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Securing Autonomous Systems in Multi-domain Tactical Environment

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ABSTRACT

The U.S. Army envisions fighting and winning future wars in congested and contested environments and multi-domain battles where revolutionary capabilities for the *network-centric warfare* (NCW) are essentially needed. NCW is characterized by the ability of geographically dispersed forces to attain a high level of shared battle-space awareness that can be exploited to achieve strategic, operational, and tactical objectives by autonomously linking people, platforms, weapons, sensors, and decision aids into a single network. Future battlefield networks will generate a massive volume of data, which can go beyond quantities. In a multi-domain battle, *novel technologies for real-time decision-making*, which is based on a large amount of heterogeneous as well as sparse, noisy, and ill-defined data under extremely uncertain environment, are specifically required. Additionally, humans have sometimes become completely comfortable with the information brought in by our sensing technologies. As a result, the command architecture, built on a massive web of information sources, becomes more receptive to potential catastrophic machine-human decision-making conflicts as well as vulnerable to incoming cyber threats including adversaries' deception, interruption, and obscuration, which can eventually introduce own sources of decision-making failure. In this paper, researchers present validation results of a conceptualized artificial intelligence-based visual analytics framework. The researchers' ultimate goal is to integrate the mature technology into the situation awareness technology for local commands and global logistics centers to enable an effective logistic command and control of aviation platforms and autonomous systems while being operated in an expeditionary multi-domain environment.

Keywords: Network-centric warfare, real-time decision making, artificial intelligence, machine learning, cyber-security, visual analytics, situation awareness, state awareness system, condition-based maintenance, zero maintenance, logistics

1. INTRODUCTION

With the implementation of the Health and Usage Monitoring System (HUMS) technology, invented about 30 years ago, operators and maintainers can monitor the health of air platforms via trend analysis for condition-based maintenance (CBM). However, the current HUMS technology and rotorcraft sustainment practices lack an overall efficiency and automation needed to meet the future operational availability and affordability demands [1] in complex tactical environment. Maintainers and analysts are presently burdened with time intensive tasks associated with engineering and analysis of a vast amount of data collected using HUMS and/or other monitoring methodologies. This "big data" analysis burden, if not addressed today, will limit the U.S. Army platform effectiveness in the future multi-domain battle space, impede their deployment, and make them expensive to operate and sustain.

To maintain military supremacy and address the Army operation and sustainment priority, a paradigm shift with respect to specification, design, manufacture, and sustainment of next-generation aircraft systems is needed. This paradigm shift, which includes the introduction of the zero-maintenance concept, is now being considered for integration into the Future Vertical Lift (FVL) overall design requirement and logistics support to increase readiness and reduce total lifecycle sustainment costs. Specifically, to ensure mission effectiveness in multi-domain battle space and lifecycle affordability, automated health state awareness, damage-tolerant, and reconfigurable aviation platform systems are essentially needed.

Automated health state awareness, damage-tolerant, and reconfigurable aviation platform systems cannot be effectively designed and implemented without the integration of artificial intelligence (AI) related technologies including machine learning, which are computer intensive and highly parallelized. As new central processing unit architectures customized for AI applications have been evolving at exponential speed, accurate and critical aircraft's health state awareness information, extracted from heterogeneous sources, can be autonomously derived with the use of machine learning in real-time or near-real-time complex environment. As a result, the next-generation of HUMS or aircraft's health state awareness technology can be developed to enable and secure the automation of data fusion and analysis, minimization of required data for trending and analysis, and more effective operation and sustainment of Army aviation platforms with little or zero-maintenance. In the expeditionary multi-domain environment, significantly smaller logistic footprints will certainly be one of deciding factors to effectively win the war.

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2. CURRENT CHALLENGES

Accurately tracking life-limited parts of rotorcraft platforms by serial numbers (S/N) is crucial in an effort to acquire critical information on the individual component usage, remaining useful life (RUL), health, and maintenance activities for an effective aviation operation and sustainment. The collected information must be fused and transformed into a comprehensive solution that decision-makers can fully understand and use to assess individual rotorcraft and fleet readiness. The results can be potentially used to meet the Maintenance-Free Operating Period (MOFP) requirements. Additionally, the desire for autonomous tracking is extremely essential while aviation platforms will be operated in a future expeditionary multi-domain tactical environment where minimum logistics are required.

Aviation records (e.g., DA-PAM 738-751, DA Form 759, DA Form 3513, DD Form 365, and DA Form 1352) are being used to update pertinent information including RUL and required maintenance actions. Nonetheless, the manual updating tasks using forms often result in inaccurate or outdated information, which may be caused by human errors or simply because of the delay or longer time in processing the data. The current updating task practice for aviation records is time intensive, non-interactive, and not automated.

The successful development and maturation of the radio-frequency identification (RFID) technology enables the U.S. Department of Defense (DOD) aviation to tag each component digitally for tracking purposes. However, since tag readability and data integrity and accuracy are sensitive to many factors, which can skew the information, data cleansing and refinement are as critically important as digitalization. Issues with the RFID technology may range from the malfunctions associated with tagging and reading to gateway transmission devices. Other RFID issues may also include erroneous data collection or human errors introduced in the processes.

3. MAIN CONTRIBUTIONS OF THIS RESEARCH

To address the aviation challenges and concerns described earlier, the development of a revolutionary state awareness technology and system will certainly require a bigger research effort, involving a diverse research areas. In this paper, we focus on a novel approach, which aim at advancing the AI-based technology focusing on machine learning (ML) and data analytics and visualization for determining the aviation platform RUL. Our ultimate goal is to integrate the mature approach including methodologies and tools into the situation awareness technology for local commands and global logistics centers to enable an effective logistic command and control of aviation platforms and autonomous systems while being operated in an expeditionary multi-domain tactical environment. Our contributions in this work include:

- We conduct a study on feasibility and effectiveness of the data analytics and AI-integrated methodology for ML technique and visualization tools to monitor, track, and predict the aviation propulsion system RUL.
- We focus on the visual characterizations of multivariable time series and real-time prediction analytics to determine the system RUL.
- We assess the effectiveness of the developed methods and tools using the aircraft propulsion simulated datasets from the National Aeronautics and Space Administration (NASA) Ames.

This paper organizes the above research and results as follows: (a) we develop a framework for an envisioned state awareness system designed for automated tracking aviation system and component state and integrity, (b) discuss the developed ML and data analytics and visualization techniques, (c) explain the benefits of developed methods and tools for securing autonomous systems in multi-domain tactical environment, and (d) present conclusions and future plan for this effort.

4. RESEARCH DISCUSSION

4.1 Framework for a State Awareness System and Technology

Texas Tech University (TTU) Institute for Materials, Manufacturing, and Sustainment and Computer Science Department's interactive Data Visualization Laboratory are collaboratively working to explore innovative and feasible approaches, which aim at advancing the AI-based technology focusing on ML and data analytics and visualization for aviation applications to be incorporated into the future state awareness system to provide revolutionary functionalities beyond the current HUMS technologies. The state awareness system framework, which is based on the TTU's current patent pending [2] and illustrated in Figure 1, is configured to have the following automated operational functionalities:

- Ingest and transform real-time unsynchronized, unstructured/structured data from heterogeneous sources (e.g., sensor signals, on-board monitoring systems, vehicle management system, electronic logbook, and data bus) into recognized patterns (A).

- Using the streamed and baseline data, the envisioned system conducts the anomaly classification task (B), in real-time or near real-time, using ML-based training models. If an anomaly were detected, relevant characteristics would be immediately transmitted to operators and stakeholders. At the U.S. Army command center or facility, high performance server systems are also designed to receive real-time inputs from the network to perform the modeling and analysis using high-fidelity models and neural network (NN). Transmitter and receiver (C) can be done via aircraft notebook, combat service support automated information system interface (CAISI), and/or very small aperture terminals (VSAT). The results from the ML-based classification would be automatically used for real-time analysis and visualization (D) to update the existing health model (E) to derive health indices and, simultaneously, display the system integrity including cyber risk. Analytics visualization techniques and tools are used to intelligently display the health state of the network and relevant information for monitoring and decision-making at the logistics and cyber-security command centers.
- Identify a set of influential operating factors (e.g., platform actual usages and operating loads and control movements including magnitude, rate, and phasing), which can also be incorporated into computational lifing methodology to predict, for example, the principal structural element (PSE) or engine component RUL (F), and develop modified control parameters (e.g., bank angle, altitude, and speed), which are autonomously fed into the control feedback loop (G).
- Provide platforms and operators options to manually or autonomously execute control authority (H) accordingly to: (a) avoid unnecessarily severe maneuvers or usages to alleviate high operating loads to minimize aircraft structural fatigue; decelerate or stop crack/damage growth; and mitigate other detected anomalies, (b) optimize in-situ operational performance, or (c) intelligently conserve platform remaining available energy and power to complete the intended mission and return to base safely.

Since the capabilities for securing autonomous system in multi-domain tactical environment may cover a variety of advanced tools and technologies, it is not feasible to address them all. In this paper, we will only focus on the analytics capability and functionality using state-of-the-art data mining, ML, and analytics and visualization techniques (D). To assess the developing technique, we use simulated aircraft propulsion data obtained from NASA Prognostics Center of Excellence.

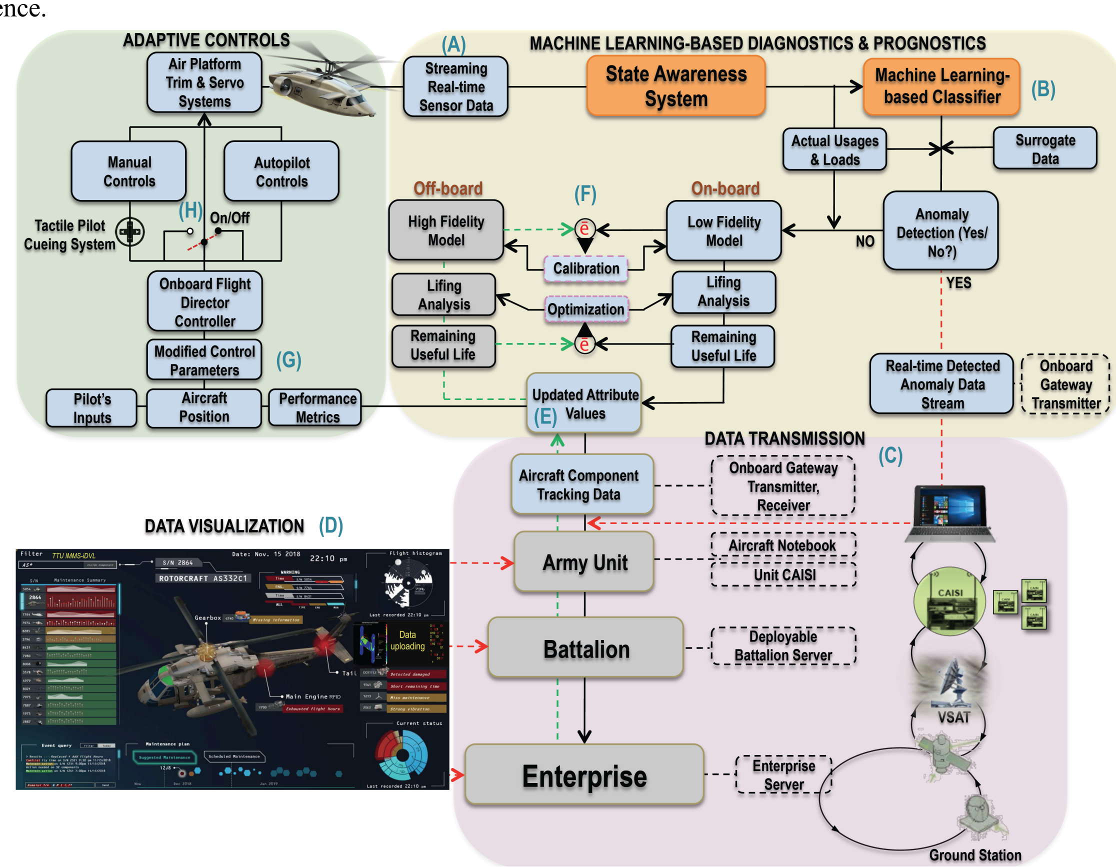

Figure 1: Overall State Awareness System Framework

4.2 Machine Learning

4.2.1 Current State-of-The-Art Machine Learning

For more than a decade, the U.S. Army has been accumulated a vast amount of data, using Digital Source Collector or HUMS, for rotorcraft safety and CBM programs including component life extension. Recognizing the potentials of ML-based technologies to improve HUMS operational functionalities, the U.S. Army Aviation Engineering Directorate (AED) has recently initiated an effort to define a suite of metrics and a process for model selection that can be used to select a ML-based diagnostic classifier for fielding directly to Army maintenance [3]. Additionally, AED has also developed a tool called Crawler used to build mechanical health classification models. Crawler has been successfully used to build, test, and deploy classifier models for detection of faults within mechanical health data [4].

There have been a number of other ML methods developed for various applications including air platform fault diagnostics and prognostics. Taking advantage of the work, which has been substantially investigated, our research extends the Long Short-Term Memory (LSTM) method, as described in [5] and integrates it with Auto-Encoder and Decoder (AE/AD) models (e.g., to classify air platform structural faults) and highly efficient structural fatigue life computation method (e.g., to determine RUL). LSTM-AE/AD models are continuously trained using the original certification load spectrum (e.g., composite worst-case spectrum (CWCS) and load (L)) and damage accumulation and hybrid fatigue-crack-growth (FCG) models to extract unsupervised features of PSEs. Combining the near real-time usage-based diagnostics and prognostics, our envisioned state awareness system presents a unique innovative AI-based health monitoring application for air platforms to address sparse data and the lack of prior knowledge of faults in PSEs.

4.2.2 Computation of Remaining Useful Life

Based on the rotorcraft damage tolerance perspective, the fatigue life of a rotorcraft PSE under cyclic loading is governed by an assumed pre-existing small flaw, which develops into observable crack and eventually grows to a critical size. Brittle fracture occurs after N_f cycles of loading. For a given material and a set of cyclic loading conditions, the cyclic crack growth rate da/dN and the stress intensity factor range, ΔK, represent crack growth behavior. The log-log plot of da/dN versus ΔK at low crack growth, which starts with a steep slope with an appearance of a vertical asymptote referred to as the FCG threshold. At a higher crack growth rate, the slope becomes steep again due to unstable crack growth just prior to final failure of the specimen [6]. For the intermediate region of crack growth rate, da/dN is related to ΔK by the Paris' law. Since a rotorcraft component is subjected to extremely high cycles of fatigue loading, the actual time to failure is relatively short after an observable crack is generated. Ideally, the allowable loading of a rotorcraft component should be such that ΔK is below the threshold stress intensity factor, ΔK_{th} [7].

In this RUL approach, a practical and highly efficient computation approach [8] can be used to modeling FCG in rotorcraft PSEs. The proposed RUL approach automates and integrates hierarchical analysis framework to enable computation both on-board, using low fidelity model, and off-board at the enterprise ground base station and/or applicable aviation high performing computing facility.

The on-board RUL software architecture includes a library of low fidelity structural fatigue life prediction (SFLP) models. During flight, observed operational usage spectrum, combined with air platform original fatigue strength and certification load data based on CWCS, are used to refine the SFLP model loading assumptions. Signals inputs, obtained from, e.g., sensors and/or other monitoring system, as well as detected anomaly characteristics (e.g., crack length, position, and orientation), if available, are also incorporated in the models for the RUL prediction. Since the current probability of detection or structural health monitoring technology is still not optimum, detectable crack size is still large. SFLP models incorporate a well-established initial equivalent crack size for use in the fatigue life prediction and determination. Additionally, the use of modified SFLP models, taking into account of actual usage and derived load spectrum, significantly removes the uncertainty in the RUL calculations in real-time. On-board solutions will be then correlated and corrected (e.g., design safety factor correction) with off-board solutions using lookup tables uploaded via aircraft notebook, CAISI, and/or VSAT.

4.2.3 Modified Control Parameters to Mitigate Fault and Damage

A study conducted on the individual effect of uncertainties in the loading spectrum, inspection methods, and material properties on the predicted fatigue life showed that the variability in the load spectrum had the largest effect, where a 20% change in mean stress resulted in a 76% change in the fatigue life [9]. Additionally, dynamic structural component loads were closely dependent on control movements including magnitude, rate, and phasing. For example, peak and vibratory loads can vary significantly between pilots and the PSE retirement life can be substantially reduced as substantiated by Forth and Le [9]. As a result, certain loading environment, particularly peak loads and usages clearly have direct relationships with the RUL of rotorcraft PSEs.

The proposed state awareness system approach, with proper interfaces communicating to on-board data buses and other avionics system, is designed to extract operational parameters including airspeed, weight, center of gravity, collective and cycle stick positions, main rotor rotational speed, yaw rate, and altitude. The on-board flight regime recognition (FRR) algorithm is used to determine the operational usages, for example, how much time certain maneuvers are being executed during flight. The FRR technology is fairly matured and based on the recognition of waveform and spectral form features of the inputs.

During flight, the envisioned state awareness system extracts and feeds actual usage information to the on-board LSTM neural network for deriving time-based mean and oscillatory parameters of the PSE derived loads (DLs). The actual usage spectrum and DLs for a particular PSE are then used to calculate the operational stress intensity factor range, ΔK *(DL)*, using the system uploaded lookup tables, and compare it with the threshold stress intensity factor, ΔK_{th}, to assess if the damage/crack may grow and, eventually, determine the fatigue-crack-growth rate and the RUL of a particular air platform PSE. The on-board computation, using low fidelity models, will continue its iterations, with the incremental reduction of applied loads, until the ΔK *(DL)* is equal to or less than the looked-up threshold ΔK_{th}. When this condition is first reached, the associate PSE is identified and control parameters (e.g., bank angle, altitude, speed, and/or control movements including magnitude, rate, and phasing) are modified, consistent with the last desirable load iteration result. Modified control parameters, based on load reduction iterations, are then fed into the flight control scheme, which can provide the platform and pilot options to manually or autonomously execute control authority accordingly.

At a designated aviation ground base station or enterprise high performing computing facility, high fidelity fatigue model of PSEs are enhanced using a selected fatigue analysis software suite to create lookup tables and upload them, via wireless systems (e.g., aircraft notebook, CAISI, and VSAT), to on-board system for real-time computation using low fidelity models. These tables, together with other relevant information including aircraft diagnostics and prognostics data, are automatically updated via on-board wireless gateway transmitter and receiver. However, if anomalies are detected (e.g., indication of progressing fault or degradation), a set of relevant data and information of a particular faulted PSE or low (or high) fidelity solutions can be immediately transmitted to or received from the aviation ground base station and enterprise server during flight using unit aircraft notebook, CAISI, and/or VSAT capabilities.

4.3 Validation and Substantiation of Machine Learning and Visualization Techniques

In this section, we use the C-MAPSS turbofan engine dataset to validate our developed machine learning and visualization tools [10]. The data contains 21 sensor readings of numerical values. Each row is a record of an operational cycle of an individual engine unit. The 21 sensor readings (columns) show the sensor data, which have been recorded from each cycle and are contaminated with sensor noise. Our system aims to summarize the typical visual pattern in consideration of the RUL. First, we apply NN to predict the RUL and explain the sensor contribute value in the prediction result [11,12]. In this use-case, we are not striving for the best model with the highest prediction results [13]. Instead, we would like to demonstrate how the data analyst could visualize the intermediate steps of LSTM [14,15], Figure 2, for model exploration purposes. We approach this use-case using NN with two LSTM layers (eight hidden nodes each), then two dense layers (eight and four hidden nodes correspondingly) [16]. The streams on top of each time series plots (on the left side) show the level of contributions of each input variable into the final prediction results using SHAP (SHapley Additive exPlanations). SHAP [17] is a unified approach to explain the output of any machine learning model by game theory and local explanations. The contributions of each variable represent the mean absolute of the SHAP values. We present each neural as a square box containing the line charts of time series and highlight the relationship between the irregular outputs and their corresponding instances in the input and the intermediate layers via a network diagram. As shown on the right panel of Figure 2, *sensor3, sensor8,* and *sensors14* have the least contributions to the final Mean Square Error (MSE) of the training process, while *sensor12* presents the strongest contributions.

The results of the visual explainable machine learning models suggest focusing on important variables for RUL of aircraft engines. Figure 3 shows eight selected variables for our visual analytics component displayed in a circular layout. In particular, the inner curve presents the min values on each dimension. The outer curve presents the max values on each dimension. And, the dashed middle curve is the medians [18]. This type of representation allows users to visually capture the multivariate data through the morphology of the radar charts [19].

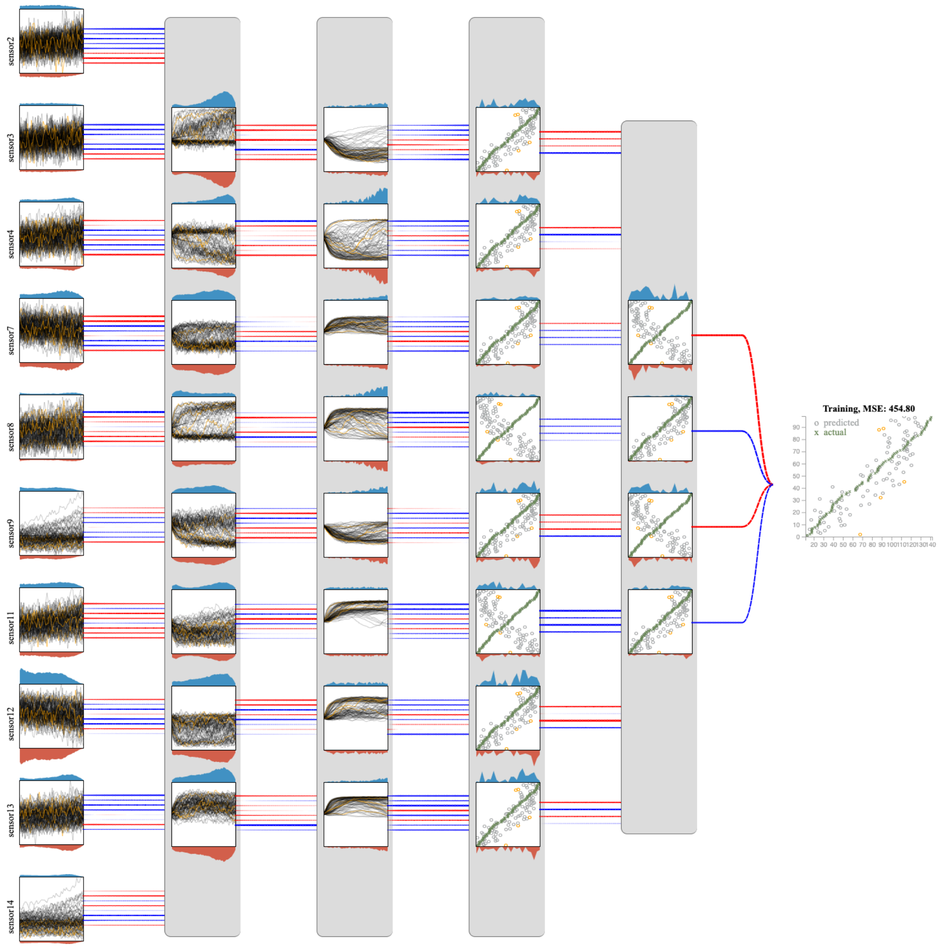

Figure 2: Our visual interface for the aircraft propulsion simulated datasets from the National Aeronautics and Space Administration (NASA) Ames. Each line plot represents a node of the LSTM network. The links between these nodes in consecutive layers present the corresponding trained weights. On the right side, the scatterplots showcase training loss.

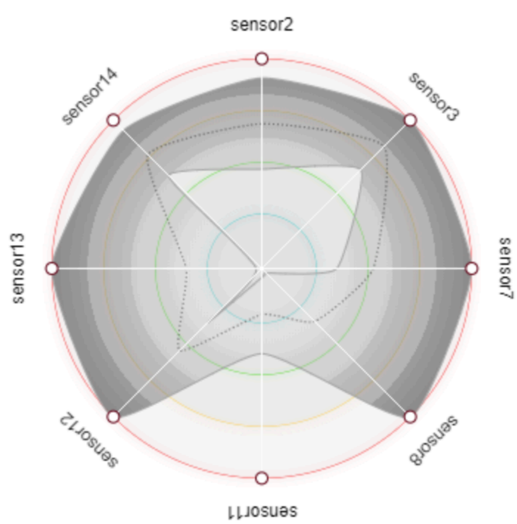

Figure 3: The eight most important variables for predicting RUL in the aircraft dataset F004.

For the input multivariate time series, our visual analytics component will first perform k-means clustering on the selected dimensions to obtain the major temporal status of the multidimensional time series, as shown in Figure 4(a). Notice that cluster 1 contains unavailable data (sensors readings are undefined or missing) while the last three clusters (groups 5, 6, and 7 in the red box) contain high readings on various metrics, which are bad indicators for engine health statuses. The histograms in Figure 4(b) summarize how long an engine undergoes for a multidimensional status: The orange cluster commonly exhibits for a short time before switching to another status. Figure 4(c) shows the timeline projection (from left to right) of engine statuses where 100 engines are listed top-down. We can simplify consecutive unchanged statuses using a color-coded horizontal line over the non-changed interval. This visual encoding approach eliminates visual clutter and allows viewers to focus on important temporal events. We can easily notice that the left part of the time series is less busy since engines, during that period of time, have just entered into service and are therefore much more stable. In contrast, red, purple, and brown are unhealthy engine statuses appearing toward the end of the timeline (RUL is close to 0). In these unhealthy clusters, brown is the most severe status, and it mainly occurs on engine failures.

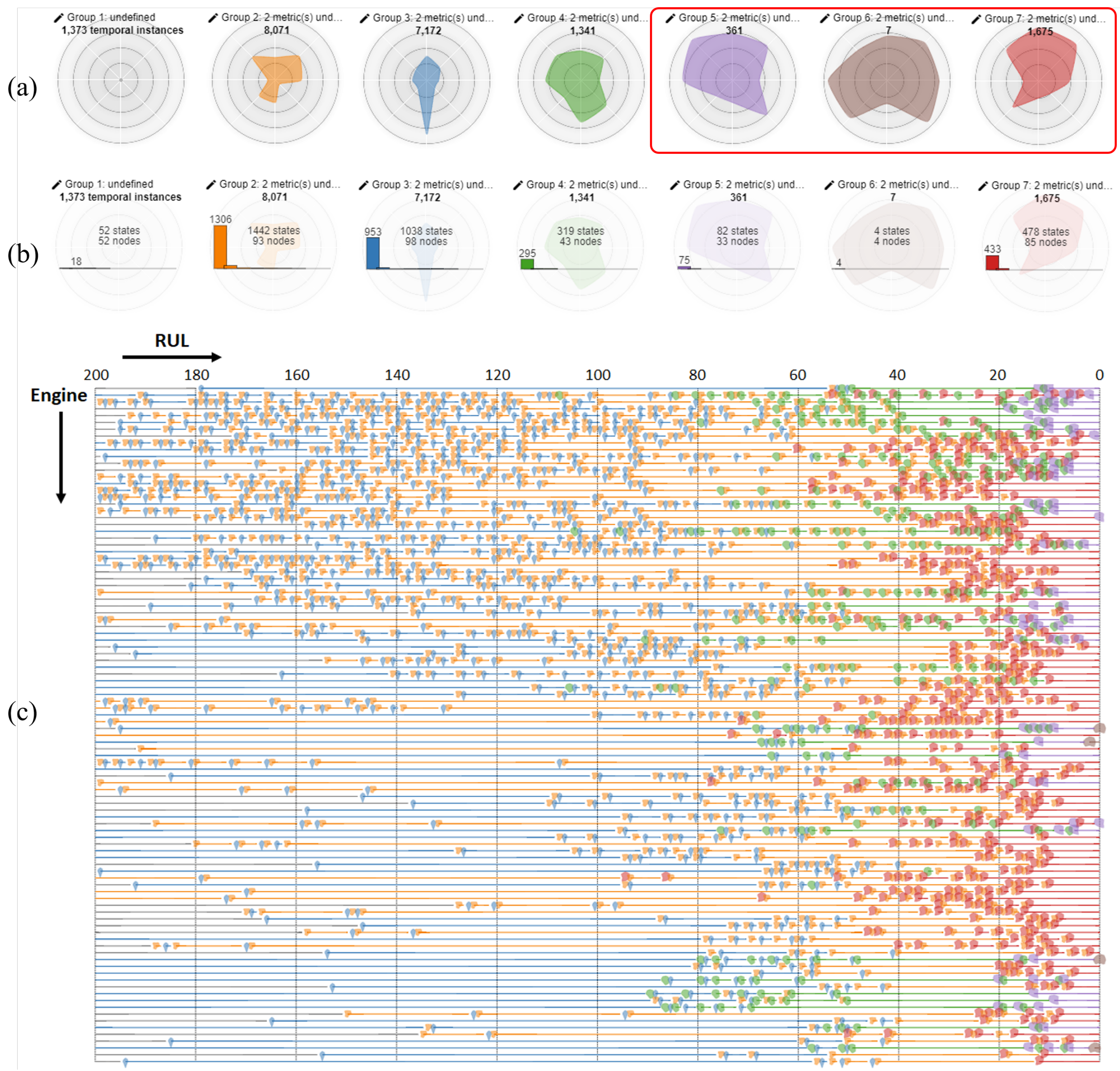

Figure 4: Our visualization component for the aircraft propulsion simulated datasets F004: (a) The seven major clusters generated by k-means algorithm are presented in color-encoded radar charts (b) Temporal summary of the k-means clusters are displayed in the histograms and (c) RUL timeline (left to right) of 100 engines (top down) in the dataset.

5. EXPEDITIONARY MULTI-DOMAIN TACTICAL ENVIRONMENT BENEFITS

The envisioned State Awareness technology, with an integrated machine-learning methodology, is not only able to predict the aircraft system and component RUL but also to provide commanders and decision-makers with a capability to assess individual aviation platform and fleet readiness [20]. The system, once fully developed and fielded in legacy as well as FVL platforms, can provide more accurate aircraft state awareness in an innovative visualization form for more effective fleet management decision. Additionally, the 'big data" analysis burden can be substantially minimized, therefore, reducing the workload of the network-centric warfare. All of these benefits will help the U.S. Army successfully introduce and achieve the aviation zero-maintenance concept and goals to operate un-sustained in a multi-domain tactical environment for extended periods.

6. CONCLUSIONS

This paper presents a framework combining the strengths of machine learning and visual analytics into a unified system. The developed methodologies and techniques can be applied to monitor, analyze, and predict large multivariate time series data, which are coming more and more popular. In the machine-learning component, data analytics and visualization support model understanding and exploration. The output of the machine-learning model allows our second component to focus on the important events in long time series. We demonstrated the feasibility and effectiveness of the developed unified system using the run-to-failure datasets of a turbofan engine simulation model obtained from NASA's Prognostics Center of Excellence in 2008. However, the proposed technique has more general implications for other application domains, including cyber-security, as well. The developed visual data analytics framework has drawn interests from researchers in different fields, such as analyzing and comparing the gene expressions under cancer treatments or crop abiotic stress tolerance, which is one of the priorities currently listed in our research plan.

7. ACKNOWLEDGEMENTS

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