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Research Article

Importance of Edge Computing in Critical Manufacturing Systems: FPGA Implementation

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Abstract

Academic and industrial studies on smart systems, which have entered all areas of our lives, continue to their rapid developments along with gaining momentum with Industry 4.0. Especially, many of the different production devices with their molding, printing, shaping, and cutting capabilities have a certain level of automation. They work together with the material information they process, and the compatibility with other machines to make the whole production system work effectively and properly. While the abundance of data acquired is an important source for better analytics, obtaining information for business purposes from this data and helping decision support systems is the most important task expected from Information Technology and Systems in the organization. In this paper, we propose an FPGA-based edge information infrastructure to evaluate critical data from the production devices, distributed sensors, and other ISs in any industrial environment to increase the utilization and performance of the total machinery. This study helps the predictive maintenance decision for a sample plastic injection molding device according to our industrial scenario. A sample data set downloaded from the Internet with the factors like speed, vibration, and the temperature was used. An FPGA (Field Programmable Gate Array) design that will run the necessary ML algorithms with the sensor data and existing information system inputs (ERP, MES) has been carried out by using Xilinx Design Tools and Vitis IDE 2020.2. In this study, the ANFIS (Adaptive Network-Based Fuzzy Inference System) system, which is an approach consisting of the integration of artificial neural networks and Fuzzy Logic, has been chosen as an Artificial Intelligence application. The estimation results obtained were evaluated over the accuracy rates achieved in similar studies in the literature.

Keywords: Edge Computing, Industry 4.0, Reconfiguration, Smart Manufacturing, FPGA, Fuzzy Logic, ANFIS.

Kritik Üretim Sistemlerinde Kenar Bilişimin Önemi: FPGA Uygulaması

Öz

Endüstri 4.0 ile birlikte ivme kazanmakla birlikte hayatımızın her alanına girmiş olan akıllı sistemler ile ilgili akademik ve endüstriyel çalışmalar hızla devam etmektedir. Özellikle üretimde kullanılan kalıp, baskı, şekillendirme, kesme vb. gibi farklı makineler, belli bir otomasyona sahiptirler. Bunların işledikleri malzeme bilgileri ve ortak çalışan diğer makinelerle uyumu bütün üretim sisteminin etkin şekilde çalışabilmesi çok önemlidir. Elde edilen verilerin bolluğu daha iyi analitik inceleme için önemliyken, bu verilerden iş amaçlı bilgi elde etmek ve karar destek sistemlerine yardımcı olmak organizasyondaki Bilgi Teknolojileri ve Sistemlerinden beklenen en önemli görevdir. Bu çalışmada üretim ortamındaki cihazlardan, sensörlerden ve işletmedeki diğer Bilgi Sistemlerinden gelen verilerin

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FPGA tabanlı bir kenar bilişim altyapısı ile değerlendirilmesi önerilmektedir. Bu çalışma kapsamında üretim ortamında kullanılan örnek bir plastik enjeksiyon kalıp cihazına ait bakım kararının tahminlemesi yapılmıştır. Bunun için Internet üzerinden erişilen temsili hız, titreşim ve sıcaklık gibi faktörleri içeren bir veri seti kullanılmış, sensör verileri ve mevcut bilgi sistemi girişleri (ERP, MES) ile gerekli ML algoritmalarını çalıştıracak bir FPGA (Alan Programlanabilir Ağ Dizisi) tasarımı da, Xilinx Design Tools ve Vitis IDE 2020.2 kullanılarak gerçekleştirilmiştir.Veri girişi için üzerinde akıllı algoritmaların çalıştırılacağı FPGA donanımı "Xilinx Zynq xc7z020" kenar bilişim altyapısının esas öğesi olarak planlanmıştır. Çalışmada hibrit bir yaklaşım olan ANFIS (Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi) sistemi Yapay Zekâ uygulaması olarak seçilmiştir. Elde edilen tahmin sonuçları literatürdeki çalışmalarda erişilen doğruluk oranları üzerinden değerlendirilmiştir.

Anahtar Kelimeler: Kenar Bilişim, Endüstri 4.0, Yeniden Yapılandırma, Akıllı Üretim, FPGA, Bulanık Mantık, ANFIS.

1. Introduction

Internet of Things (IoT), which became popular at the beginning of the 21st century, was considered a technology to switch from Industry 3.0 to Industry 4.0 with newer enhancements and capabilities for the products and processes in the supply chain (Trappey et al., 2017; Hofmann and Rüsch, 2017). Supportive technologies like the Internet and embedded systems with Industry 4.0, are brought together to effectively control and manage physical objects, people, smart machines, production lines, and operating processes (Andreas et al., 2016). While physical processes in factories can be monitored with Industry 4.0, it is ensured that appropriate decisions are made by allowing objects to communicate with each other and people.

Considering the recent studies on critical IoT systems, especially in the industrial sector, smart cities, smart energy, and smart car applications take first place (IoT application areas, 2022). The increasingly complex, automatic, and sustainable characteristics of production processes in the industrial field have revealed the need for machines to operate more simply, efficiently, and consistently (Lu, 2017; Jian et al., 2016). With the increasing technology of existing industrial communication systems, wired/wireless local network alternatives have also increased. Considering that the manufacturing data is also very critical, especially the use of wireless devices and sensors should be planned very carefully in the context of security (Ercan, 2005). On the other hand, the continuous development of information and communication technologies has offered great potential to companies in the manufacturing sector (Prinz et al., 2016).

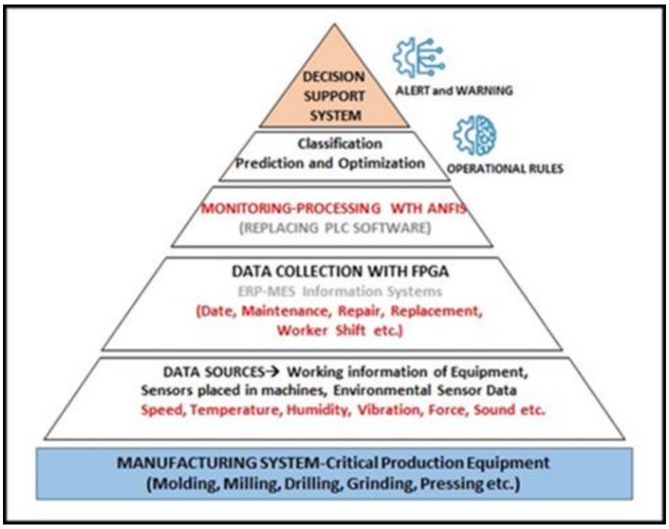

Figure 1. Sample business maintenance strategy

The Industrial Internet of Things (IIoT) has brought a major change in how we can monitor critical production systems in factories with the support of different sensors. The information obtained from the sensors, mostly when connected to a cloud-based system, can be used in more meaningful ways by production units and factories. The data collected from the production system to automate the maintenance system in the environment can be analyzed and help to make maintenance decisions (Crosser, 2020). A related layered architectural structure is designed in Figure 1.

According to this representation, the configuration to support all maintenance and reliability functions in the manufacturing systems starts from the data sources layer where the lowest device diversity can be found. The data diversity and complexity of the production environment increase as higher levels is reached. It is very important to ensure the efficient operation of production systems and follow a cost-effective process in non-planned maintenance disruptions. In the present case, the root causes of errors are tried to be found manually through controls and measurements traditionally performed by operators. Here, IIoT comes into to industrial scene and provides the required system parameters for modeling the digital twin with the sensors placed in appropriate places, instead of receiving the system data by the operators using traditional methods. Many parameters affect modelings, such as temperature, humidity, vibration, sound, and light changes.

Within the scope of this study, sensor data of the overall machinery in the environment will be used together with the information systems such as ERP and MES used in the factory environment, then a predictive maintenance diagnosis will be made with AI operations such as classification, recognition, prediction and decision making using ANFIS (Adaptive Network-Based Fuzzy Inference System) application designed on FPGA.

In the second part of the study, edge informatics involving industrial systems are examined, especially the uses of artificial intelligence in embedded systems are emphasized. In the third chapter, the FPGA-based architectural model that will work as a smart control unit for the proposed edge computing functions will be explained. In the fourth chapter, ANFIS software information about data collection and analysis on the FPGA application model is given, and the application results are evaluated in the fifth chapter. In the last section, the contributions of the study were examined and information was given about future studies.

2. System Design

Obtaining information from raw data on the IT platform and making decisions about business and processes with the help of existing IS are always done with the help of servers inside or outside the factory. The data collected from the electronic and electromechanical manufacturing devices and different sensors integrated into them, first use industrial communication protocols, then transmitted to the cloud as IP packets. Right here, there is always a need for another middleware interface in between. When real-time and critical applications run in the Cloud environment, the transfer delay cannot be compensated. To reduce the response time of the system, another service layer called edge computing is added to the entire architecture. In edge computing, IoT devices send their requests to these edge servers, Thus, as the traffic to the cloud will decrease, the response time of the system will also be shortened (Hushmat et al., (2019). The main goal here is to use protocols that provide less bandwidth with data association (Plachy et al., 2015). Smart control boxes used as middle layer elements, follow many electro-mechanical processes predefined, especially in industrial automation tasks. They can also monitor and control many sensors and actuators in the system.

Ensuring the efficiency of critical manufacturing equipment and the quality of products is an ongoing process. Therefore, unplanned downtime for machines, hardware failures, and material defects without counting human errors are accepted as the most important reasons that can negatively affect quality and productivity (Banner, 2022). Nowadays, there are many industrial devices such as wind turbines, water pumps, and regional substations operating in remote locations without the supervision of an operator.

2.1. EDGE Computing

There are two different methods by which edge computing can be installed:1) hierarchical model and 2) software-defined model/network (SDN). In the hierarchical model, edge servers can be assigned to perform a different function according to existing applications at different distances of the network (in-plant, regional, national, etc.). The use of smart PLCs (Programmable Logic Control) with the ability to connect to the internet for maintenance purposes is widespread in industrial control such as error detection and automatic intervention to possible failures (Sisman et al., 2018).

PLC control boxes have disadvantages such as cost (especially the effect of prominent company products in some areas) and software control inflexibility. Due to the constraints of IoT devices such as energy, memory, and processor, that will collect data from the production environment, it would be more rational to send the data to an FPGA device that is close by, and has higher functional capabilities and flexibility.

In power modules, which are the most important component of working electronic devices, electrical and thermal parameters that change over time can be monitored. Thus, situations such as melting at the soldering points of this module or dislodgement of the connection conductors on the card can be detected in advance (van der Broec et al., 2020). The vibration and thermal fingerprint differences between normal and malfunctioning machines from the collected data were realized with an edge-software device with microprocessor-controlled and embedded software (Akhtari et al., 2019).

In today's industry, real-time control over cloud services causes unacceptable delays. By De Blasi and Engels, open-source software that protects the PLC as the main component and optimizes its ability to have more functions has been added and a smart box solution has been proposed (De Blasi and Engels, 2020).

The thermal temperature and ambient temperature of the machine and its parts have a significant effect on the accuracy of CNC machines. In reference (Ali et al., 2015), a study conducted with ANFIS, the effect of all thermal temperature sensors was listed and grouped according to their position in the machine, and the estimation values were found successful according to the test results. Reference (Gougam et al., 2020) proposed an ANFIS algorithm successfully used in rotating part manufacturing devices, feature extraction, and autogram analysis that can find the faulty signal on bearings where it is very difficult to detect ideal operating vibrations due to the noise created by other mechanical elements.

ANFIS (Neural Fuzzy Logic Inference System), one of the machine learning algorithms that should be used as a necessity due to the abundance of data collected, was chosen in this study. It can provide the classification of operating systems according to different parameters and Predictive (Predictive) Maintenance planning by using sensor data placed in industrial systems in a planned manner. Artificial intelligence and fuzzy logic methods are actively used in many areas. However, an FPGA-based middle-layer application representing Edge Computing in industrial environments has not been encountered in the current field writing studies.

3. System Architecture

There are electronic and electromechanical devices (CNC, molding, printing, welding, cutting, etc.) in the systems that are produced depending on the industrial sector. The ability of these devices to communicate seamlessly with each other and to be managed by a control center is important for ensuring functional continuity. Resistant to factory conditions with different serial communication interfaces, allowing different devices (production, barcode, bearing, temperature, humidity, vibration sensors, etc.) to join the factory network and communicate with management equipment, with low power consumption, allowing fast installation, fast running, They need industrial serial device servers. Figure 2 shows a system architecture that we consider within the details of a former study (Ercan and Al Azzawi, 2019).

Figure 2. Proposed system architecture and Data Flow Chart

In the above design, real-time data flows from the factory ERP information system, industrial production devices, and sensors located at certain points of these devices to FPGA inputs.

In this edge information infrastructure, which works with the ANFIS algorithm on the FPGA, the incoming raw data is filtered and if necessary, the communication protocols are changed and pre-processed. Again, with the ANFIS algorithm, a possible maintenance decision is made by making maintenance estimates. While these first operations on edge smart devices analyze the data, they also help to partially overcome the difficulties that may occur while transferring it to the cloud environment (Yuriyama and Kushida, 2010).

3.1. FPGA Usage

FPGAs are digital integrated circuits consisting of programmable logic blocks and interconnections between these blocks, with wide application areas. Other circuits that can be used for the same purposes (SoC-System on Chip) can be provided with lower total costs. However, FPGA gives great flexibility and usability due to the ease of realizing all logic functions required by the designer. However, FPGAs have design and programming difficulties besides their superior features. For this reason, it is used only in very special and important areas, where advanced technology, scientific and sensitive works are required. Figure 3 shows the input/output blocks, logic, and memory blocks on the FPGA, and the communication between these blocks (FPGA Example, 2022).

With this structure, it is possible to make copies of all digital circuits that are mass-produced and to develop non-production integrated circuit software. With a language called HDL (Hardware Definition Language), flexible hardware design, ie programming, required for different applications can be made. The most important feature of industrial automation systems is that all system components and infrastructure can be operated in harmony. FPGA, which we plan to use within the scope of the study, has advantages such as flexible and reconfigurable structure, parallel data processing capacity, and multiple input/output possibilities. These different hardware features help to easily reveal the proposed original design, giving more testing opportunities for rapid prototyping. In reference (Feng et al., 2019), the authors worked on CNN-RNN (Convolutional Neural Network and Recursive Neural Network) algorithms for medical controls related to remote health. These two different machine learning algorithms were run separately on the FPGA and the CPU, and it has been shown that the FPGA performs 15.23 times fast processing.

4. Software System and ANFIS Effect

Neural Fuzzy Logic Inference System (ANFIS) is a hybrid modeling method consisting of a combination of ANN and Fuzzy Logic methods. The most important step in modeling with fuzzy logic is determining the membership degrees of input/output variables. Then, inference rules, which give the relationship between these changes made on the inputs and the appropriate outputs, are applied. ANFIS, by using the learning ability of ANN, provides optimization by determining the most appropriate membership functions and inference rules in the training dataset. ANFIS can be evaluated as a three-layer feedforward ANN.

In this network structure shown in Figure 3, the first layer is the layer where the input variables are applied and membership functions are determined with the help of ANN, the second layer is the layer where the fuzzy rules are created and inference is performed, and the last layer is the layer where the inference system result is obtained (Khazal and Ercan, 2018). In the fuzzy logic control example designed in Figure 5, the first layer predecessor and the result parameters in the fourth layer of the selected input values are improved by ANFIS below (Karaboga and Kaya, 2019).

The initial weight values, which are the most important disadvantages of using artificial neural networks, are dealt with by fuzzification, which is the first step of fuzzy logic in the model (Kar et al., 2014). The Sugeno Fuzzy model is used for learning and finding the most suitable one of ANFIS structure ANNs that are not included in this study. This method provides a mechanism that is more suitable for System modeling and control design. However, we used the Mamdani model for Fuzzy Logic Control since we only focused on general FPGA applications.

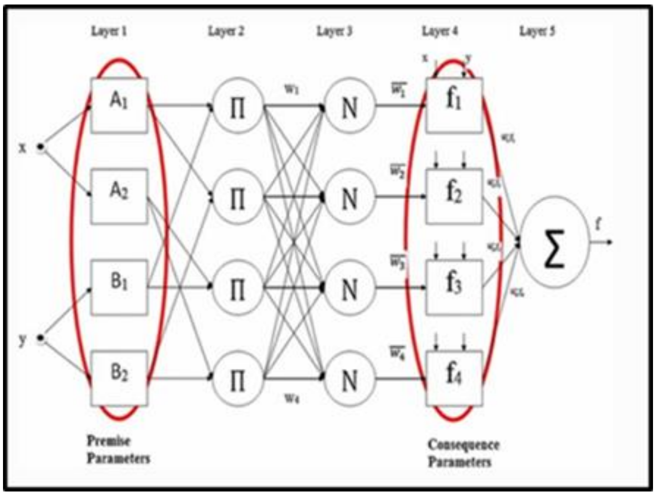

Figure 3. ANFIS responsible for Premise and Consequence parameters

VHDL (Very High-Speed Integrated Circuit Hardware Description Language), one of the two hardware programming languages (Verilog and VHDL), was used over MATLAB to implement ANFIS on FPGA integrated hardware structure.

As an example of the inputs used in the proposed model (vibration, speed, and temperature controlling the raw material input placed in any molding machine and the information from the vibration sensors in the fixed and moving parts of the molds can be analyzed. The data flow chart in Figure 2 has been followed for easy interpretation and understandability of the ANFIS classification and estimation algorithm in the study. In such a system with a maintenance decision target, the past maintenance information of the device and the device from the ERP information system and the threshold exceeding values that can be obtained with reports from a possible SCADA system can also be used for the final decision.

4.1. Detection of Anomaly in the Production Systems

The parts to be provided with data by using sensors in mold machines are generally the moving arm part of the mold chamber, the temperature of the mold raw material, or the motor that enables the movement of the raw material to the mold room. A representative picture of this is given in Figure 4, and the obtained data set is given in Table 1.

The data needed for the molding machine in the system was provided by the Huawei German Research Center on the “Predictive Maintenance Datasets” site. There are 3 different parameters and 112,002 sample records consisting of measurement values of Speed, Humidity, and Vibration sensors (Axenie and Bortoli, 2020).

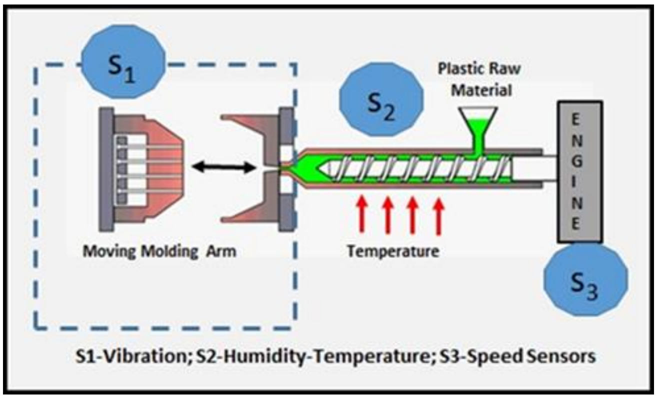

Figure 4. Proposed plastic injection molding machine and suitable sensors

The most important goals in the use of Edge Information infrastructure as a Predictive Maintenance (PdM) targeted business model are to operate power and computing resources efficiently and to keep the collected data quality at a high level.

For this reason, anomaly detection approaches, which are at the intersection of statistical, data mining, and machine learning methods, are among the prominent studies to ensure the quality of sensor data. Anomaly detection methods; With approaches such as removing duplicate data, removing noise, and estimating lost data, which are used to improve data reliability and quality, it stands in an important place in revealing unexpected patterns outside of normal data (Kalaycı and Ercan, 2018).

FPGA hardware "Xilinx Zynq xc7z020" was used in the study. Different "Intellectual Property- (IP)" s were revealed by making hardware design with Vivado High-Level Synthesis-(HLS) for each different ANFIS algorithm that will work on it (Ercan and Al Azzawi, 2019). Thus, a special hardware structure was created in which different ANFIS functions by using different memories and switches in the FPGA circuit board starting from the sensor inputs.

Table 1. Features of a Sample Set

Statistical Values	**Speed (rpm)**	**Temperature (%)**	**Vibration (Db)**
Minimum	*16.933*	*72.399*	*2.000*
Maksimum	*93.744*	*75.400*	*99.995*
Average	*55.338*	*73.236*	*28.229*
St.Deviation	*5.067*	*0.426*	*1.27*

5. Findings and Discussion

The combined Artificial Intelligence and Fuzzy Logic (ANFIS) method has been used for classification, recognition, prediction, data association, diagnosis, interpretation, and decision-making purposes, which are the areas of this predictive maintenance work, as well as being actively used in many areas. Membership values in our Fuzzy Logic system designed for these data to be used as FPGA inputs are given in Table 2.

Table 2.Fuzzy Logic Membership Values

Input Type	**Membership Values**	**Membership Ranges**
Vibration	*Low* *Medium* *High*	*2-40* *40-80* *80-100*
Temperature	*Low* *Medium* *High*	*71-73* *73-74* *74-76*
Speed	*Slow* *Normal* *Fast* *Dangerous*	*16-30* *30-55* *55-80* *80-94*

As output, options such as "Control, Monitoring, and Intervention" have been determined to make the maintenance decision in Figure 2. 10 fuzzy inference rules were designed according to the current values. While using the Sugeno Fuzzy model for the ability to find the most appropriate preliminary and result parameters together with the learning of ANFIS structure ANNs, we have used the Mamdani model as an example of FPGA application in edge computing. In Figure 5 below, our output obtained with our data entries, Membership values, and established rules for Fuzzy Logic Control functions are shown.

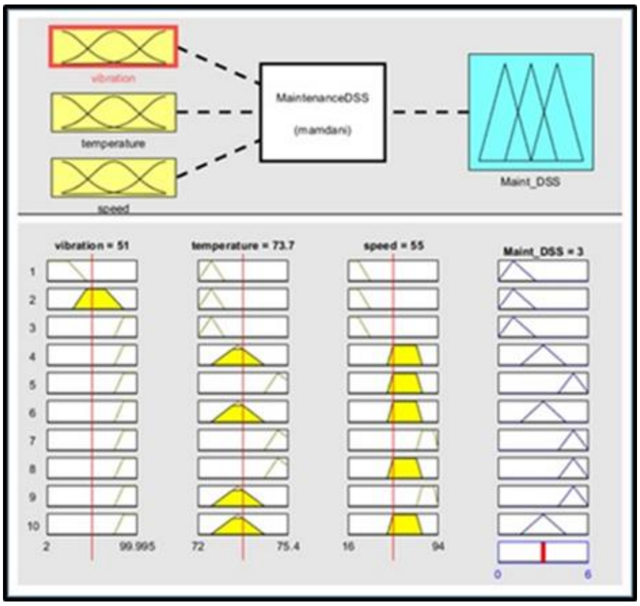

Figure 5. Fuzzy Logic Inference Model

The experimental findings were interpreted among themselves considering different experimental conditions, on the other hand, the measured values were compared with the numerical values obtained using the formulas given in the literature. In the Fuzzy Logic data analysis performed without ANN, especially when all three input data are determined to be high in the data set, our mold device gives an intervention alarm, while the temperature values are at a medium level and the monitoring output is obtained in places where vibration and speed are high. Provided that the data set remains the same, the intervention information generally does not change in the changes in membership values, but different results are obtained for monitoring. The results obtained in the study were compared with the results obtained by using the MATLAB program on desktop computers without FPGA and the results of different data mining algorithms used in the literature. The values for the speed sensor in the bearings are quite small in this data set. With a new data set and different input numbers, the ANFIS algorithm can be used with all its features.

6. Conclusions and Recommendations

In the study, for Fuzzy Logic modeling, the measurement values of the Speed, Humidity, and Vibration sensors provided from the "Predictive Maintenance Datasets" site in the Huawei German Research Center at "zenodo.org/record/3653909#. X_nBAOgzZPY" were used. Membership functions and rules string in the Fuzzy Logic system is created with these values used as FPGA inputs. A maintenance decision modeling, which is automatically determined with options such as "Control, Monitoring, and Intervention" as output, has been made. Its fast, flexible and reconfigurable FPGA architectural structure provides the opportunity to test all kinds of designs while offering added values such as performance, cost, and time savings. The availability and performance of the total equipment will automatically increase as a result of the evaluation of the devices, sensors, and other Information Systems used in the production environment with FPGA edge information infrastructure. Our two main conclusions are;

1. The use of flexible FPGA hardware as a smart control box in Edge Computing infrastructure helps to collect more critical data due to much more data input and is a perfect solution for Industry 4.0 as it allows effective analysis.

2. In the manufacturing industry of Industry 4.0, the use of different sensors for the operation and environment information of the devices contributes to the organization and management of the value chain process in the entire production infrastructure.

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