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Neuromorphic Edge Analytics for Industrial IoT

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ABSTRACT: An ever-growing quantity of on-the-move data from all facets of operations and a growing number of Industrial Internet of Things (IIoT) systems are making that demand for smart, energy-efficient processing – closer to the edge, with low latency – more and more pressing. This information needs to be sent to the cloud leading to costly communications, latency and privacy problems of traditional cloud based analytics. To this end, the authors propose a novel data analysis framework, called Neuromorphic Edge Analytics (NEA), which can process data in real-time, adaptively and can further decrease the resource usage in industrial settings. To realize the event-driven and efficient neural computing in human brain, the proposed framework combines the concepts of the neuromorphic computing and Edge Intelligence based on the SNNs.

The NEA design approach consists of four stages: Data Acquisition, Neuromorphic Processing in which concept the model is based on SNNs and used for temporal pattern recognition and anomaly detection, Edge intelligence in which it becomes a solution for local decision making and predictive analytics and Cloud integration in which model updates, data storage, system optimization etc. take place. It's not just the architecture, but an ideal one where the three following criteria could be added: low consumption, inferential speed, want to have distributed industrial systems.

In the field of predictive maintenance and fault detection, in real application, the experimental results have demonstrated high level of performance of the NEA framework in terms of latency, and bandwidth consumption with the same accuracy performance compared to the conventional deep learning methods. Moreover, it is an event-driven architecture – favorable for change in the industrial environment.

To achieve intelligent, autonomous and sustainable industrial operations, the study highlights the need for next generation of IIoT systems to adopt the neuromorphic edge analytics.

KEYWORDS: Neuromorphic Computing, Edge Analytics, Industrial IoT (IIoT), Spiking Neural Networks (SNNs), Real-time Processing and Predictive Maintenance and Energy Efficiency

I. INTRODUCTION

Today the Industrial world is witnessing a mesmerizing change with the end to end connectivity among the machine, sensor and computational platforms which is dubbed as the Industrial Internet of Things (IIoT). Real time data analytics is highly demanded in the industries to optimize operations, enhance productivity and for predictive maintenance, as the number of smart devices and cyber-physical systems continues growing. From the various sources such as sensors, actuators and monitors, the IIoT activities generate spectacularly huge data streams of diverse types. The challenge is efficiently processing this data instead – in real time – because of the latency, bandwidth, energy usage and data privacy constraints keeping this real-time processing from being a reality.

The current issue related to an IIoT system is the cloud based system – which are systems to store and analyze all the information in a centralized location. While cloud computing is a great solution with regards to scaling computation, it also works with certain serious constraints such as with reference to latency for industrial (real-time) uses. This leads to overloading in data communication and latency because large amount of data would have to be send these to remote cloud servers and wouldn't be suitable for time critical applications (safety monitoring, industrial automation or fault detection). What's more, networks carrying this data are always "on" and a problem from a congestion, security and running cost perspective.

Edge Computing is a recent paradigm which is proposed to overcome these challenges. Edge computing has the ability to decrease latency, lessen the amount of bandwidth usage, and improve data privacy. An edge analytics for providing decision making in the locality would be very important for real-time application in Industry. But, traditional edge computing approaches may be designed around deep learning approaches which demand a lot of computation resources and energy consumption and are not suitable for resource poor edge devices.

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In this context, neuromorphic computing has become an interesting subject owing to its structure and operation which takes inspiration from the human brain. Today, Neuromorphic System is a paradigm shift going on from conventional (von Neumann) computers with serial processing to event-driven and parallel processing for highly efficient, low power data processing. At the very heart of the neuromorphic computing are Spiking Neural Networks (SNNs) that instead of processing continuous signals with various values, work on spikes. This makes it ideal for IIoT applications, since many types of data in this domain are event driven, and time dependent.

This blend of the two technologies: neuromorphic computing and edge analytics is a gamechanging opportunity for next generation IIoT. Neuromorphic edge analytics is a combination of energy efficiency of adaptive learning in a neuromorphic system and latency of edge computing. This half-and-half processing can be much more suitable for very resource constrained applications, such as industrial applications, while providing near real-time processing for extremely complex streams of data, with very low power.

Neuromorphic computing has a significant potential for applications in IIoT, but at present, it is still only at an early stage. But there are a number of hurdles to overcome if it is to be in the best shape to reap the benefits. They are realizing scalable SNN architecture, designing efficient training algorithms for SNNs, compatibility with the existing industrial infrastructures, and standards for SNN hardware and software platforms. Besides, industry data is heterogeneous and the working conditions should be dynamic; in turn, adaptive and robust analytical models should be required.

The energy efficiency and processing power, such as the IBM TrueNorth chips and Intel Loihi chips, have taken a large plunge in recent advancements made in the neuromorphic project, ICT HEAR (2013 - 2016). As combined, they result in the investigation of new directions of applying neuromorphic systems to real world applications like robotics, autonomous systems and industrial automation. But, they still need to be explored further at the level of how to include sensing, processing, and decision making elements in a seamless approach in the context of IIoT.

A holistic approach towards Neuromorphic Edge Analytics (NEA) in connection with IIoT is proposed in this paper. Taking advantage of said key principles the SNNs can be used to efficiently process temporal data, which can be used for multi-layered frameworks towards real-time analytics, prediction and anomaly detection for predictive maintenance. Because intelligence is decentralized, edge nodes increase the number of systems, performance/resilience is improved and reliance on the centralized cloud-based system is reduced.

The goal of the NEA framework is to be an energy efficient, low latency and scalable solution for industrial data analytics to overcome existing solution limitations. It can overcome this by providing real-time monitoring of a process in industry to detect fault early and optimise the performance of the process. In addition, the system has 'event' driven properties which can be used for the ‘adaptive learning', the capacity of system adaptation in the changing industrial surroundings.

Beyond the technical ones, there are added reasons why neuromorphic edge analytics can play a role towards sustainability of industrial systems. It helps in minimising energy requirements and data transfers needed, promoting more sustainable practices and conforming with the increasing focus on green computing. This become a major factor when scaling up as part and parcel of a large scale deployment, the energy efficiency ultimately impacts the company's environmental liability and, hence, the costs involved in the company's operations.

There are three strands that will contribute to this study: First, it offers a new framework that puts in consideration the incorporation of neuromorphic computing and edge analytics for IoT in Industry 4.0 applications. The three (first, second, third) apply to the proposed approach with respect to others that model Students' data privacy and/or model data privacy for Individuals. Thirdly, it provides insight into lessons learnt to practically use neuromorphic systems in industry, and discoverances

II. NEED FOR NEUROMORPHIC EDGE ANALYTICS IN INDUSTRIAL IOT

With the soaring growth of Industrial Internet of Things (IIoT) systems, the amount, velocity and variety of industrial data is unprecedented. Today it is required to have things like continuous monitoring and automation, real-time analytics and so on to guarantee maximum efficiency, safety and productivity in industries. However, in such industrial context, the more traditional computing paradigms, including cloud-centric computing and more classical approaches to edge computing and analytics have significant constraints to handle the dynamicity and time-sensitivity of such a

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context. Neuromorphic Edge Analytics is an indispensable resource, a capability that combines some of the most relevant attributes of the edge computing environment (low latency and brain inspired energy efficient computing) to meet the new and evolving needs of IIoT applications.

2.1 Limitations of Conventional IIoT Architectures

But, today, most IIoT architectures have banked on conventional cloud computing as the prime increasingly important part for taking information to make decisions. While there's a lot of compute and storage in a cloud platform, it also comes with a massive amount of latencies over the network due to the data expressed. But, the time taken could become critical in an industry application, e.g. fault detection or Process control or safety monitoring application.

In addition, there are a lot of large amounts of sensing data continuously being transmitted, resulting in more bandwidth being used and more network congestion. This increases operation expenses, but also has an influence on the reliability of the system. In addition, a cloud solution has its own problems regarding data security and privacy because all the vital data necessary from industry communicates to the cloud server and the other way round. All these constraints are reminder why it's important to consider more decentralised and efficient methods of handling the data.

2.2 Challenges of Traditional Edge Analytics

One of the drawbacks of cloud-based systems is fixed by edge computing: Things can be processed locally. But, most of the traditional edge analytics revolve around complex deep learning models featuring significant complexity and lots of power usage. With limited resources by nature, however, edge devices may find it difficult to run such models without being overwhelmed, and may even need to constantly offload them to the cloud to make that happen, causing an impact on performance.

Moreover, in the sequential data flow, traditional machine learning models are able to process it in a continuous manner, which might lead to redundant computation and resource utilization. Not only that, they are not capable of dealing with temporal dynamics of industrial time-series data. Consequently, more efficient and adaptive computation models are needed, which will be able to work in the limited manners of edge environments.

2.3 Importance of Real-Time and Low-Latency Processing

Several industrial applications such as predictive maintenance, fault diagnosis and/or process automation, require real-time data analytics and instant decision making processes. When anomalies are even small, it can result in equipment failure, production downtime or can be a safety risk. Therefore, the need for latency is as important in the world of IIoT.

To address this requirement, there needs to be an event-driven processing on the edge – this is a question of Neuromorphic edge analytics. All this information is not necessarily needed to be processed by the system repeatedly but only on the remarkable changes/occurrence that leads to the saving of processing time and hence responsiveness. Especially critical to the effective and secure functioning in industrial environments.

2.4 Need for Energy-Efficient Computing

When deploying a vast array of an IIoT asset, one of the concerns that may arise is with energy consumption, especially when deploying thousands of IIoT edge devices. Simple computing models would have to use a lot of resources and energy, not to mention would not have to be applied to the energy limited environments, particularly deep learning.

The concept of neuromorphic computing could result in a much lower energy-consuming computation because of an event-driven computing architecture, similar to the one used by the brain. This is because, the only time that the power is being utilized by the spiking neural networks is the spikes and hence, the power consumption of the neural networks is reduced considerably. This makes it a perfect choice to sustainable and cost effective operation in industry, at the edge.

2.5 Handling Temporal and Event-Driven Data

Time is an inherent part of the industrial data with patterns changing with time. Conventional models may not be convenient to model such kind of temporal relationships correctly, particularly when the process dynamics is complicated. Neuromorphic systems are well suited to process what is called Temporal Data (time-series data), and as such are particularly interesting for the temporal analysis of data done in the data center.

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With a neuromorphic edge analytics system built using spiking neural network (SNN), such minimal variations in the patterns of data could be used to identify faults and anomalies at an early stage. This will contribute to maximizing the reliability of the overall system, and to optimizing the predictive maintenance.

2.6 Scalability and Distributed Intelligence Requirements

For industries, IoT is increasing in size every day and there are numerous factors playing a crucial role of which scalability is an important one. There might be devices which communicate with each other that switch off or on at the same time and this could be thousands of devices in an industrial environment. A centralized processing model is not efficient for dealing with such a scale–and this would lead to bottlenecks and poor performance.

The neuromorphic edge analytics will be used for implementing Intelligence Processing while Intelligence is distributed on local nodes, that will be provided in the edge. By using a decentralized approach, we can cut back on the use of centralized systems, improve scalability and boost system resilience. It additionally supports independent functioning of edge devices, with them functioning effectively even when they are not continuously cloud linked.

III. NEUROMORPHIC EDGE ANALYTICS (NEA) FRAMEWORK

The goal of the Neuromorphic Edge Analytics (NEA) framework is to address the challenges of latency, energy, scalability and real-time decision making of existing traditional architectures common with the Industrial Internet of Things (IIoT). It's possible thanks to the concepts of 'distributive edge intelligence' and 'neuromorphic computing' which play a key role in processing the massive streams of data in the dynamic industrial environment efficiently. In this section, the NEA framework architecture, its constituent parts, data flows and operations are detailed.

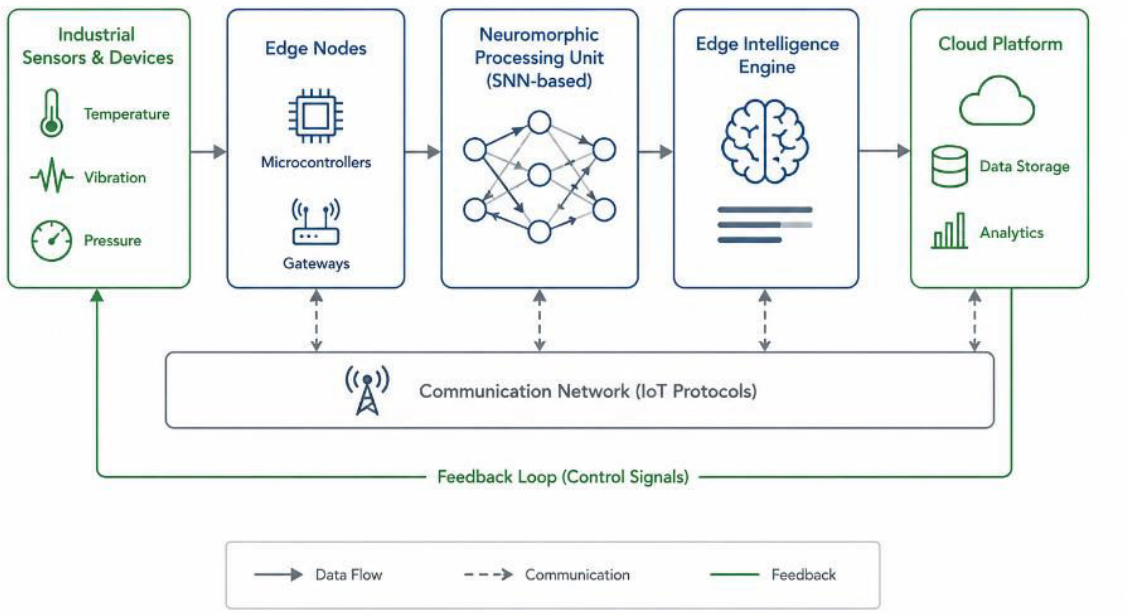

Figure 1: Neuromorphic Edge Analytics Architecture

3.1 Design Objectives

There are many goals for the NEA and many of them are applicable and can have an impact on the organisation and application of framework. This is because it has been designed to provide low latency, real-time analytics and to decrease dependence on a centralized cloud infrastructure. This is one of these spots that is a "go" and "will go" one: "Made today must be made today". Second, that including energy-efficient structure (basically, if you are trying event-driven neuromorphic events in the edge nodes where they occur, which takes very little energy out of the nodes, versus other methods of computing). Third, the system should follow a principle of scalability, so that it can be used for distributed implementation of the system in large industrial scenarios, where the devices deployed are different, and ability to compute differs.

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Also the framework shows the simplicity and adaptiveness with the inclusion of learning mechanisms to evolve with respect to their change of the industrial conditions. However, in more complex work contexts flexibility may be required due to the fluctuations that may occur between one year and the next in work practices. Finally the concept also looks at bandwidth optimisation; having the minimum amount of data transferred where it is not necessary, this is done via local processing and/or data filtering. When underlined together these goals direct the architectural design and functional linkage of the elements of the NEA.

3.2 Overall Architecture

The NEA design takes a multiple layered approach to organize its operations in four major layers: Data Acquisition Layer, Neuromorphic Processing Layer, Edge Intelligence Layer and Cloud Integration Layer. Each of these layers are different in terms of their functions, but they are significant for the successful data processing, efficient computation and effective decision making. With the multi-layer design, the modularity is very advanced and each layer (or each component) may be the optimum design based on the premise of the system integrity. This architecture also enables scalability and flexibility, making the framework scalable and adaptable for various industrial applications and scenarios.

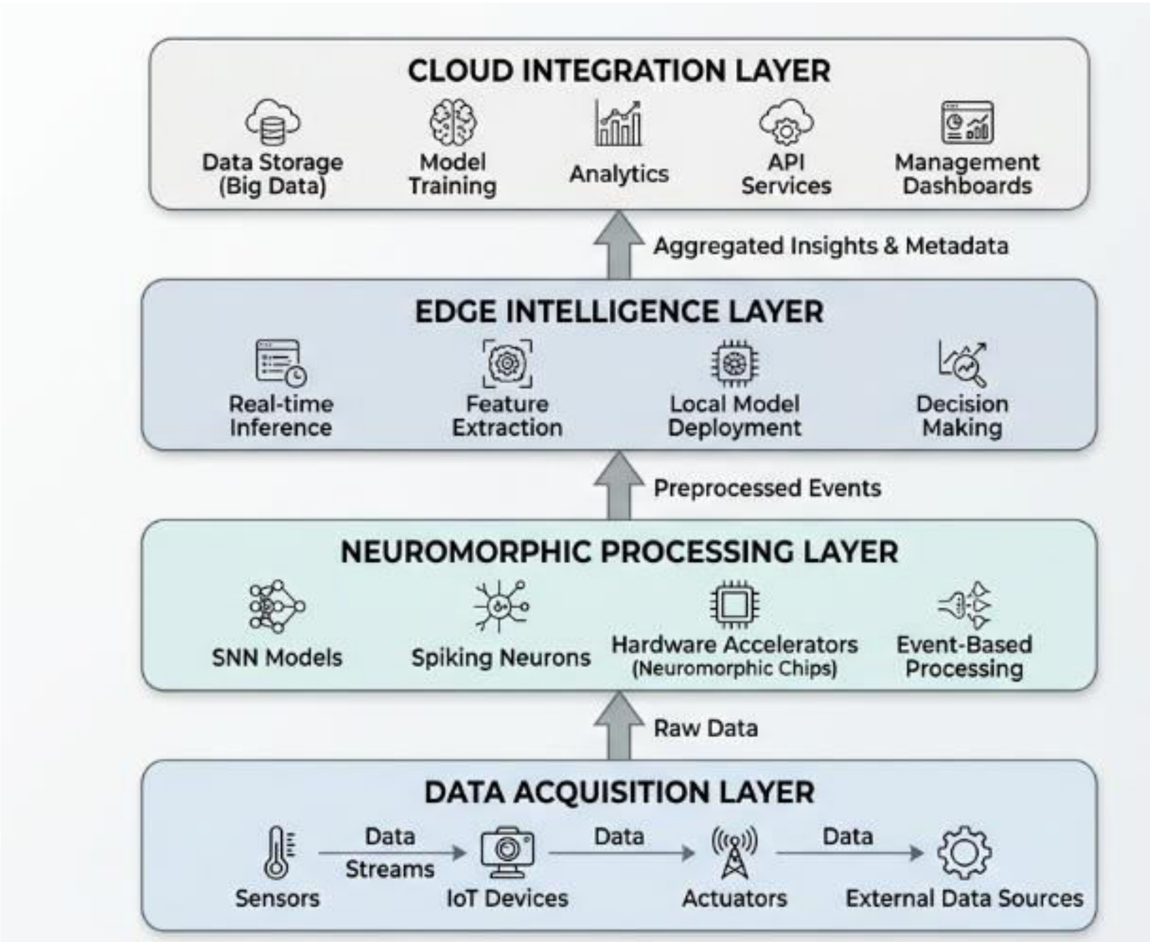

Figure 2: Multi-Layer NEA Framework

3.3 Data Acquisition Layer

Data Acquisition layer is basic and critical layer in NEA as it will be the one's where real time data from various industrial data sources will be handled. These may include different sensors, actuators, programmable logic controllers (PLCs) and embedded systems for monitoring that are spread out throughout an industrial site. These data are very diverse and consist of a mixture of temperatures, pressure, vibration, acoustic data and operation logs.

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The number of data streams, and the nature of the streams, are very high, and there is a need for efficient pre-processing mechanisms needed as the nature of the data streams change very rapidly. Hence it incorporates some mechanisms in itself like data normalization, data time-stamping, filtering for ensuring the consistency, correctness and synchronization in data before reaching the higher layers. Besides, along the data processing line data with redundant information and data noise can be filtered as early as possible, that is, functionality of edge gateway to solve the data noise is firstly integrated onto this layer. The only thing this will do is decrease the amount of data that this is stored at this level, reducing the amount of data that has to be computed at the next level. Furthermore, because it will be a light weight preprocessing approach these light weight devices, with limited resources, will be able to process the data efficiently without changing the integrity of the data.

3.4 Neuromorphic Processing Layer

The most important part of the NEA network, the brain, is Neuromorphic Processing Layer (NPL). Event-driven data representations for neuromorphic computation are created from preprocessed data in this layer. It is based on Spiking neural Networks (SNNs) that unlike traditional networks can efficiently spell out computations following biologically inspired mechanisms, by converting information into a stream of discrete spike events.

3.4.1 Event Encoding

We shall use this sub part as an example to show how the data streams (temporal, rates, latency etc) can be encoded as a stream of spikes. This is essential to provide the same 'neuromorphic' processing as SNNs data when it is processed. Spikes obviously receive info, and should only be processed when info is on it and a big change in info has occurred – otherwise, no need to process. It is particularly helpful with the time series data that is commonly employed in industry.

3.4.2: Spiking Neural Network Models.

SNNs are used in the neuromorphic processing layer for various analysis applications such as pattern recognition, anomaly detection and predictive maintenance. The temporal correlation however is an inbuilt feature in SNNs which is useful to model the dynamics of the industrial processes unlike the basic ANN. It is a framework to accommodate several types for the SNN, such as feed forward, recurrent spiking and reservoir computing. These architectures are aimed to run on a neuromorphic hardware device with the aim of being low power and-high computational efficiency.

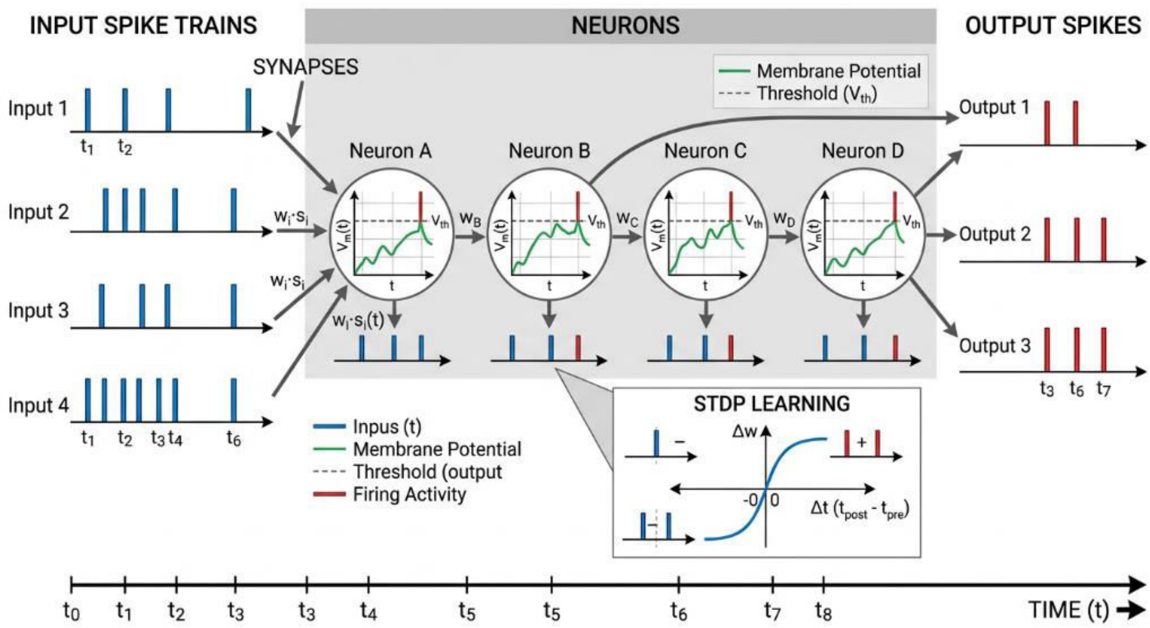

Figure 3: Spiking Neural Network (SNN) Model

3.4.3 Learning Mechanisms

There are two type of learning method such as supervised and unsupervised learning method, in order to achieve the type of adaptive and adaptive with learners' device. An important mechanism used are the so called Spike-Timing Dependent Plasticity (STDP) that can learn from the temporal correlation in the data. This type of learning mechanism

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can adaptively change the parameters of the model online, according to the input and may maintain the model to be well tuned to any change in the industrial environment without manual change of the parameters of the model. It means that it is possible to have a high accuracy level and reliability of the system for prolonged operation.

3.5 Edge Intelligence Layer

The neuromorphic processing layer's output is passed to the Edge Intelligence Layer which adds the ability for localization. The layer should know the processed information, and decide what the right action to take is, which can be applied in real-time, to make the system more responsive and autonomous.

3.5.1 Real-Time Analytics

The layer in this subsection provides advanced analytics, like fault detection and diagnostics, predictive maintenance, process optimisation and quality control. Any trend in the SNNs can then be analysed and if there is any anomaly or deviation from the normal operation of the system can then be detected. This type of function is crucial to avoid any form of breakdowns and ensure optimum performance in industries.

3.5.2 Decision Engine

The analytical results are then fed into the decision engine and along with the pre-defined industrial policies, supports automated decision making. It can be rule based, machine learning based or a hybrid one to deduce the action that is to be followed. These could be alarming, machine configuration or even maintenance procedures. Edge computing further ensures data security, decreases the centralization dependence, and facilitates rapid responding.

3.5.3 Resource Management

Here ‘dynamic' allocation and management of the computational resources in the EDs is discussed. To share the work that the system can draw upon, such as the capacities of devices, load distributing etc. By strategically utilizing resources through the framework's design, efficient operation with high performance and reliability is achieved.

3.6 Cloud Integration Layer

The Cloud Integration Layer can be used to augment the 'edge' for very large scale system computation, long term system control and/or to store information long term. The NEA concept is based on local processing however the cloud has played an important role in furtherance of the whole system.

3.6.1 Data Storage and Management

In this subsection, processed data and summarized insights are transmitted to the cloud for storage and analysis. This enables long-term monitoring, historical trend analysis, and compliance with regulatory requirements. The cloud infrastructure ensures that data is securely stored and easily accessible for future use.

3.6.2 Model Training and Updates

Cloud layer can be used to do things requiring high computational power e.g. training deep learning models, optimising SNN parameters. There are various models deployed at the edge nodes which are periodically updated so that the system is accurate and up-to-date. It's a centralized training model given along with the decentralized inference capability of edge device.

3.6.3 System Coordination

These nodes placed at the edge are distributed and can be synced and coordinated for learning with the cloud which is placed as to coordinate all the nodes. This synchronisation contributes to a higher scalability, higher reliability and higher robustness of the entire system especially when it comes to including such systems in large industrial systems.

3.7 Data Flow and Processing Pipeline

NEA's framework which manages its data has an organized data flow system that guarantees efficient and continuous data handling for industrial data. The sensors are firstly used to acquire real-time data and the data are respectively preprocessed at the data acquisition layer. This is subsequently translated to a spike representation, passed to the SNNs of the neuromorphic processing layer and the explanation results are obtained. These learnings can be combined together, and be used by edge intelligence layer at real-time decision making processes. Lastly, this data and models are synced with the cloud, thus completing the data processing cycle. It's carried out by way of this pipeline that affords the seamless nature of this whole framework.

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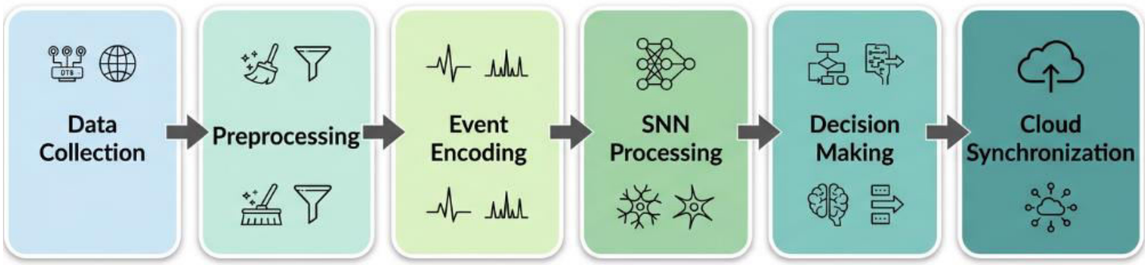

Figure 4: Data Flow Pipeline in NEA Framework

3.8 Key Features of the Framework

The NEA framework has several key and unique elements which differentiate it from the more traditional methods. It is event driven – processes only important changes of all of the data – to limit the number of events processed. Distributed intelligence model aims to ameliorate the need for one or multiple nodes (the "edge nodes") within the OTELO platform which accumulate analytics for them to be scalable and fault tolerant. The real-time response capability of the framework allows for taking quick action for critical situations and on-boarding of neuromorphic hardware leads to an energy-efficient solution. Furthermore, the system's adaptability allows it to continuously growth and development as according to the industrial section's ever-changing.

3.9 Implementation Considerations

Implementing such NEA framework involves both hardware and software and needs to be carefully done. The neuromorphic chips like the one developed by Intel (Loihi) or IBM (TrueNorth) are used as edge devices to execute SNN. In addition, there is a need for interoperability with the existing industrial systems, to enable communication among different layers, and solutions. A high level of security and data privacy are critical and one key step is implementing secure communication methods and data encryption. Further, fault tolerance protection is offered to ensure the reliability of the system now in case of failure of any equipment.

3.10 Advantages Over Conventional Approaches

The NEA architecture also has a number of advantages over the more common, cloud-based, deep learning based edge analytics devices. It greatly cuts down on latency as it allows for local processing, thus avoiding delays that go with cloud communication. Again, similar to pipelining, use of energy by the system using the event-driven computation is reduced hence making the system more sustainable. It is distributed, enabling it to be employed in large scale deployments and, more importantly, by modelling temporal data it can be used to detect some of the more complex patterns with high accuracy. Also, “work loose from cloud” allows an operator to have a higher level of flexibility than the edge nodes do regarding being always connected to the cloud.

IV. PERFORMANCE EVALUATION

The following were analysed to assess the performance of the proposed Neuromorphic Edge Analytics (NEA) framework in the Industrial Internet of Things (IIoT) Environment: the latency, energy consumed, accuracy and the bandwidth Utilization. The evaluation was performed on a synthetic industrial dataset containing time series from a variety of different sensors, such as vibration signals, temperature and pressure signals, typical for such applications like predictive maintenance and fault detection.

The efficiency of the scheme has been validated by comparing the NEA model with the existing state of the art edge analytics techniques which are based on deep-learning like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Processing latency, energy used, classification accuracy and data transmission overhead were the metrics used for the evaluation. This setup consisted of a set of resource constrained edge devices and these were used for experiments, while cloud devices were used for comparison as baseline.

The results revealed that comparative between the NEA framework and the conventional approach, the former could do a lot to reduce the processing latency, because of its event driven architecture. The SNN approach is different from the standard one that processes the data stream, as it only processes events that are relevant, such as by performing continuous computation, there computation delay is minimised. This latency decrease especially counts for real-time industrial apps, in which quick reaction times are essential for the reliability and safety of the system.

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This traditional deep learning models can be less efficient, but can be avoided by using the NEA framework. A minimum of spikes are used to conduct minimum amount of computation in neuromorphic processing layer, which has reduced energy at the edge nodes. That renders the framework extremely interesting for use in an industrial setting, where (potentially) small amounts of energy and/or a need for a large number of deployments and cost-efficiency might be involved.

They showed the NEA framework on the anomalous circumstance distinguishing/forecasting and so on, displaying equivalent or superior exactness in picking up slight changes (start stage) in deterrents utilizing a SNN (adjusted to explain commonality of the occasions in time arrangement information). In addition, due to the capability of the adaptive learning techniques the system could adapt well to frequent challenges which exist when using the system under dynamic work conditions.

In addition, the NEA work frame has been optimized with respect to the exploitation of the bandwidths. The data pre-processing and analytics were processed on-edge with little data to be pushed to the cloud. To minimize the congestion of the network, and maximize efficiency of the network, data was only broadcasted as appropriate by adding summarisation information.

Overall the test results demonstrate the NEA framework to be a low latency, high energy efficient and accurate framework which can also be bandwidth efficient. The advantages therefore indicate that it may be a good solution to address the next generation of IIoT applications that will certainly require large scale scalable and reliable solution.

V. FUTURE OPPORTUNITIES

Proposed Neuromorphic Edge Analytics (NEA) framework points towards several potential future opportunities both in research and industry. Demand for energy efficient, intelligent and autonomous systems will keep growing as systems make their way towards the IIoT and neuromorphic edge analytics becomes one of the main driving forces for the next wave of change for industrial systems.

But most importantly, is the opportunity given by the neuromorphic Hardware technologies. New processors, such as Intel's Loihi and IBM's TrueNorth, could be considered examples of this type of ultra-low-power/high-performance computing systems. The above progress might be extended towards ever smaller, lower cost, scalable and neuromorphic chips, which can be adopted by a myriad of industrial edge devices. This would make the system using NEA further practical/composable to real world applications.

One of these is the hybrid approach variants, namely, conjunction of neuromorphic method and conventional computing method with the deep learning and reinforcement learning method. All these hybrid approaches may make use of the strengths of the two paradigms: accuracy and adaptability/generalization in a variety of industrial applications. This is particularly true for higher level application such as Predictive Maintenance, process optimization and industrial/self-controlled process.

This is true in the case of the opportunity areas where the NEA model is concerned, i.e., self-learning and autonomous systems. Research will focus on the design of new learning algorithms of spiking neural networks (online learning, transfer learning and federated learning) in the future. It would introduce the smarts and responsiveness of the systems as all edge devices would get trained—without needing to wait in the middle for a retraining.

Moreover, another extension for implementing the digital twin technologies to an industrial system can also be realized. When coupled with the modelling of the comprising physical assets in a virtual environment, real-time neuromorphic analytics then promises more accurate simulation, monitoring and prediction of industries. In this scenario, decisions on running the operation might be taken beforehand and a little efficiency in the operation might be achieved.

In the ever-changing Industry 4.0/5.0 world, this represents another step on the part of the neuromorphic vision approach for edge analytics to support the industry's ever-evolving "smart manufacturing" "use-cases". NEAs framework can be used for the industries intelligent automation, human–machine collaboration and in sustainable practice in the future. Thanks to its energy-saving features it conforms to the worldwide trends towards green computing and responsible reduction of emissions.

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Last, but not least, there is a great potential in improving the security, privacy and standardization of neuromorphic edge systems. Two solid security frameworks and development of standard procedures will be a major key factor towards making deployment in industrial networks safe and reliable.

Overall the NEA has done well to establish a solid base and the future directions of the NEA can be seen as both smart and efficient systems, not to mention green industrial systems.

VI. CONCLUSION

The Industrial Internet of Things (IIoT) systems are increasing exponentially that requires efficient, scalable and intelligent data processing to process the vast amount of real time data they can generate. The challenges with the currently used methods (cloud based and deep learning based) were identified and the merging of the two concepts was proposed, Neuromorphic and Edge Analytics (NEuromorphic Edge Analytics - NEA). With the aforementioned spiking neural networks (SNNs) and the event-driven computation paradigm in the framework proposed, low-latency, energy-efficient and adaptive analytics can be performed all the way in the edge of the industrial networks.

The NEA architecture is multi-layered starting from data collection to NEA's unique neuromorphic processing, moving from edge to cloud, for seamless data flowing and distributed intelligence. The framework has shown in the performance evaluation, that it can greatly reduce the processing time and energy conservation; while maintaining a high level of performance in terms of accuracy in the different cases studied such as anomaly detection, predictive maintenance etc. Moreover, the architecture would seem to be the best when it comes to optimizing bandwidth: it doesn't seem to be maxing bandwidth where it doesn't have to be when uploading from a device to the cloud. The real time responsiveness and judicious use of resources makes the NEA framework very appropriate, requisite in today's industry.

The results are promising however and there are several opportunities and problems for future work. Scalability and robustness of scaling up of neuromorphic systems could be a topic of future work and this could enable scaling them up to industrial scale. Development of efficient training algorithms for spiking neural networks, especially for online and incremental learning are also important research topics. In addition, interfaces for connecting the very complex neuromorphic hardware with the existing industrial system need to be developed, and must be standardised and interoperable.

A novel scheme is to hybrid designs to merge the two – to get the best of both: neuromorphic and traditional deep-learning schemes to boost the performance over a wide range of applications. Additionally, there is a need for more in-depth studies of security, including that of privacy, especially for a distributed edge environment. In addition, it would be interesting in the logistical sector to validate and use NEA when implementing the framework in the real world in different industrial sectors.

Finally, the envisioned NEA framework can be utilised for moving towards a smart, autonomous and sustainable system of the IIoT. The novelty and future prospects of the field and the emerging technologies might open new avenues of neuromorphic edge analytics in industries and the involvement of smart manufacturing with the same technology to process data.

REFERENCES

[1] Intel Corporation, "Neuromorphic Computing Research," 2021. Available: https://www.intel.com/content/www/us/en/research/neuromorphic-computing.html
[2] Intel Corporation, "Loihi 2 Neuromorphic Chip Technology Brief," 2021. Available: https://www.intel.com/content/www/us/en/research/neuromorphic-computing-loihi-2-technology-brief.html
[3] IBM Research, "Neuromorphic Computing," 2020. Available: https://research.ibm.com/projects/neuromorphic-computing
[4] IBM Corporation, "What is Neuromorphic Computing?," 2021. Available: https://www.ibm.com/think/topics/neuromorphic-computing
[5] Intel Corporation, "Intel Neuromorphic Research Community," 2020. Available: https://www.intel.com/content/www/us/en/research/neuromorphic-computing.html
[6] Open Neuromorphic, "Intel Loihi Overview," 2019. Available: https://open-neuromorphic.org/neuromorphic-computing/hardware/loihi-intel/

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[7] Open Neuromorphic, “Intel Loihi 2 Overview,” 2021. Available: https://open-neuromorphic.org/neuromorphic-computing/hardware/loihi-2-intel/
[8] IBM Research, “Neuromorphic Devices and Systems,” 2020. Available: https://research.ibm.com/projects/neuromorphic-devices-and-systems
[9] IBM Research, “IBM Research Overview,” 2019. Available: https://research.ibm.com
[10] Amazon Web Services, “AWS IoT,” 2022. Available: https://aws.amazon.com/iot/
[11] Amazon Web Services, “AWS IoT Greengrass,” 2021. Available: https://aws.amazon.com/greengrass/
[12] IBM Corporation, “IBM Official Website,” 2022. Available: https://www.ibm.com/us-en