for purchase and storage can be visually made available to the concerned stakeholders using this mode of data processing and analytics. Modelling and development involve machine learning models that help bring the best market values for all the components involved in the design process. This training and modelling help investors and the third parties involved in the design to closely monitor the product prices and their stock values in real-time. Combining blockchain, federated AI, and machine learning models helps foresee the component requirements, usages, procedural functionalities, and data-driven decision-making models, thereby reengineering the overall product tracking system in a manufacturing firm. In terms of process control and design optimisation, tracking, modelling and design verification play a major role. Valuation and the processing capabilities of the smart systems can be studied and compared with the existing tools for optimised business operations.

Thirdly, the simulation and modelling provide the necessary resources for FAI analysis and the TTL estimation. As the market risk is involved in all design stages, TTL serves as a better response index starting from loading goods to product delivery in real-time. The design shows the importance of IoT devices and ML modelling mechanisms in bringing the best possible values for each component subject to their market investment and commercial values.

Fourthly, the study supports the practical usage of TTL using ML models and data analytics methods in real-time for equal distribution of resources. Energy distribution and parallel computation provisions engage IoT devices, smart sensors, and electronic controllers. Implementing smart, innovative techniques in the industrial practices streamline the industrial procedures and orient them towards profit-making from market investments, with a focus on market risk and secure product commercialisation in real-time. Thus, in this AAM design, TTL and FAI advance understanding of the role of stock pricing, market rate, commercial product valuation with intense ideation of practical usage of cost, energy, industrial standards, and smart, innovative technologies for building a better sustainable industrial ecosystem. Evaluation of the existing methods provides a standard performance metrics as tabulated in Table 8 include energy consumption and margin of wastages. This becomes more realistic while implementing the TTL in the actual business practices. Minimum modifications with maximum potential in operations, supply-chain and production factors in real-time resource assessment and management can be achieved. Besides, AAM will help foresee the requirements, usages, procedural functionalities, and data-driven decision-making models. Using smart technologies such as ML, IoT and Blockchain in industrial practices, the companies may have better accountability and sustain competitive commercial market index value. Thus, AAM directly facilitates restructuring of the overall firm's standard operating procedures.

9. Conclusion

The work provides evidence that the enhanced data collection, processing, and control procedures help in efficiently handling the data generated for the manufacturing procedures. The experimental study offers a roadmap for implementing a wide range of smart technologies for vehicle operations, control, and assembly performance valuation using data-driven modelling and analysis. The study involves IoT and supports vector machine learning for grouping, analyzing, and classifying tools, components, and other supporting goods in the assembly process. Irrespective of the market investments, these additive manufacturing strategies will help production and distribution processes and quantitatively assess the market risk and investors' returns in real-time (Alavian et al. 2020; Guo and Ryan 2021).

The design proposed a novel TTL value that spotlights the use of threshold limits in the purchase, production, and product delivery. TTL is combined with *federated learning AI mechanism* to propose a smart solution for improving profit margins. Data normalisation, vector classification, analysis, and feature evaluations are critically scrutinised throughout the process of AAM design. TTL and FAI help fix, finalise, and set the limit values for purchase, storage, usage, and distribution of goods and services commercially, irrespective of market fluctuations. The legal policy for security and liability is taken care of by smart contract as all the investors and stakeholders are legally entitled under standards industrial operating procedures. Thus, TTL helps set the limit in cost, energy usage, purchase, and processing options. It assists in building the vehicle from scratch without the worry of losses due to socio-economic crises or market stock fluctuations. TTL assists for energy usage, purchase of raw material, transportation, and delivery. The local vendor selection is mapped, modelled, analyzed, and tabulated, and verified in the industrial environment in real-time.

9.1. Limitations and future directions

The study has its limitations and offers future research avenues. First, the study does not involve any data storage with remote access. Thus, firms can consider using cloud storage for data processing and remote accessibility. All the software and codes are purchased from third-party vendors. They cannot be trusted all the time for data reliability. Hence the data used for processing may have a marginal variation of permissible range that could contribute to other errors. SC formed for this design scheme can only permit few extendable ranges of complications that include natural disasters. However, it does not involve defects in industrial design infrastructure, as that is taken care of solely by the company alone.

The simulation scheme used in the design requires skilled labourers, and Graphical User Interface (GUI) cannot be customised as they are not locally developed for industrial practice. TTL uses FAI and SVML data processing that any other ML technique can outperform. Data acquired and processed from the IoT-enabled smart sensors can have their latency in data delivery.

In the current industrial setup with more than *60–70 percent of automation* in place, the incubation and deployment of the developed AAM can be a hassle-free action. Finally, the developed design is not integrated with the existing model and warrants its customised infrastructure. The developed model can be adapted in manufacturing, warehousing, and distribution industries with minor adjustments and customised control levels, data collection mode, processing, and analytical methods. New designs may integrate AAM with other existing industrial models by customising it based on infrastructure, cost, and energy availability. A better alternative for R packages can also be tested in the design. The developed AAM with TTL and FAI can set a new benchmark for research on emerging and innovative smart technologies in real-time.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support this study is available from the corresponding author, Professor Lenny Koh (S.C.L.Koh@sheffield.ac.uk) on request.

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