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Revolutionizing Automotive Manufacturing and Distribution: Leveraging AI and Cloud Computing for Smart Supply Chains

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Abstract

Revolutionizing automotive manufacturing and subsequent distribution has been a growing debate for the industry due to electric cars, artificial intelligence, and cloud computing. Leveraging AI models for predicting passenger demand and enhancing the energy consumption of both the vehicles and warehouses are discussed. Cloud computing solutions for electrical vehicle charging station placement are surveyed and a fleet management algorithm is proposed that aims at satisfying EV driver/utility providers preferences. A multi-agent system is developed in an environment. The bridge between AI and logistics is built through an autonomous vehicle algorithm that can distribute the passengers using our predictive model about passenger demand for different areas at different times. The algorithm is applied to different solutions of the capacitated vehicle routing problem for reducing the costs of delivering the electric cars. Also, a reinforcement learning algorithm is proposed that jointly enhances the energy consumption and the robot path planning. The algorithm is used to develop a deep deterministic policy gradient agent as an assembler, and the agent is applied to the AGV scheduling optimization where the AGVs can select different feasible and safe paths across the robot cell with different maintenance tasks and obstacles. Cloud computing is delivered through the internet. Data collection is provided by the IoT devices in the robot cell while data storage is provided by a service. Despite some electrical disparities between the cloud computing and IoT devices, data processing and information output are shown to have a complementary integration.

Keywords: Revolutionizing, innovation, competitive advantage, supply chain, automotive 4.0, new mobility landscape, disintermediation, digitalisation.

1. Introduction

Smart supply chains are taking manufacturing and distribution network design to a whole new level. Boosted with cutting-edge AI and cloud technology, manufacturers can now fully automate, optimize, and simulate their network without any human intervention. The auto-revolution model presented in this work can revolutionize the way automotive companies operate, leading to tremendous cost-saving opportunities and improvement in sustainability. It leverages state-of-the-art AI and cloud computing to deal with dynamic scenarios (either long-term uncertainty or short-term disruptions) and design a smart network of manufacturing and distribution facilities. A case study for an automotive company is presented where billions worth of savings can be obtained fleetingly. The model can manage the global network of facilities (even in the cloud), making, distributing, and delivering end-products as well as dealing with the flows of intermediate products and resources between facilities including raw materials and parts. When the next generation of ultra-fast 5G and 6G networks start to roll out, entire cities could be bathed in the microwave and millimeter wave radiation that facilitates the purpose of ‘smart’ cars with ‘smart’ highways and factories. Japan is already rolling out a ‘smart road’ concept over the coming decade that will enable routine drone deliveries, self-driving cars, and trucks.

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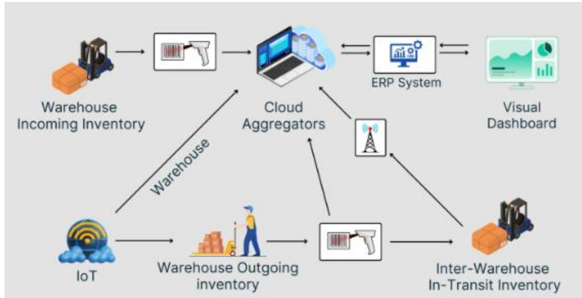

Fig 1: Leveraging AI and Cloud Computing for Smart Supply Chains

1.1. Background and Significance Smart supply chains are the backbone of Industry 4.0. Important applications of Industry 4.0 include the digitalization and horizontal integration of value and supply chains which lead to the establishment of smart supply chains. In smart supply chains, the whole value chain's data is available in real time, and the data can be exchanged and manipulated in real time between nodes of the SC. This makes smart supply chains self-learning, and with AI, self-optimizing, i.e. autonomous, and adaptive for upcoming disruptions or to minimize reaction time in already occurring disturbances. One key factor behind this strength of AI and relevance of cloud computing is the large-scale data availability in real-time due to the increasing utility of edge platforms. Smart supply chains will be of relevance in many areas as they can predict and anticipate issues before they arise. For example, if AI detects through data analysis that a delivery is likely to be performed too late, it could autonomously trigger changes in the transportation and logistics planning to ensure the timely delivery. Other applications could be predictive maintenance, warehouse automation, smart manufacturing or stock allocation. In the case of the latter, it could be decided in real time how much of a good to be delivered is manufactured in the respective country or how to optimize the routing of the good in order to reduce delivery times or costs. Smart supply chains are a relatively new research area and only estimated projects exist to grasp the potential magnitude of transformation in a near future. It can be expected that the establishment of smart supply chains will significantly change the way manufacturing, warehousing and delivery are performed. This will have implications for the stream of goods, workers and required skills in SCs present and in different areas of the supply chain. In addition, AI and cloud computing have the potential to create severe economic and sectoral changes. Estimates suggest that a decline in current jobs may be observed and a future-skilling and reskilling of workforce will be needed, specifically in the increasing demand of data analysts and scientists.

Equ 1: Demand Forecasting (AI and Cloud Computing)

$$D_t = f(P_t, C_t, T_t)$$

Where:

- D_t = Demand at time t
- P_t = Historical sales data up to time t
- C_t = Cloud-based data sources (e.g., customer preferences,
- T_t = Temporal factors (e.g., seasonality, promotions)

2. The Role of Artificial Intelligence in Manufacturing

Artificial Intelligence is the apex of the Manufacturing 4.0 evolution. AI, a discipline of computer science focused on teaching computers how to learn, can be employed to discover patterns in complexity, ultimately enabling data-driven decisions to be made across the complete automotive supply chain. With AI, stresses that modern machine learning approaches open countless opportunities for businesses in the automotive industry to optimize processes and to achieve cost savings. Hence, AI technology is set to revolutionize the traditional structure of automotive manufacturing methods.

The integration of AI with robotics advances the design of more flexible and collaborative systems capable of automating tasks that traditionally necessitated the human touch. In the automotive sector, these technological improvements enhance work safety and ergonomics, increase production line speed, and accurately adapt to customized manufacturing requirements. Cloud-managed database integration is a vital enabler for fostering productive dialogues between developments within AI and the automotive industry. Comprehensive data analytics are fundamental in supplying real-time insights across interlinked supply chain partners. Traits proposed for futuristic automotive supply chains are highly integrated platforms, supplying information in real-time for all concerned actors, advanced data security measures, comprehensive blockchain traceability, and a decision-making approach based on smart algorithms. The larger objective is to craft a globally smart automotive supply chain view, inherently resolving complex supply chain-related issues. With this future in mind, the automotive value chain can move into uncharted territory by achieving unparalleled levels of integration, transparency, and efficiency.

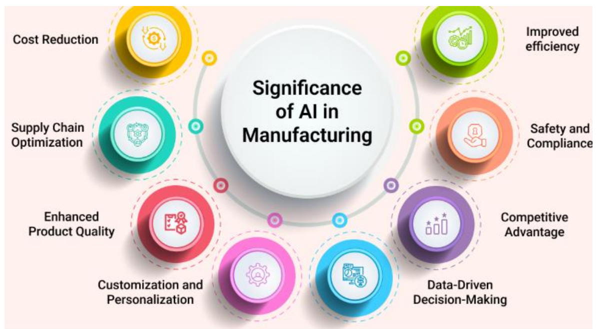

Fig 2: AI in Manufacturing Industry

2.1. AI in Production Processes The traditional production paradigm of large batch production does not offer flexibility towards satisfying the requirements of individual customers. Currently, the majority of products are custom-made, such as clothing, mobile phones, computers, automobiles, furniture, and appliances. In order to meet the market demands on customized products in a timely and cost-effective manner, a new generation of smart factories is expected to support new multi-variety and small-batch customized production modes compared with the mass production mode. High-value products will offer great prospects for both consumers and manufacturers due to the combined satisfaction of personalized needs and market advantages.

Artificial Intelligence (AI) is the centerpiece of the fourth industrial revolution and is revolutionizing the manufacture of media technologies. AI is being used for higher value-added manufacturing by accelerating the integration of manufacturing and information and communication technologies. The term AI becomes more popular in the manufacturing domain and has spread rapidly in terms such as AI manufacturing, intelligent manufacturing, manufacturing 4.0 and cognitive manufacturing. AI is about machines that are designed to do or act and think like human beings. AI technologies have the potential to empower machines to simulate human cognitive functions such as sensing, perceiving, learning, reasoning, judgment, and decision-making. A smart factory equipped with advanced AI systems can realize efficient cooperation among human beings, machines, and software systems along the entire supply chain. A host of unique AI technologies are transforming all aspects of manufacturing including product design, production process planning, material part preparation, scheduling and control, maintenance, recycling, and reverse support. Around the world, AI-based technologies are rapidly adopted in traditional manufacturing companies and have been identified as a technology frontier that leads to a competitive advantage for enterprises. The potential benefits for AI-based technologies include improved product quality, higher operational efficiency, lower maintenance costs, smarter supply chains, and lower environmental impacts.

2.2. Predictive Maintenance Using AI Revolutionizing the manufacturing environment is one of the most critical applications of Artificial Intelligence (AI) and Cloud technologies, and Industry 4.0 forms a bridge to create smart manufacturing of an efficient, flexible, and cost-effective environment with AI and the integration of communication with the internet. There are various services, devices, and environments in a manufacturing site. In most cases, these devices are not designed to be used among them. The system demands full visibility about the operating states of all these devices and processes in real-time to keep the whole operation efficient, optimize the use of resources, and obtain as much benefit in the production processes as possible. For this reason, AI-based predictive maintenance to schedule maintenance only when it is needed is desirable. This requires the advanced analysis of the data collected from applications to obtain the equipment to monitor with the right spatiotemporal resolution. Predictive maintenance is a variety of the most critical applications of AI in Industry 4.0 manufacturing and systems. A predictive maintenance policy design for structural airframe maintenance, utilizing an automated and cost-efficient methodology and the early cluster identification of sensor data in selective laser melting machine tools has been proposed within a predictive maintenance-oriented framework.

3. Cloud Computing in Automotive Supply Chains

Since the 1990s, the supply chain optimization in the automotive industry has become a crucial competitive advantage. With new terms like industry 4.0, Internet of Things (IoT) and the technological revolution of the automotive industry known as CASE (connected, autonomous, shared and electric), supply chain management has increased its importance. Cloud services in the supply chains allow the managers to have an overview of the end-to-end supply chain and can explore in detail each type of intermediary for all the different assessment cycle stages. One example of this can be found in the enterprise resource planning software, such as SAP ERP or Microsoft Dynamics 365. Such a tool can provide valuable insights about the current state of the entire supply chain and it is possible to better avoid the occurrence of stock-out situations or even better manage the delivery status. Some interesting KPIs that can be analyzed based on the extracted data from the ERP software are the fulfillment rate, order on time and inbound lead time.

The use of cloud services in a company is designed to make the processes more efficient. Cloud services allow creating a custom API for already developed or to be developed software. For example, if the same database is accessed by two different software used in a company, then it is important to avoid updating manually. Therefore, synchronization between both applications is required, and that can be done by creating a custom API. Besides these, there are also public API that are created in order to ease integration of third-party applications and can be API of the already used software. It is easy for the companies to use or create complex spreadsheets that can become endpoints. Consequently, the use of a tool that integrates with a spreadsheet is highly recommended. Automated processes in the company can be time-based. To ensure less potential errors in the data processed, it is recommended.

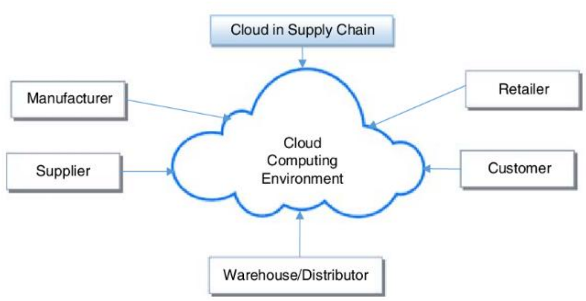

Fig 3: Cloud in supply chain networks environment

3.1. Overview of Cloud Technologies

Automotive manufacturing and distribution are currently in the process of significant change, including the adoption of intelligent smart supply chains, autonomous cars, and consumer preferences for subscription-based vehicle share services. The manufacturing and distribution environment is seeing a shift toward high path autonomy, easily reconfigurable pickup, and delivery logistics staffed by either robots or independent operators. The automobiles themselves are transforming into self-driving cars providing both passenger and parcel transportation, enabled by software stacks that can log and operate safely on user-defined commercial ride-sharing streets.

Determining the best provisioning of these goods and services under their given constraints, such as availability and spatial heterogeneity is a challenge. Unveiled here, is a cloud-based computational framework for automating the task of selecting multiple restaurant locations, automobile fleet bases, mini-markets, car dealerships, and repair centers to optimize their distribution and manufacturing utility from compound order arrival data.

The primary contribution involves four hand-crafted seed points and four personalized constraints. An explainable reinforcement learning strategy intelligently navigates the solution space employing a static-charging commodity strategy for initial convergence before incorporating redistricting, ride-pooling and small car HH-repair-behind market venues. The final policy is also able to redirect itself in the event of adverse regenerative media coverage, or during emergencies based on operator feedback.

3.2. Benefits of Cloud Computing for Manufacturers By making use of cloud storage technologies, automotive manufacturers can benefit in several ways in terms of flexibility, avoiding capital costs, effectiveness and efficiency among other things. An emerging trend in automotive manufacturing focuses on the realization of smart supply chains. In the context of building and operating smart supply chains for automotive manufacturing and distribution, the combination of the latest advances in artificial intelligence (AI) and cloud computing technologies will play an evermore vital role. A cloud computing environment suitable for smart supply chains is introduced together with the AI services it offers automotive manufacturers. It illustrates how AI and cloud computing services as an example can be brought into smart supply chains of automotive manufacturing based on production and shipment data. A comprehensive case study incorporating short-term production data from the automotive assembly shop and shipment data between a supplier and an assembly shop documenting lead times is provided. How the data can first be properly cleaned and processed before feeding into the cloud is depicted. The central cloud-based predictive models developed on AI services are explained, performance evaluated in terms of forecast accuracy, and deployment challenges to real plant operations are discussed. The main conclusions include that with cloud computing, various benefits for AI applications can be realized, such as scalability, high-performance computing, and the cost and energy efficiency revolving around Pay-As-You-Go pricing.

Equ 2: Inventory Optimization (AI-Based Decision Making)

$$I_t = \left(\frac{D_t}{S_t}\right) \times L_t$$

Where:

- I_t = Inventory level at time t
- D_t = Demand forecast at time t
- S_t = Supply rate (how much inventory can be produced
- L_t = Lead time for manufacturing or delivery

4. Integration of AI and Cloud Computing

Gone are the days where mass production on a world scale meant shipping from afar. True, the amount of international trade is still increasing. But rearming threats of trade wars are forcing diversification of production locations. Cars still made in Germany are made by robots and the efficiency is nearly uniformly human unfathomable. At the same time, there is the myth that automotive manufacturers are overregulated rainmakers. Such generalizations only run too short when Toyota's production model surpasses 100,000 yearly units in the US employs a fully human only workforce reaching model change frequency comparable to German manufacturers. Fully automatic processes are too rigid for small-scale models with high demand for customizability, potentially conflicting regulations and random product demands, such as cars, clothes and home electronics. However, expensive retooling is required for manual task automation, making required product quantity minimas a major investment risk. This is one of the reasons production in certain regions is being investigated: there are two years to check how certain models sell. Even though full automation of assembly lines is both irrational and impossible, a lot of menial work can be streamlined or automatized at low cost.

Publicly available industry data are extensively being restricted across all types. Publication of case studies is out of the question as practical problems and solutions are sensitive trade knowledge, case studies even more so. This is somewhat inconvenient as smart component suppliers are apt to stick to trade secrets and high confidence, there is no easy access to direct system information. However, it is approved for detail-less broad coverage of both smart applications and systems as a whole, discussing principles and shortcomings rather than specifics. At least this way a picture can be given on what is and will be on the market, what is happening behind the scenes of logistic systems, even what is on postponed release, on already national use or still testing. Communality of what industries in general consider supersecret trade knowledge and what is regarded as public demoscene can also be pointed out. The possibility to acquire detailed, specific information aside, the distribution of produced cases from case studies is questionable anyway being rather unrepresentative regional demonstrations.

Fig 4: Artificial Intelligence in Cloud Computing

4.1. Smart Manufacturing Systems 1. This special issue, involving several leading Chinese experts on smart manufacturing and five research papers, covers topics on customized smart factories, edge cloud computing in cloud manufacturing, cyber-physical mechanical systems, intelligent predictive maintenance, and Machine Condition Monitoring (MCM) technologies. The traditional production paradigm does not allow for the flexibility to meet individual customer requirements. A new generation of smart factories is expected to be established to support multi-variety and small-batch customized production modes. In addition, artificial intelligence is accelerating the deeper application of information and manufacturing communication technologies, promoting higher value-added manufacturing . The self-conscious, self-optimizing, self-configuring, and intelligent decision-making advanced manufacturing automation system is a critical component of smart production systems. A competitive intelligent manufacturing system should be sufficiently agile to adapt to rapid technological changes. It will allow manufacturing companies to operate resources under stressful conditions and can achieve a balance between customer-centered economic and technical goals.

Smart manufacturing is characterized by a free combination of devices such as sensors, operation, control, and production systems. These devices are connected through the network, transferring digital information to achieve smart operation and innovation of production processes. Industry 4.0 is the forerunner of smart manufacturing, emphasizing the iteration of promising technological advancements in Cyber-Physical Systems (CPS). Interoperability, transparency, and decentralization are the essential concepts involved. Smart manufacturing is seen as an advancement over industry 4.0, with the cloud-computing services of multi-item firms and user-managed mini-cloud systems playing a pervasive role. In terms of scaling and pursuing economies of operation, different cloud computing solutions have been introduced to tackle a wide variety of challenges, such as ease of access, efficient resource usage, and certain computing requirements. With the rapid rise of trends to instruct cloud computing to end, degrade the computing tasks and render the computing process closer to the data (i.e., Edge Computing), more attention is paid to utilizing cloud computing in conjunction with Edge Computing in cloud manufacturing processes.

4.2. Data-Driven Decision Making The fourth industrial revolution is revolutionizing the automotive manufacturing industry. This transformation involves leveraging a variety of disruptive technologies from different verticals. Among these, two of the most critical components are artificial intelligence (AI) and cloud computing. The combination of AI with the cloud forms the backbone for smart manufacturing facilities. AI is used extensively in various facets of automotive manufacturing and distribution such as autonomous robots, automated equipment and predictive product quality. With cloud-enabled IoT solutions, decision making at various stages of production with real-time data insights becomes feasible.

At the heart of AI enabled industry 4.0 is data-driven decision-making. The real-time decision-making in automotive robots, cranes and transport vehicles operations, which is crucial for the automation of transporting and assembling parts during production in the automotive facility. While there still exists manual operation as a part of the workflow in these processes, the intention is to enforce the automation wherever possible. In line with the ongoing trends, manual vehicles needed to be replaced by autonomous ones. This aims to minimize human involvement in dangerous or harsh working environments. As part of the transition to the autonomous setup, vehicles and arms are ubiquitously assembled with cameras and sensors to collect operational data. A challenge arises on how to extract potential facts to make decisions from this prodigious data that is being collected at an ever-growing rate. There is a need to employ analysis pipelines that sit close to the data sources. A lot of results are simply statistical about the data; e.g. positions or rotation velocity ranges of cameras. However, these statistical insights are crucial for the decision-making of certain equipment. Highly non-trivial domain-specific methods are needed to extract valuable insights from the operational data. The Aterm analytical pipeline is proposed to automatically infer fixed statistical insights from collected raw operational data, and it is intended to be utilized across different faculties at the company.

5. Case Studies of AI and Cloud Implementation

Introduction. Network operators have been added to both automotive manufacturing and distribution systems to cope with the growing complexity revolving around them. Artificial intelligence (AI) promises to optimize costs in networked production by forecasting demand or scheduling predictive operations, among other process improvements. In the logistics sector as well, a growing share of companies handling e-commerce goods leads to a growing logistics volume. Given the ongoing implementation of computer systems, cloud computing seems to be a natural way to consort with these challenges; supplier companies already recommend the positioning of important data on the cloud. This work delves into the interplay of AI with cloud solutions in building smart supply chains for manufacturing and distribution by way of AI-based support for supplier evaluation. Therefore, the key research question posed is: What is the status of such smart supply chains and how is cloud computing used as a backbone?. AI and Cloud Computing in a Supply Chain Context. Economic operators strive for satisfaction through the procurement of goods and services from suppliers. This relationship seems simple, but, in reality, is a highly complex, continuous process of counterparties evaluating potential business partners, which is referred to in the broader context as supply chains. Procurement chatbots are already being used for the automation of these processes to some extent; still, certain suppliers have never been evaluated, even those regarded as completely untrustful or economically dangerous. According to supplier companies, the initial regulatory evaluation of every new business partner must still be human-generated during a routine simplicity check. In addition, numerous commercial systems provide only fixed, outdated or fraudulent reasons for designating a particular business partner as too risky for cooperation, while also suggesting partial unawareness of the regulatory environment in a procurement sphere. Most probably, this is reasonable due to the complexity of the rules in a procurement law, and in most parts, because these are national rules.

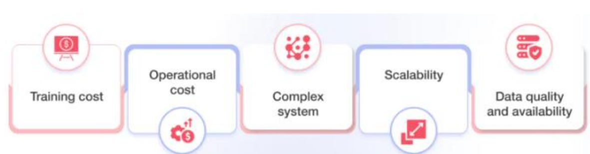

Fig 5: AI in Supply Chain Cases

5.1. Leading Automotive Companies

First, leading automotive companies are analyzed on how they approach the application of new manufacturing processes and tools in production and supply chain. The scenario technique is used to illustrate global value chains and respective strategies for the five biggest automotive markets in the world. USA, China, Japan, India, and Germany are considered in the scope of this study. Well-established, balanced, and typical portfolio of vehicle sizes is produced by car companies. On the manufacturing side, they well-applied manufacturing technologies and automation grades like electronics, robotics, and laser processing. The dependence on regional and global suppliers is relatively low so that carmakers produce the majority of the components in-house. A relatively strong focus on R&D and innovation in product and process development is found as well as an early adoption of new manufacturing processes like extrusion and stamping of aluminum for body parts. Additionally, simulation software for the entire product and process development chain and advanced methods like tagging technology to identify parts in the production process are used.

The top five automotive producers are General Motors, Toyota, Ford, Volkswagen, and Honda. The respective market developments and penetration of electric drivetrains are also analyzed. It is found that the ongoing vertical integration of the global vehicle assembly operations is increasing in complexity and needs careful handling as switching from one electric drivetrain to another once the internal combustion engine vehicles are phased out in 2020 or later. As a result of the scenario process, manufacturing and assembly operations will have to be switched accordingly and this can only be done once, as the supplier base and infrastructure for ICE components and EV components are different.

5.2. Startups Innovating in the Space Silicon Valley is known for its AI-first mentality. In fact, of over 5,000 AI companies globally, Silicon Valley has given rise to 1,100 of them with the US leading the way in AI business formation. By way of comparison, the US has almost four times the amount of AI business formations in AI over the UK with 850 registered companies. Europe's technology scene is vibrantly diverse. The European Innovation Scoreboard suggests that five types of EU countries emerge from this diversity: Denmark, Estonia, Cyprus, Luxembourg and The Netherlands are Innovation Leaders; Finland, Sweden, Belgium, the United Kingdom, Austria, France, Ireland, Slovenia, and Germany are Strong Innovators; Portugal, Poland, Czech Republic, Malta, Spain and Italy Moderate innovators; while Bulgaria, Latvia, Croatia, Greece, Hungary, Lithuania, Romania and Slovakia are shown to be Modest innovators. Together with Switzerland, Norway and Iceland, Europe made up the EEA, 232 out of 363 areas, showing a fair spread of innovation capabilities.

Equ 3: Cloud-Based Distributed Manufacturing Optimization

$$C_t = \min_i \left(\sum_{j=1}^{m} (C_{ij} \cdot x_{ij}) \right)$$

Where:

- C_t = Total cost of manufacturing and distribution at time t
- C_{ij} = Cost of producing product j at facility i
- x_{ij} = Quantity of product j produced at facility i
- m = Number of products
- i = Facility index

6. Future Trends and Conclusion

As technology has transformed our lives, Connectivity, Artificial Intelligence (AI) and Cloud Computing have transformed the automotive sector. This outlines a vision of future opportunities where the AI and Cloud Computing-enabled autonomous vehicle revolution drives a dramatic transformation, relegating private cars to a smaller role while large fleets of vehicles enable the development of efficient and almost entirely automated public transport systems in city centers. The recent deployment of shared Smart Cars and the advances in telecommunication networks and data processing are a prelude for the future roll-out of an intelligent and ubiquitous transport network. Cars will become nodes of this network, leading to new business models that will impact the current automotive sector distribution and manufacturing model. AI will enable new services in the market, such as smart supply chains or urban logistic optimization services, generating significant revenue streams.

The automotive industry is undergoing a fundamental technological transformation. The way manufacturers produce, the way customers consume, and the technologies embedded into vehicles are changing. There is an evolution of manufacturing towards smart manufacturing, based on principles like the 'Industrial Internet of Things' and other improvements. Moreover, the nature of consumption is evolving as well. Regulatory changes and driver convenience are shifting the market towards more environmentally friendly and safe vehicles, including electric, autonomous, or plug-in hybrid vehicles. Additionally, it is also expected that the ride-sharing model gets stronger, especially in bigger cities, curbing the exponential growth on car sales of recent years.

This expected drop in car sales could challenge both the current distribution and manufacturing model of the automotive sector, with a direct impact on the road freight industry that transports vehicles. To tackle this challenge, an envisaged scenario where AI and Cloud Computing are assumed to be the driving technology that has changed everything. On the one hand, manufacturing tends to have high individualization and therefore low assembly line usage. On the other hand, the sale of vehicles directly from the manufacturer or big distribution hubs has increased. Those hubs do not need to be in any way linked to a specific place as the vehicles are transported in an efficient way.

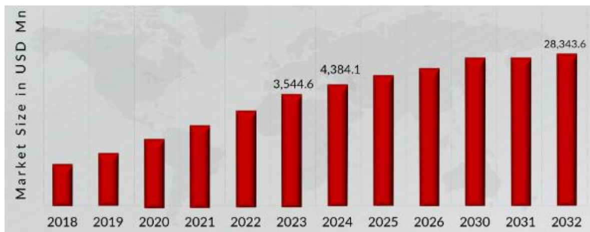

Fig : AI in manufacturing Market 2024

6.1. Emerging Technologies The following report presents future research on the development and prospects of automotive manufacturing and distribution in the light of accelerating AI and cloud computing powered development of smart supply chains. At the current time, AI projects in manufacturing usually focus on quality detection and process optimization. However, in the future many more aspects of manufacturing are likely to become ‘smart’, including product ideation, shop-floor production processes, warehousing, ERP, and the establishment and maintenance of relationships with suppliers and distributors. Therefore there is a move towards a general world of interconnected smart things from design to disposal.

Procurement is the process by which industrial retailers buy products and services. A significant part of all shopping revenue is determined here. To save costs, modern production systems often deliver products just-in-time, which helps. In modern production systems, data from suppliers and the customer must be relayed up and down the supply chain, including sales forecasts and points of demand. Typical desired outcomes are low price, high quality, timeliness, a wider variety of products on offer and occasionally innovations ex ante.

The responsibility of the art director for commercial innovation is to orchestrate a process of creating industry and developing competence-related supplier relations, that fulfills the client’s performance and logistical requirements. This involves maintaining a detailed and on-going bi- or multi-lateral relationship between the client and approximately one thousand traditional suppliers of goods, services and distribution. Usually, the products the client requires are components and materials, but can also include specialist materials such as fabrics, plastics or metalwork, mechanical or electronic components and occasionally finished products. The complex design development process includes requirements such as definition of a commercial strategy, selection of potential design themes, definition of a design brief and creative direction, agreement of forward commercial strategy and timetable, consultancy with suppliers.

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