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Towards industry 5.0 : Study of artificial intelligence in areas of application : A methodological approach

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Abstract

Industry 5.0 is AI-driven and at the forefront of human-machine collaboration, which has transformed global industries. The paper highlights the applications of AI beyond manufacturing in the healthcare, finance, transport, and agriculture sectors, all being crucial to the development of Industry 5.0. A deep sense of the necessity of bespoke AI to meet the industry's needs and to enhance human-machine interaction is emphasized by this research. This research guides researchers, stakeholders, and policymakers on AI's ability to transform multiple sectors. The paper identifies the trends, challenges, and innovative AI methodologies with industry literature reviews and more advanced analytics to optimize the scope of Industry 5.0 related to productivity efficiency and deregulation frameworks.

Subject Classification: *68T07, 68T01.*

Keywords: *Artificial intelligence, Industry 4.0, Industry 5.0, Industrial applications.*

1. Introduction

Industrial 5.0, which is human-machine collaboration, is the output of the global transformation of industries by artificial intelligence (AI). Focusing on such diverse sectors as health care, finance, transport, and agriculture, this research attempts to address AI's applications outside the manufacturing industry to contribute to the design and implementation of Industry 5.0 [1]. It refers to how it is the need to create tailored AI solutions for particular industry demands and human-machine harmony.

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The primary purpose of this research is to make researchers, industry stakeholders, and policymakers aware of the revolutionary potential of AI in the form of Industry 5.0 [2]. Industry 5.0 is the preindustrial era before Industry 1.0, and the starting point for high-tech practices to produce Industry 5.0, which involves AI, IIoT, and data analytics [3]. It is necessary to have a cognitive approach in the study of AI in Industry 5.0 to take into account the question of human cognition and interaction with intelligent machines for AI systems to be sensible and adaptive as well as to support human decision-making in smart manufacturing [4]. A branch of computer science called artificial intelligence seeks to design systems which can reason, learn, and improve by themselves. These methods include managing huge volumes of data using machine learning, cognitive computing, big data, and predictive analytics, Industrial IoT/IIoT for industrial environments. Challenges on this frontier include data acquisition and storage costs, training and computation, compliance with regulations, cost, a state space too big to handle, and talent expense [5]. Sensor data is noisy and expensive; simulations are computationally intensive. Regulatory demands may go against the AI dreams of automation. Industry 5.0 has problems with value creation measurement, integration of SMEs, and agile policies regarding innovation [6]. This study discusses the involvement of AI in Industry 5.0, considering how this advancement develops further human-machine cooperation in the manufacturing process. A literature review is undertaken to focus the analysis on trends and obstacles associated with the application of AI in industry 5.0 contexts. Case studies and interviews were composed of empirical information that concerned real applications of AI; their impacts on productivity, efficiency, and innovation were further examined [7]. Advanced analytics methods have shown patterns and correlations between AI adoption and performance metrics of different sectors such as healthcare, finance, transport, and agriculture [8]. The research aims to create new AI methodologies that will answer the needs of socioeconomic contexts in the emergent Industry 5.0, assess its value for society, and design strategies to audit industry policies and regulatory frameworks regarding AI use. This paper has an important contribution to robust methodology and a thorough exploration of AI in the context of advancements in Industry 5.0 [9]. Unlike traditional studies focused solely on manufacturing automation, the research delves into AI's potential to foster human-machine collaboration and drive innovation in non-traditional industries. The study provides practical insights into implementing Industry 5.0 principles using AI methodologies, data analytics, and robotics, demonstrating how AI can revolutionize various sectors [10].

2. Related work

To identify acceptable enabling technologies and design principles, they want to analyse the present Literature on industrial artificial intelligence with an emphasis on its implementation in real industrial settings. To increase industrial acceptance by a smooth transition to data-driven and digitized corporate values, the next step is to build a conceptual framework to link this field's research to the manufacturing sector [11]. This is one of the first studies to fully explain and offer an overview of Industry 5.0's Industrial Artificial Intelligence, detailing and analyzing its key components and most recent developments. The advantages and disadvantages of implementing AI technology in the industrial sector are examined, taking into consideration both offensive and defensive applications. It begins by defining Industry 5.0 and going through AI's function in this setting [12]. The next section looks at Operational Technology (OT), which is a primary point of attack for industrial systems, as well as security guidelines and detection techniques. To identify acceptable enabling technologies and design principles, they wanted to analyse the present Industrial AI literature with an emphasis on its implementation in real industrial settings [13]. The main benefits and drawbacks of the most popular techniques were covered in this article. From the standpoint of the manufacturer, they also gave an appraisal of their relevance for use in OT. Ahmed et al. provided a comprehensive review of AI and XAI-based approaches in the context of Industry 5.0. They examined key technologies enabling Industry 5.0, explored methodologies applied in literature, and discussed future research directions focusing on ethical AI and XAI systems crucial for high-stakes commercial applications [14]. It explored the transition from IM to SM in AI 2.0, tracing the evolution from incorporating machine learning, decentralised control frameworks, and deep learning. They detailed the differences between IM and SM and speculated on smart manufacturing's future in Industry 5.0. It highlighted advancements in data management, analytics, and knowledge fusion tools, including AI services for edge computing, digital testing grounds, and standards for AI model transfer and domain knowledge integration [15].

3. Methodology

Connecting and integrating production and service systems is the main objective of Industry 4.0/industry 5.0 to provide effectiveness, flexibility, cooperation, coordination, and efficiency. Therefore, for a fuller comprehension of the suggested framework, a link between design principles and current technology is required. Table 1 demonstrates how Industrial Internet of Things (IIoT) developments in communication and networking, and cyber-physical framework security, may be used to guarantee the compatibility of communicative components. Making use of virtualization and simulation modeling methods such as augmented reality and virtual reality, changes in current systems may also be monitored.

Table 1

Category of industry technology

Technologies	Real-time	Interoper-ability	Virtualiza-tion	Decen-tralisa-tion	Agility	Service orienta-tion	Business process
Robotics					X		
Data analytics & AI	X			x	X	X	
Simulation			X		X		
Embedded system				x	X		
Comms		x		x	X		x
Cyber security		x			X		x
Cloud					X	X	x
Manufacturing					X		
AR & VR			X		X		
RFID & RTLS	X			x	x		x

As shown in Figure 1 Industry 5.0 relies on integrating cloud technologies, big data analytics, embedded systems, and adaptive robotics for autonomy and proactive issue management. Emphasizing service-oriented design, it uses data analytics and AI to meet consumer expectations as shown in Figure 1. Integrating these technologies ensures system stability and agility. Businesses should focus on smart integration in product creation, production, logistics, marketing, sales, and after-sales services. Smart products should include a physical component, smart sensors and microprocessors, and connectivity features.

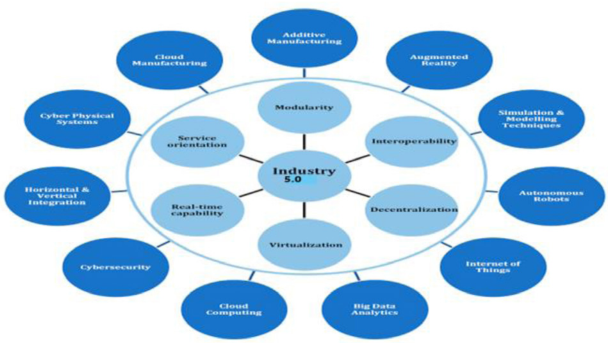

Figure 1

The overall framework of AI in the industry

Cloud technologies ensure production coordination and integration across disparate systems, improving platform compatibility for big data processing, real-time analytics, and business intelligence systems. These technologies provide real-time data management, data flow management, and information extraction, enhancing overall product performance and utilization. Technologies that provide support encompass virtualization, mobile technologies, RFID and RTLS, sensors and actuators. Augmented reality and virtual reality are essential for Industry 5.0's virtualization requirements, while RFID, sensor, and Real-time data flow is supported by RTLS technologies and capture. Mobile technologies allow for swift and remote management of the entire organization. The flowchart representation is provided in the below Figure 2.

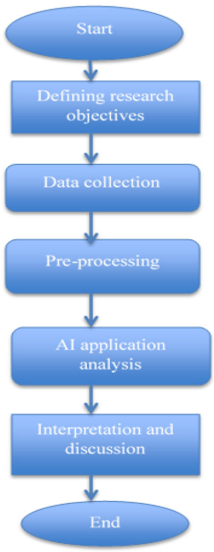

Figure 2

Flowchart representation

Enabling technology enables innovative business strategies, remote services, and ongoing manufacturing processes. Businesses are increasingly offering their products as services, focusing on the complete system rather than individual components. Continuous manufacturing involves using networking and cloud technologies to connect items and processes. Predictive analytics models help reduce errors or discrepancies between projected and actual values. In figure 3, the predictive modelling involves optimizing or training the model's parameters using a supervised learning method, with the training dataset referring to the examples used to develop the model as shown in Figure 3.

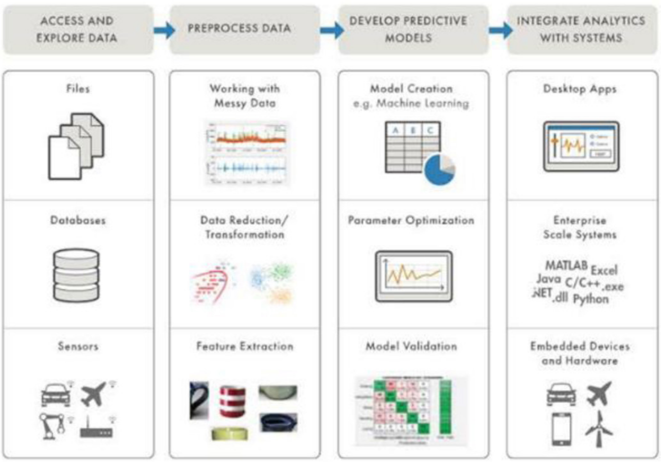

Figure 3

Predictive modeling over Industry areas

Linear Regression: The most well-known regression approach is linear regression, which aims to find the output's slope concerning the input. The concept also draws attention to the factor that influences the target variable most. A factor wi is assigned to each attribute, and a second factor is used to establish the initial value of the predicted feature.

$$y_1 = w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n \tag{1}$$

For binary classification, logistic regression is viewed as a linear classification strategy. The heart of logistic regression is the odds ratio, which is the ratio of outcome probabilities.

$$\frac{p(1)}{1-p(1)} = \frac{p(1)}{p(0)} = w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n \tag{2}$$

In Industry 5.0, technologies like Support Vector Machines (SVM) and neural networks play pivotal roles. SVM creates an optimal hyperplane that separates data into classes using kernel functions that map nonlinear data. Neural networks also consist of layers of input, process, and output data; they work by using interconnected nodes and edges to model complex relationships. Industry 5.0 takes full digitalization a step forward by incorporating AI to combine the real and virtual realms; it is consistent with the greater vision of Industry 5.0. Its basic aspect is to increase convenience and overcome societal challenges through advanced industrial AI capabilities.

The chemical industry is primarily guided by forecasting short-term and long-range trends of economies that are under constant flux. The sector also has to contend with external factors, like consumer attitudes, legislation, trade patterns, and regional economics. Supply chain analytics and advanced data solutions combine forward-looking statistics with internal data to guide decision-making in times of complexity. Planning falls into long-term periods of 1-10 years, 1-3 month short-term intervals and 3-9 month mid-term periods, thus demanding classification of information on, for instance, factory shutdowns and holidays that have a bearing on demand patterns. Macroeconomic data and input-output tables facilitate forecasting as they display industry interlinkages, which helps clarify the composition of items in an industry, thereby assisting in the forecasting of demand based on value chains from such industries as the automobile. There is a need to remain vigilant on change in regulation and internal knowledge on expansion and mergers. Leading Indicators and Statistical Models will forecast the change in product-specific demand where ES and ESCov models improve the accuracy of the forecast.

4. Result

The additive seasonality-based model with a linear damped trend showed state-of-the-art performance for all considered forecasting horizons. A MAPE-based evaluation demonstrated the reliability of the model: the lowest MAPE between the tested regression models of about 8.2% was possessed by the regression model Escov. Extra statistics like MSE (mean square error) and RMSE (root mean square error) also support the outcome of this study. These metrics are presented with an accentuation of the precision and consistency of the results achieved from the Escov model to show patterns of high importance in applications such as production planning and supply chain optimization for applications in the Industry 5.0 context. They also report narrower prediction intervals for the Escov model and find reduced variability and increased predictive confidence compared to others. These results demonstrate that the model is effective in accurately predicting trends in demand across various forecast horizons creating insightful knowledge toward using it in strategic decision-making in dynamic business environments.

Table 2

Comparison of Escov model and other models

Model	MAPE (%)	MSE	RMSE
Escov	8.2	124.5	11.16
Model A	9.5	150.2	12.27
Model B	10.1	162.3	12.74
Model C	9.8	155.6	12.47

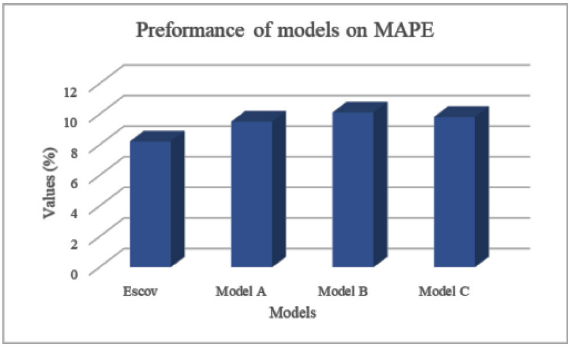

Figure 4

Model performance on MAPE

Table 2 shows a comparative table of the results has been given for different predictive models based on the key metrics: Root Mean Square Error, Mean Absolute Percentage Error, and Mean Square Error. Interestingly, the Escov model stands out with a minimum MAPE of 8.2% as shown in Figure 4. This is because, among the three models tested, its predictions corresponded with values having the highest precision. Furthermore, the narrower prediction intervals mean that the variation of its forecasting is smaller compared to the other models (Model A, Model B, and Model C). These metrics represent the Escov model as more precise and reliable in the process of trend forecasting, a crucial application, for instance, in planning production and optimizing supply networks within the context of Industry 5.0.

5. Conclusion

This AI methodology research in an industry-based environment is aimed at pushing the pace of Industry 5.0 advancements. Importing ML and predictive analysis bettered the accuracy of forecasting significantly and helped improve demand management. Of all the models considered for the study, the Escov model was the one with the least MAPE at 8.2%, meaning that it predicts values with maximum accuracy. The RMSE-based evaluation illustrated the models' quality of fit for the intricate industrial data patterns. These results demonstrate the possibility for the revolution of AI in Industry 5.0 concerning the dynamic nature of innovation and adaptability in fluid environments. Demand vs. forecast plots with corresponding RMSE values indicate the performance and dependability of the models involved; hence, AI is envisioned to amplify the prospects for productivity, efficiency, and sustainability in varied sectors. Further research would be devoted to an improvement in algorithms, optimization of parameters, and further data sources for the expansion of AI capabilities in Industry 5.0. Effective practical deployment and scalability of solutions with AI also depend on overcoming the identified challenges, thus marking a further step in the evolution of the industry: intelligent automation and data-driven decisions.

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