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A framework for capturing and representing the process to classify nuclear waste and informing where processes can be automated

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ABSTRACT

Decommissioning and dismantling of nuclear facilities are complex processes, where an accurate triage of visual and radiological characterisation is an important driver of how this process is executed. In-situ measurements before dismantling are essential for effective, optimized waste management solutions to ensure the safe and secure decommissioning of nuclear installations. Characterising nuclear structures includes a large amount of human involvement in decision making, physical inspections and even lifting and relocating radioactive waste items. The current process accounts for risks like close human contact with radioactive material for extended periods, and errors based on operator knowledge rather than automated detection systems. In this paper, we present a framework to explicitly outline the steps required to classify nuclear waste remotely, in-situ and non-destructively, and the subsequent evaluation of these steps to determine where they can be automated. This framework uses the CommonKADS methodology, a well-established approach for knowledge modelling systems, to identify the main decisions in the process of characterising a nuclear reprocessing cell in a nuclear facility. We capture the sources of knowledge required to support and justify decisions made, and the resulting models are reviewed to assess where decisions can be automated, or supported using AI tools, to ensure robust, reliable, and rapid decisions. This framework aims to provide the first step and help to support innovation, toward a system able to produce tangible benefits for enhancing the safety, economy and reliability of nuclear cell waste classification and decommissioning management. We illustrate the use of the framework with a case study application which demonstrates how a semi-automated decision support system could be built based on the framework.

1. Introduction

Decommissioning and dismantling (D&D) of nuclear facilities and related waste management issues represent a significant challenge around the world as they continue to age (Nuclear Energy Agency, 2003). The Organisation for Economic Cooperation and Development and Nuclear Energy Agency country members are amongst those with the early development of nuclear technology in the 1940s and now face the decommissioning and dismantling of these facilities and equipment. This presents a technical challenge augmented not only by the fact that the waste is usually hazardously radioactive, but also these older legacy systems often have their original documentations lost and original staff retired. This means in a lot of cases, measurements, both contextual and radiometric, are paramount in characterising and understanding the extent and nature of nuclear waste, which directly impacts the strategies needed to decommission and dismantle the facility. Characterisation also gives rise to forecasting estimates which underpins waste management plans. The main purpose of D&D is to reach the end point of the life cycle of nuclear facilities while suitably protecting the health and safety of the decommissioning workers, the public and the environment. Presently there is no universal approach to the D&D of nuclear facilities as it is a complex problem that depends on various factors: national policies, availability of staff and financial issues amongst others.

The D&D process includes classifying the nuclear waste. Measurements used to characterise the waste can be used to assign the waste to different classes and in the UK, this is according to how much radioactivity it contains (activity per unit mass) and the heat that it produces (Pöyry Energy Limit ed et al., 2017). Waste is sorted into 3 main categories: Low Level Waste (LLW) where waste content must not exceed 4 giga-becquerels per tonne of alpha activity or 12 giga-becquerels per tonne of beta/gamma, Intermediate Level Waste (ILW) where waste exceeds the limit for LLW but do not generate enough heat to be taken

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into account for storage and disposal purposes, and High Level Waste (HLW) where the temperature is significant and so must be taken into account when deciding upon its storage or disposal.

In the UK, the Nuclear Decommissioning Authority (NDA) waste classification assessment is a life-cycle approach that involves the following key steps: planning and preparation which necessitates characterisation, treatment and packaging which necessitates the retrieval of waste and sorting and segregating, and storage and disposal (Pöyry Energy Limit ed et al., 2017). In the planning and preparation phase, early characterisation of waste items can help with cost estimations, enhanced safety and provide better accuracy of characterisation and classification (INTERNATIONAL ATOMIC ENERGY AGENCY, 2007), leading to more informed waste management strategies and quality inventories. The purpose of an inventory is to provide the best available information about the nature, quantity and location of the waste, and the data used to compile these inventories needs to be of good quality and collected in a systematic way, where the data may come from measurements, or may be derived or estimated while considering practical limits (Dickinson et al., 2020). A primary objective of the National Inventory Forum (NIF) is to improve the quality of these inventories by improving efficiency of data collection (NDA, 2019). By performing a triage of the classification of nuclear waste in-situ before the retrieval phase, a more robust inventory can be compiled, and a more robust dismantling and sort and segregation process can be facilitated. Building a knowledge system for this triage process is a key challenge tackled in this work.

In the rapidly evolving landscape of nuclear decommissioning, many strategies and processes have been developed for characterisation. A widely used guidance document in the UK is the NDA "Solid Radioactive Waste Characterisation Good Practice Guide" (Jacobs, 2022) of which many characterisation providers base their own characterisation strategy. A web tool was developed within the INSIDER EU Horizon 2020 project which provides a strategy for characterisation, pointing to state-of-the-art techniques to implement (Rogiers et al., 2022). More closely related to this paper is the work of the PLEIADES project - a common platform with a defined interface and reusable models, of which ontology was the basis. This enabled a standardised approach to organising data and easier data exchange between software ("www.pleiades-platform.eu,"). In addition, although there are also some well-developed techniques for the D&D process like decontamination techniques, cutting techniques for dismantling installations, radioactivity measurement techniques and remote control techniques (Nuclear Energy Agency, 2003), it is still in its relative infancy regarding more advanced Artificial Intelligence (AI) techniques.

The nuclear industry in the UK relies heavily on experts in key areas within decommissioning processes to manually make time-consuming decisions, which may introduce human factors associated with subjectivity and may lead to overly conservative assumptions. It is important to note that these problems are not confined to nuclear decommissioning, but spans to other decommissioning activities beyond nuclear plants. Relevant knowledge often resides in domain experts' minds, along with archived documents of operating history (Nuclear Energy Agency, 2006), thus, by eliciting knowledge from domain experts and utilising archived documents, knowledge-based systems can be created which could help alleviate pressure on experts and make the decommissioning process faster and more accessible to newer staff. Because knowledge in the nuclear industry is often tactic, it is an industry where a direct application of more advanced AI methods is still difficult. The primary focus of current AI research and technology are based on "black box" techniques and can typically be impossible to interpret. Explicability is crucial for any decision-making tools regarding nuclear activities in the interest of safety and meeting regulation requirements, so for this reason reinforcing the results of the new AI methods with more conventional approaches is necessitated to provide quantitative and qualitative reasoning (Suman, 2021). Extending the functionality of the framework to triage the classification of nuclear waste to review for automation capabilities or supported by AI tools is another key challenge tackled in this work.

In summary, the main motivation of this work is that if nuclear waste is characterised early in the nuclear facility life-cycle then: it can be done more simply and accurately without the need for assumptions that will need validated, it will be less expensive, safety is increased since the waste will be handled less since characterisation will be more representative, overly conservative assumptions will be relied on less, making better use of storage and disposal facilities, and inventories and the sort and segregation process will be more robust. Another main motivation of this work is that innovation is paramount to the success of the nuclear industry and AI is central to this innovation. The nature of AI techniques poses a challenge for its viability in the nuclear industry, therefor, formulating knowledge for use in AI systems can provide the first step towards utilising AI and automation in the nuclear industry.

Large scale nuclear facility decommissioning (e.g., nuclear power plants) involves a large and diverse set of processes, therefor, for the purpose of this paper, legacy hot cell decommissioning is chosen to exemplify a proof-of-concept case study. Choosing legacy hot cells simplifies the process because radioactive material will be from a specific process, rather than a wide array associated with the whole nuclear power plant. Therefore, we propose a formal knowledge-based system for capturing and representing the key decisions in the classification of waste in nuclear cells for informing the decommissioning strategy. The emphasis lies in the creation of knowledge models rather than the direct implementation of a KBS in a computer. The objective is to investigate the feasibility of automating decisions through these models. Separating the development of KBS models from the actual code is crucial as it serves an effective means for gathering requirements, bridging the gap between model design and programming necessities. This approach ensures a clearer understanding for both knowledge engineers and programmers. This objective is realised through a framework which uses the CommonKADS methodology (Schreiber et al., 2001). The CommonKADS methodology is used to clearly identify the main decisions in the process but also capture the sources of knowledge required to support and justify the decisions made, an essential element to support a transparent decision-making process. By formally capturing this decision-making expertise, the resulting models can be reviewed to assess where decisions can be either automated or supported using AI tools. This will ensure robust, reliable, and rapid decisions are made systematically. This paper will illustrate the use of the framework with a case study application which demonstrates how a semi-automated decision support system could be built, highlighting tasks and decisions which could be automated and providing examples of some of these activities. A particular problem facing the UK is the decommissioning of reprocessing cells containing pipes, vessels, and steelwork. In this situation, a key concern is understanding the volumes, spatial distributions and types of waste radionuclides present in the nuclear cell, as establishing this determines which strategies and approaches can be employed in decommissioning plans. We present a general KBS for cases such as this, and instantiate a part of the KBS by using data from a mock-up nuclear cell drawn from a UK nuclear facility. For this work, we focus on the decisions directly involved with interpreting the data and how this might be automated, taking the existence of the data as a pre-requisite to this stage of the work. In this case study, we use a digital representation of the real-world environment, comprised of a 3D LiDAR scan of a mock-up nuclear cell, which is mainly made up of pipes entering/exiting a vessel, with radiometric overlay and spectroscopic information included. This demonstrates the feasibility of the design while satisfying real-world environments (highly contaminated and heavily shielded).

The paper is broken down as follows: a short introduction and summary of KBS in the nuclear industry, and a summary of the CommonKADS methodology outlining the main models used in the KBS presented in this paper. The subsequent section is the KBS developed for a generic case study, presenting the Organization models and Task models for classifying nuclear waste, followed by a section describing the inference model approach for reviewing manual processes and decision making, then evaluating the opportunities for introducing automation or augmentation to improve the speed and reduce the subjectivity of these expert judgments, while providing a transparent path for explanations of the resulting decisions. Finally, we examine how this approach might be expanded on and implemented in part, by using a proof-of-concept case study.

2. Background: knowledge-based systems in the nuclear industry

Knowledge-Based Systems (KBSs) are the result of Knowledge Engineering (KE), which emerged in the late 1970s as a branch of AI. This was instigated by the Information Age. Knowledge is a key resource in the modern world and managing knowledge has become a scientific discipline. KE supports knowledge management by spotting opportunities and bottlenecks in a process. KE can also be the process of taking a complex task usually carried out by a human and turning it into a task that a computer can do, requiring the collection, modelling and codification of knowledge - KBSs are the formalised methods to do this (Schreiber et al., 2001) (Puppe, 1999). They are used for knowledge intensive tasks where an expert is relied upon for their decision making. A KBS can essentially replace or aid experts in their decision making by leveraging the domain experts' knowledge, in a modelled or codified format, to imitate their thought process (Akerkar and Sajji, 2009). KBSs are powerful as they can draw on techniques from various fields of AI and engineering, including AI techniques such as ANNs, machine learning, fuzzy logic, natural language processing and knowledge modelling (Alor-Hernández and Valencia-García, 2017). The nature of KBSs means they can explicate a task so far as to facilitate partial/full automation of that task, and are therefore powerful for supporting complex processes (Schreiber et al., 2001).

To incorporate the characteristics of human experts into a computer program, there are broad steps to be carried out (Kendal and Creen, 2007) - knowledge acquisition (obtaining knowledge from experts, drawings, databases, academic research etc), knowledge representation (producing a map/model of knowledge to be codified into the knowledge base), and creation of an inference engine (applying rules to the knowledge base so that the KBS can make decisions or provide advice). The main components of a KBS are the knowledge base and the inference engine (Akerkar and Sajji, 2009).

Constructing knowledge-based-systems to use in AI systems is currently something of an ad-hoc task in the nuclear industry and many others. While many documents have been published by the IAEA on the importance of knowledge management (INTERNATIONAL ATOMIC ENERGY AGENCY, 2021) (INTERNATIONAL ATOMIC ENERGY AGENCY, 2022) (INTERNATIONAL ATOMIC ENERGY AGENCY, 2017) (INTERNATIONAL ATOMIC ENERGY AGENCY, 2016) (INTERNATIONAL ATOMIC ENERGY AGENCY, 2011a) (Chou et al., 2005) (INTERNATIONAL ATOMIC ENERGY AGENCY, 2009) and KBSs (INTERNATIONAL ATOMIC ENERGY AGENCY, 1993) (INTERNATIONAL ATOMIC ENERGY AGENCY, 1992) (INTERNATIONAL ATOMIC ENERGY AGENCY, 1990) (INTERNATIONAL ATOMIC ENERGY AGENCY, 1994) in the nuclear industry, most research surrounds modern artificial intelligence techniques like artificial neural networks (Mo et al., 2007), support vector machines (Claudio et al., 2007), and genetic algorithms (Yangping et al., 2000), and these algorithms tend to focus on fault diagnosis.

Academic studies surrounding KBSs for nuclear power plant decommissioning remain scarce. In (Chou et al., 2005), authors described a conceptual design and knowledge inference process for the organisation of nuclear decommissioning knowledge based on operator experience, expert knowledge and regulations. They used Unified Modelling Language (UML) diagrams, based off various Integrated Definition Language diagrams (IDEF), to implement object-oriented programming tools and inference engines. They clearly outline the steps to build the inference engine, including problem definition and the conceptualisation, integration, and formulation of knowledge model. Authors in (Iguchi and Yanagihara, 2016) proposed a KBS to preserve and transfer knowledge for long-term decommissioning projects, discussing various sources of knowledge and the difficulty of acquisition of tacit knowledge. An expert system was implemented in (Yanagihara et al., 2001) to model a decommissioning project, based on systematising past experience from the Japan Power Demonstration Reactor (JPDR) dismantling demonstration project, and facility information and measurements. The expert system, modelled using flow diagrams, was used to create the computer system for planning and management of reactor decommissioning (COSMARD) (Yanagihara, 1993). Following on from this work, in (Iguchi et al., 2004), authors extend the utility of COSMARD to include 3D-CAD models and VR to make informed decisions about physical characteristics and manpower necessary to cut and move items. A highlight of this work is how the data is stored and managed to effectively produce a dismantling plan in terms of cost and manpower. An AI guided reasoning-based operator support system was proposed in (Hanna et al., 2021) to provide recommendation to all modes of plant operation. Knowledge was represented using Answer Set Programming (ASP), providing reasoning about many fault diagnoses and proposed actions based on various variables. Intelligent systems such as the one in (Byun et al., 2021) aim to reduce the burden on operators during the Radiation Survey and Site Investigation process (RSSI), where the user can input information like nuclide measurements, documents and drawings, and the system produces a survey plan.

The work presented in this paper aims to capture the process to classify waste in-situ and inform automation capabilities. With a similar aim, the INSIDER project (H2020-Euratom) (Rogiers et al., 2022) (Aspe et al., 2020) examines the use of non-destructive techniques for radiological characterization in nuclear facilities undergoing decommissioning and dismantling. It provides guidance for selecting in-situ measurement techniques that can be applied in constrained environments, and discusses how to integrate constraints such as radioactivity, materials, accessibility, and hazards into the system definition. The paper also offers recommendations for implementing chosen instruments and outlines the strengths and weaknesses of common detectors for in-situ measurement techniques, along with their recommended applications in nuclear facilities.

While some of these systems are not KBSs by the definition of the term, they contain elements that are similar, such as using a knowledge base. The main difference between these studies and the work here is the modelling of knowledge, done not just with a computer or new technology in mind, but also for a human. The preservation of key knowledge in a human interpretable way is crucial for transfer of knowledge for future decommissioning projects.

3. Background: CommonKADS methodology

Knowledge and reasoning surrounding tasks associated with nuclear waste classification, and indeed the nuclear industry generally, plays a pivotal role in the success of completion of that task, and Common Knowledge Acquisition and Document Structuring (CommonKADS) (Schreiber et al., 2001) is an effective methodology to execute this. CommonKADS is the result of international research and projects on knowledge engineering starting in the early 1980s. Before this, knowledge systems were developed mainly through trial and error, highlighting the need for a more methodical approach to knowledge system development. CommonKADS filled this gap by introducing industry-quality knowledge-oriented methods and modelling for organisational analysis, complete with guidelines and techniques to engineering and managing knowledge. It can be used to support the identification of problems and opportunities, localise solutions and feasibility and improve tasks with the inclusion of knowledge, providing a better understanding of why certain decisions are made and with what knowledge. It can also highlight process issues before the coding stage.

Knowledge elicitation is an activity in the CommonKADS methodology that often precedes the knowledge modelling activity. It is a foundational step that provides information for knowledge modelling. It is a necessary step for knowledge engineers to understand domain knowledge from experts in the domain. However, in this paper we have brought this activity to the forefront, as information elicited from experts also informed activities like the organisation model, and task model, as it meant the domain was understood and therefore the need for a KBS was also understood.

The CommonKADS methodology separates knowledge systems into 3 levels, comprising of 6 models shown in Fig. 1. The model suite essentially defines 3 types of questions, the “why”, “what” and “how”. Together, the organization, task, and agent models examine the “why” question and analyses the organizational context for a knowledge system. The knowledge and communication models examine the “what” question, yielding the nature and structure of knowledge and communication, and conceptual descriptions of problem-solving functions of this knowledge. The design model asks the “how” question, analysing the technical specifications necessary for computer implementation. The construction of all these models, however, is not mandatory and largely depends on the goals of the application.

This work is primarily centred around describing the inference knowledge in the KBS. Inferences carry the reasoning element of the KBS and are indirectly linked to the domain knowledge, so serves as a promising start to identify where decisions can be automated. As such, a description of the CommonKADS ontology for the inference knowledge is included here. Ontologies describe the representation of knowledge within the CommonKADS KBS, including the representation of inference knowledge. Inference knowledge specifies the reasoning, based on available knowledge and information, that the KBS employs to make decisions.

Inferences uses “knowledge roles" to describe its data. These roles are like labels for data objects, showing what they do in the reasoning process. There are two types: dynamic roles change with each inference run (like taking in a complaint and giving out a hypothesis), and static roles stay more constant, representing the core knowledge guiding the inference. This makes it easier to see how data is used in the reasoning process.

In the knowledge model, we concentrate on the structure of the reasoning process, not direct communication with other agents (software agents). However, recognizing the importance of external interactions, especially in processes like diagnosis, CommonKADS introduce “transfer functions." These functions act as black boxes, handling the exchange of information between the reasoning agent in our model and the external world (other systems or users). There are four types of transfer functions based on initiative and information possession: Obtain (requesting information), Receive (getting information), Present (sharing information), and Provide (giving information). Detailed specifications of these functions are found in the communication model.

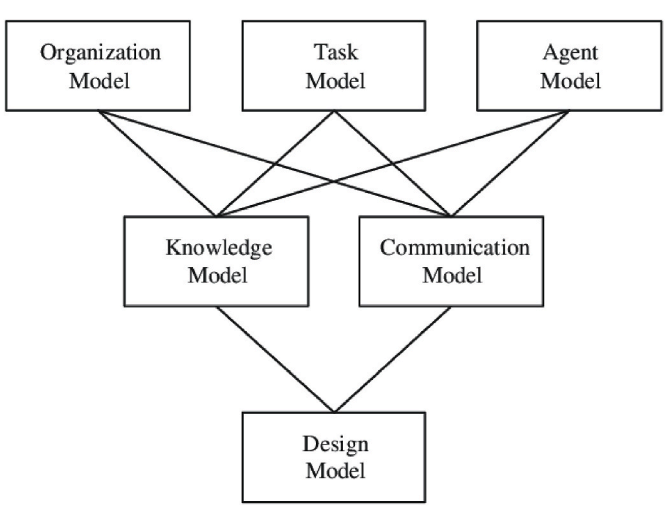

Fig. 1. CommonKADS model suite. Organisation model, task model, agent model = “why”, knowledge model and communication model = “what”, design model = “how”. The components described in this paper are the organisation model, task model, agent model and knowledge model. (Nuclear Energy Agency, 2006).

Represented graphically in an inference structure, dynamic knowledge roles appear as rectangles labelled with their names, while inferences are ovals connected by arrows showing input-output dependencies. Transfer functions, like “obtain," are depicted in rounded boxes. Static roles are represented between two lines, connected to the inferences. While optional, static roles are often included during construction. Also, a small solid circle on a data-dependency line indicates that input or output should be interpreted as a set of objects, offering clarity in cases where inferences operate on single or multiple objects.

The models in the CommonKADS methodology are method/task specific, requiring the KE to identify the decision-making requirements and select an appropriate inference model based on the nature of the problem. The types include, but are not limited to, classification, diagnosis, and assessment, all of which have different types of inputs, outputs and knowledge.

We have revised the CommonKADS methodology slightly to apply in the context of the goals of this project by creating only the first organization model to support the general context of the project from a technical perspective and not the business perspective that the CommonKADS methodology provides a structure for. We also do not analyse the communication and design models in this paper but may be included in future work. The following is the structure of our analysis.

1. Knowledge Elicitation
2 Organization model
3 Task Model
4. Knowledge Model
5. Agent Model

4. Knowledge-based system

The KBS described in this section is largely generic but is slightly tailored to a legacy hot cell example, for proof of concept. The KBS is described in Sections 4.1–4.5 and an instantiation of part of the KBS is presented in Section 5. We use a case study of a mock-up vessel with radioactive contamination. A point cloud of this vessel was generated using a FARO Focus device with a 2D radiometric source overlay, generated by the RadScan 3D gamma imaging system (Cavendish Nuclear, 2023). The vessel has loose contamination inside it of typical radioisotopes found in reprocessing.

The focal point of this project was not how to gather data but how to structure the processes and knowledge required to automate performing a triage of the classification of nuclear waste inside a nuclear cell. This KBS provides a proof of concept that is specified in some detail for the mock-up nuclear cell, however many aspects remain broad to show how it may be applied to different scenarios. This section follows the CommonKADS methodology, providing details on knowledge elicitation, the organisation model, task model, knowledge model and agent model. Results of an instantiation of part of the KBS is then presented in Section 6.

4.1. Knowledge elicitation

Knowledge engineers carry out knowledge elicitation, which is a process of acquiring knowledge from technical manuals, research papers and textbooks but also domain experts (Schreiber et al., 2001). The nuclear industry is one with an ageing workforce, and knowledge transfer to the next generation is essential for the reliable operation, maintenance and decommissioning of nuclear sites (Aspe et al., 2020). In this paper, the elicitation process was a mix of research papers and eliciting knowledge from practitioner experts, who engage in constant day-to-day problem-solving in the domain. The aim was to understand how decisions were made and to transform this knowledge into an explicit form.

4.2. Organization model

The organizational model, or context modelling, serves the purpose of listing problems and solutions concisely, essentially covering the overall visioning of the study. It involves carrying out a feasibility study where we identify problems and opportunities and determine solutions based on features of the wider organizational perspective and mission. The CommonKADS methodology is not a "one size fits all" and should be used flexibly, and, to suit the purpose of this research, we used organization model 1, Table 1, to explicate the problems and opportunities for waste management. Through online research reinforced by interviews with technical experts working in the field, the major problem found was that, currently, nuclear waste within a nuclear cell is classified manually and requires significant manpower and various steps, and the importance of an accurate inventory was highlighted.

Protective equipment for each operator is needed for the sort and segregation process and there can only be a few hours of productivity due to the nature of the working conditions. Once dismantled, a mixture of waste objects is placed into a container for transit to the waste treatment cell, and it may not necessarily be known exactly what is in each container. There are telemanipulators and telerobotics (INTERNATIONAL ATOMIC ENERGY AGENCY, 2005) to lift it from the container while avoiding damage to surrounding areas, and then trained operators with many years of experience are required for a knowledge-based approach to classifying the waste using radioactivity and physical characteristics. Once this process has been carried out, decisions are made to sort and segregate the waste into their grade classes, which requires moving the waste to the correct containers for disposal, while making the best use of space in each container. A representative site typically sorts 2–6 drums per day, where the latter

Table 1
Organisation Model 1 - Explicating problems and opportunities for nuclear waste management.

Organisation Model - 1	Problems and Opportunities Worksheet OM-1
Problems and opportunities	Driver/Opportunity: Manual classification of nuclear waste is expensive, time-consuming and relies heavily on operator knowledge and expertise. Opportunity to automate. Problem-1: No method for providing an assessment of automation suitability for classification of waste. Problem-2: Location of radiation in the cell, currently 2D radiation image is overlayed onto 3D point cloud - yields ambiguity of radiation source.
General Context (mission, strategy …)	The need for safer, faster, and more cost-efficient operations than conventional methods. Innovate to deliver nuclear services safer, faster and at a lower cost.
Potential Solutions	Soln-1: Application of the CommonKADS KBS to assess feasibility to automate the classification of nuclear waste. Soln-2: Exploiting object detection to achieve better isolation of radiation and allows for specific activity calculation to classify waste if combined with weight information.
Potential Threats	Threat-1: Dynamic nature of nuclear waste classification Threat-2: Domain expertise and uncertainty and ambiguity of available information Threat-3: Integration with existing systems

end of the scale is achieved when the radioactivity is homogenous throughout and the objects are similar, and the lower output is when the waste was very mixed (Nuclear Decommissioning Authority et al., 2020). Triage of the classification of nuclear waste, before dismantling, would increase the homogeneity of waste to be sorted, therefore, we define the overarching opportunity, problem, and potential solution, in line with the general context, as "Manual classification of nuclear waste is expensive, time-consuming and relies heavily on operator knowledge and expertise. Opportunity to automate.", "No method for providing an assessment of automation suitability for classification of waste." And "Application of the CommonKADS KBS to assess feasibility to automate the classification of nuclear waste." respectively. Potential threats to the proposed solution are also included in Table 1. Firstly, the dynamic nature of radioactive waste (decay and other processes) may pose a threat to an automated system, since CommonKADS relies on a static knowledge base. However CommonKADS is flexible, and a flexible rule engine can be implemented that can be adjusted or extended based on new knowledge. Threat 2 also addresses input data, but from another angle. Classification relies on specialised expert knowledge, often tacit, which is challenging to capture for CommonKADS. Historical records also may be incomplete or imprecise, which may pose a challenge for CommonKADS in handling uncertainty. Addressing these threats may involve effective knowledge elicitation techniques, dynamic rule modifications to accommodate changes and reduce impact of uncertainty. The last potential threat is about integration with existing systems, and, while this paper aims to address the decisions and review for automated, not the design phase of the CommonKADS system, it is important to keep in mind technical compatibility of the end result. This may be addressed by standardised data formats for data exchange, and importantly collaboration with providers of existing systems to smooth out integration, aligning the CommonKADS system with already existing technologies in use.

The next part of organisation modelling allows for the process to be modelled, ordering functions of the process in a time-ordered fashion, and implies "input" and "output" dependencies. This is done down to the level of detail that enables decision making about a task, e.g., construct a knowledge model to automate or explicate that task. We break down the process into tasks and illustrate this with a UML diagram as shown in Fig. 2, with some tasks broken down into subtasks in organisation model 3 (Table 2).

The new process of classifying nuclear waste is presented in Fig. 2. The process is time-ordered left to right, and arrows show the interdependencies of tasks. The first step is data collection from both visual and radiation inspection, and the gathering of historical information. The data from the visual inspection is an input to visual data analysis and same for radiation. The gathered historical data is an input to tasks in the visual and radiation data analysis; this, in both cases, is to match/cross check data collected via inspection to historical data, and therefor acts as a supplementary step to information we know about the cell. The last step is to categorise the waste based on information we have gathered and analysed. The primary focus in this research is the decision making that happens within each step in the process and identifying areas for (semi)automation.

Table 2 presents a worksheet (numbered OM-3) to specify the task details, identifying which knowledge assets are used, and the significance of the task based on effort required and task criticality. This gives an improved understanding of the role of each task in the process. In task No. 1 (determine likely objects), we can see that the more useful knowledge applied and evaluated here, the more accurate the outcome will be, as this task is a prerequisite to subsequent tasks.

In most waste characterisation processes (in-situ, ex-situ, sampling) existing information is reviewed and evaluated to build an initial understanding of the waste (Jacobs, 2022). Importantly, evaluating existing information and identifying the limitations in this existing data can direct us in what information, and therefor what measurements need taken, therefor building a fuller picture of the nature of the waste.

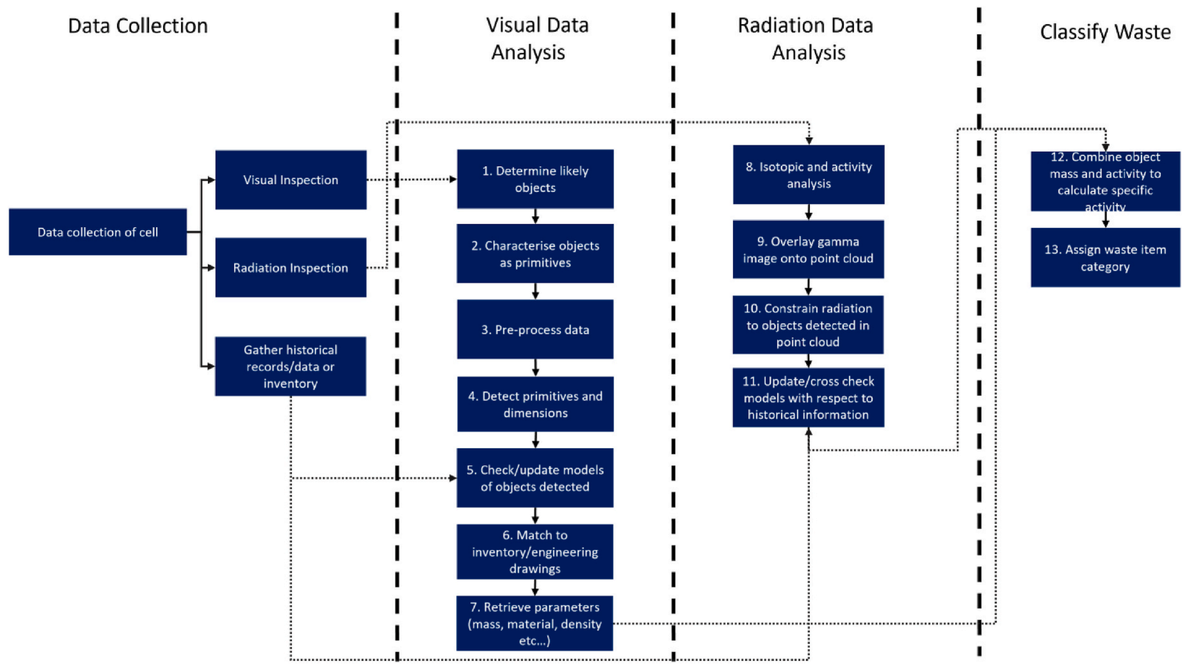

Fig. 2. UML diagram of main tasks in the process to characterise waste in a nuclear cell. The tasks are numbered and described in more detail in Table 2.

Table 2
Organisation Model 3 – Process breakdown to main tasks.

OM - 3	Process Breakdown Worksheet OM-3			
No.	Task	Performed By	Knowledge Asset	Significance
1	Determine Likely Objects	Expert	Engineering Drawings Operator Knowledge Existing Process information	This task determines which primitives MATLAB searches for, so this task must be completed with valid assumptions as it affects subsequent tasks.
2	Characterise Objects as Primitives	Expert	Object to primitive knowledge e.g., pipes are cylinders	See above
3	Pre-process data	Matlab		
4	Detect Primitives and Dimensions	Matlab	Object to primitive knowledge e.g., pipes are cylinders	
5	Check/update models of objects detected	Expert		This task ensures the prim-itives detected by MATLAB do not contain mistakes and can be matched to an item, so affects subsequent tasks and overall output
6	Match to inventory/ engineering drawings	Matlab	Engineering Drawings	
7	Retrieve Parameters	Matlab Operator	Matlab Output Engineering drawings	

Having a pre-conceived notion of what kind of waste being dealt with is can help estimate the radioactivity of the waste and therefor anticipate the safety precautions workers may need to follow, and knowledge of the process the waste has arisen can allow the concentration of easy-to-measure radionuclides predict harder-to-measure radionuclides. Existing information can be reviewed against the characterisation process objectives, including the accuracy required for certain waste management approaches, to determine utility of it.

Existing information can come in a variety of forms: engineering drawings (CAD models, blueprints) of nuclear facilities for in-situ waste are useful for estimating the volumes and materials (concrete structures, metal pipes and vessels), plant and process information to provide an understanding of how the waste was generated which, when coupled with process information like characterisation data from routine monitoring, can indicate a likely physical and chemical characterisation criteria (e.g., what radionuclides or hazardous substances are likely to be present), operational records, experience and expert judgement to provide extra detail on the history of the in-situ waste in question, e.g., spills or events, previous characterisation survey data, the age of the facility to consider temporal changes like radioactive decay and changes of parts of equipment.

Following on from the fourth part of organisation modelling, focusing attention on the knowledge assets, specified in Table 2, Table 3 provides a worksheet (numbered OM-4) to describe the knowledge assets used in more detail. This is later refined more in task modelling and knowledge modelling. The gradual construction of knowledge in this way builds an understanding of the knowledge and also gives more opportunities for flexibility in knowledge management.

In this organisation model we indicate the knowledge utility. Often in the nuclear industry, inadequate or minimal records and documentation available for decommissioning activities presents challenges. It does not cause the inability to characterise facilities however it does mean there is an extra effort to re-establish the records by inspections and measurements which means increased technical challenges and costs (INTERNATIONAL ATOMIC ENERGY AGENCY, 2011b). While existing information is evaluated to aid the characterisation process, it is a manual, case-by-case process. For example, analysis of information from Piping and Instrumentation Diagrams (P&IDs) (commonly used to describe piping structures) is challenging as it is not only extracted

Table 3
Organisation Model 4 – Knowledge assets.

OM - 4	Process Breakdown Worksheet OM-4		
Knowledge Asset	Used in	Right form?	Right quality?
Engineering drawings	1 Determine likely objects 6 Match to inventory/ engineering drawings	Yes, typically electronic.	Yes, however engineering drawings need to be up to date with latest developments e.g. equipment may have been taken away/ added since initial installation.
Operator Knowledge	1 Determine likely objects	Sometimes – depends on information management by the nuclear facility.	Can be incomplete.
Existing historical information	1 Determine likely objects	Yes, surveys conducted throughout the facility life-cycle along with purpose of cell/equipment are usually available.	Yes.
Object to primitive knowledge	2 Characterise Objects as Primitives	No, knowledge in operators minds.	Yes – not much scope for subjectivity.

manually which is a laborious task and error prone (Gao et al., 2020) but also there may be differences between the engineering drawings to actual reality because of modifications throughout the nuclear plant lifetime (Bean et al., 2009). There is also no established way to capture and codify prior knowledge and expertise; for example anecdotal information from operators with significant operational experience can be important to characterise nuclear facilities. Here, we make an attempt at this, however the work here should not be interpreted as absolute or all-encompassing of all knowledge assets.

Some evaluation of knowledge, and therefor existing information, starts to get drawn out in Table 3 in terms of if it can be improved in form, accessibility, or quality. These tasks typically require operator knowledge and existing information about the facility being characterised. Thus, knowledge sharing and having knowledge in a format where it can be used effectively in a (semi) automated system is important. The knowledge assets are summarised in Table 3 but are described below in more detail;

Engineering Drawings	Engineering drawings are commonly considered crucial knowledge assets in any decommissioning project and may include floor plans instead of engineering drawings. In terms of form, drawings tend to be inconsistent in format and presentation. Some drawings are old and therefor clarity and legibility are compromised. Consistent drawings are a major factor in successful automation. If they were standardised, they could be more efficiently processed. It is appreciated that standardisation is difficult to implement across complex nuclear facilities and the interdisciplinary nature of them. In terms of quality, their effectiveness depends on their accuracy and completeness and quality.
Operator Knowledge	Operator knowledge is often a critical component when decommissioning nuclear facilities. In terms of form, operator knowledge is sometimes documented, but is often never documented comprehensively, especially for older facilities. This information is often not very well organised and creates a substantial time-consuming task of sifting and organising this information as part of the task of characterisation. If knowledge is captured, it is almost always in a digital format, but not in a format that can be easily processed. In terms of quality, the information by nature is experienced-based insights gained from operational experience which is valuable for making informed decisions. This information is often incomplete and can only be used to create a holistic understanding.
Existing historical Information	In terms of form, this information is like engineering drawings. Information tends to be non-standardised. However, surveys like health physics surveys tend to be somewhat standardised and tabularised, meaning data can be utilised and processed easily. This may lend itself more to being used in automated processes sooner than non-standardised information such as operator knowledge. In terms of quality, it can vary widely and is contingent on several factors. The age of the facility can impact quality, as the older ones may not have had adequate investment in information management. It is also dependent on the culture. A strong safety culture usually maintains higher standards of quality in their processes and information management.
Object to primitive Knowledge	This knowledge asset is more targeted towards the KBS in this paper specifically for task 2, "Characterise objects as primitives". Objects from visual data should be in a consistent format should be structured. This ensures that any AI/algorithm used to process an object to a primitive can universally handle different structures. In this paper, this step is done using human processing rather than automation, as it is a simple task and can be done quickly by a human.

(continued on next column)

(continued)

Some knowledge is less intensive than others, e.g., determining likely objects requires operator knowledge of the process and therefor a deduction can be made, or visual inspection if possible. In contrast, characterising objects as primitives can be clearly nailed down. In both cases, a more appropriate form (electronic) would facilitate knowledge sharing.

4.3. Task model

The task model explores the tasks in more detail, and Task 5 (Check/ update models of objects detected, see Table 2), is discussed here for reference. The task model comprises Tables 4 and 5. The content in these tables decomposes each task further into subtasks, dependency and flow indicated by the task inputs and outputs, which are articulated through the utilization of a worksheet denoted as TM-1 in Table 4. This worksheet serves as a detailed refinement of information gleaned from another worksheet, OM-3 in Table 2.

For task 5 the main goal is to make sure models detected in task 4 are sound, therefor the input task is task 4 and the output task is task 6. Input

Table 4
Task Model 1 – Task analysis of Task 5 (Check/update models of objects detected).

Task Model 1	**Task Analysis Worksheet TM-1**
Task	5 Check/update models of objects detected
Goal and Value	This task aims to check the reasonableness of the objects detected in task 4. This is a necessary task as over-fitting/ under-fitting the data will lead to wrong results and overall wrong classification
Dependency and Flow	*Input Tasks:* Detect primitives and determine dimensions *Output Tasks*: Match to inventory of expected objects
Objects Handled	*Input Objects*: Objects and their dimensions within point cloud *Output Objects*: Complete set of objects that have been correctly identified
Timing and Control	*Frequency*: Once when data is received. *Duration*: This task should take a couple of days
Agents	Expert/Knowledgeable person In new situation: knowledge system, Matlab
Quality and Performance Measures	Successful execution will mean this task will have an output of detected primitives with low mean error and have been checked visually by an expert that objects detected are reasonably well fitted

Table 5
Task Model 2 – Knowledge asset characterization of engineering drawings.

Task Model 2	Knowledge Item Worksheet TM-1	
Name: Engineering drawings Used in: Tasks 1, 6, 7		
Nature of knowledge		To be Improved?
Formal, rigorous	X	
Heuristic		
Highly specialised, domain specific	X	
Empirical, Quantitative	X	
Experience-based		
Incomplete	X	
Uncertain, may be incorrect	X	X
Quickly changing		
Hard to verify	X	X
Tacit, hard to transfer		
Form of knowledge		
Electronic	X	X
Mind		
Paper		
Availability of Knowledge		
Limitations in access		
Limitations in form	X	X
Limitations in quality	X	X

and output objects handled is information content necessary to complete the task, and information gained because of the task. For task 5, the objects and the dimensions (an output object for task 4) is an input object, making the output object a complete set of items that have been correctly identified. Also shown is a temporal order and control of subtasks where "how long" and "how often" is specified for each task, and some quality measures. For task 5, a quality measure will mean the objects detected will have a low mean error and will also have been checked visually by the doer. These items in the task have a natural link to approaches and how the KBS will be implemented. Additionally, information like goal and value, and agents who perform the task and quality are re-introduced.

In task model 2 (Table 5) the knowledge assets used in the process to evaluate visual data, from is scrutinised further. Each knowledge item is described in terms of nature, form, and availability into its own separate worksheet. Table 5 describes the knowledge item "Engineering drawings".

The nature of this knowledge is formal meaning it has been made explicit in writing. It is also empirical as the drawing is a representation of the real-life scenario in the cell and is also highly specialised and domain specific. However, the nature of this knowledge is also uncertain and may be incorrect. This is because, oftentimes, engineering drawings were made during construction of the facility and haven't kept up with modifications that may have happened in real life. The developments of a facility need to be maintained in a formal format, and therefore, improved. Because of the type of hazards/contamination these cells often harbour, verifying the information in the engineering drawings can be hard to verify in person, necessitating remote/robotic techniques. This is a key area of improvement that this KBS will attempt to account for. The form of engineering drawings is electronic, usually initially in paper form and electronically scanned in. This leads to limitations in form since the information cannot be interrogated or modified easily to keep up with developments. Lastly, information is held by the facility owner so getting access to information is not always the quickest process.

4.4. Knowledge model

The knowledge model comprises of domain knowledge and inference models. Here, we explicate how knowledge is used in tasks to infer outcomes, which can then be used as specifications for system development and ultimately automation development.

For the overarching visual characterisation task, several inference structures were created that encompass each task within this process. The inference structure describes the lowest level of functional decomposition. There are several task templates for inference structure in the CommonKADS methodology. For tasks 1, 2, 4 and 5 in the visual characterisation application, the diagnosis template was chosen and modified, as is shown in Fig. 3. This structure was chosen as it fits well with the application - the annotated inference structure specifies the dynamic roles. We can see that these examples can be extended to other scenarios with other items and so this template should be reusable and useful. In words, this inference structure describes how the items in the scenario are determined and characterised as primitives, and how the models are checked for fitness. The Cover inference takes, as input, the dynamic role of the scenario needing characterised and decommissioned and produces a set of hypotheses as output. The Select inference selects one of the hypotheses and the Specify inference takes the hypothesis as input and produce a new object as output that is associated with the input. The "Specify" inference is vague, but it produces a new output from forward reasoning, using the static, heuristic knowledge that if a vessel is what we are looking for, the primitive that may be looked for in visual data will most likely be a cylinder. A "Select" inference could also be added to select an observable from a list of multiple observables specified by the "Specify" inference, incorporating nuts/bolts. The "Present" transfer function presents the observable to an external agent (in this case, it is cylinder detection in MATLAB). The "Generate" inference provides the finding given the observable. In this case, the observable is a cylinder in the visual data, so the "Generate" inference will perform cylinder detection on the point cloud data. Then, the "Verify" inference indicates consistency of the observable hypothesis with the actual finding by a simple truth value, e.g., was a cylinder found, yes/no. This inference also incorporates task 5 where the user will check the cylinder found in the visual data was not over fitted, creating specious cylinders, or indeed under fitting.

The inference structure for task 6 and 7 is shown in Fig. 4. Result 1 from the previous inference structure in Fig. 3 is the input to this inference. Given the result was that a cylinder was found in the visual data, the "Generate" inference provides possible candidates that the cylinder may be. The static knowledge is all the possible solutions the result may be matched to (essentially, the inventory for that cell). Then an attribute is specified based on domain specific heuristic rules. The rules here are that the diameter and length can be used to quickly compare two cylindrical objects. That feature is obtained from the external agent output (MATLAB object detection), and the "Compare" inference compares that feature with the candidate's, producing a truth value. If truth value is equal, inference structure goes on to obtain the mass feature from the item data sheet (see Fig. 5).

4.5. Agent model

Every task was broken down into inference models, and the approach for reviewing the manual processes and decision-making in this way supports the evaluation of opportunities to introduce automation or supporting technologies to improve the speed and cost. Every inference (oval) and transfer function (round cornered rectangle) in Figs. 3 and 4 has the potential to be automated. To demonstrate the automation of the "Generate" inference in Fig. 3 and the "Generate", "Specify", and "Compare" inferences, along with the first "Obtain" transfer function in Fig. 4, we created an agent model and give an example of automating these tasks, where the agent model specifies tasks allocated to agents (Table 6).

5. Instantiation of the knowledge-based system

MATLAB was used to perform the tasks deemed able to automate, rationalized from the inference models. A Faro Focus Laser Scanner was used to create a point cloud inside the mock-up cell, and initially, we use

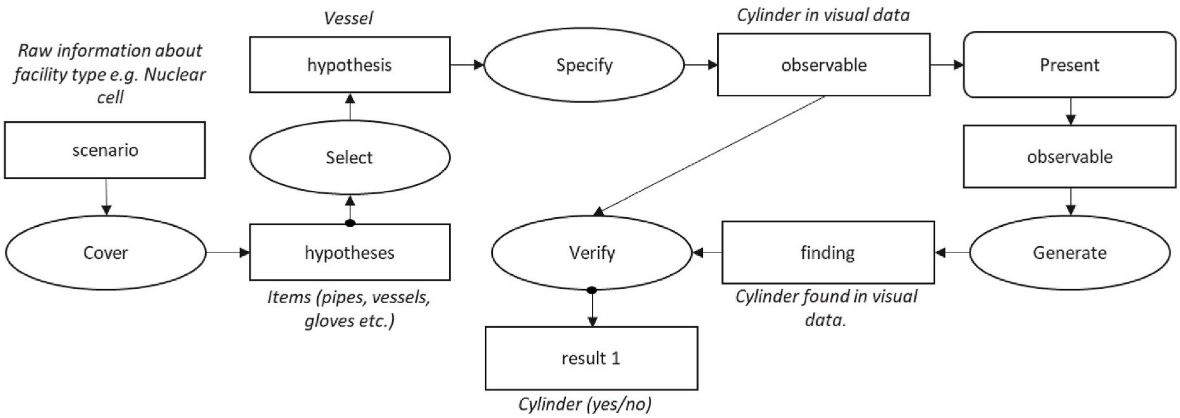

Fig. 3. Annotated inference structure for the nuclear cell diagnosis tasks (tasks 1, 2, 4 and 5).

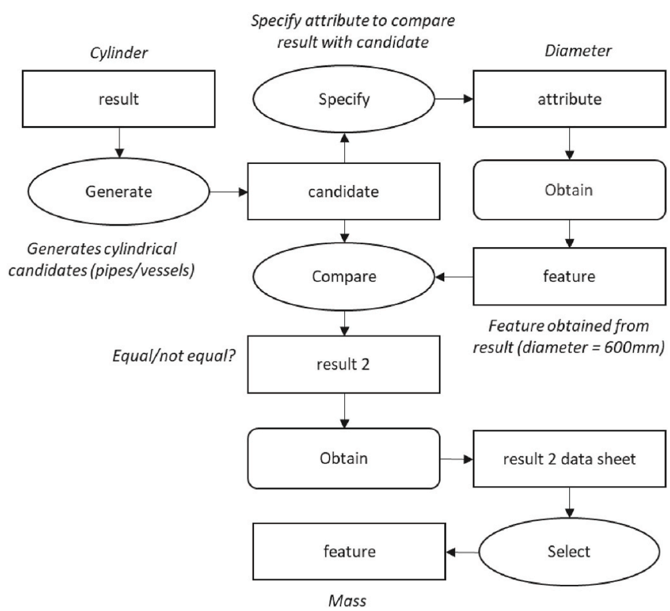

Fig. 4. Annotated inference structure for task 6 and 7.

the M-estimator SAmple Consensus (MSAC) algorithm, which is a generalization of the RANSAC estimator (Torr and Zisserman, 2000), to find the walls of the cell and extract them. This is to segment the objects within the cell from the walls containing them, as shown in Fig. 6. The algorithm chooses points at random and assumes that these points lie on a plane. Then it decides if it is a plane or not by inspecting the surrounding points, since there will be a lot of other points that lie close to that plane. It accepts the largest consensus set and those points are allocated to the first plane in the scene (Martin and Bolles, 1981). Then, after removing the points allocated to plane 1, the algorithm searches for the next largest consensus set, and, iteratively, finds all the planes in the point cloud. Certain thresholds are set and only points that lie within this threshold are used for planes. We applied the distance to the model threshold where only points within this is a planar fit, and similarly, we applied a threshold based on the angular deviation between the normal and inlier points of the plane. Setting a region of interest also minimizes wrong planar fits.

Table 6
Agent model 1 – Matlab agent.

Agent Model	Agent Worksheet AM - 1
Name	MATLAB
Organization	Programming platform
Involved in	Preprocess
	Detect primitives and dimensions
	Match to inventory
Responsibilities and constraints	The algorithm should not overfit data

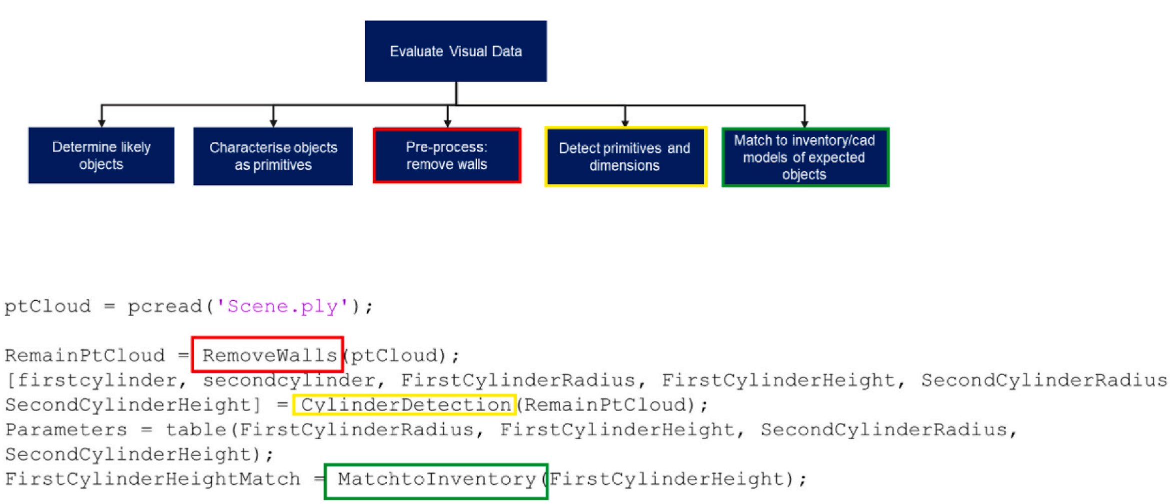

Fig. 5. UML Task model for evaluating visual data and relevant MATLAB functions performing each task.

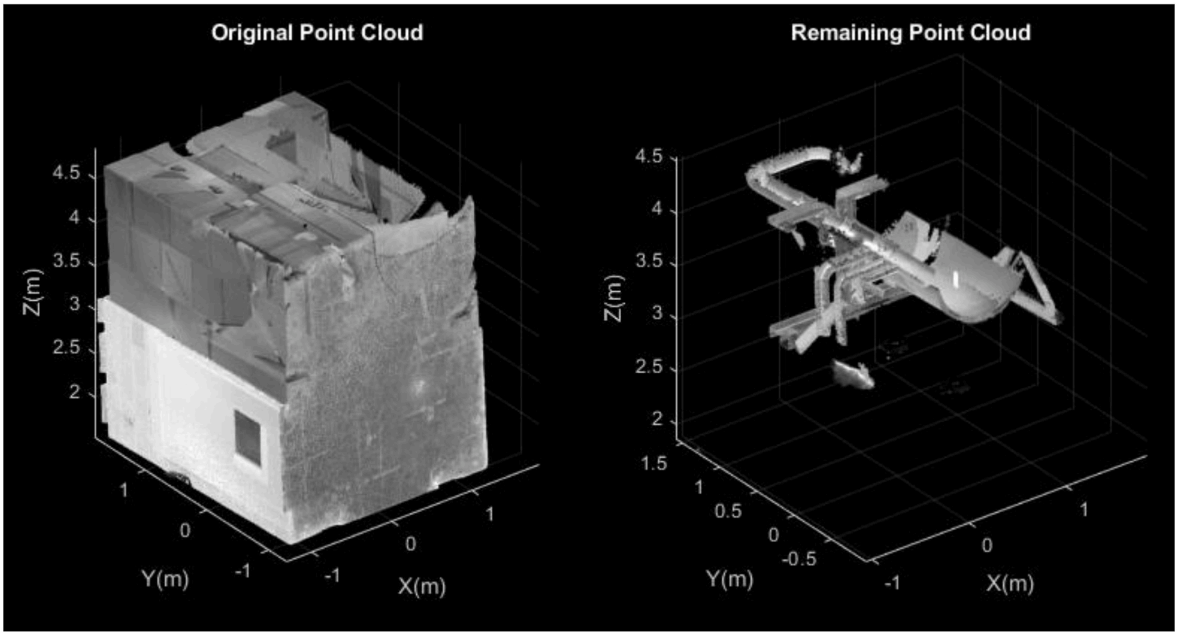

Fig. 6. Original point cloud (left) and remaining point cloud (right) with walls of cell extracted revealing the mock-up vessel and pipes.

For this project, object detection focused initially on cylindrical objects as is the output from 2. Characterise objects as primitives since pipework is significant in nuclear cells and indeed any industrial site and predictions were made on the geometric parameters. We used the MSAC algorithm again to define and estimate a model for 3D cylinder segmentation, using additional orientation constraints specified by a 1-by-3 orientation vector, and distance to the model threshold, to do so. Again, setting a region of interest also minimized the wrong cylinder fits. The detected vessel and its estimated parameters are given from the model cylinder as shown in Fig. 7. Then, we extract the first cylinder from the remaining point cloud and repeat the process to find the next cylinder in the point cloud. We choose MSAC for its simplicity and convenience, and it is considered more efficient than other methods of planar segmentation, like Hough transform (Borrman et al., 2011), and this method works as a proof of concept for the framework.

We match the parameters taken from the cylinder models above to parameters given in reference drawings of the objects in the mock-up cell. We created a simple algorithm in MATLAB to compare the parameters, radius and length of the cylinders detected in the point cloud, to the parameters of the vessel and pipework in the cell and decide upon a match, as is outlined in the inference model in Fig. 4. Parameters were manually retrieved from reference drawings as, although it is a laborious and time-consuming task, the cost of developing and deploying software to interpret this data was beyond the scope of the project. However, there exists a limited number of solutions to extract relevant information from engineering drawings (Rohit et al., 2019) (Ondrejcek et al., 2009).

6. Discussion and conclusion

In this work, we have attempted to begin the process of creating a KBS to support the safe and secure decommissioning of a cell in a nuclear facility. The work describes a CommonKADS methodology approach to define a process to triage nuclear waste in-situ, establish which parts of the process can be automated, assess automation capabilities and configure automation for proof of concept. We establish that the tasks to pre-process the point cloud of the cell, detect cylinders within and match to parameters from a CAD drawing can be automated with a human in the loop, and we provide an instantiation of this part of the KBS, showing

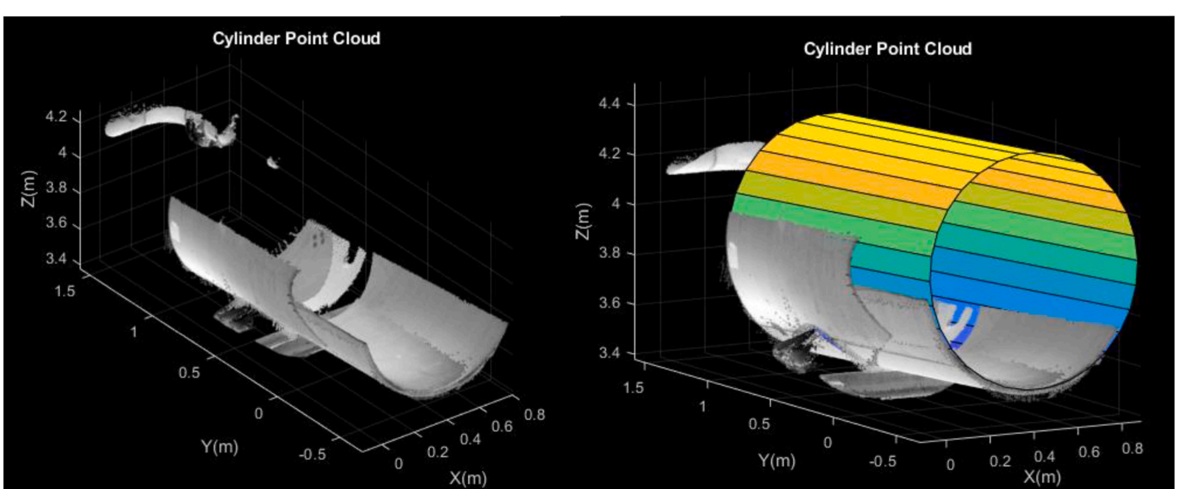

Fig. 7. Detected cylinder from remaining point cloud (left) and model cylinder (right).

a proof-of-concept example using point cloud data of a mock-up cell and implemented RANSAC-based methods to conduct planar segmentation to separate indoor walls from waste objects for processing and to detect the vessel and pipes via cylinder fitting. On the contrary, the tasks to determine likely objects in a nuclear power station and characterising these objects as primitives for straightforward object detection are more likely to stay a manual process given the nature of the knowledge asset, however creating the task process still highlights the partial but valuable role of knowledge modelling by laying out and archiving the process, which is essential for knowledge retention and can also be used later when there are advances in technology. In any respect, automation of tasks is usually only feasible if the basic plan elements are predefined, however computationally the task is usually more demanding than the task analysis. In terms of benefits analysis and future potential development, if fully implemented as a codified system, this KBS is expected to be fourfold –safety, time, sharing of knowledge, and cost.

Legacy systems, like the nuclear industry systems, can provide information and guidelines but lacks knowledge about domain-specific problems and automated solutions. Eliciting and conserving knowledge within the nuclear industry is very important, and the CommonKADS knowledge-based analysis not only reveals automation feasibility but provides a method to identify, capture and use tactic knowledge to do so.

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Seonaid Hume: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Graeme West:** Supervision.

Declaration of competing interest

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

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