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Published in:
Journal of Industrial Information Integration

DOI:
10.1016/j.jii.2021.100282

Published: 01/05/2022

Document Version
Publisher's PDF, also known as Version of record

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Please cite the original version:
Sierla, S., Azangoo, M., Rainio, K., Papakonstantinou, N., Fay, A., Honkamaa, P., & Vyatkin, V. (2022). Roadmap to semi-automatic generation of digital twins for brownfield process plants. *Journal of Industrial Information Integration*, *27*, Article 100282. https://doi.org/10.1016/j.jii.2021.100282

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Journal of Industrial Information Integration 27 (2022) 100282

Contents lists available at ScienceDirect

Journal of Industrial Information Integration

journal homepage: www.sciencedirect.com/journal/journal-of-industrial-information-integration

Roadmap to semi-automatic generation of digital twins for brownfield process plants

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ARTICLE INFO

Keywords:
Digitization
Industry4.0
Digital twin
Brownfield process plants
Automatic model generation
Simulation model

ABSTRACT

Industrial process plants have a lifecycle of several decades, and only some of the most modern plants have digital, machine-readable design information available. For all other plants, the information is often available in PDF and other human-readable formats. Based on this information, a digital twin could be constructed only with considerable human effort. There is a need for a methodology for the semi-automatic generation of digital twins for brownfields with such source information. The objective of this paper is to propose a roadmap towards a methodology for the semi-automatic generation of digital twins for brownfields with such source information as can be expected to be available for brownfields. The purpose of the roadmap is to: conceptualize the methodology, position relevant previous work along this methodology and identify further research challenges to develop the industrial applicability of the methodology. It was discovered that numerous relevant works exist, some of which do not specifically address brownfields. However, there is a lack of research to integrate such research to a methodology for the generation of digital twins.

1. Introduction

Industrial process plants have a lifecycle of several decades, and only some of the most modern plants have digital, machine-readable design information available [1]. For all other plants, the information is often available in PDF and other human-readable formats. Based on this information, considerable human effort would be required to construct a digital twin. Plant owners and operators may not be willing to invest such resources, even if there is genuine interest for a digital twin. Thus, there is a need for a methodology for the semi-automatic generation of digital twins for brownfields with such source information. A digital twin is a replica of a physical entity: through real-time transmission of data, a counterpart of the physical entity exists seamlessly in the virtual world and can be used for various value-adding applications [2]. In this proposal, a *brownfield* is defined as an operating plant, which has existing physical structures and legacy software systems, for which the design information cannot be assumed to be in digital format. A greenfield in contrast has no such limitations.

The objective of this paper is to propose a roadmap towards a methodology for the semi-automatic generation of digital twins for brownfields with such source information as can be expected to be available for brownfields. The purpose of the roadmap is to:

1 Conceptualize the methodology.
2 Position relevant previous work along this methodology.
3 Identify further research challenges to develop the industrial applicability of the methodology.

Fig. 1 shows our proposal for the methodology. The photograph, the P&ID (Piping & Instrumentation Diagram) in the top left corner and the 3D computer-aided design (CAD) model in the upper right corner are from the 'Water process' laboratory process described in e.g. [3–5]. The proposed methodology consists of 9 steps, which are summarized here and elaborated in section III:

1 A 3D model is generated based on a point cloud obtained by LiDAR scanning. The point cloud is processed to identify component types,

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https://doi.org/10.1016/j.jii.2021.100282
Received 27 May 2020; Received in revised form 21 April 2021; Accepted 30 August 2021
Available online 2 September 2021
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component parameters and 3D locations. The obtained information is digitized to a machine readable format.
2 2D image recognition is used to detect labels, symbols and connections from a scanned pdf-format P&ID. The obtained information is digitized to a machine readable format.
3 The completeness and correctness of the digitized 2D and 3D information needs to be validated, and these two sets of information need to be merged to a single information model that can be later used to generate the twin. Graph matching will be used for this purpose.
4 Humans are required to provide the information to parts of the plant model that could not be matched with high confidence. An augmented reality application is developed to give unsophisticated users the necessary context information and an easy user interface to enter the required information.
5 The completed and validated data model can be used to generate a digital P&ID. This differs from the P&ID generated in Step 2, since data from other sources has been integrated, the data has been validated by cross-checking across different data sources, and by requesting human input in Step 4.
6 A dynamic simulation model is generated automatically from the plant data model generated in Step 5. In this context, dynamic refers to the capability of the model to investigate the impact of transients such as set-point changes or equipment faults. Examples of suitable simulation packages are Apros [3–5], MATLAB/Simulink [6–8] and Modelica [9,10]. Some of the data sources such as the scanned P&ID are design time data. Other data sources reflect a more recent configuration; for example, the 3D model corresponds to the state of the process when the laser scanning was made.

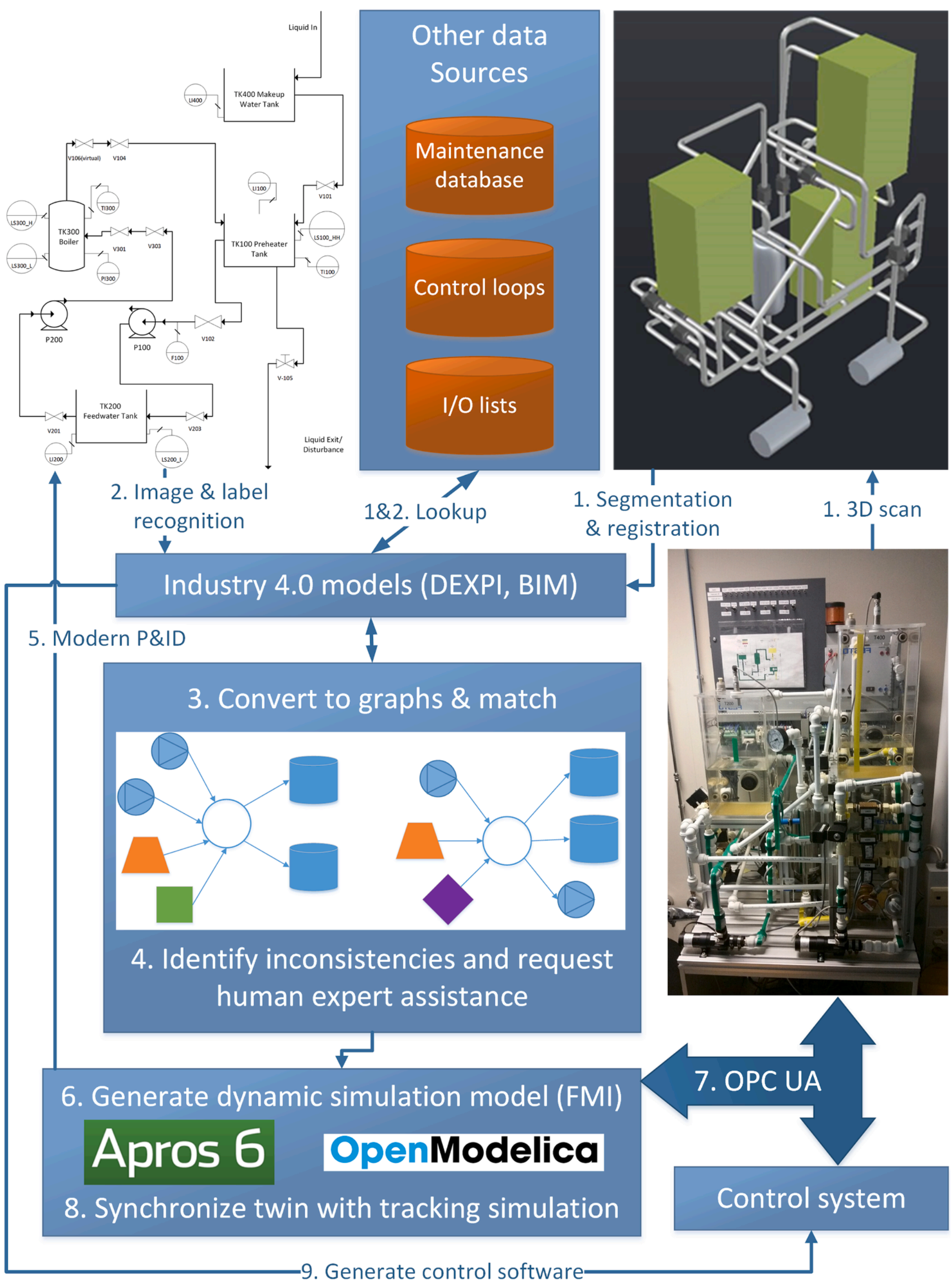

Fig. 1. Proposal for generating digital twins of brownfield process plants. After Step 8, the dynamic simulation model (in a tool such as Apros or OpenModelica) has become a digital twin.

7 OPC UA has been developed as a reference architecture to align standards in the context of Industry 4.0 machine-to-machine communication [11]. In this work, it is used to interface the generated model with the control system. In the case of a brownfield plant, a control system exists. It is now possible to run the control system against the simulation model. Additionally, OPC UA is used to interface the physical process.
8 The real-time sensor information from the physical process makes it possible to extend the dynamic simulation model generated in Step 6 to a digital twin that is synchronized with the physical process.
9 Although it is reasonable to expect that a legacy control system exists at a brownfield plant, there are several use cases that would motivate the generation of a new control system from the digital plant model generated in Step 4.

This paper is structured as follows. Section 2 reviews related research about brownfield industrial plants and automatic generation of digital twins. Section 3 presents our proposal for each of the 9 steps of the methodology in Fig. 1. Existing work relevant to these steps is presented, literature relevant to the specific step is reviewed and remaining challenges are identified. Section 4 concludes a paper by listing challenges for further research related to this methodology.

2. Related research

Models are necessary for all advanced process plants to anticipate the behavior of systems, design stable controllers and optimize the functionality of the systems. However, different modeling approaches and interfaces, combined with the lack of standardization, are obstacles to interoperability between models of different aspects of a process plant [10]. These challenges are especially topic in the era of big data. Recent developments in telecommunication technologies [12] and Industrial Internet of Things (IIoT) [13] will pave the way for more efficient data collection. The new infrastructure can provide added value for dealing with complex situations [14] and producing personalized products [15].

Industry 4.0 is driving the adoption of digital twins from different industries such as: manufacturing [16,17], port and maritime industry [18], civil industries [19], process industries [20,21], supply chain [22], healthcare industry [23,24]. There are different approaches for creating digital twins based on physical modeling, data-driven modeling and hybrid twins, which are created through the combination of big data, physics based modeling and data-driven modeling [25].

The majority of research on digital factories assumes a greenfield situation, even though this is not stated explicitly by the authors (e.g. [26–29]). However, brownfield approaches are economically, politically and environmentally preferable if they can be made technically feasible with reasonable engineering effort [30]. Indeed, according to ABB's keynote speaker Alf Isaksson at IEEE International Conference on Industrial Informatics, digitalization of existing industrial plants requires new technology to reduce the engineering effort that is involved [31]. The body of research that considers the constraints encountered at brownfield industrial plants is limited and scattered. Sorensen et al. [32] propose a concept of a manufacturing system that is able to evolve with changing product requirements while explicitly respecting the constraints resulting from the need to use a brownfield production facility. Point clouds obtained from 3D scanning of factories have been used to determine whether a layout is collision free [33], but this does not result in the necessary level of digitalization to accurately captures components and their connections. Illa and Padhi [34] propose an architecture and methodology for upgrading a legacy factory to Industrial Internet, but they do not consider the legacy design information. Most relevant to this project is the work in extracting knowledge from legacy documentation of industrial plants [35], although the authors themselves point out that further research is needed to obtain high fidelity plant models.

Several authors have addressed the problem of automatic generation of digital twins without specifically considering the additional challenges encountered at a brownfield site. Possible sources of information for the automatic generation of a digital twin of a process system are listed in [3], which source documents such as P&ID diagrams, automation IO lists, 3D plant models and equipment datasheets are considered as raw material for creating a simulation model. [36] Introduces an automated solution for developing and improving a low fidelity digital twin from high level requirements available at the initial design phase of the system. [3] presents an automatic solution for generating simulation based digital twins of industrial process plants from 3D models. [20] proposes 7-step semi-automatic methodology for generation of a steady state digital twin of a brownfield process plant from P&ID. [37] developed an automated methodology to integrate the abstract graph model of the plant from digital P&ID and 3D CAD model of the system. To integrate such models, [38] presents an automatic method to match 2D engineering drawing and 3D models of the process plant by converting them into attribute graphs and calculating the level of similarity and matching degree. Rantala et al. [39] applied graph matching techniques for reuse of process plant design information.

The automatic generation of the process plant model is not limited to the simulation models. Son et al. [40] propose a comprehensive methodology for reconstruction of as-built 3D static industrial instrumentation models for brownfield process plants from 3D laser-scan data in combination with available sources of information such as a 3D CAD database and P&ID documents. Similarly, Lee et al. [41] present an automated solution to generate an as-built 3D static pipeline model consisting of straight pipes, elbows, and tee pipes from laser-scan data. Although these are not fully fledged digital twins, they are some of the closest state of the art methods for automatic generation of process plant models from the available source information.

3. Proposed methodology for semi-automatic generation of digital twins for brownfields

The Sections 3.1–3.9 elaborate the Steps 1–9, respectively, of the methodology proposed in Section 1.

3.1. Generation of a 3D plant model

Due to the long lifecycle of process plants, design documentation often does not accurately reflect the as-built configuration. Several approaches have been proposed in recent years exploiting recent advances in scanning technologies. In [42], results of indoor scans with an infrared structured light 3D device, as an alternative technology to LiDAR and available at low-cost, are reported. The results show high accuracy at certain types of materials, but depend on the material of the surface of the scanned objects, as infrared waves can be reflected, absorbed or distorted at glassy, plastic or polished objects [42]. The majority of works is based on LiDAR. Lindskog et al. [43] aim at an accurate visualization of the plant for a human viewer. Further work combining additional technologies is needed to identify specific process components from the point clouds. Erdős et al. [44] and Meidow et al. [45] describe approaches that do not assume the availability of 3D CAD models of the process components.

A 3D model is generated based on a point cloud obtained by LiDAR scanning. The point cloud needs to be processed with segmentation and classification techniques in order to identify specific component types (e.g. tank or pump), component parameters (e.g. tank width, height and location of nozzles), 3D locations and connections between components (e.g. pipes, cables or wires). An industrial process is a cluttered environment (see e.g. Fig. 2), so accomplishing this task fully automatically with point cloud processing techniques is not feasible, considering the current state of the art [46]. Thus, our proposal involves a combination of techniques and lightweight human involvement. It is a quick task for a human to place markers on key equipment and to update these codes to the maintenance database. Then, by scanning and locating these markers, and by matching the data from the maintenance database

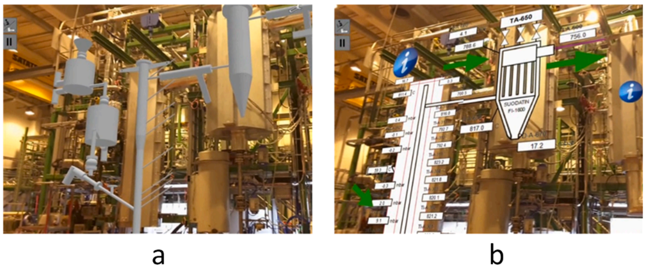

Fig. 2. 3D model that was generated manually (a), related augmented reality application (b).

('other data sources' in Fig. 1), it is possible to get the exact component type and configuration parameters. By building some tool support to a 3D CAD, it is further possible to automatically generate an accurate 3D CAD model of the equipment. Feature extraction and shape analysis methods are used to make semantic segmentation of the 3D point cloud in order to extract pipes, tanks, valves and other repetitive structures. Machine learning and 3D registration methods are used to recognize and match these 3D CAD models with the segmented point clouds. Our relevant previous work is presented in Fig. 3. This augmented reality application can be adapted to the factory environment to match 3D CAD equipment models with the 3D point cloud

3.2. Generation of a 2D plant model

Convolutional Neural Networks (CNN) are largely responsible for artificial intelligence based image recognition methods outperforming conventional methods. Recent applications in industrial context include part classification [47,48] generation of training data for part classification [49,50], surface defect detection [51,52], product inspection [53, 54], explainable artificial intelligence for product inspection [55], process quality monitoring [56], inspection of industrial processes [57,58], pipeline crack detection in brownfield plants [59].

Very few works have applied deep learning approaches such as CNNs to extract information from scanned P&IDs of brownfield process plants. Already before the era of deep learning, established approaches existed for the analysis of engineering drawings [60,35] was an early work on optical recognition of brownfield P&IDs and Sinha et al. [61] perform optical character recognition for the tabular, rather than the graphical, part of the P&ID. Few works have emerged very recently applying CNNs to P&ID diagrams. Moreno-García et al. [62] discuss the application of CNNs to analyze P&IDs, but implementation is left for further work. Rahul et al. [63] present a CNN for digitizing a P&ID, but do not address the problem of the high level of manual work for labeled training data collection, which has been an argument against machine learning based approaches [64]. A pre-trained CNN such as Yolo still needs thousands of P&ID diagram specific labeled training examples. In recent work [65], these were created automatically by extracting them from artificially generated P&ID diagrams. Such diagrams do not have to be functional designs. It is enough to put components in random positions on the diagram, with random orientation and scaling. Thus, we experiment to see if such supervised learning data can be used to retrain Yolo to find components in PI-diagrams. The Apros dynamic process simulator was used to generate the artificial diagrams, using its application programming interface that supports automatic creation and configuration of diagrams (e.g. [3,66]). 2000 P&ID diagrams were generated randomly, in them 7 types of objects. 1500 diagrams were used for training, 500 for testing.

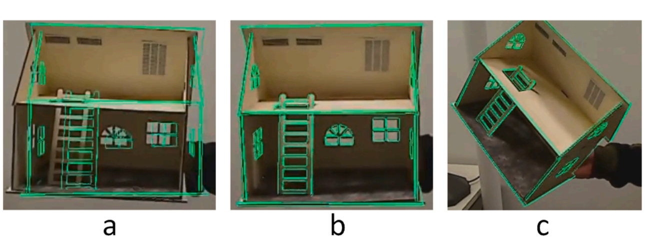

Fig. 3. Our real-time capable augmented reality application for matching 3D models: (a) before matching (b) after matching (c) updated in real-time.

The results presented in this section have been obtained by applying the methodology in [65]. Fig. 4 shows the results of applying this pretrained Yolo network to an image. The image was created by randomly generating some P&ID components to an APROS diagram and by exporting the diagram as PDF, which is the expected format for P&ID diagrams in brownfield plants. The successfully matched components have a bounding box and a label. It is notable from Fig. 4 that the solution works well for large components but failed to detect small components.

With this first implementation, components have to be above 10% of page size (in both *X* and *Y* directions) to be detectable. To work around the size limitation of the components, we tested dividing the original diagram into smaller, partly overlapping squares. Each partial image square was zoomed (up to 400% of the test diagram) so that the components are big enough for detection. Detection of small components from these partial images was successful, although a separate Yolo detector had to be trained for this purpose. Another problem was found: If a component is trained without any texts inside, but it appears in the diagrams with texts inside it, the component is not detected. Therefore, one bitmap is not enough for such components, many variations of such components with random texts inside should be generated for training. In further research, we intend to combine this approach with the works of Arroyo et al. [35], which were able to correctly identify valves, pumps, tanks and other equipment in scanned P&IDs even in the case of distortions and partially overlapping bounding boxes.

For line detection we used the OpenCV 3 (Open Source Computer Vision Library: http://opencv.org) function *LineSegmentDetector*. Fig. 5 shows the results of applying this technique to an image, which was obtained by taking a screen shot of a PDF format P&ID diagram of a brownfield plant, provided by an industrial partner. The two edges of thick lines are detected as separate lines, and this can be handled later in the post-processing. Multiple zoom levels were used, as was described above for component testing.

Further work involves taking the identified P&ID components and lines and storing them in an Industry 4.0 standard digital format. One such format is the DEXPI specification, which is broadly supported by major P&ID tool vendors [67]. Following the method described in [35], it is possible to assign labels found on P&IDs in the proximity of items such as valves, pumps, tanks, pipes, to the respective items at a high accuracy, by employing semantic knowledge from P&ID standards. Based on the detected P&ID item labels, it is possible to augment the information by querying from 'other data sources' in Fig. 1.

3.3. Cross-validation of digitized 2D and 3D models with graph matching techniques

Considering the lack of uniform naming conventions throughout the lifecycle of industrial process plants, it cannot be generally assumed that the 3D and 2D models created in Steps 1 and 2 will have tags, labels or other kinds of identifiers that support straightforward identification of the same process component from the various information sources. To overcome this problem, our proposal uses graph matching to identify corresponding process components from the 3D and 2D models created in Steps 1 and 2. Before matching, the XML representations of the 2D and 3D models need to be converted to graphs. This will abstract away information such as layouts and pipe routing, so graph matching techniques can be effectively applied to identify the corresponding components. P&IDs have been analyzed regarding structure and connectivity with methods based on graphs, as reported by Arroyo et al.

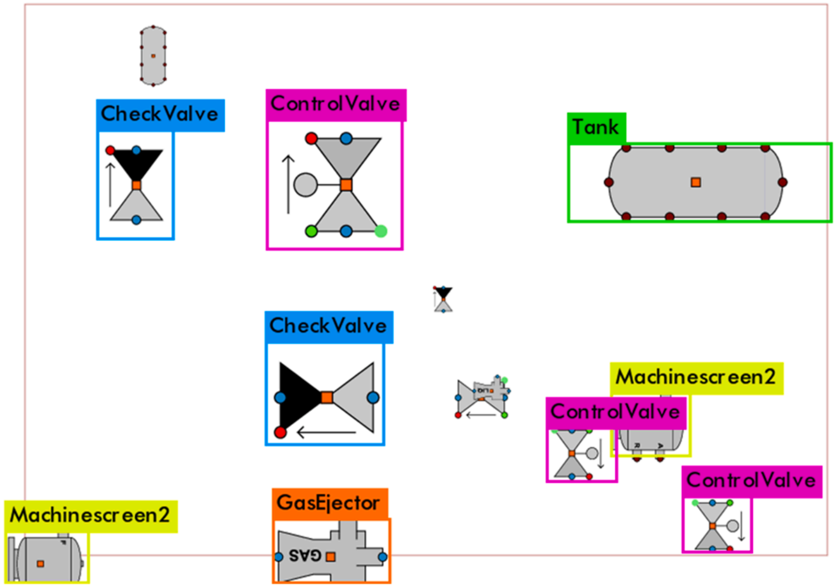

Fig. 4. Results of applying our pre-trained Yolo network to detect some randomly generated P&ID diagram components.

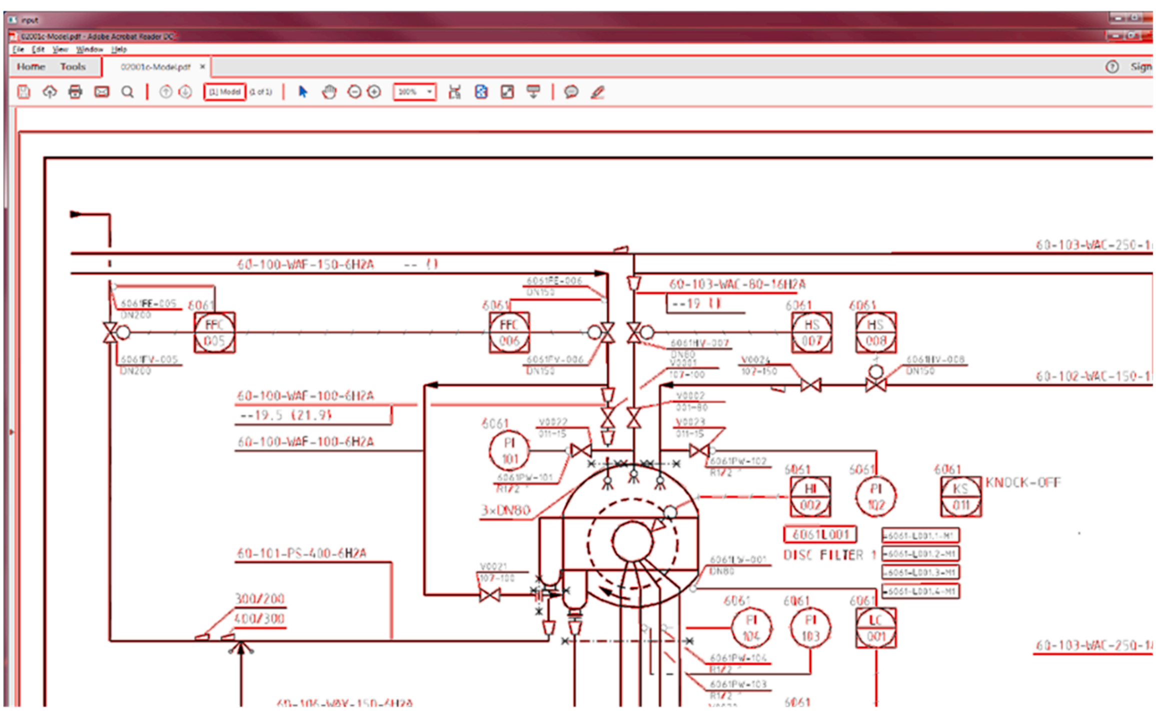

Fig. 5. Screenshot of a test P&ID diagram, in which the detected lines are highlighted with red (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

[68], but graph matching has not yet been applied for this purpose. However, in previous work, Rantala et al. [39] found that graph matching techniques are practically applicable to brownfield process plant design information. In our proposed methodology, graph matching will be used to match major process components such as tanks and pumps in the 2D and 3D models discussed in Sections 3.1 and 3.2. It will also be investigated whether smaller process components such as pipes can be matched accurately. Further research is also needed to develop a metric to capture the confidence at which specific parts of the graphs have been matched. Furthermore, it should be taken into account that the P&ID of a plant describes the "as-planned" status or, if properly adjusted during commissioning and handover, the "as-built" status, whereas the 3D model resembles the "as-is" status, including manifold changes which take place during operation and maintenance and which are rarely properly documented in 2D models.

3.4. Semi-automatic digital plant model completion with augmented reality

The 3D model is augmented with information from the 2D models for each part of the model that could be matched with high confidence in Step 3. It is especially expected that the 2D model, which originated from a P&ID, will have information related to control loops not present in the 3D model from Step 1. This results in a unified plant model with some gaps, related to any parts that could not be matched with high confidence. The augmented reality application in Step 4 in Section 1.1 will visualize the 3D CAD model, 2D plans and other information overlaid on the real-world factory system, so it can be used to identify the component or subsystem, which could not be matched in task 3. Our preliminary work is shown in Fig. 2b. The user will be prompted to enter the missing information through this application. Possible implementation approaches are the simultaneous localization and tracking technologies that are built in the mobile devices (e.g. ARCore & ARKit). The initialization of the tracking can be based on 6-DoF visual localization that is based on hierarchical matching of both global and local features that are learned from the RGB images collected during the LiDAR scanning.

Existing work on augmented reality in Industry 4.0 [69] can benefit from explicit consideration of the facility layout [70], which would be an important consideration for retrofits. The extracted 3D information in Section 3.1. permits further work to this end. The integration of 3D industrial process information with the facility layout would enable the incorporation of real-time location systems [17] to digital twins.

3.5. Generation of an Industry 4.0 P&ID diagram

After the unified digital plant model has been created from several sources in Step 4, it is possible to generate a more complete digital P&ID than in Step 2. A digital, standards compliant P&ID is essential for automating various innovative engineering workflows such as the following. A machine-readable source model is a hard requirement for any MDE (Model Driven Engineering) approach: Koltun et al. [71] and Leon and Falk [72] perform MDE to generate control software and human machine interfaces, respectively, from a digital P&ID. In order to evaluate piping layouts, Tan et al. [73] transforms a P&ID into a special data structure, a histogram of connectivity; the creation of such a data structure could be automated if a digital P&ID is available. Sierla et al. [74] generate a 3D pipe routing automatically based on the connection information in a digital P&ID. Christiansen et al. [75] and Landman et al. [76] combine connectivity information from a P&ID with process causality information for fault diagnosis. Schleburg et al. [77] apply connectivity information from a P&ID to detect causal relations of alarms, to better manage alarm floods.

3.6. Dynamic simulation model generation

In this paper, a dynamic simulation model refers to a first-principles model that can be used to investigate transient behavior, for example related to set point changes [5], equipment malfunction [78,79] or environmental disturbances [80]. Barth and Fay [81] have shown how a simulation model can be automatically generated on the basis of a structural model of a plant which is similar to the ones described in Section 3.2. This automatically generated model has proven to be suitable for qualitative tests of the control code, e.g. whether a level controller operates in the correct direction. The method has been applied successfully in the Oil & Gas industry [82]. However, the model generated by the approach of Barth and Fay [81] had no access to information about the geometry of tanks and pipes and, therefore, could not provide a model for a quantitative simulation.

Since the digital plant model created in Step 5 has detailed information such as equipment heights and dimensions, sufficient source information is available for the modeling task. In particular, details on pipe routing are dimensions are required in order to accurately capture thermo-hydraulic behavior [83]. Martinez et al. [5] automated the modeling task by using the proprietary application programming interface of a CAD tool, and compared the outputs of the generated simulation model with sensor measurements from a physical laboratory process (Fig. 6). Further research is needed for building an open, standards compliant solution. The FMI (Functional Mock-up Interface) is a promising standard for this purpose. FMI defines a tool-independent standard for exchanging models and running standalone simulation tools [84].

3.7. Real-time integration

There is a lack of a universal definition for a digital twin, so it is unclear whether the industrial process control system is part of the virtual part of the digital twin [2]. In the case of a brownfield plant, there is a legacy control system that has not been developed within the digital twin paradigm. Thus, each article should be explicit about how these terms are used. In this article, the control system is treated as being separate of the digital twin and the virtual part of the digital twin is a simulated counterpart of the physical process. The integration of a digital twin to an information architecture requires an explicit definition of the communicating entities and the information flows between them. These aspects are often not treated explicitly and thoroughly in the literature, as Koulamas and Kalogeras [2] point out. For example, Martinez et al. [4] explicitly discuss these details. Fig. 7 provides an example of an information architecture for a digital twin with two use cases: soft sensors and process optimization. The former is about retrieving process state variables from the digital twin for parts of the process for which there is no physical sensor: for example the temperature in a pipe which has no temperature sensor. The latter can involve running the virtual aspect of the digital twin faster than in real time in

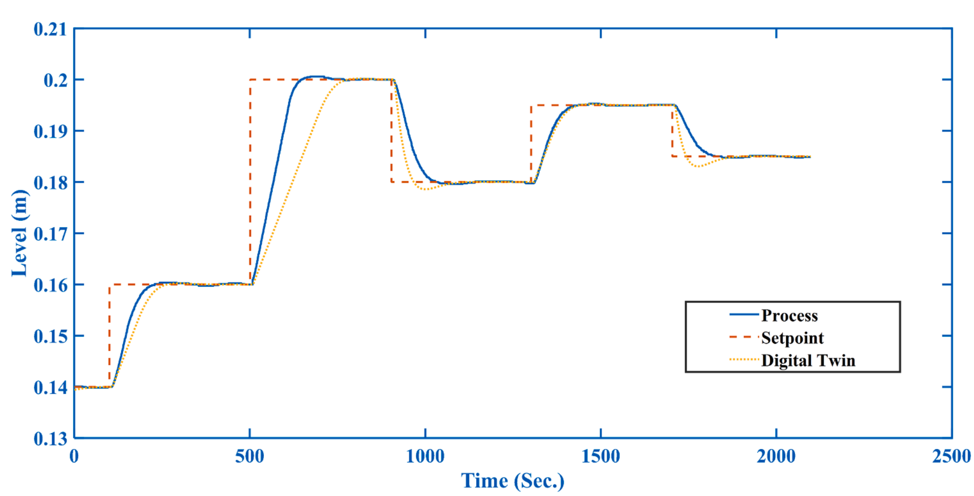

Fig. 6. Surface level of tank 200. Comparison of results between the automatically generated model and the physical process. Transients are caused by a change in the level set point of tank 200.

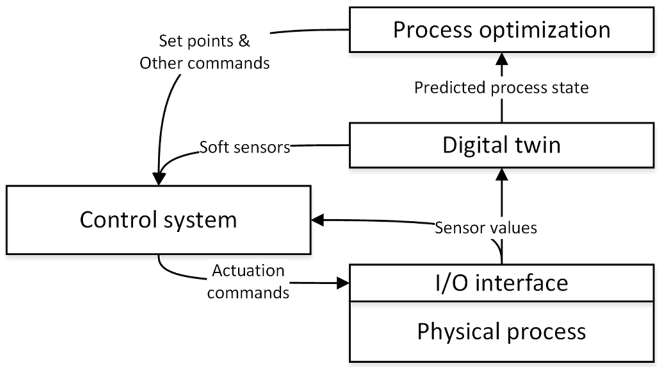

Fig. 7. Conceptual information architecture for a digital twin.

order to determine the outcome of running the process for the next hours under specific operating conditions: this can be used to determine an optimal process operation strategy before sending set points and other commands such as sequencing commands to the control system. Fig. 7 makes explicit several characteristics of the information architecture, such as the digital twin not being able to affect the physical process in any way that by passes the control system. Such a characteristic might not part of any universally accepted definition of a digital twin that may emerge after this article is published. However, such characteristics should be made explicit, so that they are understood in the same way by the developer of the information architecture as well as the other experts building and using the digital twin.

A conceptual information architecture such as the one in Fig. 7 should be realized in the context of relevant technology standardization, such as Reference Architecture Model Industry 4.0 (RAMI 4.0) developed by BITCOM (the German Association for IT, Telecommunications and New Media), VDMA (Mechanical Engineering Industry Association) and ZVEI (German Electrical and Electronic Manufacturers' Association), standardized internationally by the IEC (International Electrotechnical Commission) [85] and expected to be utilized broadly in Europe [86] and beyond, especially in China [87]. The aspect of the RAMI 4.0 architecture that is directly relevant to the information architecture in Fig. 7 is the OPC UA (Open Platform Communications Unified Architecture), which manages the heterogeneity of devices from different vendors [88,89] and supports information integration across the system lifecycle from design to operation [90], as required by the concept proposed in this article. Another major reference architecture is the Industrial Internet Reference Architecture (IIRA) developed by the US-led Industrial Internet Consortium (IIC) and standardized by the OMG (Object Management Group). An attempt to align RAMI 4.0 and IIRA has been undertaken [91]. While IIRA has received little academic attention, it includes a DDS (Data Distribution Service) specification, which has been applied especially in the context of Cyber-Physical Production systems [92–94]. DDS has similar capabilities as OPC UA [95,96], so it is an alternative for standardizing an information architecture concept such as the one in Fig. 7. Koulamas and Kalogeras [2] explicitly recognize both IIRA and RAMI 4.0 as relevant standardized architectures into which digital twins could be integrated.

The integration of digital twins to factory systems should be considered in the context of the ongoing trend of replacing the automation pyramid architecture with novel architectures [97] such as cloud based CPS (Cyber-Physical Systems) [98], Enterprise Application Integration (EAI) [99] and Reference Architecture Model Industry 4.0 (RAMI 4.0) [100]. Our work aligns partially with 'layers' dimension of RAMI 4.0 through the use of OPC UA. However, further work on extracting subprocesses corresponding to control loops could serve as a starting point to integrate this approach to the 'hierarchy levels' dimension of RAMI 4.0 [101]. This article has focused on the generation of a digital replica of the physical process, and is complemented by the work in [102] for integrating such a replica to plant floor systems with traditional or novel IoT architectures. The ongoing work on designing, synthesizing and integrating digital twins is motivated by the increasing need for virtual validation of industrial process and other cyber-physical systems [103].

3.8. Synchronizing a digital twin with tracking simulation

The simulation model is augmented to a digital twin with a tracking simulator that synchronizes the state of the simulator against measurements from the physical process [4]. Our lab scale results of applying this methodology to Fig. 6 are presented in Fig. 8. In further work, the synchronized digital twin can be integrated to the augmented reality application (preliminary version in Fig. 2b) in order to provide the user real-time information of the process state.

However, [3] has been demonstrated to be accurate only in certain process regions that were effectively synchronized between the digital twin and the physical process. One direction for further research to overcome this issue would be the integration of system identification methods [104] that have recently been applied to digital twins [105], in order to complement the first-principles modeling approach used in this article.

3.9. Control system generation

Brownfield plants have a legacy control system, which could be used together with a digital twin, such as the tracking simulator described in Section 3.8 and integrated through the information architecture described in Section 3.7. However, in many cases it can be desirable to undertake automation system modernization in conjunction with the effort of building the digital twin. MDE is a feasible approach for keeping the control software up to date with the digital P&ID specifications, as described in Section 3.5. Drath et al. [106] have shown the possibility of generating interlock control code from P&ID content that is available in the XML standard format IEC 62424 digital P&ID. [67] demonstrates control software generation conforming to the PLCopen XML standard, using as source information an ISO 15926 digital P&ID. Further work on integrating the digital twin and the generated control system includes establishing cyber-physical traceability linkages [107] from the specifications described in Section 3.5 to the digital twin described in Section 3.6, the physical components extracted as in Section 3.1, and the control system described in this section.

4. Conclusion and further work

The objective of this paper was stated in Section 1 as follows: "to propose a roadmap towards a methodology for the semi-automatic generation of digital twins for brownfields with such source information as can be expected to be available for brownfields". A list of 4 purposes was specified for the roadmap in Section 1. The first purpose, the development of a concept for the methodology, was addressed by the 9-step methodology outlined in Section 1. The second purpose, the positioning of previous works within the context of this methodology, was elaborated in Section 3. The third purpose of the roadmap was to identify further research challenges to develop the industrial applicability of the methodology. The challenges are identified in this section corresponding to the steps of the proposed methodology in Fig. 1:

1. What are the limitations of component identification methods from point clouds in a cluttered plant environment with difficult geometries such as long pipes with many elbows?
2. To what extent and accuracy can legacy P&ID diagram digitalization be automated with respect to small graphical elements, lines and text?
3. What is the most suitable abstraction level for graph matching of 3D and 2D design information?

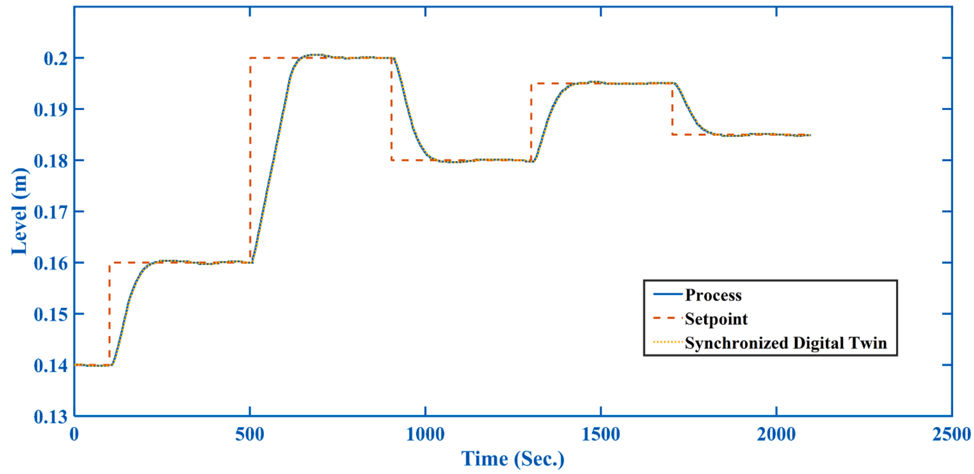

Fig. 8. Surface level of tank 200. Comparison of results between the automatically generated Digital Twin and the physical process. Transients are caused by a change in the level set point of tank 200.

4 What kind of metric could be defined for the confidence of digitalization of 3D and 2D brownfield plant information?
5 Can the industrial applicability be demonstrated by generating DEXPI format that is successfully imported by state-of-the-art tools?
6 How can dynamic process simulation models be generated in a standards compliant way?
7 What architecture can be used to non-disruptively integrate a digital twin to brownfield plants with various degrees of Industry 4.0 readiness in their legacy systems?
8 In what process operating regions are soft sensors from a digital twin trustworthy?
9 How can formalized requirements traceability be generated as a by-product of Steps 1–8?

CRediT authorship contribution statement

Seppo Sierla: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mohammad Azangoo:** Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Kari Rainio:** Conceptualization, Visualization, Writing – original draft. **Nikolaos Papakonstantinou:** Conceptualization, Visualization, Writing – original draft. **Alexander Fay:** Conceptualization, Investigation, Methodology, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Petri Honkamaa:** Conceptualization, Visualization, Writing – original draft. **Valeriy Vyatkin:** Conceptualization, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was partially supported by the Business Finland project SEED (4153/31/2019). Business Finland was not involved in the research beyond financial support. Otherwise this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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