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Research Article

A Roadmap for Digitalization of Industrial Processes*

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Abstract

Migrating the industry and society into digital area have gradually been increased in recent years. Digitalization has made our life more efficient and faster. As a result of digitalization, the Fourth Industrial Revolution, also known as Industry 4.0, was born. The Fourth Industrial Revolution, like previous revolutions, aims to facilitate life and improve the quality of life. Two terms are especially important for digitalization. These terms are Industry 4.0 and Internet of Things (IoT). Industry 4.0 and the IoT focus on the networking and automation of devices both used human being and industry. Digitalization and IoT technologies play an important role in improving energy efficiency. Digital twin (DT) technology is one of the most important key of Industry 4.0 technologies under digitalization. DT represents a digital copy of a physical system or entity. Physical objects and DT models created interact with each other. DT technologies have a wide range from manufacturing to healthcare sectors and from maritime transportation to the heavy industry. DT provides many conveniences for industries to grow with digitalization. Meanwhile, DT draws attention with its development in the academic field. In this study, an overview of DT is presented, a DT roadmap is proposed, some algorithms emerging in the concept of DT for industrial processes are explained and a case study is analyzed. This roadmap shows different methods to be applied in order to make accurate forecasting for the future applications and sustainable manufacturing with DT. As a result, DT concept is thought to attract much attention in the near future.

Keywords: Digitalization, Industry, Digital Twin, Energy Efficiency, Forecast Algorithms.

Endüstriyel Süreçlerin Dijitalleştirilmesi için Yol Haritası

Öz

Sanayiyi ve toplumu dijital alana taşımak son yıllarda giderek artmıştır. Dijitalleşme, yaşamımızı daha verimli ve hızlı hale getirmiştir. Dijitalleşmenin bir sonucu olarak, Endüstri 4.0 olarak da bilinen dördüncü sanayi devrimi doğdu. Dördüncü Sanayi Devrimi de önceki devrimler gibi, yaşamı kolaylaştırmayı ve yaşam kalitesini arttırmayı amaçlar. Dijitalleşme için iki terim özellikle önemlidir. Bu terimler Endüstri 4.0 ve Nesnelerin İnterneti (IoT) 'dir. Endüstri 4.0 ve IoT, hem insan hem de endüstri kullanılan cihazların ağ ve otomasyonuna odaklanmaktadır. Dijitalleşme ve IoT teknolojileri, enerji verimliliğini artırmada önemli bir rol oynamaktadır. Dijital ikiz (DT) teknolojisi, dijitalleşme altındaki Endüstri 4.0 teknolojilerinin en önemli anahtarlarından biridir. DT, fiziksel bir sistemin veya varlığın dijital bir kopyasını temsil eder. Oluşturulan fiziksel nesneler ve DT modelleri birbirleriyle etkileşime girer. DT teknolojileri imalattan sağlık sektörlerine ve deniz taşımacılığından ağır sanayiye kadar geniş bir yelpazeye sahiptir. DT, endüstrilerin dijitalleşme ile büyümesi için birçok kolaylık sağlıyor. Öte yandan DT, akademik alandaki gelişimi ile de dikkat çekmektedir. Bu çalışmada DT'ye genel bir bakış sunulmuş, bir DT yol haritası önerilmiş, endüstri süreçleri için DT kavramında ortaya çıkan bazı algoritmalar açıklanmış ve örnek bir olay analiz edilmiştir. Bu yol haritası, gelecekteki uygulamaları ve DT ile sürdürülebilir üretim için doğru tahmin yapmak amacıyla uygulanacak farklı yöntemleri göstermektedir. Sonuç olarak, DT kavramının yakın gelecekte çok fazla dikkat çekeceği düşünülmektedir.
Anahtar Kelimeler: Dijitalleşme, Endüstri, Dijital İkiz, Enerji Verimliliği, Tahmin Algoritmaları.

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1. Introduction

The digitalization paradigm, which is thought to have important contributions to the future, has taken important roles in all areas of human activities. When it comes to commercial activities, digitization becomes a personification for the concept of Industry 4.0 [1]. The concept of Industry 4.0 represents organization of the entire process in the manufacturing industry and the further development stage in management [2].

Fig. 1 shows the development of the four Industrial Revolutions. The First Industrial Revolution, follows introduction of mechanical production facilities operating with water and steam. The Second Industrial Revolution, follows introduction of electrical production assembly lines using electrical energy. The Third Industrial Revolution, provides automated production using electronics, Information Technology (IT) system and robotik. By digitizing the products that are the result of the Third Industrial Revolution, the Fourth Industrial Revolution takes place. The Fourth Industrial Revolution such as big data technology, artificial intelligence, cloud technology, machine learning, robotics and 3D printing, is rapidly changing the way people live.

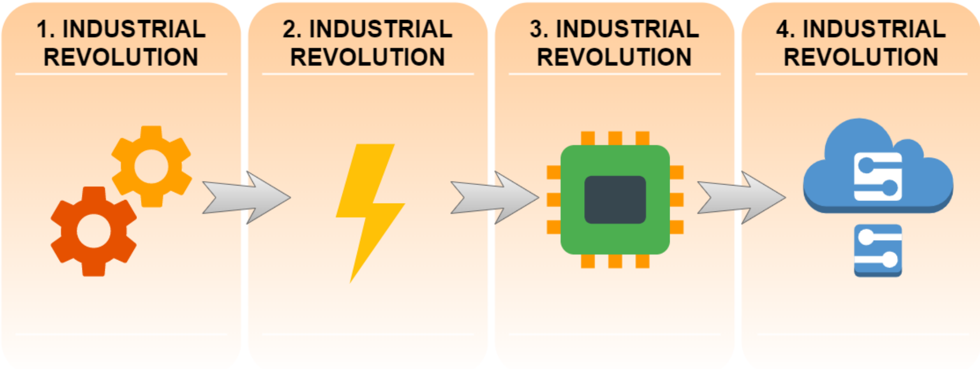

Fig. 1 Development of Four Industrial Revolutions

Digitalization accelerates the implementation of virtual product models at all stages of product creation by digitizing production [3]. In 2002, Michael Grieves was first introduced the concept of DT [4]. The National Aeronautics and Space Administration (NASA) formalized the definition of DT in 2012. In the literature, DT is defined as a multiphysics, multi-scale, probabilistic, ultra-fidelity simulation of a physical system that reflects on time using the system based on real-time data, sensor, historical data and physical model [5].

Digitalization was furthermore selected as one of Gartner's Top 10 Strategic Technology Trends for 2017 [6]. By 2021, Gartner predicts that many of the large industrial companies will use DTs for detect malfunctions and evaluate system performance and predicts that these companies will achieve a 10% improvement in their efficiency [7].

The DT is an integrated model of an as-built product, as it reflects all manufacturing faults and is constantly updated to include ongoing wear and tear during use [8]. Another definition for the DT can be defined as digital model created with data from sensors of a physical object that simulates the object in a living environment. [4].

By establishing bridges between physical and virtual assets, DTs enable realization of systems or devices by taking real-time data and identifying problems in advance, making timely analyzes, processing necessary steps and planning new developments. DT technologies have a positive effect on analysis and test costs as they provide early information about the system or device.

DTs combine data in the physical and virtual environment throughout the product life cycle. Throughout the production of a product, DTs collect data using sensors in the physical environment. In other words, DTs are used throughout the product life cycle to simulate, analyze and improve performance the product and production system without any processing on assets in the physical environment. By definition, DT develops using this data and updates itself continuously. In this way, it helps us to see and analyze the problems we will encounter in the physical environment more quickly in the virtual environment. It also allows to optimize production at very low cost. The stages of the DT in the product life cycle are: product design, production and performance.

In product design, DTs design new products to use them more efficiently. DTs analyze the performance of products in a virtual environment and show how products behave in a physical environment. In this way, the quality of the manufactured product increases, the development time and costs decrease and also it helps us to get a faster response about the product.

DTs have a significant impact on production. DTs test the suitability of conditions for production before going into production. With the positive effect of DTs in production, evaluation and optimization can be made in a plant or company without stopping production. By creating DTs of the equipment used in the production process, performance can be further increased. Using DTs, it can be predicted when the maintenance time will come. Therefore, more efficient and faster production processes will be realized. DT can be fine-tuned according to the results in the virtual system without making any changes in the physical system, and more efficient and faster production processes will be realized.

In DTs, performance analyzes the data collected from the products and evaluates the system. With the DT performance is analyzed, product and production system efficiency are increased and new business opportunities can be caught.

The relation of DT and its physical system is illustrated in Fig. 2. In the physical system, data from sensors, controllers, and actuators are collected and sent to the virtual system. In the virtual system, it is analyzed and gives us the output information.

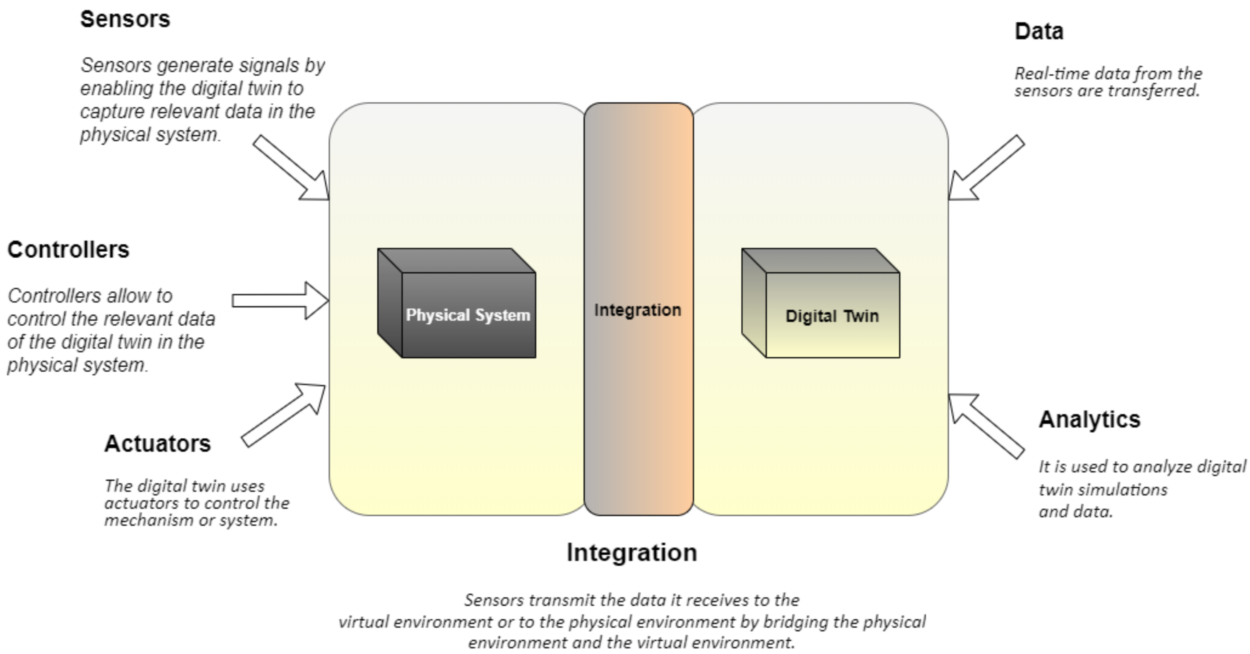

Fig. 2 Physical System and Digital Twin

Construction of a DT is divided into four stages as shown in Fig. 3. Each stage has a specific purpose and helps answer questions throughout the life cycle of the system. [9].

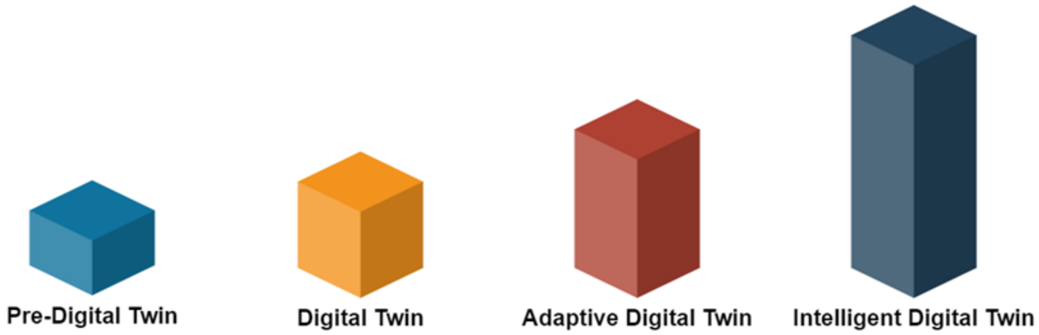

Fig. 3 Digital Twin Stages

Stage 1: Pre-Digital Twin

Stage 1 aims to predict the future with its behaviour in the virtual environment without putting a product into production. The first purpose of pre-digital twin is to identify future problems and eliminate risks. That is, a virtual prototype is often used to test the accuracy of decisions in the system and to reduce risks in the design process.

Stage 2: Digital Twin

The DT creates a virtual system by taking the data from the physical system. Physical system can use the information in the virtual system. Problems detected in the virtual system are corrected in the physical system and necessary actions are taken.

Stage 3: Adaptive Digital Twin

At this stage, DT uses an interface adaptively. Which provides that it enables the operators to examine the preferences and priorities [10].

Stage 4: Intelligent Digital Twin

This stage is called intelligent DT. The intelligent DT detects objects and patterns, and is adjusted to examine the system and the state of the situation in cases of suspense and uncompleted observation [10].

Remaining of this study is organized as follows. In section 2, under heading methodology for digitalization; overview of DT is presented, roadmap for DT is explained, the impact of DT on energy efficiency is mentioned, in the other section provides information about the methods that can be applied for the forecast algorithm, a case study on DT of a wind turbine is presented and applications of DT are listed. Finally, conclusion is given are the last section.

2. Methodology for Digitalization

2.1. Overview of Digital Twin

2.1.1. Digital Twin Data

Data from physical entities obtained from sensors are collected in the real time. The collected data are used to update virtual model of physical system.

2.1.2. Digital Twin Modelling and Simulation

The state of the system is achieved by receiving data in real time and by accessing detection components such as sensors. Submitting the data to the DT model should be compatible with the changes in the DT model's system. The sensors used to digitize the information in the system have a certain detection range and these sensors can provide information about the detected object or environment. This information is collected and transferred to the DT model through data merge. The submitted data is used to simulation of the DT model. Then, DT model is simulated, analysed and necessary operations are performed according to the simulation results of the model.

2.1.3. Services in Digital Twin

Service is an important step of DT. DT provides users with application services such as:

- Monitoring,
- Health management,
- Simulation,
- Diagnosis and prognosis,
- Verification,
- Optimization,
- Prognostic.

Also, some third-party services may be needed during the DT generation process, such as data services, algorithms services, etc. Lastly, DT's operational status requires ongoing support for a variety of services [11].

2.1.4. Connections in Digital Twin

Apart from the static model of a system, there are six interactions between the real system and its DT as shown in Fig. 4 [11,12].

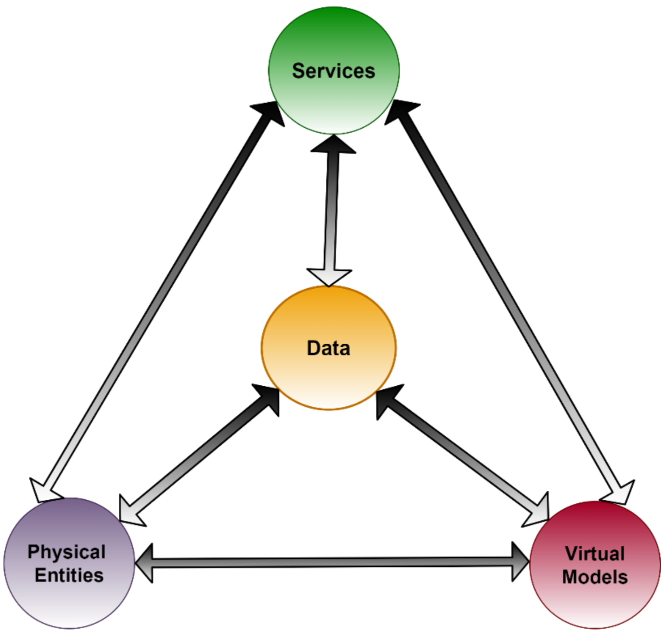

Fig. 4 Interactions of Digital Twin with Real System

2.2. Roadmap for Digital Twin

A roadmap for DT is illustrated in Fig. 5. A real-time data acquired from sensors, actuators and controllers of the physical system are collected to represent the system. Data collection is required to monitor the physical system, analysis & tests and also store the data for the future works.

Since the data is received from physical system in real time, it will be used to compare the physical system and its DT. The differences designate the error between them and are used to update the DT. This update procedure is needed to increase accuracy of the DT.

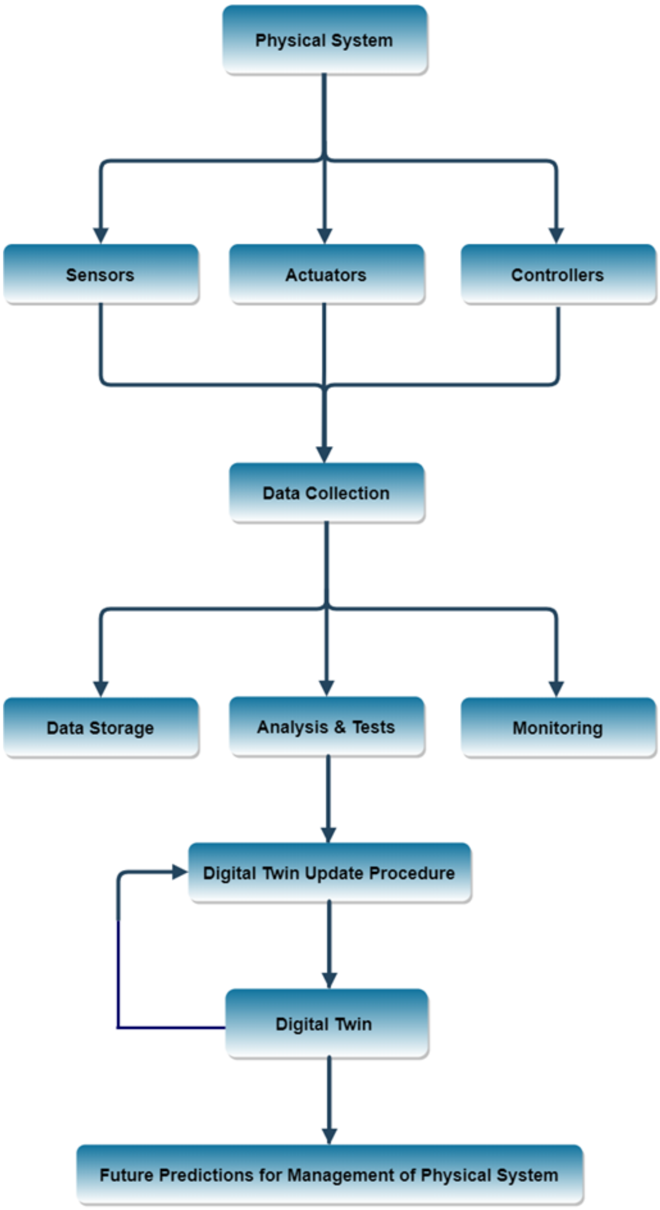

Fig.5 Roadmap for Digital Twin

Unexpected failures can be also included the DT when they occur. After analyzing the failures in the DT of a system, the necessary maintenance can be performed before the failure occurred in the physical system. In this way, it allows you to get healing results for the future.

2.3. The Impact of Digital Twin on Energy Efficiency

Digitalization and IoT technologies play an important role in improving energy efficiency. DT, virtual representation of factories or companies, can tracing the efficiency of the systems in the DT first. For example, in factories, maintenance and controls are carried out periodically to ensure the energy efficiency of industrial machines. Known faults are solved and necessary maintenance is performed. In the event of fault, the energy efficiency of the system reduces. By applying DT to the system, the control of machines can be provided much faster. By providing faster control, faults are detected more quickly.

2.4. Forecast Algorithms

In the concept of DT of industry processes, emerging algorithms, auto-regressive integrated moving average (ARIMA), exponential smoothing (ES), gated recurrent unit (GRU) and multi-objective sine cosine algorithm (MOSCA) can be used to forecast future behavior of the process output by using past values of that process output information. When a decrease in product efficiency or malfunction occurrence, it should be examined what caused it. Predictive analytics uses statistical models to forecast if there is a problem with existing data on future production equipment. [13]. These statistical models are shown in Fig. 6.

The abbreviation ARIMA is expressed as [14]:

- Auto-Regression (AR): AR is the model that expresses the relationship between an observation and some delayed observations.
- Integrated (I): I allows the subtraction of another observation from one observation in the previous time step.
- Moving Average (MA): A model that uses the dependency between an observation and residual error from a moving average model applied to lagged observations is called MA model.

ARIMA model is a commonly used method to forecasting time series data. ARIMA is an easy but powerful method in time series forecasting. Another approach with the ARIMA model in time series forecasting is ES. ARIMA models define autocorrelations in the data. ES models explain the trends and seasonalities in the data [15]. ARIMA model is divided into two as seasonal and non-seasonal, however before moving on there are two important terms. First term stationary time series, is when the mean and variance are constant over time. So, its features are not time-dependent. It is easier to predict the series is stationary than the non-stationary. The term differencing is the method of converting a non-stationary time series into a stationary time series [16].

If the differencing is combined with AR and a MA model, a non-seasonal ARIMA model is obtained. Stationarity and invertibility conditions are used for AR and MA models. The same conditions apply to the ARIMA model. This model also has the ability to model seasonal data such as non-seasonal data and non-seasonal ARIMA models [15].

Steps of ARIMA model [16]:

Step 1: First step is control of stationarity. If a time series has a trend or seasonal component, it must be done before applying the ARIMA model to forecast.

Step 2: Difference is step 2. If time series is not stationary, it must be stationarized by differencing. Initial difference is taken and then stationarity and seasonal differencing are controlled.

Step 3: Filter out a validation sample is step 3. This is used to validate the model.

Step 4: In step 4, the terms AR and MA are selected. Auto-correlation function plot (ACF) and partial auto-correlation function plots (PACF) are used to decide whether to include an AR term(s), MA term(s), or both.

Step 5: In this step, model is created. The model is created and number of periods to forecast is adjusted according to the need.

Step 6: In the last step, model is validated. The predicted values are compared with the facts in the validation example.

A new bi-directional GRU (BDGRU) method was proposed in named is as deep stacked GRU (DSGRU) model in order to predict wear value of a CNC machine [13]. A new deep heterogeneous GRU (DHGRU) model has been developed for long-term tool wear forecasting with an interlayer to prevent loss of information in model training. Along with the DHGRU model, local feature extraction can find temporary patterns hidden in a sequential mechanical signal [17].

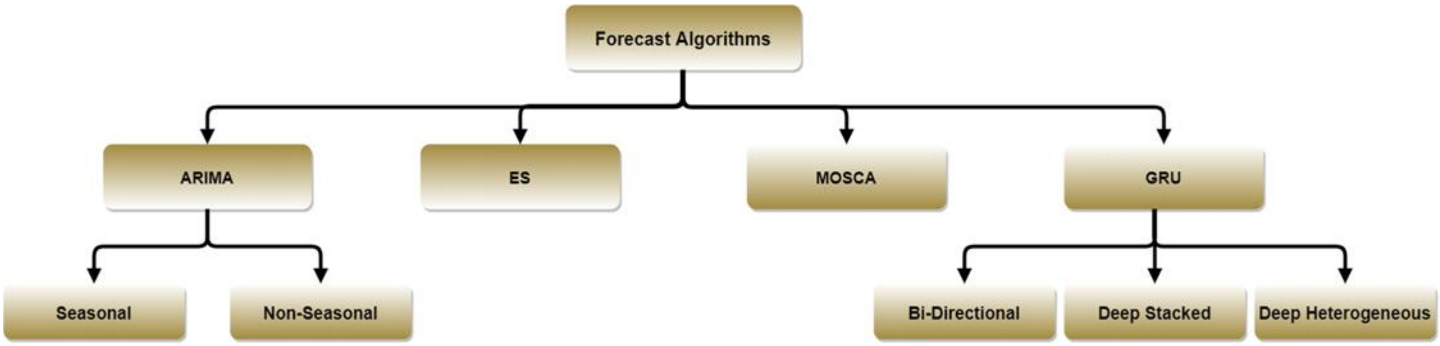

Fig. 6 Forecast Algorithms for Digital Twin Applications

Another forecast algorithm, Multi Objective Sine Cosine Algorithm (MOSCA) has been applied for wind speed forecast [18]. In previous studies for wind speed forecast, data preprocessing has been done and they focused exclusively on improving forecast accuracy. This state causes poor forecasting performance. That’s why, in this study, a hybrid forecast system based on the newly developed MOSCA has been developed. This algorithm consists of four modules: data preprocessing module, optimization module, forecasting module, and evaluation module. With these modules, MOSCA has been shown to overcome multi-objective optimization problems. In this study, results show that MOSCA also provides more accurate forecast results.

2.5. Case Study: Digital Twin of a Wind Turbine

Electricity production with wind energy has become more efficient with digitalization. With the digitalization of wind turbines, it is aimed to make future predictions to increase energy efficiency and to reduce maintenance costs of wind turbines. Maintenance of wind turbines is costing much. Thanks to these predictions, the entire plant does not need to be disabled in state of maintenance or fault. It also prevents investors from suffering losses. Due to such situations, efficiency is increased by applying DT to wind turbines. DT must be compatible with physical system. Production loss can be minimized and necessary maintenance can be performed when the loss reduces the minimum level.

Fig. 7 shows a roadmap for DT of a wind turbine. In order to get high power efficiency from wind, calculations are performed on real-time data such as wind angle, wind direction, wind speed, Nacelle angle, wind density, temperature, moisture, etc. received from the environment of the system. In order to construct DT of wind turbine, parameters in the following can be used as input of the function that represents DT:

$f(wa_{i,j})$: Wind angle,
$f(wd_{i,j})$: Wind direction,
$f(ws_{i,j})$: Wind speed,
$f(na_{i,j})$: Nacelle angle,
$f(wde_{i,j})$: Wind density,
$f(t_{i,j})$: Temperature,
$f(m_{i,j})$: Moisture,
j: Current year,
i: Current day of the year j

Estimated power generation can be constructed from the data above in the following:

$$P(x_{i+1,j}) = \text{Forecast}\ (f(wa_{i,j}),\ f(wd_{i,j}), f(ws_{i,j}), f(na_{i,j}), f(wde_{i,j})\ \ ...) \tag{1}$$

where $P(x_{i+1,j})$ represents forecast of power on the next day of the current year. This equation can be extended for the next mount and next year. The algorithms given in Fig. 6 can be used in (1).

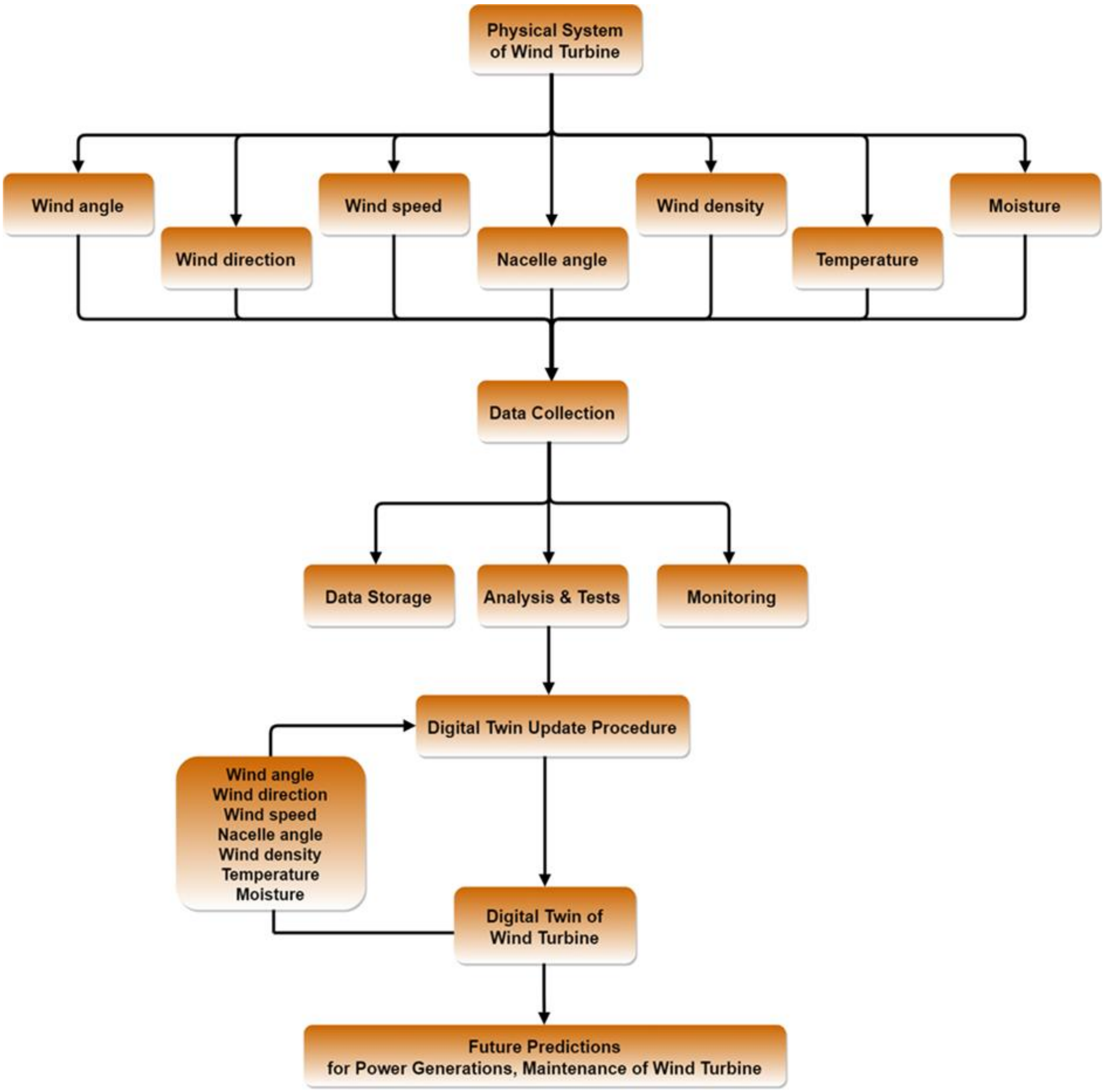

Fig.7 Roadmap for Digital Twin of a Wind Turbine

In the literature, there is a case study for wind speed forecast. MOSCA algorithm developed for wind speed forecast analyzes the performance of the forecast system and shows that forecast system is superior in terms of accuracy than the models in the study. As a result, a new hybrid forecast system based on MOSCA has been shown to work well for wind speed forecast [18].

2.6. Applications of Digital Twin

DTs have started to be applied in many different sectors. The main application areas of DTs applied to achieve better performance and improve services are as follows: vessel, manufacturing, electricity, construction, city, healthcare, aerospace, agriculture, automobile etc. As an example of the application of the DT in the literature review; In a study, describes the difficulties encountered by ship system engineers and their solution with the applied DT [19]. In another study, by creating DTs without risking public health or the environment, high quality purified water is provided [22]. Table 1 shows the different application areas of DT. There are many more studies in the literature where the DT is applied to different fields.

Table 1. Different Application Fields of Digital Twin from Literature

Year	Article	Field	Purpose
2019	Ship Smart System Design (S3D) and Digital Twin [19]	Vessel	For ship system engineers, Ship smart system design (S3D) challenges and solutions applied to these challenges.
	Usage of Digital Twin Technologies during System Modeling and Testing in Vessel Traffic Services System Project [20]	Vessel	With the implementation of a new Ship Traffic Services (VTS) software, the Design and Integration of the VTS System is to help simplify checking the applied technical and DTs and overview and interface definitions.
	Optimierung des Baumanagements im Untertagebau mittels digitaler Infrastruktur-Informationsmodelle [21]	Construction	In this article, it is aimed to create an infrastructure information model that includes three sub-models of construction site, building and construction site.
	Digital Twins: The Next Generation of Water Treatment Technology [22]	Smart City	It is aimed to provide high quality purified water without risking public health or the environment.
	A novel wildfire digital-twin framework using interactive wildfire spread simulator [23]	Agriculture	By creating a forest fire DT with a forest fire simulator, it is aimed to predict the forest fire with the detection data collected from the IoT server.
	Application of Digital Twin Concept in Condition Monitoring for DC-DC Converter [24]	Electricity	This article aims to monitor the non-invasive and additional hardware-free DT-based state for DC-DC power converters using applied method.
	HospiT'Win: A Predictive Simulation-Based Digital Twin for Patients Pathways in Hospital [25]	Healthcare	In order to improve patient care quality, it is aimed that the patient follows the road data, monitors the patient's behavior and predicts the results of the near future.
	Model-Based Design of Complex Aeronautical Systems Through Digital Twin and Thread Concepts [26]	Aerospace	In this article, the concept of DTs and yarns is presented and it is applied to an aviation case study from the CRYSTAL research project.
2018	Digital twin modeling method for CNC machine tool [27]	Manufacturing	CNC machine tool aims to enable the user to perceive, satisfy and protect without worry.
2017	The digital twin of an industrial production line within the industry 4.0 concept [28]	Manufacturing	It aims to use resources efficiently with the production structures in the automotive industry and increasing production and planning methods such as DT.

3. Conclusion

DT concept and its applications for various aspects gain high attention in the recent years. The concept of DT provides to identify problems, create a virtual system and analyze this system. Especially, technological developments allow us to digitalize all the industrial processes by using the data obtained with sensors. In the present study, a roadmap for realizing DT of industrial processes are explained with a case study. In addition, several applications from the literature are given. Due to the improvements in IoT and big data storage technologies, this concept will have much attentions in the near future.

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