Industrial Edge Computing

Enabling Embedded Intelligence

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The term *industrial edge computing* is used to describe a distributed platform that integrates communication, computation, and storage resources for performing real-time applications that can be directly accessed from the cloud. A step toward the industrial Internet revolution, industrial edge computing is designed to facilitate agile connectivity, real-time control, and data optimization, while enabling intelligent

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applications, ensuring tight security, and protecting privacy. Industrial edge computing makes use of what is known as *edge computing nodes (ECNs)*, which bridge the gap between the physical world and the digital world by acting as smart gateways for assets, services, and systems. The IEEE P2805 Standards are being developed for defining protocols for self-management, data acquisition, and machine learning through cloud–edge collaboration on ECNs.

Intelligent Services at the Device Level

Industrial automation systems are being transformed into fully digitized information systems. The legacy industrial automation systems are classified as examples of 5-level reference architecture, according to the International Society of Automation Standard 95 (ISA-95) (Figure 1) [1]. Levels 0, 1, and 2 are the focus of industrial automation control and monitoring. Typical update rates at these levels are within tens of milliseconds. Levels 3 and 4 are designed for manufacturing operation management and enterprise operations. These systems require decisions to be made on a daily, weekly, or monthly basis.

Industrial edge computing is designed to facilitate agile connectivity, real-time control, and data optimization, while enabling intelligent applications, ensuring tight security, and protecting privacy.

Existing levels in the ISA-95 pyramid are mainly classified into two groups based on real-time constraints. As indicated in Figure 1, the manufacturing execution systems and enterprise resource planning systems could be moved to industrial clouds due to low real-time requirements and high data volume. Meanwhile, levels 0–2 should remain on the shop floor due to high real-time constraints. Within the last decade, the cost of the central processing unit, storage, and communication bandwidth has fallen. With lower connectivity costs, more computing power, and larger storage space at the device level, self-management features, including self-discovery, self-learning, and self-optimization, could be achieved with high real-time constraints. In addition, intelligence could be introduced into interconnected things to enhance cooperation among edge nodes, humans, subsystems, and industrial clouds.

Edge computing provides intelligent services at the device level with optimized use of communication, computation, and storage resources [2]. In industrial applications, edge computing could introduce agile connectivity, real-time control, data optimization, and smart decision making into legacy industrial automation and supervisory control systems. ECNs include smart devices, smart gateways, smart systems, and smart local clouds.

Industrial edge computing is also facing some new challenges. One has to do with connectivity, which is so

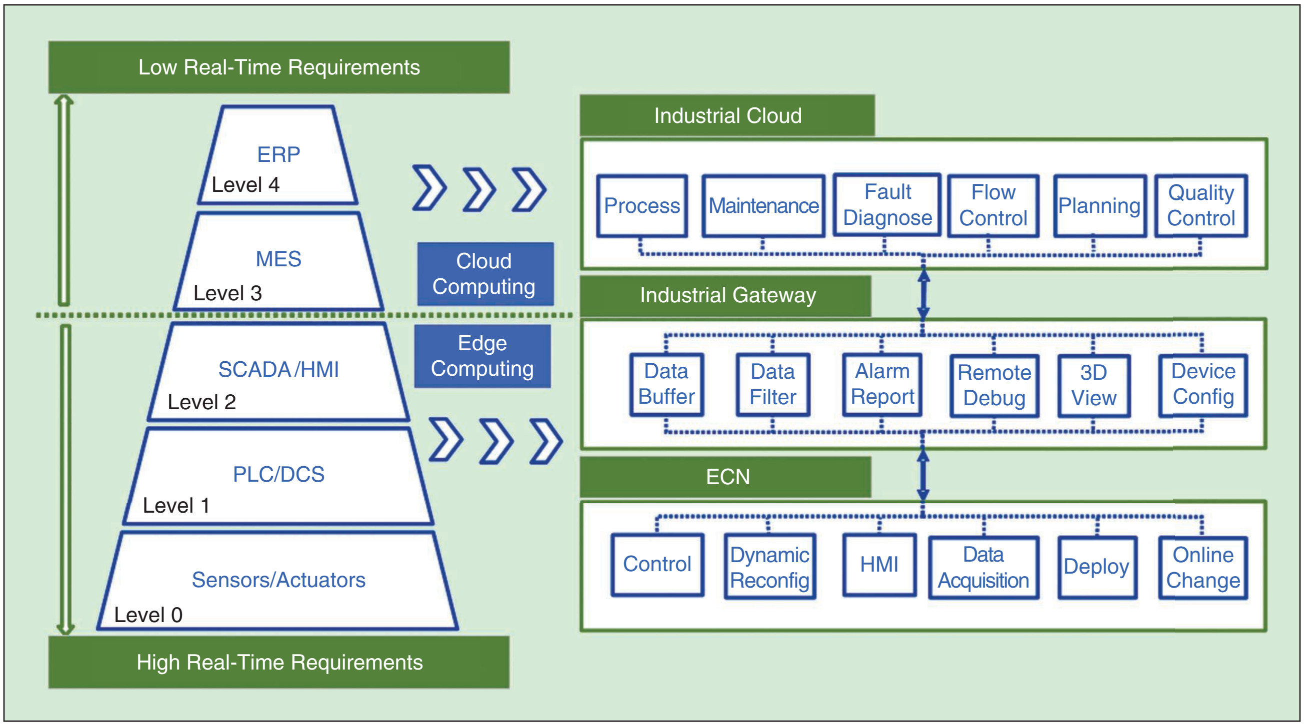

FIGURE 1 – A diagram showing the ISA-95 reference architecture mapping to industrial cloud and edge computing. ERP: enterprise resource planning; MES: manufacturing execution system; SCADA/HMI: supervisory control and data acquisition/human–machine interface; PLC/DCS: programmable logic controller/distributed control system; Reconfig: reconfiguration.

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important in distributed computing. Industrial edge computing requires interoperability among various existing industrial fieldbuses as well as emerging technologies, including time-sensitive [3], software-defined [4], and 5G [5] networks. The existing industrial fieldbuses are not compatible with each other even as defined in the International Electrotechnical Commission 61158 Standard [26]. Researchers must solve the problem of how to accommodate the real-time constraints while fulfilling demands for scalability and reliability of heterogeneous networks for industrial edge computing.

A second challenge deals with data mining, which industrial edge computing enables. Researchers must determine how best to perform effective data mining on edge nodes. The ECNs as data-acquisition entry points usually generate massive amounts of real-time process data with intervals in the millisecond range. These data could be used to examine an entire operation and be applied, for example, in product life-cycle management, preventive maintenance, asset management, and control optimization. By adopting data optimization for edge computing, timeliness and validation of processed data can be assured for these industrial applications.

Next, control and detection for industrial edges typically require response times in the order of tens of milliseconds or fewer. Meanwhile, industrial edge computing requires dynamic reconfiguration and distribution of computing and storage resources for distributed control and security. Millisecond-level speeds cannot be achieved if other functionalities, such as control, fault detection, and data acquisition, have to be performed at the same time. Thus, industrial edge computing must offer distributed load balancing, optimization, and dynamic reconfiguration.

Finally, with the syncretic view of information technologies and operation technologies, industrial edge computing faces the challenge of how to ensure the security of edge nodes, networks, and applications as well as how to provide different levels of access control without affecting real-time performance. How to ensure integrity, privacy, and ownership over distributed nodes is also a key factor for safety and data security for industrial edge computing.

Architecture, Requirements, and Values of Industrial Edge Computing

Reference Architecture for Hybrid Industrial Cloud and Edge Computing Systems

Industrial cloud and edge computing have different strengths. The industrial cloud is suitable for global, nonreal-time, and long-term big data analysis for preventive maintenance and business-decision support. Meanwhile, industrial edge computing is especially useful for handling local, real-time, and short-term data analysis crucial for real-time decision making and execution control. As stated in [6], 75% of enterprises by 2022 will have adopted distributed processing without a data center or cloud. Industrial edge computing is not intended to replace the industrial cloud. Rather, industrial cloud and edge computing should be tightly coupled to meet requirements of various industrial scenarios. The industrial edge provides support for industrial cloud applications related to real-time data mining and preprocessing. In contrast, the industrial cloud deploys optimized rules and models for industrial ECNs based on big data analysis.

In a typical industrial cloud and edge computing hybrid setup, the architecture can be divided into three layers (Figure 2). The top layer includes the industrial cloud platforms offering various applications that cover design, manufacturing, management, and maintenance. Legacy enterprise resource planning, manufacturing execution, product life-cycle management, and customer relationship management systems (CRMs) could be migrated to industrial clouds to reduce deployment and operation costs. In addition, innovative applications on industrial clouds, including device operation analysis, supply chain analysis, and energy consumption optimization, could be enhanced by real-time data collected from edge-computing devices. These services could even be provided by third parties and run on a local cloud instead of a public cloud.

The middle layer, the industrial edge gateway, is responsible for deploying algorithms; balancing computing, networking, and storage resources; and managing data-acquisition processes from all ECNs. The edge gateway ensures rapid development and agile deployment through model-driven orchestration of modular services. ECNs are also responsible for network tapping that monitors all network packet transactions among clients, terminals, Internet of Things (IoT) systems, and cloud servers. By monitoring packets, ECNs can modify these packets to provide add-on features. For example, when a new device with an unrecognized network protocol is detected by the local network, edge gateways would configure this new protocol automatically or alternatively update security policies to protect ECNs. If attacks are found from IoT systems, edge gateways would detect and block access. Similarly, attacks from IT systems could be stopped by ECNs.

The base layer contains distributed ECNs. An ECN could perform one or more functionalities, including those of protocol-converting network switches, real-time closed-loop programmable controllers, local clouds for big data analysis, and low-cost sensors. These features could be dynamically allocated to any combination of industrial edge nodes based on closed-loop feedback data in real time.

Values and Requirements of Industrial Edge-Computing Systems

As suggested in the proposed reference model (Figure 2), industrial edge computing could assist and collaborate with the industrial cloud in several ways. Industrial edge computing could self-manage and balance local computing, storage, networking, and virtualization resources at speeds in the milliseconds. Industrial edge computing might also distribute and execute strategies made by industrial clouds, including strategies for managing devices, resources, and connections.

Edge computing provides intelligent services at the device level with optimized use of communication, computation, and storage resources.

From the data perspective, ECNs are mainly used to acquire data and perform preliminary data processing and analysis based on predefined rules. Industrial clouds provide storage, analysis, and mining from

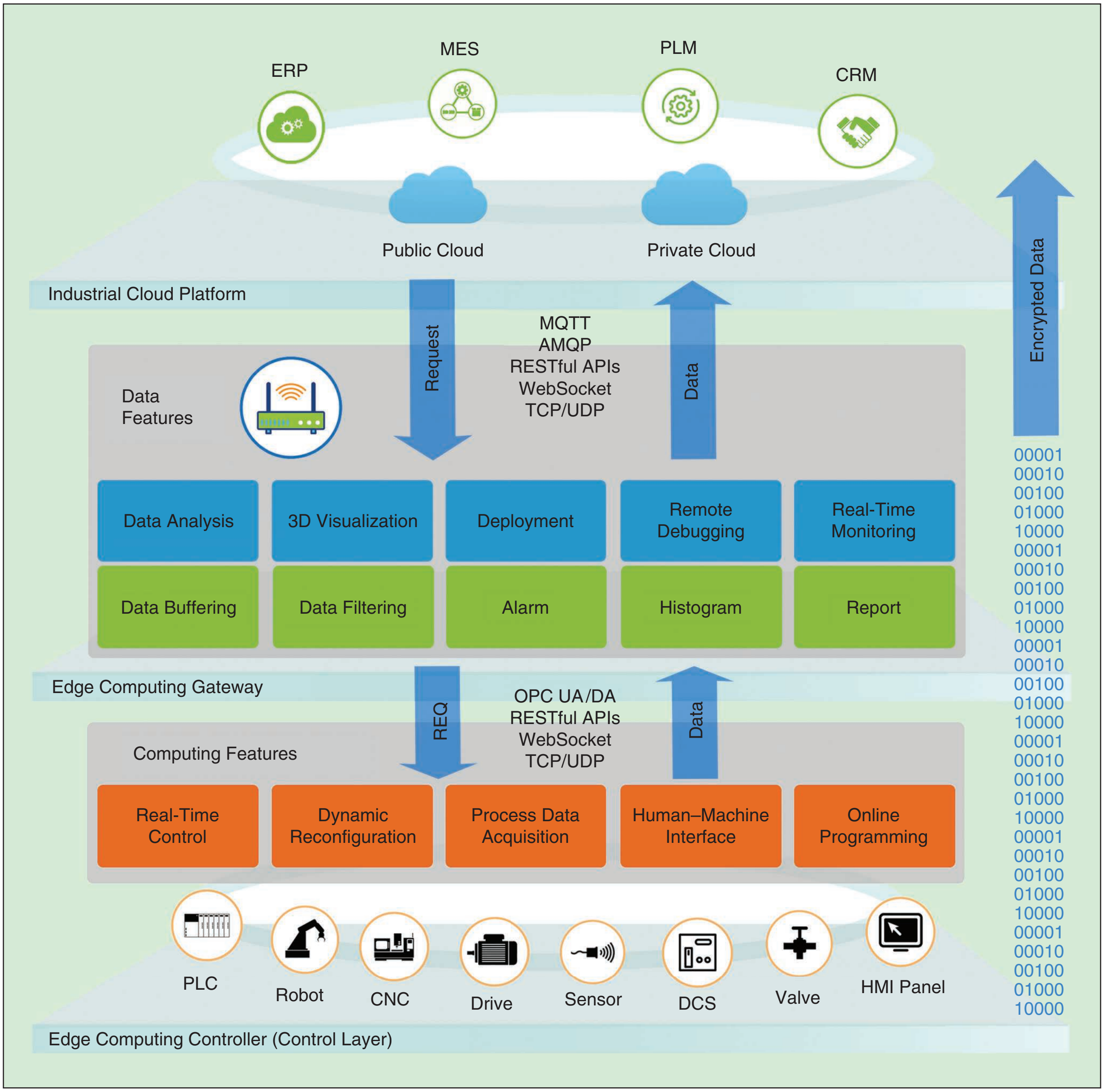

FIGURE 2 – A diagram showing the industrial edge computing reference model. ERP: enterprise resource planning; PLM: product life-cycle management; MQTT: Message Queuing Telemetry Transport; AMQP: Advanced Message Queuing Protocol; API: application programming interface; TCP/UDP: Transmission Control Protocol/User Datagram Protocol; REQ: request.

Researchers must determine how best to perform effective data mining on edge nodes.

massive amounts of data collected from multiple ECNs. With efficient data flowing between the cloud and the edge, the cost of data-driven product-quality tracing and data mining could be reduced.

In the application domain, the industrial edge provides execution environments, executes deployment plans, and monitors life cycles of deployed edge applications. For instance, after machine-learning models are trained on the industrial cloud, they might be deployed to ECNs for inferencing and reasoning. For typical applications on the industrial cloud (i.e., development, testing, digital twins), ECNs accommodate flexible and interoperable modules based on component-based design [7] and microservices [8]. However, some of these capabilities may not be necessary for certain industrial applications. For example, in nuclear power plants, industrial clouds are not recommended due to security issues.

As a supplement to industrial clouds, industrial edge computing provides interoperability, real-time data processing, and self-optimization, which are not the main focus of industrial clouds. The interoperability ensures vertical and horizontal integration from system-to-system-level data migration to device-to-device-level data exchange. With total interoperability in ECNs, flexible and distributed cooperation can be introduced into the entire cycle of manufacturing processes, including those related to product design, production, management, and the supply chain. The maximum use of resources can be achieved by applying cloud–edge cooperation into new business models. The real-time data processing on the edge will reduce the workload of industrial clouds. Data acquisition, preprocessing, calibration, and conversion can be completed in real time on edge devices without sending massive amounts of data to industrial clouds. Finally, by a mixture of industrial cloud and edge computing resources, data-driven optimization could be extended to edge nodes. Real-time constraints as well as data efficiency demands could be met by adopting pretrained machine-learning models from industrial clouds and distributed reasoning.

To achieve these targets, ECNs must meet some basic requirements for computing, storage, and communication. First, the fundamental requirement of industrial edge computing is the ability to implement automatic control. With the support of ECNs, the accuracy of automatic control for machines, systems, and processes could be enhanced with automatic fault detection, information processing, and operation control techniques while real-time constraints are assured. Second, instead of processing data using data centers or the cloud, data mining and analysis could be handled at the millisecond level by relying purely on edge-computing resources. The efficiency of data analysis will be largely improved by shortening communication delays between the edge and cloud. The final requirement is the optimization that mainly relies on data mining and knowledge discovery. Industrial edge computing should provide data filtering and buffering to reduce unnecessary communication, save on the computation costs of invalid information, and improve data accuracy for recovery and evaluations of the entire manufacturing processes.

To meet these requirements, certain resources are compulsory. One of these resources is the communication resource. Industrial ECNs not only need to ensure data completeness and deterministic transmission latency but also support flexible deployment. Time-sensitive networks [9], [10], software-defined networks [11], and real-time Ethernet-based solutions [12], [13] are the key technologies for supporting industrial edge computing. The second resource is the computing resource, especially heterogeneous computing. With computing (machine-learning models) and data structures (relational and nonrelational) from the edge side becoming increasingly complex, heterogeneous computing models that combine sensors, controllers, gateways, and even local clouds are essential for balancing performance, minimizing operations cost, trimming energy consumption, and improving portability. The third resource is the storage ability for the edge devices. To trace information in millisecond intervals from sensors connected to the physical world, massive amounts of data must be collected, filtered, and buffered prior to further analysis either on the cloud or at the edge. Time-series databases have become popular for industrial edge computing for rapid insertion and query without updating legacy data records. The last resource is virtualization technology. By introducing virtualization into embedded resources, the development and the deployment cost can be largely reduced by rapid migrating applications between different hardware and software environments.

For an edge-computing resource, some core features and functionalities are crucial for interoperability, self-management, and machine intelligence. In the automatic control domain, sensing and actuating, the abstraction of programming, information modeling, and asset management are essential functions for maintaining reliability, real-time performance, and accuracy of the control level. For data analysis, ECNs should perform stream data analysis, image and video processing, and data mining based on machine-learning algorithms. Massive amounts of data generated from sensors could be preprocessed and invalid data could be filtered to reduce the transmission bandwidth required between the cloud and the edge. Meanwhile, time-sensitive data-analysis tasks could be switched to the edge to reduce delay caused by the transfer of data. For optimization, industrial edge computing covers almost every domain. It can be applied, for example, in reducing bandwidth, conducting preventative maintenance, ensuring real-time control for parameter optimization, detecting faults, making predictions, and optimizing supply chains.

Overall, industrial edge computing provides new challenges for legacy industrial automation systems as well as information and communication systems. New data-handling methods and techniques need to be developed urgently to tackle these new challenges.

Industrial Edge-Computing Applications

Industrial edge-computing applications cover nearly every possible scenario in our daily life from the manufacturing domain to the IoT domain. With the advent of Industry 4.0 [14] and the Industrial Internet [15], edge computing together with industrial clouds provides a comprehensive solution for innovative business models, such as massive customization and service-based production [16].

Several organizations have already been formed to promote edge computing in industrial applications. These include the OpenFogConsortium [17], OpenIOTFog [18], and the Edge Computing Consortium [19]. Industrial automation vendors are shifting the paradigm to edge–cloud collaboration by creating their own cloud platforms connected with intelligent edge devices. For example, the Mindsphere cloud platform from Siemens manages edge devices and the deployment of applications [20]. Similar solutions are also offered by EcoStruxure from Schneider Electric [21], FactoryTalk Edge Analytics from Rockwell Automation and PTC [22], Edge AI Suite from Advantech [23], and the Mobility Edge Platform from Honeywell [24]. For the manufacturing domain, the top three most promising scenarios for industrial edge computing are in the areas of device preventive maintenance, quality control and optimization for process control, and product-quality tracing and optimization.

Industrial edge computing has proven benefits related to cost and performance. It can reduce development and deployment costs by enabling the replacement of multiple devices with a single edge controller that combines computing, communication, and storage capabilities. With excessive computing power, feedback data can be analyzed locally without extra jitter caused by communication between the cloud and edge. By facilitating real-time decisions, industrial edge computing improves the accuracy of control with minimum cost. In addition, with further data analysis and modeling support from industrial clouds, optimization of device use rates, operation and maintenance, and energy consumption could be achieved. By improving the use of devices and natural resources, the overall energy consumption will be reduced significantly.

Industrial cloud and edge computing have different strengths.

Applied in preventive maintenance for devices, industrial edge computing can focus on optimization of device status and performance. By monitoring device operation status and scheduling customized maintenance plans, industrial edge computing can ensure that devices always operate in good condition. This will reduce downtime caused by failures. Furthermore, by tracking and comparing the performance of devices, industrial edge computing can be used to anticipate performance bottlenecks so steps could be taken to improve production throughput. Based on the results from device-optimization analyses, vendors could improve the performance of their products and offer device-maintenance services at minimum cost to clients. From the clients' point of view, downtime could be reduced to a minimum and productivity could be increased.

For the process-control domain, including the power-generation, petrochemical, concrete, and fiber-making industries, the main concern is the optimization of parameters, such as temperature or pressure, during manufacturing processes. With online parameter optimization, production efficiency and quality control can be enhanced while the energy consumption can be reduced. For product life-cycle management, industrial edge computing, together with industrial clouds, enables interoperability among various systems and devices. Industrial systems that are fully integrated both vertically and horizontally will have a strong foundation for massive customized production, agile product development, and a zero-inventory strategy.

In a typical industrial edge-computing setup (Figure 3), ECNs control devices, acquire data, and monitor endpoints on the shop floor. At the base level, ECNs will provide services for balancing resources and working loads between distributed endpoints automatically. During manufacturing processes, any individual endpoint failure could cause a disaster. With self-manageable ECNs, failures can be predicted and prevented by dynamically reconfiguring functionalities on other healthy nodes.

At the middle layer, ECNs provide two types of functions for manufacturing. The first type of function is in the area of data analysis. With massive amounts of data collected from endpoints, technical models could be summarized by data filtering and buffering. These models could be further improved by distributed reasoning through statistical analysis, machine learning, and knowledge rules. By uploading results to industrial clouds, the optimized models of the supply chain, order allocation, logistics, and service flow can better assist vendors, manufacturing plants, courier companies, and clients.

The second type of function is used for management. The deployment and execution environment of industrial applications could be configured and maintained via application programming interfaces (APIs) through ECNs.

With efficient data flowing between the cloud and the edge, the cost of data-driven product-quality tracing and data mining could be reduced.

On top of the execution environment, all instances of applications and services could also be orchestrated or managed via APIs. Related technical applications, including those concerning production capacity, utilization rate, overall equipment effectiveness, and energy consumption, offer not only life-cycle management but also tools for developing, testing, and deploying applications.

Industrial edge computing could also be applied to autonomous cars. With the development of the Internet of Vehicles, each autonomous vehicle could be considered an edge-computing node. By monitoring and coordinating all subsystems in the car, industrial edge computing together with cloud support could introduce additional services. In addition, with coordination among the subsystems in vehicles, vehicle-to-vehicle networks, and road networks, traffic accidents may be reduced through such technologies as data-driven collision detection, lane-change warning systems, and adaptive cruise control. By collecting data from each vehicle, the traffic management system could offer alternative routes, based on density and speed data, to avoid traffic jams.

With edge computing, autonomous cars should be more reliable and secure. Through real-time monitoring of vehicles and preventive maintenance, traffic accidents will be reduced and efficiency should improve. Besides being an essential technology for autonomous cars, edge computing might also bring benefits in other industries, such as those related to elevators, smart home technology, and security.

Conclusions and Future Work on Standardization

With industrial edge computing and industrial clouds, the physical world will be tightly connected with the digital world. Industrial managers will be able to devise strategies based on digitizing and modeling techniques instead of vague impressions from experience. End-to-end services and operations can use the massive amounts of feedback data from operations to collaborate. This also enables third parties to create innovative business models for the entire industry.

However, industrial automation relies on standards. In legacy automation systems, many proprietary implementations cause interoperability issues for several reasons. First, from the controller and the gateway level, it is extremely difficult to manage these devices autonomously with multiple types of ECNs on site. There is no standard way to currently manage these nodes. Second, with massive amounts of data generated from sensors and machines, the ability to collect, process, and store these data becomes an essential requirement for edge computing and the industrial Internet. Again, there are no standards regarding managing the data-acquisition process. Finally, no one has settled on how best to use the massive amounts of data available on

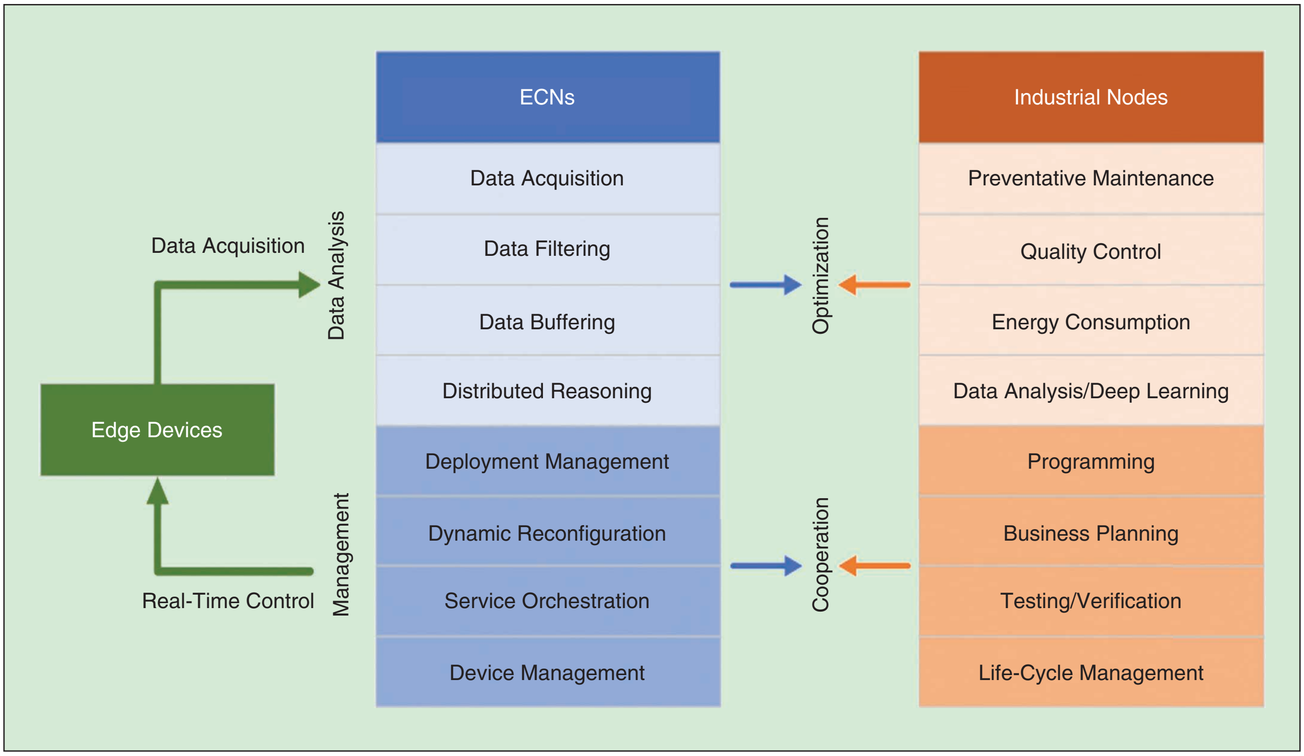

FIGURE 3 – The optimization process for industrial edge computing.

the edge for machine learning based on cooperation between edge computing and the industrial cloud.

The IEEE P2805 Standards aim to solve three challenges in industrial edge computing (Figure 4). First, with massive ECNs on the shop floor, determining how to manage these nodes automatically is a crucial step. The IEEE P2805.1 Standard aims to define self-management protocols for ECNs. This standard covers identification, resource management, backup, load balancing, and data sharing of ECNs.

Second, no agreement has been reached on how best to manage data acquisition on each ECN. The IEEE P2805.2 Standard is proposed for data acquisition, filtering, and buffering protocols for ECNs. These protocols cover how to configure data acquisitions and validate data, define rules for data preprocessing, and manage data-buffering methods on ECNs.

Finally, with massive amounts of data available for analysis, how machine-learning methods collaborate between industrial cloud and edge computing must be defined. The IEEE P2805.3 Standard defines cloud–edge collaboration protocols for machine learning and will provide guidelines for applying machine-learning algorithms for the lower-powered, cheaper embedded devices. Also, deployment of distributed machine-learning models as well as online optimization are covered by this standard. By defining these standards for ECNs, the interoperability issues could be solved, resulting in huge benefits for industrial Internet applications.

For optimization, industrial edge computing covers almost every domain.

Biographies

Wenbin Dai (w.dai@ieee.org) earned his bachelor's degree in computer systems engineering from the University of Auckland, New Zealand, in 2006 and his Ph.D. degree in electrical and electronic engineering from the Department of Electrical and Computer Engineering, the University of Auckland in 2012. Currently, he is an associate professor at Shanghai Jiao Tong University, China, the chief secretary of the Shanghai Automation Association, and chair of the working group for IEEE P2805.1/2/3 Standards for edge computing nodes. His research interests include automatic code generation for smart manufacturing and edge computing. He is a Senior Member of the IEEE.

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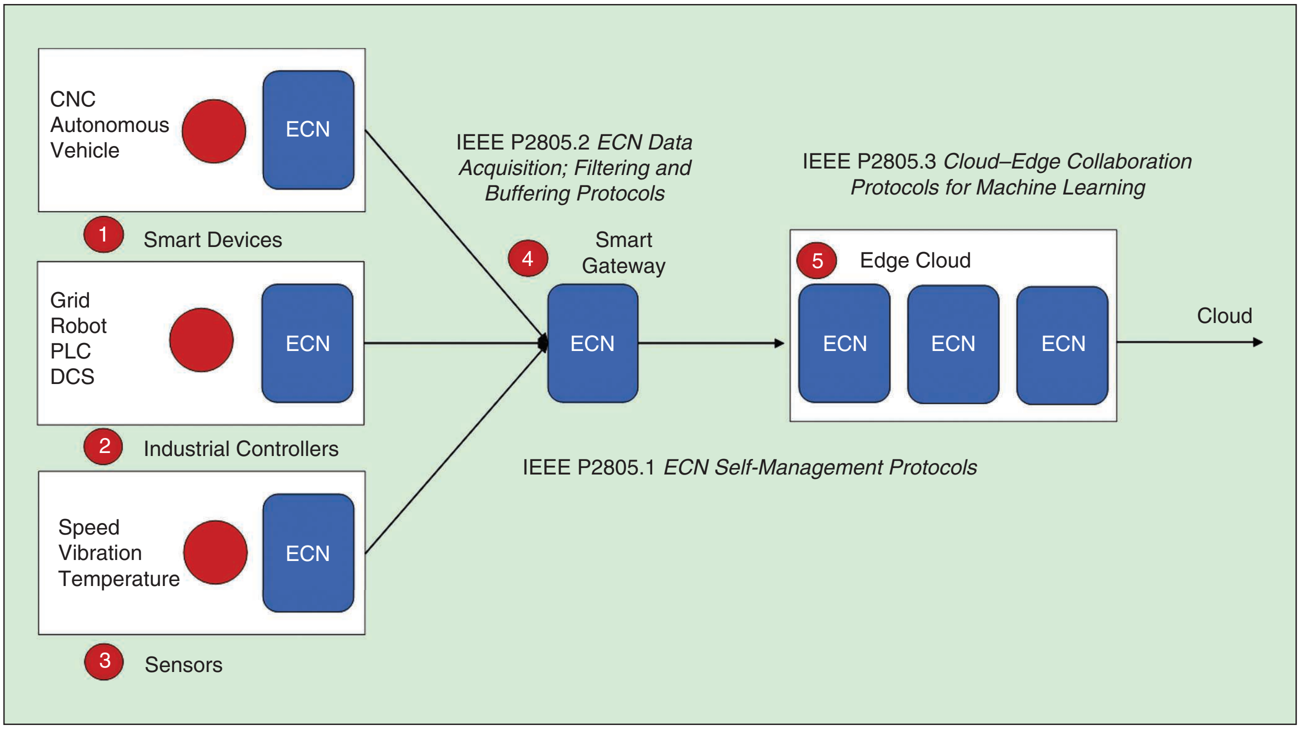

FIGURE 4 – An overview of the IEEE P2805.1/2/3 Standards for ECNs. CNC: computer numerical control.

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