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Next-Generation Computing Technology for Electric Vehicle Manufacturing – Concept, Challenges and Future Research

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Abstract

The electric vehicle (EV) manufacturing industry rapidly progresses from Industry 4.0 to Industry 5.0, next-generation computing technologies are emerging as disruptive enablers. This paper explores about the advanced computing paradigms to improve efficiency, robustness and adaptation across EV manufacturing ecosystems in the revolved vehicle industry in order to satisfy the increasing needs of intelligent automation, real-time decision-making and sustainable production. Through the integration of industrial case studies, literature reviews and rigorous technology mapping, the paper work validates the potential of these technologies to optimize resource utilization, speed up computer operations and overcome complications to extensive adoption. The results highlight the significance of strong frameworks to make balance between innovation and sustainability. Conclusion section is highlighting the convergence of cutting edge technology to propel the progress of autonomous, secure and human-centered electric vehicle production, thereby prompting the way of sustainability and industrial transformation.

Keywords: smart manufacturing, intelligent automation, human-centric automation, next-generation computing technologies.

1 Introduction

The quick growth of Industry 4.0 and its subsequent transition into Industry 5.0 is principally accountable for the innovative change in the industrial revolution. These industrial revolutions brought sophisticated digital technologies, intelligent systems and networking that completely changed the manufacturing and automation industries. In divergence to Industry 4.0, which prioritized automation, data interchange, and cyber-physical systems, the Industry 5.0 places more weight on human-machine collaboration, resilience and advanced technology industrial sustainability. The capability of industries to process huge volume of data, guarantee real-time decision-making, and create sustainable production environments that

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is made possible by next-generation computing technologies [1, 10].

A vast range of technical paradigms, including artificial intelligence (AI), machine learning (ML), blockchain, Internet of Things (IoT), cloud-edge integration and quantum computing are included in next-generation computing. When combined proper technologies with industrial environment, the system provides a high levels of computational power, speed and adaptability. This is allowing industrial system transition from traditional automation to intelligent automation. They are important not only for reshuffling processes but also for cultivating a high product quality, decreasing downtime and energy-efficient manufacturing techniques [3, 8].

Notwithstanding progresses in technology, sectors face difficulties such high competitiveness in the market, unstable supply chains, the need for personalization and the pressing need to meet sustainability targets. Because of their limitations in terms of handling speed, scalability, and adaptability, traditional computing systems sometimes fall short in handling these complexities. In order to generate resilient, adjustable, and future-proof ecosystems that can effectively handle changeableness and moving global trends, manufacturers must grip next-generation computing technology.

This research aims to explore the cutting-edge computer technologies and it's role to transform the automation and manufacturing industries by deciding current constraints and drive towards new directions. This includes the use of blockchain in supply chains, AI and ML enable real-time analysis [5]. The implementation of quantum and edge computing for unparalleled computational power. Additionally, the study explores about various advanced technologies relate to sustainability objectives, highlighting their involvement to waste reduction, resource efficiency and green manufacturing.

Analyzing how next-generation computing technologies add to refining resilience, tractability and productivity in smart manufacturing systems are the main goal of this research. Through the use of a systematic review methodology that integrates technology mapping, critical literature surveys and industry case studies, the paper provides a thorough understanding of the connected opportunities and challenges. Another key objective is to draw attention on these technologies support ethical and human-centered industrial practices and are consistent with the principles of Industry 5.0.

A multi-methodological style that combines evidence from industry case studies with theoretical exploration is used to undertake these goals. The current uses and future directions of next-generation computing tools are resulted by technology mapping and real-world adoption trends, hurdles and success stories are highlighted through case study. By casing a range of scholarly and professional viewpoints, a complete literature review supports in the validation of findings. This methodical tactic guarantees that the results are both practically related to industry stakeholders and rigorously scientific.

The results derived from this systematic survey propose that next-generation computing significantly accelerate computational processes, supports real-time and data-driven decision-making. It addresses several operational inefficiencies in industrial adoption. However, the paper also identifies critical challenges, such as workforce skill gaps, interoperability concerns and high implementation costs. These outcomes highlight the need for robust frameworks, cybersecurity measures and continuous employee upskilling to ensure the sustainable and integration of emerging computing technologies.

In summary, this paper explains how the next industrial revolution is merging of AI, IoT, blockchain, edge, and quantum computing. In addition to increasing productivity and efficiency, these technologies accelerate self-sufficient, environmentally friendly and human-centered production processes. Next-generation computing integration provides resourceful solutions to create resistant and responsible industrial ecosystems as industries move forwards to Industry 5.0. In order to facilitate technical innovation in line with social, economic, and environmental sustainability, the future scope suggests scalable adoption models with industry alliances and policy-driven frameworks.

2 Foundations of Next-Generation Computing

The requisite to handle multifaceted industrial problems with scalability, speed, and intelligence has powered the shift from traditional computing to next-generation architypes. The dispensation power and potential constraints of traditional centralized computing models have been gradually outdated by intelligent and disseminated systems that simplify real-time analytics, adaptive learning, and operational sustainability. As an example, in the past, batch data processing was a major module of inheritance systems used in the automotive industry for quality inspections, which is commonly delayed insights. Zero-defect manufacturing is now assured by next-generation computing models that enable instantaneous problem analysis and predictive by using integrated AI and IoT platforms [2, 6].

By proposing scalable storage, on-demand resources and AI-driven analysis without demanding substantial set-up investments, cloud computing has reformed industrial operations. Siemens' MindSphere, an IoT operating system that runs on the cloud and enables manufacturers to link various industrial gadgets like: sensors and other devices. It allows systems to gain useful insights from the technological application supplychain system. Businesses may decrease downtime and optimize production planning by implementing prognostic analytics on the cloud. Thus, cloud computing marks it easier for small and medium-sized businesses to access refined computing capacity, nurturing revolution while controlling expenditures.

Edge computing and Fog computing allow for decision-making faster to the data source, sinking expectancy and bandwidth consumption, while cloud computing simplifies large-scale analytics. One example is the Predix platform from General Electric, that uses edge computing to incessantly monitor the health of turbines. By treating data at the edge, GE speeds up variance detection response times and circumvents equipment failures that could result in exclusive downtime. Edge-enabled robotics in smart factories assurance the real-time assembly line coordination, attaining agility and meticulousness in industrial sceneries where linking delays with distant data centers are unaffordable.

In order to solve simulation and optimization problems that are further than the scope of classical computing. The quantum computing [5]is preliminary to appear as a paradigm shift. Volkswagen, for instance, has shown possible practices in supply chain management and logistics by trialing with quantum computing to improve transportation flow and decline bottleneck.

In fields like materials science, automotive and aerospace that are essential refined simulations, high-performance computing (HPC) is still essential. For example, Boeing employs HPC to perform computational fluid dynamics (CFD) simulations, suggestively lowering the constraint for costly wind tunnel testing. The use of HPC for drug molecule simulations in pharmaceutical sectors are also greatly reduce the development cycles. With HPC, manufacturers may condense various costs and risks while increasing resourcefulness, testing numerous varieties through virtual mode and moving up towards the product design. Advanced manufacturing has been further compressed by HPC's to meet with AI and digital twins.

The smooth incorporation of the next-generation computer paradigms with existing manufacturing settings is necessary to their success. In order to create a single digital platform throughout the value chain, interoperability ensures that cloud, edge, HPC and new computing models interface with IoT platforms, ERP and MES. One example is Bosch Rexroth's Factory of the future, where open standards afford flexibility and configurability in the collaboration of systems, machines and computing platforms. Next-generation computing patterns are essential for Industry 5.0, because of this integration that enables manufacturers to quickly adjust to shifts in demand, supply interruptions and sustainability regulations.

3 Smart Manufacturing and Automation Landscape

The ground work of Industry 4.0 and the shift to Industry 5.0 is exemplified by smart factories, that combine cutting-edge digital technologies with modern production methods to progress productivity, rigidity, and sustainability. As a virtual representation of real assets, processes or systems, the digital twin plays a vital role as enabler in this ecosystem. Digital twins empower industries to trail enactment, lag behind faults and exploit production results aforementioned to making physical environment amendments by modeling undertakings in real-time. By subscription precise and data-driven insights, this digital-physical link progresses decision-making skills while also cutting expenses and downtime [4, 7].

Incorporation of sensors, the Internet of Things (IoT), and cyber-physical systems (CPS) arrangements the basis of smart system. IoT networks permit devices on altered assembly lines to interconnect with one another. In the assembly line the connected sensors record data in real time, such as temperature, vibration, or pressure. After that, CPS connects its computational models to the machinery, ensuring smooth harmonization between digital simulations and real-world activities. These technologies work together to create a highly smart and connected manufacturing system to respond adaptively and continuously improve.

Automation and process optimization in smart manufacturing are powered by artificial intelligence (AI) and machine learning (ML) in smart factories. In its electronics invention facilities, the company Siemens, for instance, use AI-driven analytics to identify process anomalies and make real-time alterations that diminish faults. By learning from huge production data, machine learning algorithms may expect machine failures by ensuring both financial and environmental gains.

Human-machine support is equally essential in Industry 5.0, as the importance moves from complete automation to a combination of machine intelligence and human innovation [11, 12]. BMW uses cobotic (collaborative robotic) assembly lines, for example, where humans focus on precise and creative jobs such as customizing and design enhancements while robots perform heavy as well as repetitive duties. By increasing worker safety, job satisfaction and product innovation, this corporation goes beyond efficiency to start an industrial setting that is more attentive on people.

4 Human-machine collaboration in Industry 5.0

In Industry 5.0, human-machine collaboration signifies a change from fully automated production lines to an intelligent, human-centered manufacturing paradigm in which humans and machines collaborate together. This entails fusing human ingenuity, adaptability, and problem-solving abilities with the accuracy, speed, and consistency of robots in the automotive sector. Industry 5.0 makes the manufacturing ecosystem more flexible, inventive, and sustainable by striking a balance between cutting-edge technologies like artificial intelligence (AI), the Internet of Things (IoT), and collaborative robots (cobots) and human intuition and craftsmanship, in contrast to Industry 4.0, which focused primarily on automation and efficiency [13, 14].

Cobots are necessary in today's auto manufacturers because they help employees with monotonous, substantially challenging and potentially unsafe activities. Cobots, for example, do precise component assembly and heavy lifting in BMW and Audi factories, while human employees essence on quality control, customisation and decision-making. This organization agreement that the human workforce remains to be necessary to production while lowering workplace harms and increasing overall productivity. Machines free up humans from tedious tasks so they can focus on higher-value work like state-of-the-art and resourceful design, which is central for automakers as consumer demand for customized automobile enlargements.

Through the capability to make data-driven decisions in real time, artificial intelligence and machine learning further progress human–machine teamwork. In Tesla's Gigafactories, for instance, AI-powered technologies trail production data, forestall any faults and modernize assembly line processes. With these outcomes, engineers can then modify designs, supervise supply chains or put sustainability plans into action. This collaboration increases productivity as well as resistance to holdups equipment failures or shortages of materials. Integrating augmented reality (AR) tools also allows workers to see sophisticated assembly processes, that facilitates more efficient and natural machine collaboration.

5 Smart Assembly Of Electric Vehicles Using Next-Generation Computing

Electric vehicles (EVs) are speedily switching conventional internal combustion engines (ICE) in the automotive industry now-a-days. With high precision, the integration of various advanced components (lightweight materials, power electronics, batteries, etc.), and sustainability are all essential for EV assembly. Old manufacturing techniques provides the production delay, more failure rates and inefficiencies also. EV manufacturing lines are now being transformed into smart assembly lines through next-generation computer technologies and the industry set ups are integrated with cloud computing, edge computing, digital twins, AI/ML, IoT, and quantum optimization as per requirements of the industry environment.

Next-generation computer bases are encompassed into the assembly plant of a major EV manufacturer (such as Tata Motors EV Division, Tesla, BYD, etc.) for the broad production of EV vehicles. The importance and applications of these technologies are briefly described below.

Digital Twin of Assembly Line: Applying the combined competences of cloud and edge computing, a real-time digital model of the entire electric vehicle (EV) assembly industries are created. This wide-ranging digital twin incessantly monitors vital parts like conveyor belts, robot arms, welding stations, battery pack installation and final assembly processes. Industrialists can obtain reflective insights into each stage of production through the dynamic virtual

Table 1. A random sample data from Smart EV Industry.

Predictive Maintenance Sensor	Anomaly Signal Vibration	Quality Score	Robot Adaptability Index	Supply Chain Delay	Green Energy Usage	3D Printing Defect Rate
72.48357077	0.646564877	99.54376942	0.931673431	2.180818013	72.14688308	2.593953109
69.30867849	0.47742237	96.62699235	0.759614704	1.677440123	47.46280236	3.515094794
73.23844269	0.50675282	99.09248412	0.701656635	2.180697803	75.70235994	1.818148012
77.61514928	0.357525181	98.42241026	0.944638429	2.769018283	61.57368968	4.858910414
68.82923313	0.445561728	93.96849968	0.912057203	1.98208698	72.29760621	4.812236475
68.82931522	0.511092259	98.82811353	0.91870215	2.782321828	75.843652	1.258911479
77.89606408	0.384900642	86.32738753	0.931381104	0.690127448	52.720139	2.486242529
73.83717365	0.537569802	87.93974294	0.722213396	2.410951252	44.40207698	1.504391549
67.65262807	0.439936131	85.67840933	0.807539719	2.043523534	49.1174065	1.424202472
72.71280022	0.470830625	89.87995496	0.734760718	1.850496325	57.08431155	0.184434737
67.68291154	0.439829339	90.83015935	0.958931028	2.045880388	72.72059064	3.04782167
67.67135123	0.685227818	89.07023548	0.886989438	1.006215543	74.42922333	2.513395116
71.20981136	0.498650278	97.43106264	0.799269407	1.890164056	40.27808522	0.257393756
60.43359878	0.394228907	90.3512999	0.719067505	2.178556286	60.4298921	1.393232321
61.37541084	0.582254491	89.21401765	0.793294697	2.738947022	56.69644013	4.54132943
67.18856235	0.377915635	93.14044125	0.797554997	1.740864891	48.88431242	1.197809453
64.9358444	0.52088636	87.11386337	0.918881854	1.595753199	44.79461469	0.72447436
71.57123666	0.304032988	97.03295471	0.891267241	1.749121478	53.50460686	2.447263801
65.45987962	0.367181395	86.11825966	0.966163823	2.457701059	77.71638816	4.928252271
62.93848149	0.519686124	99.80330405	0.841664478	2.164375555	52.92811728	1.210276358

model's smooth data incorporation and real-time description of the plant's actions. The system controls any bottlenecks and competences as soon as they appear by using predictive analytics on the gathered data. This allows for pro-active interpositions that significantly minimize downtime and simplify efficiency. This inspired method smooths undersized production cycles and higher quality criteria in the speedily exchanging EV manufacturing scenario in addition to humanizing operational efficiency.

AI/ML for Quality Control: AI and machine learning (ML) have reformed quality control by using IoT sensors and high-resolution cameras to sensibly scrutinize essential elements such as: welding seams, paint gloss, and battery pack configuration. The finding of micro-level cracks, misalignments and other defects that are repeatedly unnoticeable to the human eye is made thinkable by these refined imaging and sensing technologies that which gather wide-ranging data that is consequently observed by AI algorithms skilled on large imperfection datasets. In assessment to manual inspections, manufacturers have critically declined defect rates by automating this thorough and precise checkup procedure [15, 16]. This has amplified product reliability and steadfastness while speeding up quality declaration processes in the automobile production environment of automobile industry.

Edge Computing for Real-Time Decision Making: By using edge mainframes to understand data locally, edge computing empowers automated guided vehicles (AGVs) and robots on the gathering line to make picks in real time. Millisecond-level responses are made possible by this capability. For example, dynamic torque modifications during bolt assigning assurance correctness and quality and AGVs can be instantly switched when hindrances are predictable to avoid delays and crashes. Edge computing momentously progresses manufacturing processes' alertness and tractability by lowering expectancy and necessity on integrated cloud services. Faster workflow continuity, assembly rates and improved overall productivity are the effects of this in the smart manufacturing system.

Forward-thinking human-machine relationship in Industry 5.0, where cobots (collaborative robots) promotes human operators to progress productivity and safety, has been made potential by next-generation computer technology. These cobots help employees in the self-propelled industry with clear-cut operations that need for both agility and thoughtful supervision, such engaging windshields and stuffing battery packs. Workers may straightforwardly steer and succeed cobots in real time expending user-friendly augmented reality (AR) interfaces, simplifying continuous synchronization and diminishing the physical strain that comes with substantial or repeated jobs. In addition to dropping ergonomic exposures and workplace balances, this integration stimulates a harmless, more industrious production atmosphere where robotic exactness and human skill operate in tandem.

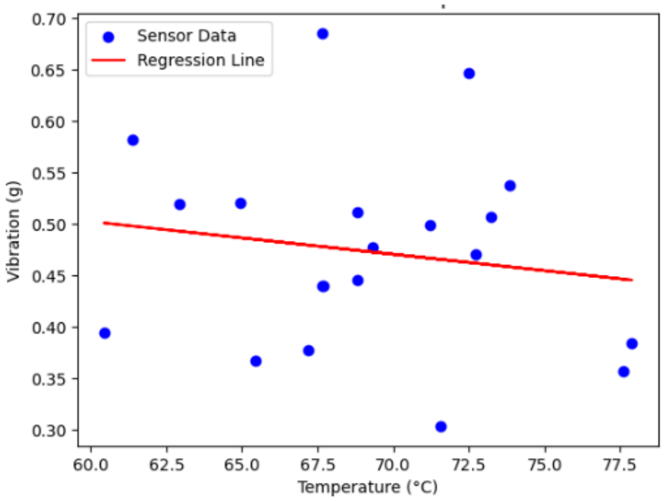

Figure 1. Predictive maintenance: Temperature vs Vibration.

As illustrated in Table 1, which provides a random sample of operational data from a smart EV assembly line, smart manufacturing depends on predictive maintenance and irregularity detection and track the condition of equipment to stop unexpected breakdowns. The scatterplot (Figure 1) shows the relationship between vibration and temperature rise demonstrations that higher vibration levels frequently specify possible component wear or worsening because they are correlated with higher temperatures. By recognizing this connection, maintenance crews can foresee problems before they become more serious. Anomalies that differ from typical operating patterns are also highlighted by the scatterplot's outliers, which point to components that could need quick examination or attention. Manufacturers can minimize production inefficiencies, increase equipment longevity, and minimize downtime by taking active measures to resolve these irregularities.

All along the production development, real-time quality checking and assurance is important to keeping high standards. According to the line plot (Figure 2) of quality scores, most of the production cycles continuously attain quality amenability levels above 90%, demonstrating a high degree of observance to quality principles. However, any notable deviations, like a descent below 88% quality acquiescence, will be perceived by the system. A programmed alert system is activated in the event of decline, allowing for fast process forms to resolve possible problems. This proactive strategy reduces faults and increases overall product consistency by ensuring that quality

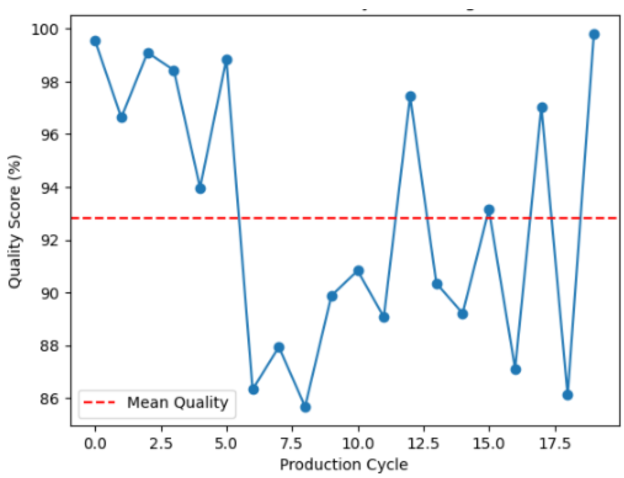

Figure 2. Real-time-time Quality Monitoring.

visits within equitable bounds.

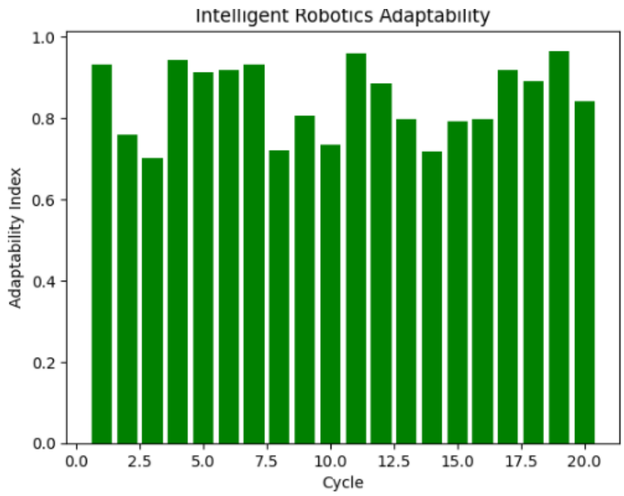

Figure 3. Intelligent Robotics Adaptability.

Adaptive automation and intelligent robotics are important for growing the tractability and effectiveness of electric vehicle (EV) assembly. The system's healthy capability to familiarize to a variety of responsibilities is validated by the bar chart (Figure 3) that shows the robot adaptableness index continuously above 0.75. The robotic systems' high adaptability index shows that they are both operative and flexible, permitting for smooth changeovers between various assembly tasks. Because of this, the production line can grip different needs and involvedness with little downtime, which ultimately enhancements output and assurances a more approachable manufacturing process.

Figure 4 provides the descending of undesirable effects of production processes on the smart manufacturing environment necessitates the use of green computing in sustainable manufacturing. The form in the use of renewable energy and indicates cycles with

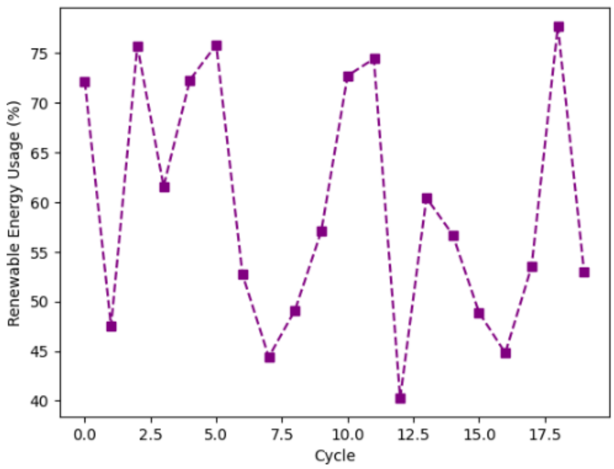

Figure 4. Sustainable manufacturing: Green Energy Usage.

40% to 80% green energy that indicates a strong enthusiasm to sustainability. By effectively integrating green computing techniques into manufacturing processes, this range positively diminishes need on non-renewable energy sources. By using renewable energy, the production process supports long-term environmental accountability and also supporting worldwide efforts to adopt cleaner and more sustainable industrial practices.

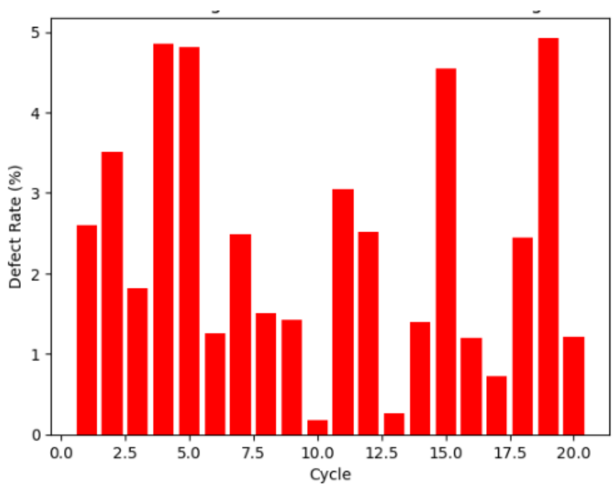

Figure 5. 3D printing Defect rates in EV Manufacturing.

Intelligent systems in combination with additive manufacturing (3D printing) significantly progress the sustainability and quality of EV part manufacture (Figure 5). A high degree of accuracy and steadiness in the complete goods is certain by the continually low defect rate of 3D-printed mechanisms, which stays around 3%. Intelligent checking systems that continuously monitor the printing process and quickly identify as well as resolve possible problems that are primarily responsible for low defect rate. These smart solutions minimize material waste and helps for the manufacturing of various components by lowering fault waste. This is not only increases manufacturing effectiveness but also promotes more justifiable production methods.

5.1 Supply chain optimization with advanced computing technology in EV manufacturing system

Advanced robotic arms, AGVs and collaborative robots simplify the Vehicle body assembly, battery integration and testing on an EV fabrication assembly line with high accuracy. At the same time, modular and flexible manufacturing concepts permit for flexibility in managing sophisticated battery and electronics integration. To confirm efficiency, less bottlenecks and safe human-robot collaboration, digital twins afford computer-generated models for simulation and optimization and flexible robotic systems with AGVs familiarize vigorously to production schedules.

A hybrid computing design empowers supply chain optimization in EV manufacturing, with edge computing safeguarding real-time processing of factory-floor sensor data for instantaneous feedback and machine control, and cloud computing handling large-scale data analytics. This data is examined by machine learning algorithms to forecast demand, optimize inventory and expect bottlenecks to assure continuous operations. Cloud-based ERP display place simplify whole connections between manufacturers, distributors as well as suppliers . These platforms integrate cutting edge technologies for accurate computation of IoT sensors in real-time monitoring, inventory management and AI-driven system for supply-demand balancing.

An integrated network of IoT sensors and smart devices attends the monitoring and control system used in EV manufacturing, promising real-time supply chain reflectivity. Production line equipment is straight controlled and monitored by SCADA and PLCs systems. While a Manufacturing Execution System (MES) keeps track of every component from raw materials to the final vehicle. To facilitate prompt decision-making, centralized AI dashboards and decision support systems assess KPIs including throughput, energy usage, and defect rates. Supporting electronics that facilitate smooth monitoring, quality control, and effective operations-such as smart sensors, barcode/RFID scanners, IoT wearables, and HMI panels-drives supply chain optimization from start to finish. A variety of electronic devices are included with the system to enable smooth operation. Every component has an RFID tag installed for accurate tracking, and real-time quality checks are carried out by smart cameras equipped with computer vision capabilities. Wearable technology is frequently used by employees to monitor their safety and give augmented reality overlays for challenging tasks. Operators and supervisors have immediate access to real-time data and control interfaces thanks to the facility's ruggedized tablets and touchscreen monitors.

This system makes all of its decisions automatically and based on data. The system makes action recommendations using prescriptive models and predictive analytics rather than human reports. AI systems, for instance, use sales data and market trends to dynamically modify manufacturing schedules and place supplier orders. By doing this, the process is changed from a reactive one, in which problems are fixed after they arise, to a proactive one, which avoids them by using clever forecasting and optimization.

Just-in-time (JIT) and lean manufacturing are the foundations of the operational concept, which is bolstered by production floor digital twins. Forecasting based on simulations assurances that material flow is in line with changing consumer demands and market demand. The computing techniques used include machine learning models for demand forecasting, anomaly detection and schedule optimization; cloud computing for large-scale data optimization; and edge computing for fast local decisions.

A highly effective, adaptable, and robust production ecosystem is the main output for the manufacturing industry based on the systems presented. Among the many advantages of combining cutting-edge computers, real-time monitoring, and data-driven decision-making is a sharp drop in operating expenses due to reduced waste and streamlined inventory. Additionally, the system's proactive approach-using predictive analytics to avert problems-improves product quality significantly and speeds up time to market. In the end, this technology framework gives EV manufacturers a major competitive edge in a sector that is changing quickly by enabling them to quickly adjust to shifting market demands and supply chain interruptions.

5.2 Technical challenges and integration issues with legacy systems

Managing the enormous amount and speed of data produced by IoT sensors, RFID systems, MES, and SCADA platforms is one of the main technological obstacles to optimizing EV manufacturing supply chains. Cloud and edge computing infrastructures must seamlessly coordinate to ensure real-time analytics with low latency, which can be challenging when network capacity is constrained or data security issues surface. As more devices become connected, cybersecurity threats also increase dramatically, revealing weaknesses in machine control and data flow. Furthermore, high-quality datasets are necessary for training machine learning models for precise demand forecasting and predictive maintenance, but they may not always be accessible because suppliers and industrial facilities have different data standards.

The implementation of modern computing technologies in EV manufacturing is made more difficult by problems with integration with existing systems. A lot of conventional factories continue to use antiquated PLCs, ERP systems, and manual processes that aren't naturally compatible with cloud-based platforms, AI-driven dashboards, or the Internet of Things. Custom APIs, retrofitting, and expensive middleware are frequently needed to achieve interoperability between old and new systems. Additionally, workers used to traditional systems can find it difficult to adjust to digital twins, MES, or AI-based decision assistance, which could lead to resistance to change [17, 18].

5.3 Data governance, privacy and interoperability concerns

Data governance, privacy, and interoperability issues are crucial to EV manufacturing supply chain optimization, in addition to technical and integration difficulties. The constant exchange of sensitive production and supplier data between IoT sensors, MES, SCADA, and cloud-based ERP platforms necessitates data ownership, regulatory compliance, and secure access control. When supplier or customer data is transferred over international networks, privacy concerns surface, necessitating stringent adherence to regulations such as GDPR or sector-specific requirements. Because older systems, contemporary AI-driven platforms, and various vendor technologies frequently employ incompatible data formats and protocols, creating silos and inefficiencies, interoperability issues arise. In EV manufacturing, the full potential of hybrid computing, predictive analytics, and real-time monitoring cannot be achieved without robust governance frameworks and standardized integration processes.

5.4 Infrastructure and workforce skill gap

The optimization of the supply chain for EV manufacturing also faces difficulties related to infrastructure, labor skill shortages, and pricing. Many manufacturers may find it difficult to implement IoT sensors, RFID systems, digital twins, cloud platforms, and AI-driven decision support since they necessitate large capital expenditures for hardware, software, and cybersecurity. Maintaining dependable high-speed connectivity, edge computing nodes, and secure cloud integration are essential for infrastructure, but many facilities, particularly those replacing legacy systems, suffer with antiquated networks and inadequate IT assistance. The workforce skill gap is a significant obstacle as well, since workers who were trained on traditional assembly lines might not be proficient in robotics, complex analytics, or AI-enabled monitoring systems. Continuous training, reskilling, and change management are necessary to close this gap and properly utilize next-generation computers in EV supply chain optimization.

5.5 Regulatory and ethical aspects

Integrating modern computing into supply chains for EV manufacturing has equally important ethical and regulatory implications. Algorithmic bias, transparency, and accountability concerns surface when production is guided by AI-driven decision-making and predictive analytics, particularly when workforce scheduling or supplier selection is automated. Concerns about ethics also apply to the appropriate use of wearables with Internet of Things capabilities and HMI panels for worker monitoring, which, if improperly handled, could violate workers' privacy and autonomy. To ensure that digital systems fulfill certification and audit criteria, manufacturers must adhere to industry-specific safety rules, data protection legislation, and environmental norms. Global vendors that share data across borders also face difficult compliance issues since different jurisdictions have distinct legal systems. In order to foster confidence, guarantee equity, and support the long-term adoption of cutting-edge supply chain technology in EV production, it is imperative that these ethical and legal issues be addressed.

6 Conclusion

By bridging the gap between automation, intelligence and sustainability, the convergence of state-of-the-art and next-generation computing technologies is composed to transform the future of electric vehicle manufacturing. EV ecosystems are skilled of reaching earlier unprecedented levels of robustness, efficiency and adaptation by utilising cutting-edge technological paradigms. The results endorse that these innovative enablers skill a human-centered strategy in addition to speeding up autonomous and secure manufacturing. In the end, Industry 5.0 will be built on the smooth integration of these technologies, guiding EV manufacturing into a revolutionary period of innovation, sustainability and industrial excellence.

The combination of AI, IoT, blockchain, and quantum computing is anticipated to enable previously unheard-of levels of transparency, security, and computational efficiency in EV manufacturing supply chain optimization, according to research orientations and future possibilities. To reduce downtime and improve workflows, emerging technologies like autonomous and self-healing manufacturing systems will make use of adaptive robotics and predictive maintenance. It is anticipated that generative AI and large-scale models would revolutionize automation and design by producing intelligent control methods, process plans, and optimal prototypes quickly. Safety, innovation, and worker well-being will be given top priority as Industry 5.0 transitions to human-centric smart manufacturing, which will prioritize human-machine collaboration. In conclusion, strong regulation and standardization frameworks will be necessary to ensure interoperability, unify technology, and direct the ethical and sustainable use of sophisticated computing solutions in future EV production ecosystems.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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