PRIORITISING OBJECT TYPES OF INDUSTRIAL FACILITIES TO REDUCE AS-IS MODELLING TIME

Eva Agapaki[1] and Ioannis Brilakis

Construction Information Technology Laboratory, Department of Engineering, University of Cambridge, Trumpington Street, Cambridge CB2 1PZ, UK

The cost of modelling existing industrial facilities is currently considered to counteract the benefits of the model in managing and retrofitting the facility. 90% of the modelling cost is typically spent on labour for converting point cloud data to the final model, hence reducing the cost is only possible by automating this step. Previous research has successfully validated methods for modelling specific object types such as pipes. Yet modelling is still prohibitively expensive. We tackle a part of this issue by identifying the most frequent object types that require modelling in industrial plants to guide future work aimed at automating the tedious current practice. We determine a priority list of the object types in these facilities based on their frequency of appearance (%) and intent of modelling. A parametric study based on Outer Diameter (OD) then finds the most frequent OD ranges for these objects. The results indicated that steel sections were the most frequent object type encountered in all case studies.

Keywords: 3D Modelling, facility management, industrial facilities

INTRODUCTION

Industrial plants can be divided into six main categories: (a) onshore and (b) offshore oil platforms, (c) chemical, (d) mining, (e) pharmaceutical plants and (f) food processing factories. The object types of industrial facilities belong to three different categories: (a) piping system, (b) steel sections and (c) equipment. More specifically, the object types of the piping system are pipes, elbows, tee and olets, valves, reducers, flanges and caps.

Maintenance, safety management and retrofitting of existing industrial facilities are vital operations in their lifecycle (BIFM 2012, Gorse and Highfield 2011). Poor maintenance and safety deficiencies lead to equipment failure, which can have significant environmental, economic and societal impacts. The Deep Water Horizon (Office of Maritime Administrator 2011) and 2008 Georgia sugar refinery (U.S. Chemical Safety and Hazard Investigation Board 2008) explosions are two recent examples of critical failures caused by poor maintenance. By 2050, the need for refurbishing and retrofitting 93% of existing facilities to meet environmental regulations will be a major focus in the UK construction industry (Edwards and Townsend 2011).

Most existing major refineries were built before the advent of CAD in 1977, therefore working models do not exist to assist their maintenance operations (Bernard 2003, Cabinet office 2012). For instance, the newest refinery with significant downstream unit capacity built in the United States is in Louisiana (Garyville Refinery) and it began operating in 1976 (Marathon Petroleum Corporation 2014). Unprecedented incidents would have been avoided if computerized control system displays were better designed (U.S. Chemical Safety and Hazard Investigation Board 2007) and enriched 3D as-built

[1] ea437@cam.ac.uk

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BIMs (Building Information Models) were present. If the inspectors have enriched as-built 3D models, they will be more proactive in dealing with similar circumstances such as leaks and ignition (Umar 2010). However, there are significant challenges that need to be addressed to make automated as-is industrial BIMs a reality.

The significant time required to model the vast number of objects in industrial facilities impedes adoption of as-is 3D modelling for these assets. Modellers use the following four main steps to manually process as-built BIMs: (a) data collection (laser scans), (b) point cloud registration, (c) geometric modelling and (d) addition of accompanying information, such as topological relationships and material specifications. Point cloud processing remains the “bottleneck” during the 3D modelling of any industrial facility given how costly and time consuming it is. A recent case study of a sugar refinery, covering an area of 65 hectares, reported that more than 80% of the modelling time was spent on point cloud processing of the scans (3Deling). According to another recent study of an offshore facility, the laser scanning process was only 4 hours, whereas 3D semi-automatic modelling of 2,602 objects (planes and cylinders) was conducted in 15 days (Fumarola and Poelman, 2011). Given these facts, the modelling process should be efficiently automated.

Safety, retrofit purposes and maintenance are three modelling intents that can determine whether an object type is critical for detailed modelling (BIFM 2012). Examples of critical object types that should be considered are given below. Hazardous subsystems in terms of safety should be modelled in finer detail. Highly hazardous object types are separators, compressors, driers and flash drums, whereas moderately hazardous ones are pipelines and pumps (Umar 2010). These elements are considered dangerous based on failure rates assessed by the Health and Safety Executive (2012). Identifying hazardous equipment elements will remarkably improve safety management.

Valves are a control element in nearly all chemical process control loops and regulate the flow through piping systems. Operation of valves can be achieved either manually by a hand wheel/lever or automatically. The performance of an industrial plant can be improved by opening, closing or changing the position of a valve. Failure to quickly locate and identify control and safety valves during inspection can result in significant damages or even massive, unprecedented disasters like Texas City Refinery (U.S. Chemical Safety and Hazard Investigation Board 2007) or Piper Alpha (Oil & Gas U.K. 2008). Safety system deficiencies that occurred due to poor inspection and inadequate maintenance are reported as some of the main factors of the devastating incidents mentioned above.

Another important control measure in industrial facilities is maintenance of pipelines and pipe supports. Insulated pipes and pipelines carrying flammable, hazardous or toxic materials are highly important for inspection. One of the most important concerns of inspectors for maintenance of pipelines is corrosion. Pipes of Nominal Bore (NB) greater than 2 inches (50 mm) are considered critical for corrosion (Singh and Britton 2001). Pipe supports and hangers are the “foundations” of a piping system and if they are not properly maintained, the entire piping system is likely to fail (Sahazizian and Zlatko 2011).

Although the "arteries" of a Process Plant are its pipeline systems, since they carry its "lifeblood", structural steelwork is vital for its structural stability and oil and gas production especially in cases of fire. Given the short lifecycles of refineries, which range from 15 to 30 years, structural design is challenging since the layout should be flexible and expandable (Gourlis and Kovacic 2017). Fatigue of steel girders is critical for maintenance, however the contribution of structural failure to the total number of historic accidents is less than 10% based on worldwide data (WOAD Database 2014). Seismic retrofitting and energy retrofit for pipes are typical retrofitting operations in industrial plants (Autodesk 2009).

Figure 1 summarizes the critical elements for each category (maintenance, safety and retrofit). The higher the impact these object types have on each category the higher they are on the list. The graphical representation of the objects is specified by the Level of Detail (LoD). The American Institute of Architects (AIA) defines 6 LoDs (AIA 2017) of which LoD 300 is used for construction (Wang *et al*., 2015). According to LoD 300, the shape, size, quantity, location and orientation of objects are modelled. The most critical and most frequent object types for modelling are considered based on this specification.

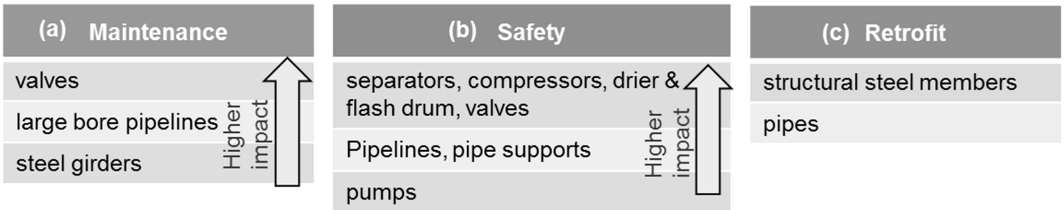

Figure 1: Critical object type list for (a) maintenance, (b) safety and (c) retrofit purposes

State of practice

Numerous commercial software packages offer a degree of automation for 3D as-built industrial facility modelling. One recently developed commercial program automatically extracts 85% of the pipes in a plant room on a typical North Sea platform with 1-3% average error (ClearEdge 3D 2013). There was a substantial manual modelling time reduction in this project from 60 man-hours to 15 man-hours. The EasyConnect tool, which automatically couples straight pipe spools ("segments") to connect the pipeline layout, solved the problem of occlusions in industrial environments. The user manually fits connections like valves and flanges into the 3D as-is data. The cost and complex manual modelling required in current practice are a barrier to broader adoption of as-is models for industrial facilities.

Leading 3D CAD software vendors (Autodesk, AVEVA, Bentley and Intergraph) have also developed software packages that manually model as-built industrial environments. PointSense Plant by Kubit has integrated functionalities that can detect pipelines from 3D point clouds. It automatically finds the best fit for cylinders. However, all software packages only extract geometrical shapes, without being designed to classify the object types automatically. For instance, cylinders can represent pipes or handrails to name a few. This step is performed manually by the integrated MEP or structural steel/concrete standard catalogues.

State of research

As-built 3D modelling of industrial facilities is focused on the detection of primitive shapes and specifically, cylinders, planes, spheres and cones, by using model based methods. It has been proved that 85 % of objects in industrial scenes can be approximated by the above-mentioned shapes (Petitjean 2002). As-built pipelines, although generally cylindrical, are a great challenge for modellers due to the variety of object types, shapes, diameters and randomness of their poses (Son *et al*., 2015). Automatic cylinder detection is mostly investigated (Kawashima *et al*., 2014; Patil *et al*., 2017; Qiu *et al*., 2014) by defining the five parameters that describe cylinder orientation, position and radius by a variety of methods. All the above-mentioned research efforts concentrate on straight pipes, thus sections of inclined pipe “spools” (segments of pipes) are neglected from this analysis. Semantic detection of object types is performed by Perez-Perez *et al*., (2016), in order to assign labels (wall, ceiling, floor, pipes) to the distinguished categories.

As-built modelling of industrial facilities is like a "zoom in" of an urban modelling problem (Patraucean *et al*., 2015). Weinmann *et al*., (2015) and Babahajiani *et al*., (2016) achieved automatic object classification by assigning semantic labels in 3D urban scenes. Therefore, interdisciplinary communication between different research fields is essential for the progress of as-built modelling.

A fully automated method that models the entire pipeline, structural members and equipment of industrial plants has not been achieved yet. Analysis on the most frequent and critical object types that will assist automation and improve quality of modelling needs to be considered. For the statistical analysis presented in this paper, only the topsides structure (structure above the sea level) of the offshore plants is considered, where crew quarters are located and typical operations take place, such as extraction, processing and storage of oil and natural gas. We can model these facilities efficiently by answering the following two questions: (a) which object types should be automatically extracted to reduce modelling time and (b) to what LoD should critical object types be modelled to have an enriched BIM model?

RESEARCH METHODOLOGY

We tackle the research question of the object types that need to be modelled by implementing a statistical analysis on the frequency of appearance of all object types present in typical industrial plants. We examine four case studies of 3D modelled industrial facilities to have a representative statistical analysis of the most frequent object types. Three case studies were typical offshore platforms with the fourth being a typical food processing refinery (sugar refinery) due to availability of data. Concerning offshore platforms, the subcategories that were examined in this paper are (a) a Gravity-Based Structure (GBS), (b) a Tension-Leg Platform (TLP) and (c) a fixed platform. The as-designed models accurately represent the as-built conditions. The only possible differences between the as-designed and as-built models are geometric, which do not affect the frequencies of the object types.

Our method is based on a statistical analysis of n objects with a range of OD ($d1$, $d2$, dn) for each object type and their observed counts ($c1$, $c2$, cn). We obtain object type counts from as-designed BIM models of these facilities. The objects investigated belong to three different object categories: (a) piping system, (b) steel sections and (c) equipment due to availability of data. Most of the object types encountered in industrial environments are presented in Figure 2. A priority list of object types was obtained by finding the percentages of appearance (%) of each object type in each facility and an average priority list for all facilities. Given the total number of objects present in a specific facility, we calculate the frequency of appearance by dividing the counts of each object type with the total number of objects.

The piping system is further subdivided in two meaningful subgroups with respect to their OD. Small bore pipes are the pipes whose OD is less than or equal to 2 inches (50.8 mm) and the rest (pipes with OD greater than 2 inches) are considered large bore pipes. This division is meaningful since large bore objects of piping systems carry flammable (oil, gas, gasoline, hydrocarbon) and highly volatile materials, whereas small bore are mostly used for hydraulic purposes or other less flammable liquids. An important geometric parameter that is useful for the recognition of each element of the piping system is the range of OD. We conduct a parametric study on the OD of each object type, in order to observe trends on the most frequent diameter ranges and infer connectivity relationships between the piping objects present in the industrial plants investigated in this paper. Probabilistic distributions and statistical properties of each object type in the piping system are calculated to provide the range of ODs for each industrial facility.

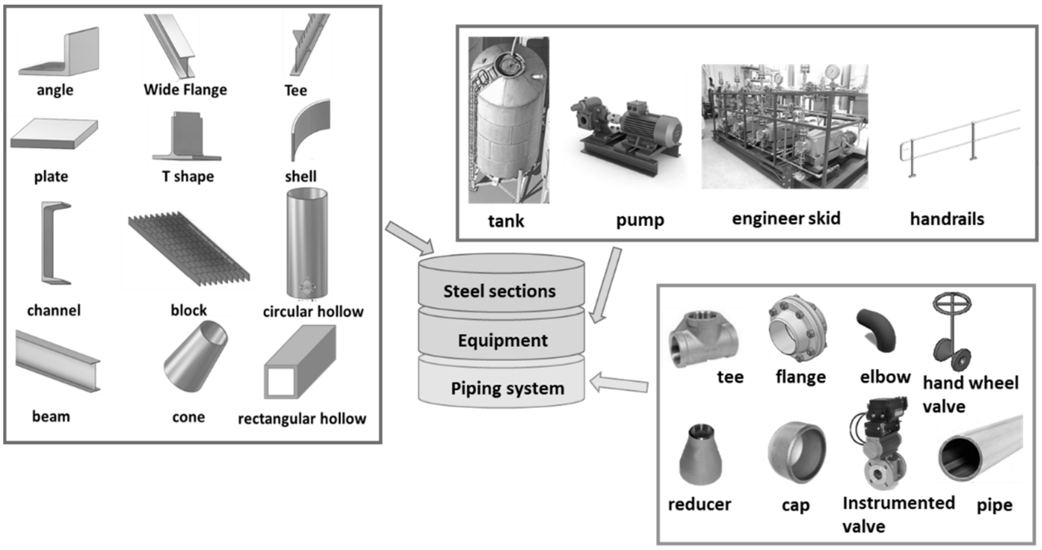

Figure 2: Steel sections, equipment and piping system representations of objects (AVEVA)

The results of this statistical analysis will assist researchers to focus on automated modelling for the most frequent object types, whereas users will manually intervene to a small subset of infrequent object types. Time efficiency will indirectly result in cost reduction, which is a crucial parameter when modelling huge assets. There are many unclassified objects in the case studies, where many units are prefabricated and not included in the designs or object types that are classified in different categories. For instance, some modellers classified hand rails as structural components and others as parts of the piping system. The prefabricated units are transported to the facilities by engineering skids, thus the objects they contain are not modelled. Also, equipment includes electrical systems, plumbing and fire protection elements. We addressed the research question (b) with a priority list of critical objects in the introduction.

RESULTS: CASE STUDIES

Figure 3 shows the object type rankings in descending order for all case studies and the percentage of large bore objects in piping systems as well as the percentage of instrumented valves in total number of valves. The facilities are anonymized since rights are reserved by AVEVA and representative pictures of typical facilities are shown in Figure 3. Steel sections are more frequent in all offshore projects with an average frequency of 50.44 % for all case studies. Pipes and other elements of piping systems follow in percentages as well as equipment. These statistics are important since most software packages and research methods that were mentioned above prioritize the modelling of pipelines, which are only 22.24 % on average for all facilities. We also show the standard deviation of the average general frequencies, which is higher for steel sections meaning that the data are more widely spread from the mean (50.44 ± 14.94 %).

(a) Gravity-based platform	
Object type	Frequencies of appearance (%)
Steel sections	47.84
Pipes	25.14
Elbows & bends	11.17
Equipment	4.45
Flanges	4.40
Tees & olets	3.09
Valves	2.12
Instruments	0.69
Caps	0.08
Total number of objects = 362,664	
(%) of large bore objects = 45.86	
(%) of instrumented valves = 67.28	

(b) Fixed platform	
Object type	Frequencies of appearance (%)
Steel sections	58.06
Pipes	17.90
Elbows & bends	8.40
Equipment	6.35
Flanges	4.24
Tee & olets	2.57
Valves	2.30
Reducers	0.18
Total number of objects = 22,487	
(%) of large bore objects =44.02	
(%) of instrumented valves = 0.00	

steelwork
piping system
equipment

(d) Tension-leg platform	
Object type	Frequencies of appearance (%)
Steel sections	68.13
Pipes	13.27
Elbows & bends	4.89
Flanges	4.86
Tee & olets	2.71
Valves	2.07
Caps	1.37
Vendor skid	1.11
Instruments	0.67
Slabs	0.53
Reducers	0.50
Equipment	0.42
Total number of objects = 288,414	
(%) of large bore objects = 42.72	
(%) of instrumented valves = 38.12	

(d) Sugar refinery	
Object type	Frequencies of appearance (%)
Pipes	32.65
Steel sections	27.74
Flanges	12.48
Elbows & bends	12.05
Tees & olets	5.21
Valves	4.26
Equipment	2.20
Instruments	1.70
Reducers	1.55
Caps	0.16
Total number of objects = 14,611	
(%) of large bore objects = 58.96	
(%) of instrumented valves =58.69	

(e) Object types	General frequencies (%)	Standard deviations (%)
Steel sections	50.44	14.94
Pipes	22.24	7.35
Elbows & bends	9.13	2.79
Flanges	6.50	3.46
Tee & olets	3.40	1.07
Equipment	3.36	2.24
Valves	2.69	0.91
Other	2.24	1.55

Figure 3: Priority list of all object types in descending order, percentages of large bore objects in piping systems and instrumented valves in total number of valves for the (a) Gravity-Based Platform, (b) fixed platform, (c) Tension-Leg Platform, (d) sugar refinery and (e) average frequencies of all industrial facilities. Pictures illustrate typical industrial facilities in each case: all pictures of offshore platforms are taken from Devold (2013) and the picture of sugar refinery from KPMG (2007)

Different classes of the same object type exist based on their use, which are not investigated in this paper. However, instrumented valves (tagged as "instruments" in Figure 3) are significant, since they can be more easily damaged compared to hand-wheel valves, thus more frequent inspection should be provided. Figure 3 shows that they constitute 67.28% out of the total number of valves in the case of the Gravity-Based Platform, whereas they are not present in the fixed platform. We also investigate the percentage of large bore objects out of the total number of objects for each type of industrial facility. This indicates that large bore objects represent around 50% on average of all modelled object types considered in this study, so modellers should give equal importance to them.

Modellers use steel sections to represent structural members, hand rails, pipe hangers or supports. Equipment lists of as-designed 3D models are composed of unlabelled or prefabricated objects. Since many objects are prefabricated in engineering skids, like the case of the Tension-Leg Platform, there are more skids than the actual as-designed equipment. Another modelling issue with the equipment list of the fixed platform is that some pipe clamps (hangers and supports) are modelled in the equipment list leading to a higher equipment frequency (6.35 %) compared to the other facility types.

We conduct a parametric study to quantify the frequency of appearance of the elements of pipe systems with respect to their OD following a discrete probabilistic approach. We cluster the data in bins of 25 mm (less than 1 inch) to achieve homogeneity for all projects and we calculate the probability density function curves based on these bins. Figure 4 shows the distributions of OD for all object types and four case studies presented above. It should be noted that the frequencies of caps were less than 1.5 % for all case studies and inexistent in the fixed platform, thus their OD distribution is not further investigated. The right skewness of data is a trend prevalent in all object types indicating the wider distribution of large bore objects. The information inferred from Figure 4 is that elements with diameters less than 100 mm have higher probabilities of appearance and elements with diameters greater than 600 mm are distributed in ranges up to 1050 mm, with probabilities less than 10%.

This finding is in accordance with typical pipe catalogues in the manufacturing industry for both plastic (ASTM D2513 - 16a 2017) and steel pipes (ASTM A53/A53M - 12 2017). Specifically, oil pipelines for Tension-Leg Platforms (TLPs) range in size up to 18 inches (457.2 mm) NB and gas pipelines up to approximately 14 inches (355.6 inches), whereas pipe diameters on fixed platforms range from 4 inches (100 mm) to 36 inches (914.4 mm) NB. It should be noted that NB is less than the OD according to the European set of standards (ISO 6708 1995).

We analyse the distributions of data for piping systems by conducting a statistical analysis. The weighted mean of the distribution of each object type is found as following:

$$\mu_i = \frac{\sum_{i=1}^{n} c_i d_i}{\sum_{i=1}^{n} c_i} \tag{1}$$

…where n is the total number of counts of an i object type, c is the number of counts per each d OD. The weighted variance is also calculated to observe the dispersion of the datasets from the weighted mean. The formula of the weighted variance is as following:

$$\sigma_i^{\;2} = \frac{1}{n} \sum_{i=1}^{n} c_i d_i^2 - \mu_i^2 \tag{2}$$

…where n is the total number of counts of an i object type, c is the number of counts per each d OD and μ the weighted mean of each object type. These statistical parameters (μ, σ, OD range) are then compared for all case studies and a {min, max} range is given in Figure 4 for all object types and case studies.

The ranges of the statistical properties are similar for all industrial facilities, which clearly indicates a trend of connectivity between all object types of the piping system. Reducers and valves have the largest and smallest mean ranges respectively. The standard deviations of the mean are quite high for all object types, indicating wide dispersion of the data. Meanwhile, the OD ranges are similar for all objects types. Figure 4 also shows the mean probability density curves for all object types along with their 95% confidence intervals. These curves have no significant variations for ODs greater than 600 mm for all object types with probabilities close to zero, so the objects with the most frequent OD ranges are below 600 mm.

CONCLUSIONS

The two main challenges that modellers of industrial facilities face are the plethora of object types and quality of BIM models. Our frequency-based, statistical analysis showed that automated modelling of steel sections and pipes will save around 72 % of the time required for manual modelling. These object types should be represented at LoD 300. A parametric study on the OD distribution of piping systems showed that objects with OD greater than 600 mm are not frequent, thus can be semi-automated.

Researchers can automatically model the primary object types that we identified and improve the cost-benefit relationship of as-is modelling. We solve the problem of large number of object types by the statistical analysis presented in this paper. Mapping the most important object types can substantially facilitate automatic detection and classification of the laser scanned objects of a facility, thus reducing modelling time.

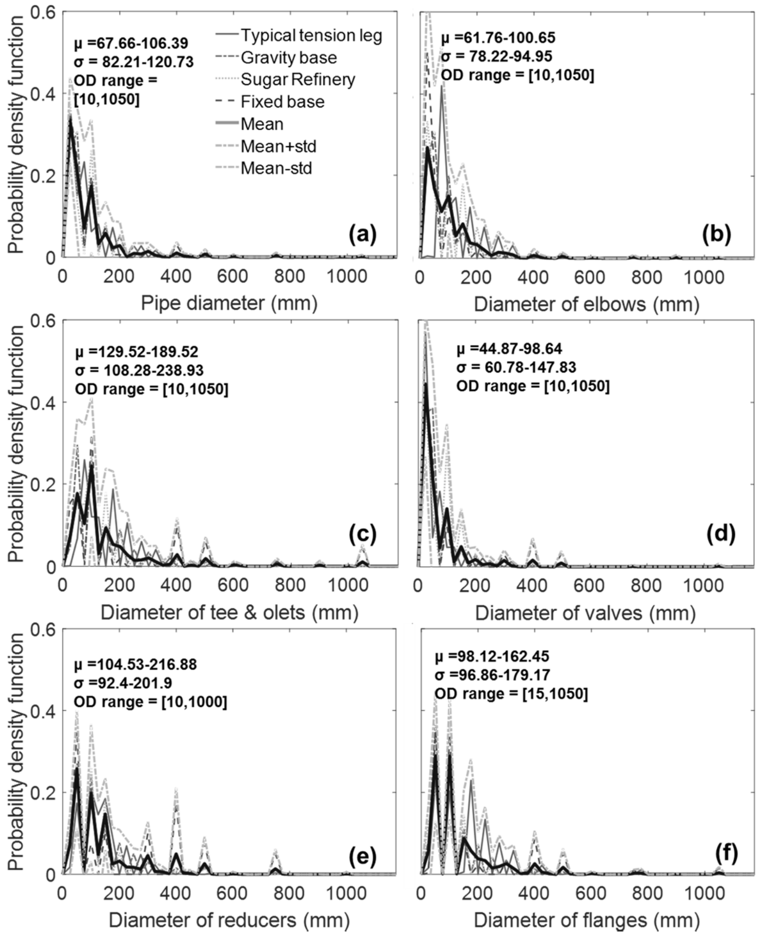

Figure 4: Mean probability density curves with respect to the OD of (a) pipes, (b) bends and elbows, (c) tee and olets, (d) valves, (e) reducers and (f) flanges for all case studies and {min-max} ranges of statistical properties for each object type

The proposed OD ranges will assist modellers to recognize false positives for object types out of the proposed OD ranges, for instance, hand rails or other cylindrical objects that are misclassified as pipes. The analysis provided herein will benefit industrial facility modellers in efficiently producing enriched industrial BIM models. These models will assist inspectors to locate critical objects easily, therefore they will contribute to maintenance, safety and retrofit of these facilities. Reduction of modelling time will significantly benefit the facility managers to obtain 3D BIM models in circumstances of required shut down of the plant. Every modelling hour saved can prevent critical failures or unexpected accidents, thus continuous production flow of these assets is achieved. Future work of this paper is to extend the object type frequencies to floors and walls and investigate objects in the engineering skids as well as structural sections.

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