Received: 5 January 2025 | Revised: 26 March 2025 | Accepted: 14 April 2025 | Published online: 27 May 2025

REVIEW

Journal of Computational and Cognitive Engineering
2025, Vol. 00(00) 1–16
DOI: 10.47852/bonviewJCCE52025158

Development of Customer-Focused Automated Systems for Transformer Design and Manufacturing: A Comprehensive Review

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Abstract: This study examined significant progress in intelligent manufacturing (IM) technologies in collaboration with a prominent producer of electric power transformers. The study particularly focused on the role of intelligent supply chain management (SCM) technologies in optimizing the manufacturing process. The intelligent SCM modules incorporated in the intelligent machine demonstration utilize an ontology to establish linguistic linkages across key aspects such as intelligent supplier selection, component ordering, and intelligent product quality prediction. These modules are essential in synchronizing orders with analytic hierarchy process analysis and multi-objective integer optimization, thereby improving both the efficiency and quality of the manufacturing process. One of the key challenges faced by decision-makers is identifying multiple feasible solutions while adhering to stringent operational constraints. To provide further insights, this study also includes a comprehensive literature review of the transformer manufacturing process, covering advanced technologies, intelligent SCM, optimization techniques in transformer design, and various IM methods. This review critically examines the advantages and limitations of existing solutions, identifying areas where further advancements are needed. By integrating intelligent supply chain technologies with manufacturing processes, this study highlights potential improvements that can enhance operational performance and decision-making in transformer production.

Keywords: intelligent manufacturing, optimization, power transformers, supply chain management techniques

1. Introduction

Modern industrial systems utilize the Internet of Things (IoT), cloud computing, and big data analytics to apply artificial intelligence (AI) techniques that facilitate smart decision-making and adjust to changing market demands [1, 2]. Many companies are improving their supply chain operations and processes to better decision-making in inventory management, production scheduling, predicting machine failures, preventing equipment breakdowns, and ensuring product quality [3]. Research is actively underway in smart manufacturing, focusing on prediction-driven product quality control and optimization. This work uses advanced predictive modeling techniques grounded in data, mainly when complex end-product characteristics are crucial and constantly changing. Predictive models are created and assessed using paired data whenever possible to quantify the critical component features that influence the final quality attributes. Predicting product quality accurately is essential for enhancing manufacturing processes and operational factors [4]. The Industry 4.0 effort is prepared to impact supply chains, strengthen the efficiency of workers and machines, boost communication, optimize data management, and raise standards among environmental and market stakeholders [5]. Entities and people are using the advantages of sophisticated technology, digital transformation, and cloud-based solutions. Market dynamics compel corporations to adapt to variable labor markets, varied product demands, and increasing material costs. The fourth industrial revolution integrates physical and digital elements to optimize processes, manage data, and automate functions to minimize costs, enhance quality, and boost efficiency and productivity [6].

Advanced manufacturing systems are designed to meet specific requirements for automation control, facility configuration, and production capacity. Information management design comprises three distinct levels: workshop logistics and production, field control networks, sensor configurations, and manufacturing execution systems (MES) [7, 8]; dynamic operations, concerning the movement of equipment and work-in-process (WIP) [9]; and static physical configuration, encompassing production line layout and equipment planning. Transformations are driven by escalating rivalry within the industry to optimize production and delivery schedules, reduce manufacturing expenses, and augment operational efficiency. These modifications are implemented to cater to the varied requirements of customers seeking more personalized, tailored, and smaller quantities of items [10].

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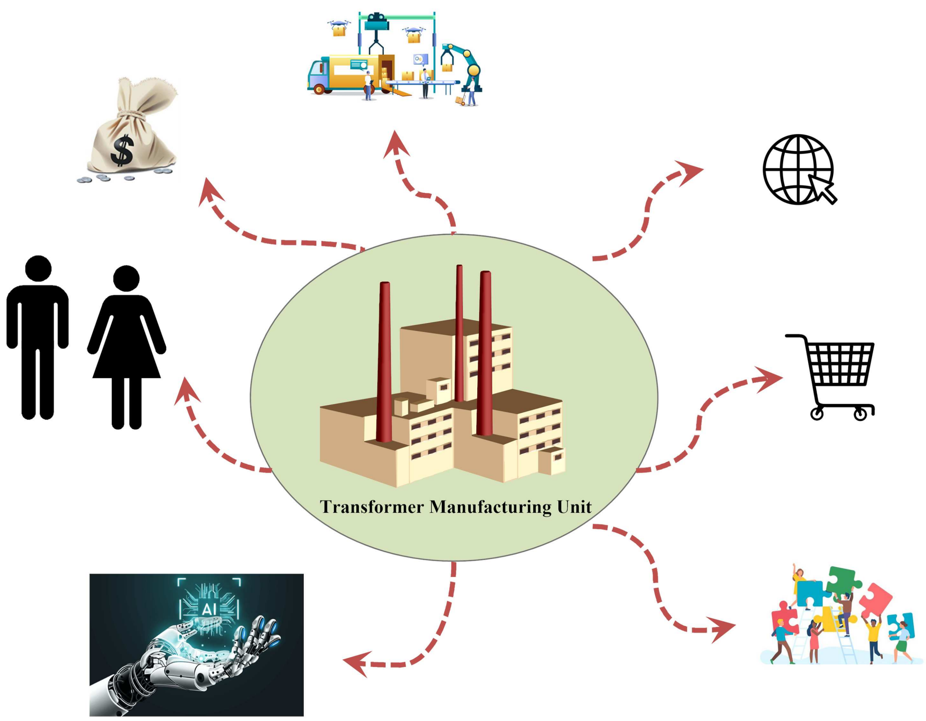
To maintain global competitiveness, organizations must prioritize robust manufacturing quality to consistently provide high-quality final goods, particularly for intricate items requiring substantial customization [11]. Overseeing intricate production processes in conventional manufacturing systems presents difficulties due to supply chain deficiencies, restricted data sets, and inadequate data digitization [12]. Numerous companies and institutions have transitioned from traditional paper-based operations to integrated information systems to tackle the issues they encounter. Integrating IoT and cloud computing facilitates the rapid collection and organization of in-process data inside production systems while concurrently assimilating information from an expanding network of suppliers [13]. This capability enhances the forecasting of final product attributes, significantly influencing their functioning, structural integrity, and longevity [14]. Figure 1 shows the transformer manufacturing unit with supply chain management (SCM). It is essential for intelligent manufacturing (IM) firms to promptly implement a traceable process and a dynamic control system that incorporates intelligent quality decision support [15]. This research is undertaken in collaboration with a leading power transformer producer that caters to a worldwide clientele with varied requirements [16]. Industrial power transformers are intricate, expensive, and engineered for specific applications. To thrive in the global market, the organization must enhance its digital connection, facilitate information exchange across the supply chain, and use intelligent decision-making in production, including predicting final product quality [17]. The firm is executing a digital transformation plan aligned with the tenets of Industry 4.0. This approach integrates sophisticated business processes with cutting-edge methodologies and digital technology to generate value for intelligent businesses, particularly within smart manufacturing value chains. Digitizing industrial operations and associated methods and making educated management choices, such as anticipating end-product quality in a supply chain, may enhance productivity, maximize resource use, minimize waste, and increase profitability [18]. Digital transformation may enhance creative communities, streamline industrial processes, and swiftly address market demands [19]. This research will use material data to forecast the product's attributes, notably focusing on power transformer iron core losses. Organizations tested samples from each batch to verify compliance with client expectations [20]. The corporation incurred significant waste in labor and raw materials when completed items failed to fulfill customer quality criteria. Manufacturers and their supply chain collaborators use sophisticated IoT apps to digitize product lifetime data [21]. Data on fundamental components may be used to forecast product quality using precise predictive models. This work presents a model that uses numerical values for iron and copper cores to forecast the quality of transformer products, including iron and copper losses that significantly influence transformer performance. The predictive model is evaluated using supervised, semi-supervised, and integrated machine learning techniques to forecast transformer quality precisely [22, 23].

1.2. Key contributions

The article primarily focuses on optimizing transformer design by integrating advanced manufacturing techniques, AI, and predictive modeling. However, transformer design is inherently linked to the broader industry supply chain, as improvements in

Figure 1
Transformer manufacturing unit with supply chain management

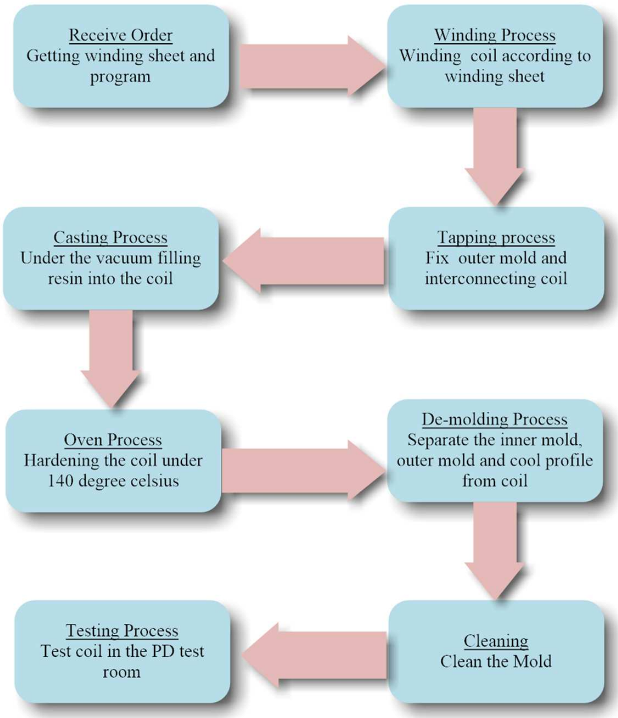


design influence material selection, production efficiency, cost-effectiveness, and overall SCM. Likewise, advancements in the supply chain—such as the adoption of smart logistics, real-time monitoring, and automated quality control—support the development of high-performance transformers by ensuring the availa bility of high-quality materials, minimizing delays, and reducing costs.

By addressing the limitations of conventional quality prediction methods, this study contributes to the advancement of IM within the Industry 4.0 paradigm. Studies emphasize how these technologies enhance operational efficiency through predictive maintenance, real-time monitoring, and smart decision-making, particularly in Industry 4.0 frameworks. Despite the opportunities, challenges remain, especially for small and medium-sized enterprises in adopting complex systems like MES. Sustainability is also a growing focus, with e-commerce and energy-efficient models becoming central to smart manufacturing. AI and machine learning continue to play a critical role in improving diagnostics and decision-making in industrial maintenance. This study serves as a step toward a more integrated, data-driven approach to predictive quality control, facilitating the broader adoption of digital transformation in manufacturing industries.

The article is structured into the following sections: Section 2 presents the manufacturing process at the industry level. Section 3 depicts a comprehensive literature survey on SCM in the power industry and optimizing transformer design using AI techniques. Section 4 elaborates on advanced technologies and systems in smart manufacturing, followed by conclusions in Section 5.

Figure 2
Manufacturing process of power transformer at Asia Trafo LLP in Shymkent, Kazakhstan



2. Power Transformer Manufacturing

The design and development of transformers in the latter half of the 19th century were pivotal to the operation of modern electricity networks. These devices efficiently convert electrical energy to the required voltage or current levels, enabling the practical use of electricity across various applications. While low voltages are advantageous for power generation and consumption due to reduced energy loss, high voltages are more effective for long-distance electricity transmission, minimizing losses over vast distances [24]. The foundation for transformer technology was laid in 1831 by British scientist Michael Faraday, who demonstrated the principles of electromagnetic induction, highlighting the essential role of transformers [25]. Over the following five decades, the application of alternating current (AC) systems solidified the importance of transformers, with the "power transformer" emerging as a vital component for electricity transmission and distribution [26]. Today, transformers play a crucial role in ensuring the reliability and efficiency of electrical systems. Power transformers, typically immersed in oil, rely on this oil for both cooling and insulating their windings and cores [27]. In some cases, additional cooling fluids are necessary to maintain optimal performance. Transformers operate by adjusting the impedance, current, and voltage of an AC source, which is achieved through the interaction of primary and secondary coils wound around an iron core [28]. A magnetic saturation transformer, in particular, regulates and isolates the primary coil by controlling these key parameters. When voltage is applied to the secondary coil, the AC in the primary coil induces an alternating magnetic flux in the iron core, allowing the transformer to convert electrical energy effectively [29].

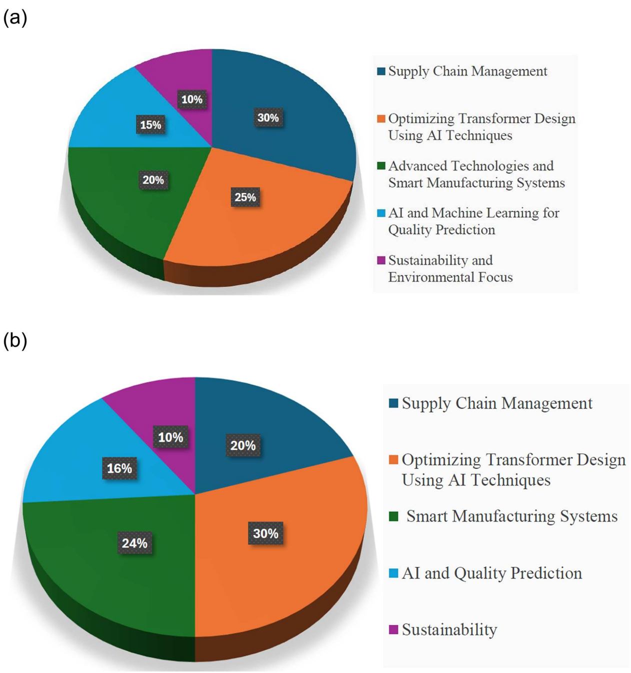
Figure 2 illustrates the industrial manufacturing process at Asia Trafo LLP in Shymkent, Kazakhstan, where transformers are produced [30]. These devices typically feature coils with two or more windings, enabling them to perform their essential functions. In essence, transformers are designed to regulate voltage, current, and impedance reliably through electromagnetic mutual inductance. The iron cores within transformers enhance magnetic coupling between the coils. They are constructed from silicon steel sheets welded together to minimize hysteresis losses and reduce eddy currents. The copper coils are insulated from the electrical system to minimize eddy currents further, and the wires or aluminum components may be encased and laminated. Eddy currents occur when ACs interact with the fluctuating magnetic field of the primary coil. Keeping these currents low is critical to preventing disruptions in the core current flow between the primary and secondary coils. The iron core plays a central role in this process, converting electrical energy from the primary circuit into magnetic energy and then back into electrical energy in the secondary circuit. This study aims to achieve better voltage regulation, reduce losses, improve efficiency, and reduce raw material costs [31].

3. Comprehensive Literature Analysis

Manufacturing high-quality products and items is essential to guarantee sustainable business operations and foster client trust. This section comprehensively reviews the transformer manufacturing process, addresses quality prediction, and summarizes ensemble learning and machine learning studies.

The key research areas covered in this section are categorized as follows: SCM (30%), optimizing transformer design using AI techniques (25%), advanced technologies and smart manufacturing

Figure 3
Focus areas (a) transformer manufacturing literature, (b) number publications in the area



systems (20%), AI and machine learning for quality prediction (15%), and sustainability and environmental focus (10%) as shown in Figure 3. This classification provides a structured approach to understanding the key research areas and their relative significance. Furthermore, this review highlights advancements in model-based manufacturing quality inspection, offering insights into the role of digital transformation in modern manufacturing.

3.1. Supply chain management in power industry

The power transformer sector has undergone significant changes in the past decade, reflecting broader trends in SCM. Smart transformers have been introduced to improve grid reliability, aligning with the global shift toward outsourcing raw materials and reducing costs [32]. However, during this time frame, there was an increase in the costs of raw materials, specifically steel and copper, which presented difficulties for major companies such as ABB, Siemens, and GE [33]. In the next year, the launch of environmentally friendly transformers, including ester-filled options, was in line with the sector's emphasis on sustainable supply chains and cutting carbon footprints amid stricter environmental rules. The rise of renewable energy led to a greater need for high-voltage transformers, as blockchain technology also started enhancing transparency in supply chains.

However, disruptions in the supply chain were caused by geopolitical tensions. There was a growth in digital transformers using IoT-based monitoring, encouraging manufacturers to adopt lean production methods to shorten lead times, even with the increasing cybersecurity threats in SCM [35]. The efforts were made to streamline installation processes through standardization and modularization initiatives, utilizing AI-driven demand forecasting to enhance supply chain efficiency. Yet, difficulties were encountered in obtaining global transformer components due to tariffs and trade barriers. The hybrid transformers integrating traditional and renewable energy capabilities emerged, with advanced analytics improving inventory management and supplier connections. However, the industry continued to be affected by economic uncertainties, which caused fluctuations in demand [36]. The COVID-19 pandemic in 2020 heavily impacted the sector, resulting in delays in projects, shortages in supplies, and a move toward more robust and adaptable supply chains focusing on local sourcing. This was followed by a surge in electrification and urbanization, leading to upgrades in transformers and the use of digital twins and AI-based tools for SCM to enable predictive maintenance despite ongoing raw material shortages and shipping delays [37]. The sector was concentrating on creating energy-saving transformers to achieve decarbonization goals, as visibility technologies in the supply chain, such as IoT and blockchain, were becoming more popular due to sustainability demands. The HVDC transformer technology was introduced to transmit power over long distances and implement circular economy strategies for recycling and reusing transformer components [38]. However, production was impacted by worldwide semiconductor shortages. The combination of smart grids and progress in digitalization will continue to improve supply chains, fueled by the use of AI and machine learning [39]. It will also tackle issues surrounding energy transition and grid modernization. Major companies such as GE, Schneider Electric, and Siemens are important figures in the changing environment of the power transformer industry as they work to manage the challenges of supply chain dynamics [40]. A comprehensive study on SCM in the power industry in manufacturing power transformers is tabulated in Table 1.

3.2. Optimizing transformer design using AI techniques

AI has played a pivotal role in optimizing transformer design, addressing challenges such as efficiency improvement, material cost reduction, and enhanced reliability. This section explores various AI-based methodologies, including genetic algorithms (GAs), artificial neural networks (ANN), and multi-objective evolutionary optimization techniques. Researchers use several AI techniques to tackle issues in improving transformer design [41, 42].

3.2.1. Genetic algorithms

J.H. Holland invented GAs in 1975, while David Goldberg and L.B. Booker demonstrated their efficacy in addressing complicated issues in 1989 and 1975 [43]. GAs are efficient instruments for optimization across several domains, including engineering, research, and industry [44]. Their comprehensive perspective, accessible design, and vast application have significantly increased their appeal. Gas-insulated systems have shown reduced costs related to the building, operation, and maintenance of transformers. Using these GAs enhances the design of the cooling system for distribution transformers. A GA-based evolutionary computational model was developed by Wong et al. [45], including identifying power transformer characteristics. GAs have enhanced toroidal core transformers and cast-resin distribution transformers. An improved

Table 1
A comprehensive survey on supply chain management in the power industry

Key manufacturing company	Key trends in power transformers	Developments in supply chain management	Challenges
ABB, Siemens, GE	Adoption of smart transformers for improved grid reliability	Global outsourcing of raw materials; increased focus on cost optimization	Rising costs of raw materials (steel, copper)
Schneider Electric, Hitachi	Introduction of eco-friendly transformers (e.g., ester-filled transformers)	Focus on sustainable supply chains, reducing carbon footprints	Environmental regulations tightening on manufacturing processes
Toshiba, Alstom Grid	Increased demand for high-voltage transformers due to renewable energy integration	Blockchain in supply chains for better transparency	Supply chain disruptions due to geopolitical tensions
Mitsubishi Electric, Hyundai Electric	Rise of digital transformers with IoT-based monitoring	Push toward lean manufacturing to reduce lead times	Cybersecurity risks in supply chain management
ABB, Siemens	Standardization and modularization of transformers for easier installation	AI-driven demand forecasting in supply chains	Tariffs and trade barriers affecting global transformer component sourcing
Schneider Electric, GE	Emergence of hybrid transformers combining traditional and renewable energy compatibility	Advanced analytics for inventory management and supplier relationship optimization	Fluctuations in demand due to economic uncertainties
Toshiba, CG Power	Impact of the COVID-19 pandemic: Delayed projects, shortages in supply	Shift toward resilient and flexible supply chains; emphasis on local sourcing	Logistics disruptions, factory closures, labor shortages
Siemens Energy, Hitachi Energy	Increased electrification and urbanization driving transformer upgrades	Digital twins and AI-powered SCM for predictive maintenance of transformers	Raw material shortages, shipping delays due to pandemic recovery
ABB, Hyundai	Development of energy-efficient transformers to meet decarbonization targets	Supply chain visibility technologies (e.g., IoT, blockchain) gaining ground	Sustainability pressures on transformer production processes
Siemens, Mitsubishi Electric	High-voltage direct current (HVDC) transformer technology for long-distance power transmission	Circular economy practices emerging in the supply chain (recycling, reusing transformer parts)	Global semiconductor shortages affecting production
GE, Schneider Electric	Smart grid integration with transformers, further advancements in digitalization	AI and machine learning fully integrated into supply chain optimization	Energy transition challenges and grid modernization demands

design for a rectifier power transformer was attained by using a GA and simulated annealing, as outlined in Wang et al. [46]. GA effectively enhanced the designs of rectifier power transformers. Georgilakis tackled the issue of decreasing transformer expenses using evolutionary algorithms and external elitism. The distribution transformer design used a hybrid optimal technique that integrated deterministic approaches, GAs, and two-dimensional finite elements to get the most efficient solution. A penalty function technique for assessing objective functions with weighted coefficients and a basic evolutionary algorithm was used in Koutsoukis et al. [47] to illustrate the ideal transformer design based on the total cost of ownership.

3.2.2. Advanced techniques in artificial neural networks

ANN provide a computational framework inspired by biological neural networks and are widely applied in transformer design and fault diagnosis. ANN models have been used to predict transformer prices, forecast magnetic core properties, and minimize iron losses during manufacturing [48]. In Cantillo-Luna et al. [49], it was suggested that ANN could be used to forecast transformer prices during the design phase. On the other hand, Santamargarita et al. [50] used ANN to forecast the properties of magnetic transformer cores and related core losses to minimize iron losses in produced transformers. Applying neural networks and evolutionary programming improved the performance of wound core distribution transformers. Hajiaghapour-Moghimi et al. [51] effectively predicted losses in distribution transformers by utilizing daily load curve data with neural networks. This eliminated the need for the utility to evaluate the load profile for each client type. In a situation with supply imbalances, neural networks were used to evaluate iron losses, and Taguchi techniques were applied to improve core manufacturing processes to minimize iron losses [52]. Kaminski et al. [53] used a neural network to assess how long transformer oil would remain effective. The model was applied to ten transformers with known transformer oil breakdown voltages. The modeling of nonlinear power transformers was accomplished using complex, valued open recurrent neural networks. Additionally, ANN often play an important role in identifying malfunctions in transformers. Wavelet signals were used in a real-time detection method described by Silva et al. [54]. This system was created to detect transformer inrush and fault currents using ANN. Sharma et al. [55] and Ekojono et al. [56] have shown how dissolved gas analysis can be used in training neural networks to identify early flaws in transformers. Meanwhile, other researchers, Elagoun and Seghier [57] and Mharakurwa [58], have demonstrated the effectiveness of an ANN in diagnosing problems with bushings. A specific neural network model was used in Torres-Huitzil and Girau [59] to identify each type of issue, showcasing the capability of ANN to classify errors.

Recent advancements in AI, particularly deep learning and large-scale models, have significantly improved transformer design optimization. Deep learning techniques like convolutional and recurrent neural networks enhance fault detection, lifetime estimation, and performance forecasting by extracting complex features and recognizing patterns. Large AI models, such as vision transformers and generative models, enable predictive analysis and automated design exploration, optimizing efficiency and reducing material costs. Additionally, integrating AI with digital twin technology allows real-time simulation of transformer behavior, enabling predictive maintenance and design adjustments to improve reliability and minimize downtime [60, 61].

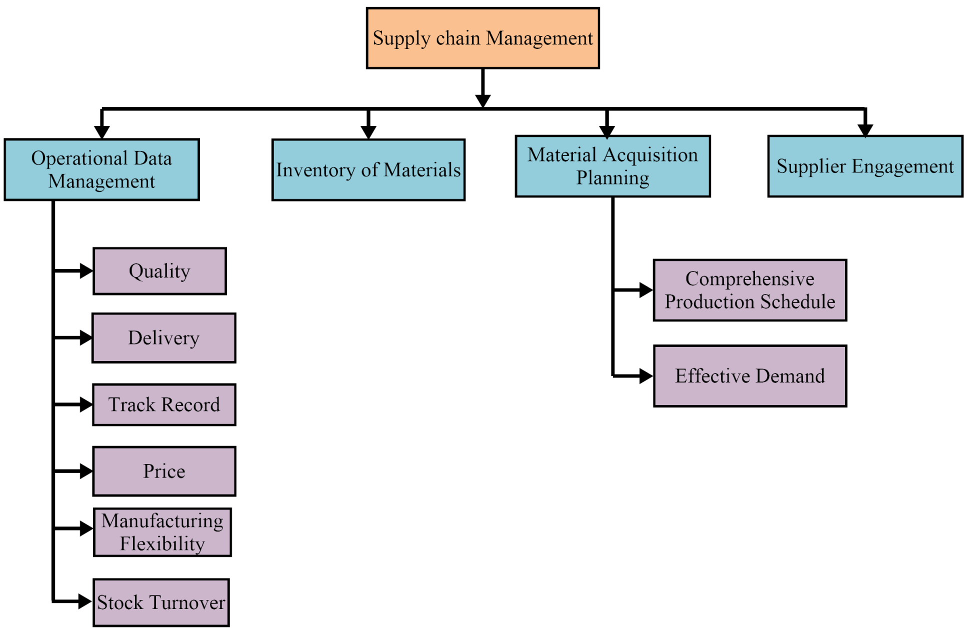
3.2.3. Optimizing transformer design with multi-objective evolutionary algorithms

Multi-objective optimization effectively identifies one or more optimum solutions for complicated problems with many goals. Numerous real-world search and optimization tasks include numerous goals. Evolutionary multi-objective optimization methods use an iterative process to assess increasing solutions, enhancing their significance in the domain. Consequently, evolutionary algorithms are advantageous for maximizing several goals [62]. The research [63] enhanced transformer design by integrating an evolutionary multi-objective optimization approach with an unbounded population size and chaotic sequences. The methodology for developing the differential algorithm using the truncated gamma probability distribution function was shown in Coelho et al. [64]. Particle swarm optimization enhanced efficiency and reduced costs [65], while GAs effectively optimized the multi-objective design of high-frequency transformers. During the design phase of transformers, a multi-objective evolutionary optimization technique was used to determine the necessary parameters accurately [66]. A bacterial foraging method was proposed by Abou El-Ela et al. [67] to achieve optimum multi-objective transformer design. The objective of this strategy was to elevate expenses while concurrently diminishing the efficiency of a 500 kVA transformer. The authors assert that advancements in the design of multi-objective optimum transformers are ongoing.

4. Advanced Technologies and Systems in Smart Manufacturing

Clients in the industrial sector have diverse needs regarding mechanical and electrical engineering products, particularly as many larger pieces of equipment are highly specialized [68]. This specialization creates a significant challenge for manufacturers, as they must meet market demand while striving to improve production efficiency, maintain product quality, and control manufacturing costs. Digital transformation plays a crucial role in addressing these challenges, yet it is a complex endeavor [69, 70]. The situation is further complicated by rapid changes in global demand and the expectation of shorter delivery times. Manufacturers of high-quality

Figure 4
Supply chain management knowledge framework



electrical power transformers, for instance, must ensure quality at every stage of operations—from procurement and production to distribution [71, 72]. Stability in production processes is crucial to avoid disruptions that could impact customer satisfaction. This section explores the essential role of SCM, machine learning, and IoT in driving digital transformation. By leveraging these technologies, manufacturers can optimize operations, swiftly respond to market demands, and enhance product quality, leading to greater customer satisfaction [73–75].

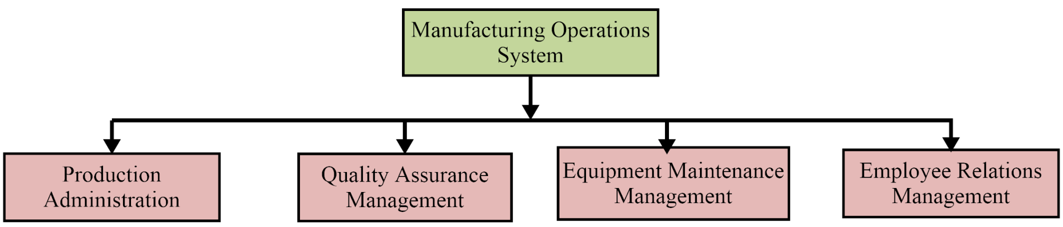
4.1. Supply chain management knowledge framework

The SCM knowledge framework is illustrated in Figure 4. Historically, vertical integration was a dominant strategy among electromechanical engineering manufacturers. However, in today's digital economy, companies increasingly rely on digital integration with global suppliers to enhance operational efficiency [76]. Advanced information technology is crucial in this shift, as it can significantly improve SCM by gathering accurate, real-time data from upstream suppliers and downstream consumers. This data-driven approach enables manufacturers to optimize their resources, ensuring they can effectively meet customer needs regarding products and services. One of the primary benefits of this digital integration is improved communication with customers, which, in turn, boosts company revenue [77]. Manufacturers can personalize their production systems by utilizing data for real-time planning and control, ensuring that products meet specific customer specifications. This capability also facilitates seamless order relaying to reliable suppliers, further enhancing efficiency. The first step in effective SCM is procuring raw materials essential for producing and selling finished goods to end users. Successful SCM involves managing key components such as inventory, demand, quality, and delivery time while integrating all suppliers into the company's internal and external product and service value chain. Supplier management encompasses the organization of the entire supply chain, including merchants, logistics providers, and manufacturers. Key steps in this process include acquiring raw materials, developing efficient production methods, and distributing products to customers. Organizations must consider multiple factors, including quality, cost, delivery time, and service when selecting suppliers to ensure they meet ISO standards. Supplier selection is a critical process involving weighing various criteria impacting customer satisfaction. Factors such as delivery time, product quality, service levels, and pricing are vital. The weighted average method is often employed to evaluate and prioritize these criteria during the supplier selection process. For example, Supplier A might offer fast delivery at a lower price but provide lower-quality goods. In contrast, Supplier B may deliver higher-quality products at a higher cost but with slower delivery. A weighted average can help businesses balance these trade-offs, enabling them to meet specific goals in a highly competitive market. Companies can enhance their competitiveness and ensure market sustainability by focusing on high-quality products. In the supplier evaluation process, opportunity costs, risks, and other quantitative factors are translated into cost measures, facilitating informed decision-making [78]. A matrix is frequently employed to outline key stages and priorities in the supplier evaluation process, using ratio and nominal scales for supplier comparison [79]. Various SCM methods are available to identify and evaluate suppliers effectively. One notable method is the Delphi technique, which anonymously gathers expert feedback through iterative questionnaires to reach a consensus. The total cost method evaluates cost ratios before selecting suppliers, while mathematical models, such as multi-objective linear or nonlinear programming, consider constraints and multiple objectives. The data envelopment analysis model assesses supplier performance across market segments. Additionally, the fuzzy analytic hierarchy process (AHP) is beneficial when information is ambiguous, and the multi-objective AHP effectively combines qualitative and quantitative factors for decision-making in commercial situations [80, 81]. Overall, AHP plays a critical role in the backdrop of business priorities and strategies, and research indicates that it effectively fosters long-term supplier relationships. By adopting these methodologies, organizations can make more informed decisions that enhance their supply chain efficiency and contribute to their overall business success [82].

4.2. Manufacturing operations management (MOM)

Manufacturers today face mounting pressure from global competition, shifting labor markets, increasing material costs, trade disputes, and regulatory constraints [83, 84]. Industry 4.0 technologies, particularly IoT, AI, and cloud computing, are critical in overcoming these challenges by enhancing efficiency, reducing costs, and increasing productivity. In this context, advancing Industry 4.0 technologies is crucial for reducing costs, enhancing quality, and significantly increasing productivity and efficiency. The IoT plays a pivotal role in this transformation by connecting the entire value chain through digitalization, AI, and automation. This integration facilitates the straightforward

Figure 5
Manufacturing execution knowledge framework



acquisition of physical equipment, efficient communication, collaborative development efforts, and real-time management of components for the bill of materials [85]. The combination of cloud computing with application systems enables the creation of intelligent industrial systems at a more affordable price, allowing organizations to remain agile and responsive in a fiercely competitive global marketplace. It is essential for buyers and sellers to collaborate effectively in customizing high-value items that are offered in limited quantities. To improve competitiveness and foster brand loyalty, businesses must enhance customer service by increasing process efficiency and lowering product manufacturing costs [86, 87]. In the typical manufacturing sector, three strategies have emerged as particularly effective for improving productivity: enhancing output, reducing labor costs, and acquiring new equipment. Analyzing current manufacturing operations can uncover opportunities to meet changing customer order demands and enhance the supply chain's equipment, workforce, and production capacity. Figure 5 illustrates how manufacturing operations management (MOM) contributes to the advancement of information-driven IM. MOM systems assist managers in reallocating human resources and optimizing production capacity to meet performance targets and objectives. This optimization is achieved through a comprehensive analysis of several critical areas, including operator and production management, quality management, machine and equipment production rates, human resource management, material loss status, and work-in-process quality. To enhance overall performance and delivery, it is essential to optimize production management, quality management, machine and equipment production rates, and human resource management. These components are defined within the manufacturing systems, and the ontology is illustrated in Figure 6. By focusing on these key areas, organizations can achieve a more efficient and effective manufacturing process, ultimately leading to improved competitiveness and customer satisfaction [88, 89].

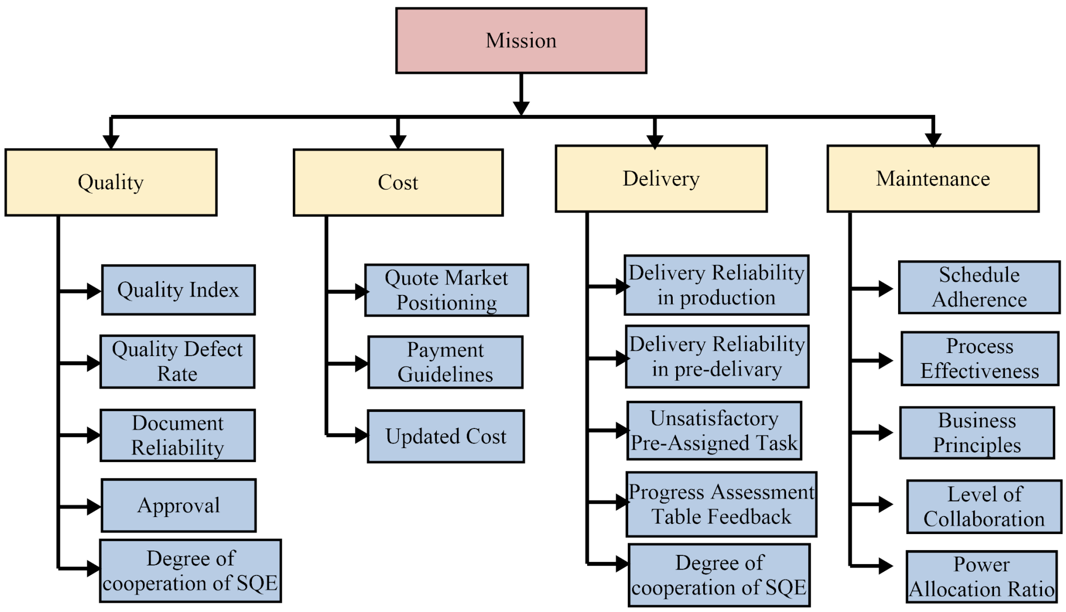
This study by Torres et al. [90] examines error-proofing strategies to document industrial quality issues and reduce variability through human error analysis. To reduce the reliability problems stemming from equipment design in the workplace, it is essential to have a clear understanding of the root causes of faults [91]. Effective supply management, analysis of equipment production rates, monitoring of manufacturing history, and the implementation of enterprise resource planning (ERP) systems are essential elements that need to be established to collect management data prior to the commencement of production for client orders [92]. Managers can meet customer requirements by optimizing machine operations, effectively managing material demand, and utilizing real-time quality management data from various sources. Twelve essential functions of MES have been defined to address the needs of the manufacturing industry.

The functions encompass resource allocation and control, production scheduling, data collection and acquisition, quality management, management of production processes, material batch management, production traceability, performance analysis, operational and detailed planning, document management, human resource management, maintenance management, and material transportation, storage, and tracking [93, 94]. Further, the MOM of top manufacturing companies is summarized in Table 2.

4.3. Material flow mechanisms in key operational units

Specialized part suppliers can improve process efficiency and minimize setup and changeover times on production lines by allocating low and irregular-volume components to additive manufacturing (AM). This process programming, which supports the idea that AM and traditional manufacturing (TM) function together, is referred to as "combinational," and this term defines it [95].

Figure 6
Hierarchical model of transformer casing components



AM simplifies the stages of TM, enhances material transportation, reduces waste, lowers work-in-process inventory, and minimizes errors. This makes it especially advantageous for companies concentrating on batching and job work [96]. Two different machining methods and components that were produced for inventory were incorporated into the TM process before the finishing, testing, and packaging stages. AM has led to a notable decrease in work-in-progress and finished product inventories [97]. The achievement arose from printing being the main production method, and there was no need for client design involvement. Producing in smaller batches can lower costs, allowing for delays in production, localization, and adjustments directly at the distribution point [98]. The order decoupling point needs to be moved to the customer's site to improve timeliness. This gives supply chain companies, usually smaller than specialized suppliers, an additional incentive to utilize technology to produce different components on their manufacturing lines. Bringing component fabrication closer to assembly facilities and delivering spare parts nearer to clients could improve the efficiency of original equipment manufacturers (OEMs). This will result in lower costs for material handling, transportation, component shortages, and inventory management. Possible areas for improvement are bottlenecks, capacity management, and line

Table 2
A comprehensive survey on MOM

Main manufacturing companies	Key trends in power transformer manufacturing	Manufacturing operations management (MOM) innovations	Challenges in MOM
ABB, Siemens	Shift toward energy-efficient transformers and high-capacity units	Introduction of basic digital dashboards to track production in real time	Limited integration of production systems, siloed data management
Schneider Electric, Hitachi	Increasing demand for compact, high-performance transformers	Early adoption of manufacturing execution systems (MES) for production scheduling and quality control	Fragmented data systems impacting operational efficiency
Toshiba, Alstom Grid	Focus on automation and optimization of production processes	Use of automated assembly lines and quality control testing using SCADA systems	High costs of implementing advanced MOM solutions
Mitsubishi Electric, Hyundai Electric	Implementation of lean manufacturing principles to reduce waste	Introduction of IIoT sensors to collect real-time data on production floor operations	Data overload due to multiple sources; managing predictive analytics
ABB, Siemens	Rise of digital twins to simulate manufacturing processes	Adoption of integrated MOM systems combining MES, ERP, and Product Lifecycle Management (PLM) for better decision-making	Cybersecurity vulnerabilities in interconnected MOM systems
Schneider Electric, GE	Standardization of transformer manufacturing processes across global facilities	Data-driven MOM systems leveraging AI and machine learning for predictive maintenance	Integration challenges with legacy equipment and systems
Toshiba, CG Power	COVID-19 pandemic leads to remote monitoring and automation upgrades	Virtual commissioning tools adopted to simulate production and reduce on-site workforce	Production delays and labor shortages impacting manufacturing schedules
Siemens Energy, Hitachi Energy	Recovery from pandemic impacts leads to increased automation investments	AI-driven process optimization for improved yield and reduced downtime	Shortages of skilled workers to manage complex MOM systems
ABB, Hyundai	Greater emphasis on sustainability in transformer manufacturing processes	Cloud-based MOM platforms enabling global collaboration and real-time data access	Supply chain disruptions affecting raw materials procurement
Siemens, Mitsubishi Electric	Use of additive manufacturing (3D printing) for customized transformer parts	Real-time visibility into all stages of production through advanced MOM dashboards	Complex compliance requirements and evolving regulations
GE, Schneider Electric	Integration of green energy in manufacturing operations for carbon-neutral production	Full-scale integration of AI/ML in MOM for predictive analytics and resource optimization	Increasing need for cybersecurity and data protection in MOM environments

balancing. Implementing AM at the factory level reduces reliance on just-in-time supplier coordination, leading to significant transportation cost savings. Additionally, minimizing material waste enhances operational efficiency. However, studies indicate that AM systems generally have lower throughput compared to TM methods, making it essential to evaluate demand rates when assessing production speed and efficiency [99, 100].

4.4. Communication flow and collaborations among essential partners

AM can significantly reduce demand planning and forecasting errors by minimizing the distance between supply chains and producing components on-site with fewer supply chain entities [101]. This results in greater collaboration among supply chain

Table 3
Comprehensive survey

Author(s)	Key findings	Drawbacks	Main decisions	Role of data enabler	Algorithms used
Wang et al. [103]	Emphasizes collaboration across the supply chain.	Lack of standardized frameworks for collaboration.	Enhance partnerships and integrate data sharing protocols.	Facilitates real-time data exchange for decision-making.	N/A
Lee et al. [104]	Identifies benefits such as improved visibility and responsiveness.	Challenges in technology adoption and workforce skills.	Invest in training and technology integration.	Provides analytics for demand forecasting and inventory control.	Regression Analysis
Gupta et al. [105]	Highlights opportunities in automation and data analytics.	High implementation costs and cybersecurity risks.	Develop a phased approach to technology adoption.	Supports automation through data insights and analytics.	Decision Trees, Simulation Models
Khan et al. [104]	Demonstrates potential for transparency and traceability.	Complexity in implementation and integration with legacy systems.	Implement blockchain in phases, starting with critical suppliers.	Ensures data integrity and security in transactions.	Hash Algorithms, Smart Contracts
Ivanov and Dolgui [107]	Discusses the importance of resilience and adaptability.	Lack of a comprehensive model for measuring resilience.	Build resilience strategies into supply chain designs.	Enables real-time risk assessment through data collection.	Machine Learning Algorithms
Akbari and Hopkins [108]	Links sustainability with digital technologies for efficiency.	Difficulties in balancing sustainability and cost.	Create sustainability metrics aligned with supply chain goals.	Provides data analytics for sustainable practices.	Multi-Criteria Decision-Making
Kar and Kushwaha [109]	AI improves decision-making and reduces operational costs.	Dependence on data quality and algorithm biases.	Incorporate AI tools for data analysis and forecasting.	Acts as a facilitator for big data analytics.	Neural Networks, Genetic Algorithms
Awotunde et al. [110]	IoT enhances real-time monitoring and tracking capabilities.	Data security and privacy concerns.	Adopt IoT technologies gradually, ensuring data protection measures.	Provides continuous data flow for operational insights.	IoT Protocols, Data Fusion Techniques

Table 4
Quantitative analysis of technical methods and outcomes in transformer manufacturing

Reference	Technical method	Application context	Quantitative outcome	Key metric
Koutsoukis et al. [47]	Hybrid GA + finite element analysis	Transformer cost optimization	15% reduction in ownership costs	Cost efficiency
Kaminski et al. [53]	Artificial neural networks (ANN)	Oil breakdown prediction	94.2% accuracy in predicting oil lifespan	Predictive accuracy
Coelho et al. [64]	Gamma Differential Evolution	Multi-objective transformer design	20% cost reduction, 10% efficiency gain	Cost and efficiency
Khan et al. [106]	Blockchain traceability	Supply chain fraud prevention	22% reduction in supply chain fraud	Risk mitigation
Lee et al. [104]	IoT-enabled logistics	Production throughput improvement	18% increase in throughput	Operational speed
Rasiya et al. [97]	Additive manufacturing (AM)	Material waste reduction	28% reduction in material waste	Sustainability
Pereira et al. [98]	AM vs. traditional manufacturing (TM)	Lead time reduction	25% faster production for low-volume parts	Lead time efficiency
Santamargarita et al. [50]	ANN-based real-time monitoring	Core loss minimization	8.5% reduction in core losses	Energy efficiency
Hashemi and Kilic [66]	NSGA-III optimization	Harmonic distortion reduction	18% decrease in harmonic distortion	Power quality
Wang et al. [103]	Blockchain integration	Supply chain transparency	40% reduction in transaction delays	Operational transparency
Kar and Kushwaha [109]	AI-driven decision-making	Operational cost reduction	25% reduction in operational costs	Cost efficiency
Mika and Goudz [34]	Material recycling initiatives	CO_2 emissions reduction	25% reduction in carbon footprint	Environmental impact

organizations, particularly in the design capabilities employed by OEMs and AM providers. Incorporating information about component management in digital design enables assemblers to reduce the number of decisions they need to make regarding scheduling and planning. Improving demand visibility can be accomplished by eliminating supply chain intermediaries through electronic commerce solutions for asset management [102]. This will improve production scheduling and optimize capacity. Co-creation improves the relationship between customers and their suppliers by enhancing the customer's membership in the supply chain. This enables more precise local decision-making based on data. Bringing manufacturing operations closer to customers enables this transformation. A comprehensive survey is enumerated in Table 3. A detailed quantitative analysis of technical methods and outcomes in transformer manufacturing is summarized in Table 4.

5. Conclusions

This article has examined the advancements in innovative manufacturing technologies and their impact on power transformers' manufacturing and design processes. Integrating Industry 4.0 technologies, particularly IoT, cloud computing, and AI, is essential for enhancing SCM and optimizing manufacturing processes. Employing current data allows producers to make informed decisions, improve manufacturing processes, and maintain quality standards across the supply chain. The study highlights the importance of collaboration among supply chain participants, emphasizing the preference for digital integration over conventional vertical integration. This modification allows organizations to more effectively respond to changing market demands and save operational costs. The findings indicate that, despite obstacles such as cybersecurity threats, technological implementation expenses, and supply chain interruptions, the strategic use of predictive analytics and machine learning may effectively mitigate these issues. The study also examines several methodologies, including GAs, neural networks, and multi-objective optimization, to enhance the performance and efficacy of transformers. The significance of data as a facilitator in this context is paramount; it is essential for forecasting, guaranteeing quality, and optimizing production levels. Manufacturers may improve their competitiveness and advocate for sustainable practices in the industry by focusing on intelligent SCM and using new technology. This research contributes to the ongoing discourse on digital transformation in manufacturing, offering insights to bolster future efforts to enhance productivity, quality, and customer satisfaction within the power transformer sector. However, the study is limited by the scope of available data, which may not fully capture the complexities and variances across different manufacturing environments. Future research could explore case studies across diverse regions and industries, considering additional challenges such as the scalability of technologies, the adaptability of workforce skills, and the long-term economic impacts of digital transformation in manufacturing. Additionally, further investigations into the integration of emerging technologies, such as 5G and blockchain, in enhancing supply chain resilience and performance could provide valuable insight.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Adilbek Tazhibayev: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing. **Irbulat Utepbergenov:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Supervision, Project administration. **Iouliia Skliarova:** Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing – review & editing.

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How to Cite: Tazhibayev, A., Utepbergenov, I., & Skliarova, I. (2025). Development of Customer-Focused Automated Systems for Transformer Design and Manufacturing: A Comprehensive Review. *Journal of Computational and Cognitive Engineering*. https://doi.org/10.47852/bonviewJCCE52025158