AI and the Potential to Create Digital Twins to Transform Military Logistics

Munish Tuli

> "Predictive maintenance can reduce equipment downtime by 30 per cent to 50 per cent and increase its life by 20 per cent to 40 per cent"
> "Businesses applying AI-driven forecasting to their supply chains can reduce errors by between 20 per cent and 50 per cent"
>
> —McKinsey

Abstract

Efficient and reliable military logistics are essential to the success of military operations. When effectively integrated into logistics planning and decision-making, Artificial Intelligence (AI) can simplify complex logistics operations. Digital twins are digital representations of physical objects, systems, or processes. When powered by AI, digital twins have the potential to make military logistics smarter, more efficient, and cost-effective. It is proposed that all military equipment (embedded with sensors) and military depots in the Indian Army should have their AI digital twins created to facilitate predictive maintenance and AI-driven demand forecasting respectively. An

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attempt has been made to explore and validate the proposed concepts through two prototype machine-learning projects. The article further delves into the implementation aspects of AI digital twin-based predictive maintenance and demand forecasting followed by key recommendations for adoption in the Indian Army.

What is an AI Digital Twin?

A digital twin is a digital representation of a physical object, system, or process. Once created, the digital twin remains associated with the entity it represents throughout its lifecycle.[1] Digital twins are used for multiple purposes: simulation, testing, maintenance, monitoring, and system integration. The digital twin must be continuously synchronised with its counterpart entity to ensure that it is always up to date. An AI digital twin, on the other hand, is a powerful combination of a digital twin and AI in one box. For example, an AI digital twin may include the entity's data and machine learning models trained on that data, both encapsulated into one entity. AI digital twins have immense potential to revolutionise equipment maintenance by implementing predictive maintenance and optimising inventory management through AI-driven demand forecasts.

Predictive Maintenance

With the advancements in AI, machine learning, and the ability to collect and process real-time sensor data, there is a paradigm shift in the equipment maintenance philosophy from preventive to predictive maintenance. It is proposed that every military equipment (embedded with sensors) in the Indian Army must have a companion AI digital twin to facilitate predictive maintenance during its useful life. The digital twin is created at the time of induction of the equipment into service and remains associated with it throughout its operational life. The digital twin will be erased while its O&M (operation and maintenance) data is archived for future analytics after the equipment is declared beyond economical repair (BER) and withdrawn from service.

The digital twin is initially machine-trained on the generic data (data extracted from the archived O&M data of other equipment of the same type and model). Over time, as more data on the equipment is accumulated, its digital twin learns specific patterns based on the equipment's peculiar characteristics and usage. This enables the digital twin to facilitate customised predictive maintenance by making progressively more accurate predictions of the equipment's health parameters over time.

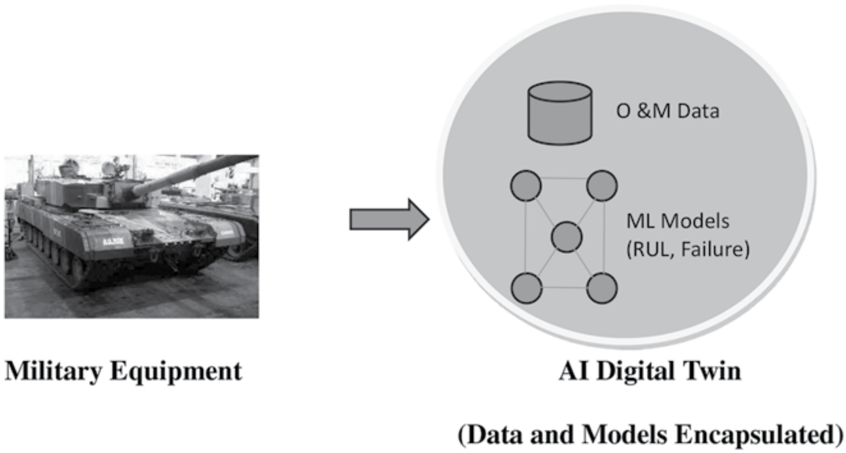
The sensory data generated by the equipment not only depends on the type, model, and age of the equipment but also the intensity of its usage. During periods of high-intensity usage such as training exercises and actual operations, the equipment may experience greater wear and tear. This may affect the sensor readings, resulting in unique patterns in the data that are continuously learned by the machine learning algorithms during the training process.

Current use cases of AI digital twins include predicting the remaining useful life (RUL), probability of equipment failure, and anomaly detection. Figure 1 depicts an AI digital twin of military equipment, and Figure 2 depicts its evolution during its lifetime.

Prototype Machine Learning Project 1: AI Digital Twin for Predictive Maintenance of Machines

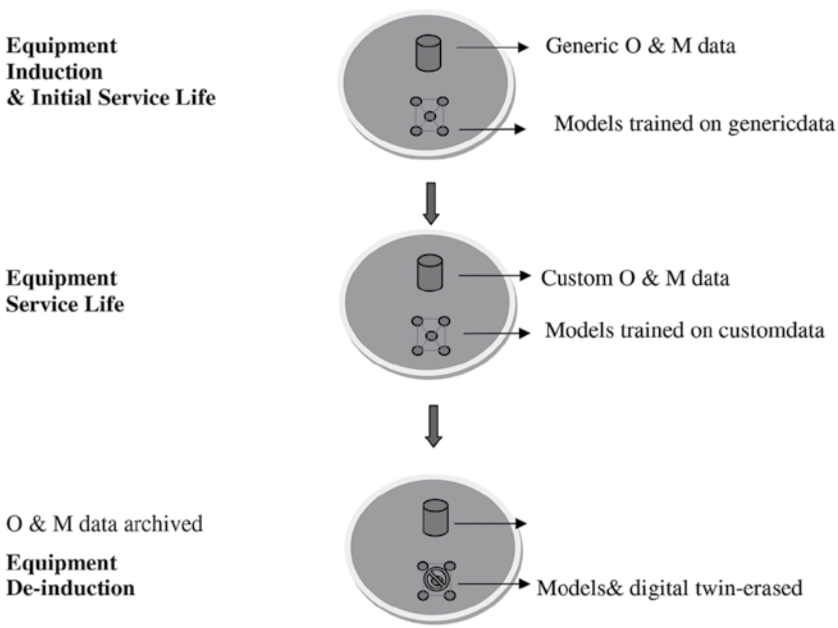
A prototype machine learning project was implemented to validate the proposed concept of AI digital twin-based predictive maintenance

Figure 1: Military Equipment and its AI Digital Twin



Source: Author.

Figure 2: Evolution of AI Digital Twin



Source: Author's own.

of machines. The AI digital twin was trained on the O&M data (sensor readings) of the machines to predict their RUL and failure probability. The dataset used for training and evaluation was downloaded from Kaggle.[2] It consists of 28,056 samples of daily sensor readings (voltage, rotation, pressure, vibration) from 100 machines of different types, models, and ages recorded over one year of operation. Each sample is labelled with the RUL (number of days left until the next failure) and a binary variable indicating whether the machine failed on that day. A machine is considered to have failed when its RUL reaches zero. In the project, four separate machine learning models forming part of an AI digital twin of a machine were trained and evaluated.

Let us assume that a machine (ID 39) has just been inducted into service. The maintenance organisation creates an AI digital twin of the machine at the time of its induction into service to facilitate predictive maintenance throughout its lifecycle. Initially, the digital twin does not have its own historical O&M (sensor data). The O&M data of the machine is recorded daily and labelled as its operational life progresses.

To facilitate predictive maintenance during the initial service life (Phase 1), labelled sensor data from other relatively newer machines of the same type and model (less than two years of age) is utilised to prepare a generic dataset. The machine learning models of the AI digital twin are then trained on the extracted generic dataset to predict the RUL and failure probability of the newly inducted machine (ID 39) during the initial phase of its life (Phase 1). The first machine learning model (Extra Trees Regressor) was trained on the training data and evaluated on the test data (sensor data obtained from the target machine ID 39 during its second week of operation). The model predicted the RUL in days for each of the test samples and achieved a Mean Absolute Error (MAE) of 15 days on the test data. The predicted RUL vs actual RUL during Phase 1 is given in Table 1 below:

Table 1: Phase 1 Predicted RUL vs Actual RUL

Test Sample	Actual RUL (Days)	Predicted RUL (Days)
1	79	64
2	78	63
3	77	61
4	76	60
5	75	59
6	74	57
7	73	57

Source: Author's creation.

A second machine learning model, the Extra Trees Classifier, was trained on the training data to predict the probability of machine failure. The model was then evaluated on the test data. Overall, the model achieved a prediction accuracy of 99 per cent. However, it can be observed that the model did not perform well in detecting machine failures. Only two out of three actual failure instances were predicted correctly, and false alarms were raised for three instances. The model's predictions versus the ground truth can be found in Table 2.

Table 2: Phase 1 Model Predictions vs Ground Truth

Ground Truth ↓	Model Predictions →	
	No Machine Failure	**Machine Failure**
No Machine Failure	294	03
Machine Failure	01	02

Source: Author's creation.

During Phase 2 (after 10 months of operational life), the digital twin is retrained using its custom O&M data to improve the accuracy and reliability of predicting customised RUL and failure probability. A third machine learning model, specifically the Extreme Gradient Boosting Regressor, was trained on the training set and then evaluated using test data. The test data consisted of sensor data from the first week of operation of the target machine with ID 39 after it had been in operation for 10 months. The model successfully predicted the RUL for each of the test samples and achieved a zero MAE on the test data. This significant improvement in prediction accuracy can be seen in Table 3, which compares the predicted RUL to the actual RUL.

Table 3: Phase 2 Predicted RUL vs Actual RUL

Test Sample	Actual RUL (Days)	Predicted RUL (Days)
1	6	6
2	5	5
3	4	4
4	3	3
5	2	2
6	1	1
7	0	0

Source: Author's creation.

A fourth machine learning model, the Extreme Gradient Boosting Classifier, was trained using the training data and then evaluated using the test data. Overall, the model achieved a prediction accuracy of 100 per cent. The model's predictions, in comparison to the ground truth, can be found in Table 4.

Table 4: Phase 2 Model Predictions vs Ground Truth

Ground Truth ↓	Model Predictions ⟶	
	No Machine Failure	Machine Failure
No Machine Failure	56	0
Machine Failure	0	1

Source: Author's creation.

Efficient military logistics balances demand with supply and optimises inventory levels of military stores and equipment. This is especially true in military operations where demand can be highly volatile and unpredictable, and there can be multiple exogenous factors such as weather and terrain that can significantly affect demands.

Apropos, it is validated that the AI models trained on the custom O&M data (sensor data) of equipment can accurately predict its RUL and failure probability from the sensor data with high accuracy, thus facilitating predictive maintenance.

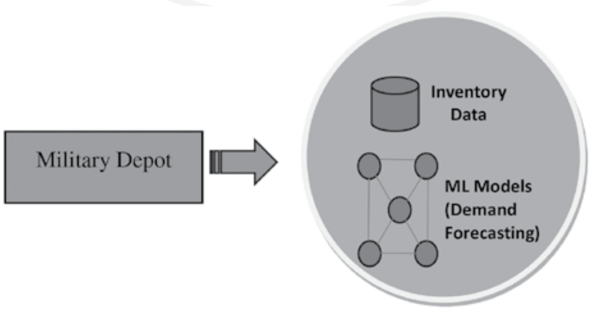
Demand Forecasting

Efficient military logistics balances demand with supply and optimises inventory levels of military stores and equipment. This is especially true in military operations where demand can be highly volatile and unpredictable, and there can be multiple exogenous factors such as weather and terrain that can significantly affect demands. AI can be leveraged by military logisticians to accurately forecast the demands of a large inventory of stores stocked in military depots and help maintain their optimal levels. This will reduce wastage by reducing overstocking and inefficiency due to understocking or stockouts. Multiple factors appear as patterns, such as trends and seasonality, in the historical demand and supply time series data that can be effectively discerned by machine learning algorithms. Therefore, it is proposed that the Indian Army adopt AI-driven demand forecasting for optimising inventory management in military depots thereby transforming its logistics decision-making process.

Some common techniques that can be used for demand forecasting are trend analysis, regression analysis, and moving averages. A classical demand forecasting method that is popularly used is moving averages. This approach is appropriate because it is a simple and effective way to smooth out the data and make it easier to identify patterns. The moving averages method is also easy to interpret and can be used to make predictions about future demand. Good statistical methods such as Simple Moving Averages (SMA), Weighted Moving Averages (WMA), and Exponential Moving Averages (EMA) have been used by logisticians to estimate future demands and plan the supply chain to fulfil the demands in the best possible manner. However, AI-driven techniques can do the job more realistically and faster, thus reducing the problems of understocking or overstocking in stores or warehouses.

In the realm of demand forecasting, an AI digital twin of a military depot is a digital entity that encapsulates its historical inventory data as well as machine learning models trained on that data to periodically (daily, weekly, monthly, or quarterly) forecast future demands of stores. Over time, as more and more inventory data gets accumulated, the accuracy of demand forecasting by the machine learning models also improves. An AI digital twin of a military depot allows for the accurate forecasting of demands, thus resulting in reduced incidents of stockouts and overstocking and thereby improving the efficiency of the functioning of depots. It is proposed that all military depots in the Indian Army, including the Field Ordnance Depot, Fuel Oil and Lubricants Depot, Ammunition Depot, Vehicle Depot, Medical Stores Depot, and Supply Depots, must have associated digital twins created for accurate demand forecasting. Figure 3 depicts the representation of the AI digital twin of a military depot.

Figure 3: AI Digital Twin of a Military Depot



Prototype Machine Learning Project 2: AI-Digital Twins for Demand Forecasting of Stores

The dataset for the machine learning project was downloaded from Kaggle. In this project, we will consider a store (military depot) with an inventory of 10 items (a typical military depot will have an inventory comprising thousands of items). The dataset contains daily sales data of stores for five years. Our objective is to train machine learning models on the historical sales data of a store to forecast the weekly, monthly, quarterly, and yearly demands of items and compare the accuracy of our AI-based demand forecasts with the traditional moving averages method as explained below:

- **Weekly Demand Forecasts:** The AI models predicted the daily sales for the next week with a mean absolute error (MAE) of 4.74 across all 10 items. On the other hand, the traditional moving averages method (averaging the past seven days' sales data and moving forward) produced a higher MAE of 7.39. Overall, the machine learning models significantly reduced the weekly demand forecast errors by 35.86 per cent compared to the legacy moving averages method.
- **Monthly Demand Forecasts:** The AI models predicted the weekly sales for the next month with an MAE of 73.30 across all 10 items. On the other hand, the traditional moving averages method (averaging the past four weeks of sales data and moving forward) produced a higher MAE of 87.07. Overall, the machine learning models reduced the weekly demand forecast errors by 15.8 per cent compared to the legacy moving averages method.
- **Quarterly Demand Forecasts:** The AI models predicted the monthly sales for the coming quarter with an MAE of 82.93 across all 10 items. On the other hand, the traditional moving averages method (averaging the past three months of sales data and walking forward) produced a higher MAE of 294.10. Overall, the machine learning models significantly reduced the quarterly demand

forecast errors by 71.77 per cent compared to the legacy moving averages method.

- **Yearly Demand Forecasts:** The AI models predicted the quarterly sales for the coming year with an MAE of 500.50 across all 10 items. On the other hand, the traditional moving averages method (averaging the past three-quarters of sales data and moving forward) produced a higher MAE of 711. Overall, the machine learning models reduced the quarterly demand forecast errors by 29.6 per cent compared to the legacy moving averages method

It is seen that AI-based demand forecasts can significantly reduce forecasting errors between 15 and 70 per cent compared to the legacy moving averages. Tables 5 to 8 show the AI-based weekly, monthly, quarterly and yearly demand forecasts of items for the given store.

AI-Digital Twins: Implementation Aspects

A suggested approach for implementing AI Digital twins would be to develop and host a centralised web application and data in the Army Cloud (Data Centre). The architecture of AI digital twin-based predictive maintenance is depicted in Figure 4.

The various components of the cloud deployment scenario described above are explained as follows:[3]

- **AI Digital Twin Application Server (VM)**. The AI Digital Twin server is hosted as a Virtual Machine (VM) on the Army Cloud. The server runs a web application and has virtual storage for storing the O&M (labelled sensor data) data and the trained machine learning models. Users securely access the web application over the Army Data Network (ADN).
- **Project Management Team (PMT)**. The PMT is responsible for detailed system analysis design and application development. The team

Table 5: AI-Based Daily Demand Forecast for Next Week

	store_1_item_1	store_1_item_10	store_1_item_2	store_1_item_3	store_1_item_4	store_1_item_5	store_1_item_6	store_1_item_7	store_1_item_8	store_1_item_9
2017-12-25 00:00:00	11	45	37	20	12	10	35	31	46	28
2017-12-26 00:00:00	14	53	44	24	13	12	43	39	53	33
2017-12-27 00:00:00	15	54	45	21	14	13	41	39	54	32
2017-12-28 00:00:00	16	59	47	23	16	14	43	44	56	33
2017-12-29 00:00:00	18	65	50	25	15	14	48	47	64	33
2017-12-30 00:00:00	20	71	55	27	17	16	52	53	65	38
2017-12-31 00:00:00	21	78	59	30	18	17	51	56	59	38

Source: Author's own.

Table 6: AI-Based Weekly Demand Forecast for Next Month

	store_1_item_1	store_1_item_10	store_1_item_2	store_1_item_3	store_1_item_4	store_1_item_5	store_1_item_6	store_1_item_7	store_1_item_8	store_1_item_9
0	129	528	449	228	139	139	411	413	531	364
1	139	531	447	212	132	129	370	356	529	365
2	131	535	449	247	157	135	377	377	528	342
3	143	543	447	264	151	136	435	373	531	368

Source: Author's own.

Table 7: AI-Based Monthly Demand Forecast for Next Quarter

	store_1_item_1	store_1_item_10	store_1_item_2	store_1_item_3	store_1_item_4	store_1_item_5	store_1_item_6	store_1_item_7	store_1_item_8	store_1_item_9
0	708	2070	1907	1101	688	610	2012	1851	2367	1742
1	696	2356	1735	1220	688	597	1953	1876	2308	1672
2	536	1568	1460	782	586	485	1254	1431	1921	1105

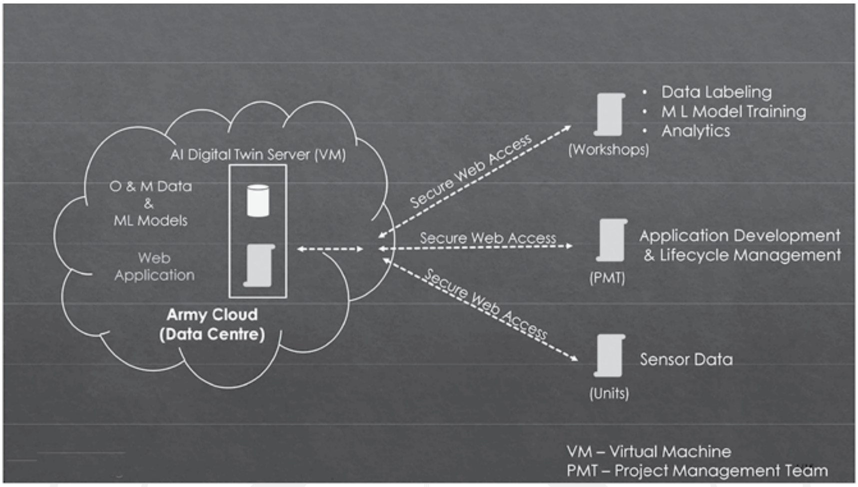
Source: Author's own.

Table 8: AI-Based Quarterly Demand Forecast for Next Year

	store_1_item_1	store_1_item_10	store_1_item_2	store_1_item_3	store_1_item_4	store_1_item_5	store_1_item_6	store_1_item_7	store_1_item_8	store_1_item_9
0	1859	9908	4146	2587	1532	1345	3672	4862	5198	3885
1	1857	7571	5855	3803	2289	2201	4992	6024	7954	5638
2	2244	6299	4933	3803	1885	1564	4992	6029	7960	5279
3	1488	6071	4933	3041	1885	1564	4992	4057	6474	3546

Source: Author's own.

Figure 4: AI-Digital Twin-Based Predictive Maintenance: Cloud Deployment



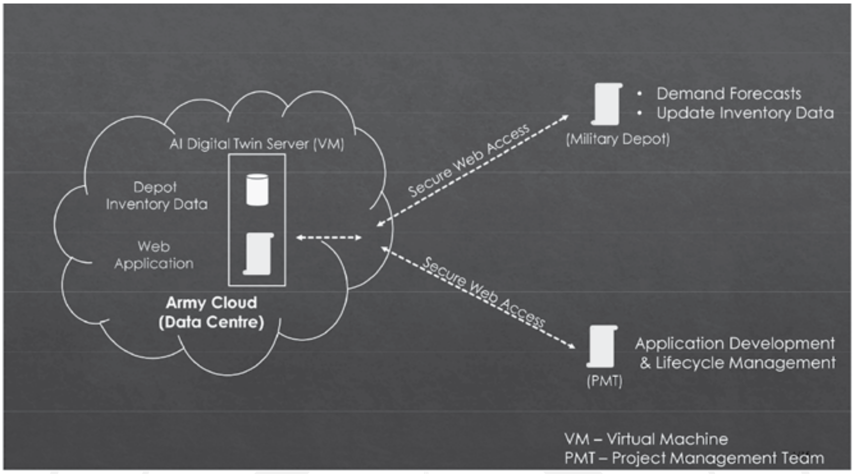
Source: Author's own.

ensures complete life cycle management support for the application, including hosting, upgrades and updates, monitoring proliferation and use, and resolving queries.

- **Workshops**. All workshops have secure access to the application through the web interface. They perform tasks such as labelling sensor data uploaded by user–units, machine learning model training, and analytics.
- **Units**. User units are responsible for uploading sensor data collected from the equipment's embedded sensors. In the Internet of Things (IoT) environment, the sensory data is aggregated through an IoT gateway and uploaded to the application data store through the provided interface.

Similarly, a suggested cloud deployment architecture for the AI Digital Twin-based demand forecasting for the military depots is depicted in Figure 5.

Figure 5: AI Digital Twin-Based Demand Forecasting: Cloud Deployment



Source: Author's own.

The various components of the cloud deployment scenario above are explained as follows:

- **AI-Digital Twin Application Server (VM).** The AI Digital Twin server is hosted as a VM on the Army Cloud. The server runs a web application and has virtual storage for storing historical inventory data and trained machine learning models.
- **Project Management Team (PMT)**. The team ensures complete life cycle management support for the application.
- **Military Depots**. All military depots have secure access to the web application on the ADN. They use the application to periodically generate demand forecasts and update inventory data.

Recommendations

The recommendations for implementing AI-digital twin-based predictive maintenance and demand forecasting in the Indian Army are as follows:

The AI-digital twin will remain associated with the military equipment throughout its useful service life to facilitate its predictive maintenance. The AI digital twin will remain associated with the military equipment throughout its useful service life to facilitate its predictive maintenance.

- All military equipment (embedded with sensors) must have a companion AI-digital twin created at the time of its induction into the service. The AI digital twin will remain associated with the military equipment throughout its useful service life to facilitate its predictive maintenance. The AI-digital twin should be erased after archiving its O&M data once the equipment is de-inducted from service. It is also proposed that the Indian Army adopt AI-driven demand forecasting for optimising inventory management in all military depots.
- A pilot project should be undertaken to validate the concept of AI-digital twins for facilitating predictive maintenance on selected military equipment. The project should aim to determine the impact of the proposed concept on the operational life of the equipment, including its downtime and availability, maintenance cost, requirement of specialised manpower, and training. Similarly, a pilot project should be undertaken to validate the concept of AI-driven demand forecasting in a designated military depot. The pilot project should aim to determine the impact of AI-driven demand forecasting in reducing occurrences of stockouts and overstocking of inventory items and in minimising forecasting errors compared to contemporary methods.
- Once tangible benefits are accrued from the pilot projects, the concept could be crystalised into developing and deploying enterprise-class cloud applications for adopting AI digital twins-based predictive maintenance and demand forecasting in the Indian Army.

Conclusion

The creation of AI-digital twins of military equipment (embedded with sensors) and military depots will be quintessential in adopting predictive maintenance and AI-driven demand forecasting in the Indian Army. AI digital twins of military equipment will facilitate the detection of equipment failures in advance, allowing corrective steps to be taken well before actual failures occur. This would result in reduced unplanned equipment downtime, increased equipment availability, lower maintenance costs, and optimal equipment utilisation. On the other hand, AI-driven demand forecasting in military depots would help reduce forecasting errors to make inventory management more efficient and cost-effective. The Indian Army should initiate pilot projects to test and validate the proposed concepts and adopt AI-digital twin-based predictive maintenance and demand forecasting to transform military logistics.

Notes

1. "What Is Digital Twin Technology And How Does It Work?", *TWI,* at https://www.twi-global.com/technical-knowledge/faqs/what-is-digital-twin#:~:text=A%20digital%20twin%20can%20be,to%20predict%20how%20they%20will. Accessed on November 25, 2023.
2. Zonta, *T. (2020). predictive-useful-life-based*-into-*telemetry.* Retrieved from www.kaggle.com: https://www.kaggle.com/datasets/tiagotgoz/predictive-useful-life-based-into-telemetry. Accessed November 20, 2023.
3. Based upon Christopher Cho, "Google Cloud launches Optimization AI: Cloud Fleet Routing API to help customers make route planning easier", April 15, 2022. Accessed on November 26, 2023 from google-cloud-optimization-ai-cloud-fleet-routing-api. Retrieved from cloud.google.com: https://cloud.google.com/blog/products/ai-machine-learning/google-cloud-optimization-ai-cloud-fleet-routing-api