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MODELING OF IOT-BASED ADDITIVE MANUFACTURING MACHINE'S DIGITAL TWIN FOR ERROR DETECTION

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Anahtar Kelimeler

Digital Twin,
Internet of Things,
Modeling,
Additive Manufacturing.

Abstract

Additive Manufacturing technology is one of the technologies that is changing the manufacturing industry. It has revealed some advantages over traditional manufacturing methods with this technology. With the advancement of information technologies, new approaches focusing on cost and improvement have begun to be adopted in the manufacturing industry. One such method is digital twin technology. A digital twin is frequently referred to as a digital replication of a physical system. Digital twins provide data and models to support the operation of design and manufacturing processes, as well as troubleshooting, diagnostics, and problem-solving. Various sensors are required to monitor the status of physical systems and transfer data to digital systems. Some of these Internet of Things-compatible sensors are already in production machines, but others can be added later. In the study, an Internet of Things-based system was proposed for the creation of digital twins using a virtual environment, and a digital twin simulation was created in order to bring the benefits of digitalization to production systems. The digital twin is modeled in the Matlab Simulink environment to perform binary classification to detect abnormal physical conditions that have the potential to disrupt the operation of the additive manufacturing machine and affect the quality of the manufacturing part. By generating a digital twin from real machine data, the proposed system will be able to detect errors.

NESNELERİN İNTERNETİ TABANLI EKLEMELİ İMALAT MAKİNESİNİN HATA TESPİTİNE YÖNELİK DİJİTAL İKİZİNİN MODELLENMESİ

Keywords

Dijital İkiz,
Nesnelerin İnterneti,
Modelleme,
Eklemeli İmalat.

Öz

Eklemeli İmalat teknolojisi, imalat sanayine farklı bir yön veren teknolojilerdendir. Bu teknoloji ile geleneksel imalat yöntemlerine göre bazı avantajlar ortaya koymuştur. Bilişim teknolojilerinin imkanlarının artmasıyla birlikte imalat sanayinde iyileştirme ve maliyet odaklı yeni yaklaşımlar benimsenmeye başlanmıştır. Dijital ikiz teknolojisi de böyle bir yaklaşımdır. Dijital ikiz, genellikle fiziksel bir sistemin dijital kopyası olarak adlandırılır. Dijital ikizler, tasarım ve üretim süreçlerinin işleyişi, sorun giderme, teşhis ve problem çözme için bilgi ve modeller sağlar. Fiziksel sistemlerdeki durumların izlenerek dijital sistemlere veri aktarımı için çeşitli sensörlere ihtiyaç duyulmaktadır. Nesnelerin internetine uygun bu sensörlerden bazıları imalat makinelerinde olmakla birlikte bazıları da sonradan ilave edilebilmektedir. Çalışmada, dijitalleşmenin avantajlarını üretim sistemlerine kazandırmak amacıyla, sanal ortam kullanılarak dijital ikizin oluşturulması için Nesnelerin İnterneti tabanlı bir sistem önerilmiş ve dijital ikiz simülasyonu yapılmıştır. Dijital ikiz Matlab Simulink ortamında, eklemeli imalat makinesinin işleyişini aksatacak ve imalat parçasının kalitesini etkileyebilecek potansiyele sahip normal dışı fiziksel şartları tespit etmek için ikili sınıflandırma yapacak şekilde modellenmiştir. Önerilen sistem, gerçek makine verilerinden bir dijital ikiz oluşturarak hataları tespit edebilecektir.

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MODELING OF IOT-BASED ADDITIVE MANUFACTURING MACHINE'S DIGITAL TWIN FOR ERROR DETECTION

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Highlights

- Digital twin for fused deposition modeling-based additive manufacturing machine
- Simulation with digital twin from representative media data
- Real-time prediction/detection of errors that may occur in the process with the internet of things and digital twin

Graphical Abstract

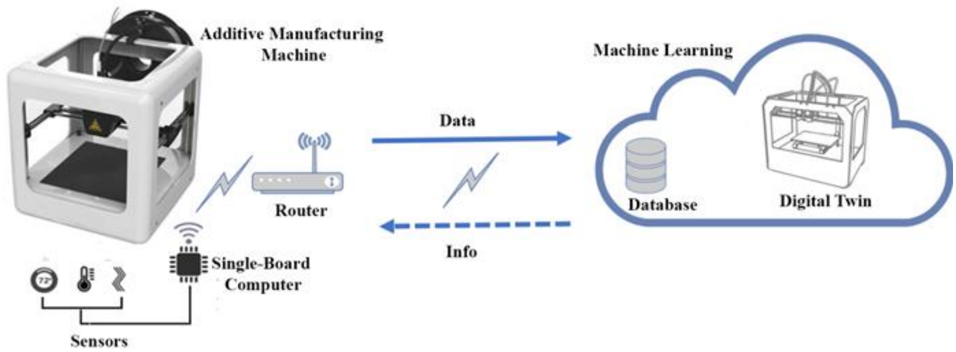

Figure. General Schematic of The Proposed System

Purpose and Scope

In manufacturing processes, where tests in real environments are costly and difficult, tests can be performed with real data in a virtual environment by creating a digital twin from the data obtained from the physical object or system. In this way, business processes are made economical and facilitated. The study, it is aimed to demonstrate a way to create real applications by making digital twin modeling and to prove its applicability.

Design/methodology/approach

In this study, based on additive manufacturing systems, a digital twin model with machine learning that can detect possible errors/malfunctions in the operation of the system has been proposed. Throughout the proposed system; AM machine consists of a single board computer and a cloud environment. It is designed that there are sensors to measure various environment variables in the physical AM machine and that there is a single board computer that provides the connection to the internet and control, apart from the embedded system that operates the machine. In the cloud environment, there is a data-based digital twin of the system, together with the structural database where the data will be recorded for analysis, diagnosis, and simulation. In Matlab Simulink software, the digital twin simulation was created with artificial data in the form of time series. In practice, the data coming from the real environment will be given as input to the previously trained classification model and it will be possible to classify it without error or error.

Findings

A digital twin simulation of a fused deposition modeling-based additive manufacturing machine has been carried out and its applicability has been demonstrated, using IoT devices for remote monitoring via sensors on the additive manufacturing machine or to be added.

Originality

In similar studies, modeling of the manufactured part using a personal computer and industrial data collection devices and thermal modeling for direct energy fusion were made. This study is different from other studies in terms of simulating the process for the additive manufacturing machine and demonstrating its applicability.

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1. Introduction

Industry 4.0, which emerged as a new industrial revolution in Germany in 2011, is becoming widespread in the academic field, especially in the manufacturing sector (Qin et al., 2017). The main components of Industry 4.0 in practice are the internet of things, cyber-physical systems, cloud computing, big data, artificial intelligence, additive manufacturing technology, and smart factories (Pamuk & Soysal, 2018). The development of Industry 4.0, known as digital technology, plays an important role in increasing quality, efficiency, and profitability in the manufacturing sector by making factories smarter. Additive manufacturing (AM), an important pillar of digital technology, is a production method that changes the manufacturing phenomenon (Mohammed et al., 2020). Additive manufacturing is a general name for manufacturing technologies that add material layer by layer to create desired physical parts. Due to the absence of material reduction processes in additive manufacturing technology, eliminates the design, production, maintenance, and other application requirements for machining tools (Standardization, 2015). This technology, which initially emerged as Rapid prototyping (RP) systems, has evolved into direct production with the development and various types of AM processes have been developed. Although there are many varieties, the most prominent AM technologies are stereolithography (SLA), 3D printing (3DP), selective laser sintering (SLS), laminated object fabrication, and melt deposition modeling (FDM) (Miljanovic et al., 2020).

Most physical assets in our lives have gained the ability to communicate over the internet with Industry 4.0. Internet of Things technology, which is one of the sub-components of Industry 4.0, has enabled this situation. With the internet of things technology, machines, systems, and people have been in communication with each other. Thus, it became possible to control, monitor, and collect data from remote objects. Significant benefits are provided by storing the collected data in cloud environments, making various analytics, and evaluating it with artificial intelligence methods.

Thanks to the Internet of Things, the necessary data is provided at a level that reflects almost all of the physical features in the environment, thus paving the way for creating a very close-to-reality digital twin model. It stands out that digital twins are mainly used in the fields of engineering and manufacturing with the Internet of Things. In cases where testing in real environments is costly and difficult, these difficulties can be overcome by performing tests on a digital twin with data obtained from the physical object or system. Thus, the digital twin has the potential to offer significant opportunities in terms of facilitating business processes together with the internet of things (Anonim, 2021; Cruz et al., 2021).

Another technology in Industry 4.0 sub-fields is the concept of the digital twin. It was first used by NASA to describe a digital copy of physical systems in space for diagnosis and outcome prediction. A digital twin refers to a virtual copy of a physical system. It uses direct sensing through sensors and indirect sensing through latent variable analysis to provide a near real-time virtual peer of the physical system. The digital twin consists of a large amount of historical status and performance data. It is anticipated to play an important role in Industry 4.0 as it allows the user to monitor, simulate, optimize and control the entire production system in a virtual environment (Chhetri et al., 2019).

In AM processes which are increasingly used in critical sectors, process monitoring, and quality control to ensure the quality of the parts to be manufactured are becoming increasingly important. In additive manufacturing, process tracking is carried out by using sensors with various online and offline methods. Rao et al., (2015) carried out a study that included a statistical method to detect error modes and initially detect process anomalies on an FDM machine equipped with a heterogeneous array of sensors including thermocouples, accelerometers, infrared (IR) temperature sensors, and real-time miniature video borescope. In a study involving an analytical method, the effect of FDM processing parameters such as nozzle temperature, fabrication temperature, and printing speed on the interfacial bond strength of TPU/ABS was quantitatively made with the Intermolecular diffusion theory (Yin et al., 2018). In order to detect undesired process/product changes caused by cyber-physical attacks, a data-driven feature extraction approach based on an LSTM autoencoder was developed and case studies were conducted using an FDM platform equipped with two accelerometers (Shi et al., 2022).

Along with these methods, the use of digital twins is becoming more and more common in AM processes due to the advantages such as real-time data communication between the physical system and the digital system, as well as monitoring, diagnosis, control, and estimation of product properties. Although digital twin research for Additive Manufacturing has focused mainly on metal 3D printers (Corradini & Silvestri, 2022), there are many studies on FDM technology.

Liu et al performed the performance evaluation approach with a digital twin to predict the material properties and structural success of the part in real-time during manufacturing with the FDM machine. In a similar study by

Chhetri et al., digital twin modeling was performed based on an additive manufacturing device with FDM technology. In this study, the modeling of the part manufactured using a personal computer and industrial data collection device was made. The 4R frame was proposed by Osho et al., and as a first step, the representation frame stage of a Digital Twin of the FDM 3D printer was created. Temperature and position data from the 3D printing process were collected and presented as data.

The studies focused on the structural properties of the manufactured part and product success. Data is presented for a Digital Twin of the FDM 3D printer, and modeling the DT of the printer with the data is not studied.

In this study, a simulation has been developed for a FDM machine in the additive manufacturing process, which has opened a new era in manufacturing, by creating a digital twin from the sensor data on the machine using the internet of things method. Thus, a way to create real applications and a preliminary study of applicability were made.

2. Theoretical Background

2.1. Additive Manufacturing

Additive manufacturing is a group of processes that produce a part by adding sequential layers of material on top of each other. As shown in Figure 1, additive manufacturing technologies In 2010, the American Society for Testing and Materials (ASTM) group "ASTM F42-Additive Manufacturing" divided the additive manufacturing processes into seven categories (ASTM, 2020). These categories are binder sputtering, directed energy deposition, material extrusion, material sputtering, powder bed fusion, sheet lamination, and cube photopolymerization (Di Angelo et al., 2020).

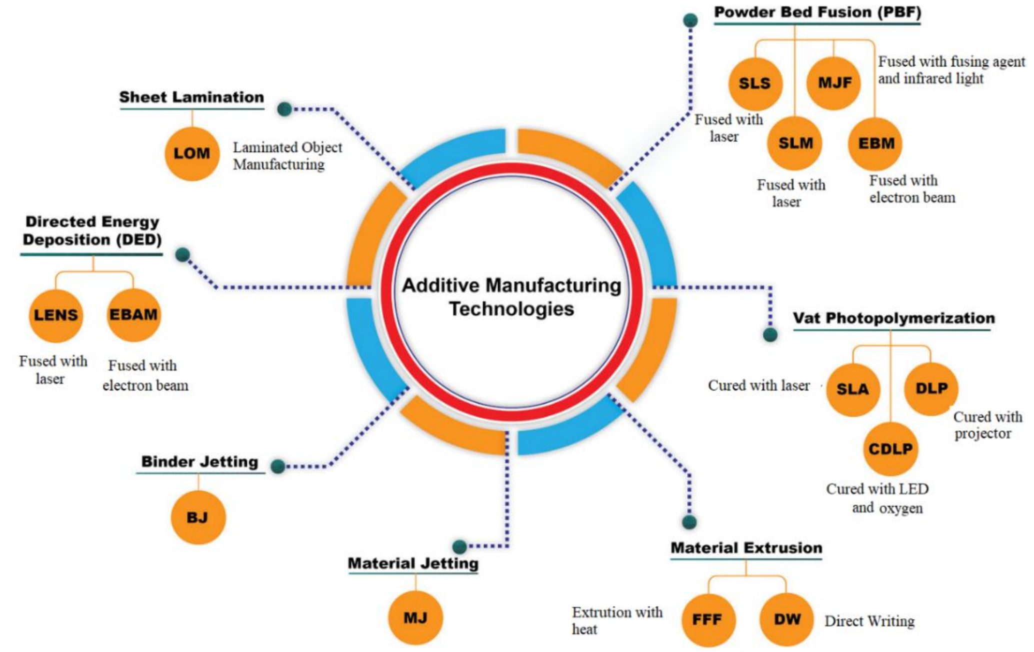

Figure 1. Classification of Additive Manufacturing Technologies (Rafiee et al., 2020)

Each of the additive manufacturing techniques has its range of applications, limitations, and benefits in manufacturing parts and producing prototype models (Rengier et al., 2010). Binder jetting can carry out the construction process from any material in powder form. Here, the printing of 3D parts is done layer by layer with equipment very similar to inkjet printers. In the construction process, the powders are connected by spraying adhesive from a multi-nozzle nozzle, and a new layer of powder is spread with a roller. Depending on the material used and the application, different additional processes such as infiltration and sintering can be performed (Chen, 2016). With the directed energy deposition technology, the desired 3D metal parts are manufactured by a metal deposition process using wire instead of powder as raw material (Karakılınç et al., 2019). The material extrusion process is a filament-based system that extrudes molten plastic, which feeds material into the heated extrusion head and cures it layer by layer to form a solid part (Çelebi, 2019). Material jet technology has ink jet processes similar to bond jets. In this technology (Polyjet-Multijet modeling), parts are produced with a photopolymer accumulating spray head. Besides the spray head technology, almost every layer is solidified by ultraviolet rays (Yap et al., 2017). In the powder feed fusion technique, a building material in powder form that can be fused when heated is spread in a thin and smooth layer, and selected areas on the surface are scanned with a laser beam or electron beam. With the heat generated at the points where the beam hits the surface, the powder material is partially melted or sintered and fuses with the other powder grains it is in contact with (Duman & Kayacan, 2016). Layer lamination technology is a process in which foil-like paper material is combined layer by layer with an adhesive. In the photopolymerization technique, technologies using liquid materials are named according to the availability of the light energy source and the material. The curing process of the liquid material in a chamber with a laser beam is called Stereolithography (SLA), and the curing process with a lamp-style light source is called Digital Light Processing (DLP).

2.2. Internet of Things (IoT)

The rapid development of information technology, and smart devices, the concept of the IoT has completely entered our lives and has become widespread with the widespread use of the Internet. The IoT can be defined as the communication of objects with technological hardware competence and the internet with each other or with other systems (Duman & Özsoy, 2019). Devices that have a unique identity, can connect to the network and produce data are expressed as objects in the Internet of Things. Thus, objects can be accessed and controlled from anywhere in the internet environment (Wiki, 2020).

The concept of the IoT dates back to 1991. At that time, images of a coffee machine were published on the internet and remained in use until 2001, thanks to the technology developed at Cambridge University and a camera system. It was first used by Kevin Ashton in 1999 at a meeting where Radio Frequency Identification (RFID) technology was used for a company (Ashton, 2009). In 2005, reports on the work of the International Telecommunication Union (ITU) were published and information was given about the usage areas and developing technologies of the IoT. In 2009, IBM's CEO, Samuel J. Palmmisano, proposed the concept of Smart Planet for the first time and then came to the fore. The use of IoT technology has increased even more since the 2010s. With these developments, IoT is characterized as the third-wave world industry after computers and the Internet (Türkay, 2018).

The IoT, which is a growing field, is also predicted numerically in the published reports. According to Statista (Statista, 2016), it is predicted that the number of connected devices within the scope of the IoT worldwide will reach approximately 75 billion in 2025 and approximately 30 billion in 2020(Figure 2). According to the Verified Market Research report, it is estimated that the share of the IoT market in the world economy will be approximately 1.3 trillion dollars in 2026 (Fernandes, 2020).

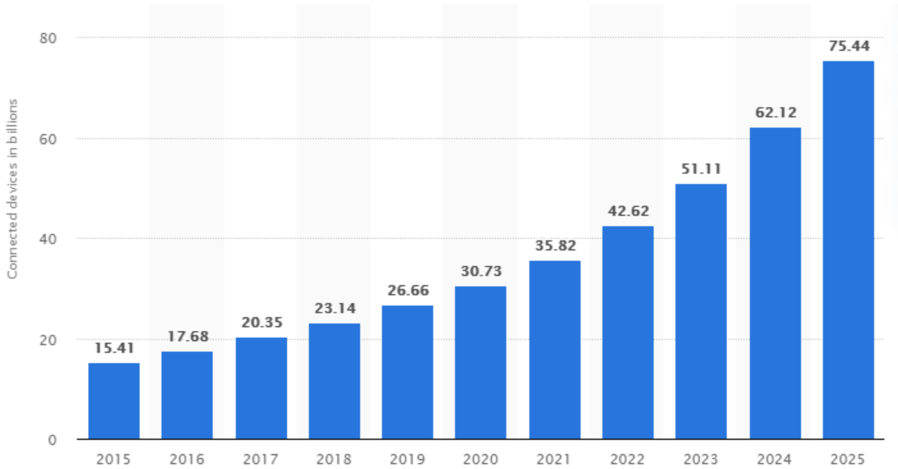

Figure 2. Change In The Number of Internet-Connected Devices Worldwide (2015-2025) (Statista, 2016)

The working infrastructure of this large communication network, to which billions of devices are connected, consists of layers, including various protocols. According to most researchers, the IoT architecture basically has three layers. However, due to the developments in IoT, more layered architectures are also suggested in some studies. The three-tier architecture is a basic architecture and provides the basic requirements of IoT. It has been proposed in the early stages of IoT. It has three layers: detection, network, and application (Figure 3). The detection layer is also referred to as the sensor layer. It is in this layer that environment variables are detected and data is collected. Protocols such as RFID, ZigBee, and NFC are used. The network layer is basically the layer where data transmission and data processing take place. The data coming from the detection layer is processed and transmitted to the upper layer by wired or wireless connection. Protocols such as IPv6, LowPAN, UDP, and ICMP are used in this layer. Application layer; It is the layer where the data can be used and the results can be observed.

CoaP protocol is used in the application layer (Burhan et al., 2018; Çavdar & Öztürk, 2018).

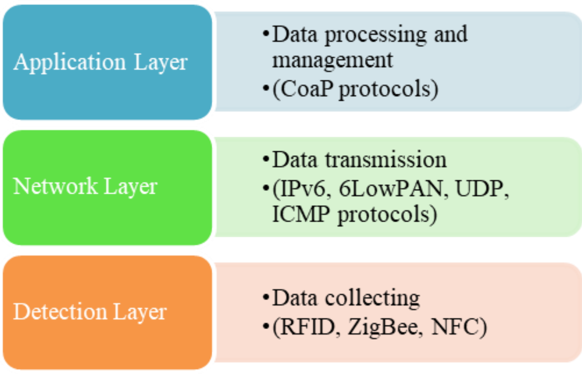

Figure 3. Three-Layer Iot Architecture

The IoT technology, which has very common usage areas such as Industry, Informatics, Agriculture, Health, Energy, Construction, Transportation, and Security (Asghari et al., 2019; Babayiğit & Büyükpatpat, 2019; Ventura et al., 2019), various applications are realized in these areas and significant benefits are provided. In applications, the data produced by the objects are stored in local storage environments through the network or by transferring to cloud data storage environments with an internet connection and evaluated within the scope of cloud computing/big data.

As the amount of data of various types generated from smart devices in the IoT increases, cloud systems will play an important role in dealing with large amounts of data. For this purpose, cloud computing/big data requirement arises to manage the big data needs of the services offered by cloud systems (Ioturkiye, 2020). It is a collection of services offered to the user based on cloud computing. These services are SaaS (Software as a Service), PaaS (Platform as a Service), and IaaS (Infrastructure as a Service). In cloud computing, analysis, reporting, retrospective monitoring, optimization, and simulation are carried out with software, various processes can be triggered according to conditions, and messages can be sent to end users over the internet. Solutions and data in cloud computing can be accessed by mobile devices and computers regardless of location (Sparkmeasure, 2020).

2.3. Digital Twin

The concept of the Digital Twin was first introduced in the Manufacturing industry by Michael Grieves of the University of Michigan in 2002. It is based on the idea that the digital information structure of a physical system can be created as a stand-alone entity (Grieves & Vickers, 2017). The data obtained from the physical system will be a copy of the information related to that physical system throughout the system's entire lifecycle. A digital twin uses real data about a physical object, product, or system as input, creates insights into the behavior of the object, product, or system from these inputs, and also monitors the status of these systems.

The Digital Twin generally consists of three components. The first is the physical system in the real environment. The second is the sensor/sensors that will convert the states in the physical system into data and enable them to be transferred to the digital environment simultaneously. Third, it is a digital medium in which the data obtained from the physical system will be transferred and stored. The second component includes not only the sensors but also the devices that will enable the sensors to communicate and adapt to the digital environment. In this case, we come across the concept of the IoT's. All data from physical systems are included in a cloud-based system. Thus, the virtual Digital Twin of the real system is created (Aynacı, 2020). There are two approaches to creating digital twins: model-based and data-driven.

By creating a digital twin of the physical system, benefits such as monitoring the instantaneous state of operating conditions, testing scenarios for different error conditions, simulation of error data, supervised learning by training the classification and prediction model, and clustering with unsupervised learning from error-free sensor data are provided (He et al., 2019).

By creating a classification and estimation model with the digital twin, operations such as error detection, predictive maintenance, and detection of abnormal situations can be performed regarding the system or product. A representative digital twin is created with the data obtained from the sensors. Analyzes can also be made on the data. Training data is prepared by preprocessing the data for developing a classification/prediction model. The developed model is trained. If the performance of the model is not at the desired level after the training, improvements are made to the model. The final version of the model is mounted in the working environment (Figure 4). The model can be updated with the new data to be obtained.

The developed models can be installed in different working environments. These environments can be edge devices as well as cloud-based systems. Digital twins can be built in cloud systems such as Google Cloud, Microsoft Azure, Aws IoT, and IBM Watson.

Figure 4. Data-Driven Modeling With Digital Twin (Mathworks, 2021)

There are uses for digital twins in industries such as aerospace, defense, healthcare, automotive, manufacturing, and energy. Siemens, General Electric, NASA, and organizations such as Tesla, Philips, IBM, and Microsoft are implementing and developing digital twins. Digital twins are being built to optimize systems consisting of gas turbines, wind turbines, engines, aircraft, vehicles, and medical devices, monitor system health, and provide solutions (Bibow et al., 2020; Entes, 2021; GE Company, 2021.; Glaessgen & Stargel, 2012; Medvedofsky et al., 2018; Siemens Healthineers, 2018).

3. Development of Digital Twin Application

Unexpected malfunctions/errors occurring during operation in industrial systems may cause work accidents, as well as a faulty product, may be obtained, and these situations may lead to financial losses for companies. Early detection or prediction of a malfunction, or a faulty product, can prevent future problems and damages. For these reasons, condition monitoring, predictive maintenance, fault detection, and diagnosis have an important place in the industry (Li et al., 2017). In this study, based on additive manufacturing systems, a digital twin model with machine learning that can detect possible errors/malfunctions in the operation of the system has been proposed.

The proposed system consists of an additive manufacturing machine, a single board computer, and a cloud environment. It is designed so that there are sensors for temperature, humidity, pressure, and vibration measurement on the physical AM machine. Apart from the embedded system that operates the AM machine, there is a single board computer that provides internet connection and control. In the cloud environment, there is a data-based digital twin of the system, together with the structural database where the data will be recorded for analysis, diagnosis, and simulation. The simulation of the digital twin was performed in Matlab R2021a software. The general schematic representation of the system is given in Figure 5.

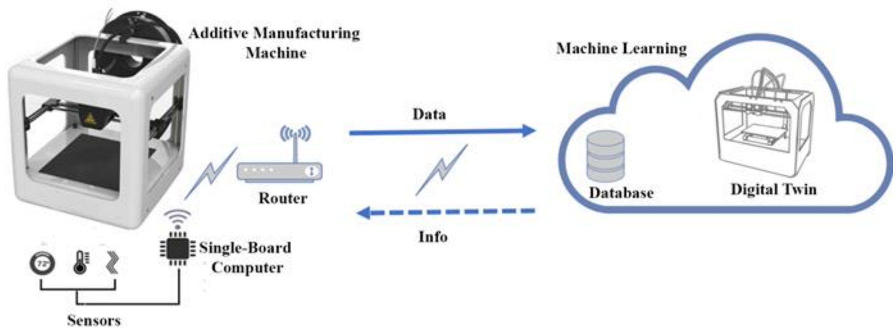

Figure 5. General Schematic of The Proposed System

The data received from the sensors are processed into the database as time series in the cloud environment. The classification model, previously trained with data such as temperature and vibration, accepts data from the real environment as input and evaluates the output without error. If the output status is desired, it can be sent to the controller on the machine from the cloud environment to intervene to stop the manufacturing process. In addition, the qualification of the manufactured part will be evaluated by analyzing the historical data kept in the cloud environment. Since the system also includes the cloud environment, the manufacturing process can be monitored instantly via the cloud via mobile or computer.

3.1. Digital Twin Simulation with Matlab Simulink

A model can be defined using data from objects connected to the internet with Matlab. A data-based digital twin model was set and a simulation was carried out for faulty error detection with the Simulink module.

First, the data set to be used in the machine learning model was taken from (Huang & Baddour, 2018) and (Mehmood, 2021), combined (Figure 6), and preprocessed. The data is divided into two parts training data and test data. In the Matlab Classification Learner plugin, the classification model support vector machine (SVM) was selected as it is seen in the literature that it gives high accuracy and low error rate in binary classification, which is one of the machine learning algorithms and the learning process was carried out with the training data. The model is saved in the Matlab environment.

20015x6 table

	1 Date	2 Temperature	3 Humidity	4 Pressure	5 Vibration	6 class
11366	21-May-2019 17:04:00	79.0062	25.1173	970.3678	0.2849	Faulty
11367	21-May-2019 17:04:00	79.0131	25.1472	970.3972	0.2839	Faulty
11368	21-May-2019 17:04:00	78.9994	25.1715	970.3917	0.2809	Faulty
11369	21-May-2019 05:14:00	77.8107	28.9520	971.5006	-0.0035	Healty
11370	21-May-2019 05:14:00	77.8153	28.9160	971.4977	-0.0025	Healty
11371	21-May-2019 05:14:00	77.8175	28.9459	971.5032	-0.0022	Healty
11372	21-May-2019 05:14:00	77.8232	28.9818	971.4653	-0.0029	Healty
11373	21-May-2019 05:14:00	77.8300	29.0057	971.5009	-0.0025	Healty
11374	21-May-2019 05:14:00	77.8368	29.0236	971.4972	-0.0015	Healty
11375	21-May-2019 05:14:00	77.8437	29.0175	971.5031	-8.8406e-04	Healty
11376	21-May-2019 05:14:00	77.8323	28.9997	971.4932	-0.0015	Healty

Figure 6. Partial View of The Data Prepared for The Model

After the training phase of the machine learning model, a digital twin block diagram was created in the Simulink module (Figure 7). Adjustments have been made to the port and model for the block diagram. The input port is arranged for 4 input variables (temperature, humidity, pressure, and vibration). The trained model is also introduced in the classification block.

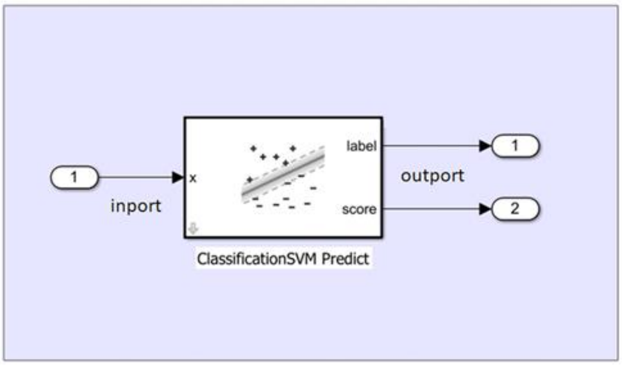

Figure 7. Block Diagram of The Digital Twin Model

In order to run the simulation, at the first stage of the process, the data divided as test data was turned into a time series and defined to the input port. The simulation was run by setting the time interval to 0-500. During this time, the test data was given as input to the classification model and the fault-free status classification at the output was taken from the output port 1 in Figure 7. The screenshot of the output data taken from the Matlab data plotter tool is given in Figure 8.

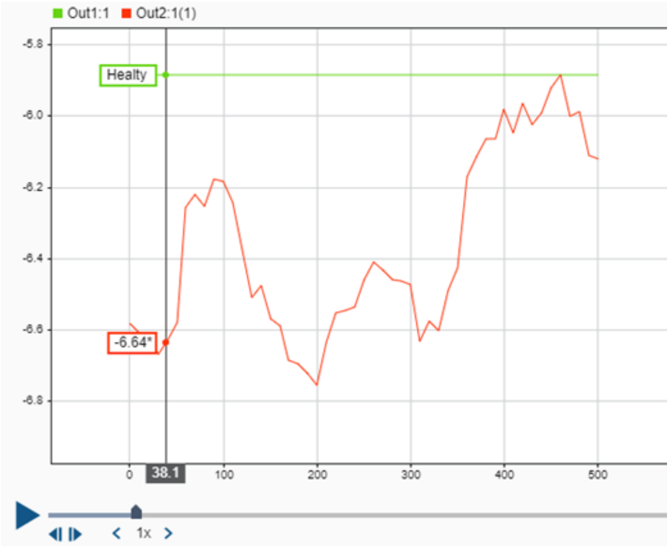

Figure 8. Model Output Ports Label (Out1) And Score (Out2) Data Graph

The final stage of digital twin modeling is deployment. The machine learning model developed with data-based modeling is mounted in different environments in order to perform the error classification task. One of these environments is edge devices and the other is the cloud environment. These environments are preferred in line with the requirements of the working system and the available possibilities. Placement of the developed model in these environments is ensured by making appropriate code conversions. For this purpose, C code was generated using the code generation tool in the Simulink module. The code generator tool can generate code in different languages for alternative hardware. A part of the generated code is given in Figure 9.

```
#include "diagnossimmodel.h"
#define NumBitsPerChar
/* External inputs (root inport signals with default storage) */
ExtU rtU;
/* External outputs (root outports fed by signals with default storage) */
ExtY rtY;
/* Real-time model */
static RT_MODEL rtM_;
RT_MODEL *const rtM = &rtM_;
......
static void rt_InitInfAndNaN(size_t realSize);
static boolean_T rtIsInf(real_T value);
static boolean_T rtIsInfF(real32_T value);
static boolean_T rtIsNaN(real_T value);
static boolean_T rtIsNaNF(real32_T value);
......
static void rt_InitInfAndNaN(size_t realSize)
{
  (void) (realSize);
  rtNaN = rtGetNaN();
  rtNaNF = rtGetNaNF();
  rtInf = rtGetInf();
  rtInfF = rtGetInfF();
  rtMinusInf = rtGetMinusInf();
  rtMinusInfF = rtGetMinusInfF();
}
/* Test if value is infinite */
static boolean_T rtIsInf(real_T value)
{
  return (boolean_T)((value==rtInf || value==rtMinusInf) ? 1U : 0U);
}
/* Test if single-precision value is infinite */
static boolean_T rtIsInfF(real32_T value)
{
  return (boolean_T)(((value)==rtInfF || (value)==rtMinusInfF) ? 1U : 0U);
}
/* Test if value is not a number */
```

Figure 9. C Code Fragment Generated for Model Insertion

4. Conclusion

In the study, an internet-based digital twin model is proposed. In the proposed method, a digital twin simulation of an FDM-based additive manufacturing machine is presented, using IoT devices for remote monitoring via sensors on or to be added to the additive manufacturing machine. Based on the sensor data from the machine, a virtual copy is created that represents the physical state of the system or its physical twin. The digital twin is modeled to detect abnormal physical conditions that have the potential to disrupt machine operation and affect the quality of the manufacturing part. The lack of an additive manufacturing machine equipped with sensors and connected to the internet in the real environment constitutes the limitation of the study.

As a result, the digital twin model simulation was carried out on an additive manufacturing machine as a case study. In the simulation, the representative media data sent by the single board computer that will make the objects connected to the internet and provide control is used as input to the digital twin. In the digital twin simulation, error situations that may occur in the operation of the machine are predicted with the analysis of the data. If the proposed system is implemented in real life, it will be possible to detect unusual errors in the manufacturing process of the additive manufacturing machine and intervene in the machine with the digital twin. In future studies, it is thought that the proposed system will be made with real devices and hardware.

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Conflict of Interest

No conflict of interest was declared by the authors.

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