Digital Twin for In-Line Fault Prediction in Military Unmanned Vehicles

John W. Heron, Ashley Forster, Ruari Milne, Daniel Milne and Robert Allen
Babcock International Group
33 Wigmore Street
London, W1U 1QX
UNITED KINGDOM

john.heron@babcockinternational.com, robert.allen1@babcockinternational.com

Keywords: Fault Prediction, Digital Twin, Condition Based Maintenance, Sustainment Cost, Extended Usable Life.

ABSTRACT

Babcock is an international aerospace, defence and security company ensuring over 30,000 military vehicles are kept mission ready. Our Research and Development (R&D) program is creating a Digital Twin to anticipate faults and prescribe maintenance before in-field failure. Asset health is continuously assessed in real time from live sensor data, providing assurance of field operation and dynamic mission reconfiguration in response to anticipated fault. This permits autonomous vehicles to report on remaining useful life of their primary components and interact with our smart supply chain to autonomously order spare parts and schedule maintenance. This paper presents the development lifecycle of our military land vehicle Digital Twin. Two diagnostic frameworks are proposed combining physics-based and data-driven formulations. By replacing driver intuition and optimising maintenance, Babcock's Digital Twin directly supports autonomous and attritable vehicle capability.

1.0 INTRODUCTION

Babcock is an international aerospace, defence and security company for militaries across the world. Our Land Defence business manages over 30,000 military vehicles, providing deployed support through to complicated strip down and refit. We manage a complex supply chain of over 200,000 spare parts that need to be in the right place at the right time to keep our customers' vehicles mission-ready.

Through our Research and Development (R&D) programme we're creating the in-service support model of the future – Digital Twin for condition based maintenance. Our system has been deployed successfully in naval marine assets, and we are committed to delivering the same success for military land vehicles.

Knowing an asset is materially fit is key to successful deployment. Babcock's technology captures live data from managed assets and extracts key health insights transmitted to a support operations centre. This permits high confidence in mission success. Predictive capabilities also ensure that during the mission, if circumstances change, dynamic asset information is available for mission reconfiguration.

Our technology relies on physics of failure. Using in-line sensors fed to an on-board processor, our Digital Twin uses advanced physical models to deliver real-time fault prediction on a per-unit basis. We enable platforms around the world to autonomously report on remaining useful life and interact with our smart supply chain to autonomously order parts and schedule maintenance. This achieves enhanced subsystem reliability, extended operational life and reduced per-unit sustainment cost.

Babcock's Digital Twin has remarkable success delivering predictive and prescriptive diagnostics in military land vehicles. This paper demonstrates these positive outcomes at various stages of the project lifecycle. The contributions are as follows:

1.1 Fault Prediction in Military Land Vehicles

Offline development of our Digital Twin system for military diesel engines was formulated in the authors' previous work in AVT-355 (Heron, et al., 2021). A physics-based thermodynamic model was developed to indirectly gauge diesel engine compression loss, among other common faults, from field-realisable sensor data.

This paper presents key findings from the laboratory and dynamometer tests of the same system, ready for verified and validated conclusions in a fleet of military vehicles in active service. The success of our system for in-line fault prediction will be empirically demonstrated from live sensor data within this fleet.

1.2 Advanced Computational Models

Literature on engine fault prediction generally falls into two categories: Physics-Based Models e.g. (Connolly & Yagle, 1993; Shiao & Moskwa, 1995; Al-Durra, et al., 2011; Arnone, et al., 2009), and Data-Driven Models, e.g. (Wang, et al., 2020a; Wang, et al., 2020b; Alex Gong, et al., 2020; Wu, et al., 2020; Maschler, et al., 2020). Physics-Based models define a specific formulation for each intended purpose. This form of analysis is rigorously time tested and highly mature. However, various required assumptions and approximations mean a significant amount of underlying physics is ignored. Data-Driven Models are capable of describing both known and unknown physics by constructing a nonlinear statistical representation of inputs and outputs, for example via machine learning techniques. However, they are brittle to the quantity and quality of their training dataset.

This paper formulates fault prediction using a combination of physics- and data-driven models. A physics-based formulation is demonstrated in laboratory testing. Meanwhile, a data-driven neural networks approach is defined to support predicted outputs. In this way, key subject-matter expertise is utilised while avoiding complications from sparse and incompatible datasets.

1.3 Digital Twin

Digital Twins are cited as one of the most disruptive technology trends this coming decade (Garfinkel, 2018; Marr, 2019). Broadly, a Digital Twin is a software representation of an asset updated in real-time using live data inputs (General Electric, 2018). This permits monitoring, optimisation and predictive maintenance during a product's active service.

A typical Digital Twin design lifecycle is outlined in (Moyne, et al., 2020) using practical examples from (Iskandar, et al., 2015; Schalkwyk, et al., 2019; Boschert & Rosen, 2016; Kibira, et al., 2016), among others. The lifecycle is divided into two phases:

- Offline Development: Data, analytics and expertise are assembled to design, develop, verify and validate Digital Twin solutions. Offline data is usually historical. 'Verification' determines whether a design meets requirements. 'Validation' determines if it meets the user's needs.
- Online Deployment and Maintenance: The qualified off-line solution is deployed, used, continuously evaluated and maintained. Once deployed, the Digital Twin uses live data from its operation environment to assess the state and condition of its aspects and make recommendations.

This methodology is directly representative of our approach, and with such, Babcock has seen great success in developing Digital Twins for Defence assets. This paper presents our land vehicle Digital Twin through its full lifecycle, from offline development through to online deployment.

1.4 Attritable Systems

Attritability is the measure of a system's reliability and sustainability against the cost of the system. Attritable Systems are developed to minimise their through-life cost by reducing overall system cost at the expense of reliability and maintainability. Successful in-line fault prediction inherently lowers sustainment cost. Accurate and up-to-date information on an asset's health and capability allows units to remain operational longer without human intervention. By triggering maintenance based on informed active data rather than regular (probabilistic) checks, unnecessary upkeep is avoided. Fewer parts need to be sourced for refit, and less time is spent in outage due to repairs. Overall, this extends quality service at lower cost, and is directly in line with the attritable system paradigm.

1.5 Autonomous Vehicles

Autonomous vehicles are rapidly emerging as the principal transport medium of the 21st century. In a military context, the transition from driven to driverless vehicles reduces the cost of casualty by eliminating human risk. However, this has profound maintenance implications. Drivers can deliver various subtle observations on engine health, such as an odd noise during start-up or the smell of oil in the cabin, triggering maintenance checks to identify faults before complete engine breakdown. Without a driver to deliver these observations, advantage for vehicle upkeep is lost. Babcock's Digital Twin provides autonomous insight into engine condition to replace driver intuition.

2.0 THE DIGITAL TWIN

Our pilot Digital Twin for military land vehicles aims to provide autonomous insight into engine condition for real-time health diagnostics. The chosen vehicle has high failure rate due to compression loss in its diesel engine. Accordingly, this project specifically targets in-line prediction of compression loss, among other common faults, to eliminate a major source of operational defect (Op Def).

2.1 System Model

A thermodynamic model for single zone cylinder pressure is detailed in the authors' previous work in (Heron, et al., 2021), using insight from (Gatowski, et al., 1984; Ramos, 1989; Shiao & Moskwa, 1995). This defines a differential model assuming uniform pressure and temperature and homogenous charge within the cylinder

$$\dot{p}_c = \frac{\gamma - 1}{V}\left(\dot{Q}_h - \dot{Q}_t\right) - \frac{\gamma}{V} p_c \dot{V} \tag{1}$$

Where p_c is pressure in cylinder c, $\dot{Q}_h$ is combustion heat release rate, $\dot{Q}_t$ is combustion heat transfer rate out of the cylinder, V is overall cylinder volume and γ the static compression ratio. $\dot{Q}_h$ is given

$$\dot{Q}_h = \dot{m}_b Q_{LHV} \tag{1}$$

Where Q_{LHV} is lower heating value and m_b is mass of fuel burnt, estimated by Wiebe function

$$m_b = m_f \left(1 - e^{-x\left(\frac{\theta - \theta_0}{\Delta\theta_b}\right)^{y+1}}\right) \tag{1}$$

Where m_f is injected fuel mass, θ is crankshaft angle, θ_0 is combustion start angle, $\Delta\theta_b$ is combustion duration, and x, y are constants.

Since swept volume is a function of θ and $\dot{Q}_t$ is directly related to $\dot{Q}_h$, the differential model in **Error! Reference source not found.**-Error! Reference source not found. can be solved numerically knowing θ, m_f and a starting pressure taken as air intake pressure p_a at inlet valve closure. The indicated torque then relates geometrically to the sum of cylinder pressure forces about the crankshaft

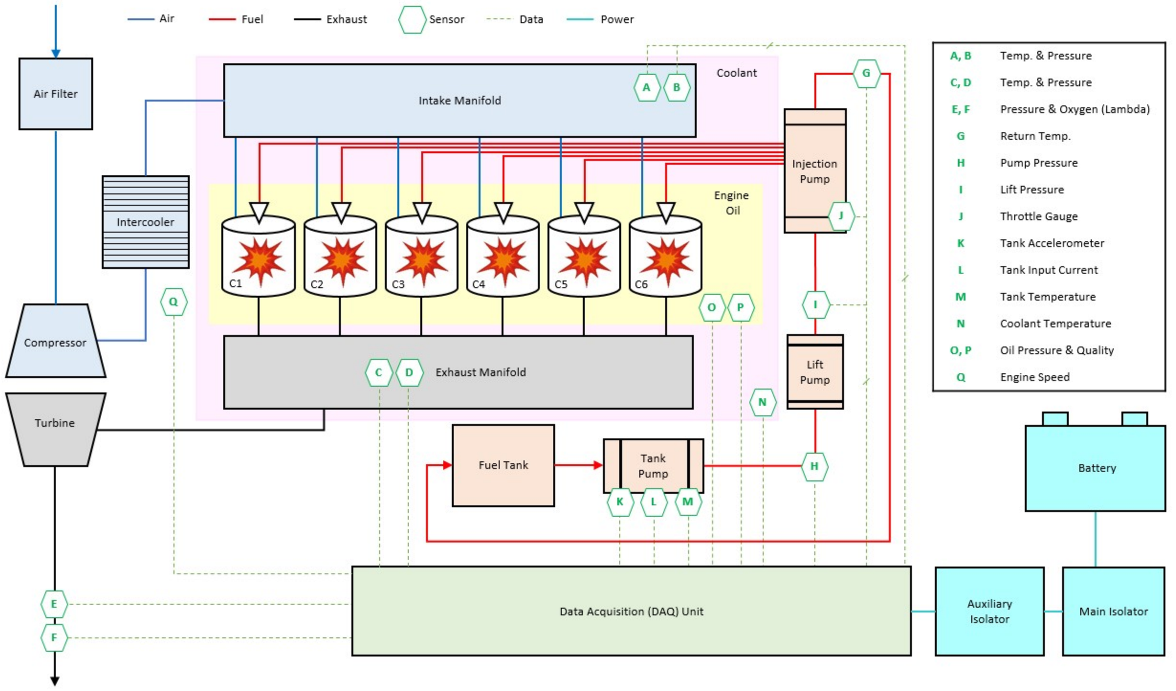

Figure 1: Complete engine system, with mounted sensors forming inputs to the Digital Twin.

in question has six cylinders interacting at the intake and exhaust manifolds, which in turn are separated from the atmosphere by a turbocharger and intercooler. Intake air and exhaust properties are therefore interdependent. Further, an in-line fuel injection pump means the precise mass of fuel in each cylinder is interdependent with cylinder pressure, as well as throttle and engine speed. This complex inter-relation of thermodynamic processes requires a virtual representation of the complete engine system, shown Fig. 1, to correctly model its operation.

Turbomachinery performance is defined by maps linking efficiency, mass flow rate and shaft speed to pressure ratios across the turbine and compressor. Gas exchange processes between engine components are approximated via quasi-steady models. These consider the engine as an interconnection of flow restrictions defined by their geometry and discharge coefficients under steady-state conditions. One dimensional flow equations then compute equilibrium gas flow rate through the system, neglecting mass accumulation between components. Quasi-steady models are effective at predicting engine performance from a thermodynamics-based analysis; however, they cannot accurately predict variation in volumetric efficiency with engine speed, since they do not model pulsating and compressible flow processes such as time-variable valve opening, intake/exhaust flow friction, gas inertia effects, tuning, choking, intake and in-cylinder heat transfer, wave propagation, etc. (Heywood, 1988, pp. 212, 825-833). These more complex processes are approximated empirically by their overall effect on volumetric efficiency, calibrated during laboratory testing.

Ricardo WAVE (2021) is a bespoke dynamic simulation tool for analysing combustion and exhaust configurations. This software is used to construct our physics-based Digital Twin for engine operation. This simulates quasi-steady interactions between engine components, including the intake, turbocharger, intercooler, intake manifold, engine block and exhaust manifold. The geometry of each component is constructed from cylindrical volumes (pipes and junctions), ensuring overall volume is consistent with the physical part.

The simulation is calibrated in laboratory using a dynamometer test rig. Dynamometers apply and measure torque at various rotational speeds. Testing is conducted by incrementing crankshaft speed $\dot{\theta}$ from 1200 to 2400 rpm at a variety of torques between 100 and 500 Nm while measuring key parameters. Intake and exhaust

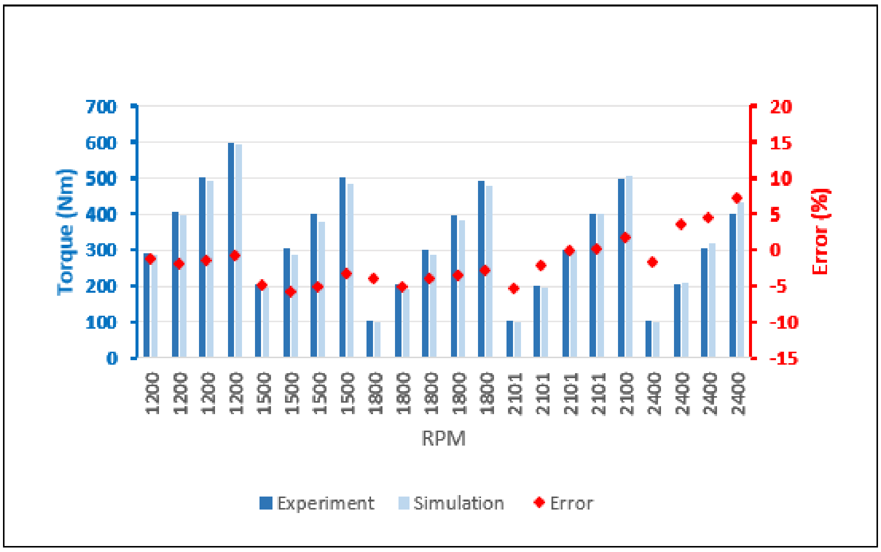

Figure 2: Brake Torque.

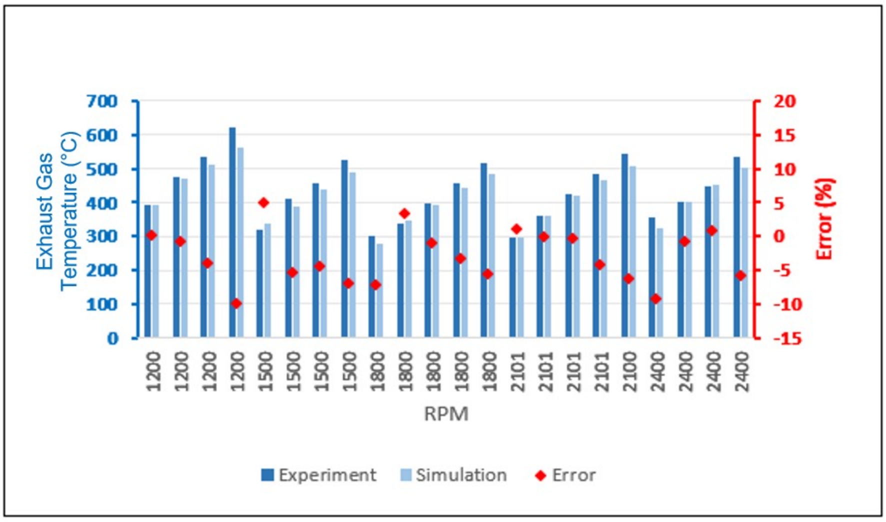

Figure 3: Exhaust Gas Temperature.

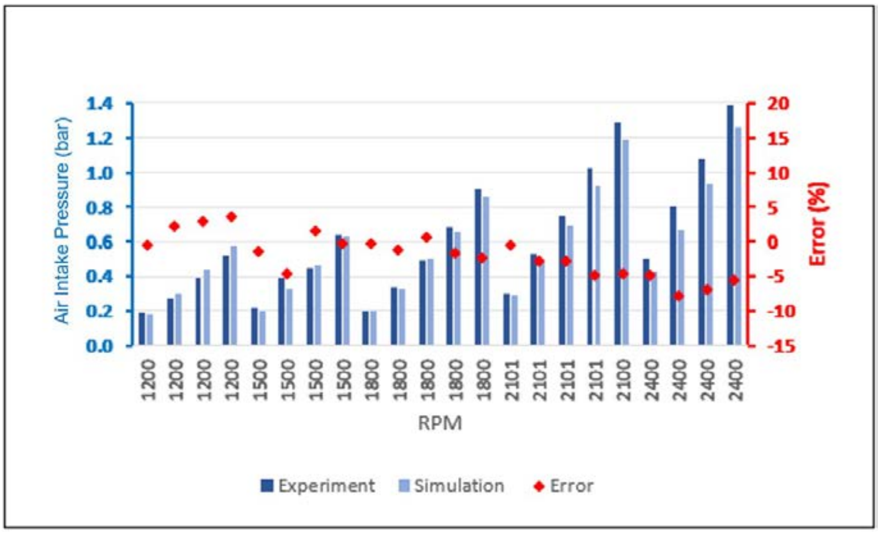

Figure 4: Intake Manifold Pressure.

properties (p_a, T_a, p_e, T_e) are measured directly by onboard sensors. Fuel mass m_f is calibrated to throttle position $\%_{th}$ by measuring overall fuel input at each speed and throttle increment. Friction torque is assessed using a Willans line approximation (Pachernegg, 1969).

Simulation accuracy is established by the difference between experimental and model-predicted outputs. These are compared for Brake torque, i.e. indicated torque minus friction, in Fig. 2, where a mean error less than 3% is achieved. A large positive error is observed at high engine speeds, where the simulation predicts higher torque than is physically delivered by the engine. This is attributed to the engine's age, where oil degradation, bearing and valve wear lead to higher hydrodynamic friction in primary components and turbulent energy dissipation in connected accessories. Further analysis will be performed following the collection of a wider population of engine data, to assess the possibility of age degradation detection using this apparent decline in torque, which could be used to intelligently impact overhaul scheduling.

The same for exhaust gas temperature and intake air pressure is shown Fig. 3, 4, respectively. Both show errors consistent with brake torque, indicating a high level of overall accuracy. A strong positive correlation is also observed between these properties and the brake torque, suggesting they are good indication of engine health.

3.0 IN-LINE DIAGNOSTICS

Sensors mounted to the engine as well as various corresponding fault mechanisms are detailed in the authors' previous work in (Heron, et al., 2021). These sensors, illustrated Fig. 1, form live data inputs to the Digital Twin that will deliver in-line diagnostics. Using these inputs, faults are detected, identified and predicted based on deviations from normal operating conditions with a combination of Physics-Based and Data-Driven Models.

3.1 Physics-Based Diagnostics

Running the engine to failure under deliberately induced faults in a laboratory test environment is undesirable due to the cost per engine unit as well as safety for staff and connected equipment. The simulation model in Sec. 2.0 permits faults to be replicated in a virtual environment, thereby avoiding this unit cost. By replicating faults in simulation, characteristic deviations required for identification are determined.

The simulation is used to construct a database of look-up tables for normal operation as well as various simulated faults. Diagnostics occur in two categories: Fault Prediction is achieved by identifying characteristic deviations from the normal operating range according to a simulated fault. Fault Detection is achieved via anomalous deviation, defined as any uncharacteristic deviation beyond a set threshold. Correct thresholds are first chosen from dynamometer data, then adjusted during in-line field testing.

The six faults to be simulated are as follows:

(a) Cylinder Leakage: To replicate worn out piston rings or head gasket damage. This is replicated by applying orifices of incremental size into the cylinder wall.

(b) Valve Fault: (For intake or exhaust)

1. *Leakage:* Occurs if valve becomes unseated. Replicated by increasing valve clearance to give a constant opening.
2. *Blockage:* Either full or partial. Occurs due to wear in the camshaft mechanism. Replicated by reducing valve clearance to give smaller opening.

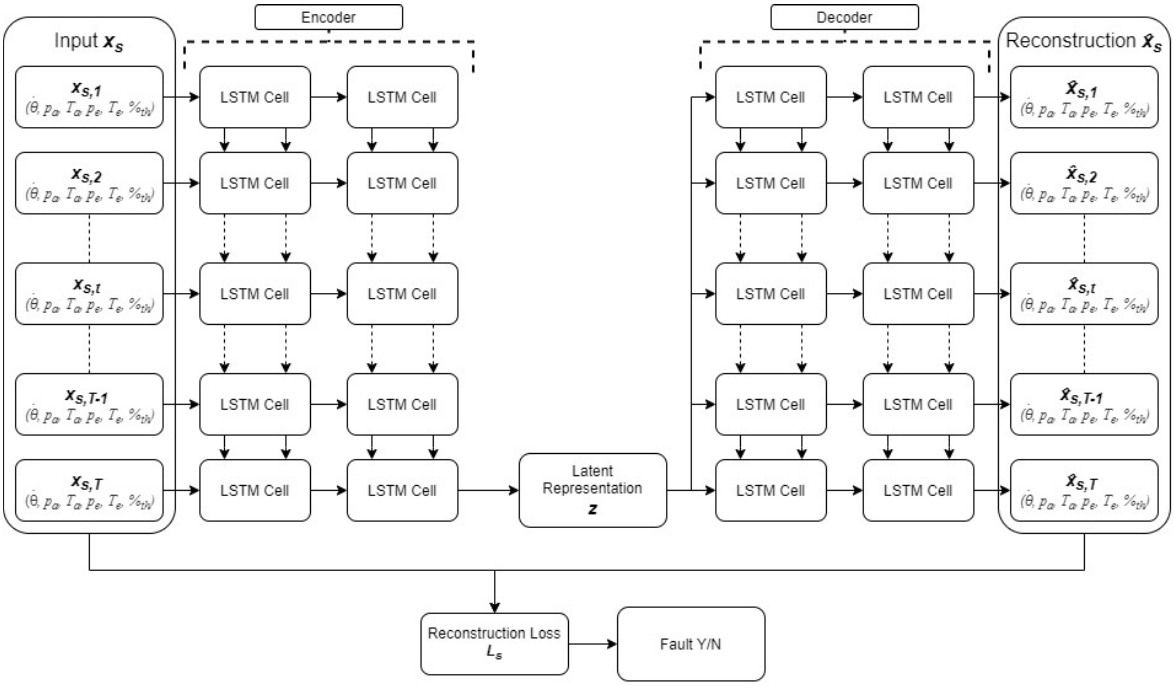

Figure 5: Recursive Autoencoder Neural Network to support Physics-Based Fault Detection.

(c) Injector Blockage: Due to fault in the in-line fuel injection pump. Replicated by reducing injection quantity.

The six faults will be applied incrementally to two, four and six cylinders, at twelve operation points in the engine's dynamic range according to the European Stationary Cycle method (Euro III, 2000). The resulting trends in operating parameters will characterise deviations for fault prediction.

3.2 Data-Driven Diagnostics

Changes to quasi-steady conditions resulting from various fault mechanisms can be deduced using physics-based models in simulation. However, this does not model pulsating and compressible flow processes, discussed Sec. 2.2, nor the numerous dynamic transients that occur before quasi-steady conditions settle. Physical modelling of these complex processes is significantly more intensive in both labour and computational resources, and practically they must be treated as noise and eliminated in post-processing. This elimination is undesirable, since these complex processes, detected by on-board sensors, contain information about engine health that can be used for diagnostics. Our Digital Twin seeks to exploit trends within this "complex" information by using data-driven modelling to support our physics-based approach. To this end, a recursive autoencoder neural network, shown Fig. 5, is trained to deliver enhanced fault detection using data from normal engine operation.

Autoencoders can be divided into Encoder and Decoder components. The Encoder maps input matrix $\boldsymbol{x}$ to a lower-dimension central hidden layer $\boldsymbol{z}$. The Decoder maps $\boldsymbol{z}$ to an output layer $\hat{\boldsymbol{x}}$ of same size as $\boldsymbol{x}$. Trained by backpropagation (Rumelhart, et al., 1986; Bourlard & Kamp, 1988), this arrangement achieves highly nonlinear dimensionality reduction (Hinton & Salakhutdinov, 2006) where $\boldsymbol{z}$ is a latent representation of $\boldsymbol{x}$. Trained only with non-anomalous data, the autoencoder will learn to produce accurate reconstructions only when presented with normal engine operation. When anomaly occurs, the network will produce high reconstruction loss as it fails to precisely replicate the input. A statistically significant reconstruction loss indicates fault (Malhotra, et al., 2016). Input matrix $\boldsymbol{x}$ consists of a multivariate time series, with each timestamp consisting of multiple sensor readings. To exploit this temporal dimension, hidden layers within the Encoder and Decoder are made recurrent in a Long Short Term Memory (LSTM) block architecture (Hochreiter & Schmidhuber, 1997).

This architecture is widely used for anomaly detection (Zhou & Paffenroth, 2017; Malhotra, et al., 2016; Principi, et al., 2019), and has advantage here as it requires only one class of data during training. This is essential, since initially only normal engine operation data will be available in sufficient quantities. Training data will be gathered in three stages:

1. *Initialisation:* Dynamometer logs combined with noise-induced simulation outputs will be used to make coarse architectural adjustments and tuning of encoder and decoder layers.

2. *Affirmation:* Field testing stage 1 (Sec. 4.0) will begin with 50km pilot trials on five military vehicles chosen for a characteristic spread of age and condition.

3. *Confirmation:* Field testing stage 2 involves twelve in-service military vehicles of varying age and condition in live field operation. Data are gathered continuously to our online database.

At each stage, newly available data will be used to test and retrain the neural network as required. Training utilises only normal operation data, while testing requires both normal and faulty engines. Engines may be identified as 'faulty' for training purposes in any stage of field testing.

3.2.1 Training

At each training stage, a subset of the non-anomalous data will be set aside to prevent overfitting. Dividing this subset into segments $\boldsymbol{x}_s$ reconstruction loss is defined

$$L_s = \sum_{t=1}^{T} \left\| x_{s,t} - \hat{x}_{s,t} \right\|^2, \qquad s = 1, \dots S \tag{1}$$

Where $\|\cdot\|$ indicates the Euclidean norm. Post-training, L_s will be used to construct a normalised probability distribution $\mathcal{L}(\mu, \sigma)$ of non-anomalous reconstruction losses via maximum likelihood estimation.

3.2.2 Testing

Testing uses class-labelled anomalous and non-anomalous segments, where label F indicates fault. For each segment, the neural network produces a reconstruction loss L_s and detects anomaly Y according to

$$Y := P(|L| > L_s) < \psi, \quad L \sim \mathcal{L} \tag{1}$$

Where $P(\cdot)$ indicates probability and ψ is a hyperparameter, optimised according to

$$\max_{\psi} \mathrm{F}_1 = \frac{P(Y \cap F)}{P(Y \cap F) + \frac{1}{2}\left[P(Y \cap \bar{F}) + P(\bar{Y} \cap F)\right]} \tag{1}$$

The F_1 score will be used to indicate the overall success of the neural network for fault detection.

4.0 FIELD TESTING

Field testing of our Digital Twin will take place in three stages. As there is no participation from the OEM, there is no historical data available, and all data used during verification and validation is collected by the Digital Twin during these trials.

4.1 Stage 1 – Verification

Pilot trials of 50km will be undertaken by three military vehicles. One of these vehicles is known to be faulty, the remaining two operate normally. The physics-based fault detection model will be tested to adjust thresholds for characteristic and uncharacteristic deviations. Training and testing data will also be delivered to affirm the neural network. The purpose of these trials is to verify that the Digital Twin meets requirements.

4.2 Stage 2 – Validation

Live data will be gathered from twelve military vehicles on active service over a period of three months. Data will be gathered continuously, feeding back to our online database via cellular and satellite link. The vehicles are specifically chosen for a characteristic spread of age and condition. The purpose of these tests is to validate our physics-based and data-driven diagnostics subject to military needs.

4.3 Stage 3 – Online Deployment

Following the successful validation of the Digital Twin in stage 2, Babcock will then deploy the Digital Twin in a wider population of the same military vehicles. As outlined in section 1.3, this begins the online development and maintenance phase and will enable a catalogue of characteristic faults to be developed from our engine log database, delivering enhanced fault prediction and detection services via increasingly nuanced combinations of physics- and data-driven approaches. In this way, diagnostic capability will be continuously improved.

5.0 CONCLUSION

Babcock is a leading in-service support partner for militaries across the world. Our R&D programme is developing Digital Twins to deliver in-line real-time health assessment of strategic assets in active service. This paper details our methodology for the development at each stage of our pilot project into military land vehicles. The contributions are as follows:

- Digital Twins are cited as one of the most disruptive technology trends of this decade. This paper presents the development lifecycle of our military vehicle Digital Twin from offline development through to online deployment.

- Two fault detection models are proposed using physics-based and data-driven formulations. Combining these approaches exploits both known and unknown physics to interpret all available information from deployed sensors.

- Real-time evaluation of asset health is directly in line with the attritable system paradigm. Successful development of the Digital Twin will result in extended quality service at lower cost by reducing down time and optimising maintenance.

- The transition from driven to driverless vehicles eliminates driver intuition as a key diagnostic tool. In-line fault prediction provides autonomous insight into engine condition to support upkeep of unmanned vehicles.

Babcock's Digital Twin permits confidence in material assets and dynamic awareness of unit health, ensuring vehicles are mission-ready when it matters most.

6.0 ACKNOWLEDGEMENT

The authors would like to thank Dr. Guohong Tian for his indispensable consultation through the course of this project, and Luca Moscattini for his assistance in constructing our Ricardo Wave simulation. Special gratitude is extended to the University of Surrey for use of their dynamometer for laboratory testing throughout this project.

REFERENCES

Al-Durra, A., Canova, M. & Yurkovich, S., 2011. A Model-Based Methodology for Real-Time Estimation of Diesel Engine Cylinder Pressure. *American Society of Mechanical Engineers (ASME) Journal of Dynamic Systems, Measurement and Control,* 133(3), pp. 031005-1 to 031005-9.

Alex Gong, C. -S., Simon Su, C. -H. & Tseng, K. H., 2020. Implementation of Machine Learning for Fault Classification on Vehicle Power Transmission System. *Institute of Electrical and Electronics Engineers (IEEE) Sensors Journal,* 20(24), pp. 15163-15176.

Arnone, L., Manelli, S., Chiatti, G. & Chiavola, O., 2009. *In-Cylinder Pressure Analysis through Accelerometer Signal Processing for Diesel Engine Combustion Optimisation.* s.l., Society of Automotive Engineers (SAE) Noise and Vibration Conference and Exhibition.

Boschert, S. & Rosen, R., 2016. Digital Twin—The Simulation Aspect. In: H. P & B. D, eds. *Mechatronic Futures.* Cham, Switzerland: Springer, pp. 59-74.

Bourlard, H. & Kamp, Y., 1988. Auto-association by multilayer perceptrons and singular value decomposition. *Biological Cybernetics,* 59(4), pp. 291-294.

Connolly, F. T. & Yagle, A. E., 1993. Modeling and Identification of the Combustion Pressure Process in Internal Combustion Engines. *Journal of Engineering for Gas Turbines and Power,* 115(4), pp. 801-809.

Euro III, 2000. *Emission Regulation.* s.l.:Directive 1999/96/EC.

Garfinkel, J., 2018. *Gartner Identifies the Top 10 Strategic Technology Trends for 2019.* [Online] Available at: https://www.gartner.com/en/newsroom/press-releases/2018-10-15-gartner-identifies-the-top-10-strategic-technology-trends-for-2019 [Accessed Dec 2020].

Gatowski, J. A. et al., 1984. Heat Release Analysis of Engine Pressure Data. *Society of Automotive Engineers (SAE) Transactions-V93-84,* p. 20.

General Electric, 2018. *The Digital Twin: Compressing Time-to-Value for Digital Industrial Companies.* [Online] Available at: https://www.ge.com/digital/sites/default/files/download_assets/The-Digital-Twin_Compressing-Time-to-Value-for-Digital-Industrial-Companies.pdf [Accessed Dec 2020].

Heron, J. W., Milne, D. & Allen, R., 2021. *Digital Twin as an Enabler for Condition Based Maintenance in UxVs.* Virtual, AVT-355 Applied Vehicle Technology Research Workshop on Intelligent Solutions for Improved Mission Readiness of Military UxVs.

Heywood, J. B., 1988. *Internal Combustion Engine Fundamentals.* 2nd ed. New York: McGraw Hill Education.

Hinton, G. E. & Salakhutdinov, R., 2006. Reducing the Dimensionality of Data with Neural Networks. *Science,* 313(5786), pp. 504-507.

Hochreiter, S. & Schmidhuber, J., 1997. Long Short-Term Memory. *Neural Computation,* 9(8), pp. 1735-1780.

Iskandar, J. et al., 2015. *Predictive Maintenance in semiconductor manufacturing.* Saratoga Springs, NY, s.n., pp. 384-389.

Kibira, D., Morris, K. & Kumaraguru, S., 2016. Methods and Tools for Performance Assurance of Smart Manufacturing Systems. *Journal of Research of the National Institute of Standards and Technology,* Volume 121, pp. 287-318.

Malhotra, P. et al., 2016. *LSTM-based Encoder-Decoder for Multi-sensor Anomaly Detection.* New York, NY, USA, Proc. of 33rd International Conference on Machine Learning (ICML) Anomaly Detection Workshop.

Marr, B., 2019. *The 5 Biggest Technology Trends Disrupting Engineering and Design in 2020.* [Online] Available at: https://www.forbes.com/sites/bernardmarr/2019/11/22/the-5-biggest-technology-trends-disrupting-engineering-and-design-in-2020/?sh=27167d21676a [Accessed Dec 2020].

Maschler, B., Vietz, H., Jazdi, N. & Weyrich, M., 2020. *Continual Learning of Fault Prediction for Turbofan Engines using Deep Learning with Elastic Weight Consolidation.* Vienna, Austria, 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), pp. 959-966.

Moyne, J. et al., 2020. A Requirements Driven Digital Twin Framework: Specification and Opportunities. *IEEE Access,* Jun, Volume 8, pp. 107781-107801.

Pachernegg, S., 1969. A Closer Look at the Willans-Line. *SAE Technical Paper.*

Principi, E., Rossetti, D., Squartini, S. & Piazza, F., 2019. Unsupervised electric motor fault detection by using deep autoencoders. *IEEE/CAA Journal of Automatica Sinica ,* 6(2), pp. 441 - 451.

Ramos, J. I., 1989. *Internal Combustion Engine Modeling.* s.l.:Hemisphere.

Ricardo, 2021. *WAVE.* [Online] Available at: https://software.ricardo.com/products/wave [Accessed 2021].

Rumelhart, D. E., Hinton, G. E. & Williams, R. J., 1986. Learning representations by back-propagating errors. *Nature,* Volume 323, pp. 533-536.

Schalkwyk, P., Malakuti, S. & Lin, S.-W., 2019. A Short Introduction to Digital Twins. *Industrial Internet Consortium Journal of Innovation.*

Shiao, Y. & Moskwa, J. J., 1995. Cylinder Pressure and Combustion Heat Release Estimation for SI Engine Diagnostics. *IEEE Transactions on Control Systems Technology,* 3(1), pp. 70-78.

Wang, S., Wang, J. & Ding, X., 2020a. *An Intelligent Fault Diagnosis Scheme Based On PCA-BP Neural Network for the Marine Diesel Engine.* s.l., Institute of Physics (IoP) Conference Series: Materials Science and Engineering.

Wang, S., Wang, J. & Wang, R., 2020b. *A novel scheme for intelligent fault diagnosis of marine diesel engine using the multi-information fusion technology.* s.l., Institute of Physics (IOP) Conference Series: Materials Science and Engineering.

Wu, Q., Ding, K. & Huang, B., 2020. Approach for fault prognosis using recurrent neural network. *Springer Link Journal of Intelligent Manufacturing,* Volume 31, p. 1621–1633.

Zhou, C. & Paffenroth, R. C., 2017. *Anomaly Detection with Robust Deep Autoencoders.* New York, NY, United States, Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.