Redefining Journeyman and Master Craftsman Competency Models

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ABSTRACT

This paper represents a preliminary model of practiced stackable competencies to support the definition of a journeyman and master craftsman in real time. Numerous competency models exist and are relatively static. Our proposal is to inject real time proficiency data sets and repetitions (sets & reps), of the craftsperson into the competency model and provide a better representation of the skill level of the individual.

Most competency models rely on a one-time proficiency demonstration. While this may be effective for a baseline of the journeyman or master craftsman this falls short in defining the true skill level of the individual. Including documented sets and reps along with frequency of proficiency demonstration provides a truer analysis of the individual. Consider a master craftsman who's only qualification is a one-time demonstration of the competency several years prior. We must consider the atrophy of a competency gained as time between mastery and repetition increases. When was the last time the individual practiced the competency and have there been changes in the competency that makes the years old qualification outdated and potentially null and void? When should a master craftsman be downgraded to journeyman?

These questions can be answered using artificial intelligence. The workforce data that is now available and easily obtainable can provide the necessary analytical data to gain a deeper definition of when proficiency of an individual competency is earned or, when it is lost. Our proposed model and associated rubrics will inform on the number of sets and reps required to determine mastery of a competency. The model will also determine a potential degradation cycle of competency proficiency. We will also recommend other competencies that are relatable and stackable to create a more realistic definition of a journeyman or master craftsman.

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INTRODUCTION

Existing competency models tend to be lists of characteristics or skills that an individual needs to have in order to perform a job or task rather than career-enabling attributes that will support imminent needs (Polo & Kantola, 2020). In this work, a recursive approach to building a career competency model designed to support craftsman throughout their careers is provided. Utilizing a recursive approach allows this model to epitomize a stackable credential model and support craftsman from apprentice, through journeyman, to master. Additionally, data-driven elements are incorporated to provide real time (daily, weekly) updates and provide a better representation of the individual's current skill level.

Real time incorporation of data throughout the craftsman career through the tracking of sets & reps as they perform maintenance and repair processes ensures that the model does not rely on the one-time proficiency demonstration that is so often the downfall of static competency models. Data-driven models are trained not only to determine which features to include, but also which of these features are most indicative of continued mastery over time.

The remainder of this paper will be organized as follows: The next section will provide background information on the legacy training program under study and previous work on data-driven competency models. Then, the section on the Apprentice, Journeyman, Master (AJM) Framework will provide the theoretical overview of the apprentice, journey, master pipeline. The next section on the data-driven AJM model will discuss how features will be extracted from data, trade-offs between different model types, and the overall data-drive model. Finally, the last section will provide conclusions and a brief discussion of future work.

BACKGROUND AND PREVIOUS WORK

Legacy Training and Apprentice - Master Progression

In the face of modernization, many legacy training programs are struggling to meld their existing models and frameworks with new data-driven models. New methods for assessment i.e., Competency-Based Learning Environment Assessment Feedback Frameworks (CB-LEAFFs) (Johnson et al. 2021) and various data-tracking tools have opened the door for continuous assessment and tracking of performance during an individual's entire career (Smith et al., 2021). Technology advancements since the Navy's Five Vector Model initiative (Kantner 2002) , advances in competency management systems, competency data collection and mapping, and competency assessment tools have created an environment where a more data driven approach to defining an Apprentice, Journeyman and Master Craftsman is achievable.

Historically, career progression from apprentice to master and personnel assignment, in the case of this paper US Navy Sailors, has relied upon the individuals rank, length of service and official schools / courses graduated earning a Navy Enlisted Classification ((NEC) code or as in other military branches a Military Occupational Specialty code (MOS). In today's environment of naval self-sufficiency, smaller workforces, and reduced pipeline training as outlined in Ready Relevant Learning (RRL) initiative (Davidson, 2018) this model falls short of being able to assign the right person at the right time to the right job for mission accomplishment. Reliance on a servicemembers NEC/MOS to define personnel readiness and make billet and work assignments is an over simplified approach when data driven competency models are available and within the enlisted personnel assignment system.

Data-Driven Competency Models

Development of data-driven competency models differs from traditional competency model development as they do not depend on the subjectivity of subject matter experts to determine model parameter weightings (Hanna et al., 2016). However, they do require a labeled data set to ascertain which features should be incorporated and how they should be weighted. This can be challenging as educational and professional development data are often proprietary and sensitive meaning they can be difficult to obtain and must be carefully stored and protected similar to other types of proprietary and sensitive data (Jiang et al., 2019). One successful method employs an approach conceptually similar to a support vector machine (Hanna et al., 2018). Other studies have used a variety of machine learning methods for feature extraction and classification , including clustering, linear regression, and tree-based methods (Li et al., 2020).

AJM FRAMEWORK

The AJM framework provides a pathway for craftsmen to work from apprentice to journeyman J1 by showing competence in fundamental shop-theory, equipment knowledge, and task performance for individual skilled trades. Advancing to proficient journeyman J2 by completing sets and reps of maintenance and repair operations for these individual skilled trades. And finally achieving career long mastery at M1 and M2 by showing proficiency across several skilled trades, a variety of billets, and other relevant certifications and trainings.

Apprentice: Path to Competency

Once a craftsman enters the maintenance trades training program under any of the available skills, they are an apprentice. The apprentice craftsman will spend the next twelve to eighteen months becoming competent across three levels that include fundamental knowledge, equipment knowledge, and skills knowledge. Each of these levels has a series of processes, and sometimes sub-processes, that the craftsman must demonstrate competency in prior to earning the requisite signature on their qualification card. In addition, for the skills processes and sub-processes, craftsmen are required to perform, simulate, observe, or discuss the specific process, which is a maintenance or repair operation in detail. Prior to being promoted to the Journeyman (J1) rank of competence, the craftsman must also pass a written test and oral board.

As an initial approach to creating a data set to describe a craftsman's proficiency rating each task required review by a small group of SMEs and aligned with Navy career pathway documents to determine a baseline weighting criterion. Since the overall goal is to have a data-driven approach, the team did not want to expend effort on a more formal modeling process for the initial rules-based approach. Each process and sub-process were reviewed for criticality, difficulty, and frequency (CDF). As an example, processes that are critical to operations, are difficult to perform and are infrequently performed would have a higher score than a process that is performed routinely and is not difficult. Using this method creates a justification for weighting the proficiency scores of perform, simulate, observe, discuss. High scoring processes should be required to be performed as they are critical to operations.

Creating a competency model without consideration of skill degradation would do little more than achieve the same outcome as a static model. Skill degradation would be part of the overall formula where knowledge decay would be an indicator of skill decay. Processes where signature was obtained by discussion or observation only would have a much higher skill decay rating as compared to one that was performed or simulated in a virtual reality or augmented reality scenario. These degradation factors would be justified against empirical data that comes from the learning records store where craftsman provides objective quality evidence (OQE) for successful completion of a subject process. This OQE would also be validated against the time between (days between events) this work process being performed and the quality of the work being performed, i.e., was rework required, were process steps missed, was inordinate amount of time taken to enact repair due to skill, as inferred in the quality package. Over time artificial intelligence will improves the initial baseline of this degradation rating system and feed back to the CDF rating for improvements of the associated competency model for each process.

Journeyman: Sets and Reps

Once the craftsman has been promoted to Journeyman (J1), it is important that they continue to practice their new skill to become proficient. By tracking individual repair operations through maintenance and repair databases, the craftsman's sets & reps are associated with their competency record. When they meet the threshold of sets and reps for proficiency, they are then promoted to the Journeyman (J2) rank of proficiency within that skill.

Master: Career-long Achievement

Finally, the rank of Master is a career-long achievement that recognizes the culmination of proficiency as a Journeyman in multiple skills along with a record of superlative service. Figure 1 shows an overview of the four overall competency areas that craftsman work in to move toward their master craftsman qualification.

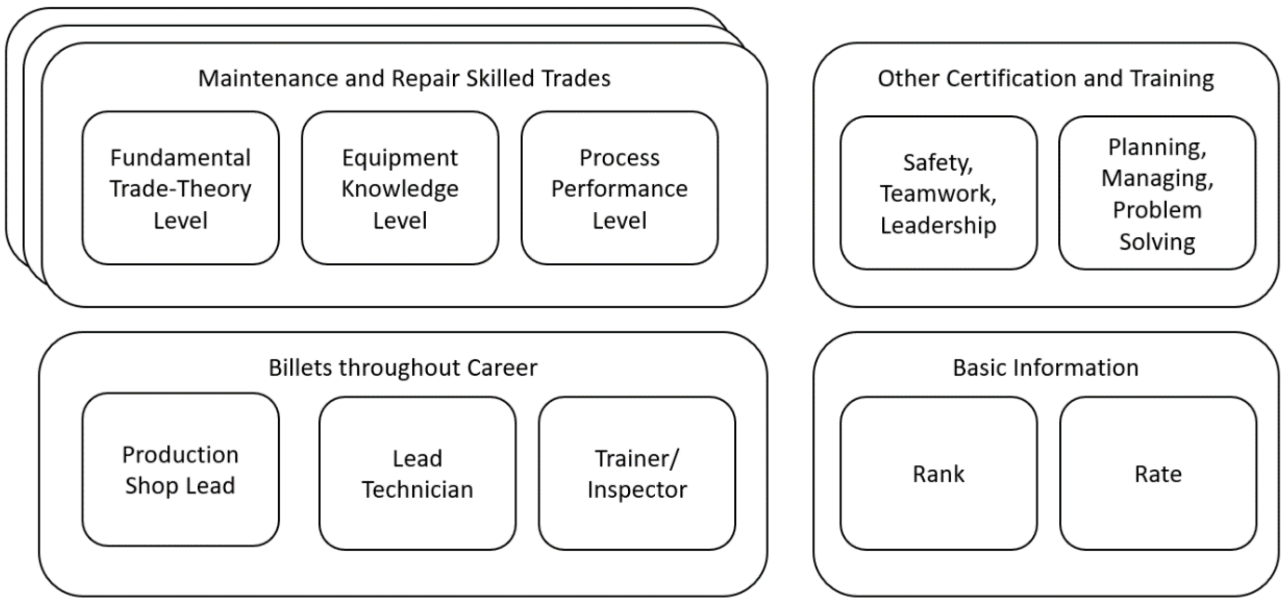

Figure 1 Master competencies.

Maintenance and Repair Skilled Trades represented the stackable credentials that craftsmen progressed through in the apprentice and journeyman levels of the pipeline. Craftsmen need to reach J2 proficiency in two or more of these trades to meet the minimum requirements for the first level master qualification, M1. Additionally, there are other training opportunities, billets the craftsmen can sign up for, and consideration of their rank and rate. Figure 2 shows the current career pipeline with no required skills training after the initials skills courses versus a proposed implementation for a Machinist Mate in the Navy over the course of a 20-year career. Inside each proposed qualification are numerous individual competencies that are stackable to achieve the qualification. Those stackable competencies are cross referenced with additional qualifications and once proficiency is obtained in one qualification the stackable competency carries across all qualifications that have that individual competency in their model. Should the earned competencies not be practiced at periodic intervals there is the potential of regression from M1 to J2.

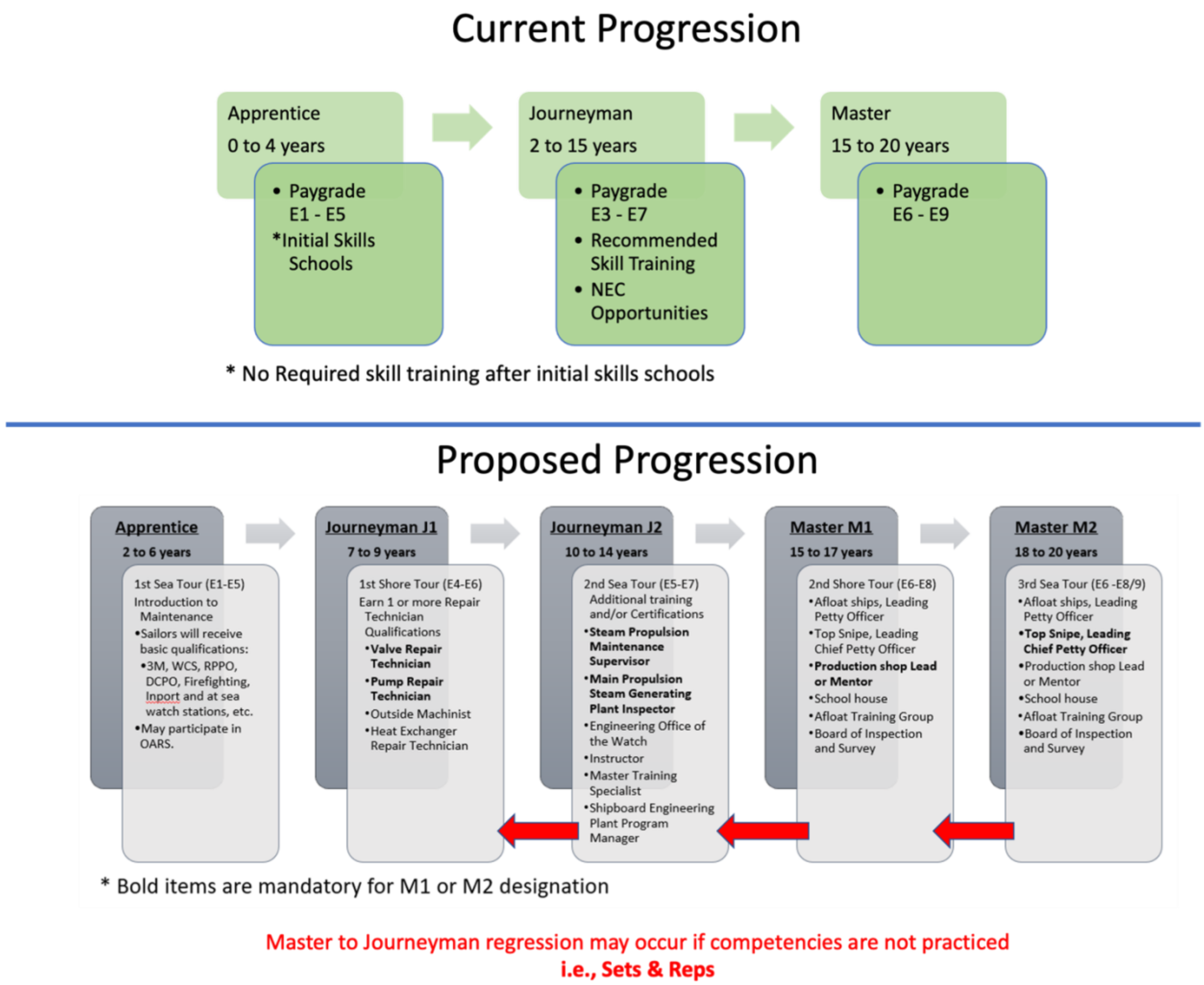

Figure 2 Master craftsman current vs. proposed career pipeline.

DATA-DRIVEN AJM MODEL

The process of defining a data-driven AJM model starts with a well-defined, clean data set. This data set includes information starting at higher levels of detail and then moving to lower levels of detail as required. In this section, an overview will be provided on the process of defining and extracting features, the benefits and drawbacks of certain modeling methodologies will be discussed, and finally an overview of an example model will be given.

Defining and Extracting Features

Based on the literature review, data available and information from subject matter experts, three main categories were chosen from which to collect data (Figure 3). Figure 3 starts with the broad overarching categories toward the center of the wheel and fans out to individual competencies which each will have a learned score associated with them near the edge of the wheel. The bold competency items indicate areas where the subject matter experts that were consulted thought the related tasks should be mandatory. These overarching categories are Experience, Training, and Basic Information. In the Basic Information category, only two variables were considered. These variables are rate, or job, to determine which competency pipeline the craftsman is working in and rank, to help determine which stage of the pipeline the craftsman should reasonably be in.

There are two main dimensions of the training category to be concerned with. The first is the training that is directly aligned with the craftsman's trade, i.e. Journeyman (J2) proficiency ratings. The other dimension is additional training they may have received that is indirectly related to, but supportive of, their craftsman career pipeline.

Finally for the experience category, there are also two categories. The first is performance of individual competency level tasks in the form of sets and reps. The second is longer billets of service that represent a period of activity for which the craftsman has served in a role.

Figure 3 Example of features extracted to inform master craftsman pipeline.

Once the feature variables are identified, the next consideration is how to quantitatively code them so that they can be ingested by the data-driven competency models. For categorical, unordered data, it is recommended to one-hot encode the data by assigning a one if a craftsman fulfilled the requirement and a zero otherwise. For example, the billets variable example from Figure 3 becomes a set of six variables all having a value of either zero or one depending on the craftsman's service record. For categorical, ordered variables, such as rank, integer encoding is appropriate. Finally, for the sets and repetitions variable, a quantitative mapping is used. There are several options for this mapping including having a separate variable for each skill or combining all skills together by weighting the individual sub-scores related to each skill.

Model Selection

Two model types were considered for the initial model. The first was multinomial logistic regression and the second was a decision tree. Multinomial logistic regression is an extension of logistic regression, which classifies into two classes, to more than two classes (Böhning, 1992). Here, the craftsmen are to be classified as M1, M2, or neither, so the extension past two classes is necessary. For the multinomial logistic regression model, each of the variables defined in the previous section is considered as an input to the model, for craftsman *i* let them be a vector of values $\overrightarrow{x_i}$. Defining the three classes as M_1, M_2, and N for neither, the probability of each would be:

$$\Pr(Y_i = M_1) = \frac{e^{\overrightarrow{\beta_{M_1}} \cdot \overrightarrow{x_i}}}{\sum_{k \in \{M_1, M_2, N\}} \overrightarrow{\beta_k} \cdot \overrightarrow{x_i}}$$

$$\Pr(Y_i = M_2) = \frac{e^{\overrightarrow{\beta_{M_2}} \cdot \overrightarrow{x_i}}}{\sum_{k \in \{M_1, M_2, N\}} \overrightarrow{\beta_k} \cdot \overrightarrow{x_i}}$$

$$\Pr(Y_i = N) = \frac{e^{\overrightarrow{\beta_N} \cdot \overrightarrow{x_i}}}{\sum_{k \in \{M_1, M_2, N\}} \overrightarrow{\beta_k} \cdot \overrightarrow{x_i}}$$

which is similar to the formulation from (Lei et al., 2019). The general rule for making class assignments using this type of model is to choose the class with the largest probability. The coefficients $\overrightarrow{\beta_k}$ are learned during model training to optimize the decision boundaries.

There are several drawbacks to this approach. First, while there are techniques to visualize the outcome and behavior of the model, such as graphing decision boundaries, these boundaries quickly become complex higher-dimensional surfaces as the number of variables exceeds two or three which is the case here. Additionally, it is difficult to include some of the requirements voiced by the subject matter experts as “must haves” in this type of model. However, in a broad comparison of models, logistic regression from another study logistic regression outperformed other models with respect to accuracy in a competency evaluation task so it should be considered as a viable option (Li et al., 2020).

The second model considered was a decision tree. Decision trees are very popular data-driven models as they are easy to visualize and explain. Essentially, when using a decision tree, an individual data point is considered, and a series of questions are asked. Depending on the variable values that characterize that individual data point, the point moves down the tree to the left or right to reach the next decision node. The training process involves passing the training data through the model and determining which decisions are best to make at each node. An example of a decision tree is provided in Figure 4. Though this decision tree is overly simplified and is not produce reasonable results, it is immediately apparent that these types of models are very easily visualized. In addition, they can encode the kind of “must have” decision” that the subject matter experts voiced as important. The main drawback to decision trees is that they tend to overfit, that is memorize, the training data. This is a well-known issue and is usually easily remedied by implementing an ensemble method such as a random forest (Dhivyaa et al., 2020).

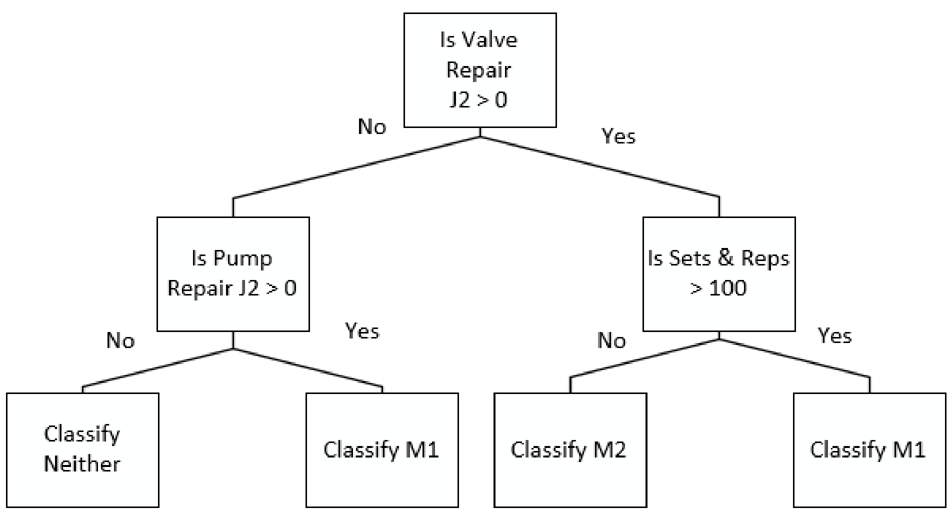

Figure 4 Simplified decision tree example for classification.

Overall Data-Driven Model

Many models in this area tend to suffer from what is known as a cold-start problem, that is a lack of data for up front train of the model. In order to combat this issue, information from a team of subject-matter experts is used to develop a rules-based classification model as a starting point for the overall machine learning model. As this model is tested on real data, its output is validated by subject-matter experts to ensure that the classifications are correct. As the rules-based classifier runs and the output is validated, a labeled data set of training data is produced. Once this data set is sufficiently large, the initial subject-matter expert information is used as prior probabilities to initialize the system weights which can then be updated by the new training data using a Bayesian approach for both the multimodal logistic regression model and decision tree model from the previous section. The results from both models are then compared to ascertain their performance in different scenarios. Since data-driven models are non-deterministic, that is they generally provide a recommendation for classification rather than a firm classification, the overall model should continue to be validated by subject-matter experts.

Finally, the data-driven model provides more than just classification of craftsman skill level. The data-driven model provides feedback to a craftsman when they are approaching a skill level boundary through skill atrophy. Consider Figure 5 showing the skill level of three craftsmen over time along with threshold levels for M1 and M2. Close to the initial time, Craftsman 1 crosses the threshold for M1 and remains above the threshold for some time. However, sometime later, their skill level begins to decrease. The data-driven system would have a warning system built in to recognize when a craftsman's skill was decreasing within some buffer distance of the thresholds and be able to alert the craftsman that they were facing skill atrophy that was threatening their earned M2 status. Additionally, though the decision boundary in Figure 5 is quite simple, the more complex decision boundaries learned through the data-driven models in this section allows the system to provide targeted feedback on which feature variable had led to the decrease in the overall skill level.

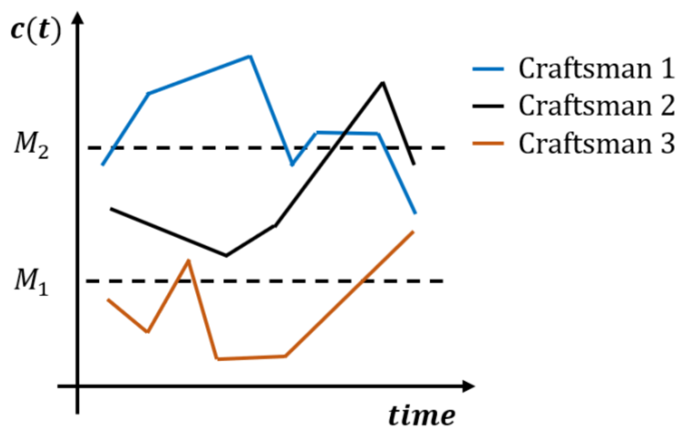

Figure 5 Example of expected craftsman skill over time with M1 and M2 thresholds.

CONCLUSIONS AND FUTURE WORK

This paper has presented the definition and example planned application for a data-driven model and artificial intelligence framework to support repair and maintenance craftsman throughout their career along an apprentice, journeyman, master competency pipeline. The model considers common pitfalls when applying data-driven modeling to legacy training programs including the initial lack of data for model training and hesitancy to apply a recommender system to assign craftsman certifications. These issues are addressed by starting with a rules-based model and validating with subject-matter experts in the loop. Finally, a plan for providing on demand and automated feedback to craftsmen to combat skill atrophy is presented and discussed.

The most important area for future work is the implementation of the model, beginning with the rules-based classifier and allowing the model to mature to a data-driven approach. Specifically, the rules-based classifier would need evaluation on the historical data from the legacy maintenance program under study to ensure that the rules provided by the subject matter experts produced a valid algorithm for classification resulting in existing craftsmen ranked at both the M1 and M2 levels. Once the rules have been established, the system can be run in the present time on current craftsman data which can then be collected and stored for later use as training data for the eventual data-driven system.

ACKNOWLEDGEMENTS

Funding for this work was provided by Valkyrie Enterprises under #VE102056ODU-REFOUNDATION.

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