1 INTRODUCTION

Nowadays manufacturing requires high volume of complex operational processes, distributed resources and international/intersectional collaborations, which cause the evaluation of performance for related engineering projects to become a challenge [1]. The performance of a project is the key factor to determine its quality of output, and the temporal changes of performance could reflect the status of project execution at current time, as well as indicate the potential issues for the near future [2]. In practice, a considerable decrease of performance can lead to certain issues, such as design failure and operation error, which could cause time delay, cost overrun or unnecessary resource consumption. As a result, monitoring the change of performance is an essential approach to ensuring the project execution to be on track. It could raise awareness of project participants upon any issue occurs, and enable them to make appropriate decisions on a real-time basis [3].

In collaborative manufacturing, such as aerospace industry, the In-Service department often offers repairing and maintaining services to different airlines, and also provides advice to certain internal departments [4]. Typically, the department needs to deal with high volume of In-Service projects constantly and concurrently, and each of them could have specific service requirements, priority settings, operational processes, testing procedures and time/resource constraints [5]. In order to achieve the committed deadlines (between the In-Service department and airlines), the efficiency of project execution needs to be maintained on a high level basis, thus the collaborations between multiple teams (both internal and external) are often necessary to be involved at different project stages.

Considering these facts, the evaluation of project performance in collaborative environments can be a complicated task and have the following major issues:

- ***Processing fragmented/distributed information***: the information of a collaborative project is likely to be generated from multiple sources, i.e., by different participants, from multiple departments, at different stages and for various purposes. Since such information has a fragmented and distributed form, its processing then becomes difficult and sometimes time-consuming, which could decrease the accuracy and efficiency in performance evaluation;

- ***Understanding inner associations among project components***: with a project, in order to evaluate its performance and make reasonable decision accordingly, the participants should have certain level of understanding on its components and their inner associations, including the connections of tasks, relations of sub-systems, responsibilities of different teams, etc. However, if the project has a large-scale, this task could become difficult for most of the participants, due to the limited time that can be spent on obtaining understandings, and large number of components that need to be understood;

- ***Dealing with large amount of information***: ICT techniques have been extensively used in recent manufacturing to improve the production efficiency, thus large amount of data can be generated and recorded on a daily basis, which includes documentations, communications, models and simulations. To process the information, the participants need to spend a lot of time on reviewing and understanding. Due to the time/resource constraints, dealing with it all is an unrealistic task, thus the participants have to select certain pieces of information to implement the performance evaluation and decision making, mainly based on their own judgements. However, the selected information sometimes may not be sufficient, if some of the participants are lack of experience or any mistake occurs during the selection process, which can cause the result of performance evaluation or decision making to be subjective or with bias;

- ***Handling legacy data***: according to the change of market demands, lifecycle of many products become considerably longer than before, e.g. the service period of an aircraft could last 30 years. During such long period of time, the ICT infrastructure of the organisation/department can be changed notably, including the mechanism of storing data, retrieving information, as well as the system interface and operational process. Therefore, obtaining the information from previous systems, and processing the information of historical projects, can be difficult tasks for the current participants;

- ***Preserving and reusing expert knowledge***: during the process of performance evaluation, most of the judgements are made or reviewed by the participants with certain level of experience. The correctness of a judgement is likely to be higher, if the experience level of its decision maker is higher. In order to improve the sensitivity and reliability of the process, using an effective way to preserve and reuse the knowledge from experienced participants is critical.

To facilitate the performance evaluation of collaborative engineering projects, this research aims to propose an automatic approach to extracting key performance indicators (KPIs) from project data, and then demonstrate how the domain knowledge could facilitate the process of KPIs identification and visualisation. The remainder of this paper is structured as follows. Section 2 reviews the related work; Section 3 describes the conceptual model of the proposed approach; Section 4 includes the examples of identified KPIs from industrial data; and Section 5 concludes the work.

2 RELATED WORK

The use of KPIs is an effective way to improve the management performance and execution efficiency for collaborative projects [6]. Many researchers aim to formalise the definition of KPIs for different industrial sectors, but there is not a general agreement yet. With different projects, the definition of their performance indicators is various depending upon the project objectives, requirements, resources, conditions, and the perspective of stakeholders [7, 8]. In "*The Iron Triangle*" model, the indicators, i.e., *cost*, *time* and *quality*, are considered as determining factors of project success, which have been used to assess project performance by numbers of management approaches [9]. However, this model has some drawbacks, i) the involved indicators are limited, thus the model cannot properly handle the projects with complex structures or/and large scales, and ii) these indicators are not sufficient for evaluating the management and operation performance at the same time, as these two have different concepts that cannot be represented by using the identical set of indicators. It means the evaluation of these two types of performance needs to involve different indicators accordingly, rather than the same ones. As a result, additional indicators are added to this model to enable it to perform the evaluation from different perspectives/with different granularities [10, 11]. Recent research has introduced various performance indicators to fulfil the different evaluation requirements, and these indicators include budget, schedule, satisfaction, technical specifications, health and safety [10, 12, 13]. Meanwhile, the high-level interpretation of such indicators has been further extended to a more detailed level, including project efficiency, impact on the customer, direct business success/organisational success and preparing for the future, which can be used as a general guidance to facilitate the creation of more types of indicators [8].

In practice, the performance indicators are unlikely to be static during project execution, so the pre-defined indicators are not always sufficient to handle all possible situations at different project stages. From the data management point of view, the project data records the detailed information of activities/processes throughout the project timeline, which covers the stage of planning, execution and evaluation. So the indicators extracted from the data in real time could be more adaptive and effective for the performance evaluation.

As shown by recent research, some data-driven approaches can successfully identify and extract KPIs from project data, which also have high efficiency and effectiveness to deal with projects that occurred concurrently/executed in collaborative environments [14]. Within this context, some researchers have studied the relations between email traffic and project management performance [15]. Meanwhile, the sentiment of email content, correlations between email sentiment and different product design phases have been further investigated on a detailed level [16]. The listed research highlighted that the communication data of projects could contain multiple indicators that can be used to evaluate and represent their performance from different perspectives.

In order to evaluate the operation performance of concurrent projects, an automatic approach to identifying the activity-related KPIs has been proposed. These KPIs are identified by analysing technical reports, documentations and communications, and then visualised together with the timeline of projects, which could facilitate both engineers and managers in monitoring, understanding and comparing the level of performance change regarding multiple projects on a real-time basis [17].

Meanwhile, an automatic approach on identifying the workflow-related KPIs has been proposed. These KPIs consist of sequential patterns of project activities that are extracted from the data of workflow systems. These KPIs could give high-level indications of workflow status regarding multiple ongoing projects, which could enable the engineers and managers to instantly perceive the problematic projects once their workflows status turning into abnormal [14]. To understand the relations between file change and operation performance, a meta-data analysis approach has been proposed and introduced by [18], which focuses on the change of certain file types at different project stages, and the correlations between the volume of file changes and the level of interactions.

However, these data-driven approaches also have some issues, i) there is no formal specification about the data selection process in different industries, ii) the identified KPIs are usually in the abstract or numeric format meaning the understanding of them could be difficult sometimes, and iii) excessive amount of indictors could be extracted if a project has high volume of data. Some indicators are to be filtered, as they are not sufficiently useful in the evaluation. As stated in [19], the expertise of specific work areas can be obtained from the experts with related experiences, and then preserved in knowledge bases for re-use purposes. In order to improve the analysis performance, the preserved knowledge is necessary to be integrated with data-driven approaches. A research attempted to model the knowledge evolution of each individual in an organisation, and then use the traceability of combined individual knowledge to evaluate the performance of a team and the projects executed by the team. It shows that the change of intangible information, especially the knowledge of single individual or a team, can be used to measure the performance change, and improve the rationality of KPIs identification [20, 21].

3 CONCEPTUAL MODEL

In the context of this research, a KPI is defined as a set of information extracted from the project data, which contains one or multiple indications of project characteristics. To improve the rationality of KPIs identification process, certain knowledge (technical and personal) is needed, e.g., the service/maintenance procedure, relation of assembly parts, dependency of activities, role/experience level of the participants, hierarchical structures of teams/departments, etc.

To minimise the processing time and manual interventions, the analysis part of this approach is to be designed as automatic. As shown in Figure 1, the main modules of the conceptual model include: *Information Fusion*, *Knowledge Capturing*, *Information Extraction*, *KPI Identification*, *KPI Visualisation* and *Feedback Collecting*.

- ***Information Fusion***: as the data of projects could be stored in separate databases with various formats, to improve the reliability and avoid the information loss, this distributed data needs to be integrated from different sources, and then merged/stored into a centralised database;

- ***Knowledge Capturing***: before performing the analysis, technical and personal knowledge needs to be captured from knowledge experts and project participants, and then preserved in a central knowledge base. The captured knowledge can be generic or domain specific. It needs to be the same set of knowledge involved in the project execution process.
  To collect knowledge from an organisation, the following methods is used: i) using survey-based mechanisms to collect the personal knowledge from participants regularly, ii) asking domain experts to create domain specific knowledge bases, and then integrating/mapping them according to the specific analysis requirements, iii) using data mining techniques to automatically discover and extract knowledge from the data of previously completed projects;

- ***Information Extraction***: this module aims to identify and extract both explicit and implicit patterns from the project data. To achieve this, semantic analysis, i.e., natural language processing (NLP), named entity recognition (NER), with other analysis techniques, i.e., clustering analysis, sequence analysis and frequency analysis, are applied collectively.
  In semantic analysis, NLP converts a block of text into meaningful tokens using tokenisation, POS tagging, stemming, stop words removal and word sense disambiguation; subsequently, NER extracts the name entities, such as people, organisation, location and date, from the tokens, which further helps the machine understand the content of the text; Clustering analysis groups similar

projects together, by considering their features that are extracted from the project data; Sequence analysis is used to identify and extract sequential patterns, e.g., the sequence of project activities/actions; Frequency analysis aims to discover the frequently occurred patterns, e.g., key terms/phrases, named entities, activities/actions and sub-sequences;

- ***KPIs Identification***: in this module, the previously extracted patterns are applied to identify the KPIs. Due to large amount of data that some projects have, the identification process needs to filter certain patterns that have less correlation with the captured knowledge. Meanwhile, a KPI is a high-level interpretation of project characteristics that could involve single or multiple patterns. To ensure the identified KPI is significant for performance evaluation and decision making, pattern selection of KPI needs to take the technical knowledge into account;

- ***KPIs Visualisation:*** the identified KPIs are then presented to the participants using interactive visualisations, which enable them to browse, retrieve, compare and share the information. In practice, some participants could have different information needs from the others (depending on their roles and experience levels). In order to fulfil their information needs accurately, the personal knowledge needs to be taken into account;

- ***Feedback Collecting***: having completed the above discussed processes, the feedback from participants is collected, which is then used to modify the structure/content of the knowledge base. This module aims to improve the quality of knowledge structure, performance of information extraction module, and rationality of the identification process.

In summary, this approach utilises data analysis and knowledge base to achieve the automatic identification and visualisation of KPIs. With a feedback collecting mechanism, the project participants can directly contribute their knowledge to a centralised knowledge base, which is then used to improve the performance and accuracy of the approach. This model suggests that advanced technologies, such as information fusion, semantic analysis, clustering analysis, sequence analysis and frequency analysis, can facilitate the automatic identification and visualisation, and provide intelligent dashboard to the participants in monitoring the project performance on a real-time basis.

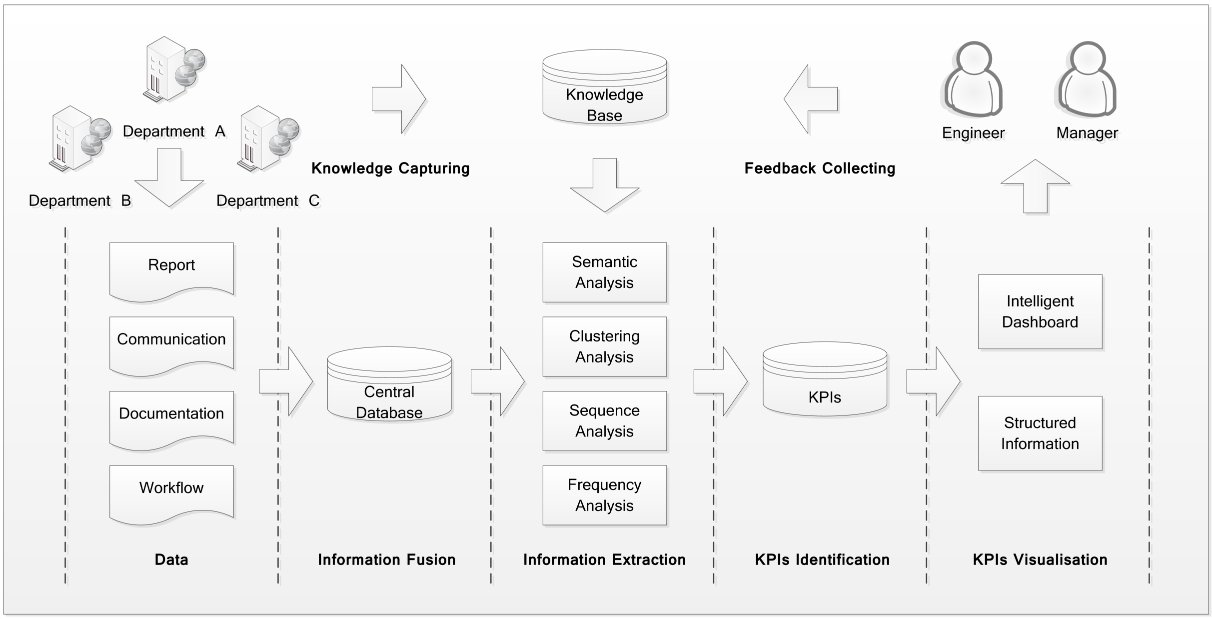


Figure 1 Conceptual Model

4 KPI IDENTIFICATION AND VISUALISATION

This section introduces the detailed process of identifying operational complexity related KPIs using a large collection of industrial data, and then demonstrates a combined visualisation of intelligent dashboard that contains multiple KPIs.

4.1 Dataset

In this research, the applied data is obtained from an international company in aerospace industry. It contains 390 In-Service projects with created dates from 2012 to 2013. Each project has its own data archive that includes technical reports, communications, documentations, workflow information and participant information. Some data can be further decomposed into multiple components on a detailed level, e.g., a technical report could contain a list of files, such as *damage information*, *assembly part information*, *repair instruction*, *design approval sheet*, etc. The data is saved in different formats, including text file (i.e., .pdf, .doc, .txt, .conf, etc.), standard image file (i.e., .jpg, .png, etc.), and image-based PDF file (i.e., scanned text, drawing, manuscript, etc.). For the proposed approach, its information extraction module is designed to process text information; however, image-based files could be also processed, if they contain meaningful text information.

4.2 Complexity Identification

For an In-Service project, the activities involved in the process could reflect the operational complexity of the project. As mentioned before, each activity could generate its own data during the execution, thus such complexity can be identified by performing quantitative analysis on the data.

4.2.1 Data Representation

To perform the analysis, each project needs to be represented using a machine understandable representation, i.e., feature vector. According to the captured knowledge, 15 file types are selected as the features to construct the vectors. These selected files are generated at different project stages, and from major activities, e.g., *stage<planning>* → *activity<request of information>* → *data<email>*, *stage<problem solving>* → *activity<issuing repair instruction>* → *data<repair instruction>*, *stage< evaluation>* → *activity<fatigue test>* → *data< fatigue test report>*. By using these file types, the vectors can be treated as the high-level representations of project process. Table 1 below shows two feature vectors, and each cell with '**Tx**' indicates the proportion of a particular file type '**x**'.

Table 1 File based feature vector

	T1	T2	T3	T4	T5	…	T15	Total
P1	0.1212	0	0. 2908	0	0.0767	…	0.1153	1
P2	0	0.1132	0.0895	0	0.3004	…	0.0916	1

4.2.2 Identification of Operational Complexity

An In-Service project could involve a lot of collaborations, thus its data can be frequently exchanged between the internal departments, or external parties such as clients and contractors. By analysing the behaviours of data exchanging, an additional feature called *transaction change* is attached to the file types containing three values, i.e., *outgoing*, *incoming* and *internal*. In general, file types related to outgoing transaction indicate the files are sent to the clients/contractors by the internal departments; file types related to incoming transaction indicate the files are received from the clients/contractors; and file types related to internal transaction indicate the files are generated by the internal departments, and only circulated among them.

By using this additional feature, the selected file types can be grouped into three categories. E.g., *request of information* and *repair instruction* is grouped into *outgoing*, *fatigue test report* is grouped into *internal*, etc. Table 2 below shows two grouped feature vectors which are generated from Table 1.

Table 2 Transaction based feature vector

	Outgoing	Incoming	Internal	Total
P1	0.3209	0.5356	0.1435	1
P2	0.5030	0.1238	0. 3732	1

To identify the operational complexity, three steps are considered: i) generating rules of complexity identification using the knowledge base, ii) clustering feature vectors based on the proportion of transactions, and iii) assigning the complexity level to each cluster based on the rules and cluster details.

The rules generated from the knowledge base include:

i) The projects with high outgoing/low incoming transactions are supposed to have low complexity. In this context, the files sent by clients/contractors, mainly include *damage information* and *enquiries*. The low proportion of these files means that the damage could be minor. Therefore, the project can be efficiently executed without many further information requests by the In-Service department.

ii) The projects with low outgoing/high incoming transactions are supposed to have high complexity. In this context, the files sent by clients/contractors take a higher proportion, which means the damage could be major, or high volume of enquiries are raised by the external parties. Therefore, the In-Service department needs to wait for further information to be received, and then make more efforts to deal with the problems.

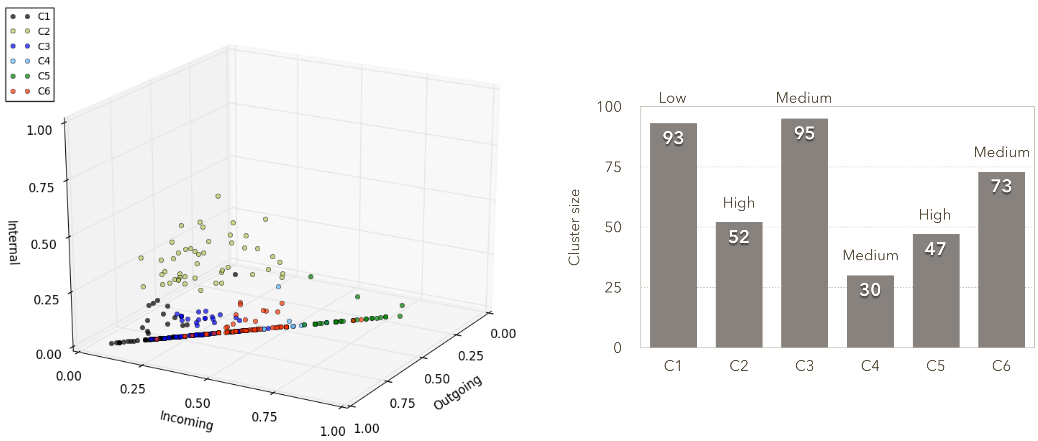
iii) The projects with high internal transaction are also supposed to have high complexity. The internal transactions contain certain file types, such as *fatigue test report*, *stress test report*, etc. Such relevant activities are usually difficult and time consuming, which could involve large amount of computation and high volume of resources, such as experienced engineers, special equipment, etc.

iv) The projects with balanced outgoing/incoming transaction, and low internal transaction, are considered to have medium complexity.

After the identification, 390 projects are grouped into 6 clusters, and the detailed result is shown in Table 3 blow.

Table 3 Result of complexity identification

Cluster	Size	Outgoing (avg.)	Incoming (avg.)	Internal (avg.)	Complexity
C1	93	0.7904	0.1967	0.0129	Low
C2	52	0.5406	0.2194	0.2400	High
C3	95	0.6956	0.2936	0.0108	Medium
C4	30	0.5238	0.4708	0.0054	Medium
C5	47	0.3883	0.6056	0.0061	High
C6	73	0.5940	0.3972	0.0088	Medium



(i) Projection of the clusters *(ii) Distribution of cluster size*

Figure 2 Visualisation of operational complexity

According to the table, the average outgoing transaction of C1 is higher than others, thus the complexity level of its contained projects (23.85%) is low; the average incoming transaction of C5 is higher than others, thus the complexity level of its contained projects (12.05%) is high; the average internal transaction of C2 is higher than others, thus the complexity level of the contained projects (13.33%) is also high; the outgoing/incoming transaction of C3, C4 and C6 are more balanced, and the internal transaction of them is low, thus the complexity level of their contained projects (50.77%) is medium.

To facilitate the understanding, the result of complexity identification is then represented by the visualisations shown below. Figure 2 (i) is the projection of feature vectors in a 3-dimensional space. In this visualisation, each data point represents one single project, and each colour indicates an assigned cluster. Figure 2 (ii) shows the distribution of cluster size and the assigned complexity level of each cluster. Both of these visualisations provide well-structured information enabling the project participants to monitor and compare the operation performance of projects.

4.3 Intelligent Dashboard

In practice, the engineers and managers always have needs of dealing with multiple projects at the same time. It is essential for the managers to understand the execution status and performance level of individual project, and then allocate resources accordingly, in order to maximise the project output. To improve the management performance, it is also critical for them to consider multiple KPIs simultaneously for the purpose of gaining the comprehensive views of team/department performance and having a better understanding of project characteristics from different perspectives.

As an example, Figure 3 shows an integration of multiple KPIs that is organised in a dashboard format. In this figure, three KPIs are included, i.e., KPI-1: ISQ volume vs time, KPI-2: Assembly vs damage location, and KPI-3: Heat map of damage locations. According to KPI-1, the managers can review the current workload, as well as the detailed information and related aircraft types; from KPI-2, they can assess the difficulties and workload required for each individual project by examining its damage locations and assembly parts; from KPI-3, they can have a comprehensive understanding on the damage locations and the frequency of damages on a particular aircraft type. With the assistance of these KPIs, the project managers are able to efficiently allocate time, people and other resources, and dynamically adjust the work plan upon any change of conditions or circumstances.

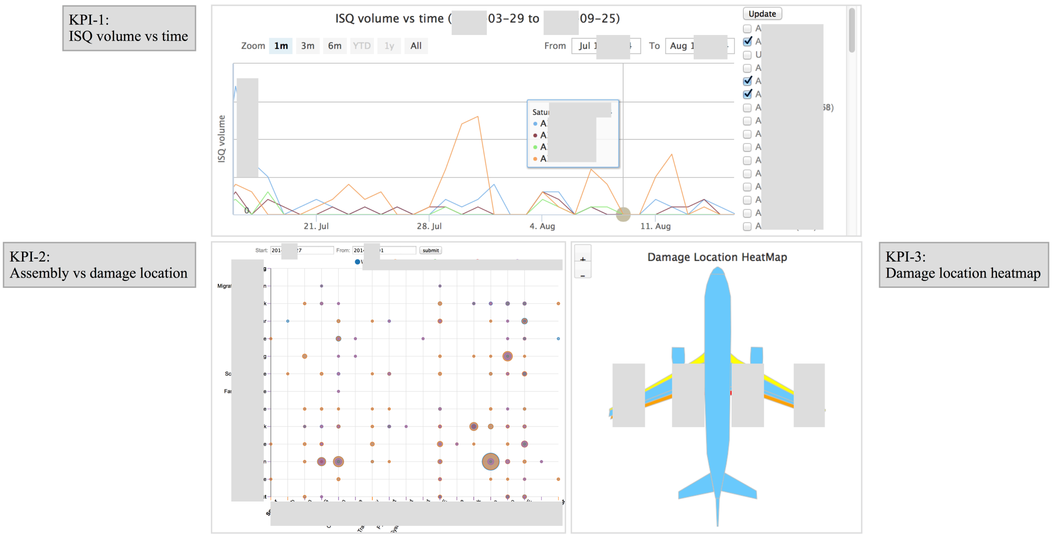


Figure 3 Visualisation of integrated KPIs: an intelligent dashboard[1]

5 CONCLUSION

The performance evaluation for engineering projects becomes more challenging, due to high volume of complex operational processes, distributed resources and international/intersectional collaborations are extensively involved. In practice, the project participants have demand to process multiple projects simultaneously under high pressures, which cause the evaluation of project performance on a real-time basis to be more difficult.

In order to facilitate the performance evaluation, this research proposed a conceptual model for a KPIs identification approach, and then evaluated the approach by applying industrial data. The approach applies information fusion, semantic analysis, clustering analysis, sequence analysis and frequency analysis, with knowledge base, to achieve automatic KPIs identification and visualisation. Given the data of 390 In-Service projects, the KPIs related to operational complexity are identified and visualised by applying the proposed approach, which could help the project participants gain a better

[1] For confidentiality reasons, some data in the figure has been intentionally removed.

understanding on the project execution status and complexity related characteristics. Moreover, a visualisation of combined KPIs (intelligent dashboard) is demonstrated, which could help improve the management performance and efficiency of resource allocation.

Further works includes the formalisation of the knowledge base, optimisation of the information extraction module and evaluation using different datasets.

ACKNOWLEDGMENTS

The research reported in this paper is funded by Engineering and Physical Sciences Research Council (EP/K014196/1). The authors would like to thank the industrial collaborators and their engineers for their input and support on this project.

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