A Simple Approach using Statistical-based Machine Learning to Predict the Weapon System Operational Readiness

A D W Sumari[1,3*], D S Charlinawati[2], Y Ariyanto[1,2]

[1]Cognitive Artificial Intelligence Research Group (CAIRG), Department of Electrical Engineering, Politeknik Negeri Malang, Jl. Soekarno-Hatta No. 9, Malang 65141, East Java, Indonesia
[2]Department of Information Technology, Politeknik Negeri Malang, Jl. Soekarno-Hatta No. 9, Malang 65141, East Java, Indonesia
[3]Abdulrachman Saleh Air Force Base, 2nd Operation Command, Indonesia Air Force, Indonesia

* Corresponding author's e-mail: arwin.sumari@polinema.ac.id

Abstract. Weapon system operational readiness is a critical requirement to ensure the combat readiness in order to guarantee the state defense sustainability time by time. Weapon systems are only operated by the military and their readiness are programmed every year based on some factors such as the amount of the allocated budget, the weapon system strength, and its circulation. Usually, the weapon system readiness is programmed based on the planner's experiences that are inherited from time to time. In this research, we proposed a simple approach by using statistical-based machine learning method called linear regression for helping the planner to predict the weapon system operational readiness faced to its affecting factors such as scheduled and unscheduled maintenance. We used a dataset from a randomized primary data for 5 years from year 2016 to year 2020 to predict year 2021. To ensure the performance of the model, two measurements are used namely, Mean Absolute Percentage Error (MAPE) to measure its accuracy and goodness, and R-squared (R^2) to measure the ability of the independent variables, the weapon system circulation, influences the dependent variable, the weapon system readiness. From the measurement results, the models, in general, are able to achieve MAPE as much as 1.99% that has interpretation as very accurate prediction with the accuracy of 98.02%. On the other hand, the system is able to achieve R^2 as much as 84.15% that means the combination of the independent variables altogether have given a strong influence to the dependent variable. The higher the value of R^2 the better the model is. Our research conclude that linear regression is the proper machine learning model for predicting the weapon system operational readiness.

1. Introduction

Protecting the nation sovereignty whether on the land, on the sea, or in the air, is the primary task for the nation armed forces of any country in the world. This task can only be done if the nation armed forces is not only equipped with the weapon systems, but also the professional and competent personnel who operated such systems. Each service in the armed forces has its own weapon systems depending on the tasks and the domain under its authority and responsibility. Defending the nation sovereignty requires the readiness of all services of the armed forces to be able to be deployed at a quick time whether in the peace time or war time. Armed forces from different countries have their own definition on combat readiness, but they have the same essential matters, namely the condition and the degree of preparedness that enable the ability of military forces to perform combat missions assigned to them [1] [2] that is measured by tangible and intangible elements that include the quality of training, manning or military personnel, and equipment as well as other related activities [2] [3].

The readiness of military equipment, especially weapon system plays a very important role to support the military forces to carry out the assigned missions. Land weapon systems such as tank, armored vehicles, and field artilleries are the main combat equipment for the Army. Sea and undersea weapon systems such as surface combat ships and submarines as well as littoral patrol aircrafts are the primary combat equipment for the Navy. Air weapon systems such as fighter aircrafts, lift aircrafts to bring the troops from one point to another point, and combat helicopter are the main combat equipment for the Air Force. The readiness of the weapon systems will increase the fighting spirit of the military personnel. Therefore, their readiness have to be guaranteed time by time because a crisis can emerge at any time in any place without warning.

In the view of Indonesian Air Force, the combat readiness was developed upon five elements, namely military Personnel, Equipment, Maintenance, Training, and Safety (PEMTS) [4]. In the new Indonesian Air Force Doctrine, the focus is shifted to operational readiness which is defined as the condition of the ability of the unit that is ready to operate using combat power in an integrated and effective manner (integrated between branches) and has been equipped with limited unit supplies for assignments in a limited environment [5]. The construction of the operational readiness includes organization, personnel, material, facility and service, system and method, and budget. Weapon systems are under material aspect. The finding on the field showed that the operational readiness is calculated based on the planner's experiences that are inherited time by time, and does not use any computation methods. In our research, we propose a simple approach using one of statistical-based machine learning technique called linear regression to predict the weapon system readiness time by time based on the number of the weapon system circulation. Therefore, we only use one independent variable to produce the prediction to one dependent variable just to show that our proposed method can work for this use-case.

In order to deliver an easy-to-understand presentation, this paper is arranged as follow. A brief introduction regarding the aim of this paper has been already given in Section I. In Section II, we deliver a brief on the combat readiness and the linear regression as well as how to measure the resulted model. The use of the proposed model will be delivered in Section III. The paper is concluded in Section IV with some concluding remarks and also ways forward to enhance the proposed method.

2. A Brief on the Relevant Theories

2.1. Combat Readiness, Weapon Readiness, and Its Measurement

As introduced in the previous section, combat readiness can be viewed from various perspectives that depends on the inherent characteristics of each country's armed forces. The combat readiness covers all aspects that support the military forces in conducting missions, They can be said as tangible and intangible aspect [2], or the core components [6] of the combat readiness. In view of tangible and intangible aspects, there are tree important aspects, namely Capability, Morale, and Quality of Life. Weapon systems as a part of combat readiness Capability subdomain called Firepower. On the other hand, manning and equipment is the first list in the core components of the combat readiness. The established readiness measurement system is the one developed by US Department of Defense (US DoD) called Defense Readiness Reporting System (DRRS) [3] where each military unit in all services of the Armed Forces has to report its readiness periodically. The report has to consist of four categories, namely personnel, equipment on hand, supply/maintenance, and training [7].

It was a hard challenge to find the mathematical formulas to measure the combat readiness especially the weapon system readiness. An approach using statistical inference was proposed to measure the aircraft fleet readiness by taking account the maintenance process to determine the mission readiness by using non-homogeneous Poisson process (NHPP) and the renewal process [8]. Another approach such as Analytical Hierarchy Process (AHP) and multi-criteria decision making also has been proposed [2], and also an approach from Operation Research (OR) which is applied to a tank battalion [9] were also used but with different perspectives. The simple ones use two metrics called as Mission Capable (MC) and Aircraft Capability (AA) as shown in (1) and (2) [3].

$$MC\ Rate = \frac{Mission\ Capable\ Hours}{Unit\ Possesed\ Hours} \tag{1}$$

$$AA = \frac{Mission\ Capable\ Hours}{Total\ Aircraft\ Inventory\ (TAI)\ Hours} \tag{2}$$

$Mission\ Capable\ Hours$ is the time that a weapons system is operating at a unit or location and the time it is inactive, but still available to be operated by a unit, while $Unit\ Possesed\ Hours$ is the total time that a unit possesses a weapons system. Differ from $Unit\ Possessed\ Hours$, TAI calculation is based on the total number of units in inventory including the ones that are under maintenance or other conditions. TAI is sometimes is called as weapon system strength, that is, the total number of weapon systems available in a unit no matter what the status is. TAI is a simple concept that is used in our research. Predicting their availability in terms of weapon system readiness will give a clear and better perspective in ensuring the performance logistics process as well as related resources [10] to make them ready for operational as soon as possible or at the determined time.

The approach proposed by [8] is purely statistical inference, while [2] collected various methods that can be used for measure the combat readiness which is more complex than just measuring the readiness of weapon system. The technique proposed by [9] actually was applied to the army that is different from the navy's or the air force's weapon system. MC and AA techniques [3] are just for calculating the number of units that are operationally ready regardless of status. However, these two very simple equations are not equipped with prediction capability. Therefore, we adopted some terminologies such as TAI and $Mission\ Capable\ Hours$ to our proposed method that is easy to operate, especially by military personnel.

2.2. Linear Regression and The Model Measurement

Regression in a very simple definition is a mathematical way to measure the impact of one or more variables to a single variable. The impact giver or impactor or predictor or explanatory is said as independent variable, while the impact recipient or response or target is said as dependent variable. In the context of regression analysis, the last term is the output of the analysis, that is the prediction or the value that has to be understood. This value is depended on independent variable(s) that is thought as the impactor [11]. One of simple methods in regression analysis is linear regression. The term "linear" has made a limitation that the relation between the independent and dependent variables has to be linear. It is a method that requires the straight-line relationship between those variables [12]. Linear regression formulas are simply shown in (3) or (4) where their used is depended on the deep of the analysis needed.

$$Y = a + bX \tag{3}$$

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{4}$$

where $b = \beta_1$ is the slope or the regression coefficient, and $a = \beta_0$ is a constant or the Y intercept, while ε is the error between the actual data and the predicted one. The value of a and b can be obtained through (5) and (6).

$$a = \frac{(\sum Y)(\sum X^2) - (\sum X)(\sum XY)}{n(\sum X^2) - (\sum X)^2} \tag{5}$$

$$b = \frac{n(\sum XY) - (\sum X)(\sum Y)}{n(\sum X^2) - (\sum X)^2} \tag{6}$$

Regression analysis can used to as a tool for delivering a description regarding the relationship between variables, for making prediction, for coefficient estimation, and for controlling a system by monitoring any change in its variables [13] [14]. Its use as a prediction method has put regression as one of machine learning tool or it is called as statistical-based machine learning method. There are many examples of machine learning algorithms that are built upon statistical method [15]. The primary measurement of a prediction is its accuracy and the goodness of the model. For the prediction resulted from a regression-based machine learning method, there are two measurement, namely Mean Absolute Percentage Error (MAPE) and the squared of residual error called R-squared (R^2) that are shown in (7) and (8).

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|Y_{ta} - Y_t|}{Y_{ta}}}{n} x100\% \tag{5}$$

$$R^2 = \frac{\left(n(\sum XY) - (\sum X)(\sum Y)\right)^2}{(n(\sum X^2) - (\sum X)^2)(n(\sum Y^2) - (\sum Y)^2)} \tag{6}$$

where Y_{ta} is the actual value of Y at time t, Y_t is the predicted value, and n is the number of data. The interpretation of MAPE is shown in Table 1, while for R^2 value show how good the model relates the predicted value and the predictor. If the value approaches 1, it shows that the model is able to show the tight relationship between the two types of variable. Meaning that, the predictor has able to give better prediction. As stated in [16] the perfect prediction is achieved when $R^2 = 1.00$. Therefore, the model development is to obtain the one that is able to produce the highest estimated value for R^2.

Table 1 MAPE interpretation adapted from [17].

MAPE Value	Interpretation
<10	Highly accurate prediction
10-20	Good prediction
20-50	Reasonable prediction
>50	Inaccurate prediction

3. Predicting the Weapon System Operational Readiness using The Proposed Model

3.1. Data Preparation

We did some preparations to ensure the validity of the data by using Statistical Product and Service Solutions (SPSS) tool. For Normality test, the result is 0.200 that is higher than significance or probability value that is 0.05. Meaning that the data is normally distributed as shown in Figure 1. It is also shown in the histogram of the data whether for the Maintenance data or *Mission Capable Hours* data for 5 years as shown in Figure 2 and Figure 3. Another requirement is the linearity of the data that can be measured by using P-P Plot as shown in Figure 4. It can be seen that the residual is scattered following the linear line or they are normally distributed.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Readiness	.194	12	.200*	.935	12	.441

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Figure 1. The result of the Normality test.

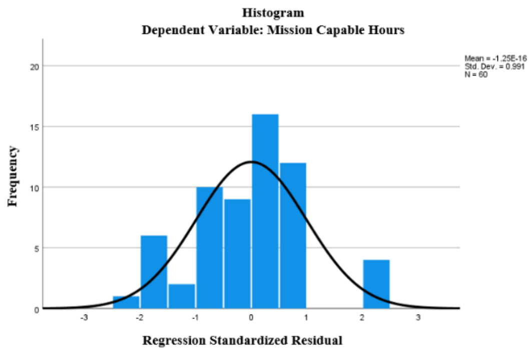

Figure 2. The histogram of the *Mission Capable Hours*.

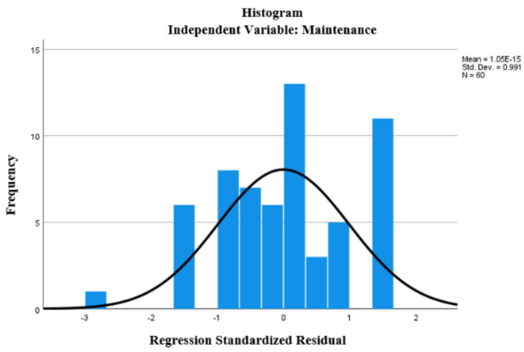

Figure 3. The histogram of the Maintenance Data.

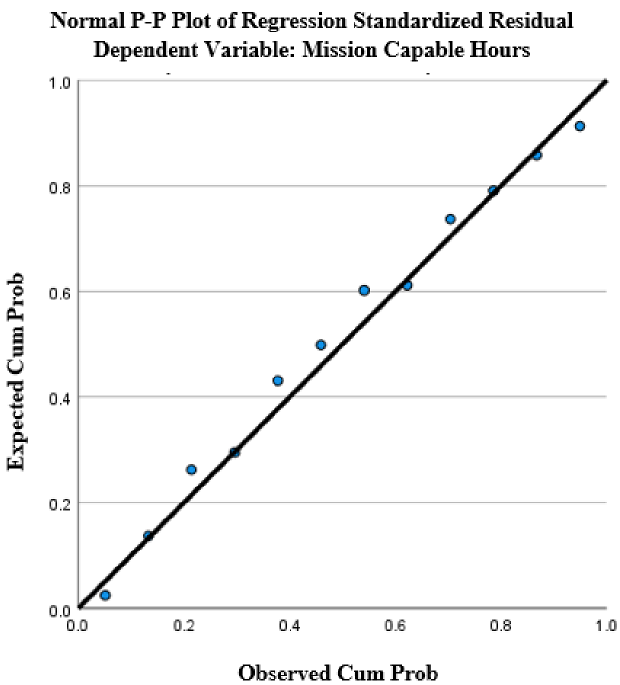

Figure 4. The normal P-P plot.

3.2. Data Processing

Performing this research needed a special effort because the data on weapon systems is not available publicly. We were glad to have some military references such as [18] that give us an insight to create a randomized data starting from 5 years back by using a free tool [19]. In this research, we use (2) as the basis for predicting the weapon system operational readiness. We assumed that the weapon system is the fighter aircrafts with TAI is 110. For our case, we made a slight adjustment to $Mission\ Capable\ Hours$ variable in (2) by changing the metric from hours to units.

$Mission\ Capable\ Hours$ is the number of aircraft units that are ready for operational because they are not under depot maintenance and we use this variable to represent the weapon system operational readiness. The affecting factors of the weapon system operational readiness we used in this research are scheduled and unscheduled maintenance, or just maintenance. So, we also created randomized maintenance datasets from year 2016 to year 2020. We only show one randomized dataset, that is for year 2017 in Table 2.

Table 2 The experiment datasets for year 2017.

Month	Maintenance (Unit)	$Mission\ Capable\ Hours$ (Unit)
January	4	90
February	3	92
March	3	94
April	2	100
May	1	105
June	2	98
July	4	90
August	2	96
September	1	105
October	3	92
November	4	87
December	2	100

3.3. Results and Discussions

We did the calculation to obtain the linear regression equations, all MAPEs, and all R^2 to all datasets from year 2016 to year 2020. The most accurate linear regression equation is obtained from 2017 model as follow, where it is able to achieve the lowest MAPE of 1.54%, $R^2 = 88.7\%$, and the highest prediction accuracy of 98.46%.

$$a = \frac{(1167)(83) - (29)(2747)}{12(83) - (29)^2} = 110.95 \qquad b = \frac{12(2747) - (29)(1167)}{12(83) - (29)^2} = -5.670$$

Then $Y = 110.95 - 5.670X$, and the results of the prediction for year 2020 are shown in Table 4.

Table 3 The prediction results for year 2020 by using the most accurate prediction model.

Month	Maintenance (Unit)	Actual *Mission Capable Hours* (Unit)	Predicted *Mission Capable Hours* (Unit)	Percentage Error (PE)
January	4	90	89.32	0.76%
February	3	92	94.46	2.68%
March	2	98	99.61	1.64%
April	1	107	104.76	2.10%
May	1	110	104.76	4.77%
June	4	90	89.32	0.76%
July	1	110	104.76	4.77%
August	2	96	99.61	3.76%
September	3	95	94.46	0.56%
October	2	99	99.61	0.62%
November	1	110	104.76	4.77%
December	1	100	104.76	4.76%
		MAPE		**2.66%**

3.4. The Model Accuracy and Goodness

To measure the performance of the models, we have collected all experiment results that are shown in Table 5. From the resulted models from year 2016 to year 2019, it is clear that the most accurate model is 2017 model with MAPE = 1.54%, R^2 = 88.7%, and the accuracy of 98.46%. Overall, all models have shown good performance in terms of the prediction accuracy that is 98.02% in average. The last model is model year 2020 that will be used to predict the weapon system operational readiness in year 2021 which the actual data has not been available yet.

Table 4 The summary of all experiment results.

Year Model	Year to Predict	Linear Regression Model	MAPE (%)	R^2 (%)	Prediction Accuracy (%)
2016	2017	$Y = 107 - 4.357X$	1.83	80.7	98.17
2017	2018	$Y = 110.95 - 5.670X$	1.54	88.7	98.46
2018	2019	$Y = 107.20 - 4.625X$	1.91	87.9	98.09
2019	2020	$Y = 109.90 - 5.146X$	2.66	79.3	97.34
2020	2021	$Y = 112.28 - 6.016X$			
		Average	1.99	84.15	98.02

We have already had two models to predict the weapon system operational readiness in 2021. The results of the predictions are shown in Table 5. For this purpose, we have randomized the number of units under maintenance as the basis for making the prediction. By observing the differences, the prediction results of the two models have a very small discrepancy where the highest one is 1.79 in month October. These results strengthen the results shown in Table 4 that all models are valid. They all have MAPE below 10, meaning that their predictions are highly accurate, while the lowest value of R^2 is 79.3 and the others are above 80. It means in general the independent variable has a strong relation to the dependent variable. It is a proof that the models, whether the year 2020 model and the most accurate prediction model, is a good model and proper to be used to this use-case.

Table 5 The prediction results for year 2021 by using the year 2020 model and the most accurate prediction model.

Month	Maintenance (Unit)	Predicted *Mission Capable Hours* (Unit) using the year 2020 model	Predicted *Mission Capable Hours* (Unit) using the most accurate prediction model	Differences
January	5	82.20	82.60	0.40
February	6	76.18	76.93	0.75
March	2	100.25	99.61	0.64
April	1	106.27	105.28	0.99
May	1	106.27	105.28	0.99
June	8	64.15	65.59	1.44
July	4	88.22	88.27	0.05
August	2	100.25	99.61	0.64
September	9	58.13	59.92	1.79
October	2	100.25	99.61	0.64
November	1	106.27	105.28	0.99
December	1	106.27	105.28	0.99

4. Concluding Remarks

4.1. Conclusions

Weapon system operational readiness that is represented by *Mission Capable Hours* is an important element for any Armed Forces combat readiness. The findings in the field have shown that the number of the weapon systems that have to be ready to be operated all the time is obtained based on the planner's past experiences that are inherited through generations. Through our research, we propose a simple statistical-based machine learning method called linear regression to assist the planner to calculate the most probable number of weapon systems units that can be ready to be operated all the time. By using only one independent variable namely maintenance which the values are generated randomly, the linear regression models in average are able to achieve very low MAPE, that is 1.99% with high $R^2 = 84.15\%$ that impact to very high accuracy, that is 98.02%. These results definitely show that the resulted models, whether year 2020 model or the most accurate prediction model has shown very good performance and suit to be applied to predict the weapon system operational readiness.

4.2. Ways Forward

This research is just a start and we have next plans to perfect this model with the inclusion of other affecting factors such as the budget, operational troubleshooting, and accidents. Another we plan to do is to use other machine learning methods such as Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), and other regression method such as Support Vector Regressor (SVR) and Ridge Regression as comparison as well as to confirm the results of Linear Regression we use in our experiment.

References

[1] O. o. t. C. o. t. J. C. o. Staff, DOD Dictionary of Military and Associated Terms, Washington DC: US Department of Defense (DoD), 2021.

[2] K. F. Wen, N. M. Nor and L. L. Soon, "Survey on The Measure of Combat Readiness," in *AIP Conference Proceedings*, 2014.

[3] G. J. Herrera, "The Fundamentals of Military Readiness," Congressional Research Service,

Washington DC, 2020.

[4] A. D. W. Sumari and A. I. Wuryandari, "Konsep Desain dan Implementasi Sistem Pemeliharaan Alat Utama Sistem Persenjataaan Udara Berbasis Kecerdasan," *Angkasa Cendekia*, no. Juli, pp. 23-46, 2008.

[5] I. A. Forces, Doktrin TNI Angkatan Udara Swa Bhuwan Paksa, Jakarta: Indonesian Armed Forces Headquarters, 2019.

[6] S. Stamatov, "Combat Readiness as a Function of Manning, Equipping, and Training The Forces," *KNOWLEDGE –International Journal* , vol. 28.6, no. December, pp. 1893-1900, 2018.

[7] M. F. Cancian and S. P. Daniels, "The State of Military Readiness: Is There a Crisis?," Center for Strategic and International Studies (CSIS), 2021. [Online]. Available: https://www.csis.org/analysis/state-military-readiness-there-crisis. [Accessed 15 August 2021].

[8] S. E. Black and K. J. Keller, "Calculating and Predicting Mission and Fleet Readiness," in *AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference*, Anaheim, 2003.

[9] J. F. Raffensperger and L. E. Schrage, "A New Paradigm for Measuring Military Readiness," *Military Operations Research*, vol. 3, no. 5, pp. 21-34, 1997.

[10] R. S. Tripp, M. A. Amouzegar, R. G. McGarvey, R. Bereit, D. George and J. Cornuet, Sense and Respond Logistics: Integrating Prediction, Responsiveness, and Control Capabilities, Santa Monica: RAND Corporation, 2006.

[11] A. Gallo, "A Refresher on Regression Analysis," Harvard Business Review, 4 November 2015. [Online]. Available: https://hbr.org/2015/11/a-refresher-on-regression-analysis. [Accessed 17 August 2021].

[12] N. S. Software, "Chapter 300 Linear Regression and Correlation," [Online]. Available: https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Linear_Regression_and_Correlation.pdf. [Accessed 17 August 2021].

[13] D. C. Montgomery, E. A. Peck and G. G. Vining, Introduction to Linear Regression Analysis Fifth Edition, Hoboken: John Wiley & Sons, Inc. , 2012.

[14] S. A. Oliver, "Forecasting Readiness: Using Regression Analysis to Predict the Mission Capability of Air Force F-16 Fighter Aircraft," Air Force Institute of Technology, Ohio, 2001.

[15] K. H. Lee, J. Kay and B. H. Kang, "A Comparative Study on Statistical Machine Learning Algorithms and Thresholding Strategies for Automatic Text Categorization," in *PRICAI 2002, LNAI 2417*, Springer-Verlag Berlin Heidelberg, 2002, pp. 444-453.

[16] P. B. Palmer and D. G. O'Connell, "Regression Analysis for Prediction: Understanding the Process," *Cardiopulmonary Physical Therapy Journal*, vol. 20, no. 3, pp. 23-26, 2009.

[17] C. Lewis, Industrial and business forecasting methods, London: Butterworths, 1982.

[18] T. I. I. f. S. Studies, The Military Balance 2021, London: Routledge, 2021.

[19] M. Haahr, "True Random Number Service," 1998-2021. [Online]. Available: https://www.random.org/.