Advanced Manufacturing Analytics: Optimizing Engine Performance through Real-Time Data and Predictive Maintenance

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Abstract

This report proposes a research activity designed to apply advanced analytics to power systems. The objective is to employ recent advances in data analytics to develop an adaptive optimization framework that continuously leverages data to accelerate engine performance optimization. The analytics will address advanced combustion monitoring and real-time diagnostic challenges and will also extend to preventative maintenance strategy development. A combination of physics-based modeling, hardware capabilities, and large data integration will be used to predict engine degradation on a component-specific level and to determine whether life optimization is required. An adaptive prognostic tool will be developed to evaluate engine degradation and determine the remaining useful life for each gas path component. The ultimate goal is a model-driven digital twin for advanced prognostics and capabilities. The project aims to benefit airline and U.S.-based engine and parts manufacturers by contributing to efforts necessary to keep the U.S. commercial aviation engine industry poised to be the world leader in performance, cost, and reliability in the future.

Keywords: Advanced Analytics, Power Systems, Engine Performance, Optimization Framework, Combustion Monitoring, Preventative Maintenance, Physics-Based Modeling, Engine Degradation, Digital Twin, Prognostics.

1. Introduction

The Engine Health Management systems are designed to protect engines by monitoring their condition relative to the limits deemed safe by the engine manufacturer. In many cases, these limits represent the minimum acceptable condition of a component. Access to real-time and historical field data for engines provides a wealth of information. With more data, advanced analytics and predictive maintenance models can be developed with higher fidelity, providing a more in-depth understanding of the system being analyzed. The kind of insights provided by advancing these models ultimately contribute toward greater safety, engines with longer service lives, servicing models that allow customers to put their engines down for maintenance during optimal time slots, and assets optimized to provide maximum service between those maintenance activities.

1.1. Background and Significance

Manufacturing companies generate huge volumes of data daily from the operation of engines and other assets. This 'big data'—which includes sensor readings, equipment usage, and metadata associated with periods, trigger events, and control settings—can be harnessed to support real-time decision-making and analytical tasks to improve performance. Decomposing datasets like these into meaningful insights with high operational impact is a major challenge. Advanced analytics offers solutions to translate the data into value—from generic patterns or condition monitoring anomalies to predictive maintenance opportunities that maximize both machines and associated logistical performance.

Predictive power generation analytics can drive profitability through reduced forced outage rates, improved maintenance planning, less avoidance of risk and market damage, mitigated load and reserve imbalance costs, and more cost-effective operations. Many companies rely on advanced analytics and decision support systems to improve and optimize performance across wind, solar, and thermal asset portfolios. The advanced power generation analytics technologies and methodologies are scalable and have been deployed by utilities, OEMs, and ISOs across the globe on different sites, from single eccentric assets to mixed fleet power plant portfolios, transmission and distribution grids, and power trading environments.

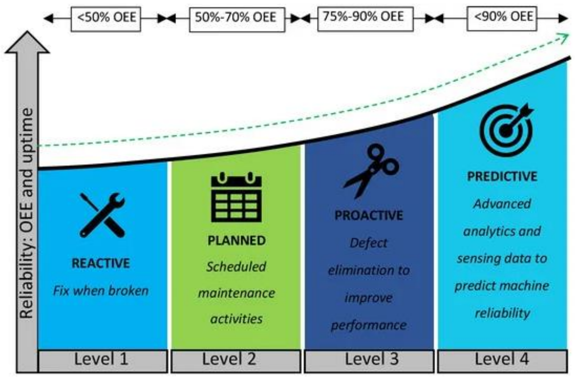

Fig 1 : Predictive Maintenance towards Sustainable Smart Manufacturing

1.2. Research Objectives

The primary research objective of this study is to take the first step in developing industrial engineering approaches to quantify the potential value of in-service engine condition data in design and operations analysis. More specifically, leveraging all forms of contemporary in-service aircraft engine data, new methodologies are employed to estimate the ripple effect of subjective inspections, data quality, maintenance actions, and operational decisions between the in-service engine performance analysis and the remaining aircraft technologies. The methodology includes: (1) data transformations to obtain the indices with the most effective diagnostic coverage, (2) investigating the relationships between engine condition monitoring sensor measurements and engineering parameters related to engine combustor repair, and (3) measurement sensor feature ranking for combustor repair solutions. This operational objective is achieved in two ways: first, we partner with engine companies to gain access to all of the proprietary data required for the engineering application. The data comes in over 1,000 dimensions, including periodic inspections, rated engine cycles, and power, summarized by major aircraft industry customer types as well as the economic reasons for replacing significant engine components. Second, advanced sensors are required to achieve accurate interval inspections, and insights are gained on the importance of examining specific engine sections with examinations sensitive to all possible failure modes. In particular, as part of exploratory analysis, we will examine engine combustor performance by assessing the dynamic temperature properties of engine components and how they are subject to change over engine life.

Equation 1 : Engine Performance Metrics

The overall engine performance *(P)* can be represented using a combination of efficiency *(E)*, power output *(PO)*, and emissions *(EM)*:

$$P = k_1 \cdot E + k_2 \cdot PO - k_3 \cdot EM$$

Where: *P* = Overall engine performance

E = Engine efficiency (%)

PO = Power output (kW)

EM = Emissions (g CO_2/kWh)

k1,k2,k3 = Weighting coefficients based on performance goals

1.3. Scope and Limitations

In this study, we propose a predictive maintenance system and framework for advanced manufacturing plants. It is important to emphasize that our study is not limited to its application to jet engine assembly and performance, although this is where we collected and implemented our IoT and machine learning design in collaboration with the airline manufacturer. Similar strategies can be adopted and implemented in any advanced manufacturing facility: automobile manufacturers to predict engine and car performance and to anticipate problems in performance, in addition to the advance signal of other possible future engine maintenance and failures, or at hospitals for medical devices and healthcare delivery equipment. A major goal in relying on the data tracked from the robots and machines is to move away from the traditional cycle, the more-than-anticipated costly repairs, and from the heavy avoidance strategies, most of them being based on regular time-based inspections, and towards an expectation of planned repairs based on real-time advanced data analytics.

However, original data scientists and designers will have to fine-tune the suggested algorithms to leverage most of them and handle the intricacies of specific advanced manufacturing settings. The most aggressive limitations of our study come from the data we had in hand, from little ex-academia experience in capturing manufacturing IoT information, and from the consecutive challenges posed by the high-frequency data of sophisticated machines used in jet engine assembly.

2. Advanced Manufacturing Analytics

Understanding a product's design, unique operating points, and resultant performance provides insights to enable its most efficient production. Advanced manufacturing analytics advance beyond root-cause analysis to provide holistic views of manufacturing performance, regardless of whether disparate data sources exist. These analytics allow manufacturers to maximize process efficiency and speed. The challenge is how to access and derive insights quickly from interconnected data gleaned from equipment, factories, suppliers, products, and logistics to optimize manufacturing results, all while meeting internal and external customer requirements and fulfilling internal commitments.

The importance of advanced analytics in manufacturing becomes clearer with an understanding of the general challenges associated with large, complex modern engines as well as the current, narrow definitions of manufacturing and assembly in today's production landscapes. Modern engines are large, complex systems of integrated components designed to operate at the extremes of temperature, pressure, speed, and endurance requirements while consuming the least amount of fuel. The developmental fabrication process often involves the production of one-of-a-kind parts with the highest priority placed on precision and structural integrity. These capabilities generally dictate a large internal capital investment to tool the necessary items while achieving short production duration, final product quality, and the best cost performance. Optimal production processes must be repeatable, retain original product and part integrity, utilize materials to their maximum potential, and produce large, complex, high-value products cost-effectively.

2.1. Definition and Concepts

Early work on predicting machine failures has examined a multitude of both time-driven and failure-driven maintenance approaches. Time-driven methods can be defined as preventative maintenance strategies that overhaul or replace components at some scheduled interval, such as 50,000 miles. Failure-driven methods, on the other hand, are real-time strategies that inspect and repair components directly upon failure. Time-driven methods have the advantage of simplicity since they require little more than a maintenance schedule and a functioning way of counting usage cycles like engine run time or miles driven. Unfortunately, failures will often begin to occur with increased frequency as a machine age, thus making the time-driven maintenance schedule suboptimal; it will result in a premature component replacement. On the other hand, failure-driven strategies require complex inspection techniques that can slow the production process considerably.

Over the last two decades, the intersection of the Internet of Things and data-driven techniques has made it possible for companies to predict the rare event of component failure in near real-time without overly impeding the normal operation of a myriad of machine types. By leveraging advanced data collection and computational methods, huge data sets of component behavior can give birth to component degradation models, which can in turn inform predictive maintenance programs. This text will focus on data-driven maintenance approaches for engines in particular because the technology needed to collect data from an aircraft's engine in real-time has matured faster than that for other types of machines. Not only has this technology been developed, but its use is thoroughly regulated by governmental bodies. The time, place, and manner in which engine data is recorded are subject to many standards, and the records themselves are subject to audit and remain part of an engine's maintenance history for as long as it operates. These regulations have effectively created a network of sensors that process information from each relevant system at a high frequency. These sensors collectively enable a detailed understanding of each machine's operation and can therefore be used to predict a much wider array of rare events that go beyond mere component failure, such as when a machine may be inefficiently using spare parts or is near to exceeding some performance threshold.

2.2. Technologies and Tools

It is important to procure analytics tools that cater to specific needs, given that a wide range of these tools are available in the market. In current times, cloud computing services have great importance as they enable real-time updates, archival, and ready access to useful information. For a long time, machine learning concepts were innovated in academic contexts, but due to the arrival of high-performance computing, many different industries have started adopting these tools. Machine learning influences decision-making processes and leads to quick problem-solving. Tools are categorized into specialized, general-purpose tools, and stand-alone tools. Stand-alone tools manage all incoming requests, and their usage demands programming activity in different skills. Due to increased flexibility, performance, and efficiency, specialized systems are gaining popularity. The future research priority is to create a software package that caters to a wider audience. Such a package, independent of the field of application, employs predictive algorithms. All improvements can be managed centrally, which facilitates the immediate usage of information. During production, functional and health monitoring is imperative, as it permits real-time operation and predictive maintenance. Industrial IoT is getting widespread attention. The most important part of the analytics is the collection of data, which is the heart of the system. Tools are classified based on features and existing research works on system monitoring in industrial IoT.

2.3. Applications in Manufacturing

The objectives of an advanced manufacturing analytics improvement process are typically focused on maintaining high product quality and reducing production costs. The collection of real-time data from sensors is a significant source of information to know and control the process's real-time performance. The in-process production data from multiple sensors can be compared to production standards from pre-production planning activities or past production information based on previous or current data records. One of the primary applications of advanced manufacturing analytics is predictive maintenance. A large use case for AMM is the breakdown and cost of production associated with mechanical handling. Advanced manufacturing analytics can be implemented with a predictive maintenance strategy. This allows for avoiding high-cost maintenance caused by machinery breakdowns.

A predictive maintenance system is a very advanced maintenance system that, by using various technologies and equipped with different types of artificial intelligence tools, is capable of predicting failures in specific devices and establishing a plan to change components before an actual failure that can produce significant damage occurs. In some cases, some machine components can be extremely costly, and for safety reasons, the temporary loss of the specific device can lead to an entire line or even an entire production unit shutdown. To avoid such shutdowns and minimize damages, predictive maintenance together with AMM can be deployed to prevent such damages. Normally, before a machinery breakdown occurs, several machine components wear, and this effect can be controlled with an advanced warning system based on real-time data analysis.

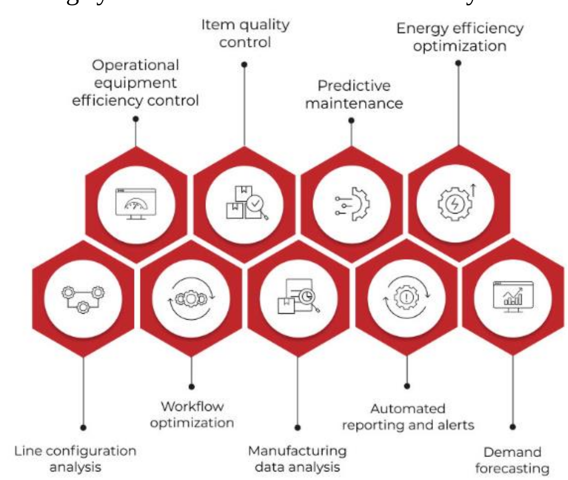

Fig 2 : Manufacturing Analytics Application

3. Optimizing Engine Performance

In his presentation, Advanced Manufacturing Analytics: Optimizing Engine Performance through Real-Time Data and Predictive Maintenance, Eduardo Aviles, manager of WorldWide Data Center Services for Caterpillar, examined how the company helps customers manage more than $2.2 trillion in assets as easily as you manage your pocketbook. What these assets have in common is that they provide power and a way to move things around the world. Think ships, trains, heavy equipment, and more. Today, more than 300 engine models are customizable and can cover a wide range of needs. The company has been doing this for at least 90 years. Its engines are everywhere, and Caterpillar is interested not just in helping customers know where their engines are, but also in helping customers when they need to know what is going on.

Eduardo explained that engines today generate a tremendous amount of data that can be used to help service the product. This data includes what is going on with the engine itself and can also include data from the equipment around it. These generate far too much data to be able to look at in real-time; they are capturing more than 100 times what you could watch. Still, real-time is important to the company. They wanted analytics that reflected where they could predict failures. By using more than 100 variables to identify the important ones, they have built predictive models that reflect real-time. The challenge of big data is not just one of volume. They had to deal with the quality of the data and the velocity at which it came. These had to be considered and handled. Their goal was to give customers the maximum operating time and downtime that they could rely on. Anything that they could do to get more time in between needed maintenance events is major because machines are tools in the world economy. What they look at is the health of the machine, in real time and relative to the point in time. The data produces specific results, and they give you the best results based on the inputs. With over 112,000 alerts generated per month, they predict what might be coming down the road using the maintenance records of the past. The decisions are based on predictive maintenance.

Equation 2 : Remaining Useful Life (RUL) Estimation

The remaining useful life of engine components *(RUL)* can be estimated using:

$$RUL = \frac{C_{max} - C_{current}}{D_{avg}}$$

Where: *Cmax* = Maximum capacity or life expectancy of the component (hours)

*Ccurren*t = Current usage (hours)

Davg = Average degradation rate (hours per hour of operation)

3.1. Challenges in Engine Performance Optimization

From the perspective of aerospace and defense, the emissions criteria for gas turbine engines with low emissions have become tighter and apply to older engines. However, this ambition has to be technically driven and cannot be a matter of legislation and certification. The interrelationships between emissions and fuel burn are crucial. The key elements for reducing engine emissions, however, generally lead to reduced engine fuel efficiency. Therefore, the scheduling and controlling of the required trade-off is important and presents one of the most significant ongoing challenges in gas turbine engine performance optimization. Data analytics using a holistic systems perspective and value-driven digital business processes are major success factors in addressing this challenge.

The detailed mechanisms of component deterioration and the associated end-of-life phenomenon for an in-service gas turbine are not completely understood. They are influenced by many internal and external combustion, mechanical, and operational events. The internal deposit formation on components is a complex and less understood process, and since it significantly degrades engine performance and imposes a risk of severe damage or failure, early identification and remedial action such as on-wing cleaning are desirable. A clear requirement is that the current lack of understanding should not restrain the development of methods that are currently possible based on current data management, signal processing, probability, and statistics and that a realistic approach with a clear expectation and strategy should be adopted as possible. Indeed, the development of data-driven or eScience-based approaches may provide new insights that could add to the understanding of these complex phenomena.

3.2. Role of Real-Time Data in Optimization

Predictive maintenance has emerged as a powerful strategy for optimizing operational efficiency. Despite numerous advantages of predictive maintenance, implementation has been poor, particularly in the aerospace industry, mostly for structural health monitoring due to the limitations of available sensors installed on the aircraft. The arrival of wireless sensors, composites, and novel instruments such as fiber optics, combined with advanced analytics and data mining techniques, has led to dramatic improvements in predictive maintenance capability. Sensor-equipped components on and in aircraft, manufacturing plants, and equipment generate a colossal volume of real-time data. Real-time data generated from advanced sensors is hidden in the layers of complexity of an industrial Internet of Things environment.

The innovative capabilities of real-time engine performance data that are rarely maximized are, however, unique and present an opportunity to optimize engine performance and efficiency. Although airlines and engine manufacturers control units periodically ingest data from the sensor-equipped engines, problems are addressed in a preventive manner. The engine health-monitoring provider captures and analyzes data sets collected from sensors and performs additional analysis to ensure adequate safety margins are maintained for the life of the engine. Automating the real-time data mining and machine learning for rapid analysis and extracting valuable intelligence from the big data deluge from the full spectrum of engine testing, ground break-in or maintenance, flight phases, initial incidents, and the impacts on the health of the engine, dynamics or time constants of transient and steady behaviors, software extrapolation of trends, detection of incipient emergence of non-deterministic behaviors, identification of thresholds not exceeded, and recalls can co-create lasting value for both industry stakeholders.

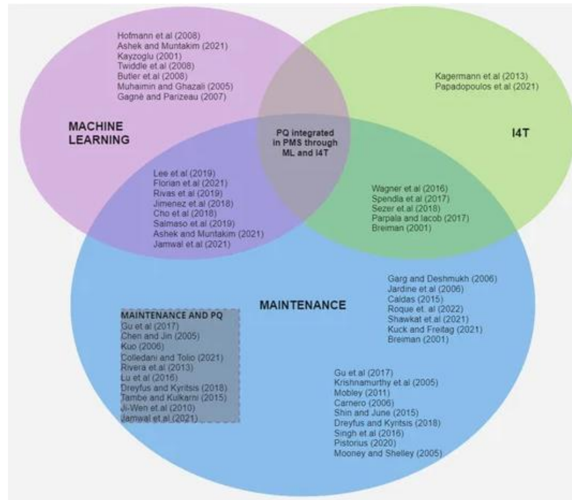

Fig 3 : Optimizing Predictive Maintenance Using Machine Learning

3.3. Predictive Maintenance Techniques

Predictive maintenance (PdM) utilizes condition-based sensor analytics to predict when problems will occur in the future. Consequently, it envisions inspection and servicing only when needed. As opposed to time-based maintenance (TBM) of preventive maintenance that occurs at regular time intervals, PdM guarantees cost-effective preventive maintenance. Deterioration in equipment condition occurs over a period, manifesting as changes in performance. It can be detected as changes in the state of operation and condition using a simple model, just before a failure and before significant equipment degradation occurs. The model prediction from performance data driven by performance sensors can raise a maintainability decision before the next event. Presently, the most promising predictive models are based on machine-learning algorithms such as neural networks, support vector machines, decision trees, etc. These techniques have been used to predict equipment failure and degradation by mining time-series component data from in-service engines.

Predictive models that combine multiple sensors generate actionable intelligence for condition-based maintenance. An effective performance monitoring system must be accurate, cost-effective, and use readily available data from existing sensors. It helps increase component life, leading to cost reductions. Onboard monitoring of system components, electrical and mechanical hardware, software logic, and the environment through sensor data leads to predictive analysis. Real-time fault classification enables just-in-time provisioning of required resources. Post-failure examination data can further aid the diagnostic response. These analyses aid the efficient diagnosis and prioritization of repair tasks. Subsequently, test and repair steps can be scheduled in the future from the diagnostic analysis of historical sensor data recorded at that time. These repairs minimize costly unscheduled fleet maintenance.

4. Case Studies and Examples

We will showcase here a few industrial examples at the seminar conference and also as industrial training cases that we have with a corporation. Please note that due to the proprietary nature (and the relationship with some industries), some specifics of each manufacturing setting may not be fully disclosed. If interested, readers are welcome to make further inquiries. Let us first showcase a predictive maintenance example with one manufacturing site.

Example 1. Company: Corporation

Maintenance and Manufacturing, Engine Manufacturing, Performance Team

Manufacturing Site: East Hartford, CT. Focus area: Predictive maintenance of engine assembly line systems using real-time data analytics. Data sources: Discrete-event manufacturing data – assembly line machines, conveyor systems, and system-related output of a massive enterprise control system. The data sources are from time production lines, each having a large number of components, parts, and subassemblies that pass through various sequences of assembly and tests in a complex multiple-stage manufacturing and testing process. The process flow also includes special tests at different stages, including the instrumentation of sensor data. The performance test data, including hundreds of high-resolution signal information and quality analyses on selected parts/regions of the product, is not only used to validate the performance of each engine but is also used for continuous improvement through various engine life and mission-specific analyses using predictive analytics.

4.1. Real-World Applications in the Automotive Industry

The car is now a cloud sensor able to provide additional insights regarding engine performance or the health of drivable and critical parts. In areas such as racing engines, real-time insights have been mandatory for years. What is new is the car’s ability to provide these insights. A race car simply cannot run around with an additional set of sensors to monitor the exhaust composition or the vibration patterns of the engine. So, ingredients are added to the fuel blend to change the pattern of the burned fuel. This results in a unique gas that can be detected by the on-car sensor. When slightly more on the condition monitoring side of the engine, the engine is being rattled by the forces of combustion. These forces lead to a unique signature that controls the tuning of the valve train of the engine as well as the suspension of the car. At the same time, the importance of predictive maintenance is increasing. Reducing unnecessary maintenance, early detection of potential issues, and decreasing the maintenance duration are, in the end, the three pillars needed for adoption. To achieve predictive maintenance, more and different types of data are required. This means that not only end consumers but also their cars are increasingly connected. Sensors and associated data processing technology need to be integrated in such a way that large amounts of real-life data are filtered, and processed, and that noise is separated from significant information. Car data arrives in rather unpredictable and sizable bursts, often at low bandwidth and fog processing is required to comply with latency requirements and the capacity of the network. To be useful in an automotive environment, the models need to adapt to the changing performance of the equipment, and this is fast enough so that the information is still useful after processing.

Equation 3 : Real-Time Data Impact

The impact of real-time data on performance optimization can be expressed as:

$$I_{data} = \frac{P_{data} - P_{baseline}}{P_{baseline}} \times 100$$

Where:

Idata = Improvement from real-time data analysis (%)

Pdata = Engine performance with real-time data analytics

Pbaseline = Engine performance without real-time data analytics

4.2. Success Stories in Aviation and Aerospace

In the aviation and aerospace sectors, manufacturers have successfully deployed advanced manufacturing analytics to ensure engine performance and reduce operation costs. One success story in point, through the use of monitoring equipment that is part of the engines and the airframe, airlines can monitor their engines in real time. Alarms are used to alert maintenance crews of potential problems when the plane lands and the engine is closely examined with probes and visual tests in the hangar. These examinations will be able to make sophisticated decisions about whether the engine needs to be replaced now or later, or can still fly for a while. In a more advanced scenario, aviation companies can make a few different maintenance decisions; for example, postponing an engine replacement decision for a few more flight segments, or utilizing the currently unused life in the engines and running them to the maximum allowed. The aviation company can consider where and how the aircraft can be utilized effectively to maximize profit, minimize downtime, or be flown in a less stressful situation. The result is that the engine survives longer than forecasted while still providing optimal service. By having engines arrive from the field with unused life, and not being entirely consumed, the maintenance reserves needed to set aside a sufficient amount of money for future expenditures can be reduced.

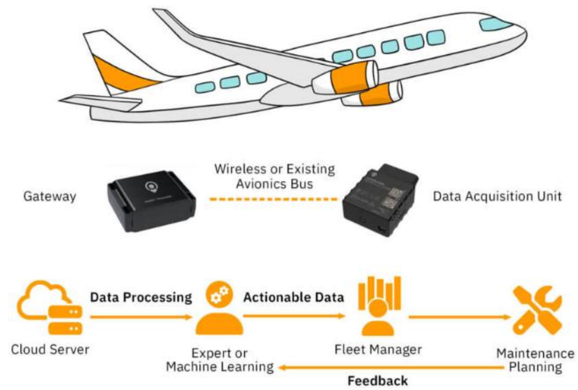

Fig 4 : Predictive Maintenance in Aviation Can Save Lives

5. Conclusion and Future Directions

We have reported on a novel framework for optimizing engine performance using real-time data analytics. Our manufacturing analytics presented several major contributions. First, we developed a semisupervised real-time data analytics framework that is capable of performing real-time optimization of engine performance. The engaged analytics examined both the performance and stability of a full-powered turbine engine. Second, we developed a novel nonlinear kernel optimization algorithm for feature search and final model calibration. Our optimization framework operates in both offline and real-time operational modes. Third, our manufacturing analytics is efficient and scalable not just for direct applications to other types of engine systems, but also for real-time optimizations of broader and more complex manufacturing processes. This paper reports on a manufacturing analytics system that was developed in collaboration with an industry partner. Like many real-world systems, our evaluations of the developed system were limited to proprietary, large-scale machinery, leading to stringent real-time operational requirements. To rigorously evaluate our framework, the experiments used both existing and collected data. Our framework is relevant for the process and energy industries to optimize parameters in large systems in the presence of complex and evolving correlations with minimal instrumentation requirements. The principle stages of the paper led to the development of a novel optimization tool that can be used in real time for broader data analytics tasks due to its feature search capability. Given its general framework nature, the utility of our approach is not limited to the performance of turbine engines but can also be extended to many areas of production for secure, reliable, and efficient services.

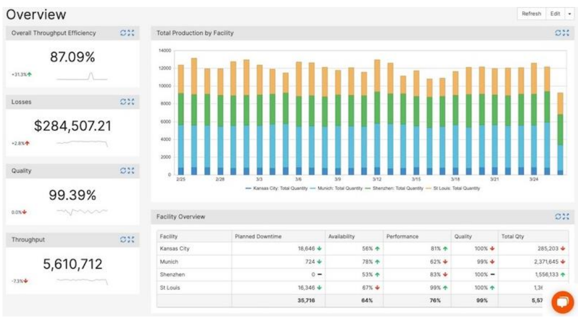

Fig 5 : Manufacturing Analytics

5.1. Key Findings and Implications

This research also began with three general research questions centered on what the most important applications of real-time data and predictive analytics frameworks are. We had initially expected that major applications would be diagnostic development, product improvement, process alterations, and resource or service management. The results confirmed this expectation, with the first three categories being the greatest focus areas, and the resource management area showing less activity. The effectiveness gap seemed to be concentrated pre-assembly in the early testing of parts and subassemblies. Engineers continued to lose the testing effectiveness that occurred once a full engine was run, but they seemed to trend in scheduled usage for testing, then in-use data for problem tracking or product improvement.

In the last few years, highly accurate virtual modeling has been paired with inexpensive computing resources. It became easy and cost-effective to both collect and analyze vast amounts of data that could provide real-time insights about the health and performance of many types of devices. An advantage of this modeling was that technologies could be used that required much less intervention, so virtual testing could be repeated many times and never had the unreliability of physical testing. Highly precise systems monitoring was developed, but the systems performance result was so unexpected that engineers often became inattentive—another forecast decision surprise. By making this technology much improved, there was a gradual development of advanced manufacturing analytics. Its use as a testing enhancement is an alternative, quicker path to knowledge management, and a way to portion the constant improvement that affects product development more effectively.

5.2. Potential for Future Research

Efforts will be made in future work to find optimal methodologies for detailed diagnostic analysis. While unsupervised learning and neural network techniques have already exhibited promising results, also in comparison to some traditional statistical methods with their rigidity concerning single or cross-source data requirements, we are yet to investigate the remarkable potential and limitations of deep learning architectures, which have started standing out as the latest breakthrough in the machine learning literature. However, the interpretability and validation of such models have to be considered with extra care. Additionally, dimensional reduction, with principal component analysis, word embedding, convolutional methods, or the most promising emerging counterparts, has to be developed and enhanced for better-capturing interactions. The performance of these models on single and multisensory data with moving windows should also improve through advanced hardware acceleration and the reduction of the generalization gap.

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