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Data-driven TRL Transition Predictions for Early Technology Development in Defence

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ABSTRACT

This paper proposes the framework of TRL (Technology Readiness Level) transition predictions for early technology development in defense. Though predicting future TRLs is an important planning tool, it has been studied less actively than the other critical issues on TRL, and previous studies mostly have resorted to domain experts. The proposed framework is data-driven and utilises both explanatory and predictive modelling techniques. As a case study, the proposed framework is applied to real technology development data from DTiMS (Defense Technology InforMation Service) which is identified as a key resource. The result of explanatory modelling shows that the two predictor variables, TRL before R&D and project cost, are statistically significant for future TRLs. Also, popular predictive models are fitted and compared with various performance indices using 10-fold cross validation. The two selected predictive models are linear regression and support vector machine models with the lowest prediction errors.

Keywords: Technology readiness level; TRL prediction; Explanatory modelling; Predictive modelling; Defence technology

1. INTRODUCTION

Assessing the maturity of technologies is a critical procedure in order to mitigate the negative consequences in decision-making on the acquisition of complex systems. Without having a clear understanding of the technological maturity, it is impossible to properly manage cost, schedule and risk factors. An incorrect maturity assessment can lead to cost overruns, time delays, and poor quality, which can stop the whole project or program[1]. One of the most widely used metric for the technology maturity assessment is the technology readiness level (TRL) scale.

TRL was introduced by National Aeronautics and Space Administration (NASA) in the 1970s to enable the maturity of technologies to be assessed more systematically and consistently. TRL is being used in many different industries and organisations including the U.S. Congress General Accountability Office (GAO) and the U.S. Department of Defense (DOD)[2].

The TRL scale consists of 9 levels as shown in Fig. 1. TRL "essentially describes the state of a technology and provides a baseline from which maturity is gauged and advancement defined."[3]. Based on the definitions and conditions of the TRL scale, TRLs of a system, subsystem, and component can be determined by an assessment team or an independent review team, which is called Technology Readiness Assessment (TRA). The assessment team is a group of experts who have knowledge and experience for the related technologies.

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The U.S. DOD formulates the TRA process in the acquisition of defence systems and maps TRLs to the acquisition system. For example, technologies should be at least TRL 4 by Milestone A, TRL 6 by Milestone B, and TRL 7 by Milestone C[1]. The Republic of Korea (ROK) Ministry of Defense (MOD) adopted the TRA process of the U.S. DOD in 2012 and has been using the process for defence programs. However, there are some challenges for TRL implementations.

The two main challenges are the subjective nature of the TRL assessment and the lack of models for TRL transitions or progression. The literature review shows that the subjectivity challenge has been studied actively and some solutions have been suggested theoretically and practically for assessing the current TRL level. On the other hand, there has been almost no progress on the TRL transitions. The TRL transition model can not only explain the factors to achieve future TRLs but also predict TRL transitions. In the early planning stages of defence acquisition programs, there is only a limited amount of information but it is essential to predict the possibility of new or immature technology developments[4]. If the future TRL can be predicted only utilising the information in the early planning stages, decision makers and program managers can reduce schedule and cost risks.

Under the challenge, this paper aims at TRL transition predictions for early technology development in defence. Also, in order to minimise the bias of domain experts, a data-driven approach is proposed for finding the patterns of TRL transitions. To the best of the author's knowledge, this is the first study to build a model of TRL transitions as a planning tool by utilising real technology development data in defence.

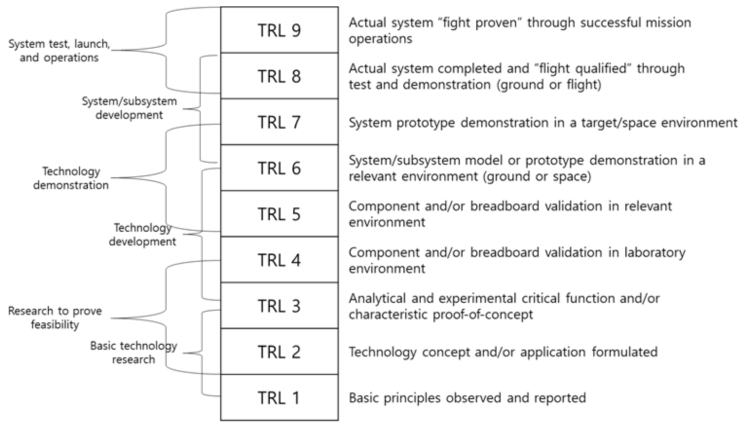

Figure 1. TRL scale (revised from[3]).

2. LITERATURE REVIEW

Mankins[5] introduced the history and definitions of TRLs with the insights of the person who was responsible for the first comprehensive set of definitions of TRLs. The set of definitions became the basis for the adoption of the TRL scale by the U.S. DOD in 2000. In the Mankins retrospective, three categories of challenges were shortly suggested for using the TRL scale. Later, Olechowski[1], *et al.* provided 15 challenges using semi-structured interviews from several different organisations, and they concluded that the identified 15 challenges could be classified as the three categories of the Mankins paper. In this section, the three categories with the 15 challenges for enhancing the TRL application are reviewed with new studies.

The first category is the assessment validity. The related challenges are the subjectivity of the assessment and imprecision of the TRL scale. Since the TRA process resorts to a human assessment team, there can be issues such as personal biases and peer pressure. Everyone has their own experience and knowledge so that it can be difficult to agree on the level of technologies, especially for complex technologies.

In order to overcome the first category challenges, two approaches were suggested. The first approach is to standardise the assessment procedure and develop a customised TRL scale. Systems engineering can provide tools such as the technology assessment process and the TRL assessment matrix for more concrete and systematic assessment[3]. Similarly, Nolte[6], *et al.* suggested the use of a TRL calculator, which is a Microsoft Excel spreadsheet in order to select TRLs with a guidance.

The second approach is to automate the TRL assessment. Cunningham[7] suggested that Big Data could be used to assess technology readiness as a short opinion piece. Researchers utilised patent documents, scientific publications, and news records for assessing TRLs. Altuntas & Gök [8], and Altuntas & Gök [9] used patent data to find the associations among wind energy technologies using data mining techniques, utility mining and social network analysis. Lezama-Nicolas[10], *et al.* suggested the bibliometric analysis of the technology records (scientific papers, patents, and news databases) to approximate the technology life cycle. They assumed that maturity levels and the characteristics of a technology life cycle could be matched using the volume of the technology records[11,12]. However, Faidi & Olechowski[13] criticised the match of technology records to the maturity of technologies and reported some unexpected cases.

This automation approach is data-driven so that it does not heavily rely on domain experts and can provide important information on technologies objectively. However, Lezama-Nicolas[10], *et al.* clearly mentioned that the bibliometric analysis method is semi-automatic which requires domain knowledge. Another issue is that the technology records are only available for some popular technologies. Defence technologies usually require protection for national security and technology records can be limited.

The second category is the system complexity. The core challenge is technologies are combined and connected as a system of technologies so that the system architecture should be reflected when a system level assessment is required. Mankins[14] proposed Integrated Technology Index (ITI) which can be calculated using delta-TRL, R&D Degree of Difficulty (R&D3), and Technology Need Value (TNV) for a system-level technology assessment. Delta-TRL, R&D3, TNV represent the difference in actual and desired TRL, expected difficulty in R&D activities, and importance of technologies. Sauser[15], *et al.* proposed Integration Readiness Level (IRL) which uses a 9-point scale similar to the TRL format for a systematic measurement.

The third category is the planning and review. The related challenges are the prediction of TRL transitions and the system development decision support based on the predicted progression. Olechowski[1], *et al.* emphasised that the predictive model was required to understand effort and likelihood for progressing to a target TRL. TRL can only provide the current state of technology maturity. Olechowski[1], *et al.* also concluded that the Advancement Degree of Difficulty (AD2)[16] and R&D3 were introduced as possible solutions but they were not commonly practiced. AD2 predicts what is required to progress from one TRL to another based on required activities and their time, cost, and likelihood that are derived from a set of questions. R&D3 is a 5-level scale to classify the degree of difficulty to move from the current TRL to the future TRL. Both indices require experts' assessments.

This paper focuses on the third category, especially the prediction of TRL transitions in defence. Rather than resorting to domain experts, a data-driven approach will be proposed only utilising the information in the early planning stages. The purpose is different but the work by Alexander[4] is noteworthy to be reviewed since it used a data-driven approach with real NASA technology project data in the early planning stages. The study aimed at identifying causal variables to estimate a project's cost and schedule using the NASA Technology Cost and Schedule Estimating (TCASE) tool which contained more than 2,900 project records. The author initially considered eight different predictor variables: system hierarchy level (SHL), TRL at the project's start and completion, R&D3, technology area, key performance parameters, total full-time equivalents of project labor, capability demonstrations, and system characteristics. Among them, only SHLs and TRLs were selected due to the sparsity and lack of data. Also, TRLs were transformed to TRL improvement level (TIL) or delta-

TRL to ensure more data. However, the aggregated level can be biased and lead to the loss of information[17]. For example, TIL 1 can be either TRL 1-2 or TRL 6-7 (TRL start-end) but the TRL transitions are apparently different. Then, finally regression models were built using SHLs and TILs with 221 data points but there was no test for predictive power.

3. FRAMEWORK OF TRL TRANSITION PREDICTIONS

While currently available approaches (e.g., AD2 and R&D3) for TRL transition predictions resort to domain experts, this paper proposes the data-driven TRL transition predictions to support decision makers along with the available approaches. Fig. 2 shows the proposed framework.

The first stage is the data collection of technology development projects in defence. In the case study, the example of technology development projects will be provided. This is the most challenging stage and this study can show the necessity of building and managing extensive database for TRL transition predictions.

The second stage is the preprocessing and correlation analysis. The modelling process in this paper is supervised learning, which requires pairs of predictor variables and responses. The response or dependent variable is the future TRLs. Possible predictor variables at the early technology development need to be paired with the future TRLs. If the data pairs have missing values, the pairs will be deleted. Before moving to the modelling process, correlation analysis is conducted to quantify the relationship between the predictor variables and responses.

The third stage is explanatory and predictive modelling. Explanatory modelling can be defined as "the use statistical models for testing causal explanations" and predictive modelling as "the process of applying a statistical model or data mining algorithm to data for the purpose of predicting new or future observations."[18] The proposed TRL transition prediction model should not only explain the predictor variables for the future TRLs but also predict the future TRLs using the information available at the early technology development. Accordingly, both explanatory and prediction models will be explored. Practically, following points can be considered for explanatory and predictive modelling[18]. In-sample R^2 values or overall F-type statistics can assess explanatory power. In contrast, predictive power refers to the performance on unseen or new data. Multicollinearity is a problematic issue in explanatory modelling by inflating standard errors while it is not a big problem for predictive modelling unless a separate regression coefficient is of interest.

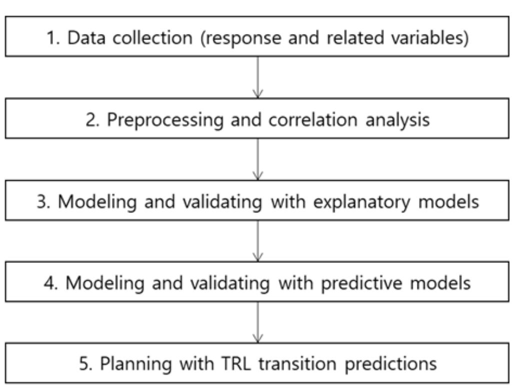

Figure 2. Framework of TRL transition predictions.

The final stage is the planning with TRL transition predictions. When there is a new technology, the TRL transition prediction model can be used. The current readiness level of the new technology can be assessed using either TRA in Section 1 or automatic methods in Section 2. By plugging in the current TRL and required information for predictor variables, the future TRL can be predicted. The predicted future TRL can support the system development decision.

4. CASE STUDY

In this section, the proposed framework is applied with real technology development data in defence. Section 4.1 covers the first and second stages and Section 4.2 addresses the rest stages of the proposed framework in Fig. 2.

4.1 Data Preparation

This investigation identified DTiMS (Defense Technology InforMation Service) as a key resource, which was the hub for the defence science and technology information provided by Defense Agency for Technology and Quality (DTaQ) in ROK. DTaQ built the system in 2008 and DTiMS could be accessed from both a local area network (LAN) and the Internet (https://dtims/re.kr). Though DTaQ keeps expanding the amount of data in the Internet, the Internet version DTiMS contains less data in comparison to the LAN version. For this reason, this study accessed the LAN version DTiMS.

The data collection conducted manually and took about more than three months due to the slow response of DTiMS. It was found that the current data structure was for providing the information of an individual project rather than analysing collected data. Table 1 summarises the data source. The collected project type is the critical defence technology R&D and the period of the R&D projects is from 2005 to 2018. The response is TRL after R&D and Fig. 3 shows the TRL improvement levels. The zero value indicates that there is no improvement of TRL.

Table 1. Data source

Source	DTiMS (LAN version)
Data collection	2020.6.1 ~ 2020.9.10
Project type	Critical defence technology R&D
Period of R&D projects	2005 ~ 2018
Response or dependent variables (TRL[a])	TRL after R&D. It ranges from 1 to 9. (TRL at the project's end)
Data points after preprocessing	172

As candidates of predictor variables, DTiMS provided a wide range of data fields, e.g., title, classification, description of the technology, possible application areas, users, investors, project management team, etc. After preprocessing for missing values and inconsistent values from the collected project records, 172 records were remained. For example, the project labor data was only available for some projects so that it could

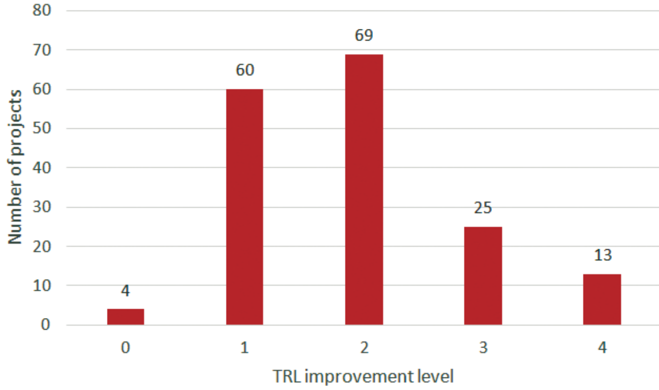

Figure 3. TRL improvement levels.

Table 3. Correlation matrix (p-values in parentheses)

	Difficulty	TRL^b	Duration	Cost	TRL^a
Difficulty	1.00				
TRL^b	0.26 (0.00)***	1.00			
Duration	-0.02 (0.75)	0.17 (0.03)**	1.00		
Cost	0.09 (0.23)	0.27 (0.00)***	0.52 (0.00)***	1.00	
TRL^a	0.25 (0.00)***	0.75 (0.00)***	0.23 (0.00)***	0.38 (0.00)***	1.00

*p<0.1, **p<0.05, ***p<0.01

not be utilised. The data loss has already been reported by Alexander[4]. Since this study focused on the early technology development, outcomes of projects were excluded, e.g., patents, reports, and academic papers. Furthermore, those outcomes did not show significant contribution to the variation of TRLs after R&D. Table 2 shows the remaining candidates of predictor variables.

Table 3 shows Pearson's correlation coefficients with p-values. The response, TRL^a, has positive correlations with the four predictor variables.

4.2 Results and Discussion

Before modelling, the logarithmic transformation was applied to both the predictor variables and the response. For explanatory modelling, regression analysis was conducted using a multiple linear regression model. Fig. 4 shows the result of regression analysis with the significance level of 0.05. Note that the value of the intercept is hidden intentionally.

The result indicates that TRL before R&D and *Cost* are statistically significant. Based on the raw data, it was observed that the project duration was not purely based on the development of technologies and sometimes included all the administrative time. This might be the reason of insignificance. Similarly, R&D difficulty can be subjective and that can lead to insignificance. Then, the multiple linear regression model was built only using the two significant variables as follows:

$$\log(TRL^a) = 0.38\log(TRL^b) + 0.077\log(Cost) + intercept \quad (1)$$

where TRL^a is the TRL after R&D, TRL^b is TRL before R&D, and $Cost$ is the project cost. The result shows that about 60% of variability of TRL after R&D can be explained by the regression model.

Regression Statistics	
Multiple R	0.785476
R Square	0.616973
Adjusted R Square	0.607799
Standard Error	0.183219
Observations	172

ANOVA

	df	SS	MS	F	Significance F
Regression	4	9.03014	2.257535	67.25024	8.32E-34
Residual	167	5.606052	0.033569		
Total	171	14.63619			

	Coefficient	St. error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-	0.276453	2.054409	0.041494	-	-
Difficulty	0.007514	0.049873	0.150655	0.88043	-0.09095	0.105976
TRL^b	0.382091	0.033779	11.31148	2.19E-22	0.315402	0.44878
Duration	0.001624	0.050211	0.032344	0.974237	-0.09751	0.100755
Cost	0.076778	0.014359	5.347147	2.9E-07	0.04843	0.105126

Figure 4. Regression analysis with four predictor variables.

For predictive modelling, linear regression, support vector machine (SVM), random forest (RF), and multi-layer perceptron (MLP) were utilised. SVM constructs the maximum margin hyperplane with kernel functions for classification and regression. RF constructs a multitude of decision trees by bagging ensembles of decision trees. MLP is a neural network by determining appropriate weights for the connections in a network using backpropagation. These algorithms were implemented using WEKA[19] which is one of the most popular frameworks for machine learning tools. Table 4 shows the environment for predictive modelling with WEKA.

The input data was grouped as the four predictor variables in Fig. 4 and the two predictor variables in Fig. 5. Furthermore, since the performance on unseen data is important in predictive modelling, 10-fold cross validation was used and the cross validation results were compared to the case with the full training data. 10-fold cross validation randomly divides the

Table 2. Candidates of predictor variables

Candidates	Description
Relative degree of difficulty (Difficulty)	It indicates the R&D difficulty of technologies relative to the most advanced technology in that area. It ranges from 0 to 200. (The most advanced)
TRL before R&D (TRL^b)	TRL at the project's start. It ranges from 1 to 9.
Project duration (Duration)	The overall time in months to spend for the project.
Project cost (Cost)	The total cost normalised to year 2019 U.S. dollars to spend for the project.

Table 4. Environment for predictive modelling

Software		Weka 3.8.4
Processor / RAM		Intel® Core(TM) i5-8265U, CPU @ 1.60GHz, RAM 8.00GB
Algorithm	Linear regression	· Standard least-squares linear regression. · An attribute selection method was not used. (When it was used, the result was identical to Eqn. (1))
	Support vector machine	· SVM for regression. · The polynomial kernel was used after trials.
	Random forest	· The number of trees in the random forest was set to 100. · The maximum depth of the tree was unlimited.
	Multi-layer perceptron	· For structures, two hidden layers were used after trials. · Learning rate was set to 0.3 and the number of epoch was set to 500.

Table 5. Performance of predictive models

			Linear regression	**SVM**	**RF**	**MLP**
4 predictor variables	Full training data	MAE	0.143	0.138	0.056	0.157
		RMSE	0.181	0.187	0.077	0.207
		RAE	59.399%	57.513%	23.451%	65.385%
		RRSE	61.889%	64.065%	26.333%	70.865%
	10-fold cross validation	MAE	0.147	0.143	0.153	0.199
		RMSE	0.186	0.189	0.203	0.241
		RAE	60.828%	59.102%	63.512%	82.349%
		RRSE	63.310 %	64.431%	69.274%	82.173%
2 predictor variables	Full training data	MAE	0.143	0.138	0.065	0.155
		RMSE	0.181	0.186	0.087	0.208
		RAE	59.509%	57.520%	26.915%	64.437%
		RRSE	61.893%	63.888%	29.810%	71.332%
	10-fold cross validation	MAE	0.145	0.139	0.172	0.186
		RMSE	0.183	0.188	0.229	0.227
		RAE	60.063%	57.842%	71.366%	77.017%
		RRSE	62.485%	63.927%	77.969%	77.276%

SVM: support vector machine, RF: random forest, MLP: multi-layer perceptron
MAE: mean absolute error, RMSE: root mean squared error,
RAE: relative absolute error, RRSE: root relative squared error
Underline: the lowest error or the best performance

Regression Statistics	
Multiple R	0.785443
R Square	0.616921
Adjusted R Square	0.612387
Standard Error	0.182144
Observations	172

ANOVA

	df	SS	MS	F	Significance F
Regression	2	9.029373	4.514686	136.0811	6.14E-36
Residual	169	5.60682	0.033176		
Total	171	14.63619			

	Coefficient	St. error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-	0.092242	6.529832	7.4E-10	-	-
TRL^b	0.383254	0.032662	11.73377	1.23E-23	0.318775	0.447733
Cost	0.077237	0.013282	5.815323	2.95E-08	0.051017	0.103456

Figure 5. Regression analysis with two significant predictor variables.

data into 10 equal sized sub-datasets, and training (9 sub-datasets) and testing (1 sub-dataset) processes are repeated 10 times. Therefore, 10-fold cross validation estimates the out-of-the-sample accuracy while the in-sample accuracy can be estimated with the full training data. As performance indices, mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), root relative squared error (RRSE) were utilised. Table 5 summarises the performance results.

Overall, when 10-fold cross validation was used, the performance indices were worse than using the full training data since the cross validation tested the performance on unseen data. The RF model showed the biggest difference between the 10-fold cross validation and full training data, and this indicated the overfitting. Also, when the two predictor variables were used, the performance indices were similar or better than using the four predictor variables. Finally, in this experiment, linear regression and SVM models with the two predictor variables showed the best performance (underlined indices in Table 5). The fitted predictive models can be saved and loaded in WEKA for predicting the future TRLs with next unseen data.

5. CONCLUSIONS

This paper proposes the framework of TRL transition predictions for early technology development in defense. Though predicting future TRLs is an important planning tool, it has been studied less actively than the other critical issues on TRL. Previous studies mostly focused on the current TRL and resorted to domain experts. The proposed framework is data-driven and utilises both explanatory and predictive modelling techniques.

As a case study, the proposed framework was applied to real technology development data from DTiMS (Defense Technology InforMation Service) which was identified as a key resource. The result of explanatory modelling showed that the two predictor variables, TRL before R&D and project cost, were statistically significant for future TRLs. Also, popular predictive models were fitted and compared with various performance indices using 10-fold cross validation. The two selected predictive models were linear regression and SVM models with the lowest prediction errors. The comparison between the full training data and 10-fold cross validation confirmed that predictive modelling should be differentiated from explanatory modelling.

The two TRL transition prediction models can support the decision making in the early planning stage by predicting future TRLs of new technology development. The required information is the TRL before R&D and project cost of the new technology. Decision makers and program managers can use both the currently available approaches (e.g., AD2 and R&D3) and the data-driven predictive models for reducing schedule and cost risks. This study also showed the importance of defence technology database and its management. The current version of DTiMS does not support the data retrieval functions so that it requires a manual data collection. Furthermore, many missing values were found and that led to the data loss for the analysis.

In the future, more predictor variables need to be studied to better capture the pattern of TRL after R&D. That might enhance the explanatory power of about 60% in this study. The limitations of the study are as follows. The result of the case study cannot be generalised due to the data loss. Under the improvement of the data management system, more data should be tested for better predictive models. Furthermore, the case study tests only four models. Other modelling techniques or the combination of them can be tested whether it can improve the predictive power.

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