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Automatic Generation of a High-Fidelity Dynamic Thermal-Hydraulic Process Simulation Model From a 3D Plant Model

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ABSTRACT Dynamic thermal-hydraulic simulation models have been extensively used by process industry for decision support in sectors, such as power generation, mineral processing, pulp and paper, and oil and gas. Ever-growing competitiveness in the process industry forces experts to rely even more on dynamic simulation results to take decisions across the process plant lifecycle. However, time-consuming development of simulation models increases model generation costs, limiting their use in a wider number of applications. Detailed 3-D plant models, developed during early plant engineering for process design, could potentially be used as a source of information to enable rapid development of high-fidelity simulation models. This paper presents a method for automatic generation of a thermal-hydraulic process simulation model from a 3-D plant model. Process structure, dimensioning, and component connection information included in the 3-D plant model are extracted from the machine-readable export of the 3-D design tool and used to automatically generate and configure a dynamic thermal-hydraulic simulation model. In particular, information about the piping dimensions and elevations is retrieved from the 3-D plant model and used to calculate head loss coefficients of the pipelines and configure the piping network model. This step, not considered in previous studies, is crucial for obtaining high-fidelity industrial process models. The proposed method is tested using a laboratory process, and the results of the automatically generated model are compared with experimental data from the physical system as well as with a simulation model developed using design data utilized by existing methods on the state of the art. Results show that the proposed method is able to generate high-fidelity models that are able to accurately predict the targeted system, even during operational transients.

INDEX TERMS 3D CAD model, 3D plant model, automatic model generation, first-principles model, process modeling, process simulation, thermal-hydraulic model.

I. INTRODUCTION

Thermal-hydraulic simulation models are used for calculating thermodynamic properties of hydraulic flow [1]–[3]. They are based on first-principles models (FPMs), which rely on rigorous engineering, physics and chemical relations to represent the behavior of the modeled system [4], [5]. Simulation models based on FPMs can be static or dynamic. Static simulation models describe a system without the time

dimension, thus they can only determine time-independent system response to a specific set of inputs [6]. In contrast, dynamic FPMs can be used to study the transient responses of a process to expected and unexpected disturbances in order to improve the design, control, operation, and safety of the process [7]. During the last decades, simulation results of dynamic thermal-hydraulic simulation models have been extensively used for different applications of industrial

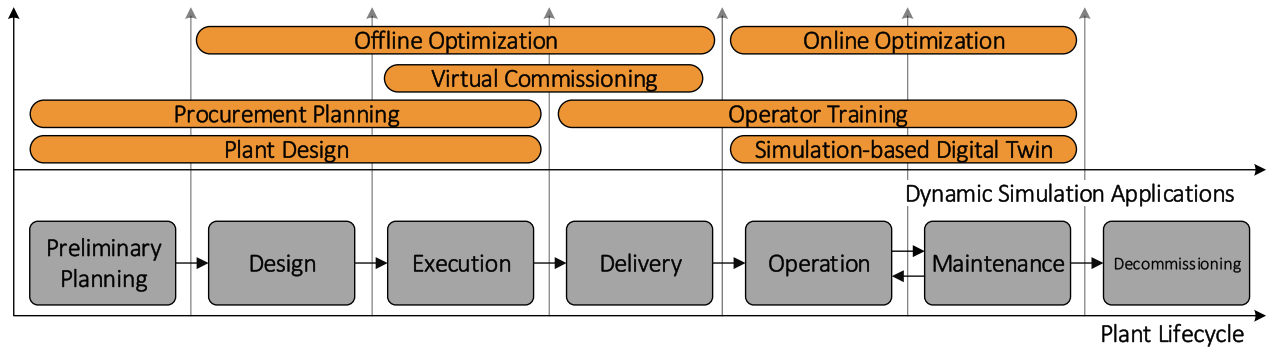


FIGURE 1. Conceptual diagram of the dynamic simulation model applications over the process plant lifecycle.

process plants in sectors such as power generation, mineral processing, pulp and paper, and oil and gas. Examples of these applications range from engineering support [8]–[10] and operation planning [11]–[13] to offline and online process optimization [4], [14], [15]. Dynamic thermal-hydraulic simulation models have become highly important for strategic decision making across the process plant lifecycle [16], [17].

Since thermal-hydraulic models are based on FPMs, they capture a higher detail of process information compared to similar alternatives based on data-driven modeling [16]. Data-driven models are those focused on finding relations between the inputs and outputs of a system based only on the data captured of such system. In contrast, FPMs can provide reliable performance estimates even before the physical system has been built and before its data has been collected [18]. Consequently, dynamic thermal-hydraulic models are essential for a number of important simulation-based applications over the plant lifecycle, as shown in Fig. 1, even during early lifecycle phases when the plant has not been commissioned or operated. However, developing FPMs can be time-consuming and expensive compared to data-driven alternatives [16]. Although re-use of existing models can help addressing issues related to the maintainability of industrial models [19]–[21], the laborious maintenance and expensive development of FPMs limit wider industrial adoption of these systems [16].

Automatic model generation (AMG) has been identified as a promising approach for further research to overcome these shortcomings of FPMs [22]. Existing AMG methods use data from engineering sources that are accessible during the process design phase. These sources include piping and instrumentation diagrams (P&ID), equipment technical data sheets and control application configuration [20], [23], [24]. However, it is not possible to generate accurate dynamic thermal-hydraulic FPMs without information on the physical dimensions of the process equipment and the process pipeline network. In particular, key parameters for such FPMs are the head loss coefficients which represent head losses due to elbows or branches in the pipelines. These parameters can be calculated only from detailed information of the structure and dimensions of curved pipe segments [25].

Since it is desired that the model is available during early lifecycle stages when the physical plant has not been built, this information can be obtained only after a 3D pipe routing has been accomplished [26]. Information available from 3D computer assisted design (CAD) models of the plant could potentially be used in combination with other engineering data to automatically generate process simulation models. Therefore, the objective of this paper is the following:

- To propose a novel AMG method which exploits 3D plant model information for enabling rapid and efficient development of high-fidelity thermal-hydraulic simulation models in order to increase industrial adoption of simulation-based tools and applications.

In this work, the data included in the 3D plant model is used for calculating piping sections lengths, elevations as well as head loss coefficients of the pipeline network, and to automatically generate a thermal-hydraulic model within a commercial simulation platform. As a result, the fidelity of the simulation model is increased compared to the one obtained following existing state-of-the-art-methods. The proposed method is demonstrated with a laboratory process system. This paper is structured as follows. Section II provides an overview of related work. Section III presents the proposed AMG methodology. The implementation of the proposed method is presented in Section IV and the results are shown in Section V. The conclusions and future work are finally presented in Section VI.

II. RELATED WORK

A. DEVELOPMENT OF SIMULATION MODELS IN PROCESS INDUSTRIES

The development of industrial FPMs is a complex task which generally involves three stages [16]. First, engineering, physics or chemical descriptions of the system are obtained. This is followed by the development of the model of the process to be controlled in the targeted simulation tool. Finally, the model development is completed with model initialization. During initialization, an initial solution of the model equations based on a nominal set of input parameters and simulation variable values is obtained [27].

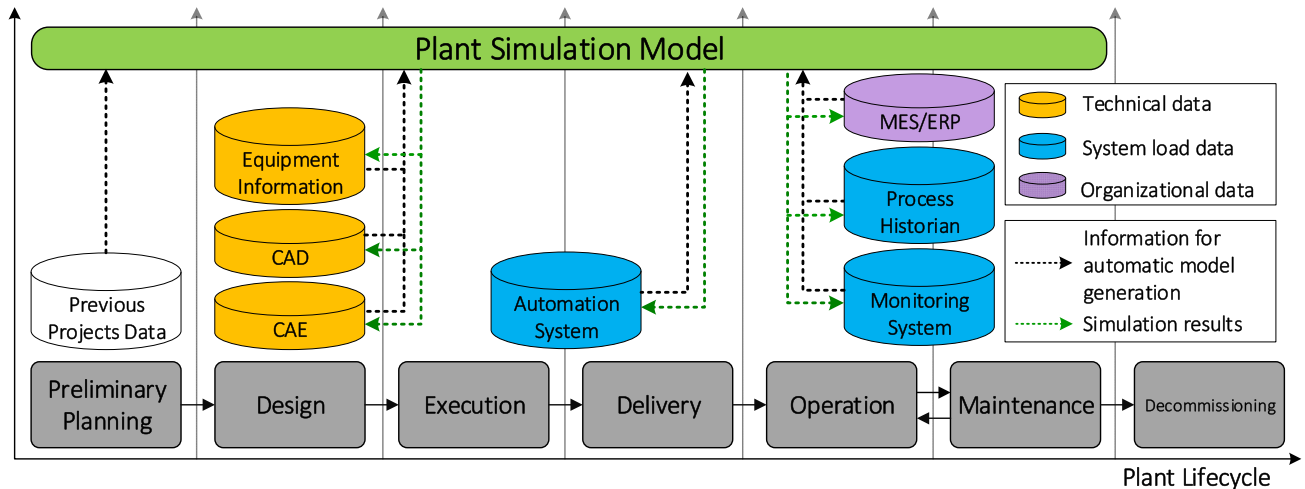


FIGURE 2. Conceptual diagram showing the data sources availability for automatic model generation during the plant lifecycle and their classification.

Model development complexity varies according to the application and it is dependent on the characteristics of the solver utilized by the simulation tool [28]–[30]. Simulation tools are classified according to the solver used for calculating model variables as simultaneous modular (SM) or as equation oriented (EO) [16], [31]–[33]. In SM tools, process units and streams are solved in a specific sequence starting with the input feed streams. In contrast, in EO tools, the model does not have a fixed solution directionality. As a result, it can be handled as a set of equations to be solved simultaneously [18], [34]. The study in [35] presents a thorough comparison between EO and SM approaches. Model development tradeoffs between EO and SM approaches are related to the amount of effort needed to achieve model initialization [36], [37].

Regardless of the solution method utilized by the chosen tool, simulation models of industrial processes are typically generated manually using flowsheet-based simulation environments [23], [38], [39]. These environments consist of graphical user interfaces for dragging and dropping process unit simulation components into a model configuration canvas, where they can be connected according to the structure of the process that is being modeled [40]. In these tools, model configuration of every component is carried out manually. Model configuration refers to the steps required to provide parameters that represent the real system to every model component. In this work, model components are all the elements that comprise the simulation model including models of process equipment, piping network and thermal-hydraulic points (TH points). A major advantage of flow-sheet-based modeling environments is that the model development can be collaboratively carried out by teams of process experts that are not necessarily familiar with the underlying simulation language. Additionally, industrial flow-sheet-based simulation environments commonly offer script-based configuration languages which can be used to speed-up the creation of

simulation model components as well as their configuration. Furthermore, the model structure can be easily explored with the graphical representation of the process. However, because these models are still generated manually, development and maintenance of industrial applications based on FPMs is still laborious and expensive [19], [41]–[43]. This makes FPMs less attractive than lower fidelity options based on data-driven approaches, which can be developed with lower engineering effort [16], [44].

B. AUTOMATIC MODEL GENERATION

AMG has been identified as a possible direction for further research to increase cost-efficiency and to reduce development and maintenance time of FPMs [22], [26]. AMG approaches use information mapping algorithms to generate a simulation model based on the targeted system information [27]. These algorithms automatically map the accessed data into the model logic specified by the simulation language utilized [45].

AMG can utilize different data sources. These sources become available in different phases of the plant lifecycle, as shown in Fig. 2. For this reason, the availability of data sources determines how early in the lifecycle it is possible to apply the automatic generation method. In the manufacturing systems domain, information sources for AMG have been classified based on the type of information they provide as *Technical*, *System Load* and *Organizational* [46]. No similar classification has been proposed for process plants, for which there are additional sources from which historical information of process dynamics and critical operating regions data can be obtained. Fig. 2 extends the classification presented in [46]. Based on our previous research in industrial process simulation [22], [47], [48], Fig. 2 places the data sources availability in the corresponding phases of the process plant lifecycle. This is significant because, as Fig. 2 shows, if the generation method is to be applied before the

plant commissioning, it should rely exclusively on *technical* data sources.

AMG methods generally follow implementation techniques classified in [49] as *Parametric*, *Structure* and *Hybrid-knowledge-based*. In *Parametric* methods, models are generated by connecting simulation components stored in simulation libraries. Simulation components are further configured based on nominal parameters available from process information repositories [50]. In *Structural* methods, model generation is based on data describing the structure and layout information of a system, available from relevant CAD and engineering systems [51]. *Hybrid-knowledge-based* methods combine *Parametric* and *Structural* approaches. *Hybrid-knowledge-based* techniques are a common approach followed by existing AMG approaches, as detailed information of the plant is seldom available only in parametric or only in structural data sources [23], [51]–[53].

A number of different AMG methods for industrial applications have been proposed. Some of the earliest implementation examples come from the manufacturing domain. In [54], a conceptual framework for the generation of simulation models from graph-based process plants and resource configurations is proposed. Similarly, in [40], [55], and [56], the proposed model generation methods are carried out through the use of libraries of simulation model components. Since the methods in [40] and [54]–[56] have been developed for manufacturing applications, they use discrete-event models, in which the operation of a system is captured as a discrete sequence of events in time. This limits their application for AMG of thermal-hydraulic industrial processes in domains such as petrochemical processes, mineral processing, heat and power generation and pulp and paper production, which require continuous models to track the system dynamics over time.

In the industrial process domain, there have been some efforts on the automatic generation of control application programs for virtual commissioning. Virtual commissioning refers to the use of computational simulation technology to test the automation system functionality during the execution and delivery phases of the plant lifecycle (see Fig. 2) before the plant operation is started [42]. In [57], a method for automatic generation of PLC (Programmable Logic Controller) control programs from simulation library components is proposed. In [19], a method for control application model development based on the re-use of interoperable simulation units [58] is presented. In [51], the automatic generation of the control application model is carried out using data from an already-operating plant. These AMG techniques are targeted mostly for the design and testing of the automation system. However, because virtual commissioning takes place during execution and delivery phases of the plant lifecycles, these methods are not applicable for plant engineering at the design phase. Moreover, they focus on the development of control application programs and not on the generation of the simulation model of the process to be controlled.

Automatic generation of simulation models already before the commissioning phase is desired, as the models available during the process design can be utilized in a wider number of applications during later stages, thereby increasing their cost-efficiency [35], [43], [59]. Additionally, early phase simulation is key for performance optimization at the system level rather than at the subsystem level [60]. As previously explained, AMG of industrial process models at the process design phases must be based on engineering data. Therefore, existing research on AMG during the process design [20], [23], [53], [61] focuses on automatic generation of process simulation models based on engineering data. In these studies, model generation is carried out using computer assisted design and engineering (CAD/CAE) systems. This information includes P&ID and data sheets of process equipment. However, pipeline network information from these sources is limited only to the piping sections diameters. Piping lengths, elevations and structure information is mandatory for configuring the model head loss coefficients of pipelines [25].

In recent decades, pushed by trends in the construction industry, process engineering and procurement companies have started developing 3D models of industrial production plants. These models are developed during plant engineering for designing and dimensioning plant facilities, processes and equipment [62]. Recently, 3D models of process plants have been developed automatically from engineering data [26], [63], [64] and applied during operation and maintenance phases for virtualization of the plant [17], [51]. Information available from 3D plant models could potentially be used for simulation model generation. In particular, pipeline route layout information available from 3D plant models could be used for obtaining lengths, elevations and structure of the piping network to calculate head loss coefficients. However, the utilization of 3D model information has only been suggested for finite-element-based flow calculations [23], [52] and no example implementation of this approach is available. Moreover, there has not been any implementation example which exploits 3D model information for AMG of dynamic thermal-hydraulic FPMs, from which information of the plant operation transients could be obtained for different important industrial applications such as engineering support, control application design, operation planning and process optimization.

In contrast, this paper presents an AMG method which utilizes information from the 3D plant model to automatically generate a dynamic thermal-hydraulic process simulation model. Although it is possible to manually search and retrieve the information from a 3D model or CAD drawings of the modeled process, often this work is considered too laborious, and thus, rough estimates are used for model configuration. Therefore, the proposed AMG method aims to reduce model development effort thereby increasing industrial adoption of applications based on thermal-hydraulic simulation models.

In particular, in this work 3D pipe routing information is utilized for calculating head loss coefficients and lengths of the pipelines as well as for obtaining process components and

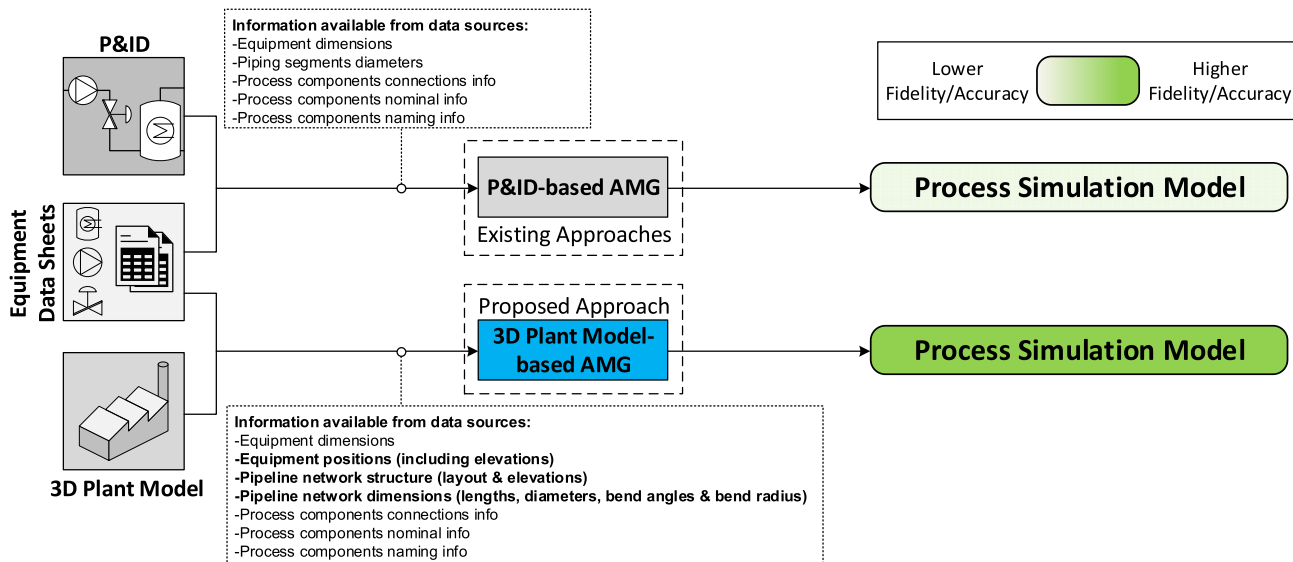


FIGURE 3. Conceptual diagram of the proposed 3D plant model-based AMG approach and its comparison with existing state-of-the-art AMG approaches which are mainly based on utilizing P&ID data and equipment data sheets.

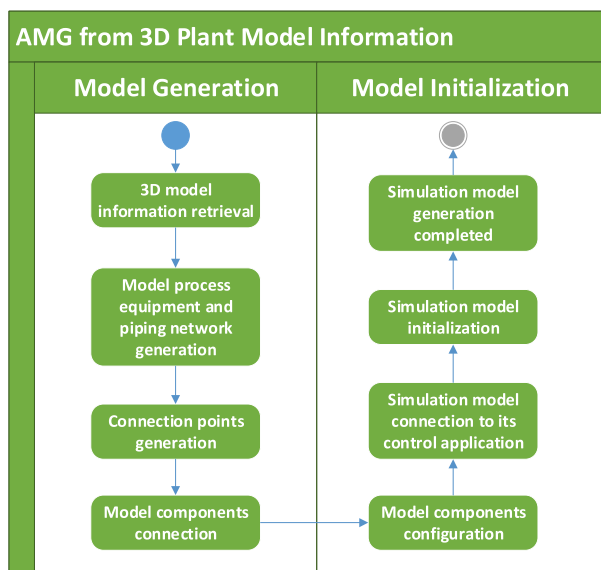


FIGURE 4. Proposed method for automatic simulation model generation from the 3D model information.

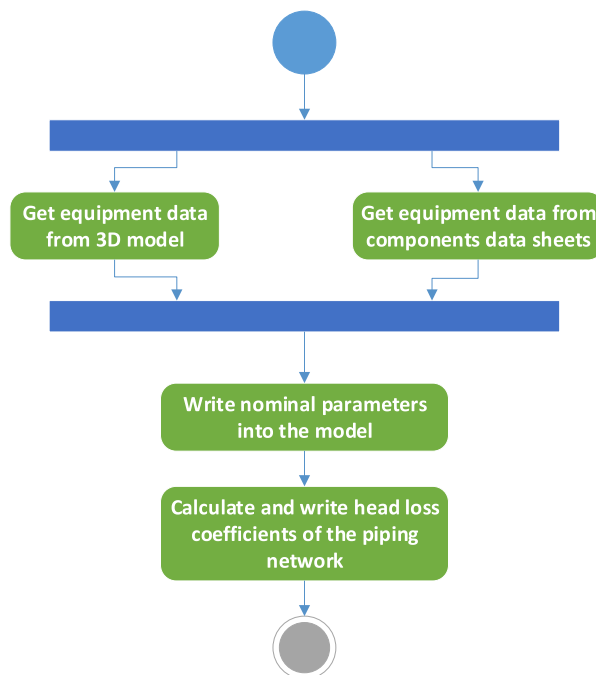


FIGURE 5. Model components configuration subprocess.

piping sections elevations. This information is highly important as the thermal-hydraulic simulation methodology follows mechanistic modeling, where structure and characteristics of the target process are modeled in detail and first principles of physics are used to describe the process phenomena, such as fluid flows and heat transfer [1], [2]. Consequently, the correctness of dimensions is utmost important. The pipeline sections' cross-sectional areas, lengths and shapes affect the flow rates and process delays, system volumes, and hydrodynamic losses. Furthermore, the elevations of the equipment and pipe sections affect the pressure levels of the system. This information is not available from a typical PI&D.

III. PROPOSED METHODOLOGY

The conceptual diagram of the proposed 3D plant model-based AMG method and its comparison with existing P&ID-based AMG approaches is shown in Fig. 3. The steps of the proposed AMG method are shown as Unified Model Language (UML) activity diagrams in Fig. 4 and Fig. 5. As shown in Fig. 4, the method is divided into Model Generation and Model Initialization. During Model Generation, 3D plant model information is retrieved. Then, the simulation process equipment and the piping network are generated

and connected. During Model Initialization, the simulation model is configured, connected to its control application and finally, controlled to an initial simulation state. As explained in Section II A, flow-sheet-based simulation tools are commonly used in process industry to model thermal-hydraulic systems in domains such as petro-chemical, power generation, pulp and paper as well as mineral processing. Therefore, the proposed method is targeted to be implemented for flow-sheet-based simulation tools. In addition to being widely adopted in industry, flow-sheet-based simulation tools offer two advantages highly important for AMG:

- 1) They include libraries of modeled process equipment, which can be connected and configured to build system-wide simulation models.
- 2) They commonly offer script-based modeling and simulation commands which can be used to ease the generation, connection and configuration of the modeled process components.

In the following sections, the Model Generation and the Model Initialization sub-steps of the proposed method are elaborated.

A. MODEL GENERATION

During Model Generation, the proposed method first retrieves information of the 3D plant model. Accessing 3D plant model information is a non-trivial task that depends on the availability of communication interfaces and on the information export options of the 3D modeling tool utilized. Commercial 3D modeling tools offer different interfaces from which information can be accessed by external systems. Common interfacing mechanisms include connectivity options either through application programming interfaces (API) or through direct communication to their data bases. 3D modeling systems also provide options for exporting model information. Common export formats include spreadsheets and tables of comma separated values (CSV). Additionally, some tools offer export options of files which are compliant with the Industry Foundation Classes (IFC) data model format. IFC is an XML-based file format standardized in ISO 16739. It is used to describe building data, including their pipelines. It has become a popular data export format as 3D modeling tools commonly used in process industry, such as *Aveeva E3D* [65] and *Cadmatic* [66], offer file export options based on this standard. However, because this standard is mainly used in construction industry, IFC currently supports only heating, ventilation and air conditioning piping networks. For this reason, 3D model information of thermal-hydraulic industrial processes cannot be represented using the IFC data model as they are comprised of complex pipelines and equipment.

Industrial standards for data modeling and exchange between process plant engineering systems, such as 3D CAD tools, have been developed during the last decades. A promising example of these standards is the Computed Assisted Engineering Exchange (CAEX) [67] standard. CAEX is a neutral data format for plant information exchange

defined in the IEC 62424 specification. It has been adopted by the industry-driven initiative AutomationML [68]. However, commercial 3D CAD tools used in the process industry do not offer export in CAEX format. More recently, the Data Exchange in Process Industry (DEXPI) [69] initiative has been working towards the development of a general data exchange standard for the process industry. The DEXPI specification is the result of this initiative. It is an extension of the ISO 15926 [70], originally intended for information exchange between P&ID and 3D modeling tools. Although the DEXPI specification is supported by a group of major P&ID tool vendors and process owners, its application is currently limited only to P&ID information exchange. A comparison of the tradeoffs between CAEX and ISO 15926 is presented in [71]. Adoption of standards such as CAEX and DEXPI would ease integration between 3D modeling tools with other industrial process systems, including process simulators.

Since commercial 3D modeling tools currently do not offer export options based on industrial process standards, the proposed method utilizes 3D plant model information retrieved in CSV format. Information available from 3D plant models includes equipment dimensions, positions, elevations and connections as well as the pipe sections' lengths and elevations. It also includes data related to the piping structure, especially elbows and branches, needed to calculate the loss coefficients of the process pipelines. In this work, position and elevations are classified separately. Positions refer to XY positions on the horizontal plane. Elevations are defined as the Z coordinate in respect to the XY plane. Finally, the 3D models also contain process equipment naming and nomenclature information. This is required if the simulation model is connected to the real control application or to an automation system emulator during plant operation and maintenance phases. Fig. 6 shows an UML class diagram of the information available from the 3D plant model of a process comprised of some of the most common components in thermal-hydraulic systems such as tanks, vessels, valves and pumps. Fig. 6 also includes different pipe geometries such as tees, and elbows.

After retrieving system information from the 3D modeling tool, the AMG method starts by parsing the information included in the retrieved CSV files. Next, the process equipment and the piping network are generated automatically using simulation configuration commands available in flow-sheet based simulation tools. Each process component is generated onto the simulator configuration canvas and positioned at the XY coordinates specified by the 3D model data. Once the simulated process components and piping network are generated, they are connected using TH points. In this work, TH points are defined as coordinate locations in space which define elevations and positions of the connections between process components and pipelines. These points play an important role in the thermal-hydraulic solution as they represent a calculation volume with a state information. Elevation data for process components and pipelines

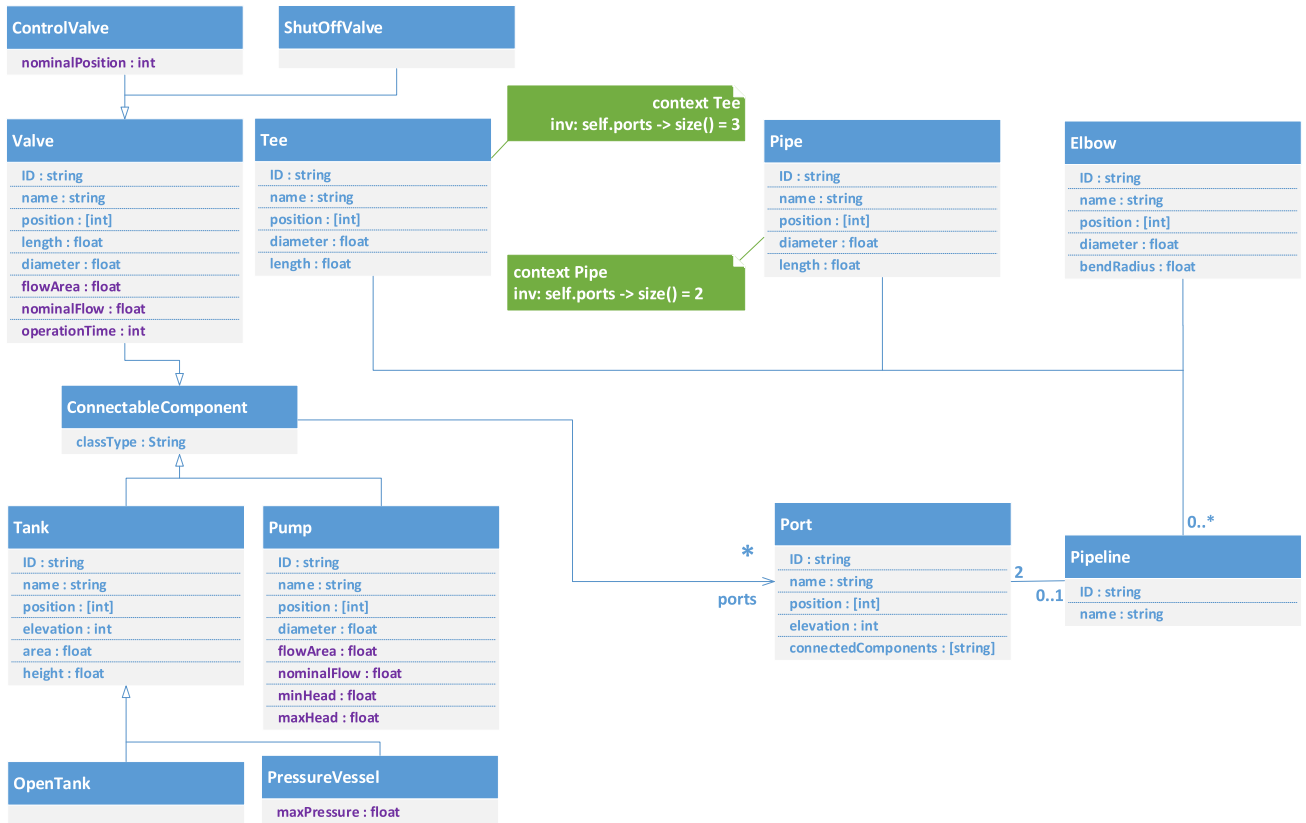


FIGURE 6. UML class diagram of the information available from the 3D plant model comprised of common components in thermal-hydraulic systems.

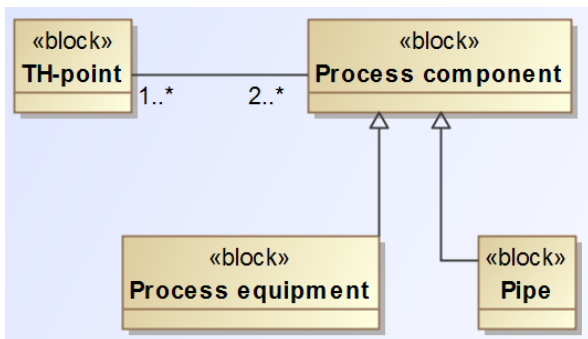


FIGURE 7. SysML block definition diagram of simulation model components. TH-points are thermal-hydraulic points.

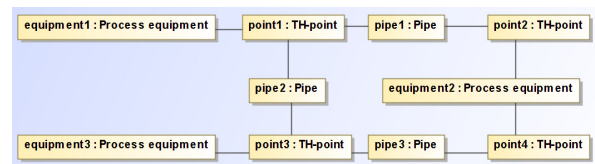


FIGURE 8. Internal block diagram that uses the block types defined in Fig. 7 for the purpose of illustrating examples of connections between process equipment and pipes through TH points.

is important, as it is needed for hydrostatic pressure calculations. Fig. 7 shows a Systems Modeling Language (SysML) block definition diagram that captures simulation model components. Fig. 8 shows an internal block diagram that uses the block types defined in Fig. 7 to illustrate examples of connections between process equipment and pipes through TH points.

B. MODEL INITIALIZATION

Model Initialization begins with the configuration of the model components. As previously defined, model components are all the elements that comprise the

simulation model, including models of process equipment, pipelines and TH points. During this configuration, nominal values are assigned to component parameters. Nominal equipment information is the de facto information which represents the conditions in which process equipment are expected to operate normally. Nominal data includes flows, positions, pressure heads, head losses coefficients, power coefficients, voltage levels, heat coefficients, etc. While geometry-related data can be easily derived from the 3D model information, other operating nominal values of process equipment, marked in purple in Fig. 6, are not typically included in 3D models. This information could be included in 3D plant models, thereby easing the automatic generation of simulation models from 3D models. However, this is not a common practice in industry. Therefore, in the proposed approach, detailed equipment

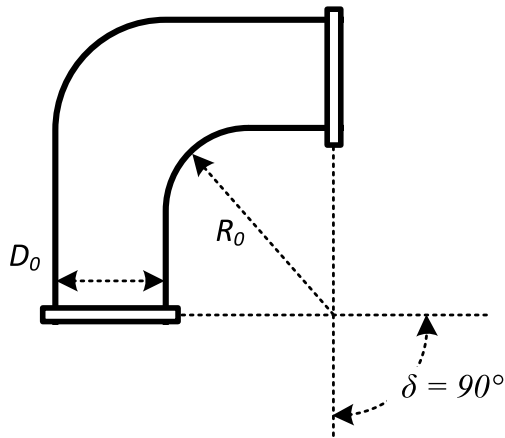


FIGURE 9. 90° Elbow fitting and its diameter (D_0), bend angle (δ) and bend radius (R_0). Figure adapted from [80].

nominal operating parameters are retrieved from data sheets of process equipment. The simulation model components configuration sub-step, in which nominal parameters are written into the model components, is shown in Fig. 5.

Model configuration also includes the calculation of head loss coefficients. Head loss coefficients are a nominal parameter of pipes, also referred as pressure loss or as form loss coefficients [72]. Head loss occurs due to friction and turbulence caused by changes in direction or cross-section area of pipelines [73]. Consequently, head loss occurs mostly in piping fittings such as reducers, expansions, elbows, tees (a 3-way connector) and 4-way connectors. There are a number of different methods for obtaining head loss coefficients in pipeline fittings [74]–[77]. Analytical methods are generally based on the Herschel-Bulkley model [78]. Alternatively, commonly used numerical models for head loss coefficients calculations of different fitting geometries can be obtained from process engineering handbooks such as [79] and [80].

Calculation of head losses in pipelines is highly important for obtaining accurate simulation models of thermal-hydraulic systems. In the proposed method, head loss coefficients are calculated after obtaining geometrical information of the pipe fittings from the 3D plant model. This information cannot be obtained from other engineering sources such as P&ID diagrams or equipment data sheets. Geometrical information of process pipelines required for head loss coefficients calculation includes the fitting type as well as its length, diameter (D_0), bend angle (δ) and bend radius (R_0). In the proposed algorithm, head loss coefficients of these and other fittings are calculated based on the equations in [80]. As an example, equations (1) to (4) show the calculations that the AMG algorithm utilizes to obtain the head loss coefficient of 90° elbow fittings, shown in Fig. 9. The total head loss coefficient ζ of a 90° elbow fitting is the sum:

$$\zeta = \zeta_l + \zeta_{fr} \quad (1)$$

where ζ_l is the local head loss coefficient of the elbow fitting; and ζ_{fr} is the friction coefficient throughout the fitting length.

$$\zeta_l = A_l B_l C_l \quad (2)$$

A_l is determined as a function of the fitting bend angle δ . In the case of a 90° degrees elbow, $A_l = 1.0$.

$$B_l = 0.21/\sqrt{(R_0/D_0)} \quad (3)$$

$C_l = 1.0$ for circular or square cross sections.

$$\zeta_{fr} = 0.0175\lambda(R_0/D_0)\delta \quad (4)$$

where λ is the friction coefficient of unit length of the curved pipe. λ varies according to the relation R_0/D_0 of the elbow and can be calculated using equations 6-12 to 6-14 of [80].

After the simulation model has been configured, model initialization is required to provide the model with a set of values which define starting conditions. Model initialization procedures vary according to the simulation tool utilized. In some SM simulators, it is possible to directly write a good estimate of the initial state into the model as they provide a method for sequentially calculating individual model variables [32]. However, especially during early plant lifecycle phases, plant state information is not available [36]. On the other hand, in EO simulators it is not possible to directly write the state of simulation variables, because the models are explicitly described as equations and not as algorithms of the solutions of such equations [22]. Steady-state process models have been used to estimate initial values for dynamic simulators [16], [81]. However, the obvious drawback of this alternative is that steady-state models must be available. Consequently, the initialization proposed in this work is performed using the control system for driving the simulation model to a given initial state. This approach can be carried out even if no steady-state simulator is available and it is applicable to both, SM and EO dynamic simulators. For this reason, before initialization, the automatically generated simulation model is connected to its control application. Upon initialization, the AMG method is completed and the simulation model can be used for the targeted application.

IV. IMPLEMENTATION OF THE PROPOSED APPROACH

The proposed methodology was implemented and tested using a laboratory-scale heat production plant (HPP) process. The HPP process, shown in Fig. 10, is considerably simpler than real power plants but has been designed together with automation professionals to ensure that it includes key automation functionalities of such processes [82]–[85]. Fig. 11 shows the P&ID of the HPP process. The process is comprised of three open tanks (B100, B200 and B400), a vessel (B300), two pumps (M100 and M200), a heating element (E100), various shut-off valves and two control valves (Y102 and Y501). The water in the tank B100 is heated using the heating element E100 and its temperature is controlled using an on-off controller. The pressure P300 in the tank B300 is controlled by a PID controller using pump M200.



FIGURE 10. Heat production plant process (HPP) used as a testbed for the proposed method.

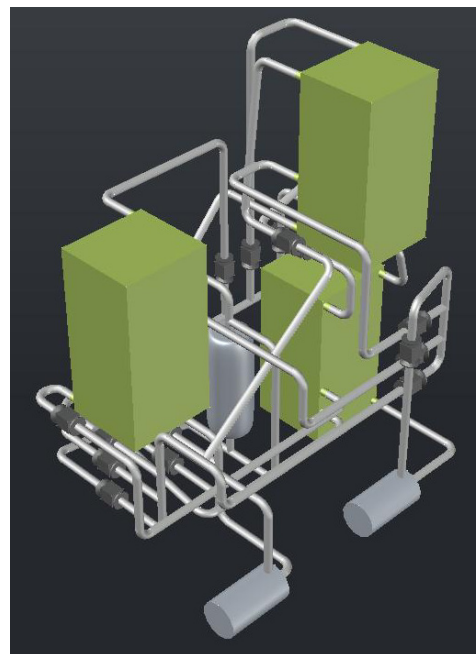


FIGURE 12. HPP 3D model developed in AutoCAD Plant 3D.

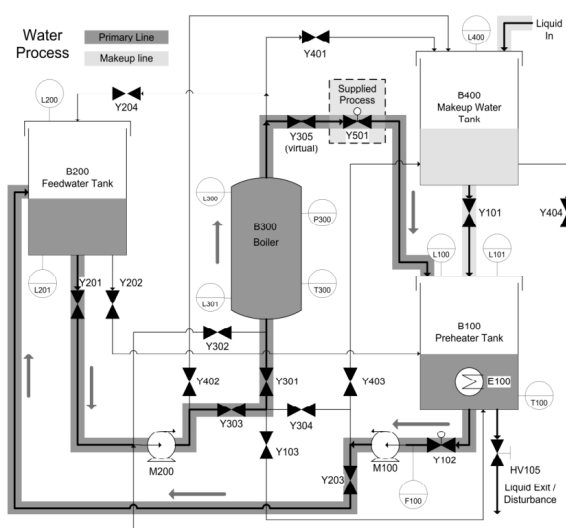


FIGURE 11. Piping and instrumentation diagram (P&ID) of the HPP testbed.

The water level L200 of tank B200 is controlled by two PID controllers connected in a cascade configuration using proportional valve Y102. The position of proportional valve Y501 is regulated to simulate a load in the consumption of hot water. The consumed water flows back into tank B100 to be re-heated. The control application of the process was developed following the IEC-61131-3 standard and runs on a soft programmable logic controller.

The dynamics in the HPP system mostly reside in the tanks, which have the largest share of the system total volume, and the level of which can change. Similarly, the control valves

are dynamic elements. In particular, the proportional valve Y102 which is used to regulate the flow F100 of the cascade configuration controlling the level L200 of tank B200. Furthermore, the pipelines introduce part of the system volume and a transport delay for the fluid flow. However, since the system is operated on a constant temperature, they have a minor dynamic role in this study. For the same reason, heat transfer or thermal inertia aspects are negligible. Generally, the control loops play a significant role in the dynamics and in the discrepancies between physical and modeled systems. In this case, this factor was eliminated by using exactly the same control application and tuning parameters in the physical and simulation systems.

The HPP testbed is an 8-year-old process and no 3D model was developed during its design. Therefore, in order to test the proposed methodology with 3D model information as is available during early lifecycle phases of a real industrial process, a 3D model of the HPP was developed in AutoCAD Plant 3D [86]. AutoCAD Plant 3D is one of the tools that are broadly used in industry. The 3D model of the physical system is presented in Fig. 12. The HPP 3D model was built after measuring physical dimensions of the real process.

The AMG method was implemented on the simulation tool Apros [87]. Apros is a commercial flowsheet-based tool for modeling and dynamic simulation of thermal-hydraulic processes. It has been used to simulate various industrial systems such as combined heat and power plants [88], nuclear power plants [89], renewable energy production systems [90], [91], as well as pulp and paper mills [92]. Apros provides simulation libraries with simulation components of common process equipment, which can be connected through pipes and TH points to simulate process sub-systems or entire plants.

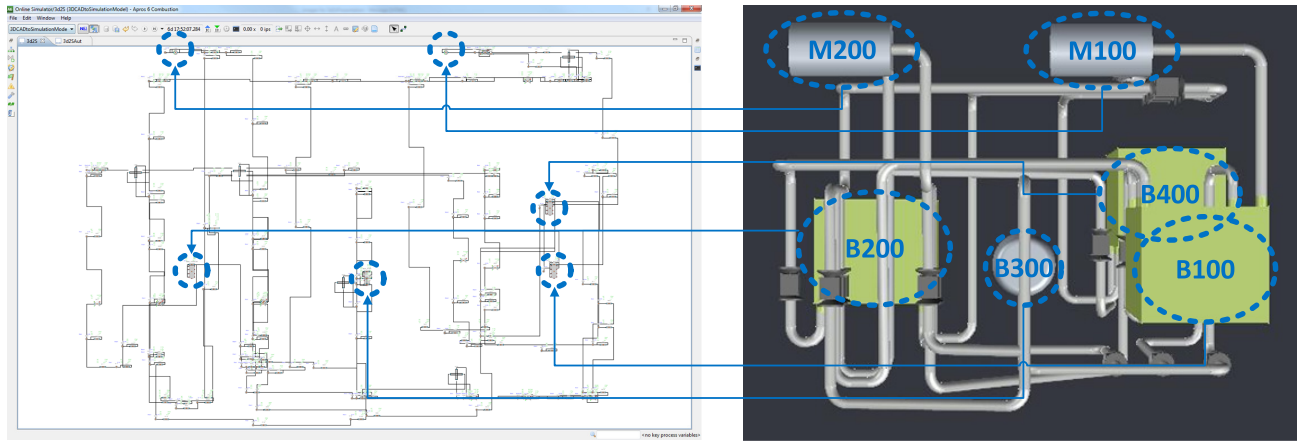


FIGURE 13. Layout of the HPP simulation model generated automatically and its comparison with the lower isometric view of the HPP 3D model.

This tool also provides functionalities to develop a model of the process automation system for independently controlling the simulation model. Apros relies on the platform's programming language Simantics Constraint Language (SCL) [93] to manage and automate different tasks related to the model creation and configuration. Consequently, the proposed AMG method was developed utilizing the SCL language.

The AMG method requires access to the data from the HPP 3D model before the simulation model can be generated. In AutoCAD Plant 3D, there are various options for accessing the 3D plant model information. These options include information access through an API or directly through the 3D model database. Additional information access options are offered as file export in CSV format. However, the format of the exported CSV files does not follow any information exchange standard. Moreover, it does not include any information on the connections between the process equipment. Therefore, the HPP 3D model information, including the connection data, is retrieved directly from the AutoCAD Plant 3D database. This information is accessed through an SQL server which connects to the data base client of the 3D modeling tool and then exports the required data as CSV files. This information is not modified nor queried, therefore, it maintains the original format as in the database.

After the information is retrieved, the AMG algorithm starts the automatic generation of the simulation model by creating the simulated process equipment models of the HPP, such as the open tanks, the vessel, valves and pumps. Next, the pipes and fittings are created. In AutoCAD Plant 3D, elbows are classified as pipe fittings, while other pipe fittings with more than two connection ports are classified as pipe sections. Consequently, pipe fittings such as tees with three or more connection ports must be distinguished from regular piping sections. Therefore, the model generation method counts the number of ports in each pipe and classifies it accordingly to the OCL (Object Constraint Language) specifications in the notes in Fig. 6.

Once the simulated process equipment models and the pipelines are generated, the algorithm creates the TH points. Model components are created and provided with information about their dimensions and, in the case of the pipping network, their lengths. The equipment, the piping and the TH points are generated in the Apros configuration canvas at the XY position specified in the HPP 3D model information. As it was previously explained, the elevation of the model components, retrieved from the 3D model is given as a parameter of the TH points. Next, the connections between all the model components are created. The resulting model and its comparison with the HPP 3D model is shown in Fig. 13. As it can be seen, the placement of the model components in the Apros configuration canvas corresponds to the lower isometric view of the HPP 3D model.

The model configuration is carried out using information retrieved from both the HPP 3D model and the process equipment data sheets. Data retrieved from the data sheets is provided to the algorithm as CSV tables, in similar way as it is done with the 3D model data. This information is mainly related to the equipment nominal parameters such as nominal flows and positions of valves as well as nominal pressure heads and nominal flows of pumps. Model configuration is completed once the head loss coefficients of the pipelines are calculated by the model generation algorithm using the equations presented in Section IV B.

Model initialization is carried out by connecting the simulation model to the control application and driving the process to the desired initial state. For testing purposes, a model of the control application was developed manually in Apros. The model of the control application replicates the real control system structure, equations and tuning parameters. Another alternative would be to utilize control application emulation systems which could be used to connect an instance of the real control application to the simulation model.

In Apros, model initialization was carried out by providing boundary conditions and then excluding the entire model from simulation. Next, model sub-systems are

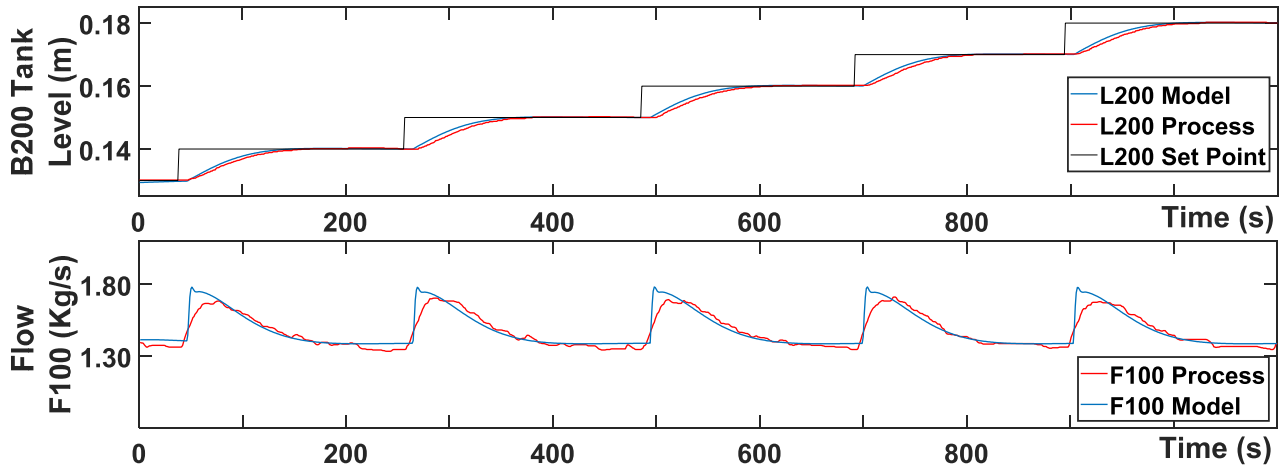


FIGURE 14. Simulation results of the automatically generated simulation model and its comparison with the HPP measurements. Transients are caused by changes in the set point of the water level L200 of the tank B200.

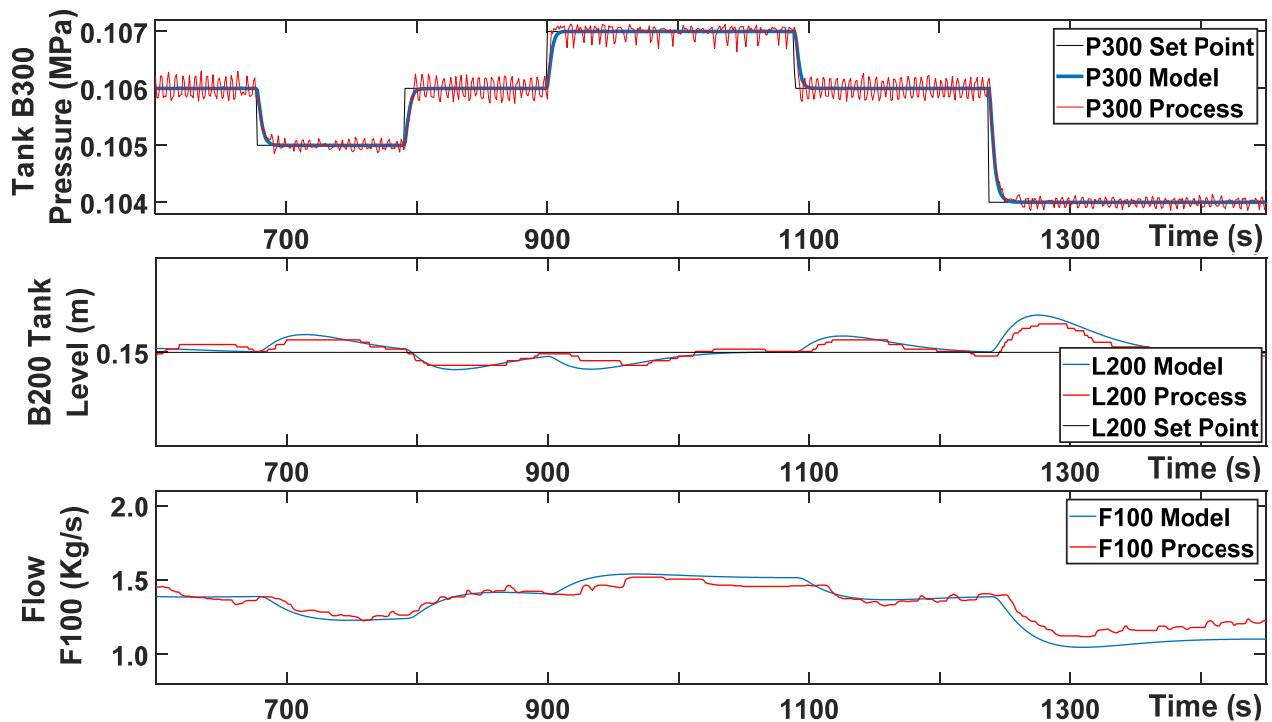


FIGURE 15. Simulation results of the automatically generated simulation model and its comparison with the HPP measurements. Transients are caused by changes in the set point of the pressure P300 in the vessel B300.

gradually included into the simulation and then controlled by the control application to the desired state. This is systematically repeated until all the simulation model sub-systems are at the desired initial state. This initialization procedure is followed to guarantee model stability at the desired initial conditions and it could be followed in other simulation tools in cases where these tools offer similar options for excluding model sub-systems from simulation. After initialization, the automatically generated model is ready to be tested.

In order to further assess the proposed method, the automatically generated model results are compared with those from a simulation model created manually. The manually created model was developed utilizing the plant P&ID and the process equipment data sheets. This is the same source information that is used in the closest state of the art literature for AMG of industrial processes [20], [23], [53], [61]. Consequently, the manually created model was developed with limited information related to the structure of the process

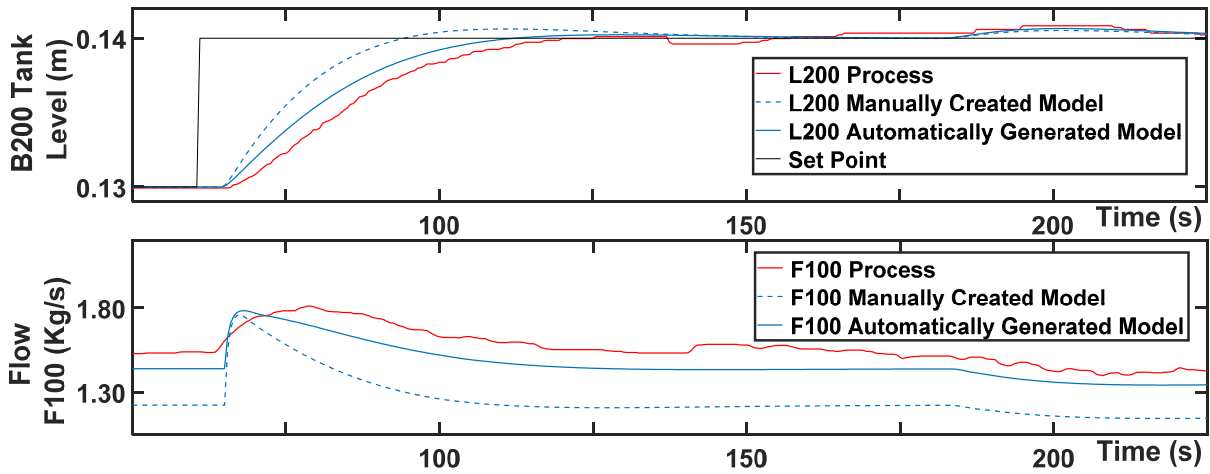


FIGURE 16. Comparison of the simulation results between the automatically generated model and the manually created model. Transients are caused by a change in the set point of the water level L200 of the tank B200.

pipelines. Since the head loss coefficients are not available from the source information used for the manual generation, the simulation tool’s default head loss coefficient value was applied. In order to perform a fair comparison, and in order to highlight the improvement of the results due to the differences on the form loss coefficients values, the process equipment elevations and pipe lengths were taken with a tape measure and then provided to the manually created simulation model. Consequently, in this respect, the manually developed model is even more accurate in respect of its parameter values than a model created with data sources utilized by state-of-the-art methods.

V. RESULTS

During the first experiment, the automatically generated model was tested by comparing its results with experimental data of the HPP process. In these experiments, the simulation model and the HPP process were run simultaneously through various transients, controlled by their respective control application. These experiments were carried out utilizing the simulation architecture described in [22]. As previously explained, the same control application structure and tuning parameters are used to control both systems. During these experiments, the physical system and the model start at the same initial conditions and the same changes in their controlled variable set points are applied simultaneously to both systems. The results of these experiments are shown in Fig. 14 and Fig. 15. Fig. 14 compares the simulation results with the process measurements during transients caused by changes in the set point of the B200 tank water level L200. The flow F100 is the water flow between tank B100 and B200, measured between valve Y102 and pump M100. Similarly, Fig. 15 compares the simulation results with the process measurements during transients caused by changes of the set point of the pressure inside the vessel B300. Results show that the behavior of the automatically generated simulation model

TABLE 1. Comparison of the normalized root mean square errors (nrmse) of the automatically generated and the manually created model in respect to the hpp experimental data.

DESCRIPTION	NRMSE
Automatically generated model	102.8
Manually created model	386.9

is in good agreement with the physical process, even during operation transients.

For the second experiment, the automatically generated model results are compared with the manually created model. As previously explained, a fair comparison was ensured by configuring the manually created model parameters as accurate as possible using information available from the physical system in addition to the P&ID and the equipment data sheets. The manually created model took an approximate of 5 hours to be developed and initialized by a process and simulation expert. In contrast, the simulation model generated following the method proposed in this work takes roughly 10 minutes to be automatically generated by the presented method.

During these comparison experiments, the manually created model, the automatically generated model and the HPP process were run simultaneously, controlled by their respective control applications with identical structure and tuning parameters. Fig. 16 shows the comparison between the manually and automatically generated models with respect to the measurements of the physical process. This figure shows the comparison of the water level L200 in tank B200 and the flow F100 during experiments in which transients are caused by a change in the L200 set point. In Fig. 16, the same initial condition has been used in both experiments for the tank B200 level. However, the difference between initial conditions for the flow F100 in Fig. 16 is an unavoidable result of the fact that the head loss coefficients of the manually created and automatically generated simulation models are different. Table 1 compares the normalized root mean squared errors (NRMSE) of the automatically generated model and the man-

ually created simulation models in respect to the process data series for the experiments depicted in Fig. 16. NRMSE is used to facilitate the comparison between datasets with different units and scales [94]. These results show that the simulation model generated automatically from the 3D plant model is not only generated with lower engineering effort, but it also has a lower NRMSE compared to the simulation model created manually. This is a result of configuring the automatically generated model using the calculated information of the piping sections exact length and elevations as well as the pipeline form loss coefficients. It is worth noting that using poor estimates of the pipeline network lengths and elevations for the state-of-the-art model that was used as a reference would have resulted in yet a larger difference between the NRMSE values.

A direct comparison to any figures in the state-of-the-art works [20], [23], [53], [61] is not possible, since the case studies are different. However, the manually created model was built using all of the source information and reasoning capabilities presented in the state-of-the-art works. Therefore, the NRSME is considered representative of the performance of the state-of-the-art methods. Since both models in Table 1 are based on the same case study and the NRMSEs are calculated from the same transient scenarios, the NRMSEs in Table 1 are directly comparable numbers that capture the performance improvement of the proposed method.

VI. CONCLUSIONS

This paper has proposed a method for automatic generation of thermal-hydraulic simulation models from the 3D plant model information. A key step in the model configuration of the proposed method, which has not been included in previous works, is the utilization of pipelines information included in the 3D plant model to calculate and configure the automatically generated simulation model. In this work, information of the pipeline structure and equipment is derived from the 3D plant model and used for obtaining piping sections' lengths and elevations as well as for calculating pipelines form loss coefficients. This information cannot be obtained from other data sources available during the process design. Experiments show that the results of the model generated following the proposed AMG method closely correspond to the process measurements, even during process transients.

In order to further evaluate the presented approach, the automatically generated model was compared with a model created from information utilized in the current AMG state-of-the-art. The results of this experiment show that, although the information in Table 1 is specific to our case study, significant improvements in NRMSE is expected also for other case studies due to the following reasons. The achieved reduction of the NRMSE is a result of calculating the head loss coefficients of the pipelines. This parameters can only be calculated using information available only from the 3D plant model. Therefore, the proposed approach is expected to generally result in significant improvements

over state-of-the-art methods that rely only on P&ID and equipment data sheet information. The specific quantitative improvement will depend on properties of the process and in particular the pipe routing, since the number and properties of elbows and tees will significantly impact the head loss coefficients for the pipelines. These parameters have a major impact on the transient behavior of dynamic simulations.

The overall results show that this work addressed the objective presented in Section I, as the proposed method enables a more rapid and efficient model development compared to manual modeling approaches. This should enable a wider industrial adoption of simulation-based applications. Additionally, the presented method utilizes process information available during the design stage of the plant lifecycle, increasing the cost-efficiency of the generated model. This is due to the fact that, as shown in Fig. 1, simulation models generated at early process design can be used for other important applications during the later stages of the process plant lifecycle.

A drawback of the presented method is its dependability on the information access options which can vary according to the 3D modeling tool utilized. This can limit the applicability of the proposed AMG method only to 3D modeling tools which provide access to their 3D model databases. For this reason, an interesting research direction is the study of intermediate formats for information exchange between 3D modeling tools and other engineering data sources. Standardization of this format would further increase industrial adoption of methods such as the one presented in this work. Moreover, in this work, the control application required to control the generated model is developed manually. Therefore, future work will also focus on the development of methods for automatic generation of a control application for controlling the generated simulation model, especially based on IEC 62424 descriptions that are available at the design phase of the plant lifecycle.

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