Digital Twin of a Data Center at an Educational Institution

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ABSTRACT

Digital twins are among the most important trends of the fourth industrial revolution. They present a crucial tool for protecting critical mission systems and the development of new services, products, and processes. This paper presents the first digital twin for a data center. The rapid growth of the Internet of things and the areas of modeling and simulation results in high demand for the development of data center digital twins (DCDT) to ensure the safety/protection of critical and costly mission infrastructure and guarantee business continuity, enhance efficiency, and sustain development. This paper presents the design and implementation of a digital twin for a university data center. Different sensory data like temperature, humidity, smoke, and water leakage are analyzed using an intelligent event detection approach, which detects abnormalities using an Extreme Learning Machine (ELM) fed with the minimum ratio between successive real-time data streams. The performance of ELM has outperformed that of both Learning Vector Quantization and Radial Basis Function-based neural network classifiers and proved much faster in abnormal event detection.

Keywords: Digital Transformation: Digital Twins: Industry 4.0: Smart Data Centers: Smart Universities: and Internet of Things.

INTRODUCTION

A digital twin is a virtual representation of a physical object through data that carries its identity, status, and context. One of the critical enablers of the fourth industrial revolution is the digital twin (DT). The digital transformation driven by digitalization in manufacturing provides the industry with a huge opportunity to achieve higher productivity, customization, and faster production cycles. The rapid evolution of connectivity and the Internet of things (IoT) facilitates real-time communication between all components and machines on a factory floor. Combining the physical components and the virtual models contributes to the mutual understanding between all objects in the factory. This leads to both faster production and less costly customization of products reaching the customer.

Sensors feed the virtual model with vast amounts of data in real-time, which contributes to optimized processing and planning. The digital twin orchestrates the mutual interaction between the simulated virtual model and the physical world. Digital twins use analytics for applications such as predictive maintenance, control of physical objects, and simulation of the “thing” they are meant to represent.

DIGITAL TWIN APPLICATIONS

A digital twin (DT) is a virtual representation of the connection from a physical object in a physical space to a virtual object in a virtual space and a data/information flow between the two spaces (Barricelli, Casiraghi, &Fogli, 2019). DT received much attention with the rise of the Internet of things (IoT) that generated big data (Alam& El Saddik, 2017; He, Guo, & Zheng, 2018; Qi, Tao, Zuo, & Zhao, 2018), and DT sensors collect information from the physical world and communicate it to the digital twin structure to ensure scalability and availability.

Some work has been done using digital twins in healthcare applications (Angulo, Ortega Ramírez, & Gonzalez-Abril, 2019; Faddis, 2018; Feng, Chen, & Zhao, 2018; Liu et al., 2019; Patrone, Lattuada, Galli, &Revetria, 2018) for elderly healthcare services as well as drug dynamics and patient-specific treatments, to move toward the personalization of healthcare (Angulo et al., 2019; Rivera et al., 2019). The digital twin concept is also used in astronomy applications (Glaessgen&Stargel, 2012; Li, Jiang, & Li, 2020) to integrate fleet data, maintain the data, and mine data from historical information related to the simulation of vehicle movement to ensure a maximum level of safety and reliability. Digital twins showed successful results in facilitating urban planning (Dembski, Wössner, Letzgus, Ruddat, &Yamu, 2020; Kaewunruen& Xu, 2018; Qi et al., 2019; Schrotter&Hürzeler, 2020; Yan, Zlatanova, Aleksandrov, Diakite, & Pettit, 2019), with applications such as maintenance, digital modeling, tracking the number of inhabitants and determining the increase in jobs in a 5-dimensional complex model.

In industry, much work has been done on smart factories and Industry 4.0 (Brosinsky, Westermann, & Krebs, 2018; Durão, Haag, Anderl, Schützer, &Zancul, 2018; Qi & Tao, 2018; Uhlemann, Schock, Lehmann, Freiberger, &Steinhilper, 2017; Wang & Wang, 2019), where seamless integration between physical and cyberspace characterizes the digital twin infrastructure (Tao, Zhang, Liu, & Nee, 2018). Integrating Automation using ML into digital twin systems (Schroeder, Steinmetz, Pereira, &Espindola, 2016) is one implementation to model manufacturing and production services. Digital twins have shown auspicious results in supply chain applications that serve Industry 4.0 needs for smart manufacturing (Ivanov, Dolgui, Das, & Sokolov, 2019; Park, Son, & Noh, 2020), traceability, and transparency (Ivanov &Dolgui, 2020; Mandolla, Petruzzelli, Percoco, &Urbinati, 2019). It was also shown that blockchain can solve data management problems when augmented with digital twin applications (Huang, Wang, Yan, & Fang, 2020).

Cloud-based digital twins have recently received attention from researchers (Borodulin et al., 2017; Coronado et al., 2018; Liu et al., 2019; Qi, Zhao, Liao, & Tao, 2018) as well as cloud service providers (IBM, 2020; Microsoft, 2020; Schneider &Strupler, 2020) for many reasons, such as scalability, intelligence, and availability. ADIL RASHEED1, OMER SAN, and TROND KVAMSDAL, "A detailed survey of Digital Twins and challenges and enablers", is given in (Rasheed, et al., 2016). Digital twins of data centers are in high demand for institutions looking to ensure the safety and protection of critical mission infrastructure and guarantee business continuity, enhance efficiency and sustain development. In this paper, we propose the design and implementation of an inhouse built DT of a data center.

DATA CENTER DIGITAL TWIN (DCDT)

Digital twins (DT) can help companies enable Industry 4.0 philosophies and processes for performance optimization and proper decision-making by connecting machines with decision-makers and other people. This allows companies and organizations to monitor and analyze the operations of their assets at all times and in real-time. The maintenance of data center equipment can also be optimized. A digital twin for a data center is a virtual representation of a physical object (data center) or system. Digital twins use sensor data, machine learning, and the Internet of things (IoT) to help data centers optimize performance, minimize damage, and control equipment.To ensure the safety of the data center, a DCDT provides the following:

- Monitor a constant stream of usage and performance data in real-time.
- Combine end-to-end data into digital threads.
- Maintain business continuity.
- Prevent equipment damage.
- Perform proactive maintenance.
- Perform predictive analytics.

Figure 1 depicts a university digital twin data center implementation.

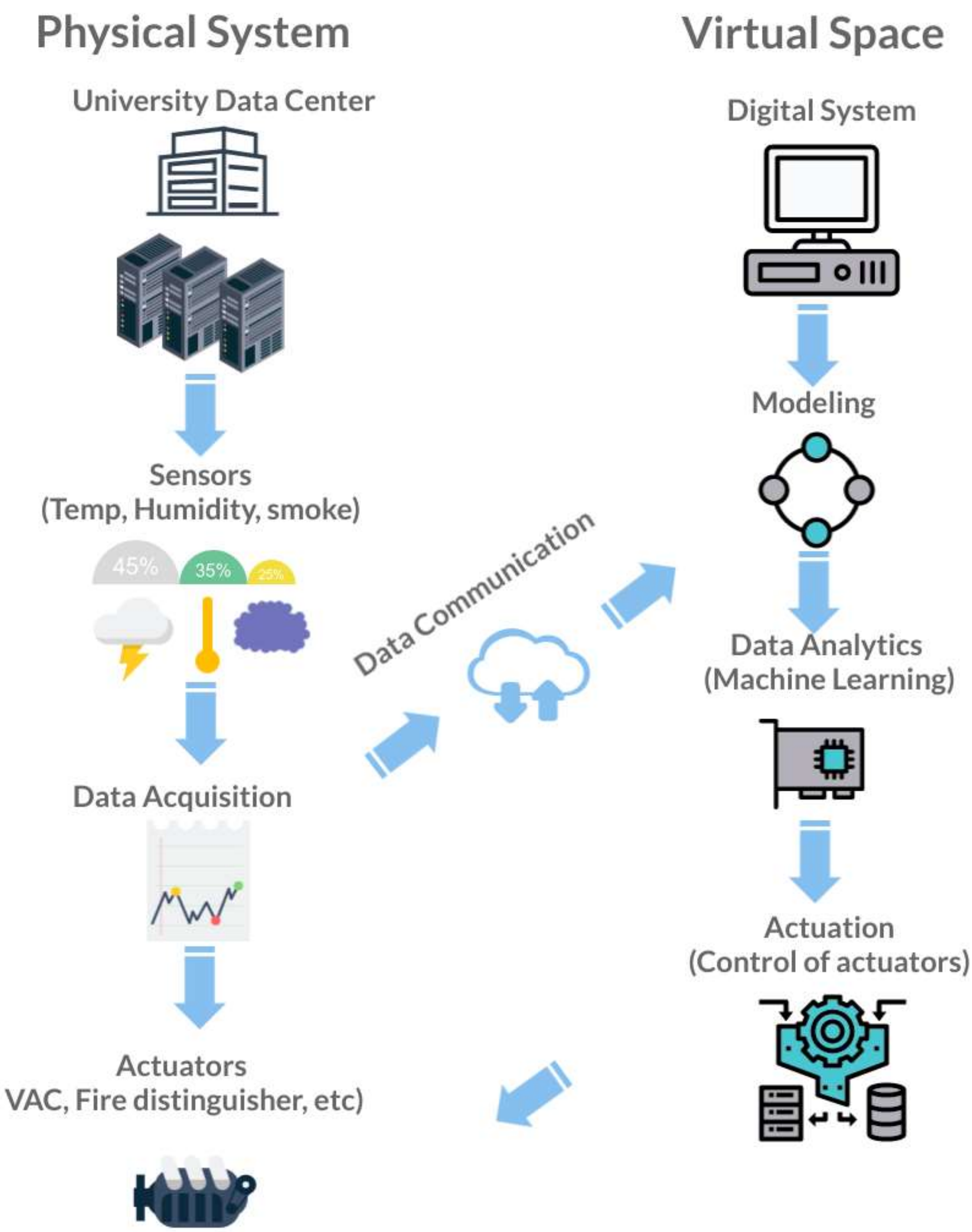


Figure 1: In-house built digital twin of university data center.**The physical layer of the DT**

Figure2 shows the layout of an environment monitoring system (EMS) that includes temperature, humidity, water leakage, and smoke sensors to monitor the environmental conditions of the data center. A set of ATtiny85 microcontrollers is used to acquire the data from the sensors, analyze the data, and send alerts to the data center staff to ensure proper decision-making. A SIM9000A GSM module sends text messages and makes calls to the intended staff. In cases where an urgent decision must be made, actuators are activated through the microcontrollers to take any necessary actions, such as shutting down servers, activating a fire extinguishing device, or enabling a second standby air conditioning system.

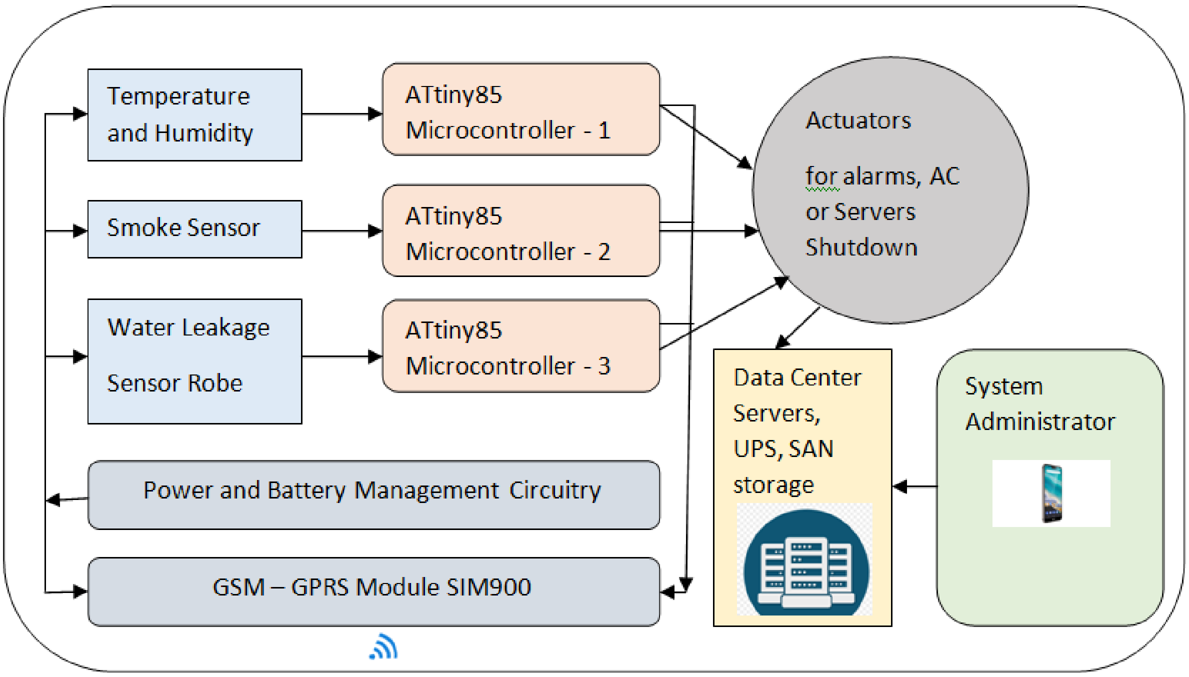


Figure 2: Layout and the physical, sensory, and communication layer of the DT.

The virtual model of the data center environment

Data collected from the sensors through the microcontrollers are communicated to the cloud in real-time for further modeling and analytics using artificial intelligence techniques provided on the cloud by the IoT platform, which provides the deep learning capabilities of MATLAB. Deep learning is used to predict any deviations of real-time measurements from normal operating conditions. Corrective actions are initiated by the actuators available in the data center.

Environment monitoring system (EMS)

The environment monitoring system (EMS) is developed to acquire and send data to the ThingSpeak platform for further analytics and event detection.“ThingSpeak,”as shown in Figure 3, is an internet of things (IoT) analytics platform tool for cloud-based gathering, visualization, and analysis of live data streams (ThingSpeak, 2020). It offers real-time representations of data provided by system gateways. It can also conduct real-time analysis and processing of the data as it arrives. ThingSpeak is often used for IoT system development and proof of concept that need analytics.

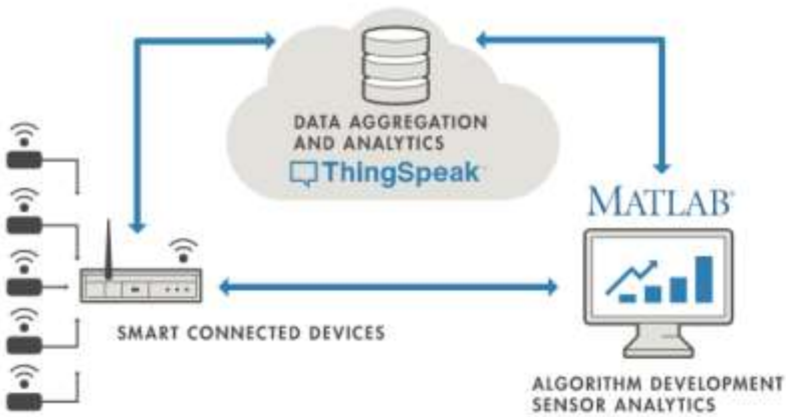


Figure 3: ThingSpeak (ThingSpeak, 2020).

Feature extraction for abnormal event detection

A real-time sensor signal, such as a temperature, humidity, or smoke sensor, is scanned over two successive windows *X1* and *X2*, each including *n* samples. The minimum ratio (*MR*) of the two windows is calculated according to the following formula as a feature for event detection:

$$MR = \frac{1}{n}\sum_{i=1}^{n}\min\left(\left(\frac{X1_i}{X2_i}, \frac{X2_i}{X1_i}\right) \right) \tag{1}$$

The *MR* feature is fed into a pre-trained classifier for abnormal event detection.

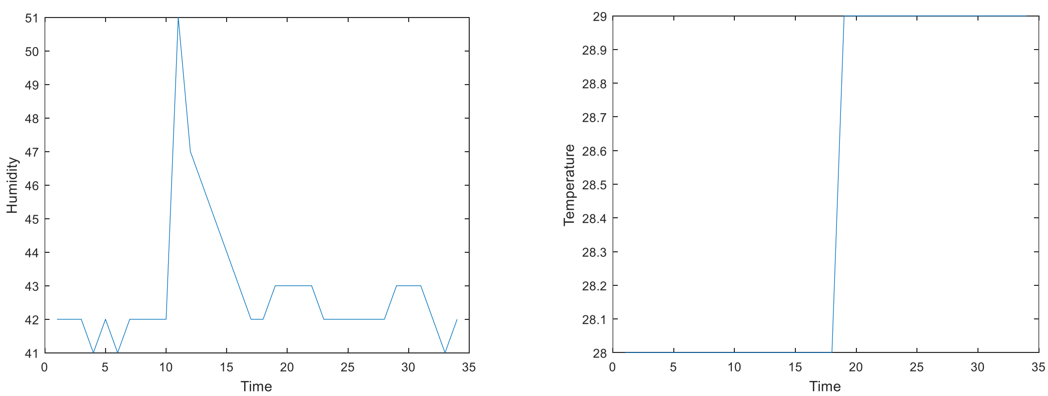
Extreme learning machine (ELM)

The ELM is a single-pass classifier used to detect events in sensor signals acquired within a data center. The ELM-based classifier possesses a single-hidden-layer feed-forward neural network. The ELM can adaptively set the node number of the hidden layer and arbitrarily allocate input weights and hidden-layer biases (Katz, 2015). The weights of the output layer are calculated based on the least-squares process. The ELM does not need parameter tuning. The ELM algorithm avoids multiple iterations and local minimization. It has been used in various fields and applications because of better generalization ability, robustness, and controllability and fast learning rate.

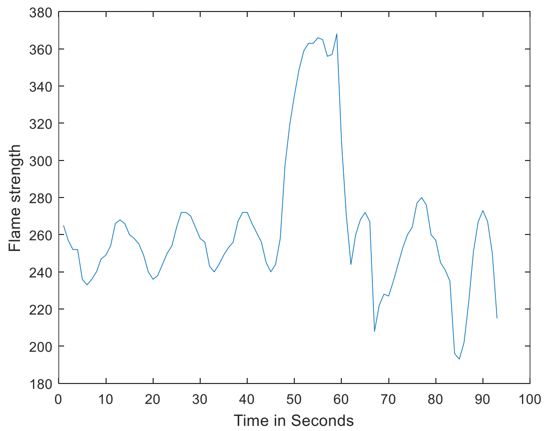
The ELM generates a unique optimal solution, overcomes the slow training and overfitting problems of traditional neural network learning algorithms, and implements fast-learning and generalized performance (Ding, Zhao, Zhang, Xu, &Nie, 2015; Katz, 2015). In this paper, we harness those valuable advantages for real-time applications, such as event detection. For a more detailed explanation of the ELM training algorithm, please refer to (Alam, 2017).

EXPERIMENTS AND RESULTS

The proposed DCDT was tested in a real environment at a university datacenter, acquired sensor data from a nonstop stream, and analyzed the data using machine learning to make the proper decisions. The EMS possesses a test bottom that enables testing of the system under different mock conditions. Figure 4 shows the real-time measured temperature and humidity at a university data center.



(a) Field 1 Chart – % Humidity (b) Field 2 Chart - Temperature (Cº)



(c) Field 3 Chart – Flame Strength (µg/m3)

Figure 4: Sensor data channels on the ThingSpeak IoT cloud platform

Data center monitoring through temperature, humidity, and dew point information

Monitoring server rooms is crucial for ensuring their safety, proper operations, and performance optimization. Cyber-physical systems provide low-cost and efficient monitoring of severe room environments by continuously measuring and analyzing temperature, humidity, and dew point. Preventing disruptions of services in a data center can be achieved by monitoring the slight variations in environmental measures. The dew point (*DP*) is a critical measure of the server room's condition. The *DP* is the temperature at which water vapor in the room starts to condense into water droplets, which causes corrosion of electronic and mechanical components. Therefore, it is essential to keep room temperature below the *DP*. Continuous measurement of both temperature and humidity and corresponding calculation of the *DP* is crucial for keeping the temperature above the *DP*. According to ASHRAE standards (Gudluru et al. 2020), the acceptable temperature range lies between 5.5°C and 15°C.

The *DP* is calculated from the observed temperature *T* in °C and the percentage of relative humidity (*RH*) according to the following formula (Lawrence, 2005):

$$DP = T - \frac{(100 - RH)}{5} \quad (2)$$

In addition to the *DP*, the maximum allowable temperature in the *DC* is 40°C.

Humidity higher than 60% can lead to corrosion of the equipment (Carroll, 2020). Humidity lower than 40% can lead to electrostatic build-up and discharge (ESD). ESD can be very harmful to devices such as NEMS (nanoelectromechanical systems) and MEMS (microelectromechanical systems) as a small static discharge can permanently damage these systems (Katz, 2015). Figure 5 shows the distributions of temperature, humidity, and *DP* over time.

ASHRAE recommendations for data centers and server rooms include:

a) minimum dew point limit of 5.5°C

b) maximum dew point limit of 15°C

c) maximum relative humidity level of 60%

According to the above recommendations, real-time data analytics in data centers through ThingSpeak tracks whether the above three conditions are fulfilled. Once these conditions are violated, ThingSpeak sends an alarm to the DC administrator through SMS and/or actuates the related equipment for dehumidification, such as a dehumidifier or a standby AC system.

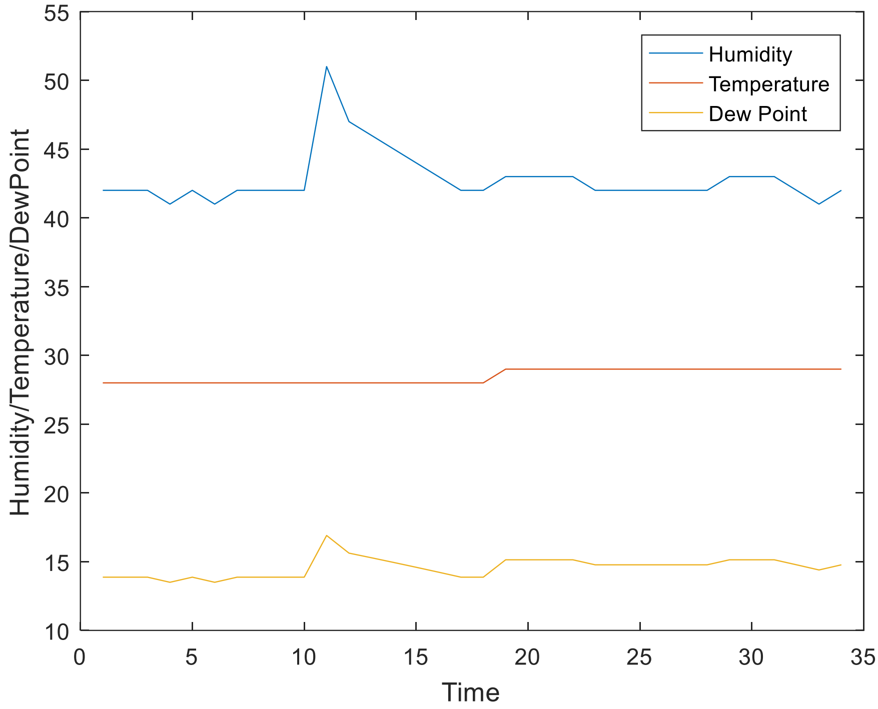


Figure 5: Dew point (Cº) , humidity (%), and temperature (Cº)

Event detection experiments

Figure 6 shows the humidity sensor signal acquired during the simulation of two successive situations with changing humidities, shown as peaks with exponential decays.

Table 1 compares the proposed *MR* system based on different classifiers: the ELM, LVQ, and RBF neural networks. The ELM shows the best and fastest performance compared to those of the other classifiers. The F1-score of the ELM is 95.87%, while the RBF and LVQ classifiers achieve scores of 90.86% and 83.45%, respectively. The RF classifier yields the worst results. The average training time for the ELM is 0.004, which is approximately 500 times faster than that of the RBF classifier.

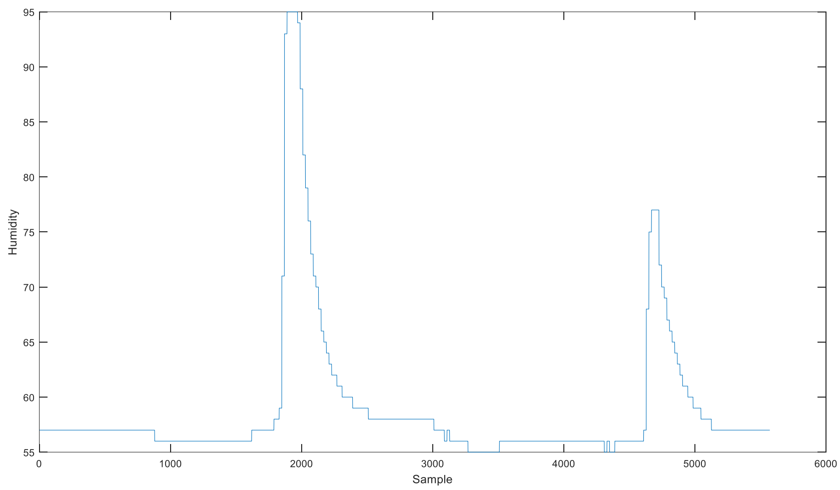


Figure 6. % Humidity distribution in a DC with two simulated events to increase humidity.

Table 1: Performance of Different Classifiers: the ELM, LVQ, and RBF Neural Networks

Indicator/Features	***ELM***	***RBF***	***LVQ***
Average Recall	92.27	84.67	75.06
Average Specificity	99.68	99.79	100
Average Accuracy	98.80	96.69	95.65
Average Precision	99.16	99.82	100
Average F1-score	95.87	90.86	83.45
Average Training Time (sec)	0.004	1.98	6.62

DISCUSSION AND CONCLUSION

Few applied case studies have been described in the literature. This paper presents the full implementation of a data center digital twin (DCDT). Controlling the physical data center environment by actuating the VAC and fire distinguisher was realized by sensing the DC environment, acquiring data, analyzing data, and then controlling the physical actuators through the virtual model of the DC. In this paper, we presented a fast-event detection system using the minimum ratio between neighborhood windows. The input sensor signal was scanned by a sliding window. The minimum ratio was computed between every two successive windows. The decision of whether a window contains an event was achieved by simply feeding the feature vector to the ELM classifier. The proposed system was evaluated on a large set of sensor signals acquired in real-time within the data center. The MR feature showed high accuracy and high speed for event detection. The accuracy of event detection was 98.8%; recall/sensitivity achieved a rate of 92.27%, and specificity was 99.68%. The minimum ratio showed high discriminative power between the successive sensor signal windows. The experimental results showed the advantages of the MR feature. Another advantage of the proposed system is its simplicity and efficiency. The proposed approach also avoids the parameter selection problem of other method since the ELM based classifier does not need any human intervention.

FUTURE WORK

We aim to construct a complete network of digital twins for all university facilities and systems (University Digital Twin - UDT), such as the student information system, finance system, human resources system, and Smart Learning Platform. A network of digital twins helps keep systems operating efficiently and securely, maintains statuses, and collaborates with systems for service continuity and improvement. Cybersecurity will be also considered using the Blockchain Technology.

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