INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED15
27-30 JULY 2015, POLITECNICO DI MILANO, ITALY

A NEW KNOWLEDGE SOURCING FRAMEWORK TO SUPPORT KBE DEVELOPMENT

Quintana-Amate, Santiago (1,2); Bermell-Garcia, Pablo (2); Balcazar, Luis (2); Tiwari, Ashutosh (1)
1: Cranfield University, United Kingdom; 2: Airbus Group Innovations, United Kingdom

Abstract

Knowledge-Based Engineering (KBE) has been traditionally used to source engineering knowledge by integrating software and expertise, thus automating repetitive tasks and speeding up the engineering design process. However, to adequately perform the knowledge sourcing process it is a must to carry out an efficient capture, manage and reuse engineering knowledge.

In this regard, this paper presents a Knowledge Sourcing Framework (KSF) to methodologically source engineering knowledge. This research makes a novel contribution to current knowledge sourcing practices thanks to the proposed integration of expert and machine knowledge in a common environment. In doing so, a better link between knowledge acquisition and KBE is delivered. To achieve the main aim of this work, research efforts were focussed on: (i) identifying AI tools to extract engineering knowledge more efficiently; (ii) adopting a widely used methodology to allow the systematic capture and reuse of engineering knowledge. Finally, a case study has been successfully realised in the context of the aerospace industry, supporting the assumptions made in this research.

Keywords: Knowledge management, Decision making, Design learning, Research methodologies and methods

Contact:
Santiago Quintana-Amate
Cranfield University
School of Applied Sciences
United Kingdom
q.a.quintanaamate@cranfield.ac.uk

Please cite this paper as:
Surnames, Initials: *Title of paper*. In: Proceedings of the 20th International Conference on Engineering Design (ICED15), Vol. nn: Title of Volume, Milan, Italy, 27.-30.07.2015

1 INTRODUCTION

The increasing competitiveness in the aerospace industry is forcing organisations to seek their profits beyond manufacturing (MFG). As a consequence, aerospace companies are changing from being *providers of products to providers of Product Service Systems* (PSS) (Selak, Butala and Sluga, 2014). This new business model involves shifting efforts from manufacturing activities to those ones related to service systems such as Maintenance, Repair and Overhaul (MRO) (Stark et al.,2014; Zhu et al., 2012). In this direction, aerospace organisations are increasingly assigning MFG tasks to their suppliers, e.g. "Power8" established by Airbus in 2007 was fostering the use of suppliers to realise certain manufacturing processes. By adopting this strategy, Airbus shared the risks while raising its profits derived from those MFG processes. In parallel, aerospace organisations are focussing their efforts on PSS (e.g. *Power-by-the-Hour* approach proposed by Rolls-Royce), aiming to increase the number of MRO tasks which have been traditionally concluded by the airline companies (e.g. Lufthansa Technik, Monarch). A clear example of this business trend is the acquisition of aviation maintenance companies by aerospace companies (e.g. Vector Aerospace bough by Airbus in 2011).

As a consequence of the implementation of this new business model, the authors have identified two major risks for future MFG. The first risk is associated to the reduced availability of MFG experts in the market. In many cases this implies the loss of relevant knowledge for the traditional aerospace leaders, most of this knowledge is now in hands of the few suppliers responsible of certain MFG activities. The second risk is the inefficient use of the knowledge for the development of future products and improvements, this may take form of a: (i) the decrease in the existent engineering models (defining structure, behaviour of a system); (ii) the increase of raw data from different manufacturers which require the use of advanced data mining tools in order to combine them and capture the required knowledge. In order to minimise the impact of these risks the aerospace industry needs to source and capture expert engineering knowledge in areas ranging from manufacturing to maintenance.

Knowledge-Based Engineering (KBE) has been traditionally used to source engineering knowledge by integrating software and expertise, thus automating repetitive tasks and speeding up the engineering design process. However, to adequately perform the knowledge sourcing process it is a must to carry out an efficient capture, manage and reuse engineering knowledge (La Rocca, 2012). Therefore, many of the existent KBE applications are not fully prepared for the industrial needs in a context where elicitation and management of both explicit and implicit knowledge has become a key feature to carry out a fast and robust engineering as required by the industry (Verhagen et al., 2012). As a response, the research reported in this work builds on previous work presenting an extended KBE methodology and providing further understanding on the role of knowledge sourcing in the KBE research.

1.1 Industrial Context

This research has been realised in the context of the aerospace industry where industrial challenges associated with the sourcing of knowledge to support decision making in design have become apparent to aerospace engineers. In this regard, Airbus Group Innovations has implemented a program named as "Return of Experience" (REX) focussed on the design, test and validation of future methods and tools to provide a more efficient manage of engineering knowledge. In fact, this research was motivated by the challenges of the REX strategy.

A general pattern found in the research activities carried out within the REX program is the focus on: (1) the capture of knowledge from downstream engineering expertise (i.e. manufacturing, maintenance) and; (2) the delivery of this knowledge to upstream phases of the Airbus products and services development organisations (i.e. design offices). An example of this approach can be found in (Bermell-Garcia et al., 2012) where research was performed to transfer manufacturing lessons learnt from the A350XWB aircraft program into new design for manufacturing KBE methods and tools for future composite aircraft design (for instance the A30X aircraft concept). In the design for manufacturing context, the REX journey revealed the requirement of sourcing engineering knowledge efficiently due to the importance of not only making the knowledge explicit to engineers but also the risk to lose the knowledge if it is not exploited in usable knowledge-based methods and tools. Two characteristics of the engineering design practice carried out by aerospace organisations substantiate the need of realising an efficient knowledge sourcing process (Bermell-Garcia et al., 2012):

- **Lack of knowledge at early design stages.** Due to the complexity of the products, engineers are usually forced to make relevant decisions (at the conceptual engineering design stage) based on low fidelity models.
- **Difficulties to establish design requirements and design solutions.** In the realisation of an aircraft program (e.g. A30X) technologies used to manufacture the future aircraft are still under development. In this regard, an example of this situation is the generation of new technologies to manufacture thermoplastic components.

In summary, the research performed in the REX program has answered questions on best practices to capture knowledge and exploit it through KBE methods and tools. However, it has also lead the researchers to new questions associated to the need to increase the efficiency of the knowledge sourcing practices leading to those KBE methods and tools. Given the high cost of the impact of the design choices made at early stages, a significant switch on research priority has recently been made in the knowledge management towards knowledge sourcing rather than only knowledge exploitation.

1.2 Identification of Research Challenges

Fast transformation of ideas into a high quality product requires maintaining the focus of designers on those tasks that add value to innovation by generating new knowledge. Doing so, time required to obtain an optimal design will be decreased, supporting designers to quickly solve knowledge intense problems. However, designers use around 30% of their time searching for information already accessible(Lowe et al., 2004). In this regard, Engineering Knowledge Management (EKM) aims the reduction of that 30% (Hoegl and Schulze, 2005). Moreover, some researches also mentioned the doing so to minimise the impact caused by knowledge loss when experts leave the company or get retired. In fact, EKM has been presented as "a key for the organisations attempting to capitalise their expertise and know-how" (Chapman and Pinfold, 1999).

Two main EKM approaches for knowledge source are recognized in the engineering design context: personalisation and codification, (Taylor et al., 2007). Personalisation instruments are focussed on tackling complex problems which require expert intervention. Therefore, the use of methods enabling expert communication and collaboration to source knowledge more efficiently such as engineering forums, are considered as personalisation tools. In contrast, codification tools are employed aiming the reuse of information by previously performing its capture and organisation. In this context, codification capabilities are usually presented as software applications focussed on the execution of inference tools, thus they use expert knowledge included as rules that can be later reused in other engineering problems (La Rocca, 2012).

In the literature, KBE is usually considered as a codification instrument enabling the capture of information (often as "IF THEN" rules) and its storage within models that can be later exploited by software tools (La Rocca, 2012; Verhagen et al., 2012). Some authors see KBE implementations beyond its mere automation and argument that it is a technology that can also allow the adequate capture, manage and reuse of engineering knowledge (La Rocca, 2012). In this direction, a study aimed to decouple the automation feature from the knowledge management by applying a methodology where the knowledge used by the KBE implementation is stored in an external database (Bermell-Garcia et al., 2012).This strategy facilitates the management of the complete Knowledge Life Cycle enabling the knowledge retention and reuse. However, to transform KBE in a knowledge-based capability able to adequately perform the source of engineering knowledge some challenges still need to be achieved (Bermell-Garcia et al., 2012):

- **Robust and reliable methodology:** KBE tools for industrial applications require methodological support to enable the capture, retention and reuse of engineering knowledge in a systematic way. A successful methodological implementation could be applied beyond the mere automation of repetitive tasks, aiming at acquiring a sustainable stream of knowledge and to adapt to the needs and changes of the industry. This would also open new avenues in long term helping KBE tools to move from case-based solutions to methodology-guided projects. Currently there is a lack of standardized and established methodologies, being this one of the commonly existing challenges.
- **Effective knowledge sourcing:** Another major bottleneck for the existence of fully automated KBE solutions is the way the knowledge is being captured. Even though some effort has been dedicated into standardizing the techniques to correctly extract knowledge from the experts, this process can be both time consuming and exposed to subjectivity, which in the long run may produce biased KBE tools. Therefore the effective sourcing of data, information and knowledge

has important implications with respect to the quality of the resulting applications. In this context, the appropriate use of Artificial Intelligence (AI) could potentially deliver a more effective knowledge sourcing process by acquiring expert knowledge more efficiently. By doing so, the time required to extract expert knowledge would be reduced, hampering the use of KBE in the industry.

As a consequence to the challenges identified above, this research proposes an extended KBE development process aiming the applicability of KBE beyond the codification of knowledge into rules to generate inference tools later used as automated software packages. This study is based on the hypothesis that an extended KBE development process can be achieved by integrating personalisation and codification views. To support the hypothesis formulated and confirm the identified research gap an extensive literature search was carried focused on finding new approaches to source engineering knowledge. More precisely, research efforts were on:

- Artificial Intelligence (AI) tools to extract knowledge more efficiently (Liebowitz, 2001; Bermell-Garcia, 2007).
- The use of methodological support to provide practitioners with a more robust and reliable KBE methodology by enabling the systematic management of engineering knowledge (Bermell-Garcia et al., 2012; Fan et al., 2002).

1.3 Framework description

In the aerospace context, knowledge creation, retention and reuse are considered as essential features directly linked with the organisation competitiveness, thus to effectively source knowledge is not enough developing isolated KBE applications. A potential solution to combine access to knowledge and automation aspects is the integration of KBE implementations within a Knowledge Sourcing Framework (KSF). In this regard, this research proposes the development of an "extended KBE development process" aiming the embracement of the advantages associated to personalisation and codification EKM views.

The KSF proposed, focuses on tackling the identified KBE key barriers by integrating personalisation and codification methods and tools. In this direction, the development of the proposed framework was achieved thanks to the realisation of three main activities described below. The first and second tasks are directly related to the efforts of this research defined in the previous section; the third one constitutes the environment where the elements required to achieve an efficient knowledge sourcing are integrated.

- **Search, analysis and exploitation of Machine Learning (ML) methods** to efficiently extract engineering knowledge. This activity was carried out aiming to: (i) support engineers not being experts in AI to select an adequate algorithm to be used in a particular problem; (ii) use of ML algorithms to extract quickly extract engineering knowledge. Firstly, to help engineers in the algorithm selection a wide range of machine learning algorithms were analysed and classified using books (Abu-Mostafa and Magdon-Ismail, 2012; Bishop, 2007; Murphy, 2012; Segaran, 2007; Witten, Eibe and Hall, 2011) and acknowledged open-source machine learning tools (Weka and Scikit-learn) as main resources. The list of algorithms was filter in order to remove those *Black Box* techniques not providing the user with essential interpretative information required to trace back the results, thus improving its reliability. Last but not least, the automated execution of ML methods to generate new knowledge was realised by embedding into a KSF platform the algorithms filtered.
- **Adoption of KNOMAD** (Knowledge Nurture for Optimal Multidisciplinary Analysis and Design), an existent methodology to enable the management of the knowledge life cycle. KNOMAD is a methodology widely used to develop KBE systems encompassing five phases (Knowledge capture, Normalization, Organisation, Modelling & Implementation and Delivery) as described in (Verhagen, 2013). Due to the disruptive nature of the proposed framework the use of KNOMAD facilitates the adoption of KSF in the industry enabling the systematic capture, retention, reuse and update of engineering knowledge, thus a more reliable and robust methodology was developed.
- **Development of a KSF web-based platform** where experts and machine learning algorithms can interact, being new knowledge created, reviewed and validated. This platform contains offline services created following the first four steps of the KNOMAD methodology (knowledge

capture, normalization, organisation and modelling) whereas the rest of the KNOMAD steps were carried out online by using the KSF platform (Figure 1). Moreover, this platform embeds several applications developed with the aim of realising the online tasks required.

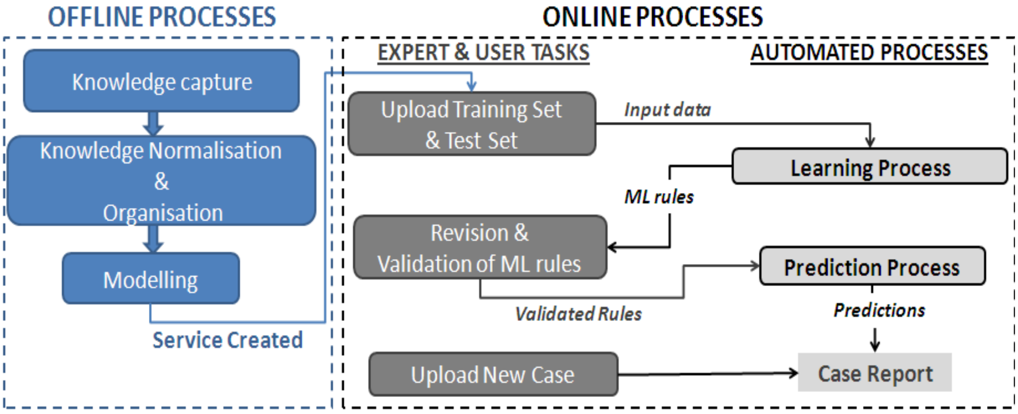

Figure 1. Service creation within KSF Platform: Process flow

1.4 Case Study Description

The aim of this section is to proof the foundations of this research by the realisation of a case study. This use case intends the design optimisation of wing covers made of carbon fibre reinforced plastics (CFRP). Once the proposed framework was developed, it scored wing design concepts in a few seconds where current methods required more than a week of man work. To do this, a service within the KSF platform has been created supporting the design optimisation of composite wing covers by quickly predicting the manufacturing time of different wing design configurations.

To achieve the main objective of this use case, codification and personalisation EKM views must be properly integrated. In this context, this research uses machine learning algorithms and the intervention of experts as codification and personalisation elements respectively. The adequate integration of both elements (personalisation and codification tools) to systematically source engineering knowledge is obtained through the adoption KNOMAD. The stages of KNOMAD realised under the scope of this case study to provide designers with the MFG time predictions are described as follows:

- **Knowledge Capture**. Knowledge belonging to two different sources (experts and ML algorithms) is acquired. In first place, experts provide to the knowledge manager with those parameters they believe are driving the time required to manufacture a wing structure. The data corresponding to these parameters defined by the experts is automatically extracted from an excel file containing structural data about the design by using a feature extraction tool developed in the context of the KSF. These design values are merged with their corresponding machine times obtained through simulation. This is followed by the knowledge creation stage where an AI technique is used to source knowledge by generating an explicit model describing the system behaviour. The model created is composed by a set of rules in the format of “IF THEN” rules.
- **Normalisation**. At this stage, the knowledge captured is modified in order to comply with an agreed format to ensure the quality of the data. Moreover, this step facilitates the visualization and automated execution of the knowledge by: (i) processing of data adapting its format to the ones required by the framework and (ii) storing the knowledge in dedicated repository items within the Content Management system used by the framework.
- **Organisation**. The data structure is defined at this point of the methodology. The definition and creation of the data architecture allows the access and traceability of the knowledge while permitting its efficient update. In this direction, to deliver a more intuitive and easy to update knowledge architecture, a domain specific ontology has been developed including the definition of the class hierarchies, relationships and, their attributes and behaviour.
- **Modelling.** In this step, all the models required by the framework are created. The models developed are associated to the Engineering Knowledge Resources (EKRs) used in this work and introduced by (Bermell-Garcia, 2007). EKRs are containers allowing the knowledge, applications

and case reports (log files generated when executing the capability) to be independently stored. In this context, three types of EKR models were created.

- **Knowledge models.** They encompass models containing informal (e.g. design descriptors) and formal (e.g. AI rules) knolwedge used by the KSF.
- **Capability models.** Information about the automated tool in charge of creating new knowledge through the use AI algorithms is stored within these models. It also includes all the functionality required to execute the learning and prediction processes.
- **Case reports models.** They contain information and knowledge used and provided by the KSF platform every time is executed.

By placing knowledge and applications within their respective EKR some benefits have been identified:

- It fosters knowledge reuse across different engineering problems within the company.
- It provides users with a simpler system which improves usability and maintenance activities.
- It enhances knowledge to be easily updated permitting the review and validation of ML rules.

- **Implementation.** This process involved the creation of the KSF which was built on top of a content management system (CMS). This content management system, containing the knowledge elements, applications and case reports, allows the implementation of KNOMAD methodology and consequently the development of a KBE system. The tools encompassed by the KSF are integrated within the system architecture as shown in Figure 2.

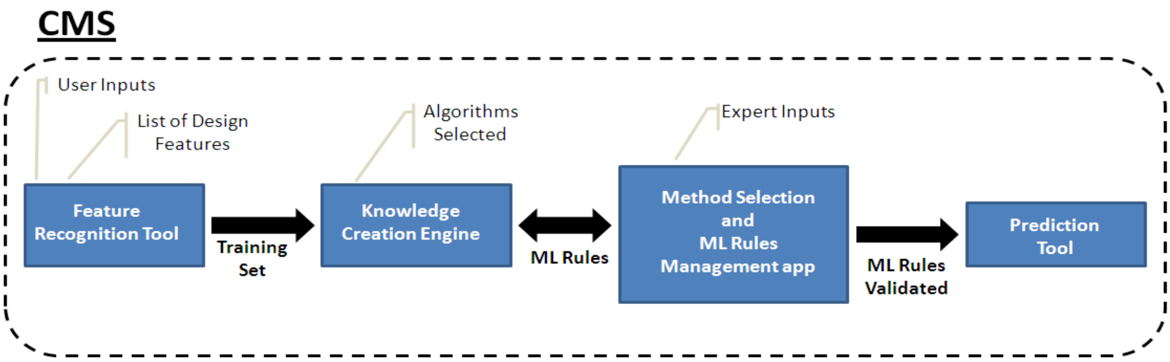

Figure 2. KBE system architecture

Those parameters driving the MFG time of wing structures –provided by experts– are used by the *Feature Recognition Tool* in charge of filtering raw data and generating a training set containing relevant information. The training set contains design descriptors (input data) and MFG times (output data obtained from simulations). This training set is used by the machine learning algorithms in the *Knowledge Creation Engine* to create an explicit model. The model generated includes a set of rules describing how the value of the input parameters affect to the time required to manufacture a wing structure. These rules are later reviewed and validated by experts using the *Rules Management Application* (RMA) provided by the platform. In case the experts are not satisfied with the results, the KSF platform enables the user to run again the knowledge creation engine using a different algorithm. Finally, the validated model is used by the *Prediction tool* to predict new design configurations helping designers to make more informed decisions.

- **Analysis and Delivery.** After the corresponding KSF service was implemented it was required to evaluate the capability developed. To do that, two type of analysis realised by experts in the domain were carried out: quantitative and qualitative. On one hand, the qualitative analysis was focussed on analysing the interpretative information provided by each algorithm with the aim of supporting the selection of the most suitable technique for this particular case. On the other hand, the quantitative analysis consisted of analysing the score values provided by the ML algorithms. The combination of qualitative and quantitative analysis enabled the algorithm selection and the later review and validation of the model.

  Finally, once the ML model was validated, the KBE capability was delivered to the client.

2 RESULTS

The dataset used in this work consists of 269 samples containing data corresponding to 5 features (design descriptors) and their respective MFG times (output class). The dataset was divided in two different files: "training set" and "test set". The training set is the file use by the knowledge creation engine to generate an explicit model in a procedure known as "learning process". In this case, the training set contains around 75% of the existing samples corresponding to 4 wing designs.

Initially, the training set is used in a cross validation (CV) activity to evaluate the model's performance. CV is an iterative process consisting of three phases. First, the data belonging to the dataset was randomly shuffled and divided into 10 cross-validation folder or subsets containing each of them the same number of samples. Secondly –in each experiment of CV– nine out of the ten subsets are used to train, being the other subset used to test the model generated. This activity is realised nine more times until every subset has been used to test the model created at a specific iteration. Finally, a ML model is provided from the average performance of the ten models generated in the CV iterations. After this, the test set containing 25% of the samples was used to validate the model produced by the training set.

The ML algorithms used in the learning process were selected after a filtering process. In the filtering task only those ML techniques providing interpretative information where chosen. The algorithms selected in this case study were: linear regression, REPTree –tree method– and M5R –rule based method–. In this research, the evaluation of the prediction accuracy of the ML techniques follows a common criteria acknowledged by the research community (Tüfekci, 2014; Kavaklioglu, 2011). This criterion is based on using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as scoring values to rate the ML algorithms. Moreover, expert intervention is needed to analyse the performance and level of understanding of the explicit model created in each case. Therefore, experts reviewed the ML scoring values (MAE and RMSE) and the level of understanding of each explicit model created. Table 1 shows the MAE, RMSE and the level of understanding obtained of the ML method utilised. MAE and RMSE were automatically produced by the ML algorithm where the level of understanding was input by the users of the KSF platform. The users of the KSF platform were six experts with more than 15 years of experience in engineering design.

Table 1. Learning process: results obtained using CV.

ML method	MAE	RMSE	Level of Understanding of the model
Linear Regression	25.68	32.45	Low
REPTree	22.45	26.57	Medium
M5R	21.07	27.44	High

Based on MAE, RMSE and the level of understanding of the model generated, experts selected M5R as the most suitable algorithm to be used in this case study. However, in order to rely on the predictions provided by the algorithm it is necessary to validate the ML model. The validation of the rules was carried out by experts in the domain. Therefore, after the selection of an algorithm, –to perform the validation activity– experts must use the RMA placed in the KSF platform. RMA enables experts to review and validate the explicit model generated with the help of a visual analytical tool. The review and validation activities are part of an iterative process realised by experts consisting on:

- Modification of the ML model if required.
- Use of visual analytical tools (e.g. charts, tables...) to identify trends in data and understand how the changes realised in the model affect to ML scoring values.
- Pre-validation of the ML model after MAE and RMSE values delivered by CV process are acceptable from an engineering point of view.
- Use pre-validated model to predict values using the test set file and if proceed validate the model as long as MAE and RMSE values provided are considered as acceptable.

Table 2. Summary of M5R results.

	Learning Process		Validation Process	
ML model used	MAE	RMSE	MAE	RMSE
Initial model provided by M5R	21.07	27.44	20.26	27.31
Model reviewed and validated by experts	10.31	15.23	13.91	19.83

The results obtained in the learning and validation processes are summarised in Table 2. This table highlights the reduction of MAE and RMSE obtained as a result of experts using the RMA to review the initial set of rules provided. More precisely, experts made the modifications to the ML model in order to increase their accuracy. The modifications realised respond to the identification of trends in the inaccuracies of the predictions by using the analytical tool provided by the KSF platform.

3 DISCUSSION

In the last decades an increase of researches integrating personalisation and codification tools have been identified (Ruiz, Foguem and Grabot, 2014; Liao, Zhan and Mount, 1999; Dolšak and Novak, 2011) . These studies use data mining implementations (i) to extract knowledge from raw data; (ii) to allow the model automatically generated to be reviewed and validated by experts. However, these researches don't employ a methodology to systematically source engineering knowledge. As a response, the work presented in this paper proposes a framework where knowledge is systematically sourced using a well established methodology (KNOMAD). Moreover, it employs data mining tools (ML algorithms) to acquire knowledge more efficiently.

The potential of the methodology proposed is evaluated in a case study, showing the benefits of integrating machine and expert knowledge in a common environment. The use case was developed following the KNOMAD steps with the aim of sourcing knowledge in a systematic manner. In this context, specific attention was set to the data preparation activity (carried out as part of the knowledge capture process) which is considered as the most time consuming in the development of the KSF service (Mlynarski et al., 2006; Alcalá-Fdez et al., 2009).

In order to generate the machine time predictions, the ML methods left after the filtering process were executed using a training set, generating a set of ML models (one model per algorithm). At the learning stage, the initial model automatically generated didn't have low error values as shown in Table 1. However, after the experts selected one of the algorithms and modified its model (using CV to evaluate the model's performance), the error of the predictions was considerably reduced from MAE of 21.07 and RMSE 27.44, to MAE of 10.31 and RMSE 15.23. To avoid over-fitting the model to the data, a validation process was performed using new data, which was not used in the learning process. Therefore, the review and performance analysis of the model was realised using the training set produced (containing 75% of the samples) where the validation was carried out employing the test set (containing 25% of the samples). Although the values of MAE and RSME were higher than the ones obtained in the learning process (see Table 2), the results obtained were considered by experts in the domain as acceptable from an engineering point of view, thus leading to the validation of the rules. Therefore, the use case verification was obtained through the acceptance of the ML model initially provided by the data mining tool and later reviewed by experts.

In summary, the outcome of the case study supports the assumptions made in this research proposing the integration of personalisation and codification to optimise the engineering design process. Based on the findings we can argue that integration of machine and expert knowledge enables the reliable and fast evaluation of design concepts with accuracy values higher than 80%. The accuracy of the results is obtained comparing the ML predictions to the results obtained using high fidelity simulation software tools. Using the proposed methodology MFG time estimations are obtained in just a few seconds where the technology commonly used to do the same activity required a more than a week of man work to generate the required time estimations. Therefore the KSF framework is considered more efficient compared to current approaches as it provides accurate enough MFG time estimations. Moreover, the efforts spent on the development of the KSF are justified as this capability is often used (around once a month) within the organisation.

4 CONCLUSIONS

In this research, a Knowledge Sourcing Framework (KSF) to methodologically source engineering knowledge has been presented. This paper has made a novel contribution to current knowledge sourcing practices thanks to the proposed integration of expert and ML knowledge in a common environment. In doing so, a better link between knowledge acquisition and KBE is delivered. To achieve the main aim of this work, research efforts were focussed on: (i) identifying AI tools to extract engineering knowledge more efficiently and implementing them within the developed KSF; (ii) adopting a widely used methodology (KNOMAD) to allow the systematic capture and reuse of engineering knowledge. Finally, a case study has been successfully realised in the context of the aerospace industry, supporting the assumptions made in this research.

REFERENCES

Abu-Mostafa, Y., & Magdon-Ismail, M. (2012). *Learning From Data*. AMLBook.

Alcalá-Fdez, J., Sánchez, L., García, S., del Jesus, M., S., V., Garrell, J., Fernández, J., & Herrera, F. (2009). KEEL: A software tool to assess evolutionary algorithms for data mining problems. *Soft Computing—A Fusion of Foundations. Methodologies and Applications*, 307–318.

Bermell-Garcia, P. (2007). A metamodel to annotate knowledge based engineering codes as enterprise knowledge resources. *Cranfield University*.

Bermell-Garcia, P., Verhagen, W. J. C., Astwood, S., Krishnamurthy, K., Johnson, J. L., Ruiz, D., Curran, R. (2012). A framework for management of Knowledge-Based Engineering applications as software services: Enabling personalization and codification. *Advanced Engineering Informatics*, 219–230.

Bishop, M. (2007). *Pattern Recognition and Machine Learning* (p. 740). Springer.

Chapman, C. ., & Pinfold, M. (1999). Design engineering—a need to rethink the solution using knowledge based engineering. *Knowledge-Based Systems*, *12*(5-6), 257–267. doi:10.1016/S0950-7051(99)00013-1.

Dolšak, B., & Novak, M. (2011). Intelligent decision support for structural design analysis. *Advanced Engineering Informatics*, *25*(2), 330–340. doi:10.1016/j.aei.2010.11.001.

Fan, I. S., Lagos-Hernández, M., Bermell-García, P., & Twelves, M. (2002). A rule level knowledge management system for knowledge based engineering applications. In *Proceedings of DETC'02. International 22nd Computers and Information in Engineering* (ISBN: 0791836223). Montreal: *ASME.*

Hoegl, M., & Schulze, A. (2005). How to Support Knowledge Creation in New Product Development: *European Management Journal*, 263–273.

Kavaklioglu, K. (2011). Modeling and prediction of Turkey's electricity consumption using Support Vector Regression. *Applied Energy*, 368 – 375.

La Rocca, G. (2012). Knowledge based engineering: Between AI and CAD. Review of a language based technology to support engineering design. *Advanced Engineering Informatics*, 159–179.

Liao, T. W., Zhan, Z., & Mount, C. R. (1999). An integrated database and expert system for failure mechanism identification: Part I - automated knowledge acquisition. *Engineering Failure Analysis*, 387 – 406.

Liebowitz, J. (2001). Knowledge management and its link to artificial intelligence. *Expert Systems with Applications,1-6*.

Lowe, A., McMahon, C., & Culley, S. (2004). Characterising the requirements of engineering information systems. *International Journal of Information Management*, 401–422.

McMahon, C., Lowe, A., & Culley, S. (2004). Knowledge management in engineering design: personalization and codification. *Journal of Engineering Design,* 307–325.

Mlynarski, R., Ilczuk, G., Wakulicz-Deja, A., & Kargul, W. (2006). A new method of data preparation for cardiological decision support. *Computers in Cardiology*, 273–276.

Murphy, K. (2012). *Machine Learning - A Probabilistic Perspective* (p. 1096). MIT Press.

Potes Ruiz, P., Kamsu Foguem, B., & Grabot, B. (2014). Generating knowledge in maintenance from Experience Feedback. *Knowledge-Based Syste*ms, 4-20.

Segaran, T. (2007). *Programming Collective Intelligence: Building Smart Web 2.0 Applications* (1st edition, p.362). O'Reilly Media.

Selak, L., Butala, P., & Sluga, A. (2014). Condition monitoring and fault diagnostics for hydropower plants. *Computers in Industry*, 924–936.

Stark, R., Grosser, H., Beckmann-Dobrev, B., & Kind, S. (2014). Advanced Technologies in Life Cycle Engineering. *Procedia CIRP*, *22*, 3–14.

Tüfekci, P. (2014). Prediction of full load electrical power output of a base load operated combined cycle power plant using machine learning methods. *International Journal of Electrical Power & Energy Systems*, 126-140.

Verhagen, C. (2013). *An Ontology-Based Approach for Knowledge Lifecycle Management within Aircraft Lifecycle Phases.* Delft University.

Verhagen, W. J. C., Bermell-Garcia, P., Van Dijk, R. E. C., & Curran, R. (2012). A critical review of Knowledge-Based Engineering: An identification of research challenges. *Advanced Engineering Informatics*, 5–15.
Witten, I., Eibe, F., & Hall, M. (2011). *Data Mining: Practical Machine Learning Tools and Techniques* (3rd Edition, pp. 664). Morgan Kaufmann.
Zhu, H., Gao, J., Li, D., & Tang, D. (2012). A Web-based Product Service System for aerospace maintenance, repair and overhaul services. *Computers in Industry*, 338–348.