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Beyond data visualization: A context-realistic construction equipment training simulators

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ABSTRACT

Virtual Reality (VR) based training simulators are successfully employed in many industries (e.g., aviation) to help train operators and professionals in a safe environment. The construction industry has also started to use this technology in recent years for training operators of heavy equipment. However, the context presented in the available training simulators is unrealistic because in many instances the training takes place in static sites where there is no mobility in the site. To realistically introduce the context of construction sites into VR scenes sensory data from actual projects can be used. However, currently, there is no systematic insight into (1) the dimensions of context that need to be present in a training simulator, (2) the types of data required to represent various dimensions of the context, and (3) methods for converting context data into a coherent context-realistic training scene that enables bidirectional feedback between trainees and the VR scene. Therefore, this research aims to develop a novel framework to generate coherent context-realistic training simulators from data collected from actual construction projects to enhance construction training simulators. The proposed framework provides a step-wise guideline into (a) collection of appropriate data for context-realistic simulators, (b) development of agents and simulation physics from actual site data and their integration into a scene, (c) scene-trainee interactions in context-realistic scenes, and (d) context-based assessment of the trainees' performance from safety, productivity, and quality perspectives. A prototype is developed and a case study is conducted to demonstrate the feasibility of the proposed framework. A workshop with expert training instructors is conducted to evaluate the effectiveness of the proposed framework for improving simulator-based training. It is shown that compared to the existing simulators, the context-realistic training simulators can significantly improve various aspects of operator training, especially safety and teamwork. The research provided an insight into the future of construction training simulator by indicating the importance and relevance of (1) collecting appropriate data, and (2) developing robust data-to-agent and data-to-physics methods.

1. Introduction

The construction industry has one of the highest incident rates among different industries [1]. Different pieces of construction equipment, e.g., excavators, trucks, etc., are reported to be the second cause of fatal injuries on construction sites [2–4]. According to statistics from the U.S. Bureau of Labor Statistics, 21% of fatal injuries on U.S. construction sites in 2016 were primarily or secondarily caused by different pieces of equipment [2]. For instance, excavators and road construction equipment have contributed to 44 and 16 fatalities in 2016, respectively. In the U.K., 10% of fatal accidents on construction sites in the period between 2012 and 2016 were caused by moving vehicle [5]. In the Netherlands, 20% of the equipment related accidents resulted in death, making vehicle-related accidents the second cause of fatal accidents [6]. Among various causes of incidents, the inadequate knowledge and skill of the practitioners are claimed to play a role in 42% of

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accidents on construction sites [7]. The lack of proper training has been identified as a major cause of accidents on construction sites [8,9], particularly in equipment-related incidents [10,11].

Normally, equipment operators go through stringent training programs. However, the following limitations compromise the efficiency of the current training programs: (1) in current training programs, safety is taught more at a theoretical level (i.e., through guidelines and regulations). This passive form of learning renders the content of training highly prone to oblivion and precipitates the trainees into the state of mindless compliance with safety codes rather than mindfully analyzing the safety. Previous studies attest to inefficiency of the current practice [12–17]; (2) the conventional operator training programs are expensive and the operators would have only limited time on the actual equipment during their training [13–16]; (3) the practical training is mainly focused on motor skills; and (4) safety risks are very difficult and dangerous to implement during the training with actual equipment [18].

In recent years, Virtual Reality (VR)-based simulators are used to train apprentices in many high-risk industries, such as aviation, firefighting, military, medicine, and manufacturing [19–24]. The construction industry also has adopted VR-based simulators for various types of training programs. Simulators are used in such areas as safety training [18,25–27], construction management and planning [28,29], and equipment training [30–35]. Many of the major construction equipment manufacturers nowadays provide training simulators that represent the design and characteristics of their equipment [36–38]. There are also several dedicated companies specialized in the development of training simulators for construction equipment [39–42]. These simulators consist of a motion platform, joysticks and/or steering wheel, accelerator and brake pedals, and one or several displays. The training simulators can considerably reduce the cost and risks involved in operator training [43,44]. Nowadays, trainees are initially trained with simulators to gain basic equipment handling skills. Only when the basic skills are acquired are trainees allowed to use the actual equipment. This practice is shown to increase the efficiency of training [45].

1.1. Problem statement

Despite the palpable advantages of training simulators and their rising popularity, there are three main shortcomings: (1) focusing primarily on theory-based physics (e.g., soil-blade interaction), fidelity, and ergonomics [30,33,46–48], these simulators use hypothetical scenarios that place the trainees in (quasi-) static settings, where equipment can execute the assigned tasks with no (or few) constraints imposed by the surrounding operations. Because operators of heavy equipment need to have a sharp situational awareness to avoid conflicts with other equipment and workers on construction sites [43,49], these static settings are not very effective in preparing the operators for the actual job on the site. Therefore, it is important for simulators to capture and represent the dynamics of construction sites. While some manufacturers have recently started to introduce agent-driven mobility in the training scenarios [42], this approach, too, has a drawback. The behaviors of the current agents, which are based on limited data or hypothetical assumptions, can hardly represent uncertainties and volatility involved in the behavior of workers and equipment; (2) In the current simulators, the interaction between players, environment, construction processes and products are modeled based on known sets of physical rules, historical data, and assumptions. Nevertheless, on one hand, these rules are mainly defined by software developers, who are not training experts and lack operational knowledge and historical data about construction activities. On the other hand, the implemented rules are usually based on well-established physical principles which, in many instances, are either not sufficient or oversimplified to cover different aspects of the interplay between actors and the environment [50]. In recent years, and with the rising power of sensors, it is possible to collect a large amount of data about how the environment behaves with regards to actions made by operators [51,52]. However, these valuable data have never been incorporated in VR-based training simulators; (3) Existing simulators leave little flexibility for training schools to develop customized curriculum. This is because the number of scenarios provided by manufacturers is limited. On one hand, the development of new scenarios at the training school requires technical know-how that is often not available or too expensive to acquire. On the other hand, given the efforts and time required for scenario development [32], manufacturers do not offer customized scenarios.

It can be argued that the problems with existing training simulators can be addressed, to a great extent, by replicating a realistic context of construction work in VR training scenarios. A realistic context representation in simulators can help the trainees better develop skills that normally require in-situ experience and cultivation.

In recent years, the advancements of the Internet of Things (IoT) and Real-time Location Systems (RTLSs) technologies has made it possible to capture various types of site and operation data that can be used to represent construction sites in VR [53–75]. Additionally, application and development of new surveying technologies, e.g., Laser Detection and Ranging (LiDAR), and modeling tools, e.g., Building Information Modeling (BIM), made it possible to capture and represent the geometry and layout of construction sites with high accuracy [76–82]. CityGML models of major urban areas are becoming increasingly available [83,84], making the realistic representation of construction sites in VR even easier [85,86]. Depending on the scope of the work, these technologies are used to reconstruct certain aspects of the construction sites in VR scenes. Most notably, site reconstruction has been used for activity monitoring [50] and process analysis [35]. These studies have indicated the value and significance of data acquisition and representation for improving safety and productivity. Nevertheless, the current state-of-the-art in construction site reconstruction is limited to replaying the construction operations in VR. This means that the developed VR scenes can only be used as materials for reviewing the executed work [87]. While very valuable, these VR scenes are only navigable and not interactable. In operator training simulators, the context needs to be interactable so that trainees' performances can instigate changes in the site and vice versa. The main challenge in moving from navigable to interactable data-driven VR scene is to make the data-driven context aware of and reactive to decisions made by trainees. For instance, in the case where the trainee is trying to load a data-driven truck with an excavator, the truck might leave in the middle of the loading if the behavior of the truck is not dependent on the behavior and state of the trainee-operated excavator. Therefore, it can be argued that the logical interaction between scene and trainees requires bidirectional feedback.

The authors have previously demonstrated the value of real data to VR scenarios [88]. However, the idea was presented at a conceptual and highly-abstract level, without providing a detailed framework, comprehensive testing, and validation. Additionally, the presented concept is limited to capturing the mobility of equipment in a VR scene.

In summary, in the current body of knowledge, there is no systematic insight into (1) the dimensions of context that need to be present in a training simulator, (2) the types of data required to represent various dimensions of the context, and (3) methods for converting context data into a coherent context-realistic training scene that enables bidirectional feedback between trainees and the VR scene.

1.2. Research objectives

Based on the aforementioned problem statement, this research aims to develop a novel framework to generate coherent context-realistic training simulators from data collected from actual construction projects to enhance the following aspects of construction training simulators: (1) safety education, (2) teamwork, (3) interface, (4) education design, and (5) versatility. The framework aims to provide a step-wise guideline into (a) collection of appropriate data for context-realistic

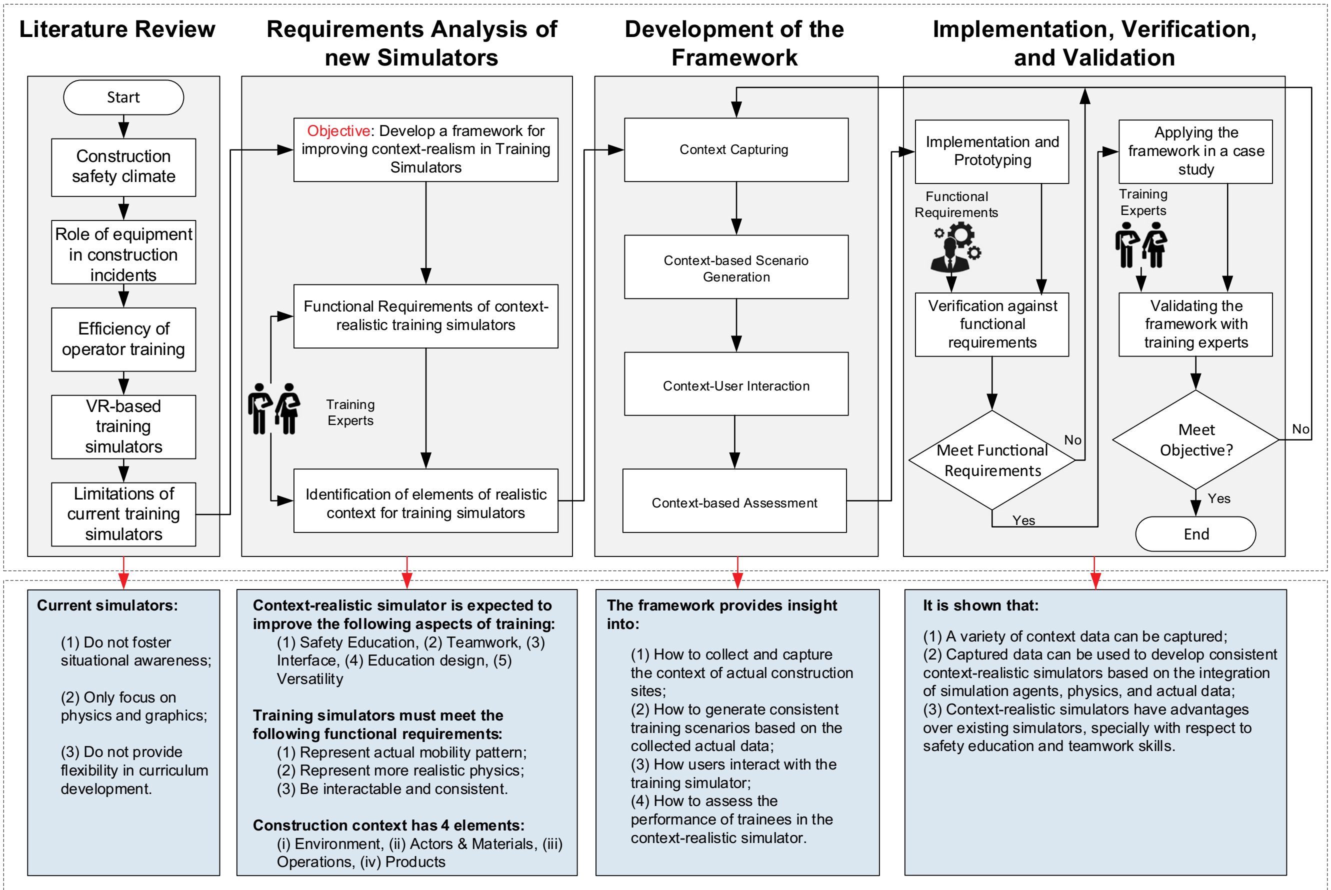


Fig. 1. Overview of the Research Methodology.

simulators, (b) development of agents and simulation physics from actual site data and their integration into a scene, (c) scene-trainee interactions in context-realistic scenes, and (d) context-based assessment of the trainees' performance from safety, productivity, and quality perspectives. It is hypothesized that by developing appropriate methods to generate simulation agents and physics from site data, the above objective can be met.

The structure of the paper is as follows. First, the research methodology and the proposed framework is discussed in detail. Then, the implementation of the proposed framework in a case study is demonstrated. Following the case study, the results and effectiveness of the framework are validated through a workshop with expert instructors from an operator training school. Finally, the conclusions are presented.

2. Context-realistic training simulators

2.1. Research methodology

Fig. 1 provides an overview of the methodology used in this research. Given the design nature of this research, a variation of design research methodology is applied [102]. The methodology has 4 main phases, namely literature review, requirement analysis, development, and implementation, verification and validation. In the first phase, the research gap is identified through an extensive literature review, as presented in Section 1.

In phase 2, first, the research objective is formulated to address the identified gap, as presented in Section 1.2. Based on the research objective, various aspects of the training simulators that are expected to be enhanced are identified, as shown in Section 1.2. These aspects are later used in Phase 4 to validate the proposed framework. Next, the functional requirements of the new training simulators are identified using the input from a number of training experts. These are the specific features that are expected to be present in the new context-realistic training simulators. This step is then subsequent by the identification of different dimensions of context that need to be present in context-realistic training simulators. This step, too, is done in collaboration with the training experts. The functional requirements and the presence of the relevant context dimensions are used to verify the proposed framework in Phase 3.

In Phase 3 of the research, the conceptual model of the proposed framework is developed by building on the findings from the literature review and developing relevant methods for generating data-driven agents and physics. The conceptual model includes guideline into (1) context capturing, (2) scenario generation, (3) context-user interaction, and (4) context-based assessment.

Once the conceptual model of the framework is developed, the framework is implemented in a prototype in Phase 4 of the research. The developed prototype is verified against the identified functional requirements. If the prototype is not verified, the framework is updated. Once the framework is verified, the framework is applied in a case study. The results of the case study are presented to training experts and the ability of the proposed framework to meet the objective of the research in improving the training simulators using context-realism is assessed. During the validation phase, the 5 expected improvement areas of the context-realistic simulators, which are mentioned in Section 1.2, are used to compare the context-realistic simulators with the existing ones. Based on the results of the validation, the adjustment of the framework is undertaken, if needed.

2.2. Requirements analysis

With the research gap and objective identified in Section 1, the next steps in the research methodology were to identify the functional requirements of the new training simulators and dimensions of the context that need to be present in the simulators. These steps were taken in collaboration with two training experts from SOMA College, which is one of the biggest operator training schools in the Netherlands. The instructors from SOMA College are deemed to be best positioned to reflect on training simulators since the college has been using 18 VR-based equipment training simulators as part of their curriculum for several years. Accordingly, the instructors have comprehensive knowledge and experience about the state of the art in the training simulators and their pedagogical value.

Based on the limitations of the existing training simulators identified in Section 1, and in collaboration with training experts, three main functional requirements are identified for context-realistic training simulator: (1) the simulator must be able to represent actual mobility patterns on the construction sites to help trainees hone their situational awareness; (2) the simulators must reflect more realistic physics based on data collected from the sites to generate a better feel about the consequence of trainees' decisions on the environment; and (3) the simulators must be interactable and coherent, meaning that there must be a bilateral feedback between the scene and trainees.

It should be highlighted that the goal of context-realistic simulators is not to require trainees to replicate the operations of the actual operators, but to allow them to interact with more realistic mobility pattern and environments. Accordingly, the users of the context-realistic simulators are not expected to follow the same paths or operational patterns as the actual operators. In this sense, the context-realistic simulators must offer the same flexibility to trainees as the existing simulators.

In the next step, the dimensions of context that add value to the training were identified in discussion with the training experts. Fig. 2 summarizes these dimensions. Essentially, the context of projects can be categorized into four dimensions: (1) Environment, (2) Actors and Materials, (3) Operations, and (4) Products.

Environment represents the hosting setting of construction projects and encompasses such elements as the site layout/geometry, permanent and temporary structures, surroundings, and weather condition. The environment dimension in the VR scene helps trainees better relate themselves to the setting of the work and better correlate the operational decisions with the site layout restrictions and different weather conditions. This contributes to creating a more realistic feel about the context of construction projects. Additionally, since the environment hosts all other context dimensions, it provides a logical basis for different movement and operational patterns.

Actors are workers and pieces of equipment (e.g., excavators and rollers) that execute different construction operations. During these operations, materials will be consumed to generate or place products. Actors and materials are of particular importance to context-realistic VR scenes because they are highly dynamic and mobile. It is the mobility of these elements that requires trainees to be continuously mindful of the surrounding to avoid collisions with other equipment, workers or materials on actual sites. The capturing and incorporation of this dimension in the VR scene generate realistic and dynamic settings wherein trainees can hone their situational awareness while acquiring technical skills. As mentioned in Section 1, the current approach in representing actors and materials on construction sites is sub-optimal because agents used in these VR scenes are not able to effectively mimic uncertainties and erraticness associated with the human behavior on construction sites.

The next dimension of context is operations. An operation is defined as an aggregation of coordinated work tasks of several actors who use materials and a unique construction method to place a certain construction product [89]. Excavation, pavement, and compaction are examples of construction operations. While several operations can also be aggregated into an activity (e.g., earthwork) [89], given the scope of VR training, which is to prepare operators for a given task, it is sufficient to limit the VR context to operations. Operations are important in VR training scenes because they (1) determine the training objectives, and thereby tasks of trainees, (2) drive the interaction between actors and materials, and (3) regulate the behavior of actors. The capturing and modeling of operations in the VR scene requires inferring of the underlying patterns of actors' mobility and their interdependences on the site. Once captured and modeled, data-driven operations can be used to develop more realistic agents that can logically interact with trainees in the VR scene.

The final dimension of the training context is the product. A product is defined as the output of operations. In this sense, products could refer to both physical products (e.g., an asphalt layer or a ditch) or changes to state/characteristics of the physical products (e.g., compacted or graded soil). Given this broad definition, modeling of products requires capturing of both the physical entity (e.g., the geometry of the ditch) and/or its state/characteristics (e.g., the degree of compaction of the soil). Products are important in training scenes because they help trainees form a frame of reference for how various actions result in different types or quality of final products. The product data must be correlated with operations to identify how different tasks in the operation cause changes in products. As mentioned above, this can be used as the basis for developing data-driven physics.

To have a realistic context in the training simulator, all the above dimensions need to be captured and accounted for. Given the heterogeneity of these data, a comprehensive framework is required to systematically collect, integrate, synchronize and incorporate the data into a coherent training scenario. To the best of authors' knowledge, such a comprehensive framework is missing in the literature.

2.3. Proposed framework

Fig. 3 shows an overview of the proposed framework, which is the result of several design iterations. In short, the proposed framework has four main phases, namely, Context Capture, Context Generation, Context-user Interaction, and Context-based Assessment. Context Capture phase is concerned with the collection of relevant context data, which were discussed in Section 2.2, from actual sites using a variety of sensors and tracking technologies, e.g., GPS, camera, Inertial Measurement Units (IMUs), infrared camera, laser scanners, etc. In Context Generation phase, the collected context data are translated into virtual models, or in other words to the digital twin of the construction operations. Hereafter, this process is referred to as virtualization. In this phase, a portion of the virtual scene that fits the profile of the trainees (e.g., entry-level skills, expected exit level skills, target equipment, etc.) is chosen for the training by the instructor. A trainee can either substitute one of the actual operators or be added to the site as an operator of a new piece of equipment. In Context-user Interaction phase, human-computer interaction media (e.g., joysticks, head and eye trackers, Kinect, head-mounted displays, etc.) are used to immerse the user in the context-realistic VR site. Eventually, a set of safety performance metrics (e.g., proximity, collisions, etc.) will be used to evaluate the performances of trainees in terms of safety and productivity. The remainder of this section describes each phase of the proposed framework in detail.

2.3.1. Context capturing

In Context Capturing phase, a set of technologies are used to collect context data. It should be highlighted that the Level of Detail (LoD) of the VR scene is directly correlated with the accuracy of the data collection technologies applied in this phase. Due to the limited resources available for accurate tracking of construction objects, it is important to identify the appropriate technologies that provide a suitable LoD for different dimensions of the construction context. Fig. 3 illustrates various types of sample technologies that can be used to capture different dimensions of the context. It should be noted that different context dimensions can accommodate different degrees of mobility of their constituent elements.

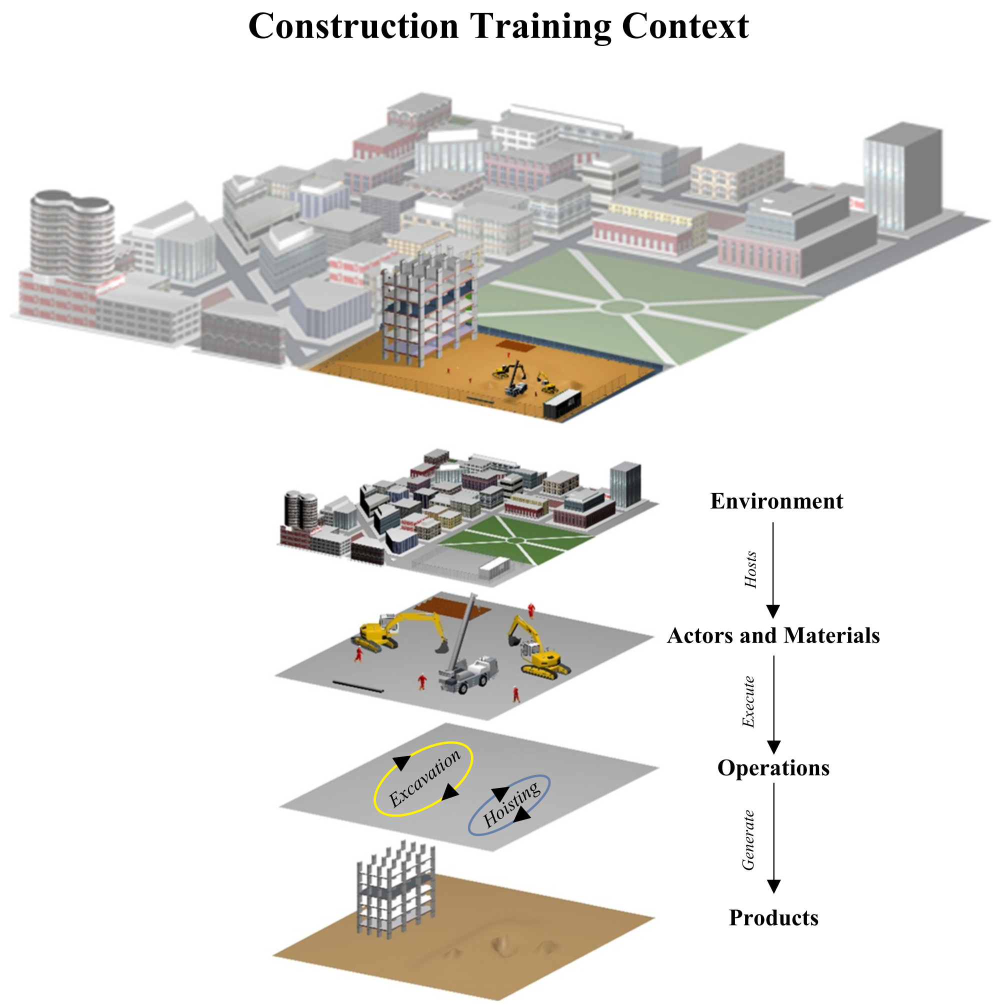


Fig. 2. Decomposition of Construction Site's Context.

Environment capturing:

Objects in the environment dimension are either static or semi-static. Static objects are those objects whose status (i.e., location, orientation, and geometry) either do not change or the changes are of a low significance to the context-fidelity of the VR scene. The best example of this category is the surrounding environment of the site, i.e., the area beyond the site perimeter where no construction activities take place. In essence, static objects of environment context can be best modeled using available CityGML and digital cadastral data, which are mostly generated from aerial photography and are often publically available. Alternatively, on-site cameras, drones or LiDAR scanning can be used for this purpose. However, given the cost and efforts required for the processing of images or LiDAR data and the lower relevance of this dimension to the training context, the use of these technologies

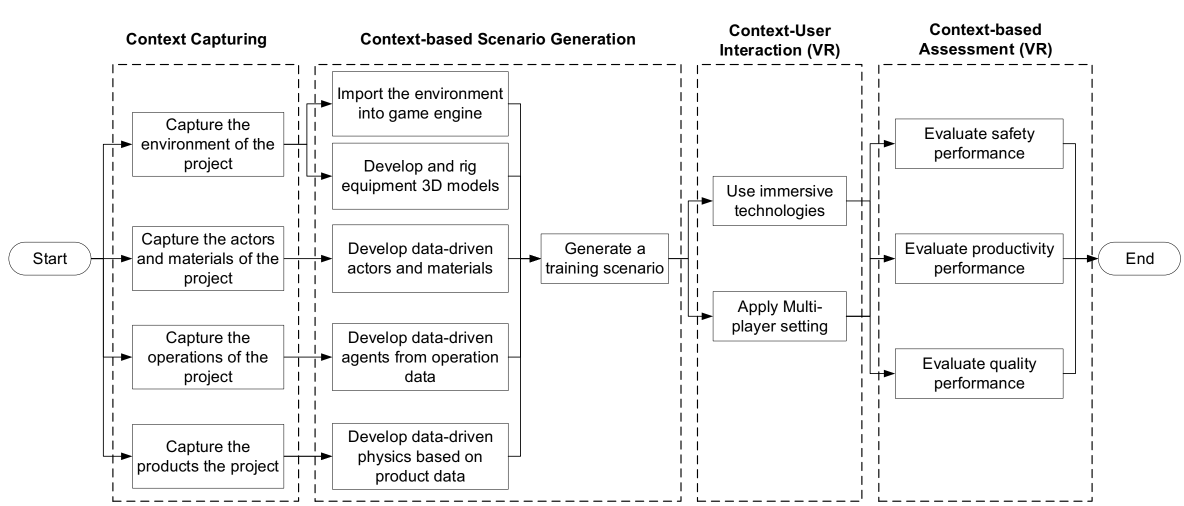


Fig. 3. Overview of the Proposed Framework.

may not be entirely justified. Semi-static objects are objects that are within the perimeter of the construction site and their statues change slowly (i.e., in the order of several days or a month). Good examples of semi-static objects are security fences and office containers. Given their low mobility level, semi-static objects can be best captured using onsite surveillance cameras. Recent research has demonstrated how camera inputs can be easily used to virtualize semi-static objects on construction sites [77]. Again, other sensor solutions (e.g., RFID, UWB) can be used, but may not be economically justified. The low update rate of the publically available cadastral data makes them unsuitable for the virtualization of semi-static objects. However, in the future, the integration of BIM models with progress monitoring data (e.g., collected by LiDAR) can be used to generate as-is 4D BIM that can be used for virtualization purposes.

Actor and material capturing:

Actors and materials dimension of the context is composed of dynamic or semi-dynamic objects. The status of dynamic objects change rapidly and there is a high degree of human factor involved in the mobility of these objects. Consequently, these objects are simultaneously the predominant causes and victims of accidents on the site and, therefore, are very important to track and virtualize. The most remarkable examples of these objects are equipment and workers. For the mobile objects to be represented in the VR scene, it is required to track the motions of the objects, which is defined as a combination of location and orientation. Depending on the controllable Degrees of Freedom (DOFs) of the equipment, motion tracking may require the integration of multiple sensory data. For instance, the motion tracking of an excavator requires a GPS for localization and at least 4 IMUs for the estimation of the pose of the superstructure, boom, stick, and bucket. Various types of technologies can be used for the tracking of dynamic objects, including GPS, UWB, RFID, and camera. Previous research has indicated the potentials of each of these technologies for tracking mobile objects [53,57,69,72,73]. Considering the cost-accuracy-reliability ratio, integration of GPS and IMU remains the most promising technology for the motion tracking of the mobile objects, especially equipment. It is noteworthy that the increasing popularity of Automated Machine Control and Guidance (AMC/G) technologies in construction sites can greatly streamline the process of data collection for mobile objects. The status of semi-dynamic objects changes at a higher frequency than semi-static objects (i.e., changes happen in the order of several hours to days). However, their mobility is usually based on a premeditated plan or schedule and as a result, the need for instantaneous human reflex based on their mobility is rather marginal. Nevertheless, these objects have a considerable impact on how operations are carried out safely (e.g., route planning) on the construction site and, therefore, are important to capture and virtualize. Examples of semi-dynamic objects are the material stack (e.g., cement bags, reinforcement stacks, etc.). These objects can also be best tracked using cameras. Alternatively, and especially for larger materials, sensor technologies can be used for the localization. Examples of using RFID for construction material tracking is presented by Song et al. [90].

Operation capturing:

As stated in Section 2.2, the operation dimension of the context is the result of inferring operational patterns/cycles from motion data captured from actors and materials. The core idea of operation capture is to identify the nature of activities (e.g., swinging, digging, compacting, etc.) of different actors and materials at different points in time. This information is usually referred to as the state of the actors/materials [91]. The inference of the state information from mobility data can be done through two main methods: (1) rule-based method: in this method, a number of heuristic rules can be applied to the mobility data of actors/materials to infer their states [91]; (2) Machine learning: different machine learning methods (e.g., deep learning, support vector machine, etc.) can be used to identify the state of the equipment based on a set of indexed historical data. Golparvar-Fard et al. [54] presented an example of how support vector machine can be used for the state identification of excavators. Once the states of different actors and materials are identified, the repetitive patterns in the behavior of actors can be extracted from the data to identify the underlying operation logic of different actors. These operational patterns can be used to develop realistic agents that can interact with the trainees in the VR scene, as will be discussed in Section 2.3.2.

Product capturing:

The product dimension of context can incorporate objects with various levels of mobility. The elements in this dimension are the most difficult to track given their highly volatile nature and the complex interaction with human-induced operations. Depending on the type of product, e.g., trench or compacted asphalt layer, different types of technologies can be used to track the changes in the state of the product. In most cases, remote sensing technologies and embedded sensors can be used to track product status in real time. For instance, as shown in the recent work of the authors [92], linescanners and embedded thermocouples can be used to track the temperature of hot asphalt in real time. Additionally, nuclear density gauge can be used to measure the density of the compacted asphalt. Another example of product capturing is the tracking of changes in the terrain states in the earthwork operations. The application of LiDAR technologies for capturing and monitoring the site topography in real-time has been previously studied [93].

2.3.2. Context-based scenario generation

Once the data about the various dimension of construction context is collected, the next phase of the framework is to translate the sensory data to a virtual scene that can be used in the training simulation. The assumption of this phase is that the data collected from the previous step are either highly accurate or processed [72] to be readily usable for the virtualization.

Environment and 3D model development:

The first step in the preparation of a scenario is the virtualization of the data. Various types of context data collected in the previous phase need to be virtualized in an interactable environment. The environment data need to be translated into a 3D model of the site and DTM. For this purpose, GIS platforms can be used for data integration, as shown in Fig. 4. The GIS platform can integrate various sensory, surveying and cadastral data in a seamless way. As shown in Fig. 4, different types of data can come from various sources and in different formats. For instance, the terrain model can be obtained from open-source heightmaps or LiDAR data. This data can be imported into the GIS platform, where they can be converted to a surface mesh. Additionally, data about the surrounding buildings, underground utilities, the road network, etc., can be extracted from the publically available cadastral data. This data can be imported into the GIS platform as CityGML data or Shapefiles. If sensors are used to track semi-static objects, the sensory information can be converted into a graphic representation of objects (e.g., buildings and fences) in the GIS platform. Finally, various types of 3D design information models (e.g., BIM) can be used to incorporate the semi-static objects into the GIS platform. These files are commonly object-oriented and data-rich. However, the attributes of objects are not of great relevance to the virtual scene. The GIS platform can convert the object-related information to geometry-only representation, which is sufficient for the training purposes. Once all the environment data are imported to the GIS platform, they can be merged into surfaces that represent the actual site. The integrated file can, then, be imported into a game engine, where it can be combined with operation-driven agents, actor/material, and product data.

Data-driven actors and materials:

As for actor/material data, the time-stamped motion data collected from sensors can be directly imported into the game engine. The sensory data must be registered with respect to (1) the tracked object, and (2) the tracked element (e.g., bucket). Another component for the virtualization of actor/material data is the 3D model of the objects. There are currently many royalty-free 3D object libraries from which these 3D

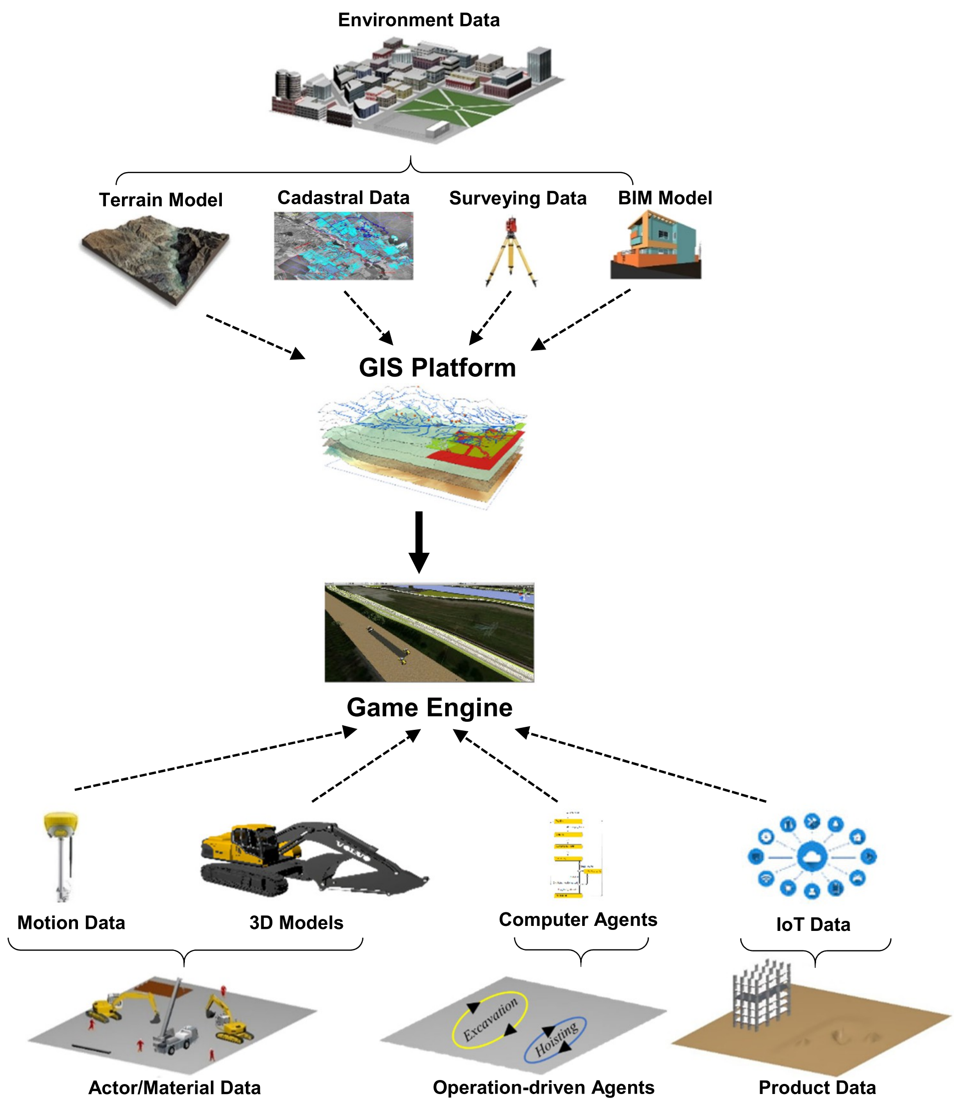


Fig. 4. Data fusion and virtualization of context data.

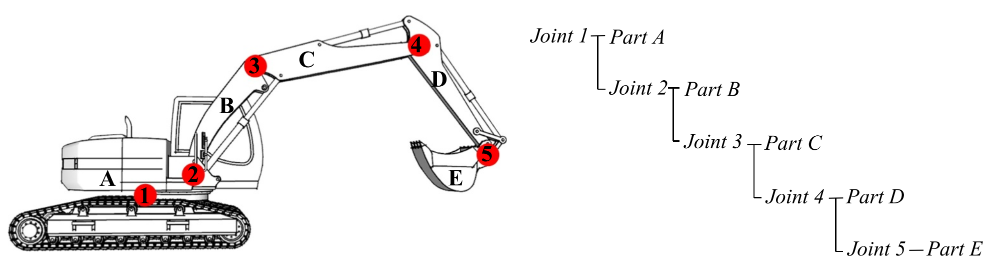


Fig. 5. Example of 3D model preparation for virtualization.

models can be retrieved. Additionally, the 3D models of equipment can be obtained from the manufacturers or by laser scanning. These 3D models can be directly imported into the game engine. It is of cardinal importance to make sure that different components in 3D models of dynamic objects are organized in such a way that the kinematic chain of actual objects is captured. For instance, as shown in Fig. 5, different joints and body parts of an excavator should be organized in the presented hierarchy to ensure easy integration with the sensory data. In the presented example, by attributing the location data to *Joint 1* and linking the Euler angles from sensors to the associated *Joints 1, 2, 3, 4,* and *5*, the motion of the excavator can be simulated in the VR scene. Concerning the LOD of the simulated or replayed workers, it is sufficient to represent their movements as walking or static figures. In other words, capturing the postures and motions of workers offer a limited advantage at the cost of additional requirements for complex data collection/preparation and computation power.

Data-driven agents:

Next component of the context-realistic scenario is the data-driven agents. These agents are essential in the scenario because interaction with only data-driven mobility on site can cause incongruity in the logical sequences of activities or unrealistic encounters. For instance, if a trainee is supposed to replace an excavator operator from an actual project, his/her working pattern and timing may not be synchronized with the motions of the truck that has worked with the actual excavator

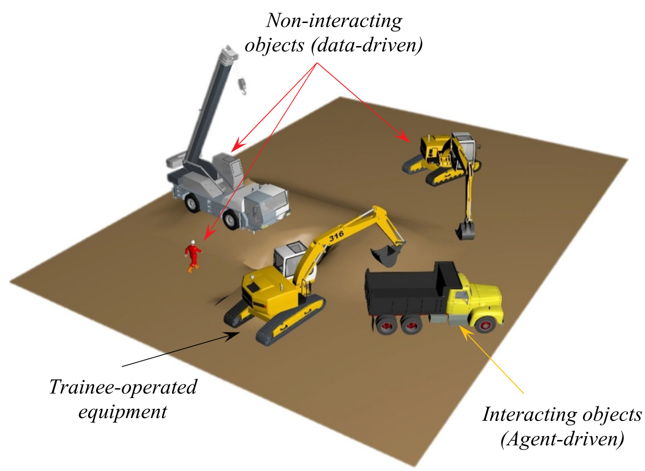


Fig. 6. Classification of equipment in the VR.

on the site. As a result, if the truck in the VR replicates the actual motions on site, there can be situations where the truck leaves in the middle of a loading operation. To circumvent these incongruities, as shown in Fig. 6, mobile objects not operated by trainees can be categorized into two classes, namely, interacting and non-interacting objects. Non-interacting objects are objects whose behavior on the site does not depend on the decisions and actions of the trainee-operated equipment. These pieces of equipment can be represented by simply replaying the motion data. Interacting objects, on the other hand, are those whose actions and operations depend on the performance of trainees. To avoid breaches in the logical progression of the scene, these pieces of equipment should be represented by computer agents. These agents represent the typical behavior of actors and materials in different types of projects and they can be modeled based on the operation data collected in the previous phase. There are two approaches to develop simulation agents, namely heuristic, and data-driven approaches. In the heuristic approach, existing simulation models and/or descriptions of construction methods are used to develop agents. In the data-driven approach, the state information is translated into state diagrams, which represent agents in a simulation, as shown in Fig. 7. An important step in the preparation of data-driven agents is the identification of correlations between the start/end point of various activities (e.g., green and red dotted lines in Fig. 7). These correlations define the communication and interaction protocols between various agents. This can be done through pattern matching and machine learning approaches. However,

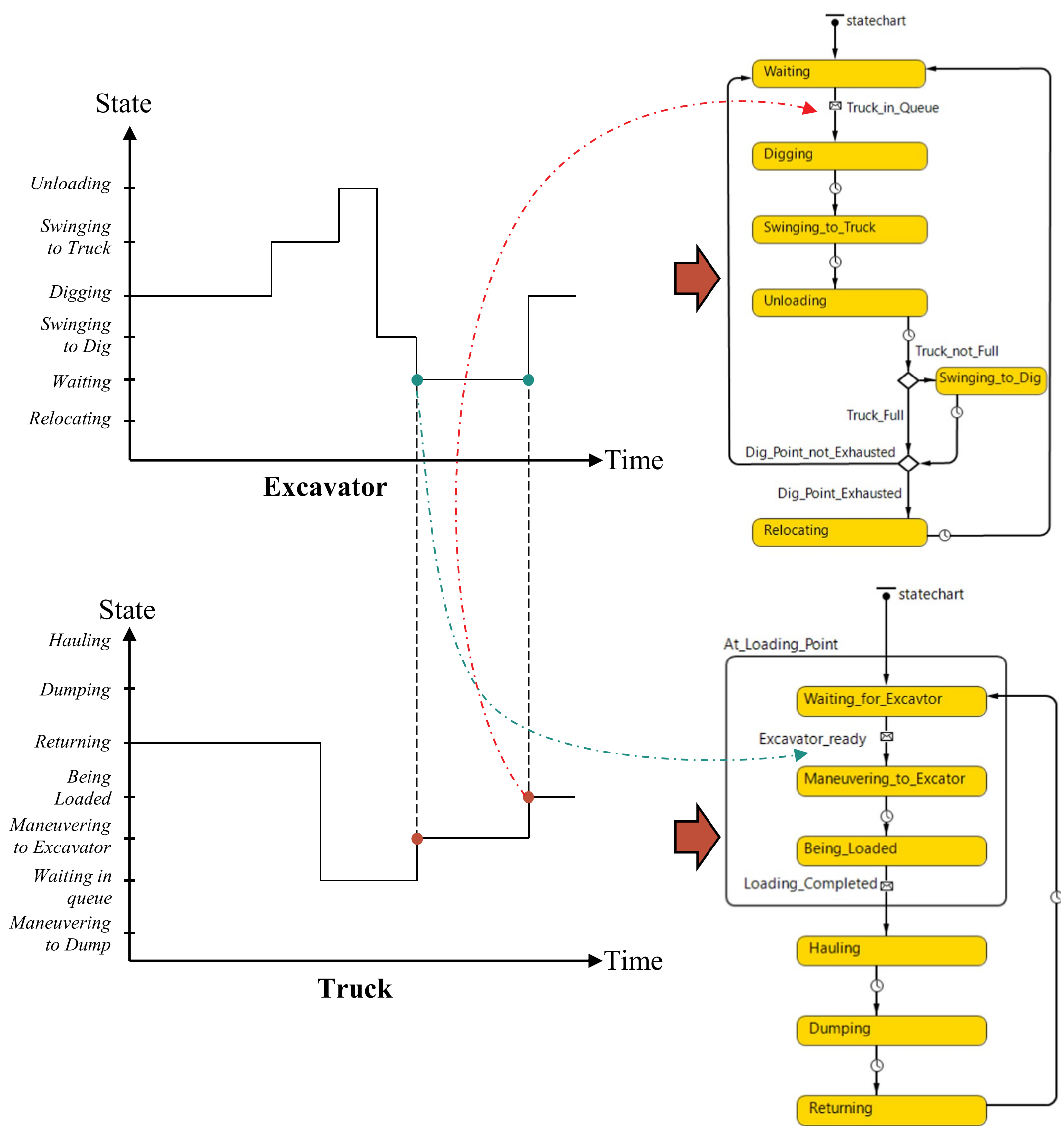


Fig. 7. Data-driven agent development.

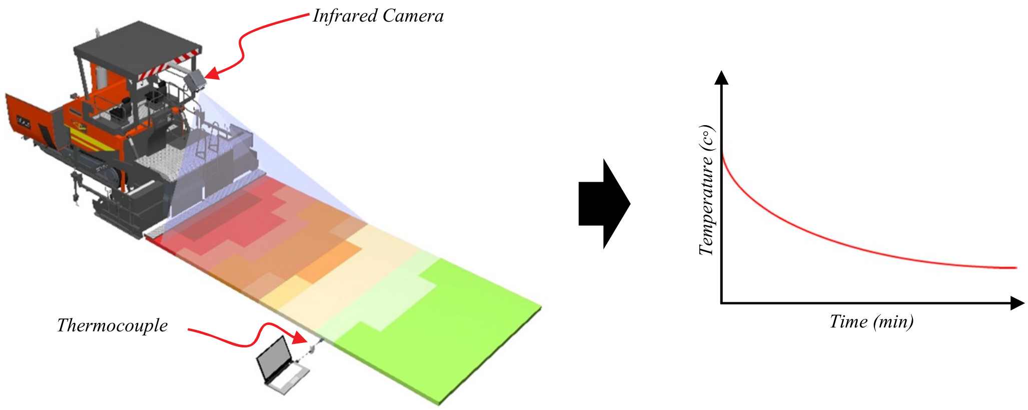


Fig. 8. Determining the cooling curve of asphalt based on embedded thermocouples and infrared camera.

further discussion of these approaches is out of the scope of this paper and will be discussed in the future work of the authors. Regardless of the source of agents (data or heuristic rules), the necessary agents can be stored and retrieved from a database of agents.

Data-driven physics:

The final component of the scenario is the product data. The product data can be used to create or augment the physics applied to the scene. These data-driven physics would help increase the realism of the scene from the perspective of the user-scene interaction and how the scene would react to decisions made by the trainees. One instance of data-driven physics can be using the soil moisture data, i.e., collected by soil moisture sensor, from the site to feed the soil physics models. The moisture can be used to determine the cohesion factor of the soil based on the site condition [47]. Another example of data-driven physics is the use of temperature data collected by infrared cameras and embedded thermocouples during paving operations to model the cooling rate of asphalt, as shown in Fig. 8. The details of the data collection procedure are presented in the previous work of the authors [92]. The cooling rate of asphalt is very important in the pavement operations because asphalt can be optimally compacted only with a certain range of temperature. The compaction outside this range results in under- or over-stressed asphalt [94]. The data-driven cooling curve can be implemented in the game to simulate how each part of the asphalt cools down after it is placed on the mat.

Scenario generation:

Once all the data are imported to the game engine, the next step is to prepare the scene. The main assumption in this step is that there is a library of projects for which virtualized scenes are available. In this phase, training instructors should make a few choices based on the learning objectives of the particular training and the skill level of the trainees. As shown in Fig. 9, the generation of the scene depends on selecting the appropriate site, the number/type of equipment, the agent-driven equipment, the time period, the site condition.

In the first step, the instructor should identify projects that would fit the learning objectives of the training. Parameters to consider in this step are the desired assignment or task, the magnitude of the project, and the location of the project. For instance, for preparing the trainees for safe excavation work in congested sites, the instructor may choose a building foundation construction project in an urban area. Alternatively, if the learning objective is to sensitize the trainees to the coordination needed for effective compaction work, a road construction project, where multiple rollers worked together, can be chosen.

In the next step, the instructor decides on the number and type of equipment that will be operated by the trainees. This decision, again, is made based on the learning objectives of the training, the number of trainees, the size of the project (i.e., to ensure the site is big enough for the given number of trainees), and the number and types of equipment available on the selected site.

The next step in the process is the selection of the portion of the work that fits the scope and learning objectives of the training. For instance, if the learning objectives include honing the situational awareness of trainees, instructors may want to isolate a part of the project where the site was very dynamic. Alternatively, the instructor may decide to focus more on the dexterity and motor skills of novice learners and, therefore, may opt for a more static part of the project. Another important parameter in selecting the period of time is the significant incidents (e.g., near misses) that happened in the project. Such incidents provide a very effective and realistic exposure for trainees to hone their skills in avoiding everyday risks on the site. These incidents, which may have been caused by expert operators on the site, can be of significant value for trainees to develop their emergency reactiveness and management.

Next, the instructor determines the level of context realism. Context can be incorporated in the simulator at different levels of completeness. This is because the exposure to the complete context can be overwhelming for novice learners who may need to focus more on the dexterity at the beginning of the training. For these trainees, a high degree of context-realism can impose cognitive overload and become counter-productive as it makes the sense of accomplishment and fulfillment for trainees more difficult to come by. The exigency of context realism will increase as trainees build up skills. For more skillful trainees, the increased context-realism will provide a better opportunity for developing situational awareness and more contextualized skills. The main advantage of the proposed framework is that it allows instructors to adjust the degree of context realism by including/excluding certain elements of the context, e.g., certain surrounding equipment or workers. The decision about the degree of context-realism can be made by tracking the performance of individual trainees and based on their progress.

In the final step of this phase, site condition can be modeled. In this step, the instructor can decide to either use the weather condition from the actual project (this can be retrieved from publically available meteorological databases) or simulate different types of weather conditions (e.g., rain, wind, snow, etc.).

2.3.3. Context-user interaction

As shown in Fig. 9, once a scenario is built, trainees can start the training by interacting with the VR simulator. Conventionally, construction VR simulators expose trainees to the scene through a set of screens. In recent years, the advent of the VR Head Mounted Displays (HMD), e.g., Oculus Rift [95], and advancements of Graphics Processing Units (GPUs) allow the replacement of the screen with VR HMDs. This would allow a deeper immersion of trainees in the VR scene and enables a more realistic interaction with the surroundings. Especially, given that the core objective of the proposed framework is to support the development of trainees' situational awareness, HMDs can better

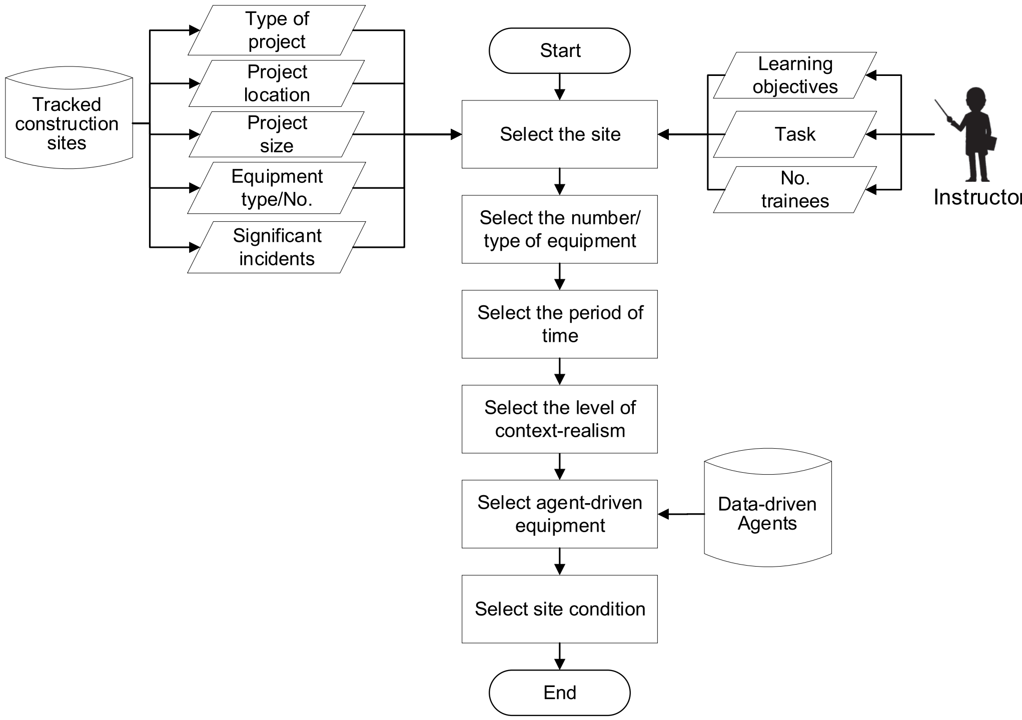


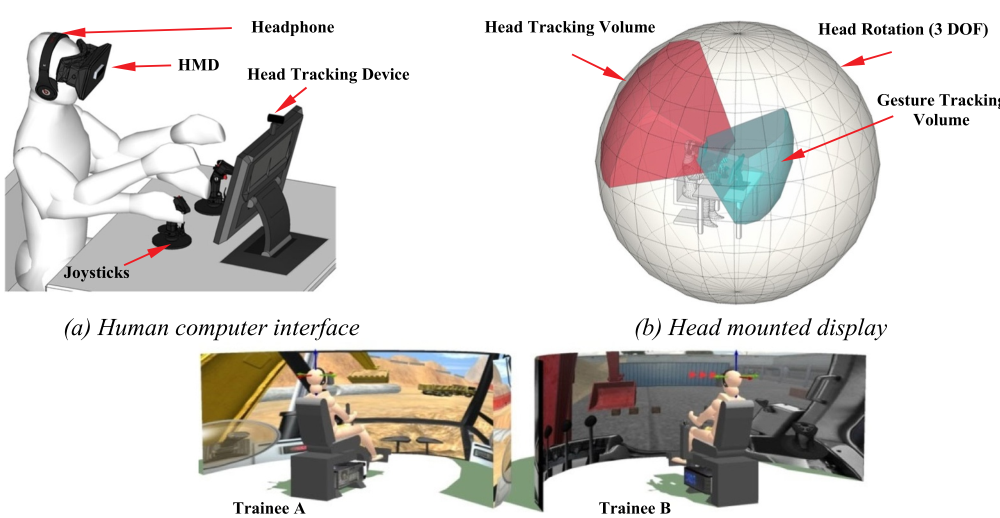
Fig. 9. Process of generating a scene.

enable trainees to navigate and monitor the site. Of particular interest of instructors is the instillment of proper manners of shoulder check in trainees [45]. This cannot be easily achieved using the conventional screen system approach. HMD, on the other hand, is ideally applicable for this purpose. The trainees can use joysticks that resemble actual control units on the equipment to steer the equipment.

Another important feature of the proposed framework is the support for multi-player training. The multi-player featured can be added to the game engine through the local network or cloud-based platform. The multi-player setting not only helps better sensitize trainees to activities of other peers but also can be used to assign collaborative tasks to multiple users. This can be used as a platform for fostering collaboration and coordination. As shown in Fig. 10, multiple trainees can work in the same team (e.g., one trainee operates the truck and another operates the excavator) or in different teams (e.g., each trainee operates an excavator). When working in a team, trainees should be aware that their performance (productivity and safety) would influence the entire operation. Trainees should try to avoid collisions with the trainee-controlled, agent-controlled, and data-driven equipment.

2.3.4. Context-based assessment

The final phase of this framework is the context-based assessment of trainees' performances. In the conventional simulators, the focus of assessment is mainly on productivity, although attention to safety started to surface in recent years. In this framework, since the focus is placed on the context realism, extra assessment can be performed with respect to how trainees operated in the context. This includes an assessment of safety performance with respect to site mobility. Additionally, since context-realistic simulators incorporate more realistic physics, the performance can also be measured from the quality



(a) Human computer interface *(b) Head mounted display*

(c) *Multi-player interaction*

Fig. 10. Immersive VR-based visualization and interaction components (Hammad et al. 2016).

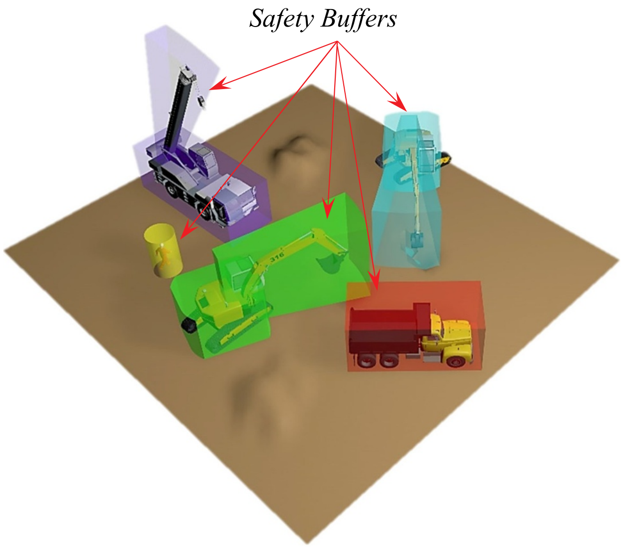


Fig. 11. Monitoring near misses using safety buffers.

standpoint in more details.

The safety performance is evaluated based on (1) number of collisions, (2) near-miss events calculated based on collisions between safety buffers of the mobile objects, and (3) head motions of the operator (i.e, the tendency for shoulder check). Of the main three safety components, the identification of near misses is more challenging. The authors have previously presented a method for real-time identification and warning of hazardous proximity based on the generation of safety buffers, i.e., dynamic equipment workspace [96]. In this approach, the complex geometry and kinematics of the equipment are considered to determine the space required for the safe operations of different equipment. The same approach can be implemented in the context of training simulators. As shown in Fig. 11, the safety buffers can be generated in real-time in the VR and any collisions between the buffers would indicate a near miss situation, whether or not they eventuate in actual collisions. The details about the shapes and sizes of different buffers can be found in the previous work of the authors [96].

The productivity performance is measured considering (1) the average cycle time of the operation, (2) the waiting time and length in the queue, (3) the length and the smoothness of the paths generated by the trainee, (4) the ability to control multiple DOFs simultaneously, and (5) the ability to coordinate with other trainees or agents.

The quality performance can be assessed based on (1) the depth and shape of the excavated area and comparison with expected design, (2) compaction rate of the asphalt at different parts of the mat, (3) the temperature window within which different parts of the asphalt were compacted, and (4) efficiency of the collaboration between different players by measuring the completeness of the work and the overlap between work zones of different players.

The proposed VR environment can record the training session and mark parts of the performance where trainees did not perform satisfactorily, from productivity, safety, and quality standpoints. The trainees can review their performances and observe their mistakes at the end of each training session.

3. Implementation and case studies

The proposed framework is implemented and tested through a case study. Fig. 12 shows the input data and modules of the developed prototype in Unity. The prototype requires the user to input environment data (i.e., 3D model of the site), actor data, processes data, and product data. The prototype comprises five main modules, namely, motion replay, equipment agent, equipment control, product and feedback modules. The Motion Replay Module is designed to read the actor data, which is represented in the form of time-stamped location data, and convert this to the movement of the associated 3D models. The Equipment Agent Module, on the other hand, uses the process data, e.g., cycle distribution information and propel the agents. The Equipment Control Module converts the trainees' command (from keyboard or joysticks) to the motion of the trainee-controlled equipment. The Product Module reads the product data, which represent the behavior of the product in response to environmental and operational stimuli, and virtualize the product. Finally, the Feedback Module tracks the performance of the trainee and assess the productivity, safety, and quality of his/her performance.

3.1. Case study

In this case study, a set of data collected from an actual road construction site in the Netherlands are used to develop a context-realistic training simulator. The captured project is a surface rehabilitation of a 250 m stretch of A-15 highway near Rotterdam. Fig. 13 shows the location of the project as extracted from Google Map.

In a typical paving operation, the paver is used to lay the hot mix asphalt on the base layer. The rollers would only start the compaction after the freshly laid asphalt is properly cooled down. The clearance distance between the rollers and paver is a factor of the type of the mix, weather condition, compaction speed, truck arrival rate, etc. Additionally, two workers move very close to the paver to level the edges of the asphalt layer using rakes. In this case study, two rollers compacted the layer laid by one paver. The three pieces of equipment were tracked using Differential GPS rovers [97]. The workers were not tracked. As for the product capturing, thermocouples and linescanners were used to track the temperature of the asphalt during the operation, as explained in the previous work of the authors [92]. This setting creates a grid on the asphalt layer and captures (1) the initial temperature of each cell of the asphalt, and (2) the average cooling rate of the asphalt.

To create the 3D model of the site, two different methods are applied and compared. In the first approach, the digital topographic data from the Dutch public services for maps [98] are used. The data, including the terrain model, building parcels, height information, water areas, and road network, are exported as Geography Markup Language (GML) file from PDOK website and imported to InfraWorks 360. Then, using the height information, the footprints of the buildings are extruded. The road network information is used to reconstruct the 3D roads in InfraWorks. Fig. 13(b) shows the output of this approach. In the second approach, the built-in feature of InfraWorks is used to reconstruct the 3D model of the site. InfraWorks extract terrain and other topographic information from OpenStreetMaps database and automatically drape them based on a set of predefined rules. Fig. 13(c) shows the result of applying this method.

Table 1 compares the two approaches based on a number of criteria. In terms of accuracy, the GML-based solution is slightly advantageous [99]. The InfraWorks-generated model has some irregularities in the representation of the road network that necessitates some manual adjustment. Based on the CityGML standard, the LoD of the model in both methods is 2 [84]. In terms of more realistic texturing and draping, InfraWorks has a clear edge. While both methods originally generate DTM that can be used in the game engine to model soil deformation, the conversion to Filmbox (FBX) causes the DTM to be transferred into a mesh. In order to enable terrain deformation, some manual adjustment is required in both methods to convert the mesh back to the terrain. InfraWorks is user-friendlier since the process is completely automated. Additionally, the data used by InfraWorks are more frequently updated [99]. BIM models can be easily integrated into the 3D model in both methods. Overall, based on the visual analysis, the model created using the built-in feature of InfraWorks 360 seems to be more photo-realistic and less laborious to create. In this case study, this model is used for the

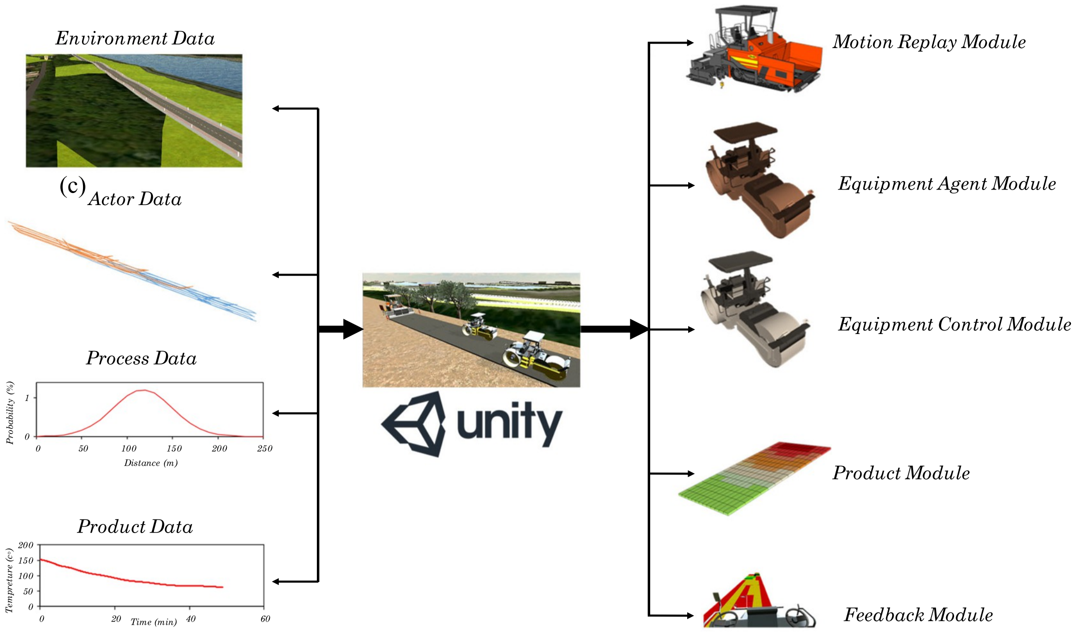


Fig. 12. The input data and modules of the implemented prototype.

Fig. 13. Project's Location (adapted from Vahdatikhaki et al. 2016).

further development of the simulation scene.

In the next step, the 3D model of the site is exported as FBX file and imported to Unity 3D [100], which is used as the game engine. 3D Warehouse [101] was used to find, clean and adjust the models representing the paver, rollers, and workers. To link the GPS data to the VR scene, the API of Unity 3D is used to program the connection

Table 1
Compassion of the two approach based on the model requirements.

Requirements	GML-based Model	Infraworks 360
Accuracy	± 2 m	heterogeneous but overall slightly lower than GML-based data (Bhattacharya 2012)
Resolution	LOD2 (e.g., buildings as generalized objects)	LOD2 (e.g., buildings as generalized objects)
Visual Realism	The terrain and the objects are not fully textured	The terrain and objects are textured
Terrain Deformability	Not available in native format	Not available in native format
Ease of Use	Requires manual integration, texturing and draping	Automated process
Reliability	Updated every 2 years (Bhattacharya 2012)	Varied but generally more updated
Extensibility	When imported to Infraworks, BIM models can be integrated	BIM models can be easily integrated

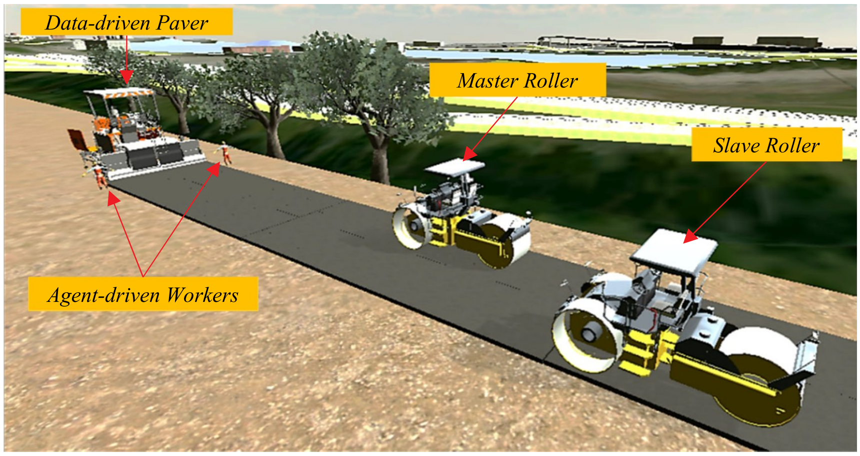


Fig. 14. Main objects in the training scenarios.

between Excel and Unity. The scene reads the GPS data from an Excel sheet and moves the 3D models of equipment based on the GPS data.

It should be highlighted that in the process of importing the InfraWorks model to Unity, the geo-referencing of the data is lost. Therefore, the site model has a local coordinate system defined by the user. As a result, all the objects in the game engine are placed in an arbitrary (or local) coordinate system. Consequently, sensory data (e.g., GPS) cannot be directly integrated into the model. To resolve this issue, the transformation matrix (M) that translates the two coordinate systems is found and used to map the sensory data of the (semi-) mobile objects into the local coordinate system of the VR scene. For this purpose, first, the latitude/longitude data are projected to the standard Universal Transverse Mercator (UTM) coordinate system. Next, the corresponding coordinates of three points in the real world (i.e., X, Y, Z) are found in the VR world (i.e., x, y, z). The transformation matrix for this system can be found based on Eq. (1).

$$\begin{bmatrix} X_1 & X_2 & X_3 \\ Y_1 & Y_2 & Y_3 \\ Z_1 & Z_2 & Z_3 \\ 1 & 1 & 1 \end{bmatrix} = M \times \begin{bmatrix} x_1 & x_2 & x_3 \\ y_1 & y & y \\ z_1 & z_2 & z_3 \\ 1 & 1 & 1 \end{bmatrix} \tag{1}$$

where:

X_i, Y_i, *and* Z_i are the coordinates of the point i in the world system
x_i, y_i, *and* z_i are the coordinates of the point i in the VR system
M is the transformation matrix

Transformation matrix has two components for rotation R, and translation T, assuming that scale is intact, as shown in Eq. (2).

$$M = \begin{bmatrix} R_{3,3} & T_{3,1} \\ 0_{1,3} & 1 \end{bmatrix} \tag{2}$$

where:

R is a 3 × 3 matrix formed based on the Proper Euler angles
T is a 3 × 1 matrix based on the Euclidean translation

Matrix R can be formed as shown in Eq. (3).

$$R = \begin{bmatrix} \cos\beta & -\cos\gamma\sin\beta & \sin\beta\sin\gamma \\ \cos\alpha\sin\beta & \cos\alpha\cos\beta\cos\gamma - \sin\alpha\sin\gamma & -\cos\gamma\sin\alpha - \cos\alpha\cos\beta\sin\gamma \\ \sin\alpha\sin\beta & \cos\alpha\sin\gamma + \cos\beta\cos\gamma\sin\alpha & \cos\alpha\cos\gamma - \cos\beta\sin\alpha\sin\gamma \end{bmatrix} \tag{3}$$

where:

α, β, and γ are rotations around X, Z, and X axes, respectively

Matrix T is shown in Eq. (4).

$$T = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix} \tag{4}$$

where:

t_x, t_y, and t_z are the value of translation along X, Y, and Z axes, respectively

The formation of Eq. (1) leads to a nonlinear 9-body problem system which can be solved numerically, provided the three points are not on the same line. Once solved, this equation would yield the transformation matrix M that transforms all the location data from the world system to the VR system.

Once the environment data are fully imported into Unity, two different scenarios are developed. As shown in Fig. 14, there are four main components in both scenarios: (1) the paver: the equipment that lays the fresh asphalt on the base layer; (2) workers: two laborers that use rakes to level the freshly laid asphalt at two opposing edges of the asphalt layer; (3) master roller: the roller that leads the compaction operation and determines the compaction pattern and path; and (4) slave roller: the roller that follows the master roller and should always remain in synch with it. In both scenarios, the paver is driven by the GPS data and workers are represented by simple agents that follow the paver at two opposing edges of the road. The first scenario focuses on the controlling ability of the trainee and requires him to operate the slave roller. The trainee should try to operate safely and remain in synch with the master roller, which is driven by the GPS data. The second scenario, on the other hand, concentrates on the strategic decision making of the trainee and requires him to operate the master roller. The trainee should lead the compaction by setting the pattern and path of the compaction. The slave roller in this scenario is driven by an agent, who observes the master roller and replicates the same path on the unpaved section of the road immediately next to the compacted area. To develop the agent, the movement patterns of two compactors were closely observed. Fig. 15(a) shows a period of coordinated compaction by two rollers. As can be seen, The slave roller maintains a distance with the master roller and performs the compaction. During this process, the slave roller travels back and forth for a certain distance. Fig. 15(b) shows the travel distances in several cycles of compaction and the changes in the states of the roller (i.e., compaction and returning). This figure represents an instance of the process capturing from actual construction sites. A similar analysis is performed for nearly 1 h of coordinated compaction. Accordingly, the probability distribution of rollers' cycle length, the distances between master and slave rollers, and

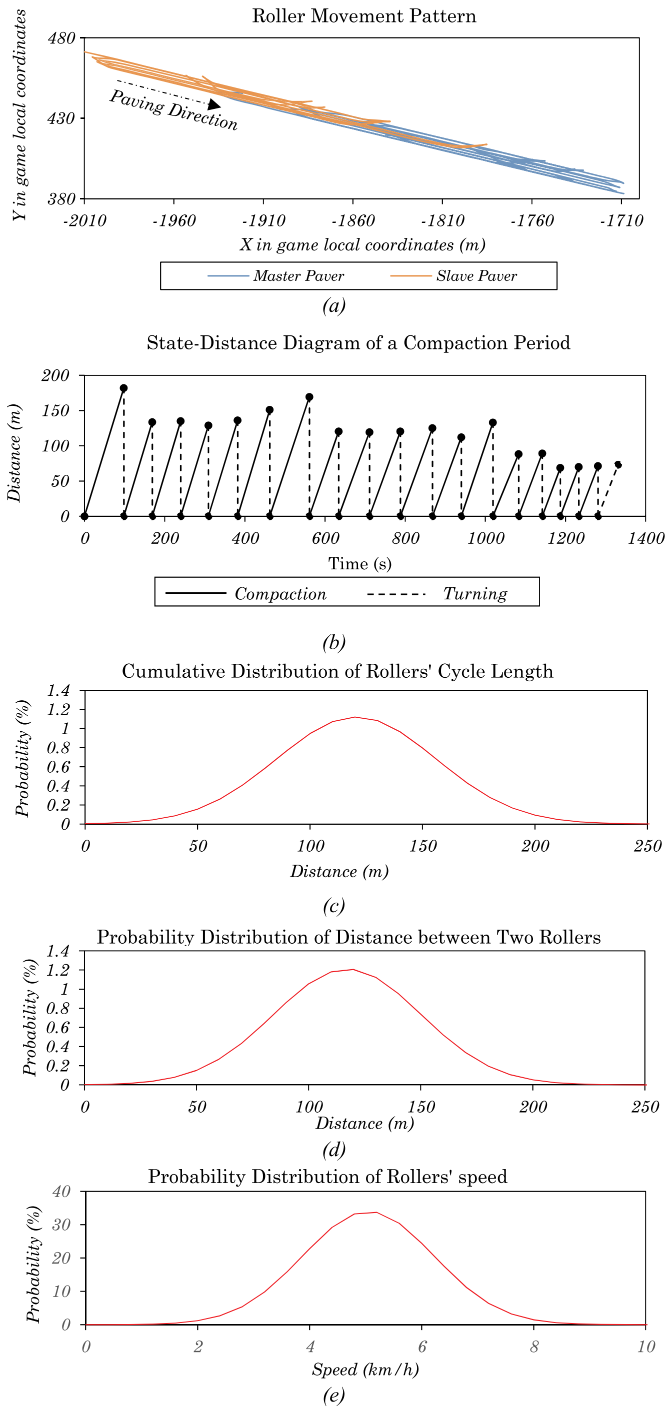


Fig. 15. (a) Example of rollers' movement, (b) State-distance diagram of the sample compaction period, (c) Distribution of rollers' cycle path length, (d) Distribution of distances between two rollers, (e) Distribution of rollers' speed.

the rollers' speed are determined as shown in Fig. 15(c) to (e). Based on the observed patterns and values, an agent is developed for the slave roller. Fig. 16 shows the roller agent developed as an example of equipment agent module. In this Figure, the slave roller waits for the master roller to position itself on the asphalt. Once the master roller starts the compaction, the slave roller as well starts the compaction at a randomly generated distance from the master roller based on the distribution shown in Fig. 15(d). After this, the slave roller starts compacting along the same direction as the master roller for a single cycle. The length of the cycle is determined based on the distribution shown in Fig. 15(c). Once one cycle is complete, the slave roller again checks the

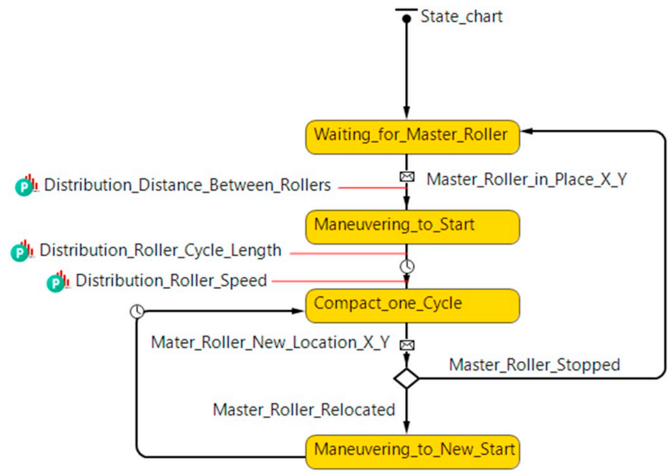


Fig. 16. State diagram of the slave roller.

updated location of the master cycle and repeats the above steps for another cycle. In both scenarios, the mission is to compact all parts of the newly laid asphalt at least thrice. As for the period of simulation, a portion of the total project is selected where the paver was working continuously, i.e., the operation was not disturbed by the arrival of trucks.

Regarding the data-driven physics, the cooling curve of the asphalt is extracted from the collected temperature data, as shown in Fig. 17(a). This curve represents the rate at which the asphalt layer cooled down on this particular site. Based on the input from the project manager, the used asphalt is best compacted at the temperatures between 120 °C and 80 °C. To implement these physics, the Product Module models the asphalt layer as a grid, corresponding to the same grid generated by the data capturing mechanism, as shown in Fig. 17(b). First, the initial temperature of each cell after the placement by the paver is determined based on the collected data. The initial temperature needs to be based on the actual data because its value varies depending on the weather condition, the time between the transportation of the asphalt to the site and placement on the mat, the type of the paver, etc. After the placement of the asphalt layer, each cell cools down based on the cooling curve shown in Fig. 17(a).

Upon the completion of the scenarios, the interaction mode of the simulator is developed. The trainee is immersed in the VR scene using an Oculus Rift. The use of VR kit allows a deeper and wider interaction with the scene, especially for safety purposes, and makes it possible to enforce and monitor shoulder check during the training. The control of the equipment is done through a keyboard. The use of the keyboard is a limitation of the developed prototype and it should be replaced with a joystick in the future. Fig. 18 shows an instance of user interaction with the simulator. The selection of the scenario (i.e., slave or master mode) is done at the inception of the training through a drop-down menu. While the training is running, the compaction contour plot is generated and provided to the operator. This contour plot demonstrates the number of times each part of the asphalt is compacted. For this purpose, a cell-based counter is used to count the number of time a roller collides with (i.e., compacts) each cell. As shown in Fig. 19(a), color coding is used to present the compaction contour plot. The trainee can use this plot to determine which parts of the road still require compaction and how many more passes. Also, the trainee can decide to speed up or slow down based on these inputs. Additionally, the temperature contour plot of the asphalt is provided on a separate smaller window on the scene. Trainees can see this information to determine the current temperature of the asphalt at different parts of the mat, as shown in Fig. 19(b).

At the end of the training session, the Feedback Module provides several types of productivity, safety, and quality-related feedback. Table 2 summarizes all feedback components provided to the trainee.

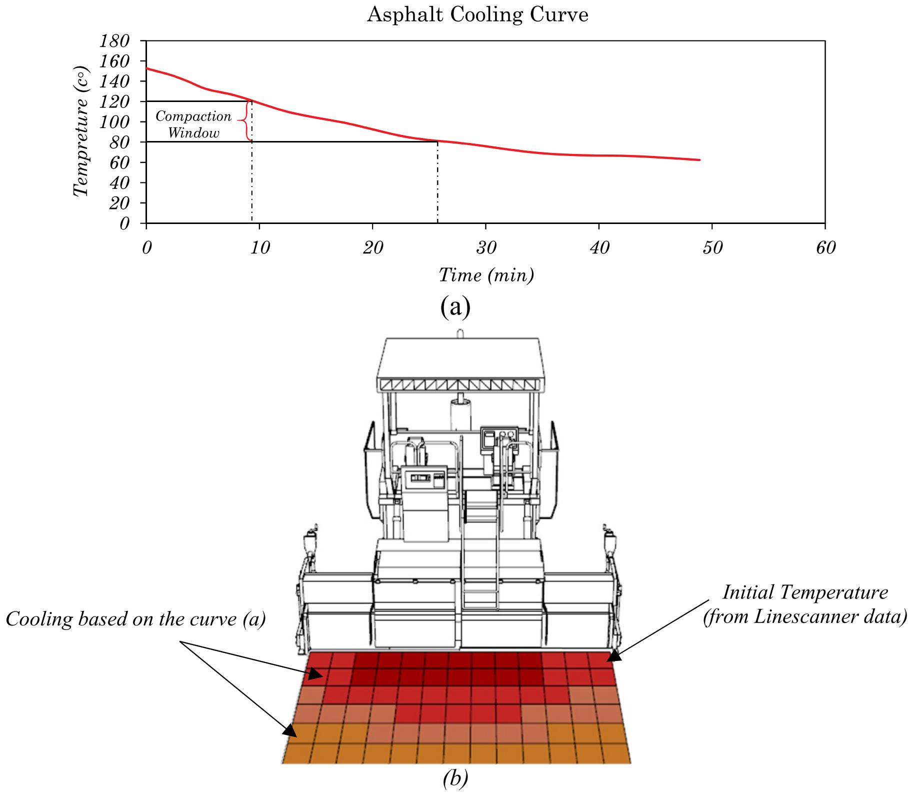


Fig. 17. (a) Data-driven cooling curve of asphalt, and (b) implementation of the cooling physics in the scene.

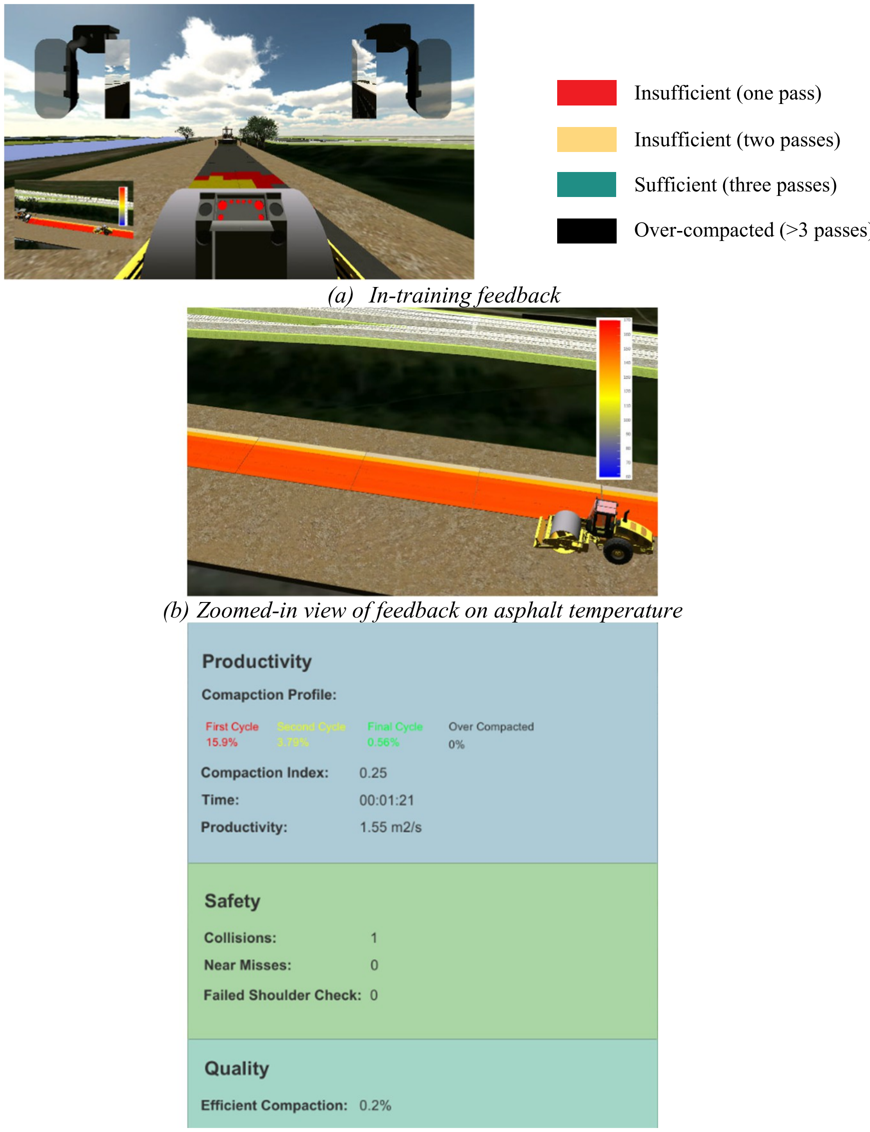
Fig. 18. User interaction with the simulator.

The productivity feedback is concerned with the percentage of different levels of compaction achieved, the average number of passes for the entire road, the training time and productivity. Productivity is defined as the completed compaction area (i.e., cells with three or more passes) divided by the overall time. The safety feedback, on the other hand, focuses on the number of actual collisions, near misses and shoulder check. Fig. 19(c) shows the feedback report provided to the trainees. Quality feedback focuses on the notion of efficient compaction. This index measures how many of the compacted cells received both the first and the last compaction within the temperature window. As an example, the compaction efficiency of 40% suggests that 60% of the cells have received at least one compaction outside the compaction temperature window.

Table 3 presents all the instruments and human capital used for this case study and the associated costs. The most significant investment was manpower. As shown in this table, many of the cost elements are not borne for this project. GPS, thermologger, and linescanner are used mainly in the operator support system of paving equipment to improve productivity and safety. These type of data are now becoming increasingly available through the automated machine guidance and control systems of construction equipment. In this sense, context-realistic simulators can be considered as a by-product of using operator support systems on construction sites. The only exclusive cost-bearing elements of the case study were (a) thermocouples used to capture the core temperature of the asphalt, which amounted to approximately €20, and (b) Oculus Rift, approximately €550. The software suites used for this project are all available freely through educational and personal licenses. The development of the prototype and implementation of the case study took about 160 man-hours. However, this includes the time to develop some of the underlying platforms that can be reused later on for other scenarios (e.g., GPS to motion module in Unity, underlying agent behavior, etc.). While they had some programming background, the development team had mostly very little background in game development, and this represents the ease with which this framework can be implemented without major skills in game development. Having said that, it should be also added that the many of the developed platforms can be used across different scenarios and the time required to prepare new scenarios based on a new set of sensory data will be considerably less. All in all, when the prototype modules are improved to commercial units, the educators are expected to be able to use data available from project with relative ease and low costs.

3.2. Validation

The proposed method and implementation have been validated through a workshop with five training experts form SOMA College. In the workshop, first, a brief overview of the proposed framework was



(a) In-training feedback

(b) Zoomed-in view of feedback on asphalt temperature

(c) Post-training feedback

Fig. 19. Context-based feedback to the trainees.

presented to the instructors. Subsequently, the developed prototype was demonstrated and offered for hands-on trials. Next, instructors were asked to fill a questionnaire to answer a few questions about the context-realistic training simulators. As shown in Tables 4, 10 questions were about scoring the usefulness of different aspects of the proposed training simulator from 1 to 5, representing the range from absolutely useless to very useful. As shown in this table, a strong majority found the use of actual context for training simulator very useful (average score of 4.8). Similarly, a strong majority found the integration between agents and real data useful (average score of 4.5). Overall, the effectiveness of the context-realism in addressing different entry levels of trainees, improving situational awareness, providing more curriculum development flexibility, improving the interface, and preparing the trainees for different types of work were all confirmed with high unanimity. However, although its value is confirmed, there seems to be less consensus on the extent to which context-realistic simulators can contribute to improving teamwork competencies (average score of 4). This can be partially because, as mentioned by the instructors, it is

Table 2
Feedback provided to the trainees.

Category	Feedback	Description
Productivity	Compaction profile	Percentages of cells with no pass, one pass, two pass, and more than two pass
	Compaction Index	Average number of passes for all cells
	Time	The overall time of the training session
	Productivity	Area of cells with two or more number of passes divided by time
Safety	Collisions	Number and instances of collisions with workers and other pieces of equipment
	Near Misses	Number and instances of collisions between safety buffers of the operated equipment and other equipment/workers
	Shoulder Check	Number and instances of failed shoulder check during reverse motions
Quality	Efficient Compaction Index	the ratio of compacted cells that received both the first and the last compaction within the temperature window

Table 3
Costs associated with the case study.

Category	Element	Purpose	Acquired for this project	Cost (approx.)	Cost frequency
Hardware	GPS	Collect location data of equipment	No	€5000	One-off
	Thermologger	Log core temperature data	No	€250	One-off
	Thermocouple	Collect core temperature data	Yes	€20	recurrent
	Linescanner	Collect surface temperature data	No	€40,000	One-off
	Oculus	Create the immersive exposure	Yes	€550	One-off
Software	Unity	Integrate data into VR scene	Yes	Free personal licence	One-off
	Trimble 3D Warehouse	Acquire the 3D models of equipment	Yes	Free	One-off
	Infraworks	Generate the environment	Yes	Free educational licence	One-off
Human capital	Development	Analyze and integrate data	Yes	160 man-hours	recurrent

better to have scenes with a bigger size of the fleet. Also, there seems to be less unanimity about the use of data-driven physics (average score of 4). However, instructors mentioned that they are slightly concerned about the cost and efforts associated with accessing/collecting the product data on the site rather than its applicability for training.

In the final part of the workshop, instructors were asked to score their existing simulators in 5 categories, namely, safety education, teamwork, interface, education design, and versatility (i.e., the ability to reflect on training for different types of job/equipment), so that a comparison can be drawn between the existing and context-realistic simulators. As shown in Fig. 20, the context-realistic simulator scored higher in all categories except versatility. The instructors mentioned that they appreciate the salve-master setting of the prototype and found it a major improvement over existing mostly static scenarios. As for education design, the instructors mentioned that they could see the benefit of the context-realistic simulators in terms of improved freedom and flexibility in curriculum design. However, when it comes to versatility, the instructors believed that the existing simulators are already very versatile and able to address various types of training. However, they appreciated the fact that the proposed framework can generate scenarios from actual data with relative ease. The instructors mentioned that they would really like to experiment with the scene preparation to better judge the ease with which the scenarios can be built.

4. Discussions

The presented work offers the following contributions to the body of knowledge: (1) the functional requirements of context-realistic training simulators are systematically identified and formulated. (2) a systematic framework that elaborates the steps required for the development of context-realistic training simulator is developed. It is shown that the development of data-driven context-realistic training simulators cannot be realized by merely visualizing the raw sensory data in a VR environment; (3) an approach for the integration of site data and computer agents is presented. It is shown that it is feasible to develop realistic agents from the site data and thus ensure that the training scene is coherent and interactable; and (4) an approach for the development of physics from site data is presented. It is shown that site data can be integrated into the VR scene to better mimic how the environment changes with respect to decisions made in the VR scene.

By highlighting the importance, relevance and feasibility of (1) collecting appropriate context data, and (2) developing data-driven agents and physics, this framework can be used by the data science and construction automation community as a roadmap for the future technological needs that can enhance the next generation of training simulators. Also, the framework contributes to the education science community by indicating the new potentials of context-realistic and data-driven simulators and by urging them to further the scope of the requirements from VR training towards instillment of safety education.

From a more practical standpoint, it is evidently shown by the case study that construction training schools can benefit from the proposed new type of simulators to better integrate their safety training with technical training. The proposed framework provides an environment for students to learn about safety issues through learning from their mistakes in the context-realistic VR scenes. Additionally, these simulators can be used to tightly couple in-simulator and on-equipment training. When on-equipment practices are virtualized (1) instructors can review and analyze trainees' performances in VR scenes using safety evaluation criteria that cannot be monitored through visual inspection (i.e., current practice), and (2) trainees can replicate on-equipment practices in the simulator to correct their mistakes. This will result in training schools being able to use their equipment-based training, which is costly and dangerous, in a more effective way.

Finally, the proposed framework offers a systematic approach towards the development of a comprehensive virtual model of actual construction projects that incorporate various levels of implicit (e.g., asphalt temperature and compaction paths) and explicit (e.g., paver motions) data. This virtual model can serve as a digital twin of construction operations that can be used for other purposes such as simulation and optimization of construction operations, safety and productivity analysis of projects, analysis of the root causes of variability in construction operations, and archiving and claim management.

5. Conclusions and future work

This research presented a novel framework for the next generation of training simulators, which focuses more on the context realism, as opposed to photo- or physics-realism. In these simulators, several types of data (i.e., product, actors, process, and environment) are used to develop a context-realistic training simulators. A comprehensive description of the construction context and a detailed description of the framework for the preparation of training simulators was presented. A prototype was developed and a case study was conducted to demonstrate the feasibility of the proposed framework. The developed prototype is presented to a group of operator training experts and it is shown that the context-realistic simulator has a great potential to improve the operator training simulators in various aspects.

It can be concluded that: (1) existing sensing and tracking technologies enable the collection of a wide variety of implicit and explicit data about construction processes, products, environment, and actors; (2) it is shown that the plethora of site data collected from the site can be synthesized into a context-realistic training simulators. It is demonstrated that data analytics approaches can be used to generate inferred knowledge about construction processes and convert this knowledge into computer agents that can replicate the behavior of actual operators. The seamless integration of site lay out, mobility data, data-driven physics, and data-driven agents in context-realistic simulators is fully demonstrated; and finally (3) through a workshop with expert training instructors, it is shown that context-realistic training simulators have several advantages over the existing simulators specially with respect to safety education (i.e., situational awareness), development of teamwork skills and the provision of more immersive and realistic training experience.

There are a number of limitations in this research; (1) the case study

Table 4
Workshop questionnaire and results.

Questions	Number of responses (out of 5 respondents)						Average score (out of 5)
	No response	Absolutely useless (score 1)	Not useful (score 2)	Neutral (score 3)	Somehow useful (score 4)	Very useful (score 5)	
Q1. How much useful is it to reflect the actual context of construction sites in a simulator?					1	4	4.8
Q2. How much useful is the integration of agents with the real data?	1				2	2	4.5
Q3. How much useful is capturing physics from actual data?				2	1	2	4
Q4. How much useful is the context-realistic simulator for better showing the consequences of trainee decisions on the quality of the final product?					1	4	4.8
Q5. How much useful is it to have a customizable level of difficulty (i.e., adjustable level of context-realism)?					1	4	4.8
Q6. How much useful is the context-realistic simulator for helping students develop safety situational awareness? [Safety Education]					2	3	4.6
Q7. How much useful is the context-realistic simulator for teaching coordination and collaborative work? [Teamwork]	1			1	2	1	4
Q8. How much useful is immersive VR (Oculus) for a better training experience? [Interface]	1				2	2	4.5
Q9. How much useful is the context-realistic simulator for helping schools better customize their curriculums? [Education Design]					3	2	4.4
Q10. How much useful is the context-realistic simulator for preparing operators for different types of work and work in different situations? [Versatility]					3	2	4.4

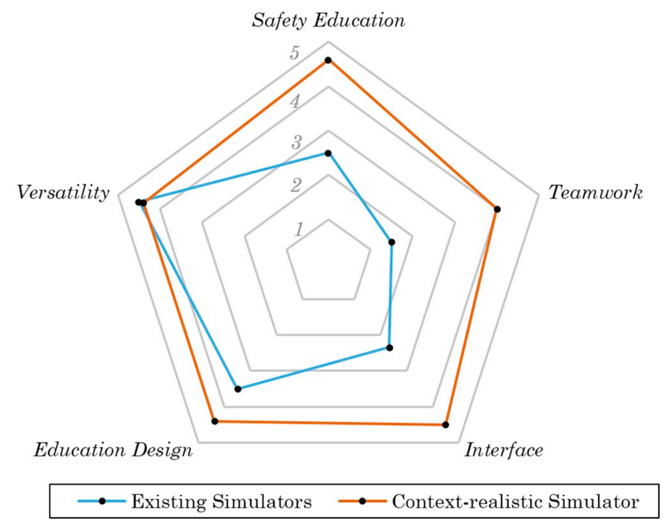


Fig. 20. Comparison of existing and context-realistic simulators.

only used GPS for tracking equipment. In the next step of this research, the full-motion tracking will be applied to more complex earthmoving equipment in the field; (2) in the current version, data to agent conversion was done semi-manually. In the future, the application of machine learning for the development of data-driven agents will be investigated. With a proper data-to-agent method that can capture uncertainties in human behavior accurately, the future context realistic simulators can become entirely agent-driven. In such simulators, data collected from the site will be translated into associated agents for all equipment, be it interacting or non-interacting. Moreover, this framework can be further extended to include scenarios where AMC/G are used. Trainees can use these scenarios to become more acquainted with the interface of this technology and work on semi-robotic sites. Finally, the validation of the context-realistic simulator can be further enhanced by conducting several training sessions with actual trainees.

References

[1] H. Lingard, T. Cooke, E. Gharaie, A case study analysis of fatal incidents involving excavators in the Australian construction industry, Eng. Constr. Archit. Manag. 20 (2013) 488–504, https://doi.org/10.1108/ECAM-08-2011-0073.

[2] U.S. Bureau of Labor Statistics, Census of Fatal Occupational Injuries, http://www.bls.gov/iif/oshwc/cfoi/cfch0013.pdf, (2014) , Accessed date: 12 September 2018.

[3] F. Emuze, J. Smallwood, Construction motor vehicle accidents in South Africa: preliminary findings, In Proceedings of CIB W099 International Conference 2012: Modelling and Building Health and Safety, 2012, pp. 203–208 http://www.irbnet.de/daten/iconda/CIB_DC25813.pdf , Accessed date: 12 September 2018.

[4] W. Wu, H. Yang, D.A.S. Chew, S.-H. Yang, A.G.F. Gibb, Q. Li, Towards an autonomous real-time tracking system of near-miss accidents on construction sites, Autom. Constr. 19 (2009) 134–141, https://doi.org/10.1016/j.autcon.2009.11.017.

[5] Health and Safety Statistics, http://www.hse.gov.uk/statistics/ , Accessed date: 12 September 2018.

[6] B.J.M. Ale, L.J. Bellamy, H. Baksteen, M. Damen, L.H.J. Goossens, A.R. Hale, M. Mud, J. Oh, I.A. Papazoglou, J.Y. Whiston, Accidents in the construction industry in the Netherlands: an analysis of accident reports using Storybuilder, Reliab. Eng. Syst. Saf. 93 (2008) 1523–1533, https://doi.org/10.1016/J.RESS.2007.09.004.

[7] R.A. Haslam, S.A. Hide, A.G.F. Gibb, D.E. Gyi, T. Pavitt, S. Atkinson, A.R. Duff, Contributing factors in construction accidents, Appl. Ergon. 36 (2005) 401–415, https://doi.org/10.1016/J.APERGO.2004.12.002.

[8] C.M. Tam, S.X. Zeng, Z.M. Deng, Identifying elements of poor construction safety management in China, Saf. Sci. 42 (2004) 569–586, https://doi.org/10.1016/J.SSCI.2003.09.001.

[9] A. Suraji, A.R. Duff, S.J. Peckitt, Development of causal model of construction accident causation, J. Constr. Eng. Manag. 127 (2001) 337–344, https://doi.org/10.1061/(ASCE)0733-9364(2001)127:4(337).

[10] C.A. Arboleda, D.M. Abraham, Fatalities in trenching operations—analysis using models of accident causation, J. Constr. Eng. Manag. 130 (2004) 273–280, https://doi.org/10.1061/(ASCE)0733-9364(2004)130:2(273).

[11] J. Hinze, X. Huang, L. Terry, The nature of struck-by accidents, J. Constr. Eng. Manag. 131 (2005) 262–268, https://doi.org/10.1061/(ASCE)0733-9364(2005)131:2(262).

[12] M.J. Burke, S.A. Sarpy, K. Smith-Crowe, S. Chan-Serafin, R.O. Salvador, G. Islam, Relative effectiveness of worker safety and health training methods, Am. J. Public Health 96 (2006) 315–324, https://doi.org/10.2105/AJPH.2004.059840.
[13] J. Tichon, P. Diver, Interactive simulator training in civil construction: evaluation from the trainer's perspective, J. Interact. Learn. Res. 23 (2012) 143–163, https://doi.org/10.1155/2018/5735820.
[14] X. Su, P.S. Dunston, R.W. Proctor, X. Wang, Influence of training schedule on development of perceptual-motor control skills for construction equipment operators in a virtual training system, Autom. Constr. 35 (2013) 439–447, https://doi.org/10.1016/j.autcon.2013.05.029.
[15] Y. Fang, J. Teizer, E. Marks, A framework for developing an as-built virtual environment to advance training of crane operators, Construction Research Congress 2014, American Society of Civil Engineers, Reston, VA, 2014, pp. 31–40, , https://doi.org/10.1061/9780784413517.004.
[16] J.-M. Burkhardt, V. Corneloup, C. Garbay, Y. Bourrier, F. Jambon, V. Luengo, A. Job, P. Cabon, A. Benabbou, D. Lourdeaux, Simulation and virtual reality-based learning of non-technical skills in driving: critical situations, diagnostic and adaptation, IFAC-PapersOnLine 49 (2016) 66–71, https://doi.org/10.1016/J.IFACOL.2016.12.191.
[17] X. Li, W. Yi, H.-L. Chi, X. Wang, A.P.C. Chan, A critical review of virtual and augmented reality (VR/AR) applications in construction safety, Autom. Constr. 86 (2018) 150–162, https://doi.org/10.1016/J.AUTCON.2017.11.003.
[18] A. Perlman, R. Sacks, R. Barak, Hazard recognition and risk perception in construction, Saf. Sci. 64 (2014) 22–31, https://doi.org/10.1016/J.SSCI.2013.11.019.
[19] S.L. Goldberg, B.W. Knerr, Collective training in virtual environments, Virtual Reality, Training's Future? Springer US, Boston, MA, 1997, pp. 41–51, , https://doi.org/10.1007/978-1-4899-0038-8_5.
[20] K.A. Dennis, D. Harris, Computer-based simulation as an adjunct to ab initio flight training, Int. J. Aviat. Psychol. 8 (1998) 261–276, https://doi.org/10.1207/s15327108ijap0803_6.
[21] C.A. Chung, A. Huda, An interactive multimedia training simulator for responding to bomb threats, Simulation 72 (1999) 68–77, https://doi.org/10.1177/003754979907200201.
[22] N.E. Seymour, A.G. Gallagher, S.A. Roman, M.K. O'Brien, V.K. Bansal, D.K. Andersen, R.M. Satava, Virtual reality training improves operating room performance: results of a randomized, double-blinded study, Ann. Surg. 236 (2002) 454–458, https://doi.org/10.1097/01.sla.0000028969.51489.b4.
[23] D.M. Oliveira, S.C. Cao, X. Fernández Hermida, F. Martín-Rodríguez, D.M. Oliveira, F. Martín Rodríguez, Virtual reality system for industrial training, Proceedings of IEEE International Symposium on Industrial Electronics, 2007, pp. 1715–1720, , https://doi.org/10.1109/ISIE.2007.4374863.
[24] M. Cha, S. Han, J. Lee, B. Choi, A virtual reality based fire training simulator integrated with fire dynamics data, Fire Saf. J. 50 (2012) 12–24, https://doi.org/10.1016/J.FIRESAF.2012.01.004.
[25] K.-Y. Lin, J. Son, E.M. Rojas, A pilot study of a 3D game environment for construction safety education, J. Inform. Technol. Constr. (ITcon) 16 (2011) 69–84 http://www.itcon.org/2011/5 , Accessed date: 2 September 2018.
[26] T. Hilfert, J. Teizer, M. König, First person virtual reality for evaluation and learning of construction site safety, Proceedings of 33rd International Symposium on Automation and Robotics in Construction, 2016, https://doi.org/10.22260/ISARC2016/0025.
[27] M. Kassem, L. Benomran, J. Teizer, Virtual environments for safety learning in construction and engineering: seeking evidence and identifying gaps for future research, Vis. Eng. 5 (2017) 16, , https://doi.org/10.1186/s40327-017-0054-1.
[28] A. Sherif, H. Mekkawi, Excavation game: computer-aided-learning tool for teaching construction engineering decision making, J. Prof. Issues Eng. Educ. Pract. 136 (2010) 188–196, https://doi.org/10.1061/(ASCE)EI.1943-5541.0000022.
[29] K. Ku, P.S. Mahabaleshwarkar, Building interactive modeling for construction education in virtual worlds, J. Inform. Technol. Constr. (ITcon) 16 (2011) 189–208 http://www.itcon.org/2011/13 , Accessed date: 2 September 2018.
[30] E. Freund, J. Rossmann, T. Hilker, Virtual reality technologies for the realistic simulation of excavators and construction machines: from VR-training simulators to telepresence systems, International Society for Optics and Photonics, 2001, pp. 358–367, , https://doi.org/10.1117/12.417320.
[31] X. Wang, P.S. Dunston, M. Skiniewski, Mixed reality technology applications in construction equipment operator training, 21st International Symposium on Automation and Robotics in Construction, 2004 (doi:https://doi:10.1.1.475.8091).
[32] R. Sacks, A. Perlman, R. Barak, Construction safety training using immersive virtual reality, Constr. Manag. Econ. 31 (2013) 1005–1017, https://doi.org/10.1080/01446193.2013.828844.
[33] T. Ni, H. Zhang, C. Yu, D. Zhao, S. Liu, Design of highly realistic virtual environment for excavator simulator, Comput. Electr. Eng. 39 (2013) 2112–2123, https://doi.org/10.1016/J.COMPELECENG.2013.06.010.
[34] Y. Fang, J. Teizer, A multi-user virtual 3D training environment to advance collaboration among crane operator and ground personnel in blind lifts, Computing in Civil and Building Engineering (2014), American Society of Civil Engineers, Reston, VA, 2014, pp. 2071–2078, , https://doi.org/10.1061/9780784413616.257.
[35] A. Vasenev, T. Hartmann, S.R. Miller, A.G. Dorée, Visualization environment for reviewing and experimenting with compaction equipment trajectories in context, Adv. Eng. Inform. 30 (2016) 95–108, https://doi.org/10.1016/J.AEI.2016.02.002.
[36] Caterpillar Simulators, https://www.cat.com/en_US/support/operations/operator-training1/simulators.html , Accessed date: 2 September 2018.
[37] Excavator simulator, https://www.hitachicm.eu/excavator-simulator/ , Accessed date: 2 September 2018.
[38] Operator Training Simulators, https://www.deere.com/en/parts-and-service/manuals-and-training/simulators/ , Accessed date: 2 September 2018.
[39] CM Labs Simulations, https://www.cm-labs.com/ , Accessed date: 2 September 2018.
[40] Oryx Simulations, https://www.oryx.se/ , Accessed date: 2 September 2018.
[41] Simlog, https://www.simlog.com/ , Accessed date: 2 September 2018.
[42] Machine Simulators for Education - Tenstar Simulation, https://www.tenstarsimulation.com/en/ , Accessed date: 2 September 2018.
[43] P.S. Dunston, R.W. Proctor, X. Wang, Challenges in evaluating skill transfer from construction equipment simulators, Theor. Issues Ergon. Sci. 15 (2014) 354–375, https://doi.org/10.1080/1463922X.2011.624647.
[44] I.M. Rezazadeh, X. Wang, M. Firoozabadi, M.R. Hashemi Golpayegani, Using affective human-machine interface to increase the operation performance in virtual construction crane training system: a novel approach, Autom. Constr. 20 (2011) 289–298, https://doi.org/10.1016/j.autcon.2010.10.005.
[45] SOMA College, https://www.soma-college.nl/ , Accessed date: 2 September 2018.
[46] D. Dopico, A. Luaces, M. Gonzalez, A soil model for a hydraulic simulator excavator based on real-time multibody dynamics, The Proceedings of the Asian Conference on Multibody Dynamics, The Japan Society of Mechanical Engineers, 2010, pp. 63245–1∼ 63245-9, , https://doi.org/10.1299/jsmeacmd.2010.5._63245-1_.
[47] D. Holz, A. Azimi, M. Teichmann, Advances in physically-based modeling of deformable soil for real-time operator training simulators, 2015 International Conference on Virtual Reality and Visualization (ICVRV), IEEE, 2015, pp. 166–172, , https://doi.org/10.1109/ICVRV.2015.64.
[48] A. Segura, A. Moreno, G. Brunetti, T. Henn, Interaction and ergonomics issues in the development of a mixed reality construction machinery simulator for safety training, Ergonomics and Health Aspects of Work with Computers, Proceedings, Proceedings of International Conference on Ergonomics and Health Aspects of Work with Computers, Berlin, Heidelberg, 2007, pp. 290–299, , https://doi.org/10.1007/978-3-540-73333-1_36.
[49] Y. Fang, Y.K. Cho, F. Durso, J. Seo, Assessment of operator's situation awareness for smart operation of mobile cranes, Autom. Constr. 85 (2018) 65–75, https://doi.org/10.1016/J.AUTCON.2017.10.007.
[50] T. Cheng, J. Teizer, Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications, Autom. Constr. 34 (2013) 3–15, https://doi.org/10.1016/J.AUTCON.2012.10.017.
[51] A. Vasenev, T. Hartmann, A.G. Dorée, Prediction of the in-asphalt temperature for road construction operations, Congress on Computing in Civil Engineering, Proceedings, American Society of Civil Engineers, Reston, VA, 2012, pp. 469–476, , https://doi.org/10.1061/9780784412343.0059.
[52] D.M. Aspari, S.M. Aspari, A.D. Aspari, Developing a real-time process control system for asphalt paving and compaction, in: Proceedings of CROW Infradagen, (2016). http://aspari.nl/uploads/documents/artikelen/2016/D Makarov developing-a-real-time-process-control-system.pdf (accessed September 15, 2018).
[53] A. Alshibani, O. Moselhi, Tracking and forecasting performance of earthmoving operations using GPS data, Proceedings of CME 25 Conference on Construction Management and Economics, 2007, pp. 1377–1388 http://centaur.reading.ac.uk/31329/ , Accessed date: 2 September 2018.
[54] M. Golparvar-Fard, A. Heydarian, J.C. Niebles, Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers, Adv. Eng. Inform. 27 (2013) 652–663, https://doi.org/10.1016/J.AEI.2013.09.001.
[55] M. Memarzadeh, M. Golparvar-Fard, J.C. Niebles, Automated 2D detection of construction equipment and workers from site video streams using histograms of oriented gradients and colors, Autom. Constr. 32 (2013) 24–37, https://doi.org/10.1016/J.AUTCON.2012.12.002.
[56] X. Luo, W.J. O'Brien, F. Leite, J.A. Goulet, Exploring approaches to improve the performance of autonomous monitoring with imperfect data in location-aware wireless sensor networks, Adv. Eng. Inform. 28 (2014) 287–296, https://doi.org/10.1016/J.AEI.2014.08.004.
[57] M.M. Soltani, Z. Zhu, A. Hammad, Skeleton estimation of excavator by detecting its parts, Autom. Constr. 82 (2017) 1–15, https://doi.org/10.1016/j.autcon.2017.06.023.
[58] R. Navon, Research in automated measurement of project performance indicators, Autom. Constr. 16 (2007) 176–188, https://doi.org/10.1016/J.AUTCON.2006.03.003.
[59] J. Teizer, D. Lao, M. Sofer, Rapid automated monitoring of construction site activities using ultra-wide band, 24th International Symposium on Automation and Robotics in Construction (ISARC), 2007, pp. 23–28, , https://doi.org/10.22260/ISARC2007/0008.
[60] T. Jackson, Technology: GPS by the Numbers, https://www.equipmentworld.com/technology-gps-by-the-numbers/ , Accessed date: 2 September 2018.
[61] S. Chae, T. Yoshida, Application of RFID technology to prevention of collision accident with heavy equipment, Autom. Constr. 19 (2010) 368–374, https://doi.org/10.1016/J.AUTCON.2009.12.008.
[62] C. Zhang, A. Hammad, S. Rodriguez, Crane pose estimation using UWB real-time location system, J. Comput. Civ. Eng. 26 (2012) 625–637, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000172.
[63] L. Song, N.N. Eldin, Adaptive real-time tracking and simulation of heavy construction operations for look-ahead scheduling, Autom. Constr. 27 (2012) 32–39, https://doi.org/10.1016/j.autcon.2012.05.007.
[64] R. Akhavian, A.H. Behzadan, An integrated data collection and analysis framework for remote monitoring and planning of construction operations, Adv. Eng. Inform. 26 (2012) 749–761, https://doi.org/10.1016/J.AEI.2012.04.004.

[65] A.H. Behzadan, V.R. Kamat, Georeferenced registration of construction graphics in mobile outdoor augmented reality, J. Comput. Civ. Eng. 21 (2007) 247–258, https://doi.org/10.1061/(ASCE)0887-3801(2007)21:4(247).

[66] N. Pradhananga, J. Teizer, Automatic spatio-temporal analysis of construction site equipment operations using GPS data, Autom. Constr. 29 (2013) 107–122, https://doi.org/10.1016/j.autcon.2012.09.004.

[67] E. SUN, A. NIETO, Z. LI, GPS and Google Earth based 3D assisted driving system for trucks in surface mines, Min. Sci. Technol. (China) 20 (2010) 138–142, https://doi.org/10.1016/S1674-5264(09)60175-7.

[68] Y. Tan, Operations modeling and analysis of open pit, Proceedings of the Winter Simulation Conference, 2012, pp. 1309–1320, , https://doi.org/10.1109/WSC.2012.6465062.

[69] A. Montaser, O. Moselhi, Tracking scraper-pusher Fleet operations using wireless technologies, Proceedings of 4th Construction Specialty Conference, 2013 https://www.researchgate.net/publication/282076511 , Accessed date: 2 September 2018.

[70] L.Y. Ding, C. Zhou, Q.X. Deng, H.B. Luo, X.W. Ye, Y.Q. Ni, P. Guo, Real-time safety early warning system for cross passage construction in Yangtze Riverbed Metro Tunnel based on the internet of things, Autom. Constr. 36 (2013) 25–37, https://doi.org/10.1016/J.AUTCON.2013.08.017.

[71] H. Li, G. Chan, J.K.W. Wong, M. Skitmore, Real-time locating systems applications in construction, Autom. Constr. 63 (2016) 37–47, https://doi.org/10.1016/J.AUTCON.2015.12.001.

[72] F. Vahdatikhaki, A. Hammad, H. Siddiqui, Optimization-based excavator pose estimation using real-time location systems, Autom. Constr. 56 (2015) 76–92, https://doi.org/10.1016/j.autcon.2015.03.006.

[73] J. Teizer, M. Venugopal, A. Walia, Ultrawideband for automated real-time three-dimensional location sensing for workforce, equipment, and material positioning and tracking, Transp. Res. Rec. 2081 (2008) 56–64, https://doi.org/10.3141/2081-06.

[74] E. Rezazadeh Azar, B. McCabe, Part based model and spatial–temporal reasoning to recognize hydraulic excavators in construction images and videos, Autom. Constr. 24 (2012) 194–202, https://doi.org/10.1016/J.AUTCON.2012.03.003.

[75] J. Yang, P. Vela, J. Teizer, Z. Shi, Vision-based tower crane tracking for understanding construction activity, J. Comput. Civ. Eng. 28 (2014) 103–112, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000242.

[76] M. Williams, D. Schofield, B. Denby, The development of an intelligent haulage truck simulator for improving the safety of operation in surface mines, in: J.-C. Heudin (Ed.), Virtual Worlds, Springer Berlin Heidelberg, Berlin, Heidelberg, 1998, pp. 337–344.

[77] C.-W. Liu, T.-H. Wu, M.-H. Tsai, S.-C. Kang, Image-based semantic construction reconstruction, Autom. Constr. 90 (2018) 67–78, https://doi.org/10.1016/J.AUTCON.2018.02.016.

[78] U. Isikdag, S. Zlatanova, Towards defining a framework for automatic generation of buildings in CityGML using building information models, 3D Geo-Information Sciences, Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 79–96, , https://doi.org/10.1007/978-3-540-87395-2_6.

[79] R. de Laat, L. van Berlo, Integration of BIM and GIS: the development of the CityGML GeoBIM extension, Advances in 3D Geo-Information Sciences, Springer, Berlin, Heidelberg, 2011, pp. 211–225, , https://doi.org/10.1007/978-3-642-12670-3_13.

[80] C. Mignard, C. Nicolle, Merging BIM and GIS using ontologies application to urban facility management in ACTIVe3D, Comput. Ind. 65 (2014) 1276–1290, https://doi.org/10.1016/J.COMPIND.2014.07.008.

[81] Esri CityEngine, https://www.esri.com/en-us/arcgis/products/esri-cityengine/overview , Accessed date: 3 September 2018.

[82] InfraWorks, https://www.autodesk.com/products/infraworks/overview , Accessed date: 2 September 2018.

[83] City of Montreal, http://donnees.ville.montreal.qc.ca/ , Accessed date: 2 September 2018.

[84] T.H. Kolbe, Representing and exchanging 3D city models with CityGML, 3D Geo-Information Sciences, Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 15–31, , https://doi.org/10.1007/978-3-540-87395-2_2.

[85] D.-I. Bodo Randt, D.-I. Frank Bildstein, T.H. Kolbe, Use of virtual 3D-landscapes for emergency driver-training, Proceedings of the International Conference on Visual Simulation IMAGE, 2007 http://www.redaktion.tu-berlin.de/fileadmin/fg227/Publications/IMAGE2007-RDE-DrivingSim-5-Letter.PDF , Accessed date: 2 September 2018.

[86] F. Vahdatikhaki, A. Hammad, L.L. olde Scholtenhuis, S.R. Miller, D. Makarov, Data-driven scenario generation for enhanced realism of equipment training simulators, Proceedings of 6th CSCE/CRC International Construction Specialty Conference, 2017 (doi:9781510865358).

[87] H.C. Pham, A. Pedro, T. Le Quang, D.-Y. Lee, C.-S. Park, Interactive safety education using building anatomy modelling, Univ. Access Inf. Soc. 1 (2017) 1–17, https://doi.org/10.1007/s10209-017-0596-y.

[88] A. Hammad, F. Vahdatikhaki, K. El-Ammari, Conceptual framework of training simulator for heavy construction equipment integrating sensory data, actual spatial model, and multi-agent system, Proceedings of 16th International Conference on Computing in Civil and Building Engineering, 2016 http://www.see.eng.osaka-u.ac.jp/seeit/icccbe2016/Proceedings/Full_Papers/205-149.pdf , Accessed date: 2 September 2018.

[89] D.W. Halpin, L.S. Riggs, D.W. Halpin, Planning and Analysis of Construction Operations, Wiley, 0-471-55510-X, 1992.

[90] J. Song, C.T. Haas, C. Caldas, E. Ergen, B. Akinci, Automating the task of tracking the delivery and receipt of fabricated pipe spools in industrial projects, Autom. Constr. 15 (2006) 166–177, https://doi.org/10.1016/J.AUTCON.2005.03.001.

[91] F. Vahdatikhaki, A. Hammad, Framework for near real-time simulation of earthmoving projects using location tracking technologies, Autom. Constr. 42 (2014) 50–67, https://doi.org/10.1016/j.autcon.2014.02.018.

[92] D.S. Makarov, F. Vahdatikhaki, S.R. Miller, A.G. Dorée, A methodology for real-time 3D visualization of asphalt thermal behaviour during road construction, Advances in Informatics and Computing in Civil and Construction Engineering, Springer International Publishing, Cham, 2019, pp. 797–804, , https://doi.org/10.1007/978-3-030-00220-6_96.

[93] S. Singh, State of the art in automation of earthmoving, J. Aerosp. Eng. 10 (1997) 179–188, https://doi.org/10.1061/(ASCE)0893-1321(1997)10:4(179).

[94] R. Delgadillo, H.U. Bahia, Effects of temperature and pressure on hot mixed asphalt compaction: field and laboratory study, J. Mater. Civ. Eng. 20 (2008) 440–448, https://doi.org/10.1061/(ASCE)0899-1561(2008)20:6(440).

[95] Oculus, https://www.oculus.com/ , Accessed date: 2 September 2018.

[96] F. Vahdatikhaki, A. Hammad, Dynamic equipment workspace generation for improving earthwork safety using real-time location system, Adv. Eng. Inform. 29 (2015) 459–471, https://doi.org/10.1016/j.aei.2015.03.002.

[97] Trimble, Transforming the Way the World Works, https://www.trimble.com/ , Accessed date: 2 September 2018.

[98] PDOK, https://www.pdok.nl/ , Accessed date: 2 September 2018.

[99] P. Bhattacharya June, MSc Thesis in Geomatics Quality Assessment and Object Matching of OpenStreetMap in Combination with the Dutch Topographic Map TOP10NL, http://www.gdmc.nl/publications/2012/Object_matching_OpenStreetMap_TOP10NL.pdf, (2012) , Accessed date: 2 September 2018.

[100] Unity, https://unity3d.com/ , Accessed date: 2 September 2018.

[101] 3D Warehouse, https://3dwarehouse.sketchup.com/?hl=en , Accessed date: 2 September 2018.

[102] K. Peffers, T. Tuunanen, M.A. Rothenberger, S. Chatterjee, A design science research methodology for information systems research, J. Manag. Inf. Syst. 24 (2007) 45–77, https://doi.org/10.2753/MIS0742-1222240302.