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Towards Intelligent Industrial Informatics: A Review of Current Developments and Future Directions of Artificial Intelligence in Industrial Applications

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Abstract

Research, the universal pursuit of new knowledge, is embarking on a fresh journey into Artificial Intelligence (AI). Nature reports that *AI* arose nine places to fourth most popular search-term, and that search-terms *machine-learning* and *deep-learning* appeared in the top-20 search for the first time in 2018. It is pertinent for Industrial Informatics to embrace this renewed surge of interest in AI with clear direction and purpose that engages scholars, practitioners and professionals alike. This article aims to motivate, formalise and inform that engagement by contributing a blueprint for the advancement and convergence of AI in Industrial Informatics, rigorously based on past work and recent developments in both disciplines. A review of the state-of-the-art developments of AI across five primary domains of Industrial Informatics; Energy, Transport, Factories, Industrial Processes, and Cyber-Physical Systems. A reference framework for research innovation in AI, and a reference architecture for the manifestations of AI in Industrial Informatics are major contributions of this article. A case study on intelligent renewable

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energy generation and consumption followed by a discussion on future directions of AI pledges a fitting segue to its imposing success in Industrial Informatics.

Index Terms

Artificial Intelligence, Industrial Informatics, Machine Learning, Deep Learning, Internet of Things, Industrial Applications, Industrial AI, Industrial Processes, Factory Automation, Robotics, Optimization, Symbolic AI, Probabilistic Reasoning, Artificial General Intelligence.

I. Introduction

Industrial Informatics is a branch of information engineering and information processing which involves the practice of information collection, integration, analysis, distribution, and actions to achieve higher efficiency, effectiveness, reliability, and security from physical operations and physical systems, within an industrial environment [1]. Artificial Intelligence (AI) has been an enabler and facilitator of Industrial Informatics with varying degrees of interest and success over time. Recent advancements in computational infrastructure, algorithmic novelty and the availability of industrial big data generated by the increasing digitalisation of process, systems and interactions, have proliferated into a paradigm shift in the use of AI. In past work, the main practical focus has been on the development of industrial AI which sought to transfer knowledge from engineers and domain experts to algorithms and computer systems for increased operational efficiencies. In the current context, the ability to leverage AI for real-time monitoring and real-time control is predicted (and in some instances actualised) to be the primary driver of tactical leverage, strategic advantage, competitive strength, leading towards fully autonomous, intelligent systems that achieve organisational objectives, as well as social, economical, and environmental obligations.

Artificial Intelligence (AI) was first conceived in the minds of philosophers as ”mechanical tripods” and ”intelligent non-humans” for reflecting on the purpose of humanity; the Wizard of Oz [2], a more recent and conceivable embodiment of such intelligence. It is pertinent to revisit the history of AI, in chronological order, to not only serve the purpose of record, but also an exemplar for current work and an inspiration for future innovation. The birth of AI is generally attributed to the two-month workshop at Dartmouth in 1956, where the term was coined by John McCarthy, and Logic Theorist [3] was demonstrated to simulate human reasoning. A string of elementary successes, the General Problem Solver [4], the Geometry Theorem Prover [5], LISP [6], the world of blocks and Huffman's vision project [7], and the perceptron [8], was followed by the first AI winter, due to exaggerated claims and lack of progress. A resurgence in the 1980s was driven by the seemingly strong methods of reasoning, which were in contrast to the weak methods of 1960s. The Dendral project [9] and MYCIN [10] popularised these strong methods of reasoning as expert systems, separately connectionism came of age owing to back-propagation [11], Hopfield nets [12] and the general notion of parallel distributed processing [13]. However, a second AI winter emanated in mid 1980s due to receding interest from government and industry funding bodies. A more cautious approach firmly based on the scientific method was adopted in the 1990s which saw AI become commercially successful, with first applications in optical character recognition, speech recognition and computer vision. Although not commonly referred to as AI due to significant failings in past efforts (the AI winters), this wave of interest has persevered through to the present date, guised in the terminology of intelligent agents, data mining, industrial robotics, intelligent search, neurocomputing, machine learning, fuzzy logic, evolutionary computation, analogy-based learning and more recently a fresh interest in predictive analytics, data science, deep learning and artificial general intelligence. In retrospect, Marvin Minsky's definition of AI from 1968, ”the science of making machines do things that would require intelligence if done by humans”, [14] continues to be ubiquitous and permeating across all innovation thus far, including Industrial Informatics.

The current continuum of AI is extensive, ranging from the more structured end of symbolic AI and probabilistic reasoning to the unstructured end of unsupervised generative and deep learning on unstructured data. In terms of a logical organization of the discipline of AI, the five major topics of AI are; 1) Symbolic AI (Deduction and Induction, Decision trees, Random Forests, Fuzzy Logic), 2) Probabilistic Reasoning (Naive Bayes, Bayesian Networks, Markov Chains), 3) Evolutionary Computation (Genetic algorithms, Swarm Intelligence, Neuro-evolution), 4) Analogy-based Reasoning (k-Nearest Neighbor, Support Vector Machines, Association Rules) and 5) Connectionism (supervised/Semi-supervised/Unsupervised machine Learning, Deep Learning, Reinforcement Learning, Transfer Learning). A multitude of content on the theoretical and application potential of each topic and technique is available in online and research literature, and beyond the scope of this article.

Authors initiated this review on past work and current developments by conducting a comprehensive study of all research articles published in the five years to-date, 2014-2019, across the domains of Industrial Informatics. Each article was classified based on AI technique (also referred to as AI methods/technologies/approaches) and domain of application. The tree-map in Fig. 1 depicts the most prevalent AI techniques in this collection of articles. Based on this depiction, it is appropriate to infer that computer vision applications of image classification, object recognition, and video tracking using convolution neural networks/supervised learning techniques dominate the industrial landscape.

Authors identified the primary domains of AI in Industrial Informatics as, 1) Power and Energy, 2) Transport, 3) Internet of Things and Cyber-Physical Systems 4) Manufacturing, Factories and Buildings, and 5) Industrial Processes, Real-time Monitoring and Control. The following section delineates and reviews recent developments in each domain.

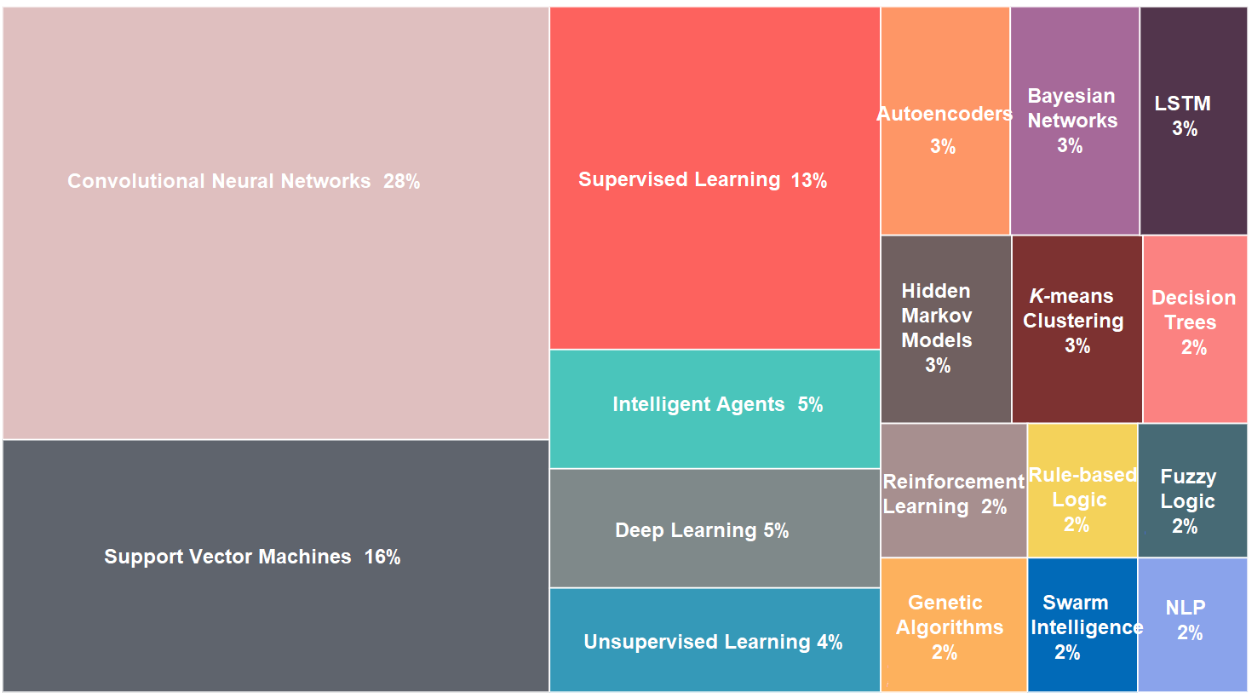

Fig. 1. A tree-map representation of AI techniques and ratio of usage in Industrial Informatics

II. Review of Current Developments

A. Power and Energy

In the power and energy domain, AI research has focused on detection, forecasting, management and real-time control from primarily structured data generated by sensors attached to power systems and energy infrastructure. In [15], authors introduce an IoT-based deep learning approach to automatically extract features from the captured data, to generate an accurate estimation for load forecasting. A similar approach is proposed in [16], where a long short-term memory-based (LSTM) deep-learning framework accounts for appliance consumption sequences to improve demand forecasting accuracy. Extraction of usage patterns from compressed smart meter data is the focus of [17], where a sparse representation technique, composed of two phases, dictionary learning and sparse coding, is used to decompose load profiles which allows the smart meter data to be compressed and hidden usage patterns to be explored. A temporal multilabel classification approach in the domain of nonintrusive load monitoring is proposed for the identification of electrical appliances inside residential buildings in [18]. In [19], authors propose a hierarchical smart grid architecture with hidden mode Markov decision process model and Q-learning-based approximate dynamic programming for real-time decision-making on demand forecasting.

On anomaly and fault detection, authors propose a three-stage multi-view stacking ensemble machine learning model based on hierarchical time series feature extraction, for detection of electricity theft and unplanned power loss, in [20]. In [21], a wide and deep convolutional neural networks (CNN) model is proposed for the same challenge of electricity theft detection, the deep CNN component identifies nonperiodicity of electricity theft as opposed to periodicity of normal consumption, and the wide CNN identifies global features of one-dimensional consumption data. A novel method for single and simultaneous fault location in distribution networks by means of a sparse representation vector, using fuzzy-clustering is proposed in [22]. Its performance is validated by implementation on a real distribution network with noisy and noise-free measurement. A decision-support framework that operates within the IoT ecosystem is proposed in [23]. This framework leverages smart meter network communication-quality data to improve cost predictions for field operations of technical faults.

Multi-agent approaches for the control of various industrial systems [24] has been widely explored in the last two decades as a means to achieve adaptability to internal and external disturbances. It takes inspiration from the behaviour of neuro-biological phenomena in both humans and animals. A review of the application of multi-agent approaches in the smart energy domain is presented in [25], while [26] elaborates on broader classes of intelligence approaches in future electric energy systems. The practical application of multi-agent architectures in the smart energy domain required addressing a number of issues related to backward compatibility with industrial practices, standards and requirements. Zhabelova et al [27], [28] present an architecture that integrates multi-agent organization with industrial standards IEC 61850 and IEC

61499 for increased industry adoption. Modelling of natural language requirements with semantic knowledge models can be used for finding inconsistencies and ambiguities in the requirements of smart grid automation and automatic code generation, as demonstrated in [29]. An optimization model for rooftop photovoltaic distributed generation with battery storage was proposed in [30]. Separately in [31], a comprehensive survey of smart electricity meters and utilization focusing on key aspects of the metering process, stakeholder interests, and the technologies used to address stakeholder interests are reported, with an overview of the increasing popularity of cloud environments for smart meter data processing. A review of data analysis for intelligent energy networks is reported in [32]. The focus is on pattern recognition, machine learning, data mining, statistics methods, with a discussion on the unaddressed challenges in big energy data.

B. Transport

Intelligent traffic prediction, infrastructure maintenance, pedestrian movement, and smart city insights generation are the primary areas of focus for AI research in transport. In [33], authors report the first effort to use deep learning for traffic prediction, where a deep architecture consisting of two parts, a deep belief network (DBN) for unsupervised feature learning and a multitask regression layer above the DBN for supervised prediction. In [34], authors report on the usage of deep learning in predictions of several traffic indicators, such as traffic speed, flow, and accident risk, using traffic data from road infrastructure, trajectory data from vehicles and automatic fare collection from transit systems. A deep CNN that collectively counts the number of vehicles on a road segment based solely on video images, without special attention to an individual vehicle as an object to be detected separately, is proposed in [35]. A further CNN approach is proposed in [36] for classification of road traffic conditions based on video surveillance data, to establish measures of congestion of observed traffic. In [37], authors propose a unified online and offline learning framework for traffic sign detection, tracking, and recognition task using a mono-camera mounted on a moving vehicle. This framework utilises contextual information, improves tracking performance and localization accuracy, and provides stable classification output. A vehicle type classification scheme using images acquired from multi-view visual traffic surveillance sensors is proposed in [38], where data augmentation with balanced sampling is applied to on unbalanced data, followed by a CNN constructed with parameters learned on the augmented training data. A novel traffic forecasting method based on long short-term memory (LSTM) network is proposed in [39]. It considers temporal-spatial correlation in traffic system via a two-dimensional network composed of multiple memory units. In [40], an intelligent personalized driver intention prediction system for T-intersections is proposed.

On transport infrastructure maintenance, rail track defect detection is improved by combining multiple detectors within a multitask learning framework in [41]. It overcome the challenges of diverse failure modes, false positives, and unbalanced training samples. A study reported in [42] attempts to predict granular carbon emissions for an enitre city, based on spatio-temporal data from taxi GPS, traffic, road networks, points of interests and meteorological data, using a three-layer perceptron neural network that infers emission volumes.

Pedestrian movement is essential for transport and surveillance in smart cities. In [43], authors detect pedestrian movement and direction of movement, using a CNN based on conventional detection techniques of histograms of oriented gradients. Noting the performance deficiency in conventional CNN, a fast regional detection cascaded with CNN for real-time pedestrian detection is proposed in [44], with 97.5% accuracy at 15 frames per second, without a Graphical Processing Unit (GPU). An intelligent framework based on deep learning with the use of multiple sources of local patterns and depth information for on-road vehicle and pedestrian detection, recognition, and tracking is proposed in [45].

Recent research focusing on smart city insights generation has been diverse. In [46], deep reinforcement learning (DRL) techniques have been proposed for model-free unmanned vehicles control to collect crucial traffic and movement data in sensing regions. A further semi-supervised DRL approach is proposed in [47] that consumes both labeled and unlabeled data to improve the performance and accuracy of a generic learning agent, which is then used as an inference engine for generalizing optimal policies in smart city settings. A big data architecture consisting of three planes; storage plane, processing plane, and application plane is proposed in [48] for providing satisfactory Quality of Experience to smart city users. An infrastructure-independent approach for anomaly detection and identification based on data collected through a smartphone application is proposed in [49], which uses supervised machine learning algorithms to classify obstacles into predefined categories. In [50], brain-computer interfaces for identifying drowsy driving states were motivated with the development of a recurrent fuzzy neural network to increase adaptability in low resolution imaging.

C. Internet of Things (IoT) and Cyber-Physical Systems (CPS)

A large body of AI research in IoT and CPS focus on embedding AI techniques and methods into edge devices, smart devices, wearable devices and smart sensors. In this regard, novelty of structure and function of the intelligent algorithms is required to reduce the computational and communication overhead for insights generation, such as detection, prediction and prescription. In [51], an overview of algorithmic and processor techniques for transitioning deep learning to IoT and CPS is provided. A hybrid framework for privacy-preserving, accurate, and efficient analytics of IoT and CPS data based on user-centered edge devices and cloud computing is proposed in [52]. In [20], authors attempt to use industrial IoT to detect anomalies in power consumption based on a multi-view stacking intelligent ensemble. In [53], a novel approach for automatic retraining in real-time without labelled training data for activity recognition is proposed. Self-evolving AI for enabling data interoperability in IoT, CPS and video surveillance settings is proposed in [54]. In [55], authors propose an intelligent privacy-preserving traffic obfuscation framework for protecting smart homes from malicious internet traffic analysis. A hierarchical framework for feature extraction in the social IoT using map-reduce computation is proposed in [56]. On context-aware IoT systems, the detection and adaptation of concept drift based on the cognitive principles of machine learning was proposed in [57].A hierarchical distributed fog computing architecture to support the integration of infrastructure components and services using fiber optic sensors and sequential learning algorithms was proposed in [58].

An efficient, intelligent and incentive-based peer-to-peer knowledge market to make knowledge tradeable in edge-AI enabled IoT [59], a performance optimization framework for blockchain-enabled IIoT systems [60], a fog-embedded privacy-preserving deep learning framework [61], and an AI-driven approach for edge computing-based industrial applications [62] are further indications of the importance of low-energy AI for IoT and CPS. Energy-efficient AI as a focus area for new research is further discussed in Section VI.

D. Manufacturing, Factories and Buildings

In manufacturing and factory automation, the general area of interest continues to be Industry 4.0, with specific focus on fault detection, process optimisation, process management and predictive maintenance. The development of Industry 4.0 in intelligent manufacturing, transforming the digital factory into the intelligent factory is presented in [63]. A recent review article on the state-of-the-art and future developments specifically focuses on Industry 4.0 and Made-in-China 2025.

The latter aims to transform China beyond the world's workshop into a world manufacturing power, based exclusively on AI in Industry 4.0 settings. In a smart factory setting, the challenges of anomaly detection and localisation for real-time video surveillance has been addressed using an incremental spatio-temporal learning algorithm [64].

On fault detection, an approach for distributed fault isolation using Vector symbolic architectures (VSA), which is a fast and efficient implementation of a machine learning technique due to fixed-point computation was proposed in [65]. A virtual metrology (VM) challenge of estimating quantities that are costly or impossible to measure in a process control mechanism is addressed using deep learning. This approach automatically extracts highly informative features from the data, providing more accurate and scalable VM solutions [66]. A data-driven approach for assessing the health-status of machines in a factory environment using discriminative deep belief networks and ant colony optimization is proposed in [67] as a predictive maintenance approach, and a novel pipeline for detecting and isolating hotspot areas in photovoltaic modules using K-means color quantization and density-based spatial clustering is reported in [68].

In application of AI for fault diagnosis in manufacturing environments, a CNN based approach which discards hand-crafted features, and works solely on process signals that are converted into two dimensional images, was proposed in [69]. An approach based on sparse autoencoder and deep belief network has been proposed in [70] and [71] for multisensor feature fusion for bearing fault diagnosis. In [72], authors propose a novel fault diagnosis method for complex circuit board design using feed forward neural networks and support-vector machines that learns from repair history and localizes the root cause of a failure. In [73], X. Han et al formulate active object detection in industrial settings as a sequential action decision process, and apply a deep reinforcement learning framework, the deep Q-network (DQN) with dueling architecture to solve this formulation, by learning an optimal action policy. A deep neural network based two-stage automated approach for estimating the remaining useful life (RUL) of bearings in industrial machinery is proposed in [74], and in [75], authors model disassembly sequence planning as an NP-hard (non-deterministic polynomial-time hardness) many-objective problem, and solve this using the tensorial memetic algorithm that combines genetic computations with local search. In [76], authors formulate long-term and short-term utility of stakeholders in manufacturing service sharing for Industrial Internet platforms as a multi-objective optimization problem, and solve this using an improved non-dominated sorting genetic algorithm that combines Tabu search (an improvement over local neighbourhood searching) and K-means (which segments n observations into k clusters).

In building automation, most research is focused on energy management. An intelligent approach to address the void between predicted and actual energy performance in public building [77], prediction models for next-day building energy consumption and peak power demand [78], a data mining framework for improving building operational performance [79] and fault detection using data mining for a cluster of buildings [80] have been reported in the literature.

E. Industrial Processes, Real-time Monitoring and Control

The rapid automation of complex industrial processes has led to a disconnect from model-based solutions for monitoring, control and management of such processes [81]. This void has been suitably addressed by data-driven solutions that are based on AI techniques, alongside the pronounced benefit of real-time insight generation. It is promising to note that the two application fields, network-based systems and new power systems, highlighted by authors of [81], have continued to expand in this space. A combined fault-tolerant and predictive control scheme for network-based industrial processes is proposed in [82], where the tracking problem at device layer and the optimization problem at operation layer were solved using Markovian chains and radial basis functions, respectively. The performance-based control design problem for double-layer networked industrial processes has also bee explored using a similar approach [83]. A review of the generalised performance capability of support vector machines, and its suitability for applications with small samples of training data has also been reported [84]. More recently, a recursive slow feature analysis algorithm for adaptive process monitoring, based on the receipt of streaming data samples has been developed and evaluated on a crude heating furnace system [85]. A neuron adaptive splitting and merging radial basis function neural network that identifies dynamic behaviors of an industrial process has been developed and evaluated to control the iron removal process in a zinc hydro-metallurgy plant [86]. A fog-computing-aided process monitoring and control architecture for large-scale industrial processes has been proposed and demonstrated through the case study on the Tennessee Eastman benchmark system [87].

In [88], authors propose the use of Gaussian-type security inputs and a convex optimization approach for an asymptotic stabilization problem across the cloud and fog, into a controlled device. They demonstrate feasibility of this approach by tracking the reference signal of storage batteries in smart grids. A reinforcement-learning-based online optimal control method for hybrid energy storage system (HESS) in AC/DC microgrids with photovoltaic systems and diesel generators, is proposed in [89]. The learner is used to estimate the nonlinear dynamics of HESS based on the input/output measurements, and to learn the optimal control input using the estimated system dynamics. In [90], authors propose an overall distribution maximum power point tracking algorithm integrated with particle swarm optimization (PSO) to rapidly search for global maximum power points in solar photovoltaic systems under partial shading conditions. The advantage of using PSO is in that a global scan of power–voltage curve in not required, leading to less sampling points and lower computational costs. Supervisory Control and Data Acquisition (SCADA) systems are essential to most industrial technologies, however they are vulnerable to cyber attacks. In [91], a real-time monitoring technique for SCADA-specific intrusion detection is proposed. It demonstrates automatic identification of consistent and inconsistent states of SCADA, and automatic extraction of proximity detection rules from identified states, based on unsupervised fixed-width clustering. A distributed robust adaptive neural network controller with a local observer for the distributed consensus tracking problem of uncertain multiagent systems with directed communication topology and a single high-dimensional leader, is proposed in [92]. Authors demonstrate that in a fixed communication topology containing a directed spanning tree at the leader, the states of followers can track its output within bounded residual errors. A novel deep learning approach for automated fault detection and isolation in automotive instrument cluster systems in computer-based manufacturing assembly lines is proposed in [93]. Authors report improvements in fault detection, adaptation to changes in fault sources and automatic identification of new fault types, based on experiments conducted on a real-time module integrated on an auto calibration station. The unique combination of highly sensitive acoustic sensors as input to a convolutional neural network (CNN) is proposed in [94] for process monitoring in additive manufacturing. The CNN was used to classify features from categories defined based on porosity contents of the additives. The reported classification accuracies are 78%-91% indicating potential for in-situ and real-time quality monitoring in additive manufacturing.

Multi-agent architectures have been researched as a solution for adaptability of manufacturing and logistics industrial processes. Authors of [95], [96] prove that multi-agent control can be practically applied in material handling applications, where each unit (e.g. a conveyor section) implements autonomous behaviour, collaborating with neighbouring units, but together they are capable of implementing same functionality as the centrally controlled systems, but with improved level of adaptability and robustness to disturbances. Sorouri et al [97] extends this approach to intelligent mechatronic systems, such as modular manipulators. Mukhutdinov et al.

[98] take a novel step in implementing agents, by using recurrent neural networks for a single agent functionality implementation. The network of agents trained on examples of behaviours of agents from [96] not only exhibit routing capability of the distributed Bellman-Ford algorithm, but also demonstrate improvements in energy consumption.

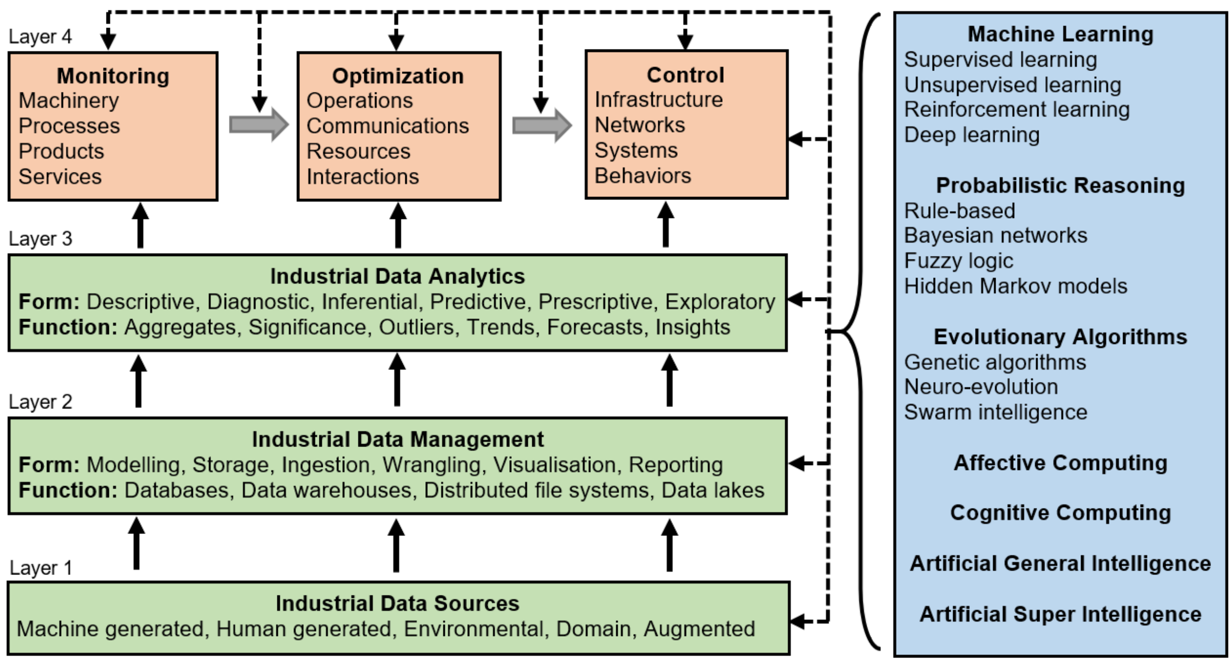

Fig. 2. A Reference Framework for Intelligent Industrial Informatics

III. A Reference Framework for Intelligent Industrial Informatics

Although the terms Big Data, Industrial Internet of things (IIoT) and Industrial AI have been used to describe the overarching impact and transformational value of AI on industrial environments, there has been no clear discussion how this new environment relates to Industrial Informatics and how Industrial Informatics has evolved to embrace and accommodate this changing environment. In order to address this gap, authors propose a Reference Framework for Intelligent Industrial Informatics. This framework is an amalgamation of findings from the five primary domains of Power and Energy, Transport, Internet of Things and Cyber-Physical Systems, Manufacturing, Factories and Buildings, Real-time monitoring and control, as well as overarching concepts, commentary and critique reported in the reviews [99], [100], [101], [102]. Authors have materialised the key priorities for the advancement of Intelligent Industrial Informatics across its diverse domains as; monitoring, optimization and control. The aspirations of

AI for the empowerment of Industrial Informatics are two-fold, 1) internally - growth within each individual priority area, and 2) externally - increasing levels of intelligent automation that advance monitoring, optimization and control, in-sequence, towards full autonomy, while incorporating intelligent and ethical human interactions. In order to achieve these aspirations, it is important to consider the bottom-up contributory nature of the supporting objectives of AI. Fig. 2 illustrates these objectives overlaid upon the current state of AI in Industrial Informatics. This reference framework consists of three layers, 1) Industrial Data Sources, 2) Industrial Data Management and 3) Industrial Data Analytics which sequentially feed into the 4) three priority areas of Monitoring, Optimization and Control. The techniques and methodologies of AI, ranging from machine learning to ensembles of artificial general intelligence, collectively work towards the *empowerment* of Layers 1) through 4).

Layer 1: The sources of industrial data remain the same, primarily machine, human, and environment generated along with domain knowledge representations and data augmentation efforts using external sources, past data and generative AI methods.

Layer 2: Industrial data management requires new thinking as the volume, velocity and variety of industrial data expands. This framework separates data management into form and function. Form begins with an extensive design phase, which includes, data modelling, conceptual design, design and implementation of physical storage. Design is followed by a data ingestion and wrangling phase, where transformations, imputations, normalisation as well as further representational revisions are conducted. Finally, the management layer is used for visualisations and reporting from structured and formulated data storage, which includes databases, data warehouses, and distributed file systems for use with scalable computing infrastructure.

Layer 3: Industrial data analytics formalises and summarises a range of use cases and application scenarios of AI in industrial settings. From the reactive notions of descriptive, diagnostic and inferential analytics to the proactive notions of predictive, prescriptive and exploratory analytics, this layer generates the functional outputs of aggregates, level of significance, outliers, trends, predictions and actionable insights that motivate decision-making in monitoring, optimization and control.

Layer 4: The complexity of automation increases from left to right, beginning with monitoring machinery, processes, products and services, that contribute towards the optimization of operations, communication, resources and interactions, leading into intelligent control of the encompassing infrastructure, networks, systems and behaviors.

It is important to make note that the suite of AI techniques depicted on the right-hand side of Fig. 2 contribute towards each layer, as well as the transitions across each priority area of Layer 4. The suite of AI techniques consist of: machine learning for data-driven problems, probabilistic reasoning for knowledge-based representational problems, evolutionary algorithms for intelligent search and optimisation, and affective computing for social and human-centric intelligence. These primary AI techniques collectively contribute towards the development of high-order intelligence and cognition encapsulated in cognitive computing, and provide a potential formulation towards artificial general intelligence and artificial super-intelligence.

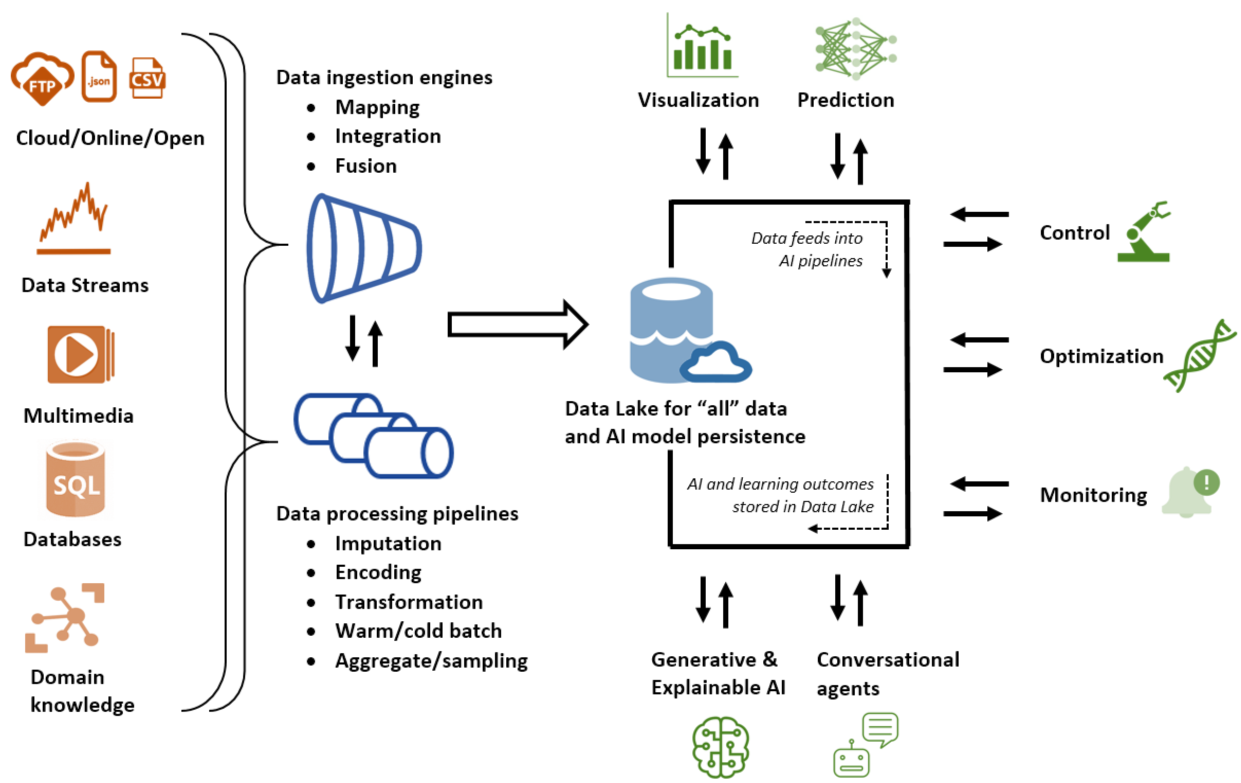

Fig. 3. A Reference Architecture for Intelligent Industrial Informatics

IV. A Reference Architecture for Intelligent Industrial Informatics

The actualisation of this reference framework in a real-world industrial environment requires a further innovation, a reference architecture. Authors propose such a reference architecture for Intelligent Industrial Informatics (Fig. 3), that is generic across all Industrial Informatics domains, but also captures the nuances of industrial Big Data. Authors posit this architecture will provide forward-thinking industrial organizations a blueprint and roadmap towards the implementation of an end-to-end AI enabling technology stack. The reference architecture (Fig. 3) is read left to right; industrial data sources on the left are gradually transformed into intelligent insights to the right. A variety of sources contribute towards the volume, volatility, variety and complexity of industrial data. Some examples are online/open data sources (weather data, public access datasets), data streams (e.g. IoT, CPS, video and other sensors), multimedia (unstructured datasets of text, audio, video and virtual reality formats), conventional databases, and ontologies/taxonomies of domain knowledge.

These varied data sources are channelled through several data processing pipelines. The pipelines will conduct imputation (missing, erroneous and incomplete data points), encoding into effective data formats (e.g. human-readable to machine-readable), transformation of feature spaces (e.g. Fourier transform, vector symbolic architectures, vector space modelling), warm or cold batch processing (i.e. accumulating a stream of data for immediate or latent batch processing), and compute aggregates or select samples for further processing. Simultaneous to processing pipelines, all data feeds will also be received by a Data Lake infrastructure. A Data Lake is defined as a repository for ”all” types of data generated by multiple systems and functions within an organisation [103]. It can also accommodate external data feeds, all of which are stored and managed in an inclusive format that enables data analysis and streamlined application of AI algorithms. The format, encoding and requirements of the data are not defined until a purpose is determined. This makes the entire data storage and management function extensible and generalisable (loosely-coupled data accumulation) for any type of algorithmic application. It should also be noted that a two-way communication exists between the Data Lake and pre-processing pipelines so that processed data feeds can be sent and received.

The Data Lake now becomes the source for all Intelligent Industrial Informatics initiatives. The data feeds from the Data Lake operate in the format of a bus, sending data and receiving insights from numerous AI functions. Visualisation and federated search ensure effective access to any level of granularity of the stored data, raw data points to aggregates. Many visual analytics tools can be used to understand the distribution of datasets/ data sources and their progression over time. Prediction of expected outcomes from industrial systems and processes is a prime application of AI algorithms. Random forests, conventional neural networks and the more recent deep neural networks (popularly known as machine and deep learning algorithms) can be applied individually or in ensemble format to determine likelihood of outcomes with degrees of accuracy.

The direct contribution of AI in industrial settings is manifested in control, optimization and monitoring functions. As noted in the reference framework section, these operate in sequence and independently. More recently, the industrial sector is moving towards the usage of conversational agents to streamline activities in the control, optimization and monitoring functions. Industrial chatbots can directly communicate with end-users of industrial processes and systems, reducing the need for continuous human involvement. Finally, the application of Generative AI will be useful to determine the gold-standard of operations in the context of internal and external variables. Generative AI will create latent spaces of all parameters, which is instrumental in identifying the unknown limitations, opportunities for improvement and productivity gains. Along with Generative AI, Explainable AI (XAI) will provide justification and supporting evidence for overarching decisions that can transform the entire industrial setting, process or function.

V. Case Study: Intelligent Renewable Energy Generation and Consumption

A major limitation in the energy sector is the imbalance due to electricity being produced and consumed at different times. IoT is an enabler for the coordination of smart distributed energy resources. However, without a coordination solution, the addition of solar and wind power will necessitate massive investments to electricity storage, leading to an unsustainable high demand for rare earth metals. How can artificial intelligence be used within a cyber-physical system to solve this challenge?

A. The Cyber-Physical Environment

Before answering this question, it is necessary to identify the cyber-physical environment in which this system operates. The physical aspect of this environment is the power grid, which needs to maintain its frequency within a deadband of 50Hz at all times. The cyber-aspect of the environment includes the digital marketplaces on which the flexible capacities of the smart distributed energy resources can be traded. This market aspect is frequently glossed over by researchers, resulting in a lack of coordination of efforts between the academic and industrial communities. Flexible capacities can be thought of as services to produce, store or consume electricity, which are activated during grid frequency deviations. The technical specifications of the marketplace determine whether the activation is automatic or manual, and whether the grid operator or the operator of the distributed energy resources is responsible for detecting the deviation. This has two implications. Firstly, the flexible capacities need to be designed and validated according to the market specifications. Secondly, the owners of individual resources cannot be assumed to have the capability to validate and operate them according to the market specifications, so an aggregator is needed to provide this service to a pool of resources.

B. The Virtual Power Plant (VPP)

The cyber-physical system for aggregating and trading the flexible capacities of the distributed energy resources is often referred to as a Virtual Power Plant (VPP). Fig. 4 illustrates the VPP in its cyber-physical environment considering real existing markets for the ancillary services, which ensure that the grid frequency is maintained within acceptable limits. The markets and their names are not unified across the globe, but the following markets are available throughout Europe: Frequency Containment Reserves (FCR) for continuous frequency control and automatic Frequency Restoration Reserves (aFRR) and manual Frequency Restoration reserves (mFRR) to return frequency to the normal range (Fig. 4). In this article, the Finnish markets operated by Transmission System Operator (TSO) Fingrid is used as a case example. Fig. 4 illustrates some

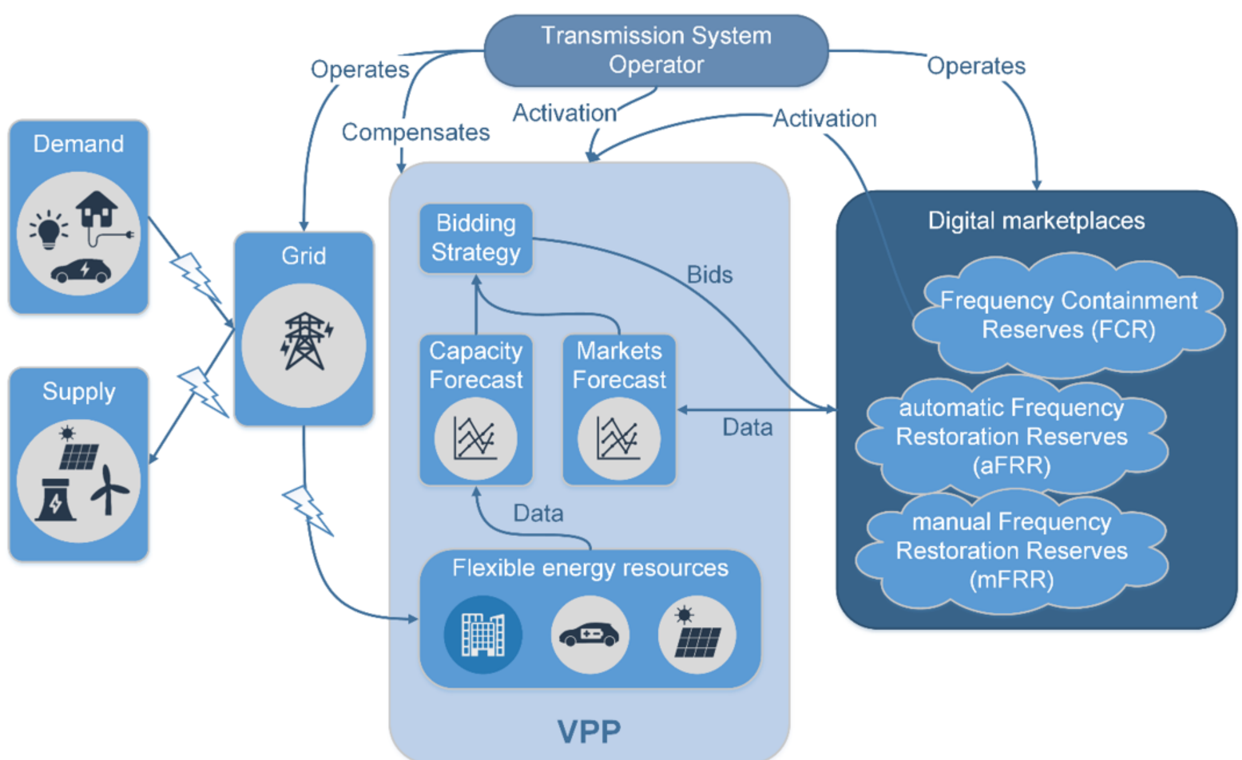

Fig. 4. The VPP (Virtual Power plant) as a cyber-physical system. Arrows with the electricity symbol represent power flows in the physical world. The other arrows represent flows of information and control in the cyber-world.

salient aspects of the VPP's cyber-physical environment, which need to be understood before designing a VPP. The TSO operates the market by running an auction and deciding how much reserves it needs to procure. The VPP bids the reserves, stating the volume of the reserves and the required financial compensation from the TSO. If the bid is accepted, the VPP needs to activate them if needed. In the case of FCR in Finland, the VPP is required to perform a local grid frequency measurement and activate the reserves according to FCR technical specifications, without any involvement of the TSO. For aFRR and mFRR, the TSO sends an activation signal. In the case of all of these markets, the VPP gets compensated according to the accepted bid regardless of whether the reserves were activated during the time period that was covered by the bid. It should be noted that the distribution system operator (DSO) is abstracted away from the figure. As long as the VPP meets the requirements for the minimum bid, it can do business directly with the TSO, at least in certain European countries where independent aggregators are permitted to operate.

C. An AI-based VPP

The VPP performs both aggregation and trading. The aggregation is a technical solution for combining several flexible energy resources so that they behave as one large resource according to the technical specifications of the market. For instance, [104] presents a solution for aggregating a large number of household appliances and validates it according to the Finnish FCR specifications. The 'Flexible energy resources' in Fig. 4 refers to such a pool of aggregated resources. These characteristics of the VPP's operating environment raise fundamental questions about the application of artificial intelligence to develop the VPP. One approach is to train a machine learning model, using all of the available data, in order to obtain the bidding strategy. However, due to the said complexities of the bidding on several markets, this approach may not be feasible and no author has proposed it. Another approach is to decompose the problem to parts that can be addressed by various techniques under the broad umbrella of AI. The VPP in Fig. 4 shows one proposal in this direction. A major aspect of the problem is coping with the uncertainty related to the market prices and the volume of flexible resources available to the VPP during the upcoming bidding period. For example, in Finland, FCR and aFRR bidding is day-ahead and mFRR bidding is hourly. This necessitates forecasts of the markets and capacities, and machine learning could be applied for that. Since historical data for the variable to be predicted is available, supervised learning is applicable. Based on the forecasts, techniques such as genetic algorithms or fuzzy logic could be used to generate the bids. Work towards this vision has been done for the forecasting of the FCR prices in Finland as reported in [105]. The entire system has since been validated with an online deployment which has been continuously operating for over one year.

D. Using the Reference Architecture for New Directions in AI-based VPP

In this sub-section, the case study is considered from the perspective of the reference architecture proposed in section IV. Data sources for market forecasting include online web interfaces for weather data and TSO data. Data sources for capacity forecasting are typically databases on dedicated servers or in the cloud for the data generated by the distributed energy resources. Batch processing will be frequently used, as many source datasets are updated hourly or daily. The timing of batches is dependent on the need of predictions, which is determined by market rules. For example, a day-ahead market requires bids to be sent by a specific time on the preceding day. All batch processing needs to be timed so that AI models can be trained with the latest data and so that they can be used to make the predictions before the bidding closes. It is notable that the relevant markets operate on different timeframes, which are expected to change as markets evolve rapidly and as harmonization efforts of national markets are underway in Europe. For example, typical intervals for making bids may be at 15min, 30min or 60min intervals. The data sources may have the data at such intervals, or preprocessing such as interpolation may be required. Further, to build the input data structures for training the AI model, and for making predictions with the trained model, the Data Lake would need to be sampled at intervals corresponding to the market specification. AI-based prediction in the field of VPPs is currently focusing on specific markets, and further research is needed to develop general solutions that adapt to markets in several countries as market specifications evolve rapidly due to the digital disruption of the energy sector. thereby, VPPs are a comprehensive case study for demonstrating and further investigating the significance of the reference architecture proposed in section IV.

VI. Future Directions

Forward-thinking organizations have been making significant investments in AI and working towards collaborative academic research that expands the current boundaries of AI. Acquisitions have been the primary vehicle of investment in AI, with 635 reported acquisitions in AI since 2010, 140+ in 2019 alone (as of September 2019)[106]. As anticipated, the leading technology companies FAMGA (Facebook, Apple, Microsoft, Google, Amazon) have been the primary acquirers with 59 total acquisitions since 2010.

More specifically on Industrial AI, Boeing acquired Liquid Robotics in 2017 to enhance their capabilities in sensor based prediction models and provide real-time data on weather and ocean conditions for defence and security, as well as their ”digital ocean” initiative. Amazon acquired Kiva Systems in 2012, a robotics-based automated material handling solution, Dispatch in 2019, a six-wheeled urban delivery robot, and Canvas in 2019, a robotic cart for autonomous inventory transport. These are firm indicators of the potential of AI to define organizational success and even competitive existence. It is also an attestation to invest in new technology and conduct research into the next generation of AI theory and techniques. With all evidence pointing towards new industrial environments essentially defined by AI, the following section focuses on future directions, in terms of Research and Applications.

A. Advances in Research

Deep Learning: Deep learning [107] continues to be the most prominent recent development in AI that encompasses feature engineering and feature representation into the machine learning process [108], [109], [110], [111]. This inclusive capability should be further explored beyond supervised learning, focusing on unsupervised, one-shot, reinforcement and transfer learning tasks. On the other hand, the increasing prevalence of sub-optimal deep learning neural network models indicates that the development of meta-learning techniques for optimised model configuration is an emerging need [112]. In Industrial Electronics, this should potentially lead to new meta-learning techniques specific to each industrial domain.

Self-structuring AI and Unsupervised Learning: The paradigm of self-structuring AI lies beyond learning model development and configuration. Self-structuring AI is defined as learning structures that autonomously evolve with the unstructured and unlabelled nature of data; spatially, temporally, laterally and semantically. In most conventional AI, a model development phase is mandatory. This model would usually consist of a number of input, output and hidden layer nodes, the size and shape of network architecture and the weight initialization and learning mechanism. Model development requires human expertise, time and effort while also restricting the autonomy of AI, as it quickly becomes obsolete or impractical in new industrial environments where data is generated and updated frequently. Several research initiatives have recently focussed on addressing this void, in the notion of ”AI building AI” or ”self improving AI” as proposed by Google [113], self-constructive AI [114], and structure adapting feature maps [115], [116].

Incremental Machine Learning: Most of the data in new industrial environments will be machine generated, high-volume, high-velocity streaming data, which is also tightly-coupled with time. Incremental learning advances conventional machine learning to continuously acquire new information, extend and adapt current knowledge to suit new knowledge. Incremental learning overcomes the stability-plasticity dilemma and catastrophic forgetting to achieve perpetual learning. This is important in industrial settings where training data becomes available gradually over time and it is necessary to adapt to new representations and dimensionality while maintaining a recallable memory of past learning outcomes. Early efforts towards incremental learning are reported in [117], [116], [118], [119].

Energy-efficient AI: The annual growth rate of worldwide electricity consumption is close to 3%, the corresponding growth rate in the ICT sector is between 5% and 10% [120]. The ICT energy footprint is complex, as it is composed of support systems and logistics, which include security, lighting and cooling systems besides the actual technology infrastructure. This makes the joint optimization of all parameters an extremely complex problem. Breaking down the global optimization task into the optimization of the specific components reveals new field-specific fundamental challenges. In terms of computations, microprocessors accounts for 40% out of 26% of total energy footprint of a data center due to servers and storage, and a recent study shows that training machine learning models for natural language processing expends as much energy consumed by five cars during a full life-cycle [121]. These figures present a strong motivation for future AI research on reducing the energy footprint of computing technologies. Nature-inspired computational methods present a promising new research direction for computing hardware design, where computationally complex operations that consume orders of magnitude less energy are successfully performed in brains of small insects [122], [123], [124]. The development of AI algorithms that only consume ultra-low energy on such new hardware designs is a new challenge. Vector symbolic architectures (VSA) and hyperdimensional computing are a transformational area of research for low-energy AI that is compatible with the novel nature-inspired hardware and can address the primary challenges of intelligent IoT and CPS systems, through the transition from floating-point computations to fixed-point, and corresponding efficiency gains. This is amply demonstrated in [65], [125], where authors propose an approach for distributed fault isolation in a generic system of systems, using the problem of fault isolation in a complex power plant model. An architecture for memory-recall of sensor stimuli, through the use of VSA is also proposed in [126]. This has been further explored in models of autoassociative, distributed memory that can be naturally implemented by neural networks in [127], [128], [129], [130].

Data fusion and Scalability: The diversity and distributed nature of data will be common in futuristic industrial environments. Not only multimodality (sensors, video streams, industrial processes) but also devices from different manufacturers and technologies will add to this diversity. Increasingly, industrial environments are distributed across multiple locations and the data will also be widely distributed. Even within a single physical location, the ability to combine multiple data sources is essential to automate processes and detect machine malfunction or breakdown. It has been suggested that data fusion and integration based *virtual digital twins*— as a means of addressing current limitations [131]. A further essential requirement of future directions in AI and machine learning, which can be discussed alongside data fusion is the need for scalable algorithms. The volumes of data collected are increasing in petabytes and when fused will increase into volumes and complexity which most current AI cannot handle. Scalability is considered as one of the key factors to make AI applicable to future industrial settings [132]. An unsupervised machine learning based scalable fusion model for active perception has been proposed in [133], [134], [135].

AI Safety and Ethics: It is evident that AI will soon become the norms of practice in all industrial and organisational settings. Alongside other domains [136], it is crucial that research in Industrial Electronics focuses on the design, development and deployment of AI that is responsible, safe and ethical [137]. It is imperative that future research initiatives establish an ethics policy, guidelines and standards for Industrial Informatics that ensure AI-based insights, feedback, control and decisions are safe, reliable and accountable [138].

B. Advances in Industry

Smart Buildings: With AI integrated into its structure, architecture and sensory devices, buildings of the future will become *living entities* that demonstrate intelligent behaviors, such as creating personalized experiences for occupants, and providing energy and cost savings for owners. Incorporation of AI into commercial and industrial buildings is being investigated where AI for speech recognition, video content recognition, computer vision, virtual personal assistants, and robotics are being trialled.

Smart Factories: Cognitive and collaborative bots (or Cobots) that can be programmed through assisted movement will gradually become widely used. These Cobots will be able to handle more cognitive tasks and make autonomous decisions based on real-time industrial data, leading to industrial machines and processes that operate autonomously without human presence. This will enable not only *lights out* factories but also industrial settings which do not require heating and cooling. Factories of the future will also use AI empowered machine vision to read barcodes, inspect packages and contents, improve safety, inspect product assembly, and identify microscopic imperfections in production lines.

Industrial Blockchain: Smart devices and IoT will provide the ability to *sense*, AI techniques will provide the ability to *make informed decisions* and Blockchain will provide *memory* for AI empowered industrial informatics. This memory feature of Blockchain will achieve transparency and strict rule enforcement across a network of machines and processes that will provide time efficiencies, reduction in human errors and increased deployment of bot-based *lights out* factories.

5G Cellular Networks: The steady expansion of 5G, fifth generation cellular network technologies, presents new and unique opportunities for AI. High-speed, low-power and low-latency 5G networks will generate massive volumes of data from Industrial IoT, tactile Internet and robotics. By enabling the deployment of AI at the network edge, essentially a distributed AI architecture, 5G underlies the infrastructure required for massive amounts of data generation and communication. AI can then facilitate insights generation from the complexity of 5G-based data. More specifically, the low-latency of one millisecond (versus human reaction time of 250 milliseconds) will enable rapid proliferation of AI-driven automated decision-making across all industrial domains. Self-drive vehicles, optimised energy utilisation, time-critical industry automation, life-saving medical treatment and highly individualised products and services are some examples. A review of the relationship between AI techniques and candidate technologies in 5G cellular networks is reported in [139]. The use of AI on 5G infrastructure management, such as intelligent network traffic management [140], beamforming, network slicing, massive MIMO [141] are further opportunities to be explored.

VII. Conclusion

This article commenced with an exploration of the role of AI in present-day Industrial Big Data settings, which was substantiated with a comprehensive literature review across five domains of Industrial Informatics. Based on this literature survey and related reviews of industrial AI, a reference framework for Intelligent Industrial Informatics was proposed in Section III, followed by a reference architecture for technological design and implementation of Intelligent Industrial

Informatics (Section IV). The article further presented a case study on intelligent renewable energy generation and consumption (Section V) and a discussion of future directions of AI that address emerging challenges of new industrial environments (Section VI) . It is pertinent to conclude that AI will continue to contribute positively towards the advancement of Industrial Informatics, with increasing potential for disruptive and transformational innovation. Exciting times ahead.

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