Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 55-2 (2022) 114–119

Federated Learning for Enablement of Digital Twin

Amit Patwardhan*. Adithya Thaduri*. Ramin Karim*. Miguel Castano*

**Division of Operation and Maintenance Engineering,*
Luleå University of Technology, Sweden.
(e-mail: amit.patwardhan@ltu.se; adithya.thaduri@ltu.se; ramin.karim@ltu.se; miguel.castano@ltu.se)

Abstract: Creation, maintenance, and update of digital twins are costly and time-consuming mechanisms. The required effort can be optimized with the use of LiDAR technologies, which support the process of collecting data related to spatial information such as location, geometry, and position. Sharing such data in multi-stakeholder environments is hindered due to competition, confidentiality, and security requirements. Multi-stakeholder environments favor the use of decentralized creation and update mechanisms with reduced data exchange. Such mechanisms are facilitated by Federated Learning, where the learning process is performed at the data owner's location. Two case studies are presented in this paper, where LiDAR is used to extract information from industrial equipment as a part of the creation of a digital twin.

Keywords: Digital twin, federated learning, LiDAR, point cloud, railway catenary.

1. INTRODUCTION

The operation of industrial systems depends on effective and efficient maintenance actions to provide the required performance. Maintenance actions are triggered when there is a deviation between the required performance and the provided performance, either in the current operation or in the planned operation. A maintenance policy is a general approach to the provision of maintenance and maintenance support based on the objectives and policies of owners, users, and customers (IEC, 2004). It describes the interrelationship between the maintenance echelons, the indenture levels, and the levels of maintenance to be applied for the maintenance of an item (IEV, 2021).

Condition based maintenance (CBM) depends on i) measurable parameters that correlate with the degradation over time and onset of failure, ii) changes in the measurable parameters obtained from data collection, while iii) data collection is performed while keeping the object operational (Ben-Daya *et al.*, 2016). Knowledge of the history and current condition of the system is crucial; however, prognostics depends on overall understanding and methods of describing the system and its environment. To best describe a system its physical attributes, environmental conditions, changes over a period of time like operations and maintenance actions are required. The twin concept started at the National Aeronautics and Space Administration (NASA) as a physical ground-based twin similar in every aspect of the flying vehicle. The concept of digital twin (DT) was introduced by NASA as an ultra-realistic simulation with a physical model, sensor data, data exchange. and the capability to recommend changes to mission profile to increase both the life span and probability of mission success (Shafto *et al.*, 2012).

The following definition is used for the current work, a DT as an integrated multi-physics, multi-scale simulation of a complex product which uses available models and information updates (such as sensor measurements, procurement and maintenance actions, configuration change) to mirror an asset during its entire lifecycle. Technologies such as Industrial AI (Lee *et al.*, 2019), visualization, and maintenance analytics may be integrated with the DT for augmented decision making. The main components of DTs are: i) a physical asset belonging to the physical space, ii) a virtual asset belonging to the virtual space, iii) and connected data which ties in the physical and virtual assets and belongs to the information space (Karim *et al.*, 2021).

Creation, maintenance, and update of a DT is a costly, time-consuming, and complex affair. Collection of design information, replication of design of physical systems into models, updating configuration changes, non-conformity of as-designed to as-built are some of the issues that plague the DT design. Hence, the cost and complexity of the creation and maintenance of the digital twin of physical systems is a major deterrent in its adoption (Ariyachandra and Brilakis, 2019).

In the construction domain, Building Information Modeling (BIM) provides a digital representation of physical and functional aspects of physical spaces. The process of generating BIM from the point cloud is called "scan to BIM". It is generally created during the initial phases, however, over the lifecycle of the system with operations and maintenance process the BIM may not be the true representation of the physical space. The BIM can be used for the creation of the DT and eventually the DT can be used to update the BIM. Scan to BIM process today depends on manual intervention, is time-consuming, and does not generate very accurate results (Xiong *et al.*, 2013). Hence, automation of the update process is the critical threshold for simplifying the integration of digital twins in several situations.

The complexity of DT design of physical assets increases due to inherent requirements like system modeling, sensor data, different and changing environmental factors, a fleet of

10.1016/j.ifacol.2022.04.179

systems. Distributed digital twins in terms of functionality, data aggregation, information generation, and decision support can simplify the overall design of the DT in multi-stakeholder environments. These stakeholders although working in the same domain in association with each other may not be able to share the data due to confidentiality and data security requirements. In the railway scenario, these stakeholders can be the infrastructure manager, vehicle owner, operator, maintenance service provider. Federated Learning (FL) (Shokri and Shmatikov, 2015) allows model training at the data owner's location and aggregation of models at a central location. This can be preferable in many scenarios involving multiple competing stakeholders like railways and energy.

The creation of geometric DTs from physical features through LiDAR scanning has been explored in various domains. LiDAR (light detection and ranging) (Taylor, 2019) utilizes a LASER beam to measure the distance of objects in its surroundings. This provides output in the form of a point cloud, with spatial information of scanned points in 3D space. The availability of LiDAR technology for positional data acquisition, cloud computing for data storage and processing, and finally visualization, and machine learning tools for information generation support the creation of pipelines for data processing and automating the process of digital twin initialization and update.

The purpose of this paper is to study the requirements for the creation of DT through FL using LiDAR point cloud in multi-stakeholder environments. Two industrial systems namely railway overhead catenary and industrial rolling sieve have been used as candidates for the exploration. The main contributions of this paper are to highlight areas of interest for FL in DT and LiDAR data processing flow for input to the DT process.

The flow of the paper is as follows, section 2 provides an overview of related work in the domain of DTs, LiDAR, and FL. Section 3 discusses aspects impacting federated learning for the DT process, section 4 presents two use cases, and finally, section 5 presents the conclusions and sets the direction for future research.

2. RELATED WORK

The growth of simulation technology has been from the initial individual application to standard tools for a specific design, to simulation of multi-disciplinary systems to finally as a digital twin is the core functionality of the system (Rosen *et al.*, 2015). DT provides a way to integrate four dimensions of modeling i.e. geometry, physics, behavior, and rule modeling (Tao *et al.*, 2019). Further, machine vision as an input method is suitable since the cost structure for data acquisition is fixed irrespective of the amount of tracking performed (Uhlemann *et al.*, 2017). DT of physical assets requires high-resolution data collection for precise representation and repetitive data collection to represent effects of factors like environment and maintenance. Further, information about the physical asset, events, and digital interface has to be structured to allow DT functionality to external applications (Steinmetz *et al.*, 2018).

LiDAR scanning has been utilized in various domains to create a 3D environment and accurate measurement of physical structures. The most important features of the LiDAR system are accuracy, precision, resolution, data collection rate, and lack of human intervention during data collection through aerial or mobile (ground-based) scans. LiDAR scans are being used for the physical reconstruction of large areas in domains like archeology spanning over an area of 200 sq km to reveal previously undiscovered structural groups, agricultural fields, and causeways (Chase *et al.*, 2011). Understanding pre-failure deformations and recognition of different phases of deformation evolution through LiDAR scans to detect rock activity in mines (Royán *et al.*, 2014). Geometric digital twinning of cable systems through the use of LiDAR has been explored in different domains such as railways and power transmission (Ariyachandra and Brilakis, 2020; Cheng *et al.*, 2014).

FL takes another step towards bringing data to a central location, it comprises of a loose federation of participating devices and coordinated by servers, the clients generate and train on a local data set and only update the global model on the server following the principle of data minimization (H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, 2017). Further, distributed ledgers like Blockchain have been utilized for secure storage and verification of the clients and use of FL for accelerating the consensus process (Lu *et al.*, 2021). The clear advantages of this structure are the independence of model training from raw data requirements while providing a collective benefit to the participants while maintaining data privacy.

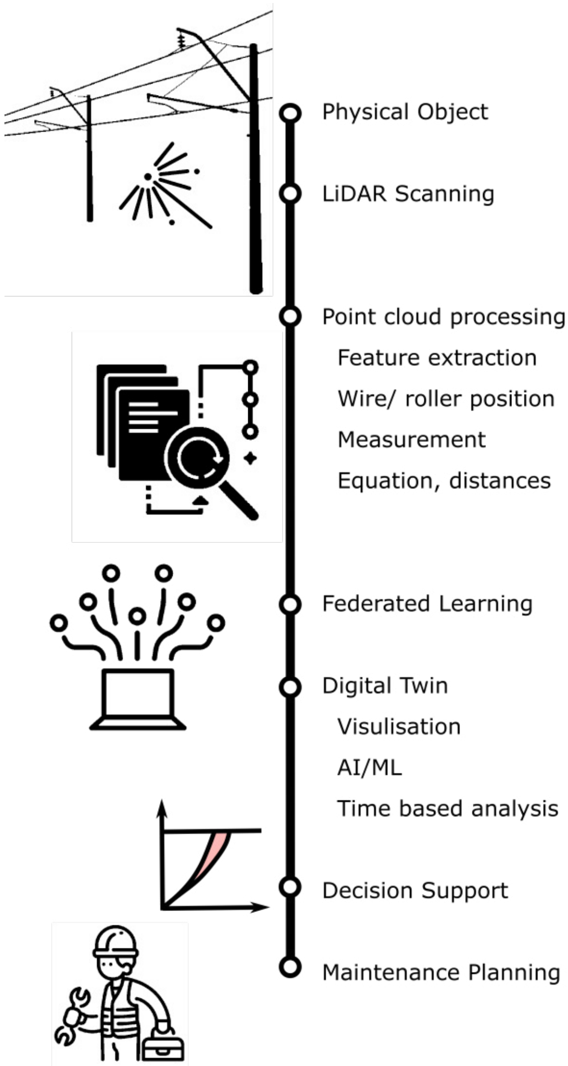
3. SYSTEM MODEL

DT can play an important role in the overall lifetime of the equipment. Starting from the design, production, execution, and optimization the stages can be seen as a part of a large loop. All these interconnected and interdependent stages can benefit from the insights to be used as a knowledge base and testing ground for knowledge development.

DTs are seen as a step forward from the simulation-based development cycle. Since DTs allow for the amalgamation of knowledge from not only the working of the system but also external factors like environment, changes over a period of time, configuration updates. Figure 1 represents the process of creation of DT from LiDAR point cloud through the use of FL.

The development of DT's is complex and complicated due to dependency on a large number of factors through the lifetime of the system, integrations of high-fidelity models, and requirements of accommodating data from various kinds of sensors. The data collection and sensors may not only be digital but also depend on human designers, operators, and maintenance crew. In the case of fleet systems dissimilar environmental effects, configuration updates, and usage patterns. create difficulties in the utilization of the knowledge developed in individual instances.

FL can provide various advantages to improve the overall design of DT. Since FL creates model requests instead of data



requests it differs from the client-server model and changes the computation model and security requirements.

3.1 Computation effort

Since the computation effort is divided among the servers and devices, computation effort at the device end can be written as:

$$E_{di} = \frac{P_{ci} D_i}{P_{Ai}} \tag{1}$$

Where, P_{ci} is the processing power (as CPU cycles) required per data sample at the device d_i, D_i is the locally generated and processed dataset. P_{Ai} is the actual processing power (as CPU frequency) of the device d_i. Finally, E_{di} is the effort required in terms of computation time at the device.

$$A_{sj} = \frac{P_{sj}}{P_{Aj}} \sum_{i=1}^{N} r_i \tag{2}$$

Where, P_{sj} is the processing power (as CPU cycles) required per data sample at the server s_j, r_i is the result submitted by the device d_i with the total number of devices as N and P_{Aj} is the actual processing power (as CPU frequency) of the server s_j. Finally, A_{sj} is the model aggregation effort required in terms of computation time for the server.

$$T_{di} = \frac{s_{ri}}{b_{di}} \tag{3}$$

Where, s_{ri} is the size of the result generated (bits) at the device d_i, and b_{di} is the maximum theoretical bandwidth (bits per second) of the slowest link between the device and the server. Finally, T_{di} is the time required for data transfer to occur (seconds).

$$T_{sj} = \frac{\sum_{i=1}^{N} s_{ri}}{t_{sj}} \tag{4}$$

Where numerator represents data received by the server from all the devices, t_{sj} is the actual throughput at the time of transfer (bits per second), and T_{sj} is the time required for the transfer to occur (seconds).

In a client-server architecture, servers are required to be powerful devices, however, computation effort at the server $E_{sj} \gg E_{di}$ and $T_{sj} \gg T_{di}$ since all the data generated at the clients will be transmitted to the server and the server will be responsible for computation. As the number of devices grows servers can be overwhelmed and devices may face DOS (denial of service), and more servers will be required to mitigate the problem.

In the case of FL, A_{sj} and T_{sj} are reduced since only updated training weights instead of the dataset, configurations, environmental reading are transmitted. Further, A_{sj} and T_{sj} are reduced since the servers collect training weights only from selected devices in each model update round. This improves the overall scalability of the system. However, in some cases of FL, the size of the weights generated may be larger than the data to be transmitted, in the case studies presented in the paper data size exceeds by a large factor.

3.2 Privacy

Privacy of transmitted data is a core requirement for personal and commercial data-sharing applications. Privacy and confidentiality are paramount for data sharing in a multi-stakeholder environment. FL is suitable for such conditions due to the non-requirement of data sharing. Further, FL provides excellent privacy as the weights to data ratio decreases, mitigating the possibility of data extraction from shared information. In our use cases a ratio of approximately 5×10^{-6} (8KB/ 1.6GB) was observed.

3.3 Cybersecurity

Cybersecurity in networks with FL is required due to internal and external threats of model contaminants. Providing authentication for the devices, provenance of shared information, while maintaining security and ownership for the data is a critical factor in multi-stakeholder environments. Private distributed ledgers working with a Proof-of-stake mechanism can efficiently support these requirements.

3.4 Model quality

In machine learning systems data from under-represented entities with environmental heterogeneity may appear as outliers and may be discarded. This can introduce a bias in the model. FL takes place in rounds where the server can select the devices which will share weights for the next round of learning. Overall learning of the system can be improved by the selection of devices required for contribution to providing better opportunities for devices with inadequate representation.

3.5 Model state management and serialization

DT design through FL learning will depend on state management of the model due to interrelated and interdependent parts required to create model sharing pipeline. Such state management is required to keep devices in the correct state even in case of intermittent network connectivity. Further, serialization is important for the storage, distribution, and versioning of the model.

3.6 Delegated DT

To manage the complexity in DT a delegation-based architecture, where different aspects of the DT are compartmentalized and separated is suitable. However, a mechanism to extract and merge information from such delegated models and suitable representation of this information for consumption and distribution at that time or in the future becomes necessary. Hence an overall architecture with delegated DT, FL for model development, serialization, ownership, and versioning of models will be required.

3.7 Threats

System complexity: Best possible design of DT is through hybrid models i.e., a mix of physics-based, and data-driven systems. The design of DT depends on the availability and understanding of the physics of the system, and the selection of suitable data processing and model design.

Processing complexity: Edge computers have less storage and processing capabilities as compared to servers, if the algorithmic complexity or memory requirements are high or selected processing algorithms require GPU support, the edge system will not be able to cope with the requirement. However, improvements in hardware technology increase the processing power and available memory while decreasing the cost of equipment.

Insider threats: FL servers utilize the weights being provided by the devices and share the result with all the devices. Misconfigured or malicious devices can submit erroneous weights to corrupt the shared model, this presents an insider threat.

External threats: Authentication and authorization of devices participating in the learning process is a requirement. Improvement in the model is dependent upon the fair representation of systems with outlier data. However, if devices not a part of the network can masquerade and submit fake models this can hamper the universal model.

4. CASE STUDY

In this paper two industrial systems, namely railway overhead catenary and industrial roller sieves were investigated. Point cloud data was acquired and processed to create a data processing pipeline for model initialization and update. A railway catenary is an example of a linear asset spread over a large area, while a roller sieve is process equipment fixed at a single location. Both assets have different requirements in terms of data collection, digital twin design, condition monitoring.

4.1 Railway catenary

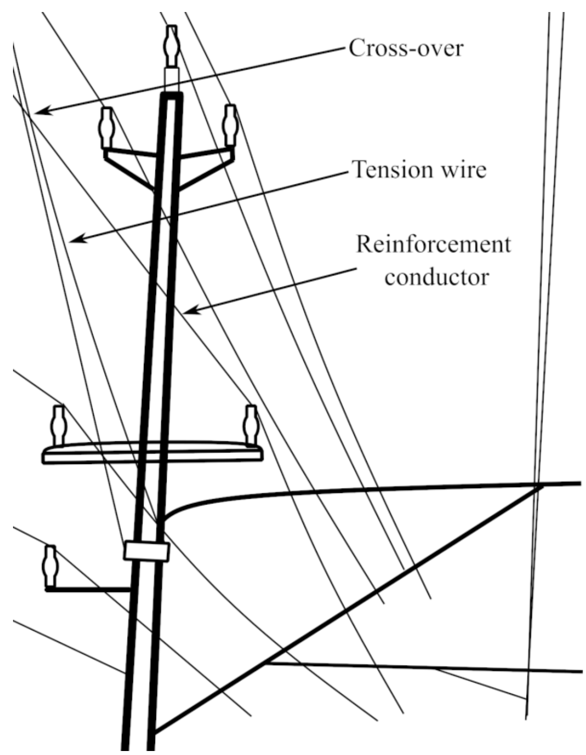


Figure 2. Railway catenary and cross-over point

The data collection was performed by mounting a LiDAR sensor in front of the locomotive, the raw data is processed and sliced into smaller files. The data is provided as “las” files of average size 250MB and provide point cloud covering approximately 200 meters along the tracks.

4.1.1 Requirement

The project aims to extract the position of the reinforcement conductor and detect the presence of other cables in the vicinity. The reinforcement conductor carries 15 KV and hence as per standards should have a clearance of 150 mm in static and 100 mm in a dynamic state. The cross-over point between the reinforcement conductor and tension wire is of special interest due to the hazard of short-circuit as shown in Fig. 2. Along with the catenary system about every 500 meters the tension wire crosses over in the close vicinity of the reinforcement conductor. Fig. 3 shows a projection of point cloud data and the cross-over point detected during data processing.

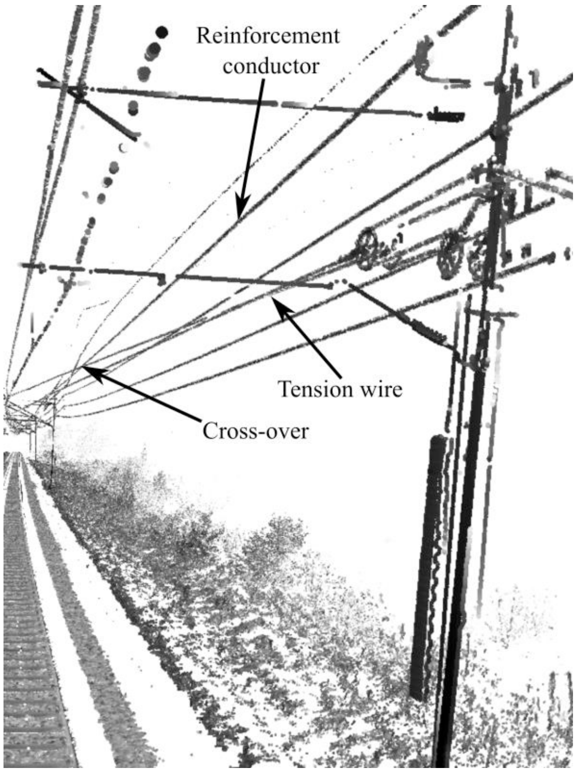


Figure 3. Point cloud projection with cross-over point

4.1.2 Information extraction

The point cloud scan contains railway tracks, sleepers, masts, beams, catenaries, power cables, vegetation around the tracks, and geographical features. Data extraction is performed through various stages of processing namely filtering, ground plane removal, clustering, asset detection, and extraction.

The wire cable points are extracted and fitted to polynomial equations. The relative locations of the curves to masts are used to classify the cables. Distances between the cables are used to calculate the vicinity of the conductors. From the detected tension wire curve, points in the vicinity are collected to detect infringement of standard distances. The data generated is exported as a hierarchal model.

4.2 Rolling Sieve

The point cloud is created with handheld LiDAR and multiple scans are performed and stitched together to provide full coverage of the sieve. The used file is about 1.6 GB in size with about 64 million points.

4.2.1 Requirement

The equipment for digital twinning is a roller sieve used to extract mineral pellets of a certain predefined size from the rest of the material with high consistency. The rollers in the sieve are adjustable to set the gap between them. An electro-mechanical system is used to adjust the gap between individual rollers. The inter-cylinder gap of the individual roller can change over a period of time. This results in inconsistency in the size of the pellets retained at the end of the process.

4.2.2 Information extraction

Cylindrical rollers extraction was performed through segmentation and edge data from the cylinders was extracted since it has minimal wear. The top curvature of the individual cylinders was extracted and peak-to-peak distances in 3D space were extracted. The same processing was applied at both the ends of the cylinders. This data is exported and contains information on the position of the cylinders in 3D space. This data allows extracting sufficient information about the structural layout of the cylinders like the angle of the cylinder array, linear distance, and height information. This position information allows to store and analyze the positioning errors at a point in time and allows to observe degradation over a period of time.

4.3 Creation of Digital Twin

The first stage of the creation of the digital twin is the extraction of data and representation in a standardized format. In the case studies, the data is extracted through LiDAR sensor and exported as location, positional, or mathematical representation and not in the raw point cloud format. This allows reducing the amount of data to be transferred and shares a model of the equipment for the creation of DT using the FL model.

Development of geometric DT of the models hence received is performed at a central location and updates the positional information of the equipment. This data is further processed to extract current conditions such as distance between wires in the case of railway catenary and relative positions of rollers in the case of the rolling sieve. The current processing has been limited to geometric analysis since a single scan per location has been performed. In the future work time-based analysis to extract the effect of weather and operating conditions will be performed.

Additionally, as shown in Figure 1 visualization is an important part of the digital twin in the case of the physical infrastructure. This allows inspection of equipment located at various locations from a centralized point. The equipment model data is exported as 3D models for virtual reality and augmented reality systems.

5. CONCLUSIONS

This paper explores the requirements for the creation of Digital Twin (DT) through the use of Federated Learning (FL) in multi-stakeholder environments using LiDAR as the data source. Process flow for information extraction from point cloud data has been implemented and requirements of FL for DT have been explored. Data serialization, model ownership, provenance, and delegated architecture of DT have been identified as gaps in the current research. The future work will explore information generation from the DT for decision support, model state management, and serialization in the light of distributed ledgers.

REFERENCES

Ariyachandra, M.R.M.F. and Brilakis, I. (2019), "Understanding the challenge of digitally twinning the geometry of existing rail infrastructure", *12th FARU*

International Research Conference (Faculty of Architecture Research Unit), Colombo, Sri Lanka, pp. 25–32.

Ariyachandra, M.R.M.F. and Brilakis, I. (2020), "Digital twinning of railway overhead line equipment from airborne lidar data", *Proceedings of the 37th International Symposium on Automation and Robotics in Construction, ISARC 2020: From Demonstration to Practical Use - To New Stage of Construction Robot*, pp. 1270–1277.

Ben-Daya, M., Kumar, U. and Murthy, D.N.P. (2016), *Introduction to Maintenance Engineering*, *Introduction to Maintenance Engineering*, John Wiley & Sons, available at:https://doi.org/10.1002/9781118926581.

Chase, A.F., Chase, D.Z., Weishampel, J.F., Drake, J.B., Shrestha, R.L., Slatton, K.C., Awe, J.J., *et al.* (2011), "Airborne LiDAR, archaeology, and the ancient Maya landscape at Caracol, Belize", *Journal of Archaeological Science*, Elsevier Ltd, Vol. 38 No. 2, pp. 387–398.

Cheng, L., Tong, L., Wang, Y. and Li, M. (2014), "Extraction of Urban Power Lines from Vehicle-Borne LiDAR Data", *Remote Sensing*, Vol. 6 No. 4, pp. 3302–3320.

H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, B.A. y A. (2017), "Communication-Efficient Learning of Deep Networks from Decentralized Data", Vol. 54, p. 10.

IEC. (2004), *60300 (3-14): Dependability Management - Part 3-14: Application Guide - Maintenance and Maintenance Support.*, International Electrotechnical Commission, Geneva, Switzerland.

IEV. (2021), "International electrotechnical vocabulary", International Electrotechnical Commission, available at: https://www.electropedia.org/ (accessed 10 September 2021).

Karim, R., Galar, D.P. and Kumar, U. (2021), *AI Factory: Theories, Applications and Case Studies.*, Manuscript in preparation. CRC Press.

Lee, J., Singh, J. and Azamfar, M. (2019), "Industrial Artificial Intelligence", *ArXiv Preprint ArXiv:1908.02150*, available at:https://doi.org/10.1360/SST-2020-0383.

Lu, Y., Huang, X., Zhang, K., Maharjan, S. and Zhang, Y. (2021), "Communication-Efficient Federated Learning for Digital Twin Edge Networks in Industrial IoT", *IEEE Transactions on Industrial Informatics*, Vol. 17 No. 8, pp. 5709–5718.

Rosen, R., Von Wichert, G., Lo, G. and Bettenhausen, K.D. (2015), "About the importance of autonomy and digital twins for the future of manufacturing", *IFAC-PapersOnLine*, Elsevier Ltd., Vol. 28 No. 3, pp. 567–572.

Royán, M.J., Abellán, A., Jaboyedoff, M., Vilaplana, J.M. and Calvet, J. (2014), "Spatio-temporal analysis of rockfall pre-failure deformation using Terrestrial LiDAR", *Landslides*, Vol. 11 No. 4, pp. 697–709.

Shafto, M., Conroy, M., Doyle, R., Glaessgen, E., Kemp, C., LeMoigne, J. and Wang, L. (2012), "Modeling, Simulation, information Technology & Processing Roadmap", *Technology Area 11*, pp. 1–38.

Shokri, R. and Shmatikov, V. (2015), "Privacy-Preserving Deep Learning", *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security*, pp. 1310–1321.

Steinmetz, C., Rettberg, A., Ribeiro, F.G.C., Schroeder, G. and Pereira, C.E. (2018), "Internet of things ontology for digital twin in cyber physical systems", *Brazilian Symposium on Computing System Engineering, SBESC*, Vol. 2018-Novem, pp. 154–159.

Tao, F., Zhang, H., Liu, A. and Nee, A.Y.C. (2019), "Digital Twin in Industry: State-of-the-Art", *IEEE Transactions on Industrial Informatics*, IEEE, Vol. 15 No. 4, pp. 2405–2415.

Taylor, T.S. (2019), *Introduction to Laser Science and Engineering*, CRC Press.

Uhlemann, T.H.J., Lehmann, C. and Steinhilper, R. (2017), "The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0", *Procedia CIRP*, The Author(s), Vol. 61, pp. 335–340.

Xiong, X., Adan, A., Akinci, B. and Huber, D. (2013), "Automatic creation of semantically rich 3D building models from laser scanner data", *Automation in Construction*, Elsevier B.V., Vol. 31, pp. 325–337.