Digital Twin in Military Ground Vehicles: Design and Predictive Maintenance

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DIGITAL TWIN IN MILITARY GROUND VEHICLES: DESIGN AND PREDICTIVE MAINTENANCE

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
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by
Conner William Eddy
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Accepted by:
Dr. John Wagner, Committee Chair
Dr. Laura Redmond
Dr. Cameron Turner
Abstract

Digital twin technology builds upon virtual engineering models, computer simulation, and real-time field data streaming to enable next-generation designs and predictive maintenance. A digital twin is a computer-based high-fidelity collection of models that predicts the performance of dynamic systems per operating cycles, input feature parameters, and data communication from a physical plant. Product Lifecycle Management (PLM) is growing in importance and is central to virtual design processes where the digital twin toolset fits into this emerging architecture. The product design process can be advanced using digital twin resources by eliminating the need for, and cost from, continual physical prototyping, reliability testing, and outdated maintenance practices. Digital twin virtual tools enable improved product performance evaluations early in the design cycle which leads to manpower savings for the enterprise. The mobility needs of individuals, corporations, and government entities require careful attention to product design. With increasing ground vehicle complexity in electrical components and propulsion hybridization, the digital twin plays a role in predicting, understanding, and designing vehicle systems. The ability to couple streaming field data with digital twin estimates generates a powerful tool for diagnostic and prognostic methods.

In this research project, digital twin technology is explored, developed, and applied to off-road ground vehicles for design engineering studies and predictive health maintenance. The research goals included integrating mathematical models for ground vehicle components into a digital twin, application of the digital twin for vehicle design, examination of predictive maintenance methods, and creation of two surveys to measure usefulness and time savings metrics available with digital twin technology. The modeling of wheeled and tracked vehicles in MATLAB/Simulink/Simscape enabled the assembly of a 14-degree-of-freedom virtual vehicle system consisting of body dynamics, engine curves, wheel kinematics, driveline systems, and suspension characteristics piloted by a virtual driver and environment inputs. The digital twin tool assisted in tradespace analysis studies within
the Clemson University VIPR-GS Center. Predictive maintenance, with machine learning, was applied to the off-road digital twin by seeding 6 anomalies into a virtual model and leveraging statistical algorithms based on neural networks. For the numerical study, 176 logged signals across 275 total simulations were utilized in the predictive maintenance framework to successfully predict 92% of trained validation results and 40% accuracy of untested compound anomalies. Metric surveys evaluating usefulness and time savings were deployed to DO13/14 vehicle engineering teams on the Clemson University International Center for Automotive Research (CUICAR) campus and the results showed a positive Likert scale response to digital twin usefulness with the greatest perceived benefits in model organization and design validation. The advantages and opportunities available with digital twin technology have been explored in these individual studies and deployed in the VIPR-GS Center. Given the growing awareness of digital engineering design methodologies, digital twins represent a cornerstone of many future endeavors.
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Nomenclature

$\alpha_f$  Tractive force anomaly magnitude
$\alpha_t$  Transmission slippage degradation amplitude
$\delta_i$  Steering angle (rad)
$\delta_z$  Vertical tire deflection (m)
$\dot{y}_{CG}$  y-direction inertial velocity at the vehicle center of gravity (m/s)
$\mu_G$  Ground friction coefficient
$\omega_e$  Engine speed (rad/s)
$\omega_{PS}$  Prop shaft speed (rad/s)
$\rho$  Mass density of ambient air (kg/m$^3$)
$\varphi, \dot{\varphi}, \ddot{\varphi}$  Yaw angle position, angular velocity, and angular acceleration (rad, rad/s, rad/s$^2$)
$A_D$  Vehicle frontal area (m$^2$)
$a_i$  DTTU normalization gain for each factor, $i$
$b$  Transmission slippage degradation frequency (rad/s)
$b_b$  Vehicle width from center of gravity to center of track/wheel (m)
$b_c$  Vehicle length from center of gravity to front axle (m)
$b_d$  Vehicle length from center of gravity to rear axle (m)
$b_i$  DTTS normalization gain for each factor, $i$
$b_t$  Half tread (m)
$c$  Track stiffness (N/m)
$C_D$  Aerodynamic drag coefficient
$C_t$  Prop shaft torsional damping coefficient (Nm · s/rad)
$C_w$  Wheel damping coefficient (N · s/m)
$C_z$  Suspension shock damping coefficient (N · s/m)
$d$  Track damping coefficient (N · s/m)
e  Element displacement (m)
\( F_D \) Aerodynamic drag force (N)
\( f_i \) DTTU factors \( (i = 1, 2, \ldots, 6) \)
\( F_t \) Tractive force (N)
\( F_x \) Longitudinal force (x-direction) (N)
\( F_y \) Lateral force (y-direction) (N)
\( f_{ij} \) DTTU sub-factors
\( F_{de} \) Degraded tractive force (N)
\( F_{xwl} \) Longitudinal tire force in the wheel plane (N)
\( F_{ywl} \) Lateral tire force in the wheel plane (N)
\( g_i \) DTTS factors \( (i = 1, 2, \ldots, 5) \)
\( g_{ij} \) DTTS sub-factors
\( I_t \) Track moment of inertia \( (kg \cdot m^2) \)
\( I_z \) Vehicle moment of inertia \( (kg \cdot m^2) \)
\( I_{wy} \) Wheel moment of inertia \( (kg \cdot m^2) \)
\( K_t \) Prop shaft torsional stiffness \( (N \cdot m/rad) \)
\( K_z \) Suspension spring coefficient \( (N/m) \)
\( L \) Track length (m)
\( l \) Left track
\( L_m \) Mesh length (m)
\( m \) Vehicle mass (kg)
\( M_z \) Moment about the z-axis \( (Nm) \)
\( n \) Number of sub-factors for each factor, \( i \)
\( P_t \) Tire pressure (Pa)
\( R \) Wheel radius (m)
\( r \) Right track
\( r_s \) Sprocket radius (m)
\( t \) Time (s)
\( T_b \) Braking torque \( (Nm) \)
\( T_c \) Torque command \( (Nm) \)
\( T_e \) Engine torque \( (Nm) \)
\( u \) x-direction vehicle velocity \( (m/s) \)
\( v \) y-direction vehicle velocity \((m/s)\)
\( v_e \) Element velocity \((m/s)\)
\( v_t \) Track speed \((m/s)\)
\( v_{z1} \) z-direction front-left axle velocity \((m/s)\)
\( W_m \) Mesh width \((m)\)
\( x, \dot{x}, \ddot{x} \) x-direction inertial position, velocity, and acceleration \((m, m/s, m/s^2)\)
\( X_K \) Kurtosis signal statistic
\( X_P \) Peak value signal statistic
\( X_S \) Skewness signal statistic
\( x_z \) Longitudinal wheel offset \((m)\)
\( X_{CL} \) Clearance factor signal statistic
\( X_{CR} \) Crest factor signal statistic
\( X_{IF} \) Impulse factor signal statistic
\( X_{PG} \) Pulse generator signal
\( X_{SF} \) Shape factor signal statistic
\( y, \dot{y}, \ddot{y} \) y-direction inertial position, velocity, and acceleration \((m, m/s, m/s^2)\)

**AIAA** American Institute of Aeronautics and Astronautics
**AIA** American Institute of Aerospace
**CAD** Computer-aided design
**CAE** Computer-aided engineering
**CNC** Computer-numerical control
**DTTS** Digital twin time savings
**DTTU** Digital twin technology usefulness
**DT** Digital twin
**EKF** Extended Kalman filter
**EOBD** European on-board diagnostics
**FNR** False negative rate(s)
**HIL** Hardware-in-the-loop
**IOT** Internet of Things
**NASA** National Aeronautics and Space Administration
**OBD** On-board diagnostics
PCA  Principal component analysis
PLM  Product life-cycle management
PLS  Projection to latent structures
PT   Physical twin
QTA  Qualitative trend analysis
RMS  Root mean square
RUL  Remaining useful life
SINAD Signal to noise and distortion ratio
SNR  Signal to noise ratio
STD  Standard deviation
THD  Total harmonic distortion
TPR  True positive rate(s)
TSA  Time-synchronous averaging
V&V  Validation and verification
Chapter 1

Introduction

The digital twin (DT) is a relatively new virtual prototyping tool used to improve the virtual design process and complement the Product Lifecycle Management (PLM) paradigm. To begin this journey, the engineering design process will be reviewed to identify opportunities for contributions using digital twin technology. These opportunities are explored, and a solution is proposed by utilization of DT technology and where it fits within the design process. Furthermore, a formal definition of the DT tool is investigated. The DT has many benefits and value-adds which are explored and listed across several industries and applications. Different means of DT implementation are discussed to consider current usage of the technology as well as potential future uses. Additionally, military ground vehicles will be the focus for DT application in a comprehensive manner, identifying possible benefits. Principle research objectives, goals, and methods are introduced in this chapter.

1.1 Engineering Design Process

For any component, system, or process to be engineered, it must undergo a form or type of design process. Engineering design has been defined, implemented, and refined over a long period of time [1]. A formal definition is offered by the Accreditation Board for Engineering and Technology (ABET) [2] stating that engineering design is a decision-making process that utilizes engineering concepts to accomplish a desired objective within a form of bounds or constraints. Figure 1.1 provides the summary of a widely accepted engineering design process map from Pahl et al. [3] regarded as the benchmark for systematic design, with the highlighted scope for digital twin application. This out-
lines the design process in four systematic stages: task clarification, conceptual design, embodiment design, and detail design. Conceptual design outputs concepts for solutions that involve engineering structures and principles that could be utilized for proposals. This is followed by embodiment design which develops the concept solutions further and selects preliminary layouts to be evaluated against the clarified task criterion. Lastly, the detail design phase finalizes details and documents needed for production and implementation of the component, system, or process designed. Digital twin uses and advantages span three of the four categories in the systematic engineering design process including conceptual design, embodiment design, and detail design.

In most stages of the systematic engineering design process, there is opportunity for advancement in optimization and development of solutions through digital twin utilization. Each stage of the decision-making process can be improved with more modularity, manufacturing, and PLM considerations. By elevating each stage of the design process with these considerations, overall time, cost, and engineering expense is economized. Modularity utilizes similar components or systems across a platform to reduce time and resources over time. Manufacturing often changes designs due to quantity or expense of production, and considerations in fabrication should be applied in every design stage. PLM evaluates the entirety of the component or system’s life-cycle, anticipating health monitoring, maintenance, and future behavior or performance. The conceptual design phase is able to explore more solutions by use of modularity, increasing potential to realize optimal solution spaces. Testing and refining of a product or system is seen mostly in the embodiment phase where efforts and costs can be reduced through use of digitization or virtual prototyping as stated by Zorriassatine et al. [4]. As the component or system enters into the detail design phase, PLM considerations can be enhanced in documentation and implementation of the product.

Opportunities for systematic engineering design process advancement are explored through the implementation of a DT virtual engineering tool. The DT itself has a model design process which follows similar to that of the systematic design process. Zhang et al. [5] discuss the importance of requirement descriptions, relating to task clarification, in the model engineering design process for digital twin development. Standard engineering design processes are limited by their domain which is generally physical and observable only with a tangible plant. The DT allows engineers to explore greater quantity and complexity of concepts, providing opportunities by way of more availability in data, visualizations, and machine learning algorithms. Pursued design concepts, often surveyed and evaluated against preliminary criteria, can be eliminated due to limited time availability and
Figure 1.1: Systematic engineering design process.

can be built and tested virtually, optimizing the embodiment phase by reducing prototype and manufacturing costs. With all components or systems built virtually, documentation of specifications and production details are created simultaneously or automatically, expediting the detail design phase as well.
1.2 Digital Twin Definition

Engineering tools are rapidly moving into the digital and virtual realms. Ovtcharova [6] discusses the shift from digital engineering to virtual engineering, pushing the design boundaries from CAD tools and analytical simulation software to process simulation and real-time system behavior prediction. This introduces the digitization of not only engineering and scientific methods, but organizational and business activities that coincide with them. Utilization of big data and communication of this information to inform virtual environments is central to virtual engineering. Lemu [7] offers a definition of virtual engineering in its role of design and manufacturing, in short, by using a virtual model to simulate a real-world system. Virtual engineering encompasses the realization of cyber-physical systems including that of DT technology as described by Falah et al. [8]. Figure 1.2 depicts two major categories in virtual engineering processes described by Cecil et al. [9], virtual product design and virtual manufacturing. DT technology is able to combine both of these processes, virtual product design and virtual manufacturing, in addition to applied system monitoring with one virtual engineering tool. Virtual engineering, digitization of models, and the design process point to implementation of the DT engineering tool.

![Virtual Engineering Process Categories and Applications](image)

Figure 1.2: Virtual engineering process categories and applications.

A definition of a digital twin paradigm is offered and contextualized for this research. Wright et al. [10] discuss how the definition of a DT is widely debated and often misconstrued from one researcher or enterprise to the next. There are debates on the basic understanding of DT technology, with oversimplification defining it plainly as a model of a system. Understanding of
what a DT is, its intended purpose, and application is clarified before moving forward. Hughes [11] describes the DT in simplicity as “an executable virtual model of a physical thing or system.” This is an oversimplification of DT technology; its benefits reach beyond that of standard virtual models. DT ideation was formed in the aerospace industry in an attempt to better understand rover spacecraft behavior remotely. Glaessgen et al. [12, p. 7] with NASA research defined the DT as “an integrated multiphysics, multiscale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its [physical] flying twin”. A more recent definition of the DT is proposed by Dreisbach with NAFEMS as “a physics-based dynamic computer representation of a physical object that exploits distributed information management and virtual-to-augmented reality technologies to monitor the object, and to share and update discrete data dynamically between the virtual and real products” [13, p. 37]. With these accepted definitions of DT technology, common themes observed include an executable virtual model, a growing set of data streamed from the physical system to the model, and a continuous updating of the model based on the data received.

The physical to virtual connection is the distinguishing feature of a digital twin. This two-way connection is illustrated in Figure 1.3. The physical system begins a communication cycle by sending sensor data and relevant system information to the DT. This sensor data and information is utilized by the library of models within the DT to simulate system behavior, perform virtual analyses, make assessments regarding manufacturing, perform system health monitoring, and increase validation & verification (V&V) accuracy. Additionally, the DT utilizes this data to update and enhance model fidelity overtime to make more accurate predictions regarding its physical counterpart, the physical twin (PT). The DT uses those analyses and predictions to send information back to the PT through data streaming tools. The PT reads the information and data sent from the DT to adjust behavior in the control system or alert system operators to adjust the components. The constant exchange of data, information, and commands is what differentiates the DT from other virtual modeling techniques. In summary, the DT is a virtual engineering tool that models a physical system, or twin, utilizing evolving streams of data to update the environment of models to predict behavior, monitor health conditions, and make future decisions.
1.3 Digital Twin Application in Military Ground Vehicles

A digital twin can support product design and development through the integration of models and data streaming which in-turn supports predictive maintenance and field reliability. With these benefits and advantages, the DT has a wide variety of applications as depicted in Figure 1.4 [14]. Uhlenkamp et al. [15] assess current and popular applications of DT technology along with implementation goals, information acquisition, and focuses for specific application type. The initial curators and users of DT technology is NASA, some application in current work of systems engineering is discussed in [16]. Cimino et al. [17] review DT applications in manufacturing, where innovations are being made in smart, additive, and advanced manufacturing processes. DT technology is oftentimes applied to aerospace systems for health monitoring, Ye et al. [18] additionally utilize the DT to perform structural health monitoring activities for bridges. Vering et al. [19] consider DT application in operational efficiency for HVAC systems which is a popular field of implementation. An emerging field of DT utilization is in automotive, applying virtual engineering techniques to components of vehicles along with fleet level systems. Bhatti et al. [20] review DT technology in smart electric vehicles along with the benefits and potential future use of the DT in the automotive industry.

Applications of DT technology have spanned across a multitude of industries including aerospace, automotive, HVAC, fluids, electrical power, structural, building management, and others. As the effectiveness of this technology becomes evident, military applications become a logical target. Tao et al. [21] mention that initial DT employment was restricted mostly to the military
Figure 1.4: DT applications across industries proportional to use-case percentages

and aerospace fields. DT implementation is discussed by Mendi et al. [22] as necessary in military applications due to low fault tolerance in critical systems, additionally exploring current DT applications and identify where future implementation should be considered. A DT framework for large-scale military use is proposed by Wang et al. [23] with utilization of cloud computing. Erol et al. [24] state that DT technology utilized in the military has gone as far to introduce creation of virtual soldiers to better treat patients on and off the battlefield. Li et al. [25] provide a general implementation architecture for DT in military application based on practice and known benefits exhibited in non-military fields. Considerations regarding military administration point to specific application of DT technology to individual and fleet-level ground vehicles.

Digital twin technology can be found in a number of advanced manufacturing and business fields. Industrial sector examples include manufacturing, aerospace, energy, automotive, marine, and more for purpose of simulation, monitoring, and controls according to literature surveys from Enders et al. [26] and Liu et al. [27]. West et al. [28] evaluate the affordability of DT implementation across military applications and communicate the need to apply DT technology “at all costs”. Current defense applications include aircraft and space activity. DT operation in military ground vehicles, including personnel vehicles, utility vehicles, and other wheeled or tracked vehicles is of most recent
consideration. The reason this is regarded as an “at all costs” technology is because fleet level data management, system improvement, and health monitoring benefits are difficult to procure in military settings due to lack of mass production and operation. In military ground vehicles, advantages of the DT include improvements on trade space analysis, V&V, design specification & analyses, prognostics & diagnostics, fleet operation, upgrades, smart manufacturing, and data mining. With unique vehicles, such as those intended for military use, military ground vehicles require a higher level of understanding and prediction. Through its data streaming and updated model library, the DT provides the engineering understanding and predictive capabilities required to prevent failure and optimize performance. Military application of DT technology yields the ability to improve and advance ground vehicle systems as well as explore possibilities for future DT implementation.

1.4 Thesis Objectives and Approaches

The research presented in this thesis intends to achieve the following research objectives:

1. Develop a framework for an intelligent wheeled vehicle DT model utilizing pre-existing team dynamics libraries.

2. Design and evaluate a failure diagnostic/prognostic strategy for military ground vehicles with integration of field data from on-board sensors to inform system decision-making.

3. Construct a quantitative metric to prescribe and evaluate benefits of DT implementation in the engineering design process.

To attain these objectives, the following goals are employed:

1. Review literature in history and current use of DT definition and application as well as history and current state-of-the-art methods alternative to the DT approach.

2. Create an operational dynamics based wheeled vehicle model using pre-existing libraries where available.

3. Design a working tracked vehicle model with dynamics-based libraries similar to the wheeled vehicle architecture.
4. Develop a prognostic health maintenance framework using both the developed wheeled and tracked DT vehicle models.

5. Evaluate preventive maintenance framework developed in 4 utilizing a virtual case study involving both wheeled and tracked DT vehicle models.

6. Create a Digital Twin Technology Usefulness metric to assess DT potential utility for an enterprise.

7. Create a Digital Twin Time Savings metric to quantify benefits incurred against other current design methods after implementation of the DT tool.

8. Expand upon prognostic health maintenance framework to a predictive maintenance approach based on results from 5.

9. Perform a case study with wheeled vehicle DT model using the predictive maintenance framework outlined in 8.

1.5 Thesis Organization

This thesis is comprised of five chapters outlining the objectives and approaches achieved throughout the entirety of the research. The research explores the topic of the DT virtual engineering tool and its application to military ground vehicles. Chapter One introduces background material necessary to understand the research presented. Beginning at a high-level engineering view, narrowing down to the topic and application of the thesis. Brief introductions on more specific topics are provided in each chapter based on their objectives and approaches. A general outline of techniques is presented to provide insight to the content of the paper. A framework for health monitoring and preventive maintenance is presented in Chapter Two. This framework begins with understanding and developing ground vehicle models, both wheeled and tracked, using mathematical and dynamic libraries. These models are then applied as DT tools to perform a virtual case study of health monitoring methods. The case study identifies possibilities of DT technology as well as gaps and opportunities for improvement.

A predictive maintenance approach and case study are presented in Chapter Three. In evaluation of the health monitoring case study from Chapter Two, a preventative maintenance
method is studied and developed for DT implementation in a wheeled military ground vehicle. The approach presents model-based prognostics and use of statistical analyses to predict vehicle behavior, remaining useful life, and prevent anomalies from becoming uncontrolled degradations or failures. A virtual case study is investigated using a wheeled vehicle model, with intentionally embedded noise and degradations analyzed by the DT tool to make maintenance predictions. Chapter Four explores the creation of a DT quantification metric. Several literature surveys reveal the absence and need of DT metrics to quantify the value-add of the technology. Two metrics are proposed, one is considered prescriptive, and the other, descriptive. The prescriptive metric evaluates an enterprise’s readiness to implement and utilize the DT tool, answering whether the DT would be useful to the enterprise or not. The descriptive metric quantifies the benefits the DT after its implementation and use. Outputting a value that the DT tool added or lost in utilization compared to other methods. Chapter Five concludes the thesis with a summary of the research conducted along with further research recommendations and opportunities for advancements. The conclusion is followed by appendices supporting the research performed including the computer code and models used for simulation and further contributions to the research goals. Finally, a list of references surveyed in contribution to this thesis follows.
Chapter 2

Application of a Digital Twin Virtual Engineering Tool for Ground Vehicle Maintenance Forecasting

2.1 Abstract

The integration of sensors, actuators, and real-time control in transportation systems enables intelligent system operation to minimize energy consumption and maximize occupant safety and vehicle reliability. The operating cycle of military ground vehicles can be on- and off-road in harsh weather and adversarial environments, which demands continuous subsystem functionality to fulfill missions. Onboard diagnostic systems can alert the operator of a degraded operation once established fault thresholds are exceeded. An opportunity exists to estimate vehicle maintenance needs using model-based predicted trends and eventually compiled information from fleet operating databases. A digital twin, created to virtually describe the dynamic behavior of a physical system using computer-mathematical models, can estimate the system behavior based on current and future operating scenarios while accounting for past effects. In this manner, the collection of real-time data of the
physical vehicle can be compared with the virtual counterpart to assess the likelihood of degraded operation and recommend maintenance. This paper creates a digital twin for an off-road tracked ground vehicle with an accompanying parameter database. A modular architecture enables different design reconfigurations to evaluate various chassis subsystems and vehicle-ground mobility interfaces. A preventive maintenance algorithm is applied to monitor the operating behavior of the vehicle. The prediction tool, operating in parallel with the digital twin, may use model-based and sensory signal condition indicators to monitor vehicle performance. A case study investigates two operating scenarios: a virtual wheeled suspension system is degraded; and a virtual tracked vehicle experiences missing trackpads, which subtly alter the performances. The numerical results will offer insight into the pathway to begin creating a digital twin-based maintenance forecasting strategy.

2.2 Introduction

Digital twin technology offers the next level of design, analysis, and operational support for complex multi-disciplinary machines and systems over their lifecycle. A digital twin is the collection of dynamic models, parameter databases, manufacturing criteria, and engineering materials that can be assembled with actual or representative operating cycles to predict overall performance. When combined with available sensory data from field transmissions or plant installations, it can estimate future performance based on past recorded behaviors. The availability of lumped parameters and statistics-based mathematical models can generate the system response based on the supplied database. Supplemental use of computer-aided-design (CAD) and computer-aided-engineering (CAE) models can also create G-code for computer numerical control (CNC) machining and additive manufacturing to create the subcomponents for assembly. The availability of a digital twin enables future product enhancements for enhanced reliability, occupant safety, and new mission requirements to be digitally addressed. A virtual engineering design process can lead to quicker solutions and product-to-market time. Lastly, health monitoring can be readily accomplished within this context by observing both analytical and physical information to predict ideal behavior in comparison with observed behavior leading to prediction and diagnosis.

A brief literature review on digital twins will be offered. Shafto et al. [29] provided a digital twin definition of "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the
life of its flying twin” in their NASA report. An AIAA and AIA position paper [30] on digital twin technology provides definitions and value propositions. A digital twin survey by Jones et al. [14] identified the knowledge gaps and research opportunities. In the transportation sector, digital twins have been applied for vehicle design [31, 32, 33], autonomous ground and marine vehicles [34, 35, 36], and manufacturing [37, 38, 39]. The military has recognized the transformative advantages of digital engineering technology [13,14] for aerial, ground, and naval platforms [12, 40]. Aivaliotis et al. [41] and Balakrishnan et al. [42] have examined physics-based modeling and machine learning for predictive maintenance for digital twin prognostic applications. The emergence of digital twin technology is gaining recognition, and many opportunities exist to apply it within the transportation sector for engineering design, digital manufacture, and improved vehicle performance.

Ground vehicles have featured onboard diagnostics (OBD) since the early 1980s with the advent of the check engine light and real-time computer-controlled engine management. These control systems have evolved to include transmission shifting, antilock brakes, traction, electronic stability, adaptive cruise, lane-keeping, obstacle avoidance, electric motor drive, and battery pack management. The complexity and sophistication of these diagnostics continue to grow with the addition of sensors and computational power. For instance, OBD-I was required by California in 1988, OBD-II for all cars sold in the United States in 1996, and EOBD in 2001 for European Union gasoline vehicles [43]. Military on- and off-road vehicles face significant challenges over their lifecycle due to harsh environments, aggressive operating cycles, different drivers, and cargo loadings while trying to deliver optimal performance levels. Further, the lifespan of a product can be years or decades, with replacement part availability a concern as these items may gradually disappear from commercial shelves or need to be stored in distant warehouses.

The digital twin concept is an evolution in the model-based engineering design and manufacture paradigm, which continues to gain interest given advancing hardware, software, and additive manufacturing capabilities. As shown in Figure 2.1, the availability of a virtual model, or models of varying fidelity levels, to generate (transient response of) system behavior can support a host of tasks that may have been previously completed in a piece-wise fashion. Concept validation can occur against requirements using Tradespace Analysis methods [44, 45, 46] coupled with performance estimates in the initial design effort. The underlying CAD/CAE models provide a pathway to CNC and additive manufacturing processes for subassemblies in production. During field operation, prognostics and diagnostics can be executed when integrated with streaming sensor data and...
field observations. Further, the next design cycle for subsystem upgrades or to determine whether an expanded mission can be accommodated may begin at any point with this digital tool.

Figure 2.1: Digital twin landscape for initial design, manufacturing, health monitoring, and upgrades to support field deployment.

A digital twin for off-road ground vehicles will be investigated to support engineering design studies and preventive maintenance for improved mission reliability. The remainder of the paper is organized as follows. Section 2 discusses the opportunities offered with digital twin technology. The architecture and modules in a wheeled and tracked ground vehicle digital twin are presented in Section 3. A preventive maintenance strategy is introduced in Section 4, followed by a case study on suspension spring degradations and trackpad anomalies in Section 5. The conclusion is contained in Section 6 and a complete Nomenclature List in the Appendix.

2.3 Digital Twin Paradigm

A digital twin of a physical product can serve many purposes, including system design studies, advanced manufacturing cues, field support, and health monitoring. The target application will guide the underlying composition of the overall simulation models and architecture, including interface with the outside world. The fidelity of the software models can be a higher level to support general feasibility studies regarding solution suitability, available sizing of components for the given vehicle, etc. On the other hand, a detailed set of models can be used to design pieces by exploring
performance expectations, CNC machining instructions, etc. The engineering experts will judge the best approach in describing the system based on the design requirements. The assembled models can be executed individually or collectively to generate dynamic transient responses, steady-state estimates of peak loadings, and a host of other information. An important consideration is the documentation of assumptions, prevalence of comments, identification of constraints, preliminary databases, and other pertinent details so that current and future users will have insight into the limitations and opportunities of the created digital tool. The development of models for a digital twin must consider the software package(s) available for implementation. The question must be asked: what software is suitable and available? Although an important decision, it is not critical given that other software may be selected during the process that may be better suited for the given task. Integrating and switching software becomes more manageable with an identified structure or architecture that enables exported functions. Some of the software packages include Amesim®, ANSYS®, COMSOL®, Matlab®, Simscape®, and Simulink® as well as CAD/CAE packages such as CATIA®, NX®, and Solidworks®. A consideration in software decision-making is the execution speed of the complete computer code. A hardware-in-the-loop application [47] requires real-time execution, while a design study evaluating subsystem performance per different operating schedules may run as a background job on a desktop computer. System data storage, performance results, and field testing can be a critical requirements, especially if the files will be shared across the enterprise. Lastly, for purposes that require sensory data, communication with external hardware and computer systems for this input streaming will be necessary.

The computer hardware basis for the digital twin may range from a desktop computer to high-speed parallel processing on numerous computer nodes. In a traditional control system configuration (bottom of Figure 2.2), the physical plant interfaces with onboard sensors, real-time controller with analog-to-digital converters, software, digital-to-analog converters, and actuators to impact plant operation. As mentioned earlier, a hardware-in-the-loop application would feature a realistic environment for the controller hardware/software while emulating the sensors, physical plant, and actuator in a combination of laboratory instrumentation and models [48]. A digital twin (top of Figure 2.2) will provide a complete virtual representation of the physical system. However, it may be interfaced with field data streaming to help track actual operations and perform health monitoring by comparing the estimated and occurring behaviors. This data arises from the onboard plant sensors and local environmental conditions meteorology sensors transmitted back to the home
office for logging and mining. The growing availability of data from the Internet of Things (IoT) offers insight into the future direction of streaming across product lines and applications.

### 2.4 Architecture of a Ground Vehicle Digital Twin

The architecture of the digital twin models and the provision of signals between them is not unique but reflects a working solution to address all stakeholders. The possible stakeholders include engineers and technicians from design, validation & verification, test, hardware-in-the-loop (HIL), system health monitoring, and manufacturing. The assembled vehicle models can be configured in many different manners, but the selected architecture will follow SAE J3049 [49]. This standard offers a hierarchical structure for assembling dynamic models to realize a modular configuration for
the various subsystems. This approach also provides a framework for a partial or complete vehicle 
representation dependent on the given application. In Figure 2.3, the ground vehicle architecture 
is displayed, beginning with the environment, driver, and vehicle. The latter is divided into vehicle 
control, propulsion, chassis, and possible trailer, while the next level down shows the main chassis 
elements. This SAE standard is a recommended practice for general use, and the models in this 
project will follow the guidelines for both the wheeled and tracked platforms.

Figure 2.3: Representative configuration and subsystems for a ground vehicle within the digital twin 
arquitecture.

At the highest level, the digital twin user will view the main blocks of the virtual representation, 
including the environment, driver, controllers, and vehicle, as shown in Figure 2.4. These 
blocks can be expanded to view the underlying structure and details that may interest the engineer 
and technician. The design is modular and can be reconfigured as needed. The selected software 
that hosts the digital twin should accommodate the various subsystem models, which may be treated 
as simply black boxes or code that can be executed within the chosen package. Regardless, the ar-
chitecture should be flexible and adaptable for a wide array of models and model types to create a 
holistic view of the system. Creating a virtual tool to investigate off-road vehicles that will operate 
in harsh environments needs to consider both wheeled and tracked designs. There will be common 
model blocks shared between each solution, but differences will exist in the implementation. For 
instance, a wheeled system will receive driver input commands for the steering wheel angle as well as 
the throttle and brake positions in the driver block. On the other hand, tracked vehicle inputs can be 
modeled as speed and yaw rate commands. The vehicle yaw may be implemented with either a dual
lever system that controls each track speed individually or a steering yoke with an accompanying control algorithm to interpret the signals. The way the vehicle propels itself will also differ, but the propulsion plant (e.g., diesel engine, electric motor) will be similar.

Figure 2.4: Driver, environment, controller, and vehicle blocks within the simulation of the digital twin toolset at the highest level.

The primary differences in the wheeled and tracked platform descriptions come down to the chassis module and select subsystems. In a wheeled simulation, the transmission (within the power module per SAE J3049) interfaces with the power source to deliver torque at the tire/road interface to the drive wheels. The resulting reactive forces move the vehicle in the intended direction with speed dependent on the vehicle load, terrain, ground slope, and other environmental factors. Similarly, a tracked vehicle routes the transmission output torque to each drive sprocket on which the continuous track plates or rubber tread engage to deliver tractive forces at the tread/ground interface. The subsystem models for the wheels/tracks in Figure 2.3 will address these differences and provide the respective tractive forces that will act on the vehicle. To give more insight into the various modules, the chassis dynamics, track kinematics, tire forces/moments, wheel dynamics, and environment plus controllers will be discussed.
2.4.1 Chassis Dynamics

The selection of a chassis model will be dependent on the focus of the engineering study. A three degree-of-freedom model will be presented to cover the fundamental dynamics for vehicle motion. The application of Newton’s Law in the longitudinal (x-axis), lateral (y-axis), and yaw (rotation about the z-axis) directions enable the accelerations to be written as

\[ m(\dot{u} - \rho v) = F_x \quad (2.1) \]

\[ m(\dot{v} - \rho u) = F_y \quad (2.2) \]

\[ I_z \dot{\gamma} = M_z \quad (2.3) \]

where \( \dot{u} \), \( \dot{v} \), and \( \dot{\gamma} \) are the velocities, respectively. The tractive forces, \( F_x \) and \( F_y \), and aligning torque, \( M_z \), will be due to the tire or track forces at the ground interface, depending on the configuration.

For a standard wheeled vehicle, typically four wheels corresponding to a light-duty truck, the summation of tire forces including the aerodynamic drag force and the aligning torques can be expressed as

\[ F_x = F_{x1} + F_{x2} + F_{x3} + F_{x4} - F_D \quad (2.4) \]

\[ F_y = F_{y1} + F_{y2} + F_{y3} + F_{y4} \quad (2.5) \]

\[ M_z = b_b (F_{x1} - F_{x2} - F_{x3} + F_{x4}) + b_c (F_{y1} + F_{y2}) - b_d (F_{y3} + F_{y4}) \quad (2.6) \]

For a dual (left, right) tracked vehicle with multiple rollers, the summation of tire forces, including aerodynamic drag force and aligning torques yields

\[ F_x = F_{xl} + F_{xr} - F_D \quad (2.7) \]
\[ F_y = F_{yl} + F_{yr} \]  
\[ (2.8) \]

\[ M_z = F_{zl} + F_{zr} \]  
\[ (2.9) \]

The drag force, \( F_D \), is a function of the vehicle’s aerodynamic drag coefficient, \( C_D \), air density, \( \rho \), frontal vehicle area, \( A_D \), and the longitudinal vehicle velocity, \( u \), so that

\[ F_D = \frac{1}{2} C_D \rho A_D u^2 \]  
\[ (2.10) \]

### 2.4.2 Wheeled Dynamics

Most manufactured ground vehicles are equipped with rubber tires mounted on steel wheels/rims to interact with the ground, which is often concrete, asphalt, gravel, or hard-packed dirt surfaces. In this study, a front steering vehicle configuration with four wheels will be considered. The platform uses Ackermann steering and differential gears to have the outside wheel turn slightly faster than the inside one to avoid slippage in contrast to a tracked vehicle platform since the steering is explicitly achieved by changing the tracks’ speeds individually.

The longitudinal and lateral tires forces in the body axis can be written as

\[ F_{xi} = F_{xwl} \cos \delta_i - F_{ywl} \sin \delta_i \]  
\[ (2.11) \]

\[ F_{yi} = F_{xwl} \sin \delta_i + F_{ywl} \cos \delta_i \]  
\[ (2.12) \]

where \( \delta_i \) is the steering angle of the \( i \)th wheel while \( F_{xwl} \) and \( F_{ywl} \) are the longitudinal and lateral tire forces in the wheel plane, respectively. The latter two may be determined based on the individual slip, \( s \), road surface friction coefficient, \( \mu_G \), normal load on the tire, \( F_z \), and tire force.

The rotational dynamics for the wheel consider the rotational acceleration and speed based on the moments about the wheel. By applying Newton’s Second Law, the expression for moments about the wheel rotational axis is

\[ I_{wi} \dot{\omega}_i = T_{bi} + F_{xwl}(R - \delta_{zi}) - F_{zi} x_{zi} - C_{wi} \omega_i \]  
\[ (2.13) \]
where \( I_{wy} \) is the moment of inertia of the wheel, \( \omega_i \) is the angular velocity of the \( i^{th} \) wheel, \( T_{bi} \) is the braking torque, \( R \) is the wheel radius, \( \delta_{zi} \) is the vertical tire deflection, \( x_{zi} \) is the longitudinal offset, and \( C_{wi} \) is the wheel damping coefficient.

### 2.4.3 Track Kinematics

A continuous metal track, or discrete metal links connected to form a continuous band, can help propel a ground vehicle across ground surfaces with low friction coefficients. Most notably are sand, mud, and terrain with steep grades that may be encountered across the globe. The actual track tread that interfaces with the ground may be metal or rubber, depending on the operating scenario (e.g., highway or off-road). The track kinematics subsystem divides the track into 50 individual elements, which can be tabulated iteratively in a fashion similar to a mesh. Both the left and right tracks are considered, as shown in Figure 2.5. To propel the vehicle forward, the propulsion torque is supplied to each sprocket through the transmission, and the rotational track inertia, normal loadings, and terrain are considered to calculate the longitudinal and lateral track forces and moments.

The \( i^{th} \) sprocket drive torque, \( T_{ci} \), enables the track speed, \( v_{ti} \), to be calculated considering the ground interface so that

\[
v_{ti} = r_s \int \frac{T_{ci} - F_{xi}r_s}{I_t} dt, \quad (i = r, l)
\]

Figure 2.5: Track-ground interface dynamics with support chassis dynamics, track kinematics, and track forces and moments.
where $F_x$ is the track force experienced in the x-direction. Track forces and moments experienced in the x- and y-directions may be expressed as

$$F_i = e_i c_i + v_{ei} d_i, \ (i = x, y) \quad (2.15)$$

where $e_i$ is the element displacement which is a function of the track and nodal velocities, $c_i$ is the track stiffness, $v_{ei}$ is the element velocity, and $d_i$ is the track damping coefficient.

The elemental velocity is calculated using the track velocity, $v_{tj}$, and the vehicle velocity so that

$$v_{ei} = v_{tij} - u, \ (i = x, y, j = r, l) \quad (2.16)$$

The moment about the z-axis, $M_{zj}$, experienced by each track is expressed as

$$M_{zj} = -F_{xj}(W_m + b_h) - F_{yj} \left( L_m - \frac{L}{2} \right) \quad (2.17)$$

where $W_m$ and $L_m$ correspond to the width and length of the mesh elements, respectively.

The node displacements and velocities are calculated based on the track and vehicle velocities, as well as the vehicle weight distribution with a friction coefficient.

### 2.4.4 Controller and Environment Subsystems

Two necessary modules in Figure 2.4 are the environment and controllers containing information concerning the digital twin’s operating conditions and the control systems regulating subsystem operations. Some of the possible environmental conditions may include the ambient temperature, wind speed, visibility, road surface conditions, road grade, surrounding vehicles, traffic patterns, etc., that the assorted dynamic models will require.

The controller block is targeted for the various control systems that may exist. For instance, in wheeled systems, this may include anti-lock brakes, traction control, vehicle stability, lane-keeping, adaptive cruise control, etc. Similarly, a tracked system may feature steering, track power, and suspension control. In each case, the driver inputs plus the environmental and plant signals are provided to determine the resulting actuator commands shared with the respective subsystems. More importantly, the controller functionality is assigned a specific location in the digital twin.
2.5 Preventive Maintenance Strategy

A digital twin provides an engineering tool to support design studies throughout the entire lifecycle, evaluate operating conditions on overall performance, and offer a gateway to product manufacturing. In addition, the assembly of system models can estimate system operation based on the supplied inputs and conditions. When coupled with data streaming from the field, such as a vehicle or machine, the actual performance can be compared with the estimated behavior to determine the machine’s health status. For ground vehicles, the onboard diagnostic system can share this information in support of data mining. The opportunity for predictive maintenance will be explored to diagnose emerging problems in a vehicle’s operation.

One advantage of a coupled digital twin with a diagnostic module is predictive maintenance which will be explored. Detection of a hard system failure after it has occurred is known as fault diagnostics. However, with a preventive maintenance algorithm, the progression of small degradations can be noticed, and repair recommendations are promptly issued. Avoiding a failure by identifying degradations, their cause, and their effect on the system operation will help eliminate the total loss of components, minimize repair costs, and increase product availability. Prognostics are advanced indications of future events with respect to degradation and ultimate failure. The prognostic process entails collecting operating data, extracting crucial signal features, processing, analysis, and exportation, as shown in Figure 2.6.

Figure 2.6: Predictive maintenance analysis process with a comparison of healthy and field operating (possibly degraded) data.
Data sets must be typically gathered to help determine normality and pinpoint degraded operation to forecast maintenance needs. Specifically, the goal is to evaluate instances of success and failure and find the root cause. By comparing the healthy and degraded data signals within each subsystem and component, the nature of potential failure can be determined. This signal comparison process evaluates condition indicators to determine whether the system is operating within a specified zone of acceptance. The degraded operations should cover the spectrum of soft and hard anomaly scenarios that need to be considered. Ideally, the data can be obtained from physical systems operating in the field. Preventive maintenance measures may use models in the analysis process, which leverages the efforts to create a digital twin.

When degraded signal data may not be available from a physical system (e.g., a prototype does not exist, limited production due to cost), the digital twin can be used to create the required databases. One version of the model(s) can be maintained as the normal (healthy) system. A second version will feature degradations by modeling degraded component operation, introducing signal bias and noise, etc. For instance, slippage in transmission components may be modeled by output torque variations, while a loose rubber pad on a metal track by variations in the tractive road forces. Overall, the selected degradations should correspond to likely or observed scenarios while gradually leading to failures. In this manner, data can be produced for training to allow the predictive maintenance algorithm to notice and recommend repairs before hard failures occur.

Once enough data is collected, including scenarios of both healthy and unhealthy data runs for selected conditions, this database can be analyzed for indicators. This process works using time-series and frequency domain analyses such as noise reduction, time-synchronous averaged signal difference, and power spectrum. Specifically, the signals are pre-processed, filtered, and analyzed to establish the foundation for healthy and unhealthy behavior. The diagnosing features are then placed into the predictive maintenance algorithm, which monitors the plant output for anomalous tendencies. In Figure 2.7, the physical plant (ground vehicle) and prognostic algorithm operate in a parallel fashion while the latter monitors the system output for degradations. Given the impending maintenance issue, the digital twin may be utilized to evaluate the impact of corrective recommendations or penalties associated with continued operation.
2.6 Case Study: Degraded Performance of Digital Twin Wheeled and Tracked Vehicles in Preparation for Predictive Maintenance Training

The functionality of a digital twin in supporting a preventive maintenance strategy will be demonstrated on off-road wheeled and tracked vehicles. The goal was to understand the utility of the digital twin in describing regular vehicle operation and the opportunity to introduce virtual anomalies into the simulation to explore prognostic methods. The case study will examine the ground vehicle’s wheeled suspension system which manages the sprung mass dynamics and the track subsystem which provides tractive forces. A virtual 2500 kg vehicle of 5 m length and 3 m width will be subject to two degradations. The first study will examine loss in spring force from the front suspension of a wheeled vehicle. For the second study, discrete treads on the track belt will gradually lose traction to the ground from imbalanced normal weight forces. Each of these scenarios will impact the maneuverability of the vehicle and provide opportunities for fault detection. The vehicle will be traveling at a longitudinal speed of 20 m/s and perform a J-turn representative of an avoidance maneuver. Representative numerical results will be presented and discussed that highlight
the deviation of these gradual anomalies from typical system performance. A recommendation for
maintenance to the driver, fleet operator, and specific subsystem will help prevent these degradations
from resulting in complex subsystem failure.

To begin the preventative maintenance study, simulation data was collected for normal and
degraded operations. The available sensory data included the vehicle position, vehicle speed, yaw
rate, driver commands, wheel & track speeds (left, right), individual wheel bounce, and tractive
forces (left, right). The training data sets for each case were combined to create a comprehensive
database. Next, condition indicators were developed based on patterns of recognition and applied
during the evaluation phase to evaluate the wheeled and tracked subsystem. Note that the same
exact anomaly scenarios (e.g., magnitude, timing) were not implemented in the demonstration to
help draw distinctions. In some instances, drivers may be requested to perform some calibration-
inspired maneuvers each time the given vehicle is initially operated to periodically gather baseline
performance of the subsystems. Otherwise, the regular operation will afford standard maneuvers
that can be observed for anomaly evaluation.

2.6.1 Case Study A: Suspension Spring Anomaly

The first degradation analyzed within a wheeled vehicle is a suspension spring degradation
which impacts the front independent suspension for each wheel. Vehicle chassis anomalies may occur
due to wear-and-tear, fatigue, off-road impact, and torque delivery issues. Suspension faults can
generally occur inside the shock assemblies or springs (coil, leaf) which introduce material property
changes. When a suspension degradation occurs, roll and pitch properties change, resulting in ride
quality and longitudinal dynamic behavior that differs from normal operation. The suspension
type varies by vehicle, whether individual, MacPherson, solid axle, or other configurations. The
suspension spring constant can be varied. In this study, the degradation will be considered to occur
slowly instead of a rapid failure.

The front suspension examined was a MacPherson strut. The degraded suspension spring
constant, $K_z$, is described by material properties such as number of coil turns, coil diameter, spring
free length, and deflection. The spring constant is multiplied by a scaling coefficient (between 0 and
1) of 0.5 to simulate a degradation.

The prescribed J-turn maneuver will be impacted by a reduced suspension spring constant
such that the trajectory deviates from normal vehicle performance due to normal force distribution
changes. If the driver intervenes to compensate for the increased turning radius, then an examination of the driver commands can be performed from the steering command. As the spring constant of the front wheels will degrade below the normal operating level, those front wheels pitch and roll will be affected differently than expected, resulting in a decrease in turning radius. In Figure 2.8, a reduced vehicle turning radius from the faulty front suspension results in a J-turn that does not follow the expected profile.

![Figure 2.8: Case Study A–J-turn tracked maneuver for regular and degraded operation.](image)

Using a predictive maintenance toolbox, the vehicle operating data for a degraded suspension spring constant may be statistically compared to healthy behavior. The primary signals to examine as fault indicators include the vehicle ride quality such as, pitch, roll, bounce, and longitudinal acceleration. Multiple simulations were executed with the digital twin for varying suspension conditions on the front wheels. The available feature analysis methods, including root mean square, peak value, and clearance factor, may be applied to determine the probability of a fault before it occurs. In this study, the roll and pitch velocities exhibited clear probability distinction using a root mean square statistical analysis. After implementing the exported feature code, the simulation was executed to evaluate whether suspension degradation may be detected or not. Using different driver scenarios, the same statistical probability analyses can reveal a distinction between healthy and faulted data, indicating the need for maintenance attention based on observed behavior. To determine useful remaining life, a detailed model of the drivetrain will be necessary in the digital twin.
2.6.2 Case Study B: Track Pad Anomaly

The suspension system typically uses torsion bars with rotary shock absorbers to distribute the load and motion to the metal tread cleats or rubber pads on tracked vehicles. The propulsion system torque is communicated to the drive sprocket, which interfaces with the track, road wheels, and idler wheel. The vehicle weight is distributed at the ground contact patch, and tractive forces are generated based on the available surface coefficient, normal load, and pad interaction with the soil. As the track is composed of discrete tread elements linked together to form a continuous band, the individual tractive forces can be diminished when a pad does not fully engage with the surface. Similarly, a road wheel, including the torsion bar and shock, may develop problems that interfere with the transmission of normal loads to the track. As shown in Figure 2.9, the road wheels directly engage with elements on the track and corresponding loading of the track sections. In this study, element positions 24 through 26 (of a 50-element track) do not fully generate tractive forces at the surface contact patch due to emulated pad degradation. In the track model, the discrete tread forces are summed together to realize a net tractive force. Accordingly, this tractive force will be periodically adjusted to correspond to the anomalous pad(s) entering and exiting the contact patch. The vehicle performance will be evaluated under different levels of degradation and the corresponding impact on the tractive forces.

![Figure 2.9: A tracked vehicle with distributed treads and contact patch.](image)

A J-turn maneuver was considered with irregular surface tractive forces due to trackpad interactions with the ground difficulties. The required training data was generated using the digital twin for healthy and slightly degraded operations. The prognostic algorithm was trained to identify
the condition indicators leading to preventative measure recommendations for the tracked subsystem. The degraded value of the tractive force at the specified track pad will be calculated by scaling the output for the respective track pad tractive forces.

As shown in Figure 2.10, the end position of the tracked vehicle when completing a J-turn differs significantly from normal to degraded due to tractive forces issues. The left side of the vehicle does not generate the same level of traction as the nominal case, which results in a shallower turn. Similarly to the previous case study, the predictive maintenance algorithm results indicate that the stream of condition indicators can be viewed and analyzed using discrete probability analyses to generate preventative maintenance recommendations in real time. Differing driver scenarios again were used resulting in indication of a need for maintenance operation by the same statistical probability analyses. Again, a more descriptive model of the individual track segments with cleats or rubber tread that interacts with the ground will be required to diagnose the actual source further.

![Figure 2.10: Case Study B–J-turn tracked vehicle maneuver for normal and degraded contact patch interactions per irregular tread pads.](image)

**2.7 Summary**

The creation and assembly of analytical models that describe a physical machine is the basis of a digital twin to virtually explore the design and performance for prescribed operating conditions and cycles. An off-road ground vehicle digital twin has been presented for design studies regard-
ing the next generation tracked vehicle concept and upgrades to existing vehicles to accommodate mission changes. A preventive maintenance algorithm has been introduced that integrates with the digital twin and vehicle field data to predict the onset of anomalies. The case study considered suspension system and select trackpad degradations in wheeled and tracked vehicles to highlight the utility of the digital twin for health monitoring. The next step will be validation of the digital twin for select vehicles, including the planned Deep Orange off-road vehicle [50] under development at Clemson University.
Chapter 3

Predictive Maintenance of a
Ground Vehicle Using Digital Twin Technology

3.1 Abstract

The safety and reliability of ground vehicles is a motivating factor for periodic maintenance which includes fluids, lubrication, cleaning, repairs, and general observation of key subsystems. The scheduling of maintenance activities can occur at different rates such as daily, weekly, or perhaps operating time based on collected historical data and general guidelines. The availability of a digital twin (DT), which offers a virtual representation of the vehicle behavior, enables virtual system simulations for different operating cycles to explore the dynamic behavior. When field operating fleet data can be integrated with the digital twin estimates, then this supplemental information can be combined with the existing maintenance plan to provide a more comprehensive approach. In this paper, a digital twin with a statistical based predictive maintenance strategy is investigated for a wheeled military ground vehicle. The underlying models and mathematics are presented to establish a basis for this engineering tool. A case study is examined in which a DT is utilized in a computer simulation mode as a physical vehicle was unavailable to generate numerical data for signal features and condition indicators. Representative results show a high validation accuracy.
and reasonable training times can be achieved in support of predictive maintenance classification models. The steady progression towards a virtual engineering design and product support framework for transportation systems relies on the presence of digital twin technology and prognostic-diagnostic methodologies.

3.2 Introduction

Health monitoring and general maintenance strategies are developed from classic diagnostic methods where post-failure analyses identify a root cause of a degradation to make improvements for a future system. Jardine et al. [51] recognized these post-failure analyses as diagnostics because they evaluate the system and its components in their current state, potentially after a degradation occurs. These diagnostic methods are costly in testing for failure and time consuming. In current existing practice, Zhang et al. [52] observed that these diagnostics are upheld by data collection onboard the vehicle in which the vehicle must be taken to a service location where the data is uploaded for analysis. To avoid failure testing and reduce cost, maintenance began to move from reactive to prescriptive. Scheduled maintenance, a popular strategy, provides the operator with a method to determine when certain upkeep procedures should occur to avoid reliability issues. In scheduled maintenance, upkeep and updates are performed on the system based on data from general operating cycles and environment conditions. While scheduled maintenance considers a range of vehicle conditions, it does not conduct operator specific assessments and suggestions based on specific vehicle scenarios.

The scheduled maintenance strategy is useful, but a need exists to forecast maintenance and degradations by remaining useful life (RUL) and fault identification. Cocheteux et al. [53] and Lee et al. [54] noted that failure prediction alone is the focus of prognostic methods with minimal consideration of performance atrophy. Heng et al. [55] state the fact that most all health maintenance strategies have shifted from a post-failure breakdown maintenance to an intelligent predictive system with mass data collection integrated with computer generated analysis to predict the current state of a system. These authors also define maintenance forecasting as a prognosis of the ‘remaining operational life, future condition or probability of reliable operation of an equipment based on the acquired condition monitoring data.’

The planned approach to creating a solution for these gaps in maintenance forecasting is
to design a predictive maintenance method that identifies RUL and when and where a failure will occur at current operation. This will be done by comparing healthy model data to degraded model data using virtual prototyping. Once the data is collected, the two sets will be compared using statistical analyses including time-series and frequency-domain analyses. These statistical analyses will identify a distinguishing factor or condition between healthy and degraded data sets based on type. Once identified, the statistical method will be implemented into the controller of the system to predict when that type of failure will occur, well before it happens, as well as predicting RUL and performance of the system or component. This is done using live streamed data from the system to have regularly updated maintenance predictions. A further study and comprehensive literature review of diagnostics and prognostics for complex systems including ground vehicles is given by Soleimani et al. [56].

A predictive maintenance strategy can be readily integrated into a digital engineering approach as shown in Figure 3.1. The digital backbone includes data streaming, system maintenance, missional updates, and more activities that can be recorded in an on-line database accessible by all stakeholders. The DT is an assembly of virtual models to estimate system behavior. The dynamic models involve operation profile, environment conditions, and seeded anomalies to compute system performance. The DT environment utilizes CAD/CAE tools and engineering resources along with fleet and streaming data to generate predictive maintenance algorithms. In this instance, prognostic algorithms can forecast plant behavior based on computer simulations and strengthen them when integrated with physical data streaming.

The planned approach to creating a solution for these gaps in maintenance forecasting is to design a predictive maintenance method that identifies RUL and when and where a failure will occur at current operation. This will be demonstrated by comparing healthy model data to degraded model data using virtual prototyping on a small-scale which can be applied on a multi-scale basis. Once the data is collected, the two sets will be compared using statistical analyses including time-series and frequency-domain analyses. These statistical analyses will identify a distinguishing factor or condition between healthy and degraded data sets based on type. Once identified, the statistical method will be implemented into the controller of the system to predict when that type of failure will occur, well before it happens, as well as predicting RUL and performance of the system or component. This is done using live streamed data from the system to have regularly updated maintenance predictions. A further study and comprehensive literature review of diagnostics and
prognostics for complex systems including ground vehicles is given by Soleimani et al. [56].

Figure 3.1: Configuration of a digital twin for ground vehicle design studies and fleet preventative maintenance monitoring.

The research objective is the development of a digital twin based predictive maintenance framework for military ground vehicles that is configurable and applicable to future transportation systems. A predictive maintenance strategy can be readily integrated into a digital engineering approach as shown in Figure 3.1. The digital backbone includes data streaming, system maintenance, missional updates, and more activities that can be recorded in an on-line database accessible by all stakeholders. The digital twin is an assembly of virtual models to estimate system behavior. In this instance, prognostic algorithms can forecast plant behavior based on the computer simulations and strengthen them when integrated with physical data streaming. The remainder of the paper is organized as follows. Section 2 discusses current system health strategies, diagnostics & prognostics, as well as a strategy for predictive maintenance utilizing the Digital Twin. Section 3 provides an overview of the digital twin created for a military ground vehicle with model dynamics, architecture, and vehicle scenario. A Case Study is offered in Section 4 that investigates PM application to the
3.3 Predictive Maintenance Method

To understand predictive maintenance strategies, it is important to be familiar with current approaches to health monitoring and their evolution. The methods to be reviewed include diagnostic, a post-failure data interpretation, and prognostic, prescriptive failure-prevention, approaches. An emerging trend in system health monitoring integrated smart technology and learning algorithms to improve failure prevention and overall system health. The DT is an innovative, virtual tool that improves areas of the design process instituting new technology in the health monitoring process.

3.3.1 Current Health Maintenance Methods

Health monitoring is categorized into diagnostic and prognostic classifications. Diagnostic methods monitor and interpret past system data to assess the current state of a component or system. Booyse et al. [57] and Randall [58] define diagnostics as a step above detection, leveraging the ability to make distinctions between different types of failures and anomalies after their identification. Diagnostic methods are classified by literature [59, 60, 61, 62, 63, 64] into three high-level types: physics-based (quantitative model-based), knowledge-based (qualitative model-based), and data-driven (process history based). Observers, fault trees, structural knowledge, expert systems, and statistical classifiers are specific examples of monitoring methods under the three types shown in Figure 3.2. Model-based methods provide the capability to build diagnostic systems that have either structural, behavioral, functional, or pattern matching knowledge according to Milne [65]. All methodologies listed require a form of fault data or anomalous behavior detection from the system to discern root causes and apply health monitoring or maintenance measures. Regardless of the diagnostic approach, statistics play an important part to minimize false alarms and improve the overall accuracy of the diagnostic system.

Prognostics aim toward future behavior modifications to prevent failures while improving system performance. Prognostic methods use similar fundamental concepts as diagnostics with a focus on scheduled maintenance, preventative maintenance, and predictive maintenance. In essence, prognostics seek to prevent system failures through improvements in preemptive servicing. Preventative maintenance, after statistical analyses, details a scheduled procurement determining an
appropriate timeline of maintenance to prevent a degradation from resulting in catastrophic failure. Predictive maintenance leverages statistical analyses to output a diagnosis of current system health, a prediction of RUL and system behavior in addition to forecasting performance. Preventative and predictive maintenance involve comparing data from the physical system with virtual models, which undergo statistical analyses to identify features and distinguish factors associated with both healthy and degraded system conditions. The predictions from the preventative maintenance method are created as feature identifications which are implemented using intelligent feedback processes into the physical system. Those features are then used to correct current system behavior and make predictions informing prospective maintenance needs.

When reviewing diagnostic and prognostic approaches, a gap has been identified relative to infusion of machine learning and intelligence into the health maintenance process. General Electric (GE) aircraft engines and renewable energy are implementing DTs to advance health monitoring and maintenance using statistical analyses [66]. Sankavaram et al. [67] exercise physics-based and data-driven techniques in automotive and electronic applications providing examples of current diagnostic and prognostic approaches. By learning existing approaches and establishing best practices, a physics-based approach is integrated with both knowledge-based and data-driven methods. This technique is implemented through the utilization of the DT, leveraging the advantages offered by
virtual technology. The physics-based approach uses mathematical descriptions of a system in a model, applying statistical estimations that track degradations. Knowledge-based approaches use signal-processing, expert, or fuzzy systems for prognostics especially suitable for coupled systems where root cause isolation is possible in complex systems. Data-driven is the preferred approach when physics-based models are unavailable, utilizing monitored data to understand and forecast system degradations and failures. A call for an improved “integrated diagnostic and prognostic process” by Pattipati et al. [68] leads to innovative DT implementation.

3.3.2 Digital Twin Predictive Maintenance Method

The DT is a tool used in design and monitoring processes to prepare and assess systems quicker with more accuracy than other methods as illustrated in Figure 3.3. Shafto et al. [29] define the DT as “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc.,” to mimic its physical counterpart. The DT mirrors physical system conditions and response using big data streaming between real and virtual allowing the DT to be a model that produces physical simulations based on the experiences of the system’s physical counterpart in addition to perfect, no-noise simulations. The data is logged and collected over time, processing the information through analyses utilized to implement algorithms, statistics, and deep learning features that are required for predictive maintenance and health monitoring strategies. The prognostic method utilized to develop predictive maintenance in the DT is outlined following a general two stage approach by Kordestani et al. [60] for fault prognosis. Stage 1 is the ‘failure model identification stage’ where a failure model is constructed to gain data from the system, and Stage 2 is the ‘prediction stage’ where the forecasting of system life occurs through a battery of analyses to make decisions on future behavior or needs. Statistical analysis and signal processing methods used for predictive maintenance in the DT are categorized as knowledge-based approaches. Antonio-Daviu et al. [69] state that the signal processing-based prognosis is known to have the highest accuracy in RUL predictions by investigating faulty signals. This knowledge-based approach is applied to the DT to process signals virtually using physics and dynamical models. DT technology addresses the gap in prognostic applications by integrating and embedding intelligent systems, thereby enhancing predictive maintenance methods with advanced learning capabilities.

The DT instrument leverages a continuous collection of data from physical systems (or
Figure 3.3: Benefits of predictive maintenance illustrated with general repair cost and complexity over time for progressive system anomalies.

Simulations that model physical behavior) at the individual or fleet level. The dataset employs big data transfer and Internet of Things (IoT) technologies to facilitate the transmission of signal information between physical systems and virtual analysis tools. After collection and sorting, the DT receives all the data and utilizes operational inputs to run simulations, estimating the current health status of the system by assessing metrics such as the Remaining Useful Life (RUL) of parts or subsystems, as well as identifying potential failures. Figure 3.4 compares the DT role in health management to traditional maintenance strategies. Physical sensors read outputs from the system which are sent through a control framework filtering and tuning actuators in feedback of the physical system. Traditional maintenance diagnostics and prognostics observe field data streamed from the control system to detect and identify failures and perform on-board scheduled maintenance. The DT environment, however, utilizes both field data and operating conditions in conjunction with a virtual vehicle model that employs design requirements and system models. The DT then integrates diagnostics and prognostics through physics-based, knowledge-based, and data-driven synergy. Lifecycle management and maintenance predictions are made continuously with the DT and are then implemented to the control system for application in the physical system regularly.
Figure 3.4: Predictive maintenance in the digital twin environment contrasted with traditional and OBD-based maintenance strategies.

DT technology aids in health maintenance through big data collection, complete simulations, and intelligent analyses of mechanical, electrical, and civil systems. Jones et al. [14] state that maintenance decision making is a perceived benefit of the DT tool across multiple disciplines and practices. Macchi et al. [70] investigate the role of the DT in lifecycle management and find that DT technology is useful for assessment of health status and providing analytics to design features for diagnosis, limiting unreliable conditions. To leverage the perceived benefits in health maintenance of the DT, Venkatesan et al. [71] provide a detailed case study exploring monitoring and prognostic behavior implementation of an electric vehicle motor, proving useful in prediction of anomalies and failures. Zheng et al. [72] propose an application framework for lifecycle management utilizing DT technology with a provided case study. This framework and case study identifies an opportunity to develop a general health maintenance methodology. A similar DT implementation framework for entire military ground vehicle fleets was reviewed by Madni et al. [73] describing “simulation-based analysis of operational, maintenance, and health data from the physical twin” as a means to promote optimization, improve maintenance strategies, and predict system operation. Military vehicle systems make an excellent candidate for exploring DT framework implementation and study.
3.4 Smart Predictive Maintenance Strategy

Recent advances in machine learning (ML) and artificial intelligence (AI) can be coupled with digital twin technology to realize fleet wide predictive maintenance. The ML/AI methods include statistical classification, regression analysis, deep learning, and anomaly detection to couple with PM algorithms. Digital twin technology enables data mining to perform statistical regressions and analyze them achieving anomaly detection through deep learning. Advantages of digital twin collaboration with predictive maintenance methods include harnessing big data, sorting and filtering streamed data sets, and predicting failures and their causes across fleets. In this section, signal generation, signal preparation, applicable ML methods, and digital twin integration will be presented.

The model-based digital twin based predictive maintenance strategy illustrated in Figure 3.5 analyzes physics-based estimates of plant behavior. Simulation tools including lumped parameter system models, neural networks, and machine learning models utilize plant inputs to calculate the plant behavior. Inputs for ground vehicle investigation include operating cycles, vehicle databases, libraries of dynamic and kinematic models, intentional fault scenarios, and noise. Predictive maintenance training filters collect data and classify it to identify and estimate future behavior. After analyzing the output signals, \( x_{ij} \in \mathbb{R}^{nxm}, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \) where \( i \) is the recorded vehicle signals and \( j \) corresponds to the collected signal data points. The matrix of data points, \( x_{ij} \), is analyzed as features split into three different categories: statistical features, impulsive metrics, and signal processing metrics. The statistical matrices are denoted as \( X_S \) where \( S \) is the type of statistical feature.

To calculate the statistical features, analyze them for trends in different domains, and forecast plant behavior by estimating RUL computer algorithms can be applied. The statistical features evaluated include mean, standard deviation (STD), root mean square (RMS), shape factor, kurtosis, and skewness. The shape factor, \( X_{SF} \), for each signal, \( j \), may be computed as

\[
X_{SF} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_{ij}} / \sqrt{\frac{1}{n} \sum_{i=1}^{n} |x_{ij}|}, (i = 1, 2, ..., n), (j = 1, 2, ..., m)
\]  

(3.1)

and corresponds to the signal’s structure. A signal’s peakedness or Kurtosis, \( X_K \), becomes
corresponding to the second and fourth central moments of the data set. If \( x_{ik} > 0 \), then it is considered leptokurtic while \( x_{ik} < 0 \) means it is platykurtic. Terms lepto- and platykurtic identify whether the data is heavy- or light-tailed in distribution of outliers, respectively.

The skewness, \( X_{SK} \), is defined as

\[
X_{SK} = \frac{1}{n} \sum_{i=1}^{n} \left( x_{ij} - \bar{x}_{ij} \right)^3, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \tag{3.3}
\]

which quantifies the asymmetry of a signal distribution. When a fault or degradation occurs, it may affect the symmetry of the distribution which increases the level of skewness.
The impulsive metric denotes the signal peaks including the peak value, impulse factor, crest factor, and clearance factor. Peak analysis is able to provide early warnings to faults upon initial formation. The peak value, $X_P$, is an extremum signal given as

$$X_P = \max_i |x_{ij}|, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \quad (3.4)$$

The impulse factor, $X_{IF}$, is expressed as

$$X_{IF} = \frac{x_{jp}}{\frac{1}{n} \sum_{i=1}^{n} |x_{ij}|}, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \quad (3.5)$$

The crest factor, $X_{CR}$, is computed as

$$X_{CR} = \frac{x_{jp}}{\sqrt{x_{ij}}}, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \quad (3.6)$$

and tends to apply to rotating machinery and components. Finally, the clearance factor, $X_{CL}$, becomes

$$X_{CL} = \frac{x_{jp}}{\left(\frac{1}{n} \sum_{i=1}^{n} \sqrt{|x_{ij}|}\right)^2}, (i = 1, 2, ..., n), (j = 1, 2, ..., m) \quad (3.7)$$

The signal processing metrics utilize distortion measures which interpret perceivable signal quality. Degradation of a system or its components can be indicated by a signal-to-noise ratio (SNR) increase, a change in harmonics respective to fundamental power known as total harmonic distortion (THD), or a combination of the two calculated as the signal to noise & distortion (SINAD) ratio.

After performing time- and frequency-domain signal harvesting, the signals are sorted using one-way analysis of variance (ANOVA), a multi-class condition variable ranking technique. One-way ANOVA is a parametric test that compares the statistical means of two or more independent signals to quantify separability of data. Once ranked, the superfluous signal features are eliminated and the remaining features are sent to a classification learner where model training, validation, and testing takes place. The model uses the signal features to make fault condition predictions and calculate validity. Model validation corresponds to the percentage of correct predictions to the total number of observations made. New external data is then tested from the trained and validated model to assess signal feature ability to distinguish fault conditions.
The digital and diagnostic concepts with mathematical metrics covered will now be applied to create a preventative maintenance strategy for ground vehicles. A four-wheeled ground vehicle is investigated that undergoes various driving scenarios subject to soft anomalies for the case study. The predictive maintenance toolbox within MathWorks seamlessly integrates with the created digital twin modeling framework. The models provide a 14 degree-of-freedom system tested to accurately represent ride, handling, suspension, powertrain, controls and more. The software allows user input boundary conditions and constants to best simulate the profile of the vehicle at hand. The versatile tool is able to collaborate with data streaming platforms, to collect and analyze data from different environments, and to execute predictive maintenance methods. This digital twin will be utilized to create data for both training and testing purposes.

3.5 Case Study: Vehicle Predictive Maintenance Strategy

A case study is presented to illustrate the predictive maintenance strategy implemented with digital twin technology of a ground vehicle system. The vehicle models contained within the study will correspond to the Clemson University Deep Orange 13/14 track off-road vehicle that has been designed, fabricated, and field tested. While the Deep Orange 13/14 vehicle is a tracked vehicle, the nature of the dynamic models in this paper for a wheeled vehicle provides an outline to follow. The wheeled vehicle model discussed offers a verifiable baseline for predictive maintenance to the Deep Orange project. This section provides an overview of the digital twin tool, a review of the predictive maintenance strategy, and showcases numerical results from the case study.

3.5.1 Overview of digital twin models

A digital twin is an impactful tool in the design and support of off-road ground vehicles subject to harsh environments. Eddy et al. [74] discuss ground vehicle DT architecture and development. Wheeled vehicle and chassis dynamics are also discussed, identifying type of vehicle model used in this study along with corresponding mathematical descriptions. A free body diagram of vehicle body dynamics is provided in Figure 3.6, illustrating the forces and moments acting on the vehicle at the wheels and the center of gravity (CG). The input signals from the driver, or operator, and the environment are sent to the control system—which run in a feedback loop with the vehicle dynamics—which performs certain behaviors and maneuver commands for the vehicle system to
undergo. The mathematical equations model an off-road vehicle with four wheels. The suspension system consists of independent MacPherson struts on the front axle with solid rear-axle suspension.

The body forces, $F_x$ and $F_y$, and moment, $M_z$, may be calculated based on the forces acting at each wheel as

$$F_x = F_{x1} + F_{x2} + F_{x3} + F_{x4} - F_D \quad (3.8)$$

$$F_y = F_{y1} + F_{y2} + F_{y3} + F_{y4} \quad (3.9)$$

Figure 3.6: Vehicle dynamics diagram with tire/road interface and suspension subsystems.
\[ M_z = b_b (F_{x1} - F_{x2} - F_{x3} + F_{x4}) + b_c (F_{y1} + F_{y2}) - b_d (F_{y3} + F_{y4}) \]

where \( F_{xi} \) and \( F_{yi} \) denote the longitudinal and lateral forces, respectively, acting on each wheel. These forces include longitudinal and lateral slope resistance and rolling resistance acting at the wheels. The aerodynamic drag force, \( F_D \), acting on the vehicle is expressed as

\[ F_D = \frac{1}{2} C_D \rho A_D u^2 \]  

(3.10)

The longitudinal, lateral, and yaw accelerations of the vehicle body are provided as

\[ m(\ddot{u} - rv) = F_x \]  

(3.11)

\[ m(\ddot{v} + ru) = F_y \]  

(3.12)

\[ I_z \dot{r} = M_z \]  

(3.13)

where \( u \) and \( v \) denote the longitudinal and lateral velocities of the vehicle, respectively, and \( r \) describes yaw rate angular velocity. The normal forces are dependent on the normal loads at the wheels, \( F_{zi} \), so that

\[ F_{z1,2} = -\frac{mg b_d}{2(b_c + b_d)} + \frac{hF_x}{2(b_c + b_d)} \pm \frac{hF_y K_f \phi}{2b_l (K_f \phi + K_r \phi)} \]  

(3.14)

\[ F_{z3,4} = -\frac{mg b_c}{2(b_c + b_d)} - \frac{hF_x}{2(b_c + b_d)} \pm \frac{hF_y K_r \phi}{2b_l (K_f \phi + K_r \phi)} \]  

(3.15)

Rotational wheel dynamics, illustrated in Figure 3.7, are given by

\[ I_{wy} \dot{\omega}_i = T_i + F_{xwi}(R - \delta_{zi}) - C_{wi} \dot{\omega}_i - F_{zi} x_{zi} \]  

(3.16)

which apply Newton’s second law for rotational systems in the wheel plane about the wheel spin axis (y-axis).
3.5.2 Predictive maintenance strategy review

Predictive maintenance training is a deep learning, neural network of data leveraged to learn and predict vehicle behavior. A baseline of vehicle information is necessary including its specifications, various operating scenarios, and field data streaming capability. The digital twin is a computer model that is able to simulate real-time vehicle behavior and apply updated vehicle information to enhance simulation accuracy and provide more up-to-date predictions. Through data streaming and artificial intelligence, the digital twin can validate and verify the system models and generate more reliable simulation forecasts. Known failures and failure types must be assessed and implemented into the digital twin to initialize anomaly detection. Training and validation is performed to verify correct fault predictions and vehicle anomalies. Figure 3.8 illustrates the predictive maintenance process applied in the case study, showing the application of fresh data to be analyzed to predict remaining useful life of a vehicle system. All of this data is analyzed through the three levels of anomaly identification. The first, level 1, is detection, which determines whether
a fault occurred. Level 2 is localization, which assesses where the fault occurred, in what subsystem or component. And level 3 involves severity, analyzing how damaging the fault is and estimates remaining useful life in the part or system post-fault.

![Figure 3.8: Predictive maintenance and case study application flow diagram.](image)

A description of the simulation software model and methodology is provided. MATLAB Simulink vehicle dynamics libraries are used in model creation for DT and PT analysis. The subsystems and associated signals within the model are depicted in Figure 3.9. The model libraries utilize pre-existing dynamics models to simulate total vehicle behavior including engine, steering, transmission, driveline, braking, body, suspension, and wheel dynamics. The models simulate a 14 degree of freedom (DOF) passenger vehicle with environment signals, linear predictive driver commands, and control system feedback as inputs to the vehicle. The lightweight four-wheel off-road vehicle features rack-and-pinion steering along with a 10-speed automatic transmission. The spark ignition engine uses a torque and speed map to output signals to the vehicle body. To gather fleet-level data, a range of simulations is performed with the PT model.

The ground vehicle dynamics introduced in the previous section served as the basis for the predictive maintenance case study. A series of prescribed driving maneuvers and seeded anomalies were numerically gathered and assessed. A double-lane change maneuver induces translational and rotational motion in all 3 body axes. The longitudinal acceleration from 0 to 9 m/s produces bounce and pitch which applies additional load to the suspension. Roll, pitch, and yaw are observed when
the vehicle shifts into the left lane, 3 m, while maintaining constant speed at 10 seconds. At $t = 20s$
the vehicle returns to the original lane. Seeded degradations are applied to the vehicle dynamic
simulation in the predictive maintenance process as shown in Figure 3.5.

A suite of eight soft failures were introduced into the digital twin environment to create
a healthy and non-healthy database for training purposes. The catalog of parameters in Table
3.1 summarizes the parameter values and how the seeded faults are applied in the ground vehicle.
Suspension damping and spring coefficient anomalies emulate impact and wear over time through
rigorous and extended off-road operation (e.g., constant suspension vibration from off-road driving
can affect the viscosity of damping fluid or puncture the damper resulting in a leak of fluid). Propul-
sion systems experience faults in damping and stiffness of prop shaft power transmission through
manufacturing misalignments and normal wear-and-tear of off-road driving conditions. Ground con-
tact affects tire pressure and friction coefficients when faults occur including air leaks and tread
wear. All seeded fault scenarios consider five levels of degradation severity utilizing gains $a_i$ and $b_i$
for $i = (1, 2, \ldots, 5)$, where $a = [1.2, 0.9, 0.8, 0.6, 0.3]^T$ and $b = [0.9, 0.8, 0.7, 0.5, 0.3]^T$. The organized
fault code simulations were compared to 100 non-degraded simulation runs of the drive scenario along

Figure 3.9: Vehicle dynamics schematic for digital twin model.
with a combination fault consisting of suspension spring degradation compounded with a loss in tire to ground friction. Each of the 275 total simulations gathered provide 176 logged output signals serving as a basis for numerical and statistical analyses in the predictive maintenance process.

Table 3.1: Summary of degradation scenarios (Tests A-F) and simulation conditions for double-lane change maneuver.

<table>
<thead>
<tr>
<th>Parameter/signal</th>
<th>Healthy value</th>
<th>Degradation value</th>
<th># of simulations</th>
<th>Fault code</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1. Suspension shock damping coefficient</td>
<td>$C_{z1} = 5565.2 \left( \frac{N, m}{m^2} \right)$</td>
<td>$a_iC_{z1}$</td>
<td>25</td>
<td>11</td>
</tr>
<tr>
<td>A2. Suspension spring coefficient</td>
<td>$K_{z1} = 52451.0 \left( \frac{N}{m} \right)$</td>
<td>$b_iK_{z1}$</td>
<td>25</td>
<td>12</td>
</tr>
<tr>
<td>B1. Prop shaft torsional damping coefficient</td>
<td>$C_t = 10 \left( \frac{N,m,,s}{rad} \right)$</td>
<td>$a_iC_t$</td>
<td>25</td>
<td>21</td>
</tr>
<tr>
<td>B2. Prop shaft torsional stiffness</td>
<td>$K_t = 5000 \left( \frac{N,m}{rad} \right)$</td>
<td>$b_iK_t$</td>
<td>25</td>
<td>22</td>
</tr>
<tr>
<td>C1. Tire pressure</td>
<td>$P_t = 224000 (Pa)$</td>
<td>$a_iP_t$</td>
<td>25</td>
<td>31</td>
</tr>
<tr>
<td>C2. Ground friction coefficient</td>
<td>$\mu_G = 1$</td>
<td>$b_i\mu_G$</td>
<td>25</td>
<td>32</td>
</tr>
<tr>
<td>D. Healthy (no subsystem degradation)</td>
<td>Various</td>
<td></td>
<td>100</td>
<td>00</td>
</tr>
<tr>
<td>E. Combination of tests A2 and C2</td>
<td>Various</td>
<td></td>
<td>25</td>
<td>50</td>
</tr>
</tbody>
</table>

3.5.3 Numerical results

The accumulated numerical data from sensors executed using the digital twin is analyzed and processed per filtering techniques, time- and frequency-domain analyses, and condition exploration methods. This process is applied to all signals described in Table 3.1, however, only one signal of left front axle vertical velocity is shown for conciseness to illustrate the framework presented. Some additional signals and statistical analyses are provided in Appendix D. Pre-processing approaches prepared the numerical results for analysis through methods including filtering, averaging, and spectral computation. Periodic disturbances are eliminated and excessive noise is smoothed through time-synchronous averaging (TSA) of the numerical results before further statistical analyses. Figure 3.10 shows the time trace and TSA filtering results for all 275 simulations. Filters and averages are used as an additional aid for the predictive maintenance algorithm of which will be ranked and validated, not all signals will leverage these statistical measures to ensure the stochastic nature is not lost. Statistical analyses begin with time-domain techniques, once pre-processing has appropriately
filtered the data set, including mean, root mean square, standard deviation, peak value, crest factor, shape factor, clearance factor, kurtosis, and skewness. Additionally, frequency-domain analyses are conducted including signal-to-noise ratio (SNR), total harmonic distortion (THD), signal to noise and distortion (SINAD), and band power. Equations and computation of both time- and frequency-domain analyses are detailed per Section 4.2. The analyses compute values for each condition providing metrics to gauge distinguishability between fault codes. The output values of these statistical analyses, or features, indicate condition type, providing ability to organize and differentiate simulations by fault code.

To construct the fault code mappings, features will be extracted and ranked through a statistical process. Effectiveness of features developed from the time- and frequency-domain analyses vary dependently on system parameters and available numerical results. The statistical metrics provide a framework for feature exploration measuring their ability to distinguish fault types by numerical results. A fault code mapping is a statistically evaluated feature assessing fault type on a regular time interval. Some features indicate condition status more accurately, requiring a ranking metric of statistical features by way of analysis of variance (ANOVA) testing. Independent variable influence on dependent variables are tested using the ANOVA method, ranking viability across all statistical feature results. A second ranking procedure, monotonicity testing, evaluates features for preserving or reversing constant order over a time interval. All features tabulated providing statistical effectiveness are ranked in Figure 3.11 primarily by one-way ANOVA and secondly by monotonicity. Statistical mean, signal to noise and distortion ratio (SINAD), and standard deviation prove to rank highest in condition indicating ability signal analysis of the front left axle vertical velocity.

The visualization of the diagnostic training, mapping, and validation enable insight into the effectiveness of each feature. A confusion matrix prediction map, illustrated in Figure 3.12, depicts the effectiveness of the selected features and their mappings. Statistical features appropriately predicted and mapped fault codes as true class anomalies are true positive results (TPR) and incorrect mapping of fault type yields false negative results (FNR). True positive results for healthy system behavior (Fault code 0) yielded a 93% prediction accuracy, reflecting in a highly accurate detection ability relating to level 1 anomaly identification. Suspension shock damping anomaly (Fault code 11) shows a 56% true positive result accuracy, however there is a 36% false negative result of predicted suspension spring constant degradation. This shows that even though a large
Figure 3.10: Signal trace (top) and time synchronous averaging (bottom) of the left front axle vertical velocity, $v_{z_1}$, for Tests A-E during first lane change.
percentage of results were incorrectly predicted, they were still found in the same vehicle subsystem, which demonstrates the classification learner’s ability to localize some of the anomalies per level 2 anomaly identification.

The classification learner’s ability to predict behavior in its given data set is the starting point for predicting future anomalies. Validation of fault code statistics is achieved by simulating new maneuvers and vehicle behavior with similar seeded anomalies. Fault code 50 is used as a new data set, fresh vehicle information previously not seen by the classification learner, to validate the predictive maintenance algorithm. This fault code represents a compound fault of 2 anomalies, suspension spring degradation occurring simultaneously with a ground friction variation. The ex-
tracted features predict fault class with the newly seeded anomalies correctly in both the suspension spring and ground friction coefficient anomalies as shown in the green validation boxes in Figure 3.12. This validates the mapping by testing new data with current statistical features, yielding a 40% prediction accuracy of the new compound numerical test results.

The remaining useful life (RUL) of an asset can be estimated by analyzing past and current operating conditions to project future performance. RUL is able to assess how much damage a part of subsystem has incurred and in turn how much more damage it is able to withstand, representing level 3, severity, of anomaly identification. Increasing the sample size of the available field data or the simulated numerical results should improve the accuracy of RUL prediction. The RUL is
determined by plotting the predicted point of failure based on historical data over time. Historical
data can be extrapolated from accelerated simulation results to provide a baseline of future vehicle
behavior estimation. Analyzing the numerical data from the degradation scenarios in Table 3.1 with
extended time samples predicts the time of failure.

To demonstrate the PM concept, a different platform degradation will be considered in the
left front suspension system corresponding to a softening spring. Figure 3.13a displays a healthy
spring travel in the vertical (z-axis) direction due to normal stiffness. After approximately 100
minutes (80 km) of the degradation, Figure 3.13b illustrates axle displacement showing a greater
deviation from nominal motion. As expected, the spring softening results in a sagging of the chassis
on that corner of the vehicle as evident by the reduced mean vertical displacement. The spring
softening will likely require component replacement to ensure continued mission availability. Fig-
ure 3.13c shows both the accelerated and nominal velocity profiles in addition to normal, healthy
behavior for anticipated spring life with PM recommended (fault code) for the ML algorithm. The
boundaries of the oscillations have a useful life range shown; when outside of the range, fault de-
tection and maintenance notifications are prompted. With a softened spring the velocities decrease
in magnitude as shown since there is less spring force overcoming the dampener to accelerate the
corner of the sprung mass vehicle.

3.6 Summary

Optimization of maintenance is integral to military ground vehicle application and design
in consideration of time and repair cost/complexity. Health monitoring was discussed with cur-
rent methods including diagnostic and prognostic approaches. The PM method gathers data from
a physical system and analyzes it against healthy data. Fault conditions are identified through
signal analyses which are trained in a classification learner to implement prediction capabilities in
the model. Data analysis included time-domain signal and frequency-domain spectral feature pro-
cessing, utilizing statistical analyses to develop condition indicators. DT technology leverages data
management and virtual-to-physical communication to implement continuously updated PM strate-
gies. A case study logged 66 outputs, where four were studied in detail, from a vehicle PT model
that were analyzed using the PM approach. Signal and spectral features were designed and ranked
using a diagnostic feature designer and a one-way ANOVA ranking method. The features were sent
Figure 3.13: Before degradation affects (top), degradation over time (middle), remaining useful life over time (bottom). PM protocol is estimated but should be based on actual vehicle historical operating data when available.
through classification learning and compared by number of signals, more signals yielded an increase in model validation accuracy and a decrease in validation cost, prediction speed, and training time. The overall results from a four signal feature model included a trained validation accuracy of 92% with a validation cost of 24 observations. The model saw a prediction speed of approximately 20,000 observations per second with a training time of 0.613 seconds. Combination faults are the most difficult to identify with the model created but still prove great ability to indicate conditions and fault codes with a 40% test accuracy between a compound of suspension spring and prop shaft torsional damping degradations. Validation accuracy and potential to identify fault code types with combination faults increases greatly with larger streams of data, greater signal exploration, and more drive time and vehicle behavior references.
Chapter 4

Usefulness and Time Savings
Metrics to Evaluate Adoption of Digital Twin Technology

4.1 Abstract

The application of virtual engineering methods can streamline the product design process through improved collaboration opportunities among the technical staff and facilitate additive manufacturing processes. A product digital twin can be created using the available computer-aided design and analytical mathematical models to numerically explore the current and future system performance based on operating cycles. Of interest to companies is the strategic decision to implement a digital twin; whether the required financial and workforce resources will be worthwhile. In this paper, two metrics are introduced to assist management teams in evaluating the technology potential. The usefulness and time savings metrics will be presented with accompanying definitions. A case study highlights these metrics for the “Deep Orange” prototype innovative off-road hybrid vehicle that was design and fabricated at Clemson University. The results demonstrate that model repertoires can be leveraged to new product cycles and fill the knowledge gaps with new engineers joining the development team. Overall, the metrics establish a basis to generate discussions regarding embracing emerging workplace technology.
4.2 Introduction

Digital A Digital Twin (DT) is a computer model-based entity that parallels a physical system to predict and simulate the dynamic behavior. This advanced modeling tool may serve as a basis for system design studies, enhanced additive manufacturing cues, system upgrades including mission expansion, next generation products, and health monitoring with predictive maintenance. To achieve these objectives, data may be collected from the virtual and physical systems for evaluation of current and future behavior, prediction of response due to different operating cycles, and statistical analysis with data mining. The DT, a powerful virtual engineering tool, has the potential to benefit many industries and engineering enterprises. The possible gains include manpower savings, reduced product design times, enhanced collaboration, and greater product quality. The identification and careful consideration of the potential advantages are important when evaluating the impact of digital twin technology in both engineering and manufacturing processes. The general placement of a DT within a product lifecycle management (PLM) approach offers a holistic approach over conventional engineering processes as shown in Figure 4.1. The typical engineering workflow often features a linear design process where projects are worked on by individual(s) who finish their tasks before moving to the next group. In contrast, the DT within a PLM structure, encourages synergy amongst all enterprise groups including business (e.g., human resources, accounting, legal services, executive suite, etc.), engineering, manufacturing, and field service for the product.

A brief open literature review will be presented on digital twin technology. Sahfto et al. [29] from NASA provided an aerospace engineering DT definition with “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin.” An aeronautical position paper [30] offers a DT description with the discussion of numerous applications. Schleich et al. [75] explored the benefits of the DT including how essential it is to bring the design and manufacturing activities closer together as well bridge the chasm between virtual and physical worlds. Madni et. al [73] provided nine important factors which distinguish DTs from CAD/CAE models so that the benefits are more discernable. A notable benefit mentioned across several papers, including Magargle et al. [76], is the DT usefulness in observing degradations or abnormalities which are not easily observed in physical testing and/or with sufficient quantity to accurately train maintenance algorithms. Among all of these qualitative benefits, Jones et al. [14] provides a systematic review
Figure 4.1: Introduction of a Digital Twin within a PLM structure and contrast with a typical engineering process.

of DT technology with the identification of both strengths and gaps within the field. Further, these authors issued a call for “metrics” to describe the benefits and utility of a digital twin. As they noted in their article, the DT is an emerging technology that often lacks clarity on actual usefulness and utility so a metric would be helpful.

To understand the creation of a DT metric, a distinction between prescriptive and descriptive quantifications must be established. A prescriptive quantification looks at whether the DT would be a useful tool to an enterprise before the implementation of it. In other words, a prescriptive metric serves as a basis to determine if the tool is worth considering prior to its use. The prescriptive Digital Twin Technology Usefulness (DTTU) metric can help guide decision making in determining whether a DT may be useful to the company. And if so, which type of DT, or level of sophistication, would best suit the specified application. On the other hand, a descriptive quantification examines the utility and savings that a DT may provide during and after its implementation. The descriptive
Digital Twin Time Savings (DTTS) metric evaluates the DT measurable benefit to the enterprise or project. Specifically, the assessment of realized savings and their respective areas to quantify the DT benefits. Together, the prescriptive and descriptive quantifications offer a solution to the DT metric as suggested by Jones et al. [14].

The creation of DT metrics, which has not been holistically described and applied in the open literature, has been explored in this project. Specifically, what questions can be posed and to help assess the usefulness of this emerging virtual technology within an enterprises. The remainder of the paper is organized as follows. Section 2 provides the prescriptive Digital Twin Technology Usefulness metric. In a similar manner, the descriptive Digital Twin Time Savings Metric is presented in Section 3. Section 4 contains a Case Study with the application of these metrics to an off-road prototype vehicle undergoing design and fabrication at Clemson University. Finally, the conclusion is presented in Section 5.

4.3 Digital Twin Technology Usefulness

The prescriptive Digital Twin Technology Usefulness metric enables an enterprise to assess whether the DT would be helpful prior to implementation. The metric gauges future benefits and potential costs to help quantify associated uncertainties before application. Moreover, the metric provides useful insight into the type and sophistication of the DT. This quantification is helpful since new technology comes with a steep learning curve which may lead to the abandonment thereof due to workforce limitations, employee buy-in, and/or associated costs. The focus in determining technology readiness measures and potential usefulness has been outlined in Table 4.1. These readiness measures include Design Modularity (Factor 1), Model Organization (Factor 2), Design Validation & Verification (V&V) per Factor 3, Manufacturing (Factor 4), Health Monitoring (Factor 5), and Opportunity Cost (Factor 6) which help determine whether a DT application would be useful and beneficial. As observed in Table 4.1, each of these factors have two or three subfactors listed that should be evaluated in the assessment. Overall, these DTTU metric factors and subfactors are based on the necessity and advantages of the DT technology for individual enterprises.

There are varying levels of DT sophistication which can be tailored to different engineering and manufacturing applications. In this research project, the DT tool levels have been displayed in Figure 4.2. Stage 0 corresponds to the recommendation of DT avoidance; the stage where the tool
Table 4.1: List of DTTU subfactors and their ranking descriptions.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Subfactor</th>
<th>Label</th>
<th>Ranking description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design modularity</td>
<td>f₁₁</td>
<td>Product life</td>
<td>Long anticipated lifetime of the product requires modularity in updates or upgrades.</td>
</tr>
<tr>
<td></td>
<td>f₁₂</td>
<td>Platforming</td>
<td>Multiple products or systems utilize a common component or architecture creating a platform that utilizes modularity.</td>
</tr>
<tr>
<td></td>
<td>f₁₃</td>
<td>System complexity</td>
<td>Complex systems involve a large quantity of subsystems and components which incentives modular design.</td>
</tr>
<tr>
<td>Model organization &amp; documentation</td>
<td>f₂₁</td>
<td>Model library</td>
<td>The quantity of components and subsystems affects difficulty to organize and document models appropriately.</td>
</tr>
<tr>
<td></td>
<td>f₂₂</td>
<td>System naming convention</td>
<td>Many and similar signals and parameters shared across multiple subsystems require more organization and documentation.</td>
</tr>
<tr>
<td>Design V&amp;V and reliability</td>
<td>f₃₁</td>
<td>Validation &amp; verification</td>
<td>Processes to increase fidelity and ease of V&amp;V methods.</td>
</tr>
<tr>
<td></td>
<td>f₃₂</td>
<td>Safety</td>
<td>Ensuring system safety for operators, designers, and stakeholders.</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>f₄₁</td>
<td>Scale</td>
<td>Quantity of product accounts for economies of scale and mass customization.</td>
</tr>
<tr>
<td></td>
<td>f₄₂</td>
<td>Complexity</td>
<td>Production complexity in assembly processes, machining methods, and/or need for specific fabrication tools.</td>
</tr>
<tr>
<td></td>
<td>f₄₃</td>
<td>Planned improvements</td>
<td>Preconceived upgrades to the system require manufacturing consideration to account for later design improvements.</td>
</tr>
<tr>
<td>Health monitoring</td>
<td>f₅₁</td>
<td>Anticipated life</td>
<td>Necessity of health monitoring increases as anticipated system lifetime increases.</td>
</tr>
<tr>
<td></td>
<td>f₅₂</td>
<td>Diagnostics &amp; prognostics</td>
<td>Recognition of degradations and failures before they occur, identification of root cause, and proposed maintenance solutions.</td>
</tr>
<tr>
<td>Opportunity cost</td>
<td>f₆₁</td>
<td>Implementation</td>
<td>Software, training, engineering expertise, onboarding, financial, and educational expenses associated with DT implementation.</td>
</tr>
<tr>
<td></td>
<td>f₆₂</td>
<td>Other methods</td>
<td>Benefits of current or traditional engineering methods in contrast with DT application.</td>
</tr>
</tbody>
</table>

should not be considered. Stage 1 is a limited version of the tool intended for ease of implementation with benefits that suit specific needs excluding superfluous design tools. Stage 2 suggests a Digital Twin tool that includes virtual to physical connection while maintaining low implementation costs which can reduce prototyping needs and enhance the overall performance of the system. Stage 3 includes all the benefits from Stage 2 in addition to production and manufacturing optimization using virtual modeling. Finally, Stage 4 increases the sophistication of the interaction between the virtual and physical systems improving performance and reliability as well as the introduction of health monitoring. Stage 4 is the highest level of a Digital Twin which includes all tool benefits to
design the best product or system possible with prognostics and performance management.

Figure 4.2: Stages 0-IV of an enterprise based digital twin.

The DTTU metric consists of the six usefulness factors, $f_i, (i = 1, 2, ..., 6)$, per Table 4.1 with normalizing gains, $a_i$, so that

$$DTTU = \sum_{i=1}^{6} a_i f_i \quad (4.1)$$

where the gains, $a_i$, may be positive or negative to reflect benefit or cost.

Each of the usefulness factors, $f_i$, contain a sequence of subfactors, $f_{ij}$, that describes the given category in more depth so that

$$f_i = \frac{1}{n} \sum_{j=1}^{n} f_{ij}, (i = 1, 2, ..., 6) \quad (4.2)$$

where $n$ is the total number of subfactors for the $i^{th}$ factor. Note that the individual factor values are the average of their subfactors.

The factors-subfactors are evaluated using a Likert Scale rating approach to assess the potential usefulness of DT technology to the enterprise based on application needs and requirements. The Likert scale ratings range from 1 to 7 where a rating of 1 signal that the factor has negligible
significance in the design process. In contrast, a rating of 7 indicates that the factor is exceedingly important in the system design. A middle rating of 4 denotes a factor to have relevance but may not be a necessary significance. The ratings in between support a spectrum of rating options to consider future DT utility. Figure 4.3 depicts the layout of the Likert Scale for self-ranking.

Figure 4.3: Likert scale ranking for use in the digital twin DTTU metric assessment process.

4.3.1 Factor 1: Design Modularity

Design modularity is a benefit of the DT which increases utility in consideration of its three subfactors: product life, platforming, and system complexity. Design modularity is described as a system that can be divided into smaller parts, or modules, which can be independently created, modified, replaced, or exchanged with other modules. As product or system’s life, need for platforming, and complexity increases, so does the need of modularity. When an enterprise considers the implementation of DT technology, the subfactors in design modularity will influence the usefulness and type of DT application.

The first subfactor, $f_{11}$, for design modularity consideration is product life. This considers how long the designers want the system to last, how long the system should last, and how long it actually lasts. Other considerations include the influence of external factors on product life. If expected product life is short and there is no desire to lengthen it, then data streaming and data collection is minute, resulting in little to no usefulness of the DT benefits. The second subfactor, $f_{12}$, is platforming, which is the ability to use subsystems or platforms across different products to optimize manufacturing efficiency. Platforming is inherently modular, thus the increased need or desire in platforming for an enterprise increases the DT usefulness. The third subfactor, $f_{13}$, consideration is system complexity. With minimal system complexity, there is less of a need for modularity thus reduced utility of DT technology.
4.3.2 Factor 2: Model Organization and Documentation

Model organization and documentation of a system is a natural benefit of Digital Twin technology which is defined with the consideration of model library and system naming convention. In application there are many models and modules that make up a system, all of which must be well documented and organized. Oftentimes these models and modules are designed across different engineering teams and are sent through manufacturer and servicers where all are influenced by finance, accounting, human resources, and legal teams. The Digital Twin houses all models and signals in a unified location, creating a natural organization of systems, their signals, and documentation. The consideration of the subfactors for model organization and documentation result in defining another factor of Digital Twin usefulness for a system.

![Signal sharing and flow between computer models for consideration in DTTU Factor 2 (Model Documentation).](image)

The first subfactor, \( f_{21} \), for model documentation and organization consideration is model library. The quantity of models or modules used in design of a system is closely related to system complexity. The greater the number of models, and variation of models, the more likely it is to lose or mistake model intent and proper application. This increased quantity or complexity in models requires increased organization and documentation across groups for effective communication in technical material. For longer expected or desired life of the model library, the need for organization and documentation is also greater. The second subfactor, \( f_{22} \), considers system naming convention. Larger quantities of models, and variations of models, requires proper naming convention. With many engineers and groups working on and sharing different models there is an opportunity for signals and parameters to be lost, misused, or repeated. The Digital Twin benefits in housing and all models, signals, and parameters in one location to unify naming convention across an enterprise.
Figure 4.4 shows how signals or outputs from one model may be used as inputs in one or more models, even if they are not explicitly interconnected.

### 4.3.3 Factor 3: Design Validation & Verification and Reliability

Design validation verification and reliability is another advantage of the DT which aids in the VV processes during the design and development phases as well as increasing reliability of the system and its components. This factor improves the overall system and finished product in addition to the overall design process in terms of VV and reliability. In application the greater the fidelity determined by VV, the greater the interpretation of model behavior and predictions of performance. With model organization and documentation noted from factor 2, VV processes are accelerated because all the dynamic models abide in a single virtual space. Howard [77] discusses, with the use of engineering design automation tools, the DT accelerates development of a product through virtual validation. Data streaming increases reliability significantly because of the mass amount of field and sensor data extracted over time from physical systems. DT technology utilizes IoT and big data streaming to acquire mass amounts of sensor readings that are leveraged to alter the virtual models over time, increasing its reliability. Depending on how necessary or difficult VV is in an enterprise’s design process, the DT poses an advantage to the designers. The greater the need for reliability in virtual modeling, the more significant the role for the DT.

The subfactors, \( f_{31} \) and \( f_{32} \), for design VV and reliability are VV and safety, respectively. Subfactor, \( f_{31} \) or VV, is critical to model development to understand system behavior with increased fidelity and accuracy. Sargent [78] further discusses the importance of VV in model simulation providing a suggested process outline which is made easily achievable through the DT. When considering DT technology usefulness for implementation, designers must evaluate how necessary and difficult the VV processes are. The more complex or necessary VV is the better support the DT will be. Subfactor, \( f_{32} \) or safety, is supported by the DT as well. Wang et al. [79] make use of DT application by monitoring battery safety for electric ground vehicles. A common issue in lithium-ion batteries is thermal runaway which the DT can detect through anomalies using proper training of models. This highlights the significance the DT has in safety. Safety of the system, its operators, and manufacturing processes. When considering DT implementation, designers must understand the importance of safety for the system at hand. If safety is a nonissue for the product, the DT will not be as imperative as when the product requires high degrees of safety.
4.3.4 Factor 4: Manufacturing

DT technology improves manufacturing and its processes under consideration of production scale, complexity, and planned (future) improvements. Traditional and current engineering processes consider manufacturing toward the end of the design process. Kritzinger et al. [80] note that the digitization in manufacturing is becoming more necessary to accommodate the growing desire of mass customization and need for software components in the current market. Acknowledging manufacturing and its effects throughout the design process optimizes production for overall system quality, cost, and quantity. Smart, additive, and advanced manufacturing methods are becoming more in-demand due to new challenges in the market such as the increase in mass customization and use of software components as stated earlier. These intelligent methods reduce overall costs, increase production capacity, and reduce potential anomalies. Lu et al. [81] discuss the application of smart manufacturing in relationship to manufacturing assets, people, factories, and production networks through use of the benefits of DT technology. Figure 4.5 demonstrates the benefits in digitization of manufacturing when integrating DT technology to create further intelligent systems and processes in the overall design. This digitization improves the manufacturing processes and methods as well as equipment selection and equipment maintenance.

Figure 4.5: DT influence on manufacturing processes, decision making, and equipment performance.

The first subfactor, $f_{41}$, for manufacturing consideration is scale. Scale is notably the most important factor in deliberation of DT implementation. With larger scale production, DT benefits
greatly increase. A production DT is used to verify manufacturing processes and support decision making in the design process. The production DT is beneficial for both large- and small-scale production lines but becomes more necessary as the scale increases. Furthermore, product DTs are the virtual models used to simulate and predict behavior, performance, and maintenance. A system of product DTs can be created for all the manufacturing equipment to optimize performance and maintenance of both the processes and the tools used therein. The second subfactor, \( f_{42} \), is complexity. In general, the larger the scale of production, the greater the complexity. Smaller scale considerations have challenges in complexity too, such as minimizing cost while maintaining optimized performance whereas large quantity productions can leverage economies of scale. With increased complexity, the DT poses greater use to the manufacturing process to validate and optimize processes as well as equipment. The third subfactor, \( f_{43} \), for manufacturing consideration is planned improvements. Some products and systems have little to no room for innovation, having no need for future improvements. Other products may be designed with potential upgrades or changes in mind which will require manufacturing updates. The modularity of the DT allows for planned improvements which simultaneously considers manufacturing processes for those developments.

4.3.5 Factor 5: Health Monitoring

Health monitoring is a major benefit of DT technology defined by anticipated life and diagnostics prognostics. Current engineering methods in the design process rely on post-failure analyses to create maintenance schedules and failure detection devices, which is costly and time consuming. Lee et al. [54] deem it necessary for enterprises to move from traditional ‘fail and fix maintenance practices to a predict and prevent methodology.’ Intelligent predictive and preventative systems monitor performance and degradation as opposed to identifying faults after they occur. A system is design with an anticipated life in mind which is important to the product itself and the operator. Remaining useful life (RUL) is a metric that predicts how much longer a system or component can operate with acceptable performance. Venkatesan et al. [71] highlight the capability of the DT by performing remote health monitoring and prognostics of an electric vehicle motor using metrics such as RUL. Big data streaming using cloud communication and Internet of Things (IoT) is a benefit of the DT that leverages live updates for performance predictions and maintenance needs. Figure 4.6 illustrates a high-level process of system forecasting, comparing system data with DT outputs using statistical analyses to make a RUL prognoses and recommendations for future
maintenance. Health monitoring is a natural advantage of the DT for all types of engineering systems.

Figure 4.6: DT technology using live streamed data to predict system behavior and perform health monitoring diagnostics and prognostics on individual and fleet level vehicles.

The first subfactor, \( f_{51} \), for consideration of health monitoring is anticipated life. Anticipated life is defined as the time, miles, revolutions, or any variable that the engineers designed for and expect to see based on requirements and modeling. If the anticipated life of the system is extremely short, health monitoring including predictive maintenance may not be as useful or necessary. As anticipated life increases, the more likely there is a need for monitoring current and future health conditions and making maintenance predictions. The second subfactor, \( f_{52} \), is diagnostics and prognostics. DT technology offers a lot in terms of identifying degradations and determining maintenance needs before a failure occurs. Diagnostics and prognostics are methods that identify degradations or anomalies and determine their root cause as well as providing a maintenance strategy to avoid future failure. There must be a gauge for how valuable diagnostics and prognostics are to a system and its components. For a system that is relatively inexpensive to design and build the DT is excessive. But for a complex system with potential high risk of failure, diagnostics and prognostics become more necessary.

4.3.6 Factor 6: Implementation and Opportunity Cost

DT technology provides great benefits, it also may inherit losses which stem from application implementation and opportunity costs. Moyne et al. [82] describe a need for better quantifiable metrics highlighting the benefits of the DT, discussing some opportunity costs and implementation strategies in application examples. These costs are important to define because alternate benefits will be foregone due to implementation of the DT. An enterprise must consider current engineering practices and what methods, or processes will be removed or enhanced by way of DT application.
Creating DT models incurs a front-loaded cost where most of the effort and expense comes from the initial startup. After this, costs reduce significantly over the lifespan of the DT in proportion to its implementation. To best quantify the potential usefulness in the DTTU metric, the alternative engineering methods must be considered and compared.

The first subfactor, $f_{61}$, is implementation cost. These costs are a product of software, hardware, and computing expenses. This can be seen in acquiring modeling programs and suites capable to perform DT activities and appropriately model the applied system or components. More other implementation costs are a result of engineering and training. There must be engineers and trained staff that understand the ability and execution of the DT and its systems. Other implementation costs include simulation, data collection, and analysis expense. These incur from the large amounts of data required and extracted from models and physical systems to perform high fidelity analyses. The second subfactor, $f_{62}$, is opportunity cost. Opportunity cost is defined as the losses sustained from choosing the DT over other potential methods in the design process. These costs consider the traditional or current engineering methods that would be alternatives to the DT and weigh the benefits and costs between the options. A comparison is made from the alternatives and what opportunities are lost by choosing the DT is the opportunity cost.

To visually illustrate how each factor, normalized with a weighted gain, contributes to the summed DTTU value, the reader is directed to Figure 4.7. The metric is designed to be suitable for a wide variety of applications by giving enterprises authority to select the normalization gains for each factor based on relevance and importance in that field.

### 4.4 Time Savings Metric Concept

The descriptive Digital Twin Time Savings (DTTS) metric provides an enterprise the ability to assess the benefits gained from the DT after its implementation and use. This metric evaluates the advantages and disadvantages of the DT to quantify its usefulness and time savings after application. This approach proposes a solution to a call for quantifiable metrics issued by Jones et al. [14]. Moyne et al. [82] recognized that current DT metrics tend to exclusively consider profit gains. The DTTS metric gives another method of quantification of benefits besides financial net value-added. The savings measures are nearly identical to the DTTU measures in Table 4.1 except for the Implementation and Opportunity Cost factor as shown in Table 4.2. These measures, Design
Figure 4.7: Summary of DTTU and DTTS metrics topology with associated subfactors, harvested data sets, normalization terms, and summation.

Modularity (Factor 1), Model Organization (Factor 2), Design Validation Verification (Factor 3), Manufacturing (Factor 4), and Health Monitoring (Factor 5), have revised descriptions. As previously shown in Figure 4.7, each factor with normalization multiplier contributes to summed DTTS value based on the relevant importance of their presence in the enterprise.

The DTTS metric consists of five savings factors, \( g_i \) \((i = 1, 2, ..., 5)\), with normalizing gains, \( b_i \), given as

\[
DTTS = \sum_{i=1}^{5} b_i g_i
\]  

(4.3)

where the gains, \( b_i \), are self-denoted values signifying importance of each factor. These normalization gain values sum to 1, acting as percentages of the overall DTTS metric so that

\[
\sum_{i=1}^{5} b_i = 1
\]  

(4.4)

where an equal distribution for each factor would result in \( b_i = 0.2 \) for all \( i \).

Each factor, \( g_i \), contains a sequence of subfactors, \( g_{ij} \), that describe the factors in more
Table 4.2: List of DTTS subfactors and their ranking descriptions.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Subfactor</th>
<th>Label</th>
<th>Ranking description</th>
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<tbody>
<tr>
<td>Design modularity</td>
<td>$g_{11}$</td>
<td>Product life</td>
<td>Considers how useful modularity of the DT was regarding length of the product life for making updates, changes, or upgrades over the lifespan of the system.</td>
</tr>
<tr>
<td></td>
<td>$g_{12}$</td>
<td>Platforming</td>
<td>Evaluates product platforming and ability to save time with respect to shared components or modeling architecture across the system.</td>
</tr>
<tr>
<td></td>
<td>$g_{13}$</td>
<td>System complexity</td>
<td>Accounts for time saved concerning the DT ability to reduce system complexity by modular subsystems and components.</td>
</tr>
<tr>
<td>Model organization &amp; documentation</td>
<td>$g_{21}$</td>
<td>Model library</td>
<td>Assesses size and organization of the library of models benefited by DT technology.</td>
</tr>
<tr>
<td></td>
<td>$g_{22}$</td>
<td>System naming convention</td>
<td>Surveys time saved through DT by organization of quantity and necessity of signal and parameter names involved in the system.</td>
</tr>
<tr>
<td>Design V&amp;V and reliability</td>
<td>$g_{31}$</td>
<td>Validation &amp; verification</td>
<td>Examines DT benefit throughout V&amp;V operations throughout the design process increasing reliability by data collection.</td>
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<tr>
<td></td>
<td>$g_{32}$</td>
<td>Safety</td>
<td>Evaluates overall time saved regarding safety considerations from testing and implementation.</td>
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<tr>
<td>Manufacturing</td>
<td>$g_{41}$</td>
<td>Scale</td>
<td>Considers how DT saves time with respect to increase or decrease in manufacturing scale for the whole of the design process.</td>
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<tr>
<td></td>
<td>$g_{42}$</td>
<td>Complexity</td>
<td>Accounts for system manufacturing complexity from quantity of parts, assembly processes, production automation, and manufacturing technology.</td>
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<tr>
<td></td>
<td>$g_{43}$</td>
<td>Planned improvements</td>
<td>DT technology accommodates for planned or future improvements, this factor accounts for the time saved by the DT in these changes and updates.</td>
</tr>
<tr>
<td>Health monitoring</td>
<td>$g_{51}$</td>
<td>Anticipated life</td>
<td>Examines anticipated life compared to the measured life of the system due to implemented DT health monitoring techniques.</td>
</tr>
<tr>
<td></td>
<td>$g_{52}$</td>
<td>Diagnostics &amp; prognostics</td>
<td>Evaluates time saved and optimized from predicted maintenance needs and prevented degradations and failures through diagnostics &amp; prognostics.</td>
</tr>
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\[
g_i = \frac{1}{n} \sum_{j=1}^{n} g_{ij}, (i = 1, 2, ..., 5) \tag{4.5}
\]

where $n$ is the total number of subfactors for the $i^\text{th}$ factor. Note that the individual factor values are the average of their subfactors.

To quantify these factors, a Likert scale rating has again been applied. Figure 4.8 illustrates the overall framework of the Likert scale for enterprise self-assessment.

Table 4.2 lists each factor associated with the DTTS metric and their descriptions of ranking according to time saved. While the factors from the DTTU and DTTS metrics are identical, except
for Opportunity Costs, they differ in how they are measured. The DTTS metric ranks each subfactor by evaluating how those benefits or considerations saved time or posed greater advantage over alternative current engineering solutions. The descriptions column of Table 4.2 provides association tools to identify methods to apply a ranking for each subfactor. In addition to the subfactor ratings, an enterprise must appropriately determine normalization gains, \( b_i \), with respect to their application. This is accomplished by assessment of relevance for each factor to the enterprise. Where, for example, manufacturing of a product required no sophisticated assembly processes and had no complexity in machining or dimensions, the normalization of the manufacturing factor should be considerably lower than other factors to indicate significance. With appropriate and relevant gain values, each factor is normalized according to application needs. Normalized factors are summed to quantify the overall benefit of DT implementation.

4.5 Case Study

To exhibit the utility of the DTTU and DTTS metrics, a case study will be investigated using the Deep Orange (DO) Design Team which is designing an off-road vehicle. Over the past 12 years, the Department of Automotive Engineering at Clemson University has designed, fabricated, and tested a variety of unique vehicles (DO1-DO13) [15,16,17]. In the current effort, a hybrid propelled tracked vehicle is being designed and produced for search and rescue missions. Specifically, a diesel engine driven generator with accompanying lithium-ion battery pack, twin electric motor drives for the tracks, and payload platform for equipment and supplies as the vehicle is autonomous. The vehicle is outfitted with suitable sensors to accumulate data for on-line and off-line analysis. The interested reader is referred to https://cuicardeeporange.com/ for more information concerning this unique graduate level hands-on vehicle course [83] including design studio (refer to Figure 4.9).

A total of 27 engineering students are designing the D013/14 specialized vehicle over a
multi-year period. Typically, a two-year cycle occurs to design and fabricate a vehicle. However, a hand-off approach was followed, starting with the DO13 off-road tracked vehicle, given the COVID-19 pandemic. The reliance on virtual engineering tools, talented design team members, and advanced manufacturing/assembly methods, makes this an ideal setting to evaluate the potential of digital twin technology. Recently, the DO team has rigorously utilized model-based design methods so there will be familiarity with the underlying survey concepts. The students were provided with an IRB-approved DTTU survey (refer to the Appendix) to capture their perception of the usefulness of the new DT technology. The DT, in this instance, would be integrated vehicle dynamics, suspension system, tire/road interface, and other subsystem models simulated using MATLAB/Simulink/Simscape. Driver and environment inputs, engine and power supply, steering, braking, transmission, vehicle body dynamics, track kinematics, and road interface are captured in the DT system. The sensor data from the physical vehicle is sent using cloud technology to the DT which receives the information to run updated simulations of the model to predict performance, vehicle behavior, and forecast maintenance needs.

The DTTU metric survey identifies whether the DO team considers a digital twin to be a good fit for the project vehicle(s). Combining the responses of the students in the process described by Equation 4.1 resulted in an aggregate DTTU metric score of 5.4 out of 7. The interpretation of this score is provided by imposing the Likert scale ranking shown in Figure 4.3, which indicates that the students found the potential utilization of digital twin technology as partially significant. There is also value in considering the distribution of DTTU metric score based on each student’s individual
response, as shown in Figure 4.10. The histogram displays a positively skewed distribution, centered around the aggregate metric. The standard deviation of the responses was 0.8. The aggregated metric is a good indicator of the group average, showing the benefit of increased sampling for this organization. These scores do not include 3 subjects who failed to answer the survey completely, reducing the pool of respondents to 24. These remaining respondents were favorable to DT technology. Though DO activities have utilized cyber-physical systems before, fully integrated DTs have not been implemented likely due to rapid turnover of participants and pace of schedule.

A more nuanced breakdown of survey responses by the subfactors defined in Table 4.1 is offered in Figure 4.11b. The focus on individual subfactors can guide future DT adoption. DT technology is varied in purpose and implementation; DT implementers must distinguish between the benefits of different vectors of digitalization. The survey responses indicate greatest perceived value in technology focusing on safety, $f_{22}$, and system naming convention, $f_{32}$. Future efforts to integrate a DT solution may consider beginning with a study on these two subfactors and related factors to determine profitability and cost of implementation.

An examination of the study sensitivity is displayed in Figure 4.12 with the factor ranking average versus the number of respondents. The initial fluctuation is due to the limited number of respondents, allowing for large swings in the average ranking. As the number of respondents
Figure 4.11: DTTU survey results from DO vehicle design team – (a) Factor importance rankings where each factor is ranked as a percentage, with median values indicated over each factor; and (b) Sums of sub-factor rankings using Likert scale.

increases past twenty, the variations no longer change as drastically.
4.6 Summary

The emergence of virtual engineering tools such as a digital twin can positively impact the design process to enhance product development time, reliability, and quality. The creation of metrics to evaluate the usefulness and time savings associated with DT technology has been investigated in this article. A series of subfunctions have been identified and summed for each to provide a numerical range to help potential and actual practitioners to assess the toolset merits. A case study focused on the Deep Orange off-road tracked hybrid vehicle team has been presented to demonstrate the surveys and brief discussion of the results. Overall, the metrics and accompanying surveys help to establish a baseline to evaluate this digital technology. In the future, the DT metrics will be expanded to include technology readiness levels (TRL) and manufacturing readiness levels (MRL) to better encompass enterprise needs [84]. Further, a more comprehensive study should be conducted that covers industrial applications of digital twin tools and involves more human subjects.
Chapter 5

Conclusions

This research explored the use and benefits of digital twin technology in engineering design processes including advanced modeling methods, product life cycle management techniques, and validation & verification procedures. Engineering design is enhanced through digitization of its processes, eliminating need and waste along with saving time by removal of physical prototyping and testing. A digital twin virtual engineering tool is created and studied as a solution to the growing need for digital engineering design methods. In conjunction with data streaming and statistical analysis, a digital twin is a virtual model-based system that simulates behavior of a physical system, making performance, health, and manufacturing predictions. The conclusions in this section discuss research accomplishments including general remarks concerning digital twin technology, time savings metrics, digital twin wheeled vehicle creation, and predictive maintenance implementation followed by future research recommendations.

5.1 Research Accomplishments

Digital twin technology is a useful resource that leverages dynamic computer models to represent, and communicate with, a physical system to monitor and update plant behavior. Dynamic computer models range from simplified spark-ignition engine curves that map torque and power with speed to predicting high-fidelity 14-degree-of-freedom vehicle body dynamic and kinematic behavior. Digital twins leverage data and information from one or more physical plant to enhance those computer models, training over time to produce higher fidelity and accuracy. Artificial intelligence
is used to implement model training and machine learning in neural networks to take advantage of continuous data transfer to better predict future behavior and improve model verification. Using cloud technology, the shared information can be transferred both ways, from physical to digital and reverse, allowing the digital twin to inform and influence physical system behavior. This information can help to optimize system performance as well as alert operators when routine maintenance should occur to increase product lifetime in addition to avoiding catastrophic failure and damaged components.

Virtual engineering design procedures utilizing digital twin technology in this research provided a range of perceived benefits to enterprises and organizations. General digital twin benefits lack clarification and the ability to be quantified to assess overall usefulness. This research formed two digital twin metrics to classify and quantify value-add from the robust digital design tool. The first quantification method outputs a value that signifies the potential usefulness in digital twin implementation for a certain application prior to use named the digital twin technology usefulness (DTTU) metric. The DTTU metric considers the factors for design modularity, model organization & documentation, design V&V & reliability, manufacturing, health monitoring, and opportunity cost to diagnose enterprise proclivity to digital twin technology execution. The second metric, called the digital twin time savings (DTTS) metric, quantifies the value-add from implementation and use of the digital twin engineering tool. The metric considers the first five factors from the DTTU metric, with change in descriptions to reflect a post-application diagnosis of benefits. Surveys were created to guide enterprise self-assessment for both metrics, determining if a digital twin tool would be useful prior to implementation and the benefits produced after implementation as well.

A wheeled vehicle virtual model was demonstrated to visualize and understand vehicle behavior with a high-fidelity, kinematic 14 degree-of-freedom system. Driver behavior including longitudinal velocity and lateral position were input through a predictive driver architecture. These inputs produce acceleration, deceleration, and steering command signals to the vehicle system along with environment and controller inputs. The wheeled vehicle virtual tool models engine, transmission, driveline, steering, braking, suspension, wheels, tire/road interface, and a 14 degree-of-freedom vehicle body dynamics. The four-wheeled off-road military ground vehicle with a spark-ignition engine and 10-speed transmission has independent MacPherson suspension on the front axle and solid suspension on the rear axle. The DT tool was able to simulate vehicle behavior and yield over 150 sensory outputs which were used to collect, analyze, and share information between the
virtual and physical environments. With this high-fidelity model, case studies are examined for validity and used to predict system behavior. Furthermore, the DT is showcased to simulate seeded faulty behavior in both a wheeled vehicle model as well as a tracked vehicle model. The digital twin models support digital design studies including assessment of virtual tool benefits and diagnostic & prognostic activities.

The creation of an intelligent health monitoring diagnostic and prognostic method was developed by a predictive maintenance framework. The digital twin engineering tool was utilized to run 300 lane-change maneuver vehicle simulations with 5 different anomaly implementations and embedded noise. Seeded anomalies created artificial faults in the system behavior to visualize and understand how the vehicle would respond under varying boundary conditions. Four signals were analyzed by statistical features, impulsive metrics, and signal processing including standard deviation, kurtosis, impulse factor, and signal-to-noise ratio. The features and metrics output condition indicators which are measures that differentiate healthy and degraded data as well as identify types of faults occurred in simulations. The condition indicators are used in feature exploration to model future degradations. Predictive maintenance algorithms are developed through a classification learner of the design condition indicators which test for validation accuracy in correctly identifying observations. The 4 signals studied through this framework yielded an 85% validation accuracy with a validation cost of 45 incorrect observations. The study also resulted in a 26,000 observations per second prediction speed with a 1.294 second model training time. Model and fault classification learning was accomplished through data training from the seeded anomalies, implementing deep learning to predict healthy and faulty system behavior.

5.2 Future Research Recommendations

The following includes recommendations of future research and work to extend and develop the creation of the digital twin virtual engineering tool, usefulness and savings metrics, and predictive maintenance methods.

Continuation of research to further the development of the digital twin tool for implementation and metrics surveys is provided. Development in package synergy and system integration is necessary to provide increasingly modular design across disciplines. Digital twin packaging can be updated to be applied across enterprises with differing objectives and levels of sophistication. A
need exists to further expand the digital twin tool to accommodate a range of applications with an encompassing, integrative package to be installed for a project. There exists a need to further expand the digital twin metrics that quantify its usefulness and time savings. A baseline and premise was offered in this thesis for metrics application and study. Leveraging the digital twin package, a broad range of enterprises in varying projects should be surveyed and evaluated more intensively. The purpose in furthering these studies is to better develop tools to understand how beneficial digital twin technology is to a project across many disciplines and enterprises.

Another major pathway in future research to promote continuous engineering improvements includes furthering predictive maintenance studies. After laying out a framework in this thesis, a case study following one signal was offered to showcase utility and application. A need exists to review a greater number of signals to develop a more integrated classification learning algorithms. Additionally, more simulations should be ran, accumulating a higher quantity of data to generate more realistic models with better accuracy. With more simulations and data points gathered from different signals, more subsystems and vehicle components are able to be analyzed for total vehicle health. All of these signals should undergo statistical studies, classification learning, and validation for each type of fault or degradation. Further studies should include harnessed real-time data from a physical twin to provide provide the machine-learning with continuously updated information to yield instantaneous predictive maintenance results with physical data. Additional opportunities include severity level and remaining useful life estimations in real-time based on the gathered results from physical plant data. All results and estimations made from predictive maintenance can be analyzed through the three levels of fault identification including detection, localization, and severity. Fleet level data streaming should be considered and applied in the predictive maintenance framework as a concluding step to support all of the previous studies outlined.
Appendices
Appendix A  Wheeled Vehicle Modeling

This appendix outlines the topics that were not discussed in the papers due to information but gives more insight into the details and explanation of some topics.

A quarter car model details the wheel and suspension of one of the wheels of a vehicle. The model consists of a sprung mass—the vehicle chassis—and an unsprung mass which represents the wheel. A MATLAB Simscape quarter car model is shown below in figure A.1

![Quarter Car Model MATLAB Simscape](image)

Figure A.1: Quarter car model MATLAB Simscape.

A pulse generated signal is input to the model simulating a ground height profile excitation to the unsprung mass. The spring and damper of the unsprung mass represents the stiffness and damping of a tire model. The sprung mass spring and damper represent the suspension of the vehicle. A position sensor detects the position, $P$, and velocity, $V$, of the sprung mass in reference to the ground translational reference source. Two simulations are run, one with sprung mass spring stiffness at 100% and another at 50% to illustrate the behavioral differences of the position and velocity curves. This shows how the velocity magnitudes and positional displacement decrease with a softened spring stiffness. Figures A.2 and A.3 shows 100% and 50% spring stiffness results, respectively.
Figures A.2-A.3 reference the virtual tool used as the wheeled digital twin. High-level system and subsystem architectures are given to provide insight to how the simulation tool operates.
Figure A.4: Most high-level overview of MATLAB digital twin computer model.

Figure A.5: 14 degree-of-freedom vehicle system incorporating suspension, body, and wheel dynamics.
Figure A.6: Overview of the driver subsystem and models.

Figure A.7: Vehicle reference cycle input for driver.

Figure A.8: Simulated driver outputting vehicle commands based on reference cycle inputs.
Figure A.9: Ideal mapped engine based on torque and speed curves given driver input acceleration commands.

Figure A.10: Kinematic steering model provided driver steering wheel angle command.

Figure A.11: Transmission, driveline, and hydraulic brakes are modeled with driver and engine inputs with applied vehicle noise.
Figure A.12: Wheels and tires leverage suspension information of the sprung mass to calculate forces acting on the wheels on each of the four corners of the vehicle.
Figure A.13: 2 degree-of-freedom slip wheel model with disc brakes.
Figure A.14: MacPherson front suspension with solid rear axle suspension mimicking the likely configuration of an off road type vehicle.

Figure A.15: 6 degree-of-freedom vehicle body dynamics.
Appendix B  Digital Twin Technology Usefulness Survey

This appendix provides the Digital Twin Technology Usefulness (DTTU) survey that was created and administered to the CU-ICAR DO13/14 teams as a case study provided in Chapter 4.

![Survey Instructions and 1. Design Modularity Table]

1. Design Modularity

1. Product life: The ability of a system to last the length intended by designers
2. Platforming: The use of similar subsystems across distinct products
3. System Complexity: The overall complexity of the system
2. Model Organization & Documentation

1. Model library: The quantity of components and subsystems in a whole system
2. System naming convention: The maintenance and establishment of proper naming for signals and parameters shared across multiple subsystems

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3. Design V&V and Reliability

1. Validation & verification: Processes to increase fidelity and ease of V&V methods
2. Safety: Ensuring system safety for operators, designers, and stakeholders

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4. Manufacturing

1. Scale: Quantity of products produced, accounting for economies of scale and mass customization
2. Complexity: Production complexity in assembly processes, machining methods, and/or need for specific fabrication tools
3. Planned improvements: Scheduled upgrades to the system requiring manufacturing consideration to account for later design improvements

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5. Health Monitoring

1. Anticipated life: The length of life for the product; Long lifespans (>20 years) are more relevant
2. Diagnostics & prognostics: The ability of recognizing degradations and failures before they occur to prolong the lifespan and/or increase product performance

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6. Implementation and Opportunity Cost

1. Implementation Cost: The expenses associated with DT implementation, such as new software, training, engineering expertise, onboarding, financial, and educational programs
2. Opportunity Cost: The anticipated losses derived from switching current engineering methods to a Digital Twin process

![Table showing relevance levels and ratings for implementation and opportunity costs]

Rate the following factor groups as the percentage of overall importance to the specific product or system. Note that all scores must add to 100%.

These are the same factor groups presented above. They are summarized here for your convenience:

1. Design modularity: Ability of a system to be divided into smaller parts (modules), which are independent of other modules in the system
2. Model organization and documentation: The establishment of an organized and well documented system, encompassing a model library and system naming convention.
3. Design validation & verification and reliability: The processes of ensuring system behavior matches the behavior it was designed, specified, and intended for
4. Manufacturing: The production of the product or system
5. Health monitoring: The continual observance of the functional behavior of the product after its release
6. Implementation and Opportunity Cost: The losses associated with implementing a Digital Twin
Importance to Product

Design modularity

Model organization & documentation

Design V&V and reliability

Manufacturing

Health monitoring

Implementation and opportunity cost

Total: 0
Appendix C  Digital Twin Time Savings Survey

This appendix provides the Digital Twin Time Savings (DTTS) survey that was created and administered to the CU-ICAR DO13/14 teams as a case study provided in Chapter 4.

Instructions:
This survey consists of 15 questions. Each question will ask for insight on one of several factors. Please consider a single product or system* at your enterprise or organization. Each factor has a short description. Please read the description, then consider the relevance of that factor to that single product or system.

*Note that the product or system could be:
- Something the organization produces (e.g., a car, software, food items)
- Systems used in development (e.g., manufacturing equipment, an assembly line, a building or shop floor)
- Non-tangible systems associated with organizational focuses (e.g., supply chains, weather patterns, economic analyses).

1. Design Modularity Product life: Digital twin's ability to update, change or upgrade the product during the product's life Platforming: The time savings from shared components promoted by the digital twin System Complexity: The complexity reduced by implementation of the digital twin

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2. Model Organization & Documentation
Model library: The digital twin’s ability to organize models and documents
System naming convention: Time saved from the digital twin’s organization of naming parameters throughout the system

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3. Design V&V and Reliability
Validation & verification: The effectiveness of the digital twin during validation and verification operations and throughout the design process
Safety: The time savings from safety considerations included in the digital twin

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4. Manufacturing
Manufacture Scale: The digital twin’s ability to save time during an increase or decrease in manufacturing scale
Complexity: Overall complexity of manufacturing simplified by the digital twin
Planned improvements: Time saved from digital twin’s ability to accommodate planned or future improvements

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<th>Effective, but not significant</th>
<th>Partially significant</th>
<th>Mostly significant</th>
<th>Significantly effective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complexity</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Planned improvements</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>
5. Health Monitoring: Anticipated life: Ability for the digital twin to provide accurate anticipated life of product compared to the measured life of the product. Diagnostics & prognostics: Time saved through predicted maintenance needs, prevented degradations & failures.

Rate the following factor groups as the percentage of overall importance to the specific product or system. Note that all scores must add to 100%.

These are the same factor groups presented above. They are summarized here for your convenience: Design modularity: Ability of a system to be divided into smaller parts (modules), which are independent of other modules in the system. Model organization and documentation: The establishment of an organized and well-documented system, encompassing a model library and system naming convention. Design validation & verification and reliability: The processes of ensuring system behavior matches the behavior it was designed, specified, and intended for. Manufacturing: The production of the product or system. Health monitoring: The continual observance of the functional behavior of the product after its release.
Appendix D  Predictive Maintenance Algorithms and Results

This appendix provides additional insight to the algorithms and results found in Chapter 3. Table D.1 numerically ranks the statistical features that were analyzed in the predictive maintenance case study from Chapter 3. The features are ranked by importance via One-way ANOVA, and the corresponding monotonicity values are shown for additional detail.

Table D.1: Ranking of predictive maintenance statistics based on One-way ANOVA and the corresponding monotonicity results.

<table>
<thead>
<tr>
<th>Feature</th>
<th>One-way ANOVA</th>
<th>Monotonicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>12.9</td>
<td>0.003</td>
</tr>
<tr>
<td>SINAD</td>
<td>10.2</td>
<td>0.301</td>
</tr>
<tr>
<td>STD</td>
<td>10.1</td>
<td>0.023</td>
</tr>
<tr>
<td>Spectral band power</td>
<td>9.6</td>
<td>0.010</td>
</tr>
<tr>
<td>RMS</td>
<td>9.6</td>
<td>0.030</td>
</tr>
<tr>
<td>SNR</td>
<td>8.9</td>
<td>0.010</td>
</tr>
<tr>
<td>Peak value</td>
<td>8.1</td>
<td>0.003</td>
</tr>
<tr>
<td>Clearance factor</td>
<td>7.4</td>
<td>0.010</td>
</tr>
<tr>
<td>Shape factor</td>
<td>7.3</td>
<td>0.030</td>
</tr>
<tr>
<td>Impulse factor</td>
<td>6.8</td>
<td>0.023</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.7</td>
<td>0.003</td>
</tr>
<tr>
<td>Crest factor</td>
<td>5.2</td>
<td>0.017</td>
</tr>
<tr>
<td>Skewness</td>
<td>5.2</td>
<td>0.017</td>
</tr>
<tr>
<td>THD</td>
<td>1.5</td>
<td>0.010</td>
</tr>
</tbody>
</table>

Figures D.8-D.11 show where in the digital twin model seeded anomalies were implemented. Formulas embedded in the digital twin were used in conjunction with MATLAB code to provide percent decrease (or increase) in input signals to simulate degradations.
Figure D.1: Histogram plots for statistical analyses, total harmonic distortion (top) and standard deviation (bottom), displaying distribution versus probability for left front axle vertical velocity traces.
Figure D.2: Histogram plots for statistical analyses, root mean square (top) and peak value (bottom), displaying distribution versus probability for left front axle vertical velocity traces.
Figure D.3: Power spectrum trace of left front axle vertical velocity for all anomaly fault scenarios to illustrate another aid to analyze differentiating factors between fault codes.
Figure D.4: Power spectrum band power statistical histogram plot illustrates how well band power differentiates between anomaly fault codes.
Figure D.5: Signal trace of vehicle body lateral velocity for all anomaly fault scenarios to initiate predictive maintenance estimations.
Figure D.6: Histogram plots for statistical analyses, total harmonic distortion (top) and standard deviation (bottom), displaying distribution versus probability for vehicle body lateral velocity traces.
Figure D.7: Histogram plots for statistical analyses, root mean square (top) and peak value (bottom), displaying distribution versus probability for vehicle body lateral velocity traces.
Figure D.8: Seeded degradation applied to the torsional stiffness and damping of the driveline axle shafts for simulated fault anomalies.
Figure D.9: Seeded degradation applied to the spring stiffness and shock damping of the front independent MacPherson suspension for simulated fault anomalies.
Figure D.10: Seeded degradation applied to the tire pressure of the front left tire while keeping the rest nominal for simulated fault anomalies.
Figure D.11: Seeded degradation applied to the tire friction and ground contact of the front left tire while keeping the rest nominal for simulated fault anomalies.
The following code was used to implement degradation values for specified simulations. The code defined the degradation value as a variable and applied different values for various simulation collections. This example of code runs 25 total simulations in batches of 5 with 5 different degradation values. The data is collected into an ensemble for viewing and predictive maintenance training.

```matlab
% Whl_PM1_Fault1.m

% Wheeled vehicle 'Physical Model'
% Main code
% When running, select option to "Change folder"
% Only use clear and clc if necessary

warning('off')

Whl_PM1_Noise1_param; % Open noise parameter file
mdl = 'Model_Wheeled_v1'; % define model name
prj = "VehMdl_Wheeled_v1.prj"; % define project name

if exist(mdl)
    open(mdl) % open defined model if project is already open
else
    open(prj)
    open(mdl) % open project and model if neither is already open
end

if isfolder('./')
    delete('./.*.mat') % delete all .mat files in current folder
end

dgr = 1.2; % degradation initialization value
n = 25; % total number of simulations
```
for ct=1:n % define degradation value for each simulation
degradation_value(1:5) = 1.2; % dgr = 1.2 for sims 1-5
degradation_value(6:10) = 0.9; % dgr = 0.9 for sims 6-10
degradation_value(11:15) = 0.8; % dgr = 0.8 for sims 11-15
degradation_value(16:20) = 0.6; % dgr = 0.6 for sims 16-20
degradation_value(21:25) = 0.3; % dgr = 0.3 for sims 21-25
simInput(ct) = Simulink.SimulationInput(mdl); % define dgr as input
    simInput(ct) = setVariable(simInput(ct), 'dgr',
degradation_value(ct));
end

[ok,e] = generateSimulationEnsemble(simInput,'.'); % generate data ensemble
ens = simulationEnsembleDatastore('.');
ens.DataVariables;
FrntAxl.Rght.Disp.Y",...
FrntAxl.Rght.Vel.Zdot",...
InertFrm.Hitch.Vel.Xdot",...
",...
RearAxl.Lft.Vel.Zdot",...
RearAxl.Rght.Vel.Xdot",...
TireFrame.Alpha",...
TireFrame.My","Wheels.TireFrame.Mz",...
dz","Wheels.TireFrame.z","Wheels.TireFrame.zdot"];
reset(ens)
Fault_AxlDamp1 = readall(ens); % output results, change each
iteration

Fault_AxlDamp1.Var67(1:n) = 32; % output results, change each iteration

Fault_AxlDamp1.Properties.VariableNames{67} = 'FaultCode';
The following code was used to implement noise for the digital twin to provide unique and realistic results for each degradation value. The noise is helpful to provide varying results for each degradation value.

```matlab
%% Vehicle noise parameters
% Suspension: vehicle/wheel force, velocity, and angle noise

% Suspension vehicle forces (3x4)
Noise.Susp.Veh.F.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Susp.Veh.F.variance = 0.001; % Gaussian (Ziggurat method) variance
Noise.Susp.Veh.F.st = 0.01; % sample time
Noise.Susp.Veh.F.spf = 1; % samples per frame

% Suspension vehicle moments (3x4)
Noise.Susp.Veh.M.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Susp.Veh.M.variance = 0.001; % Gaussian (Ziggurat method) variance
Noise.Susp.Veh.M.st = 0.01; % sample time
Noise.Susp.Veh.M.spf = 1; % samples per frame

% Suspension wheel forces (3x4)
Noise.Susp.Whl.F.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Susp.Whl.F.variance = 0.001; % Gaussian (Ziggurat method) variance
Noise.Susp.Whl.F.st = 0.01; % sample time
Noise.Susp.Whl.F.spf = 1; % samples per frame

% Suspension wheel velocities; xdot, ydot (1x4)
```
Noise.Susp.Whl.V.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Susp.Whl.V.variance = 0.01; % Gaussian (Ziggurat method) variance
Noise.Susp.Whl.V.st = 0.01; % sample time
Noise.Susp.Whl.V.spf = 1; % samples per frame

% Suspension wheel angles (3x4)
Noise.Susp.Whl.Ang.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Susp.Whl.Ang.variance = 0.00001; % Gaussian (Ziggurat method) variance
Noise.Susp.Whl.Ang.st = 0.01; % sample time
Noise.Susp.Whl.Ang.spf = 1; % samples per frame

%%% Engine noise parameters
%%% Engine torque noise

% Engine torque (1)
Noise.Eng.Trq.mean = 0; % Gaussian (Ziggurat method) mean
Noise.Eng.Trq.variance = 0.0001; % Gaussian (Ziggurat method) variance
Noise.Eng.Trq.st = 0.01; % sample time
Noise.Eng.Trq.spf = 1; % samples per frame

%%% Transmission, Driveline, & Brake noise parameters

% Driveline engine speed (1)
Noise.TransDriveBrk.EngSpd.mean = 0; % Gaussian (Ziggurat method) mean
Noise.TransDriveBrk.EngSpd.variance = 0.0001; % Gaussian (Ziggurat method) variance
Noise.TransDriveBrk.EngSpd.st = 0.01;  % sample time
Noise.TransDriveBrk.EngSpd.spf = 1;  % samples per frame

% Driveline axle torques (1x4)
Noise.TransDriveBrk.AxlTrq.mean = 0;  % Gaussian (Ziggurat method)
   mean
Noise.TransDriveBrk.AxlTrq.variance = 0.0001;  % Gaussian (Ziggurat
   method) variance
Noise.TransDriveBrk.AxlTrq.st = 0.01;  % sample time
Noise.TransDriveBrk.AxlTrq.spf = 1;  % samples per frame

% Driveline propshaft speed (1)
Noise.TransDriveBrk.PrpShftSpd.mean = 0;  % Gaussian (Ziggurat method
   ) mean
Noise.TransDriveBrk.PrpShftSpd.variance = 0.0001;  % Gaussian (Ziggurat
   method) variance
Noise.TransDriveBrk.PrpShftSpd.st = 0.01;  % sample time
Noise.TransDriveBrk.PrpShftSpd.spf = 1;  % samples per frame

% Brake pressure (1x4)
Noise.TransDriveBrk.BrkPrs.mean = 0;  % Gaussian (Ziggurat method)
   mean
Noise.TransDriveBrk.BrkPrs.variance = 0.0001;  % Gaussian (Ziggurat
   method) variance
Noise.TransDriveBrk.BrkPrs.st = 0.01;  % sample time
Noise.TransDriveBrk.BrkPrs.spf = 1;  % samples per frame
References


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