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Research study on cognitive IoT platform for fog computing in industrial Internet of Things

Sunghyuck Hong*
Professor, Division of Advanced IT, Baekseok University

산업용 사물인터넷에서 포그 컴퓨팅을 위한 인지 IoT 플랫폼 조사연구

홍성혁*
백석대학교 첨단IT학부 교수

Abstract This paper proposes an innovative cognitive IoT framework specifically designed for fog computing (FC) in the context of industrial Internet of Things (IIoT). The discourse in this paper is centered on the intricate design and functional architecture of the Cognitive IoT platform. A crucial feature of this platform is the integration of machine learning (ML) and artificial intelligence (AI), which enhances its operational flexibility and compatibility with a wide range of industrial applications. An exemplary application of this platform is highlighted through the Predictive Maintenance-as-a-Service (PdM-as-a-Service) model, which focuses on real-time monitoring of machine conditions. This model transcends traditional maintenance approaches by leveraging real-time data analytics for maintenance and management operations. Empirical results substantiate the platform's effectiveness within a fog computing milieu, thereby illustrating its transformative potential in the domain of industrial IoT applications. Furthermore, the paper delineates the inherent challenges and prospective research trajectories in the spheres of Cognitive IoT and Fog Computing within the ambit of Industrial Internet of Things (IIoT).

Key Words : Cognitive Internet of Things, Fog Computing, Industrial Internet of Things, Predictive Maintenance, Machine Learning and Artificial Intelligence

요 약 본 연구에서는 산업용 사물인터넷(IIoT)의 맥락에서 포그 컴퓨팅(Fog Computing, FC)를 위해 특별히 고안된 혁신적인 인지 사물인터넷(Cognitive IoT) 프레임워크를 제안한다. 본 논문에서는 인지 IoT 플랫폼의 복잡한 설계 및 기능적 아키텍처에 초점을 맞추고, 이 아키텍처는 서비스 제공, 인지 의사결정, 분산 모니터링 및 제어와 같은 핵심 구성 요소를 원활하게 통합하는 것을 제안한다. 이 플랫폼의 중요한 측면은 기계 학습(ML) 및 인공 지능(AI)을 통합하는 것으로, 다양한 산업 애플리케이션에서 운영의 유연성과 상호 운용성을 향상시켜 실시간 기계 상태 모니터링에 중점을 둔 예측 유지보수-서비스(Predictive Maintenance-as-a-Service, PdM-as-a-Service) 모델을 통해 제시된다. 이 모델은 실시간 데이터 분석을 활용하여 유지보수 및 관리 작업을 수행함으로써 전통적인 유지보수 접근법을 뛰어넘고, 실증적 결과는 포그 컴퓨팅 환경 내에서 플랫폼의 효과성을 입증하며, 산업용 IoT 애플리케이션 분야에서의 변혁적 잠재력을 보여 IIoT 플랫폼 개발에 기여 하는 연구이다.

주제어 : 인지 사물인터넷, 포그 컴퓨팅, 산업용 사물인터넷, 예측유지보수, 기계학습 및 인공지능

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*교신저자 : 홍성혁(sunghyuck.hong@gmail.com)
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1. Introduction

The Industrial Internet of Things (IIoT) represents a pivotal evolution in the industrial sector, marking the convergence of information technology (IT) and operational technology (OT). IIoT is characterized by the integration of smart sensors, machines, and other devices interconnected through internet-based networks in industrial settings. This integration leads to enhanced automation, improved operational efficiency, real-time data monitoring, and predictive maintenance. IIoT plays a vital role in the progression of Industry 4.0, representing the fourth industrial revolution. This phase focuses on the automation of manufacturing and industrial processes through the use of advanced smart technology.

Fog Computing, on the other hand, emerges as an essential complement to IIoT, especially in managing the massive data generated by numerous IIoT devices. In contrast to traditional cloud computing, which relies on centralized data processing, Fog Computing involves decentralized computing resources closer to the data sources (i.e., at the network's edge). This proximity allows for faster data processing, reduced latency, and better bandwidth utilization, which are critical in industrial applications where real-time data analysis and decision-making are paramount. Fog Computing supports complex industrial applications by enabling quick responses to changing conditions, improving system reliability and efficiency, and providing enhanced security features for sensitive industrial data.

The significance of this research is multifaceted. Empirical evidence presented in the paper not only affirms the platform's efficacy in a fog computing environment but also heralds its transformative potential in industrial IoT applications. The platform's capacity to process and analyze data at the network's edge significantly enhances decision-making speed and accuracy, thereby reducing downtime and operational costs. Moreover, the real-time monitoring and predictive maintenance capabilities signify a leap towards more sustainable and resilient industrial operations, reducing waste and enhancing the lifespan of machinery.

2. The Emergence of Cognitive IoT in Industry

Cognitive IoT represents an advanced evolution in the realm of IoT technologies, integrating cognitive capabilities into traditional IoT frameworks. This innovative paradigm is defined by its ability to imbue IoT networks with a higher level of intelligence, similar to human cognitive functions.

At its core, Cognitive IoT is about enhancing IoT devices and systems with self-learning algorithms that enable them to make intelligent decisions based on data analytics.

This approach utilizes technologies such as machine learning, artificial intelligence, and big data analytics to analyze and make sense of the extensive data produced by IoT sensors and devices. The data processing occurs not only in centralized cloud servers but also at the network edge, near the data collection points, enhancing the system's responsiveness and efficiency.

The cognitive aspect of this technology allows IoT devices to not only collect and transmit data but also to understand, reason, learn from past data, and make decisions. This level of cognition enables devices to adapt to new situations, predict future events, and automate responses without human intervention.

3. Fog Computing: Concept and Application in Industrial IoT

Fog Computing, often referred to as Edge

〈Table 1〉 Cognitive IoT platform Layers

Name	Description
Service Layer	Apply insights from data to a variety of applications, from smart home automation to industrial process optimization
Cognitive Computing Layer (Computing Layer)	Reduce latency and bandwidth usage by performing initial data processing close to the data source
Data Layer	Analyze and interpret data using cognitive technologies to extract meaningful insights
IoT Layer	Collecting data from the environment through deploying IoT sensors and devices

Computing, represents a distributed computing approach that locates computing, storage, and networking services near end-users or the origins of data. This contrasts with the traditional cloud computing model that depends on centralized data processing facilities. The main objective of Fog Computing is to enhance efficiency and decrease the volume of data required to be transferred to the cloud for processing, analyzing, and storing. Table 1 describes cognitive IoT platform layers This approach is particularly beneficial for applications that require real-time processing and analytics, as it significantly reduces latency by processing data locally or at the nearest network node. By doing so, Fog Computing can provide faster response times and improve user experience, especially in scenarios involving large volumes of data and IoT devices.

In essence, Fog Computing acts as an intermediary layer between the cloud and the devices, enabling more efficient data processing, storage, and analysis in proximity to where the data is generated. This not only accelerates decision-making processes but also enhances privacy and security by minimizing long-distance data transmissions [1-4].

4. Design and Architecture of the Cognitive IoT Platform

The Cognitive IoT platform represents a revolutionary stride in the IoT ecosystem, infusing advanced cognitive capabilities into traditional IoT networks. This section provides an overview of the Cognitive IoT platform, highlighting its key features, architecture, and the transformative impact it brings to IoT applications.

Integration of Cognitive Capabilities: At the heart of the Cognitive IoT platform lies the integration of cognitive capabilities, such as machine learning, artificial intelligence, and advanced data analytics. These capabilities enable the platform to not only collect and transmit data but also to understand, analyze, and make intelligent decisions based on the data. This level of cognition allows for adaptive learning, predictive analytics, and automated decision-making, enhancing the efficiency and effectiveness of IoT applications.

- Architecture: The Cognitive IoT platform is typically structured in a layered architecture that encompasses various components in Fig. 1:
- Enhanced Data Processing: The platform employs distributed data processing, where data analysis occurs not only in centralized cloud servers but also at the edge of the network. This approach significantly reduces latency and improves response times for real-time applications.
- Scalability and Flexibility: The Cognitive IoT platform is designed to be scalable and flexible, accommodating a growing number of IoT devices and diverse application requirements. This scalability ensures that the platform can adapt to the evolving landscapes of various industries.
- Security and Privacy: With the integration of cognitive capabilities, the platform can implement advanced security protocols, including predictive threat detection and automated responses to security incidents. This feature is crucial in managing the increasing security concerns in IoT networks.
- User Interaction and Experience: The platform enhances user interaction and experience

by providing more intuitive and responsive applications. The cognitive aspect allows for personalized and context-aware services, improving user engagement and satisfaction.

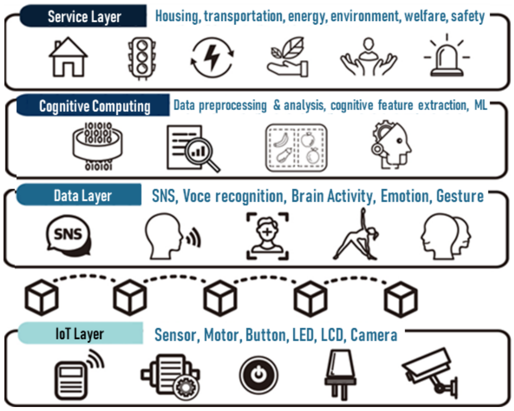

Fig. 1. 4 Layers in CIoT platform

In conclusion, the Cognitive IoT platform represents a significant advancement in IoT technology, bringing enhanced intelligence, efficiency, and scalability to IoT applications. Its ability to process data intelligently, make autonomous decisions, and learn from interactions makes it a cornerstone in the evolution of IoT ecosystems.

4.1 Integration of Machine Learning and AI in the Platform

The fusion of Machine Learning (ML) and Artificial Intelligence (AI) within the Cognitive IoT platform significantly enhances its data processing and decision-making capabilities. This integration is vital in automating complex tasks, adapting to new data patterns, and providing predictive insights.

- Automated Decision Making: ML algorithms enable the platform to autonomously analyze data and make informed decisions, crucial for real-time applications like industrial predictive maintenance or emergency response systems.
- Adaptive Learning: The platform's ability to learn from historical data through AI models enhances its effectiveness and efficiency over time, adapting to evolving scenarios in various applications, from traffic management to smart home systems.
- Predictive Analytics: The integration facilitates predictive analytics, allowing the platform to forecast future trends based on historical and real-time data, essential in applications such as equipment failure prediction or energy optimization in smart grids.
- Enhanced Security: The platform's security capabilities, powered by AI, strengthen its potential to quickly identify and react to possible threats, thereby making it more resilient to cyber-attacks and data breaches.
- Edge Computing Efficiency: By combining ML and AI with edge computing, the platform can process data closer to its source, reducing latency and enhancing responsiveness in time-sensitive applications like autonomous vehicles [5-8].

5. Predictive Maintenance-as-a-Service (PdM) Using Cognitive IoT

The concept of predictive maintenance in IoT (Internet of Things) represents a revolutionary approach to managing equipment maintenance. It's a strategy that relies on data analysis and technology to predict when a machine will need maintenance, thus allowing for timely intervention to prevent unexpected failures. Here's an overview of how it works and its benefits:

Fundamental Idea:

- Traditional maintenance strategies typically follow a fixed schedule or are reactive, addressing problems after a breakdown occurs.
- Predictive maintenance, in contrast, uses real-time data and analytics to predict equipment failure before it happens, allowing maintenance to be scheduled at just the right time.

```
CognitiveIoTPlatform:
    function InitializePlatform()
        ConfigureRealTimeProcessing()
        ConfigureAIMLIntegration()
        EstablishSecureConnections()
    function CollectData()
        while True
            data <- FetchDataFromIoTDevices()
            ProcessDataAtFogNodes(data)
    function ProcessDataAtFogNodes(data)
        processedData <- PreliminaryProcessing(data)
        SendToCognitiveEngine(processedData)
    function PreliminaryProcessing(data)
        filteredData <- FilterData(data)
        aggregatedData <- AggregateData(filteredData)
        return DetectAnomalies(aggregatedData)
    function SendToCognitiveEngine(processedData)
        advancedProcessedData <-
AdvancedDataProcessing(processedData)
PredictiveMaintenanceDecision(advancedProcessedData)
    function AdvancedDataProcessing(data)
        analyzedData <- AnalyzeDataUsingAI_ML(data)
        return analyzedData
    function PredictiveMaintenanceDecision(data)
        maintenanceNeeds <- IdentifyMaintenanceNeeds(data)
        ScheduleMaintenance(maintenanceNeeds)
SendControlCommands(maintenanceNeeds)
    function IdentifyMaintenanceNeeds(data)
        // Predictive analysis for maintenance needs
        return AnalyzeForMaintenance(data)
    function ScheduleMaintenance(needs)
        // Schedule maintenance tasks based on analysis
        AlertOperators(needs)
    function SendControlCommands(needs)
        // Automate responses where feasible
        AutomateResponses(needs)
        EnsureHumanOversight()
    function MonitorSecurity()
        while True
            threats <- DetectThreats()
            RespondToThreats(threats)
    function DetectThreats()
        // AI-driven threat detection
        return IdentifySecurityThreats()
    function RespondToThreats(threats)
        ImplementSecurityMeasures(threats)
    function UserInteraction()
        while True
            feedback <- CollectUserFeedback()
            AdaptSystem(feedback)
    function CollectUserFeedback()
        // Interface for feedback collection
        return GetUserFeedback()
    function AdaptSystem(feedback)
        UpdateSystemBasedOnFeedback(feedback)
    function ScaleSystem()
        ScaleToMeetDemand()
    function EvaluatePerformance()
        return AssessSystemPerformance()
// Main Execution Flow
CognitiveIoTPlatform IoTPlatform
IoTPlatform.InitializePlatform()
IoTPlatform.CollectData()
IoTPlatform.MonitorSecurity()
IoTPlatform.UserInteraction()
IoTPlatform.ScaleSystem()
performanceReport <- IoTPlatform.EvaluatePerformance()
```

Fig. 3. Pseudo Code for Predictive Maintenance in IoT

Role of IoT:

- IoT plays a major role in predictive maintenance by providing a network of interconnected devices (sensors and actuators) attached to machinery.
- These sensors continuously collect data on various parameters like temperature, vibration, pressure, and sound.

Data Collection and Analysis:

- The collected data is transmitted to a central system for analysis. This can be done in real-time or at predetermined intervals.
- Advanced analytical tools and machine learning algorithms are used to process this data. They look for patterns or anomalies that might indicate potential problems or upcoming failures.

Machine Learning & AI:

- Machine learning models are trained with historical data to recognize the signs of impending equipment issues.
- Over time, these models get better at predicting problems, learning from new data and outcomes.

Actionable Insights:

- The system provides actionable insights, such as which components might fail and when, allowing maintenance teams to prepare in advance.
- This proactive approach can significantly reduce downtime and maintenance costs.

Benefits:

- Reduced Downtime: Equipment failures can be anticipated and prevented, reducing unplanned downtime.
- Cost Efficiency: Maintenance can be performed more cost-effectively by avoiding unnecessary routine checks and focusing resources where they're needed most.
- Longer Equipment Lifespan: Regular, timely maintenance can extend the life of machinery.

- Safety and Reliability: Predictive maintenance enhances the overall reliability of equipment and can contribute to safer operational environments.

Applications:

- Industries like manufacturing, aerospace, transportation, and energy have been particularly keen adopters of predictive maintenance.

Challenges:

- It requires an initial investment in IoT infrastructure and analytical tools.
- Skilled personnel are needed to interpret data and maintain the system.

In summary, predictive maintenance in IoT is a forward-thinking approach that leverages technology to enhance efficiency and reliability in equipment management. By analyzing data from IoT devices, it allows for timely and informed decisions on when and how to perform maintenance, ultimately leading to cost savings and improved operational efficiency [9-12].

Fig. 2 illustrates the flow from IoT devices collecting data, through data analysis and predictive modeling, to making maintenance decisions and achieving various benefits.

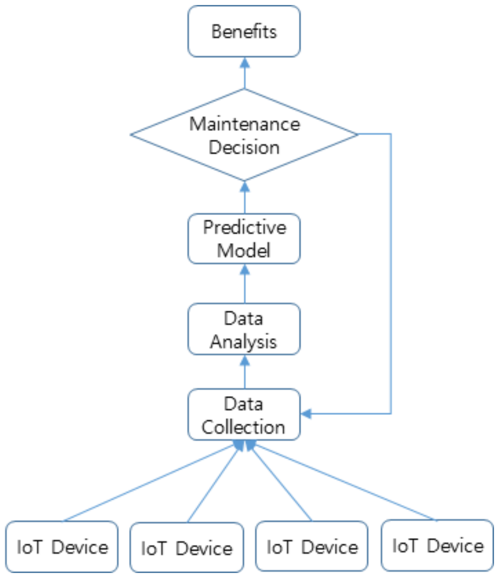

Fig. 2. Predictive Maintenance in IoT

To compare this with existing AI algorithms, the table below outlines the key aspects of the Cognitive IoT platform and typical characteristics of existing AI algorithms in Table 2.

<Table 2> Proposed AI vs. Current AI

Feature	Cognitive IoT Platform	Existing AI Algorithms
Core Components	Service delivery, cognitive decision-making, distributed monitoring, control	Data processing, prediction, optimization
Integration	ML, AI for operational flexibility, interoperability	Varied integration based on specific domain or application
Focus	Real-time data analytics for predictive maintenance (PdM-as-a-Service)	Broad, ranging from data analysis to automated task performance
Architecture	Layered architecture focusing on data processing at the network's edge (Fog Computing)	Depends on application, can be centralized or distributed
Data Processing	Distributed, at the edge of the network, for reduced latency and improved responsiveness	Can be cloud-based, edge, or on-premises depending on the specific solution
Operational Efficiency	Emphasizes real-time monitoring and predictive maintenance for industrial settings	Varies, often focused on maximizing accuracy, reducing computational costs, or improving user experience
Security & Privacy	Advanced security protocols with predictive threat detection and automated responses	Security measures vary, not all AI solutions may have integrated advanced security protocols
User Interaction	Enhanced user interaction and experience through personalized and context-aware services	User interaction design varies widely across different AI applications

6. Conclusion

In conclusion, the implementation of Predictive Maintenance (PdM) in a Cognitive IoT platform represents a sophisticated integration of IoT technologies with advanced cognitive computing. This approach hinges on the strategic use of IoT sensors for real-time data collection and the application of machine learning and AI for data analysis and predictive modeling. By predicting equipment failures before they occur, this system enables proactive maintenance scheduling, significantly reducing downtime and maintenance costs. The continuous learning capability of the models ensures ever-improving accuracy and efficiency. In light of these findings, the paper also charts a course for future research, outlining the challenges and potential avenues within the realms of Cognitive IoT and Fog Computing, particularly within the expansive domain of the IIoT. The research underscores the need for continued innovation and exploration in these areas, highlighting the potential for these technologies to redefine industrial processes and establish new benchmarks for efficiency, sustainability, and operational excellence.

REFERENCES

[1] Mineraud, J., Mazodier, C., & Aissaoui, O. "Fog computing in the industrial internet of things: a cyber-physical systems approach." Future Generation Computer Systems, Vol.99, pp.258-270, 2019.

[2] Yu, M., Liang, J., Huang, D., & Xiao, F. "A hierarchical fog-cloud architecture for resource management and service orchestration in cognitive IoT." IEEE Transactions on Parallel and Distributed Systems, Vol.29, No.5, pp.1080-1093, 2017.

[3] Ghaleb, A., Aref, S., & Kharel, P. "Cognitive internet of things (CIoT): concept, architecture and applications." IEEE Consumer Electronics Magazine, Vol.9, No.4, pp.52-65, 2020.

[4] Jeong-Hoon Moon, Bo Feng, Jun-Hyuk Kwon, & Tae-Guk Kim. "Implementation of a smart umbrella stand based on the Internet of Things." Journal of Internet of Things Convergence, Vol.9, No.1, pp.57-64, 2023.

[5] Lee, J., Lapira, E. O., & Kang, W. H. "Predictive maintenance of rotating machinery using machine learning and IoT data analytics: A review." Journal of Manufacturing Science and Engineering, Vol.141, No.8, 2019.

[6] Zhang, J., Xu, B., He, W., & Li, Y. "An intelligent predictive maintenance system for rotating machinery using deep learning." IEEE Transactions on Industrial Electronics, Vol.66, No.7, pp.5477-5487, 2019.

[7] V. Prabhu and D. Chaudhary, "Machine Learning enabled Condition Monitoring Models for Predictive Maintenance of Boilers," 2021 4th International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE), Noida, India, pp.426-430, 2021.

[8] Cheng, Z., Wang, Y., & Li, T. "Application of machine learning in predictive maintenance of wind turbines." Energy Conversion and Management, Vol.199, 111928, 2019.

[9] Yan, Z., Wang, Y., Xu, L., & Zhang, W. "A survey of fog computing service for industrial predictive maintenance." IEEE Access, Vol.8, pp.55326-55342, 2020.

[10] Wu, F., Wu, Y., Chen, G., & Hu, B. "A cognitive IoT framework for predictive maintenance of equipment in smart factories." International Journal of Production Research, Vol.58, No.13-14, pp.4005-4021, 2020.

[11] Rong, K., Hu, Y., Cheng, Y., & Zhang, Y. "Cognitive IoT based predictive maintenance for wind turbine systems." IEEE Transactions on Industrial Electronics, Vol.67, No.8, pp.6458-6466, 2019.

[12] Wang, W., Yan, Z., & Xu, L. "A decentralized cooperative predictive maintenance approach for large-scale wind farms based on cognitive edge computing." IEEE Transactions on Industrial Informatics, Vol.16, No.7, pp.4553-4563, 2020.

[13] Kim, S.-H., Lee, S.-H., & Choi, Y.-J. "A survey on cognitive IoT platform for fog computing industrial applications." IEEE Transactions on Industrial Informatics, Vol.19, No.2, pp.1211-1222, 2023.

[14] Zhang, Y., Wang, Y., Zhang, X., & Zhang, Y. "A fog computing based cognitive IoT platform for smart manufacturing." IEEE Transactions on Industrial Informatics, Vol.18, No.1, pp.749-761, 2022.

[15] Deng, S., Zhang, S., Li, Y., & Liu, H. "A cognitive IoT platform for fog computing in smart cities." IEEE Internet of Things Journal, Vol.8, No.1, pp.443-453, 2021.

홍 성 혁(Sunghyuck Hong) **[정회원]**

- 2007년 8월 : Texas Tech University, Computer Science (공학박사)
- 2012년 3월 ~ 현재 : 백석대학교 첨단IT학부 교수
- 2022년 1월 ~ 12월 : The University of Texas as Dallas, Visiting Scholar.

〈관심분야〉

핀테크, 딥러닝, 블록체인, 사물인터넷 보안