What Objects are Most Important when Modelling Existing Industrial Facilities?

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Abstract:

The cost of modelling existing industrial facilities currently counteracts the benefits these models provide for maintenance and retrofit of these assets. 90% of the modelling cost is spent on labor for converting point cloud data to 3D models, hence reducing the cost is only possible by automating this step. The highly-cluttered scene and large number of industrial objects increase the required modelling time. Therefore, modelling is prohibitively expensive. We tackle a part of this issue by identifying the most frequent object categories and object types that require modelling in industrial plants to guide future work aimed at automating the tedious current practice. The industrial facilities investigated are: (a) offshore platforms, (b) food processing facilities and (c) petrochemical plants. The industrial object types obtained from BIM models are hierarchically ordered based on their frequency of appearance and modelling intent. The results showed that structural elements, the piping system and electrical equipment were the most frequent object categories encountered in all case studies. The most frequent object types in these categories are then determined by implementing a statistical analysis on their frequency of appearance in all case studies. The modelling intent of the most frequent object types in these categories is then explored to determine the most important object types. These are in descending order: electrical conduit, straight pipes, circular hollow sections, elbows, channels, solid bars, I-beams, angles and flanges. Automatically modelling these frequent and critical object types can guide future researchers interested in modelling these assets.

Keywords: Industrial Facilities, Facility Management, Building Information Modelling

1. INTRODUCTION

"As-Is" Building Information Models (AI-BIMs) are the 3D digital representation of the existing condition of facilities and encompass geometric definitions at different levels of aggregation and parametric rules (Volk et al., 2014). The clear majority of large refineries were built before the advent of CAD in 1977: as-is models, therefore, do not exist to assist their maintenance operations (Cabinet Office, 2011; Tornincasa and Monaco, 2010). AI-BIMs of industrial plants have substantial impact in various applications. Some of these include maintenance, strategic planning of their operations, revamping purposes, retrofitting of old sites and preparation for dismantling (Kawashima et al., 2014; Rabbani et al., 2006; Son et al., 2013; Veldhuis and Vosselman, 1998).

Inexistence of AI-BIMs will result in time lags for these operations. This is crucial for industrial managers, since without detailed planning, productivity will be substantially affected, and the agreed budget and timeline expectations will not be met. Moreover, there are thresholds on the acceptable shut down duration that will not impede production, and those limits cannot be violated without incurring extra costs. For instance, Sanders (2001) reported that 40 % of the total 3D modelling cost of retrofitting a Chevron plant was spent on data-processing labor and the shut-down time was limited to 72 hours to avoid additional costs. Every modelling hour saved can prevent critical failures or unexpected accidents, thus continuous production flow of these assets is achieved. This paper aims to assist the tedious current practice in this regard.

Geometric modelling is the "bottleneck" during the Scan-to-BIM modelling process of any industrial facility given how costly and time consuming it is. Recent studies have reported that geometric processing takes 90 % of the modelling time (Fumarola and Poelman, 2011; Hullo et al., 2015). Hullo et al. (2015) reported that 10 operators were needed to process 1084 scans of a nuclear reactor and model its objects in around 6 months using Dassault Systems SolidWorks and Trimble Realworks. In contrast, laser scanning of the plant was completed in only 35 days. This significant time required to model the large number of industrial objects impedes adoption of as-is 3D modelling for these plants.

The research presented in this paper is exploratory in nature, not causal. It does not seek to solve the problem of automating modelling of industrial facilities. It rather seeks to improve our understanding of the problem and the extent to which it has been resolved so far and provide a foundation for future researchers interested in solving it. This is why the main objective of this paper is to identify the most important industrial object types given how frequent and valuable they are for modelling. The authors identified the most frequent objects based on a frequency-based, statistical analysis of 3D modelled industrial objects in a variety of industrial plants. The most important industrial object types were ranked based on their frequency of appearance and modelling intent. This analysis will substantially assist automated modelling efforts to efficiently reduce modelling time and facilitate facility management.

2. BACKGROUND

Industrial plants can be divided into ten main categories (Douglas, 1988): (a) onshore and (b) offshore oil platforms, (c) chemical, (d) mining, (e) pharmaceutical plants, (f) power plants, (g) water and wastewater treatment facilities, (h) natural gas processing and biochemical plants, (i) refineries, (j) food processing factories, (k) defense facilities, (l) metal production facilities, (m) nuclear plants, (n) research facilities and (o) warehouses and silos. The object types of industrial facilities belong to the main object categories: (a) structural elements, (b) piping system, (c) electrical, (d) safety and (e) general equipment, (f) architectural elements, (g) instrumentation, (h) Heating, Ventilation and Air Conditioning (HVAC) and (i) civil elements.

2.1 Value of modelling industrial object types

Petitjean (2002) proves that 85 % of objects in industrial scenes can be approximated by planes, spheres, cones and cylinders. These primitive shapes, however, have not been assigned to specific industrial object types. The value of modelling those is measured in terms of safety, maintenance and retrofitting (British Institute of Facilities Management, 2012). Extensive research has been conducted to identify critical industrial objects under these values of modelling (Baker and Stanley, 2008; Kala, 2015; Mechhoud et al., 2016; Moss and Strutt, 1993; Ruijters and Stoelinga, 2015; Thompson, 1999; Umar, 2010). Susceptibility to failure is measured based on failure rate metrics. The nominal mean failure rate (λ_0) is the frequency that an industrial object type or object component fails and is usually expressed in failures per year (Moss and Strutt, 1993). Sources of failure data rates are given in (Moss and Strutt, 1993). Steel sections are also critical for fatigue and fire, dependent on the load imposed and welding (Baker and Stanley, 2008; Kala, 2015). What is missing, though, is a justified study on which critical objects should be modelled for maintenance, safety or retrofit purposes.

Examples of critical object types that should be considered are given below. Hazardous subsystems should be modelled in finer detail for safety purposes. Highly hazardous object types are separators, compressors, driers and flash drums, whereas moderately hazardous ones are pipelines and pumps (Umar, 2010). Valves are a final control element in nearly all chemical process control loops and regulate the flow through piping systems. Failure to quickly locate and identify control and safety valves during inspection can result in significant damages or even massive, unprecedented disasters such as Texas City Refinery (US Chemical Safety and Investigation Board, 2007) or Piper Alpha (Landau, 2008). Safety system deficiencies 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 are considered critical for corrosion (Singh and Britton, 2001). Structural steelwork and equipment are also vital for the structural stability of the plant 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). Seismic and energy refurbishments for pipes are typical retrofitting operations in industrial plants (Autodesk, 2009). AI-BIMs can significantly assist these operations, should accurate as-is models of these objects be created.

Table 1. Critical object type list for facility management in terms of value for modelling

Value for modelling	High Impact ($\lambda_0 \geq 10^{-4}$) yr^{-1}	Medium Impact ($10^{-5} \leq \lambda_0 \leq 10^{-4}$) yr^{-1}	Lower Impact ($\lambda_0 \leq 10^{-5}$) yr^{-1}
Maintenance	Valves	Small bore pipelines	Large bore pipelines
Safety	Separators, reciprocating compressors, driers & flash drums, valves, large vessels, tanks, electrical conduit, circuit breakers	3 mm diameter pipelines, pumps, reciprocating compressors	4 mm diameter pipelines, 25 mm diameter pipelines, 33 mm pipework diameter, pressure & spherical vessels
Retrofit	-	3 mm diameter pipelines	4 mm diameter pipelines, 25 mm diameter pipelines, 33 mm pipework diameter

Table 1 summarizes the critical elements for each category (maintenance, safety and retrofit) based on their failure rates λ_0 (high, medium and lower impact) based on Umar (2010) and Keeley et al. (2011). These values are calculated for major accidents that involve dangerous substances and cause serious damage/harm to people and/or the environment. The piping system is generally subdivided in two meaningful subgroups with respect to their Outer Diameter (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. Table 1 shows that small bore pipelines are considered to have higher impact than large bore.

The critical industrial object types have been investigated in the literature. However, those that need automated modelling due to frequency of appearance have not been identified. If an object type is critical but not frequent, there is no need to automatically model it. On the other hand, even if an object type is frequent but is not critical, this paper can ignore modelling it.

2.2 Frequency based studies

There is no substantive study that prioritizes industrial objects based on their frequency of appearance as explained in Section 2.1, however there are related fields where object importance is considered for object classification (Spain and Perona, 2011; Zhou et al., 2017). SceneParse150 (Zhou et al., 2017) is an image dataset, part of ADE20K, used for image classification that contains the eight most frequent object classes (‘person’, ‘building’, ‘car’, ‘chair’, ‘table’, ‘sofa’, ‘bed’, ‘lamp’) and 150 objects in these classes found in a variety of everyday scenes. The uniqueness of this dataset compared to other benchmark datasets, such as ImageNet (Russakovsky et al., 2015) and Pascal (Xiang et al., 2014), is that the distribution of objects that appear in the selected images is diverse, which mimics object occurrences in daily scenes. This dataset, however, is limited to everyday scenes and not extended to industrial facilities. Therefore, the statistics of most frequent industrial object types are not determined.

2.3 Gap in knowledge and research question

Critical industrial object types have been identified in the literature based on their value for modelling, but no scientific study investigates modelling those. It is therefore still unclear which industrial object types are important for automated modelling based on frequency and value for modelling. The aim of this work is to solve the gaps in knowledge by answering the following research question: what are the most important industrial object types in terms of value for modelling and frequency of appearance?

3. RESEARCH METHODOLOGY

The research conducted in this paper is exploratory in nature and follows the methodology framework depicted in Fig. 1.

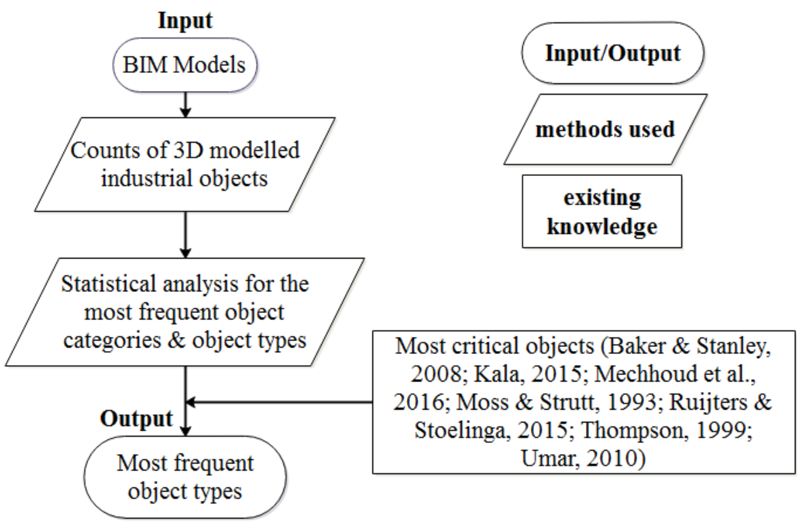

Figure 1 Research methodology

We analyzed the counts of 3D modelled industrial objects obtained from as-designed BIMs by hierarchically ordering those based on their average frequency of appearance in sample case studies. The output is the rank order of the most frequent object types. Only the critical object types that are also frequent are considered for modelling.

3.1 Data Collection and Assumptions

Five case studies of 3D modelled industrial facilities were examined to find a statistically representative sample of object types in industrial facilities. Three case studies were offshore platforms, one was a petrochemical plant and the fifth was a food processing refinery (sugar refinery). The subcategories of offshore platforms that were examined in this study are (a) a Gravity-Based Structure (GBS), (b) a Tension-Leg Platform (TLP) and (c) a fixed platform. These facilities are anonymized since rights are reserved by AVEVA Group plc. and British Petroleum (BP). An assumption was made for electrical, safety equipment, HVAC and civil categories of the offshore platforms and sugar refinery due to unavailability of data. This assumption for electrical and HVAC categories is reasonable, since the pipe network and fittings can be simulated with conduit and valves/flanges. The percentages of these categories for the petrochemical plant were used to calculate the respective percentages in the other case studies presented. For instance, in the case of electrical equipment, around 27 % of the total objects in the petrochemical plant was assumed to be present in the tension-leg platform, which has 289,943 objects in structural, piping system, equipment, architectural and instrumentation categories. These categories represent 67 % of the total objects in the facility, which are 434,780 in this case, assuming safety objects constitute around 6 %, HVAC 0.6 % and Civil 0.05 %. The same concept is applied to identify the object counts in the other missing categories of the case studies. This assumption is followed for consistency between different sources used to gather the data.

A sensitivity analysis on the total number of industrial objects that a plant can have, is conducted to observe the range of percentages for each object category. Fig. 2 shows the average curves on the data available from the counts of as-designed BIM models of industrial plants. The range of total number of objects is defined based on the existing datasets ($1.5*10^4 – 6*10^5$ objects). The average frequency of appearance based on our data is a linear function for object categories shown in Fig. 2(c), object types of the pipe system and structural elements in Fig. 2(a) and Fig. 2(b).

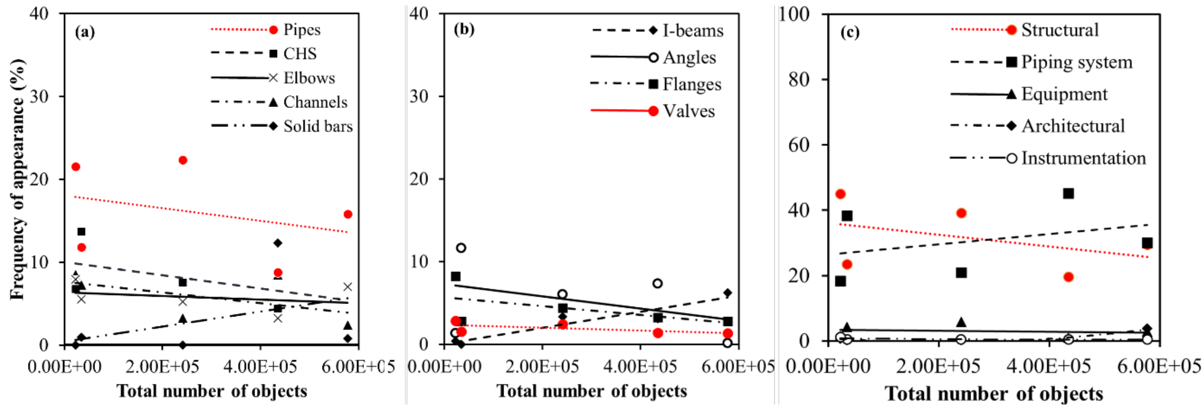

Figure 2 Estimated frequency of appearance (%) of (a) & (b) industrial object types and (c) industrial object categories with respect to the total number of objects in the five case studies of industrial plants

Equipment, architectural elements and instrumentation are less than 5 % in all case studies. These observations substantiate the assumptions for the average frequencies of the categories with unknown data, since the average frequency of appearance is invariant to changes in the total number of objects. We observe that piping elements and structural elements vary from 20 – 40 %, given our data. No correlation between the size of the plant and the frequency of appearance is observed. There is no clear definition of the size of a plant compared to its total number of objects. The results on object categories show a decreasing trend with increasing total number of objects, except structural elements that have an increasing trend. The same trend is observed for all object types other than solid bars and I-beams, whose average frequency increases with the total number of objects.

4. RESULTS

4.1 Most frequent industrial object categories

The object categories that need to be modelled are determined by implementing a statistical analysis on the frequency of appearance of all object categories encountered in typical industrial plants. The frequency of appearance is calculated by dividing the total counts of each object category (n_i) with the total number of objects of the same object category in all case studies (N_i). The total counts of each object category were calculated by running a Programmable Macro Language (PML) script in as-designed 3D models. Subsequently, the most frequent object types of these categories are presented. The standard error of each object category between the five case studies using the inter-project standard error (S.E.) is given in Equation (1) (Press et al., 1992):

$$S.E._{1-5} = z\sqrt{\sum_{k=1}^{5} \frac{p_k(1-p_k)}{n_k}} \tag{1}$$

where $k \in [1;5]$ for each individual case study

p_k: probability of appearance of each object category in case study k, n_k: number of objects in each category, z: Z-score corresponding to the confidence level of a Gaussian distribution

The object category rankings are calculated in descending order for all case studies in Table 2. Structural elements are most frequent in all case studies with an average frequency of around 33 %. The piping system and electrical equipment follow in percentages being 28 and 27 % respectively. These statistics are important since most software packages and research methods are designed to automate only the modelling of pipelines, electrical conduit and Circular Hollow Sections (CHSs), which are all cylindrical objects. Each object category follows a binomial distribution where N is the total number of objects in all independent object categories existing in our case studies (1,308,936 in all five projects) and p_i the probability of appearance of the specific object category i. A binomial distribution can be approximated to a Gaussian distribution if the following conditions, as shown in Equation (2) are met (Walker, 1985):

$$N_i > 30,\ \ N_i p_i > 5,\ \ N_i\left(1-p_i\right) > 5 \tag{2}$$

Table 2. Priority list of object categories for all case studies

Object category	Frequency of appearance (average) (%)	Sample size (n)	Standard deviation (average %)	Standard error (95 % Confidence Level)
Structural	33.40	437,530	540	0.92
Piping	28.20	368,428	515	0.88
Electrical	26.90	352,170	507	0.87
Safety	5.70	74,860	266	0.46
Equipment	2.80	36,310	188	0.32
Architectural	2.00	24,557	160	0.27
HVAC	0.60	8,431	81	0.14
Instrumentation	0.50	6,066	88	0.15
Civil	0.04	584	21	0.04

The results show that all conditions are met for every object category, thus the approximation to a Gaussian distribution is valid. The sample size of the binomial distribution of each object category, the standard deviation and standard error of the sample mean are also presented in Table 2. The sample size of the object category i is defined in Equation (3) (Press et al., 1992):

$$n_i = N_i p_i \tag{3}$$

where p_i : frequency of appearance of the object category $i\ \epsilon[1;9]$, since there are nine independent object categories for each case study

The standard deviation and standard error of each object category i are calculated using the equations for a binomial distribution in Equation (4) (Larsen and Marx, 2012; Press et al., 1992):

$$\sigma_i = \sqrt{Np_i\left(1-p_i\right)}\ \ ,\ \ S.E._i = \frac{z\cdot\sigma_i}{\sqrt{n_i}} \tag{4}$$

The definition of the standard error implies the sample follows a Gaussian distribution (Press et al., 1992) as proved above. The standard deviation for the structural category is 540 objects, meaning that there is a higher variance from the mean of all projects (437,530 ± 540 objects) compared to the other object categories, but is low compared to the magnitude of the mean. The standard error with 95 % confidence level is low for all object categories, meaning that the sample mean is close to the population mean (1,308,936 objects) for all object categories. For instance, if more samples of each object category are considered, there is 95 % confidence level that the average frequency of appearance will be the same as calculated herein. The inter-project standard error, as shown in Table 2 is almost negligible for all object categories implying that the variability of object counts between different case studies for the same object category is very low.

4.2 Most frequent industrial object types

The most frequent object categories being around 90 % of all objects modelled in these facilities are: structural elements, the piping system and electrical equipment. Table 3 shows the priority list of object types belonging to these categories with the same statistical properties evaluated for the object categories.

The results show that Circular Hollow Sections (CHSs) are the most frequent structural elements present in these studies with an average percentage of around 19 %. They are one of the object types in this category with highest standard deviation (261 objects) and inter-project standard error ($\sim 1.8*10^{-2}$), meaning that their distribution among the five case studies is quite widespread from the sample mean (84,688 objects) compared to the other object types.

However, the standard deviation is two scales of magnitude lower than the sample size (n) meaning that the average frequency of appearance is invariant to the sample size, and the samples are large enough to give accurate results. Channel sections, solid bars and I-beams follow with approximately 14, 13.5 and 13 % respectively. The priority list of piping elements is also provided in Table 3. Straight pipes are more than half of the total objects in this category (52.1 %) with a slightly higher standard deviation compared to structural elements (303 objects). Elbows and flanges follow with 19 % and 12 % respectively and lower standard deviations.

Table 3.Priority list of objects for all case studies in piping element categories

		Frequency of appearance (average) (%)	Sample size (n)	Standard deviation (average)	Standard error (95 % Confidence Level)	Inter-project standard error
Piping object type	**Straight pipe**	52.1	192,081	303	1.0	$1.56*10^{-2}$
	Elbow	19.3	70,945	239	0.8	$1.25*10^{-2}$
	Flange	11.8	43,308	195	0.6	$1.09*10^{-2}$
	Tee & Olet	6.1	22,460	145	0.5	$0.81*10^{-2}$
	Valve	5.6	20,591	139	0.4	$0.76*10^{-2}$
	Other	2.2	8,137	89	0.3	$0.18*10^{-2}$
	Reducer	1.8	6,570	80	0.3	$0.36*10^{-2}$
	Cap	1.2	4,336	65	0.2	$0.17*10^{-2}$
Structural object type	**CHS**[a]	19.4	84,688	261	0.8	$1.77*10^{-2}$
	Channel	14.3	62,634	232	0.7	$1.72*10^{-2}$
	Solid bar	13.5	58,934	226	0.7	$0.34*10^{-2}$
	I-beam	13.1	57,314	223	0.7	$0.58*10^{-2}$
	Angle	11.9	51,886	214	0.6	$1.2*10^{-2}$
	Others	10.8	47,273	205	0.6	$0.98*10^{-2}$
	RHS[b]	9.2	40,439	192	0.6	$0.2*10^{-2}$
	PFT[c]	7.5	32,699	174	0.5	$0.28*10^{-2}$
	T-brace	0.4	1,663	41	0.1	$0.16*10^{-2}$
Electrical object type	**Conduit**	90.2	317,572	177	$29.8*10^{-2}$	
	Cable tray	6.1	21,585	142	$23.9*10^{-2}$	
	Electrical panel	2.1	7,397	85	$14.3*10^{-2}$	
	Lights	1.4	5,009	70	$11.8*10^{-2}$	
	Miscellaneous	0.07	250	16	$2.7*10^{-2}$	
	Alarm	0.05	190	14	$2.3*10^{-2}$	
	Speaker	0.03	120	11	$1.8*10^{-2}$	
	Others	0.01	39	6	$1.07*10^{-2}$	
	Power outlet	0.003	11	3	$0.53*10^{-2}$	

[a] Circular Hollow Section (CHS), [b] Rectangular Hollow Section (RHS), [c] Parallel Flanged Tee (PFT)

Electrical equipment is mostly comprised of conduit (90.2 %) in the petrochemical plant as shown in Table 3. An assumption was made that the proportion of electrical equipment in each project will be the same for all case studies as discussed in Section 3.1, thus the inter-project standard error is zero. The standard error with 95 % Confidence Level for the electrical equipment has the highest range compared to all the other categories, indicating the different scale of total numbers of objects in the five case studies investigated. The standard deviation of the sample considered is also low compared to the sample size in terms of order of magnitude, so the average frequency of appearance is a reliable estimation.

This statistical analysis gives us the most frequent object types in object categories that are among the most critical object types for modelling industrial plants as shown in Table 1. The most frequent object types of these categories are in descending order: electrical conduit, straight pipes, circular hollow sections, elbows, channels, solid bars, I-beams, angles, flanges and valves. The results are presented in Table 3. It is noteworthy that the rest of the object types present in our datasets were less than 1 % of the total number of objects, thus neglected from our analysis. Fig. 4 shows a distribution of ranked object types with their corresponding average frequencies for the five case studies investigated. The distribution follows the Zipf's law (Powers, 1998b) and is typically found in everyday scenes as explained in Section 2.2. This means that the average number of industrial objects and their ranking are inversely proportional. Therefore, the most frequent object category (electrical conduit) will occur approximately twice compared to the second most frequent category (straight pipes), three times as often as the third most frequent category (CHSs) and so forth. The 10 rank-ordered object types can be used for automated modelling.

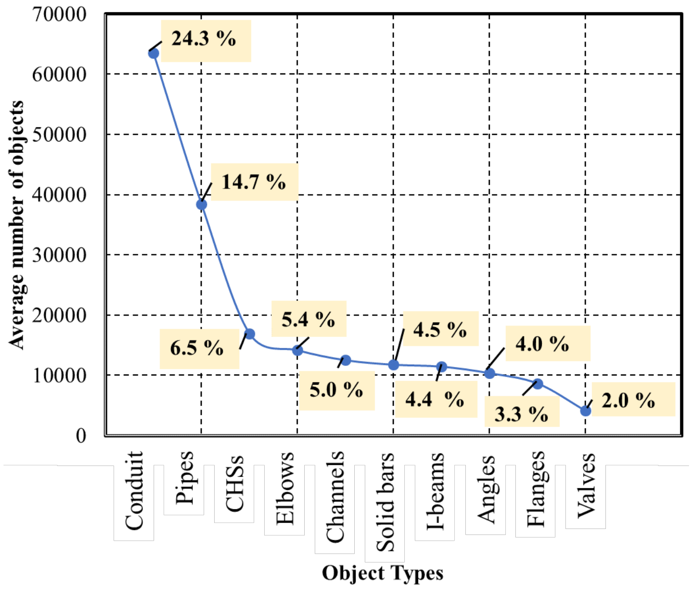

Figure 3 Object types sorted by frequency of appearance in average number of objects

4. CONCLUSIONS

The ten most important object types in the three most frequent industrial categories (structural elements, piping network and electrical equipment) are ranked based on their frequency of appearance and modelling intent. The results showed that cylindrical objects (straight pipes, electrical conduit and circular hollow sections) represent 45.5 % of the total number of objects in an industrial plant on average.

This paper marks the first study specifically aimed at identifying the most frequent industrial object types. Our contribution is therefore the discovery of the most frequent object types in industrial facilities. The presented research has room for improvement and some limitations of this study can direct future research. This study focuses on the industrial objects that are important to model, however methods on how to automatically model those were not investigated. Future work involves implementation of automated classification algorithms (e.g. machine learning) for the most important object types to minimize the modelling time. Application of these algorithms for hundreds of classes of different objects that have strong similarities (e.g., pipes, electrical conduit, CHs) is a very difficult multi-classification problem, that will be substantially benefited from the results of this exploratory research for the important objects to model in these complex environments. Overall, a training library of the object classes that are critical for industrial facility operations, frequent in industrial environments and laborious to model can be established to assist further research aimed at automated detection of these classes. Application of the findings of this paper will guide researchers on investigating methods for automatically modelling these objects.

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