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The Industrial Transitions and Their Impact on Wind Solar Hybrid Power Generation with Inference Model Approach

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Abstract. The industry 5.0 revolution has an objective to enhance the performance of the specialized user with efficient integration, intelligent collaboration and manipulation of processes towards the precise and accurate results in order to optimized the resources in combination with the user in comparison to industry 4.0. In this article, the short comings of the industry 4.0 are faced regarding their application with wind-solar hybrid energy sector and highlights its solutions against challenges that enhanced its transformation toward the adaptation of the industry 5.0 revolution. We have elaborately discussed a potential application of industry 5.0 that proposes an architectural concept describing a transformation of industry 4.0, which implies a cyber physical system to the newly emerging industry 5.0 revolution adopting a human cyber physical system (HCPS) specifically for wind solar hybrid power generation plants. The proposed Industrial Internet of Things (IIoT) based model is presented in order to optimize the feedback and control system for the efficient utilization of energy resources for electrical power generation/consumption in connection with the micro grid connectivity. The presented model will be standardized and regulate the supervisory control and data acquisition system mediated by machine learning modeler and well-informed decisions.

Keywords: industry 4.0 and 5.0, human cyber physical system, intelligent collaboration, digital hybrid farms

Introduction

The innovation of electricity beginning in second industrial revolution, which accomplished by utilizing the steam engine and manual labour that were worked as main resource of industry. The concept of assembly lines for producing efficient manufacturing of goods was emerged in the second revolution known as industry 2.0 (Mokyr and Strotz, 2000). The integration of datasets and computer technology into factories was a remarkable effort that emerged another revolution as industry 3.0 which was utmost adopted as industrial revolution around the world especially in developing countries (Rifkin, 2011).

Furthermore, these advantages of factories transformed them towards more precession and accuracy of processes. The cyber physical system (CSP), internet of things (IoT), big data addition gave concrete support and emerges 4.0 revolution where human integration with the system was not necessary and machines could take self decisions (Fan *et al.*, 2018). This new digital technological era has initiated as data analytics and IoE that evolved as common technologies for manufacturing and production processes for improved, accurate and error free products (Shukla *et al.*, 2019). The implementation of advanced production systems with the integration of devices and equipment leads the industries towards a emerging concept of smart factories, which provide strategies for optimizing processes, reducing risks and maximizing profits favoured the dissemination of industry 4.0 revolution (Deya *et al.*, 2021).

In general, the self decision process and real time control of machines with precession and granularity are true features to adopt Industry 4.0 into an automation system of future factories (Shukla *et al.*, 2019; Vaidya *et al.*, 2018). Figure 1 shows the industrial transitions that shows major parameters and the concepts related to industry 4.0 (Alcacer and Cruz, 2019) and several industries such as oil/gas, energy utilities, aviation and other industries have extensively adopted IoT by means

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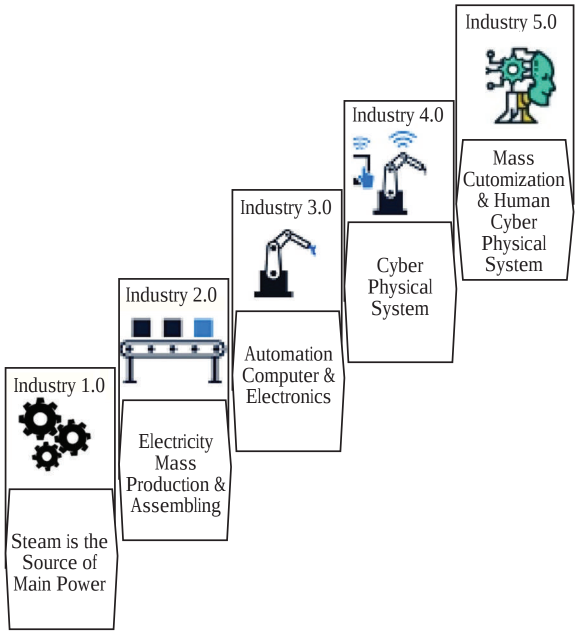

Fig. 1. Illustration of industrialization from steam-based technologies to précised mass production in smart factories through automation and digitization of old systems.

of communication, intelligent information systems and decisions against services (Ramamurthy and Jain, 2017).

Industry 4.0 standardized the integration within and between the devices to ensure decentralization, interoperability, transparency, real time data availability and information sharing (Czvetkó and Abonyi, 2023). The operational efficiency and automation achieved by industry 4.0 revolution objected as an industrial internet of things (IIoT) that performed smart digital transformation. The low integration of humans with machines on the opposite side decreased the customization of processes and produced lead time for more advancement. The IIoT rapped various applications for further digital transformation as an industrial revolution that eventually achieved operational efficiency and automation (Rajarajan *et al*., 2021).

By integrating several technologies, the industry 4.0 revolutionized every industry under the title of “smart” and ignored human interaction with machines. It is true that many technical visionaries believe that transformation towards a newly evolved industry 5.0 with human integration significantly benefit to industry (Zheng *et al*., 2020) with an expectation that this revolution will append the high speed, accurate machines and critical cognitive learning of humans. The major foresee motivations and benefits of industry 5.0 revolution may include an important contribution of industry 5.0 will be mass personalization, wherein the industrialist can prefer customized production according to market trends. It is also anticipated that industry 5.0 result in considerable increase in the efficient production with flexibility to alter among user-machines interface which return as responsible and authority for constant monitoring activities with an aim to increase the coordination among humans, machines and processes to uprise industrial growth at a rapid pace. It will improve the qualitative analysis of the industrial product by performing repetitive and monotonous tasks to machines and the tasks which need critical thinking to the humans. Which will create more jobs as compared to industry 4.0 due to integral conversion of simple cyber physical systems (CPS) to human cyber physical systems (HCPS), industry 5.0 mainly focuses on mass customization where humans will supervise robots to provide customer satisfaction, while the industry 4.0 robots will be engaged in large scale production. The interesting benefit of industry 5.0 is the protection of natural resources and environment and enhance the concept of clean and green earth (Demir *et al*., 2019). The predictive works and intelligence in operations not only edit and improve models but also creates, that aim at making more accurate and less unstable decisions. The majority of the reduction process will be automated as the real time data will be obtained from processing plants & machines in collaboration with highly equipped specialized personals.

Materials and Methods

Recently, the various technological trends such as electronically commutated (EC), digital twin (DT), internet of everything (IoE), big data analytics, COBOTS, 6G and block chain have progressively been integrated with artificial intelligence (AI) skills and innovations that can help renewable energy based power generation sector to perform effective transformation from industry 4.0 to industry 5.0 (Maddikunta *et al*., 2022).

The review (Hassan *et al*., 2023) discussed hybrid renewable energy system (HRES) with incorporation of the energy storage devices, such as batteries, super capacitors, pumped hydro, compressed air, gravity, thermal, hydrogen and fuel cells. Indeed, the higher up-front cost is needed as initial capital but increase the efficiency and peak hours performance several fold.

However, the option is still too expensive but recently a large scale (in mega-watts) energy storage station is on-line in China, which might help us to get insides and feedback for their future adaptability on large scale. The review (Roy *et al*., 2022), is discussed for the hybrid renewable energy systems in by consideration of their various parameters of the invertors, convertors, interfaces, couplings used in the hybrid energy systems and explained in details about the design, topology, architectures in combination of their algorithms and schemes such as various MPPT (maximum power point tracking) schemes that already in-use as a marketed products, with their efficiencies, convergence speeds and their system integrations.

Industry 4.0 evolution. The human plays a vital role in industry 4.0 revolution which is associated with the integration of digital transformation of industries where various methods and processes deign and developed by German industries (Golovianko *et al*., 2023; Oztemel and Gursev, 2020). In (Lasi *et al*., 2014) expresses that the human-free manufacturing environment composed of product, intelligence, machine-to-machine communication and networking are based on industry 4.0 as an emerging new vision. Cyber physical systems, the Internet of everything, cloud computing, artificial intelligence, machine learning and cognitive computing are main stack holders in transformation of conventional factories to smart factories (Soori *et al*., 2023). The digitization and intelligentization of manufacturing process introduced by industry 4.0 that promoted the idea of machine autonomy (Righi *et al.*, 2020; Vaidya *et al*., 2018).

Processing of different products in a manufacturing companies got a potential impact by adoption of industry 4.0 technologies (Zheng *et al*., 2020). The industry 4.0 paradigm accepts that manufacturing depends more on robots self decisions make easy in autonomous systems human involvement minimized in the process coordination and problem solutions and most of the data coordination carried out between machines rather than between humans. Such smart manufacturing improved the effectiveness of communication and analysis that make systems and processes more consistent robust and agile and therefore added many efficient business models. The manufacturing processes in industry 4.0 are flexible, adaptive, autonomous, unmanned and mostly sensor based that leads the system as a cyber physical system (CPS). In the article (Cortés *et al*., 2020) an industrial 4.0 human-cyber-physical systems (HCPS) framework and subsystems are analyzed in (Wang *et al*., 2022) where the advancement in human-centric smart manufacturing (HSM) explained in view of trend towards the integration of human-in-the-loop with technologies that addressed challenges of human-machine interactions. Such study resulted a mechanism for augmented operators which relies on intelligent personal digital assistants. Most of the field experiments have proven that the human centric approach is demonstrated a real impact on the operators learning. The main supervisory module is optimized for in combination with smart operators and working units.

Cyber physical system and wind solar hybrid system. Interfacing cyber physical systems (CPS) with a wind power hybrid system involves integrating digital and physical components to enhance the monitoring, control and optimization of the energy generation processes. The system comprises of many components whereas wind turbine, solar panels arrays, energy storage and power management components are playing major role. Sensors and data acquisition with a communication network utilizing edge and cloud computing including a control system provided integration between cyber physical system and wind solar hybrid system. Such interconnection is highly beneficial to improve efficiency, enhance monitoring and early detection of plant issues which determined the smooth operations and timely prediction of sustainable energy production.

Industry 5.0 evaluation (human interaction with machines). After almost ten years since the introduction of industry 4.0, the European commission announced industry 5.0 as a response to the evolving societal challenges (Lachvajderova *et al.*, 2023; Innovation, 2021). Industry 5.0 broaden the scope and enhance vision of industry that targeted beyond competence and generation to honour human values and contributing a vital role according to need. It sets the worker's wellbeing with other values such as the employees, the customers and society by focusing the manufacturing/production processes (Reddy *et al*., 2022). It is believed that emerging industry needs the transformation from the efficient use of industrial automation (industry 4.0) towards development (Haleem and Javaid, 2019) of implementing additional variables from onsite/ instantaneous decision making of existing user / trained worker. Maddikunta *et al*. (2022) proposed an upgradation of the current technologies such as edge computing, digital twins, collaborative robots, internet of everything and development of new applications such as intelligent healthcare, cloud manufacturing, supply chain management, etc. The current state of industry 5.0 regarding the related research trends has been analyzed in (Abdelmajied *et al*., 2022).

The industrial sector such as renewable energy, oil and gas etc. are critical stakeholder (Wanasinghe *et al*., 2021) where monitoring, production, process control and other parameters involves many challenges, including security issues. It is recommended to adopt latest emerging technologies such as smart sensor system, wearable or mobile appliances, data analytics, edge computing, extended reality technologies, robotic systems and drones in order to address the key constrains found in these avenues.

Renewable energy sector and industry 5.0 transformation. This paper will be discussing the concept of IIoT for the renewable energy sector, especially for a wind-solar hybrid power generation. The integration of IIoT in renewable energy industry will impose a demand-service model that creates customized energy farms as digital hybrid farms (DHF). The benefit of combining AI and IoE in designing the DHF may result in a success story under the title of smart grid with automated supply chain management, predictive production of electricity and prognosis of faults (Muhanji *et al*., 2019).

The number of parameters such as improvement of operational efficiency, increment in productivity, reducing asset lifecycle including safety and innovation are the key contributions of IIoT.

Therefore, the implementation of IIoT in renewable energy industry may eventually get results in high performance of operational efficiency that will enhance the confidence of industrialist in return towards the revolutionized renewable energy industries. In the area of wind-solar hybrid power generation, the prime purpose of IIoT is not limited to make accurate predictions of individual wind turbine or photovoltaic panel's output but also to enable accuracy, reliability and timely completion of assessment of entire generation system. In this connection, an IIoT based wind-solar hybrid power system is proposed in Fig. 2.

Three layered model. To understand the proposed DHF model, the authors have assumed a large wind solar hybrid power generation plant comprising a number of wind turbines interconnected to each other in parallel to a solar panels array where all are integrated through IIoT to predict various important parameters of the plant such as optimal power generation, timely production of electricity, etc. In this connection, an efficient and interdisciplinary approach is presented in this paper to theorize the whole power plant, which is comprised of three layers where every layer performs different tasks that are not independent.

IIoT based digital hybrid farms (DHF) model. *The scenario.* The simplified and brief structure is expressed in Fig. 2 where proposed IIoT model is comprises of three layers the first layer is IoT layer where the responsively initiated from conversion of solar and wind kinetic energy into electricity, the sustainable optimal electricity production approach, sensors and actuators logging, data transmission to cloud, local control system and a numerical layer.

The second layer is a numerical layer, which performs the decisions and takes actions against them such as prognosis of machinery/plant in parallel with manufacturer and OEM (operation and maintenance), forecasting of production and others. This layer received all signals from the IoT layer, evaluated them by pre-processing and prepared data for the machine learning layer. The third layer, which is the machine learning layer and also responsible for modeling as well as executing data mining or machine learning algorithms. The whole architecture in detail is illustrated in Fig. 3 that further explains in next secession.

IoT layer. Adekanbi (2021) explained in his study that the development of the IoT layer that enhances hybrid renewable energy systems is a challenge and a difficult task. The seasonal and daily variability in the climatic conditions can act as a primary difficulty in operating conditions at any instance in time is a subject to address as another challenge (Pai *et al*., 2020). The variability in operations means that is a need to determine the frequent time when the various output power of a system is robustly stable and optimal. Various external factors are not monitored here that may affect the power output of a plant.

Most of the signals from sensors and actuators in the proposed model are monitored and sent to the cloud utilizing the SCADA system in parallel with the internal communication data acquisition system. The numbers of mechanical and electrical sensors direct their typical data after driving by electronic circuitry by means of cable connections and network GPS system. Cloud connectivity is beneficial for manufacturers and operators of hybrid power plants to perform a number of functions

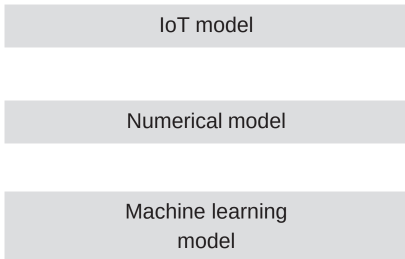

Fig. 2. The layered model of proposed architecture.

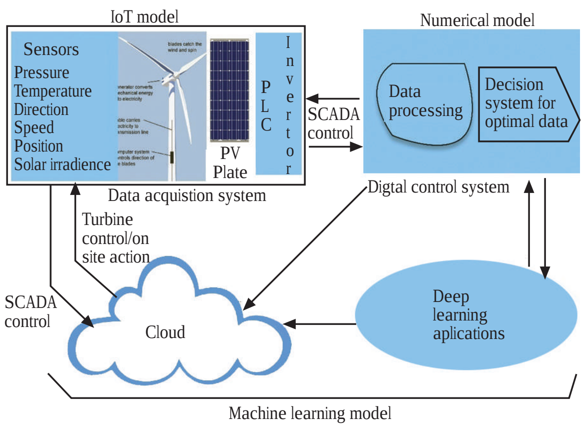

Fig. 3. Illustration of proposed architecture.

such as timely bounded power output, faults findings, weather effects monitoring.

Numerical layer. The information obtained from the defined scenario which consists of renewable energy plant as a modern power generation plant is huge, which can be integrated into the numerical layer to add a further level of realism to the prediction. Integration of data towards machine learning layer offers many possibilities such as the use of LiDAR (laser imaging, detection and ranging) on wind turbines to measure incoming wind speeds and directions that can be used to run preemptive/real time prediction of wind power output (Qadir *et al.*, 2021). The information received from sensors termed as a component, can be preprocessed to provide selection of data concerning variability to better predict lifespan of modern power generation and fault mechanisms. The data frames received and transmitted from the digital control system used by machine learning algorithm for further processing and prediction.

Machine learning layer. There is a need of forecasting for a sustainable production and supply of electricity to consumers from renewable sources that required regular monitoring and generation of electricity which is highly unpredictable due to its intermittent nature. Machine learning and its sub-field deep learning has been expanding rapidly (Wang *et al.*, 2019) due to tremendous development in industrial growth and associated technologies. Tremendous incremental growth in machine learning addressed many challenges and random issues such as prognosis of faults in large wind solar energy plants which are spread on squares of kilometers, power optimization at off peak and on peak periods and many others. Additionally, some studies have utilized a single machine learning model for forecasting hybrid renewable energy parameters and some using combine or hybrid prediction models due to the varied databases, time stamps, forecasting ranges/ settings and performance indicators.

Proposed IIoT based hybrid power plant. The growth of the renewable energy industry rises with the increment of size and number of equipment that has produced a large number of challenges. The use of computing to model and simulate power plant issues will be essential in improving efficiency as well as reducing the operational cost, therefore, the development of such computing architecture can play a vital role in the electricity market. A large number of models and methods are already implemented that utilized maps, climate, roughness, elevation and turbine data to simulate renewable energy power plants on different scales

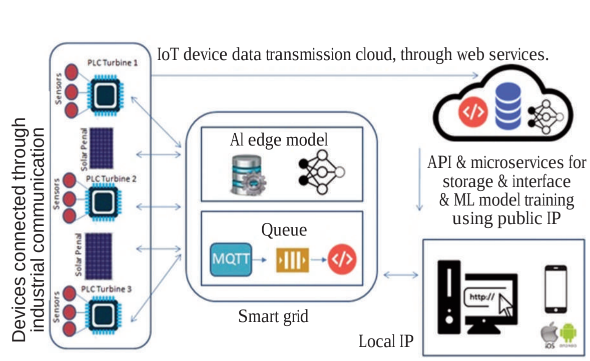

Fig. 4. Process flow of model digital wind solar hybrid farm (sensors transmit signals parallel to smart grid and cloud from devices where decisions are shared with GUI and micro services).

including their physics dynamics. In this respect, the API's, micro services and simulators could perform a key role in the design and development process, however, a certified trend towards models encircles a broad spectrum of technology and science as observed in published data. The futuristic approach to develop versatile and enhance models with computing advancement for renewable energy power plants are increasing in order to optimized the reliability, error management and feedback.

The authors believe that the growth of computing power with easy availability and its trends of coupling through scales and disciplines would produce an opportunity for IIoT based hybrid renewable energy power plants. It connects and corelate the independent technologies currently being undertaken into homogeneous scenario. Advanced smart grid system that leverages IoT devices, AI edge computing and cloud based services to optimize energy production and management is illustrated in Fig. 4. It highlights the flow of dataset frames sending data from sensors and actuators installed at programable logic controllers (PLC's) of wind turbines and array of solar panel modules. The edge processing of data stored on cloud perform analytics that ultimately provide accessible insights and control through web and mobile interfaces.

It also expresses the connections among IoT devices including their data flow and cloud connectivity to understand the proposed model where a windfarm integrated with solar farm. The hybrid power plant comprises a number of wind turbines and solar panels connected to a smart grid station in such a way that all turbines and solar arrays are locally communicated for optimal production with a cloud control decision, which is termed as a cyber physical system (Hao *et al*., 2021) such as wind pro, wind sim, open wind, wind farmer and many others can interface to cyber physical system and perform all operations, simulations, decision making and interacting with other systems. Furthermore, the turbines and solar arrays transmit data to cloud storage that is utilized for different decisions such as forecasting of power generation in peak hours by utilizing various machine learning algorithms. The data on cloud would be accessible for the manufactures of power plant components as well as to the smart grid applications developers. The user interface provided the real time condition of each and every wind turbine and solar electricity generation parameters graphically, as well as overall production status of plant. The cyber physical system in this model overcomes the discussed challenges, which is a difficult job to handle by an addition of human's interaction offering a transition to industry 5.0 revolution upgrading the existing industry 4.0 providing an emerging human cyber physical system. The chat GPT, Meta AI and various similar AI base bots are not able to substitute the human intelligence in order to reached the robust, customized and human friendly decisions and diversions by surpassing the cyber physical system such as training, counseling of AI based system for the humanity, sympathy and other unavoidable circumstances in plants where human interactions is highly impressive to compensate time line processing of wind solar form design and development.

Conclusion

The low integration of humans with machines in industry 4.0 reduced the customization of methods, processes and produced lead time for more advancement to integrate heterogenous technologies in industries. The IIoT based wind solar hybrid power generation model is an architectural concept to reduce this lead time. The model comprises of three layers; the IoT layer is responsively initiated the conversion of solar and wind kinetic energy into electricity. The second layer received all signals from the IoT layer, evaluated them by pre-processing, and prepared data for the machine learning layer which is responsible for modeling as well as executing machine learning algorithms. As a result, the proposed architecture is enhance accuracy, reliability and timely completion of assessment of entire generation system of such industries.

Nevertheless, the proposed model will be applicable to other sectors providing high performance such as automobile, satellite manufacturing and other industrial mass manufacturing industries. The advancement by the proposed model will enable the wind solar hybrid power generation plants towards realization of customized autonomous. Transitions from industry 4.0 to industry 5.0 performed industrial realization in a precise way and dealing uncertainty by utilizing rapid growth of industrial internet of things (IIoT), cloud manufacturing, huge data analytics and cloud computing.

Conflict of Interest. The authors declare they have no conflict of interest.

References

Abdelmajied, F.Y. 2022. Industry 4.0 and its implications: concept, opportunities and future directions. In:

Supply Chain - Recent Advances and New Perspectives in the Industry 4.0 Era, edited vol. Intechopen, Egypt.

Adekanbi, M.L. 2021. Optimization and digitization of wind farms using internet of things. *International Journal Energy Research*, **45:** 15832-15838.

Alcacer, V., Cruz-Machadoab, V. 2019. Scanning the industry 4.0: a literature review on technologies for manufacturing systems. *Engineering Science and Technology, an International Journal*, **22:** 899-919.

Cortés, D., Ramírez, J., Villagómez, L., Batres, R., Lopez, V.V., Molina, A. 2020. Digital pyramid: an approach to relate industrial automation and digital twin concepts. In: *Proceeding of 2020 IEEE International Conference on Engineering, Technology and Innovation* (*ICE/ITMC*). IEEE.

Czvetkó, T., Abonyi, J. 2023. Data sharing in industry 4.0 - automation ML, B2MML and international data spaces-based solutions. *Journal of Industrial Information Integration*, **33:** 100438.

Demir, K.A., Döven, G., Sezen, B. 2019. Industry 5.0 and human-robot co-working. *Procedia Computer Science*, **158:** 688-695.

Deya, B.K., Bhuniya, S., Sarkarc, B. 2021. Involvement of controllable lead time and variable demand for a smart manufacturing system under a supply chain management. *Expert Systems with Applications*, **184:** 115464.

Fan, C.F., Chan, C.C., Yu, H.Y., Yih, S. 2018. A simulation platform for human-machine interaction safety analysis of cyber-physical systems. *International Journal of Industrial Ergonomics*, 89-100.

Golovianko, M., Terziyan, V., Branytskyi, V., Malyk, D. 2023. Industry 4.0 vs. industry 5.0: co-existence, transition, or a hybrid. In: *Proceeding of 4th International Conference on Industry 4.0 and Smart Manufacturing*. *Elsevier*, *Procedia of Computer Science*, **217:** 102-113.

Haleem, A., Javaid, M. 2019. Additive manufacturing applications in industry 4.0: a review. *Journal of Industrial Integration and Management*, **4:** 1930001.

Hao, W., Yang, T., Yang, Q. 2021. Hybrid statistical-machine learning for real-time anomaly detection in industrial cyber-physical systems. In: *IEEE Transactions on Automation Science and Engineering*, pp.1-15.

Hassan, Q., Algburi, S., Sameen, A.Z., Salman, H.M., Jaszczur, M. 2023. A review of hybrid renewable energy systems: solar and wind powered solutions: challenges, opportunities, and policy implications. *Results in Engineering*, **20:** 10162.

Lachvajderova, L., Kadarova, J., Sanchis, E.J., Rybarova, D., 2023. Industry 5.0-a sustainable human-centric solution. In: *Proceeding of Conference*, *Novus Scientia*, Kosice, Slovakia.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., Hoffmann, M. 2014. Industry 4.0. *Business and Informatiom System Engineerings*, **16:** 239-242.

Maddikunta, P.K.-R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T., Rukhsana, R., Liyanage, M. 2022. Industry 5.0: a survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, **26:** 100257.

Mokyr, J., Strotz, R.H. 2000. *The Second Industrial Revolution*, 1870-1914. Semantic Scholar Publisher, Rome, Italy. WCAS; Corpus ID: 16047909.

Muhanji, S.O., Flint, A.E., Fari, A.M. 2019. eloT: *The Development of Energy Internet of Things Infrastructure*, Springer, Switzerland.

Oztemel, E., Gursev, S. 2020. Literature review of industry 4.0 and related technologies. *Journal of Intelligent Manufacturing*, 127-182.

Pai, P.-F., Chen, C.-H., Lai, J.P., Chang Y.-M. 2020. Review a survey of machine learning models in renewable predictions. *Applied Sciences*, **10:** 5975.

Qadir, Z., Khan, S.I., Khalaji, E., Munawar, H.S., Turjman, F.A., Mahmud, M.A.P., Kouzani, A., Khoa, N.A.L. 2021. Predicting the energy output of hybrid PV–wind renewable energy system using feature selection technique for smart grids. *Energy Reports*, **7:** 1-11.

Rajarajan, S., Renukadev, S., Basim, N.M. 2021. Industrial IoT and intelligent manufacturing. In: *Futuristic Trend in Intelligent Manufacturing*, pp. 182-203. DOI: 10.1007/978-3-030-70009-6_12.

Ramamurthy, A., Jain, P. 2017. The internet of things in the power sector: opportunities in Asia and the pacific. *Asian Development Bank Working Paper Series*, vol. **48**. DOI:10.22617/wps178914-2.

Rifkin, J. 2011. The third industrial revolution. In: *How Lateral Power is Transforming Energy*, *The Economy and the World*, Palgrave Macmillan, NY. USA. ISBN: 978-0-230-11521-7.

Righi, R.R., da silva, F.S., Crovato, C.D., Righib, R.R. 2020. Looking at energy through the lens of industry 4.0: a systematic literature review of concerns and challenges. *Computers and Industrial Engineering*,

143: 106426. DOI: 10.1016/j.cie.2020.106426.

Roy, P., He, J., Zhao, T., Singh, Y.V. 2022. Recent advances of wind-solar hybrid renewable energy systems for power generation: a review. *Industrial Electroincs Society*, *IIEE Open Journal of the Inustrial Electronic Society*, **3:** 1-1.

Shukla, A.K., Abraham, A., Abraham, A. 2019. Industry 4.0: a bibliometric analysis and detailed overview. *Engineering Applications of Artificial Intelligence*, **78:** 218-235.

Soori, M., Arezoo, B., Dastres, R. 2023. Internet of things for smart factories in industry 4.0, a review. *Internet of Things and Cyber-Physical Systems*, **3:** 192-204.

Vaidya, S., Ambad, P., Bhosle, S. 2018. Industry 4.0 – a glimpse. *Procedia Manufacturing*, **20:** 233-238.

Wanasinghe, T.R., Trinh, T., Nguyen, T., Gosine, R., James, L., Warrian, P.J. 2021. Human centric digital transformation and operator 4.0 for the oil and gas industry. *IEEE Access*, **99:** 1-1.

Wang, B., Zheng, P., Yin, Y., Shih, A., Wang, L. 2022. Toward human-centric smart manufacturing: a human-cyber-physical systems (HCPS) perspective. Elsevier; *Journal of Manufacturing Systems*, 471-490.

Wang, H., Lei, Z., Zhang, X., Zhou, B., Peng, J. 2019. A review of deep learning for renewable energy forecasting. Elsevier: *Energy Conversion and Management*, **198:** 111799.

Zheng, T., Ardolino, M., Bacchetti, A., Perona, M. 2020. The applications of industry 4.0 technologies in manufacturing context: a systematic literature review. *International Journal of Production Research*, **59:** 1922-1954.