Predictive Analytics in IoT and CPS: Enhancing Industrial Machinery Reliability through Sensor Data-Driven Remaining Useful Life Estimation

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2023 IEEE International Conference on Big Data (BigData) | 979-8-3503-2445-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/BigData59044.2023.10386141

***Abstract*—The rise of the Internet of Things (IoT) and Cyber-Physical Systems (CPS) has brought about a new era of connectivity, building intelligence into the very structure of our society. There are both challenges and possibilities that come with this change, especially when it comes to maintaining industrial machinery. When it comes to big, important machines like electrical transformers, predictive maintenance is very important because the costs of unplanned downtimes can be too high to bear. This essay looks at how the IoT can be used to actively keep an eye on these tools, with a focus on how sensor data can be collected and used to keep operations running smoothly. We look at how machine learning (ML) and deep learning (DL) can be used to look at this data and guess how much useful life a piece of machinery still has. This lets the machine be shut down for repair and keeps it from breaking down without warning. Even though these technologies have clear benefits, there isn't much written about how to combine them into a unified business process for predictive analytics. This study fills in the blanks by proposing a business process made just for analyzing sensor data and predicting Remaining Useful Life (RUL) of industrial machinery. To facilitate testing of the proposed business process, we provide a prototype implementation and discuss its details. We also present a way to evaluate this business process by applying the prototype implementation to a real-world dataset. The evaluation results show that the proposed business process is promising.**

***Index Terms*—IoT, CPS, predictive maintenance, RUL estimation, sensor data analytics, deep learning, industrial reliability, business process design**

I. INTRODUCTION

An industrial revolution of networked smart devices has been sparked by the incorporation of the IoT and CPS into our existing infrastructure fabric [1]. This all-pervasive network has been extremely beneficial, as it has made it possible to automate and monitor complicated systems in a seamless manner. In this context, large-scale industrial machinery, such as electrical transformers, becomes a focal point due to the high costs associated with their operational disruptions [2]. A sudden halt in the functioning of such machines can lead to enormous amounts of costs, not just in monetary terms but also in terms of societal impact, given their critical roles [3]. As a result, the capacity to anticipate the occurrence of future breakdowns and carry out preventative upkeep is not highly useful; it is absolutely necessary. These insights could forestall catastrophic breakdowns and maximize the longevity of these equipment, ensuring that the dependent systems receive uninterrupted service.

The importance of the IoT within the context of this predictive paradigm cannot be emphasized. It is possible to receive a constant stream of data on operational parameters such as temperature and noise levels by fitting these devices with a network of intelligent sensors [4]. This sensor data, which provides real-time insights into the performance of the equipment, forms the bedrock of any predictive maintenance approach [5]. The use of IoT devices for data collecting ensures a constant vigil over the health of these systems, which makes it easier to discover anomalies at an earlier stage, which could indicate that breakdowns are imminent. This preventative method not only makes the gear more reliable, but it also adds an extra level of intelligence to the way that it is maintained.

It is essential to have a solid understanding of the RUL of industrial gear such as electrical transformers [6]. When operators have accurate information of RUL, they are able to schedule maintenance and prospective downtimes in a controlled manner. This allows them to avoid unplanned outages, which may be expensive and disruptive. A precise prediction of the RUL enables the strategic allocation of resources, which helps to ensure that the machinery is kept in peak condition, which in turn extends its operational life and maximizes its contribution to the industrial environment [7].

In this context, the application of ML and DL approaches emerges as an essential tool [8]. These methods, which include analyzing sensor data, are able to recognize trends that human operators might be unable to notice. The results of such a study can provide estimates for the amount of time that remains before a machine enters a critical state, which makes it possible for timely interventions to be carried out. ML and DL can transform raw data into actionable intelligence, guiding the decision-making process in machine maintenance, and ensuring operational efficiency [9]. The current processes frequently lack the requisite level of sophistication to successfully deal with the intricate and variable nature of sensor data

[10]. This paper addresses this gap by introducing a robust ML/DL business process designed to analyze sensor data and accurately predict the RUL of industrial machines.

Our contribution is a methodologically sound business process that not only predicts RUL but also provides a framework for evaluating the efficacy of such predictive systems. We demonstrate the applicability and efficiency of our strategy by walking through the steps of putting it into practice using datasets derived from real-world scenarios. The encouraging findings open the door for a new standard in predictive maintenance, which combines data from IoT sensors with powerful ML and DL analytics.

This article is organized in a way that follows a logical development and is meant to lead the reader through the complexities of the research that we conducted. After this brief introduction, we will proceed to describe the primary research questions that have guided our investigation. The third section provides an in-depth analysis of relevant research and literature, so laying the groundwork for the forthcoming discussion. In section 4, we go into further detail about the technique that we have proposed, and then in Chapter 5, we offer the details of the prototype of the proposed business process and conduct an in-depth analysis of it. In section 6, we bring the discussion to a close by summarizing our findings, drawing conclusions, and discuss future work.

II. RESEARCH QUESTIONS

The importance of guaranteeing the dependability of industrial machinery has grown significantly due to the emergence of the industrial IoT and CPS [11]. The precise prediction of the RUL of machinery using sensor data is not only a technological obstacle but also a crucial necessity for businesses [12]. The key research issue addressed in this study pertains to the development and execution of a business procedure that utilizes sensor data to improve the dependability of machinery by accurately forecasting its RUL. The analytical capabilities of this method must not only be robust, but it also needs to be practical for application in the industry [13]. To this end, this study investigates the following research questions.

Research Question Related to Business Process Design (RQ1): What elements are essential for the development of an effective business process focused on the prediction of RUL ? The present study aims to investigate the fundamental characteristics that effectively shape the operational behavior of industrial machinery. This study aims to comprehend the essential factors necessary for predictive analytics and the methods by which they may be acquired, processed, and evaluated within the context of a business process framework.

Research Question Regarding the Utilization of DL Techniques for RUL Calculation (RQ2): How can deep learning techniques be optimally employed to model the operational patterns of industrial machinery? The implementation of a business process entails the practical application of said process in a real-world context. In order to successfully implement a business process, careful consideration must be given to the specific requirements and constraints of the given scenario. This inquiry explores the suitability of employing DL techniques to model the operational patterns of industrial machinery. This study investigates a range of DL architectures that have the potential to enhance the accuracy of RUL calculations by taking into account the intricate nature and diverse characteristics of sensor data.

Research Question Regarding Evaluation Methods for the Business Process (RQ3): What are the appropriate methods for assessing the predictive performance of this business process? This inquiry centers on the assessment approach and measurements that can be utilized to evaluate the precision and dependability of the RUL predictions. Additionally, the consideration of the anticipated outcomes when implementing the aforementioned procedure on a real-world dataset, as well as the potential for these outcomes to substantiate the efficacy of the method, is taken into account.

The pursuit of a dependable and effective business procedure for forecasting the RUL of industrial machinery encompasses various dimensions, including design, implementation, and evaluation [14], [15]. This study seeks to solve the research issues listed in order to provide a solution that not only predicts machinery failure but also recommends maintenance steps to prevent probable periods of inactivity. The achievement of effectively designing, implementing, and assessing this process will represent a notable progression in the realm of IoT and CPS, carrying extensive implications for the future of industrial operations [16], [17].

III. RELATED WORK

The prediction of RUL is a fundamental concept in the maintenance plans of industrial machinery [18]. It plays a critical role in avoiding downtime and prolonging the lifespan of assets [19]. This literature review aims to investigate the extensive body of research concerning RUL prediction. This topic has attracted significant attention within the domains of the IoT and CPS. This section seeks to summarize the progression of methodology, the incorporation of sensor data analytics, and the evaluation of sophisticated ML and DL techniques in the estimation of RUL. This will be achieved through a comprehensive assessment of research that explore different approaches to RUL estimation. The literature survey functions as a comprehensive analysis of the current literature, laying the foundation for the suggested business process aimed at improving and optimizing RUL forecast in industrial environments.

Liang et al. [20] used a recurrent neural network to propose a health indicator for bearings, aiming to estimate the RUL values of bearings. They used a double exponential model to validate the proposed method. Although our study shares a similar goal, the method and structure we present are entirely different. We aim to perform predictive maintenance in IoT systems and, for this purpose, we provide a business process using DL to predict error time. Akbar et al. [21] proposed an architecture for proactive IoT to predict complex events. They presented a model using historical and real-time data with Complex Event Processing (CEP) and ML. However, the focus of our work is different. We are presenting an architecture that provides predictive maintenance in IoT systems, utilizing DL for the purpose of self-healing. Dimara et al. [22] introduced a sophisticated IoT management system that doesn't depend on sensors and makes sure that all smart home devices can work together without any problems. Their system uses health-monitoring algorithms to find and fix network problems on its own, so technicians don't have to go there. A very important part is the addition of an AE-LSTM, which has an 99.4% error forecast rate. Initial tests show that system problems have slowed down a lot. Dundar et al. [23] addressed the challenges of fault tolerance in IoT applications within heterogeneous computing contexts. They proposed a methodology focusing on architectural constraints and a self-healing mechanism. Their strategy relies on service replication and topic-based messaging protocols.

In the field of RUL prediction, researchers have investigated different approaches in order to improve the precision and effectiveness of predictions [24], [25]. For example Wang et al. [26] utilized the RF algorithm in the initial stages of RUL prediction to extract pivotal features impacting the engine's operating cycle. This approach effectively mitigated the adverse effects of data redundancy, showcasing a marked improvement in the model's accuracy. The incorporation of the Bayesian parameter updating algorithm in the subsequent stages facilitated the optimization of hyperparameters within the MLP model. An extensive analysis was conducted to evaluate the impact of different parameters on the model for predicting RUL. This analysis resulted in the identification of the most effective parameters that minimized the Root Mean Squared Error (RMSE). Peng et al. [27] proposed an innovative approach to automatically extract features with minimal prior knowledge and construct a Health Indicator (HI) curve. Addressing the challenge of diverse feature information in the input data, an attention mechanism was incorporated to enhance the RUL prognosis performance.

The approach proposed by Zheng et al. [28] involves the utilization of LSTM networks for the assessment of RUL. The approach employed by the researchers leverages the extensive data obtained from sensor sequences, allowing for the identification of hidden patterns in different operational scenarios, fault occurrences, and degradation models. The results of extensive testing on three well-known Prognostics and Health Management datasets demonstrate that the LSTM-based approach for RUL prediction outperforms traditional RUL estimation techniques. To avoid the high costs of unexpected maintenance, Lei et al. [29] pointed out how important it is to predict the RUL of machinery so that it can be maintained more efficiently. Due to the growing attention and inherent difficulties in this field, they suggested a new model-based approach for predicting machinery's RUL. Ma an Mao [30] proposed a new way to predict RUL in the fields of prognostics and health management. They used a deep neural network called the convolution-based long short-term memory (CLSTM) network. They combine convolutional processes within both the input-to-state and state-to-state transitions of the LSTM. This captures information about time-frequency and temporal signals. This system keeps the good things about LSTM and also makes better use of time-frequency features. Using run-to-failure tests on bearings to compare it to other DL models, the CLSTM network was more accurate and used less computing power to predict RUL.

Yang et al. [31] suggested a new way to predict RUL using a double-CNN model design, which takes advantage of CNN's strong feature extraction abilities. This method handles raw shaking signals without using extra feature extractors, which helps keep as much useful data as possible. The forecast process is split into two steps: first, the first CNN model and the innovative principle are used to find faults; then, the second CNN model is used to predict the RUL. They added an intermediate reliability variable before forecasting RUL because they knew that RULs could be different for components that were the same. This measure of reliability is then turned into RUL by a mapping method. Using four bearing degradation tests for empirical validation showed that the method was more accurate and durable than other methods, proving that it has promise and can work. Ordonez et al. [32] utilized a combination of the auto-regressive integrated moving average (ARIMA) model and support vector machine (SVR) methods to predict the RUL values. Asif et al. [33] developed a new way to predict how long turbofan engines will last using LSTM. They found that preparing the data properly before feeding it into the LSTM model made the predictions more accurate. They introduced a new method to estimate the starting point of engine wear, which helped improve accuracy. The team tested different settings to get the best results from the LSTM model. They used Nasa Turbofan Engine dataset to test their model and found that it's better to have a separate model for each part of the dataset because each part behaves differently.

In the literature, there are extensive studies on RUL prediction; however, there is a notable gap in the literature regarding RUL prediction specifically in the context of business processes related to industrial machinery. In this study, we address research issues to investigate the development and execution of a business procedure that utilizes sensor data to improve the dependability of machinery by accurately forecasting its RUL. To do this, we propose an end-to-end process design for predicting RUL of industrial machinery. We observe studies focusing on distributed computing techniques and service oriented architecture based systems to achieve certain tasks in different domains [34]–[37], [39]–[50]. Different from these studies, we focus on designing and building a DL based data processing pipeline to predict the RUL of industrial machinery. We leave out the distributed computing aspects of the proposed end-to-end process for future work. We observe different business processes using ML and DL techniques in different domains such as combinatorial optimization, natural language processing, and image processing [51]–[53]. Different from these studies, we study DL based business process for time series data analysis and prediction for estimating the remaining life time of industrial machinery.

There are studies focusing on processing and modeling the users-system interactions data to understand how these systems are being used by the end-users [38], [54]–[57]. In this study, we only focus processing and modelling the data about the status of industrial machinery (such as noise, temperature). We utilize IoT systems where each node of the system is a sensor, collecting data from the machinery. We leave out the analysis interaction data, which is about how these systems interact with their environment, for future work. There are studies analyzing the quality of software products [58], [59]. However, in this study, we leave out software quality analysis of the prototype for future work.

IV. Proposed Methodology

This section presents a detailed methodology that forms the foundation of our suggested business process. The objective of this process is to leverage the capabilities of the IoT in order to improve the dependability of industrial machinery by implementing predictive maintenance strategies. The fundamental aspect of this procedure is a systematic methodology for the acquisition, organization, and examination of data, utilizing an advanced IoT network to collect sensor data, such as temperature measurements, noise levels, and other essential variables, from industrial machinery. The procedure is initiated by implementing a resilient topic-based publish/subscribe messaging system, which functions as the fundamental infrastructure for acquiring real-time data. The purpose of this system is to effectively capture sensor data and direct it to a Data Preprocessing Module. Within this module, the data is transformed into a structured feature vector format, starting with an offset data. The preparation phase additionally encompasses the crucial duty of assigning labels, thereby generating a dataset that is prepared for the upcoming stages of training and evaluating DL models.

Given the availability of a dataset that has been appropriately labeled, we proceed to incorporate a Data Splitter module in order to divide the data into separate training and test subsets. This step is crucial as it lays the foundation for the subsequent creation and evaluation of predictive models. The Model Training module utilizes DL techniques to train on the dataset, resulting in models that can accurately estimate the RUL of the machinery. The following Model Evaluation Module thoroughly evaluates the predictive performance of these models on the test dataset, guaranteeing that only the most precise models are utilized for future predictions. The systematic methodology described above concludes with the utilization of these verified models on fresh sensor data, enabling the generation of real-time prognostications on the RUL. This, in turn, aids in making well-informed judgments regarding maintenance activities. We discuss details of each of these modules in detail, below.

Sensor Data Collection Module: This module functions as the principal data source. The system gathers up-to-date information from a diverse range of IoT devices, capturing metrics that are individual to each item. These measurements can offer valuable insights into the operational health and performance of the device. IoT devices utilize sensors to capture and document crucial characteristics and measurements. Subsequently, the data undergoes formatting and timestamping procedures before to being transmitted for subsequent processing. In the Data Collection section, we extract sensor data and IoT metadata, operational parameters, environmental conditions, and historical failure data from IoT devices embedded in the systems. To simulate this in our studies, we employ the Cooja network simulator. Devices operating on the Contiki NG operating system present this data to the internet via an RPL border router. REST services are offered both to retrieve this data from external systems and to send commands to IoT devices when an action needs to be taken within the system.

Gateway Module: The gateway serves as a crucial intermediary that connects IoT devices to the broader system. The intermediate layer functions to enhance the seamless transmission of data, hence enabling efficient integration of device-generated data into the system. The gateway collects data from IoT devices using established IoT protocols, conducts initial processing if required, and subsequently transmits the data for further processing and analysis.

Messaging Queue Module: The number of IoT devices in a system can be vast, depending on the system's requirements. Real-time data collection in such scenarios can pose certain challenges. Utilizing message queue structures, based on the producer-consumer model, can enhance system error tolerance and prevent system downtime due to the influx of large volumes of data. Data sent to this structure can be seamlessly received by the processing structures subscribed to these services, ensuring system reliability. In order to effectively manage the substantial volume of data originating from a diverse range of devices, the utilization of a message queue is essential. Here, a distributed event streaming platform, is employed to establish a data queue, thereby guaranteeing data integrity and enabling asynchronous processing. The data received from the gateway is enqueued in Apache Kafka. This feature facilitates a buffer mechanism, enabling the subsequent modules to retrieve and analyze data at their individualized rates.

Data Preprocessing Module: To ensure the robustness of model training and evaluation, the data is subjected to a number of preprocessing methods. The process of data cleaning is performed in order to identify and address any occurrences of data that is either missing or inconsistent. Any differences that have been detected are resolved by applying suitable imputation techniques or, in some instances, completely eliminating them. Normalization is a method that is consistently implemented on all features in order to address the issue of differing scales in sensor readings. This ensures that a uniform scale is maintained across the whole dataset. The consideration of input data scale is of utmost importance when utilizing LSTM models, as these models are highly sensitive to variations in data scale. The utilization of Min-Max scaling is an excellent approach for standardizing sensor data, ensuring that it falls within the range of [0,1].

The process of feature selection is considered a crucial

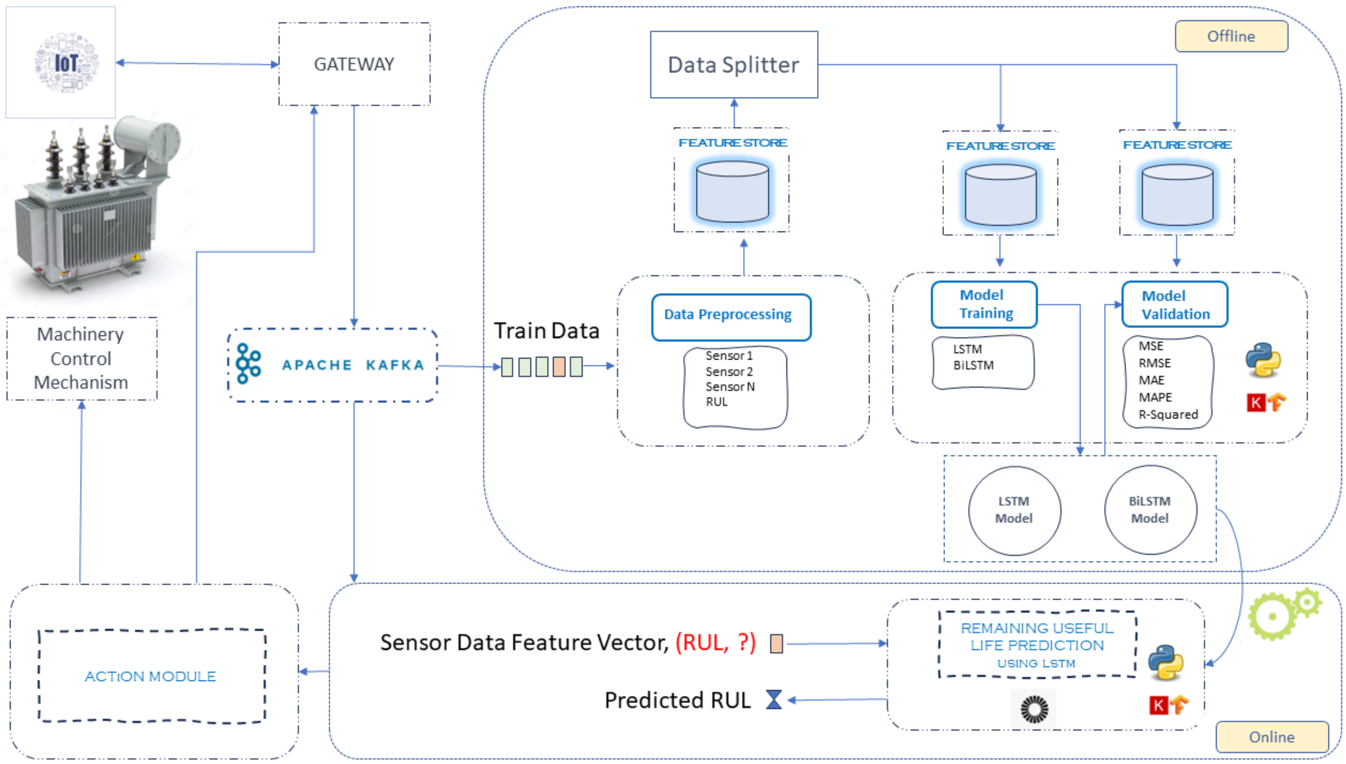

Fig. 1: Proposed flow diagram illustrating the step-by-step process of calculating the RUL for IoT devices. The flow captures the data input, processing methods, and the final RUL determination

stage in the predictive modeling process. In the dataset, a multitude of readings are acquired from various sensors. It is imperative to acknowledge that not all of these readings may possess relevance in precisely predicting the RUL. Hence, it is possible to utilize feature selection methods, such as recursive feature elimination, in order to find and preserve solely the best predictive traits.

The design of LSTM models necessitates careful consideration in order to effectively analyze sequential data. Given the temporal nature of the data, the sensor readings are converted into successive sequences of a predetermined length (e.g., 50 cycles) that exhibit overlapping properties. The construction of input-output pairs for LSTM models involves a meticulous process wherein each sequence is paired with the corresponding RUL value of its final cycle.

Model Training Module: DL models, including LSTM and BiLSTM, need to undergo consistent retraining and evaluation in order for the system to function as intended. The models are continuously retrained and fitted to the system in an appropriate manner while data is batched from the database. This method of constant adaptation assures the relevance and accuracy of the models in estimating the RUL. It also enables the incoming data to adjust to shifting patterns and complexities.

Data Splitter Module: To enhance the effectiveness of model training and validation, the dataset is divided into two separate sets.

In conventional practice, the division of the dataset into training and test sets is commonly conducted using ratios such as 80% for training and 20% for testing, or alternatively, 70% for training and 30% for testing. The specific allocation is contingent upon the characteristics of the dataset and the particular methodologies employed.

After the conclusion of the training procedure, the model's efficacy is evaluated by employing a dataset that has not been encountered before. The objective of this evaluation is to assess the model's ability to generalize and ascertain its suitability for real-world applications.

This methodology guarantees that the model is exposed to the whole range RUL values during the training and validation phases.

Model Validation Module: After training the LSTM model using the specified training data, its performance is later evaluated by validating it on a different dataset. The evaluation is conducted using a specific set of indicators to thoroughly assess the accuracy of the model in predicting the RUL of industrial machinery.

Metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (also known as the coefficient of determination) can be utilized in this evaluation process.

The results obtained from these measurements provide a comprehensive perspective on the model's ability to make accurate predictions and identify specific areas that require additional improvement.

RUL Prediction Module: This feature is very important for predictive maintenance. By figuring out how much of a device or component's RUL is still left, it is possible to fix or replace it before it breaks, which cuts down on downtime. The Predictive Maintenance Module gets data from the Kafka queue, runs it through the right ML models, and then sends out predictions or alerts based on RUL estimates and errors it finds.

Action Module: After obtaining information from the Predictive Maintenance Module, potential courses of action are determined. This could involve sending notifications to the appropriate individuals, performing automatic device recalibration through the machine control mechanism, or even initiating the replacement of devices.

The Action Module reads the outputs from the Predictive Maintenance Module and takes appropriate steps based on predefined rules and thresholds. This ensures the system's self-healing capability, reducing the need for extensive human intervention and maximizing service efficiency.

V. PROTOTYPE APPLICATION OF PROPOSED METHODOLOGY

We developed a prototype to evaluate the efficacy of the proposed methodology. The prototype underwent performance testing, and we assessed the methodology using a real dataset. In this study, we focused on the RUL of a system or a component within a self-healing IoT system. Specifically, we employed the NASA dataset [7], utilizing C-MAPSS to simulate engine degradation under various operating conditions and failure modes, a focus that aligns with our emphasis on RUL. The dataset is comprised of four subsets, each representing a unique combination of operating conditions and failure modes, and contains no labeled data. We utilized dataset number-4, which includes distinct datasets for training and testing. We first identified the RUL values in the existing data.

We employed Keras and TensorFlow for the training and testing of real-time streaming IoT data. The training process was executed on a machine equipped with a 4-core CPU, 16GB RAM, and operating at 2.9 GHz.

A. Data Set

In the evaluation of our proposed methodology, we employed the NASA Turbofan Jet Engine dataset [60] for its comprehensive volume of records and intricate challenges associated with anomaly detection. This dataset is derived from the NASA Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) a simulation tool for turbofan engines, incorporating fourteen distinctive input parameters that facilitate the simulation of a diverse range of operating behaviors.

The dataset encompasses operational data pertinent to industrial equipment, specifically NASA turbofan engines. Each instance elucidates the engine's performance, characterized by various attributes including material compositions and data acquired from IoT sensors operating in real-time environments. The presence of anomalies, which are discernible by their distinctive temporal decay, is instrumental in extrapolating system failures [61].

Dataset Name	FD004
Time Dimension	Cycle
Total Engines Number	497
Cycle Record Number for all Engines	102,461
Sensor Count	21
Operating Conditions	6
Fault Mode	2

TABLE I: Dataset Summary Table

Training Engine Number	249
Training Data Number	61,248
Min Cycle	128
Max Cycle	543
Average Cycle	245.97

TABLE II: Training Data Summary Table

The data is organized in a structured format, encapsulated within a compressed text file. It comprises 26 columns, each delineated by integers. Each row epitomizes a distinct sample of data amassed over a singular business cycle, with every column signifying a distinct variable. This structured presentation of data ensures meticulous and comprehensive analysis, underpinning the rigorous evaluation of the proposed methodology.

We present an example from the dataset we used below.

Unit	Cycle	OpSet1	Sensor1	Sensor2	...	Sensor21	RUL
1	1	42.0049	445.00	549.68	...	6.3670	320
1	2	20.0020	491.19	606.07	...	14.6552	319
1	3	42.0038	445.00	548.95	...	6.4213	318
1	4	42.0000	445.00	548.70	...	6.4176	317
1	5	25.0063	462.54	536.10	...	8.6754	316
1	6	34.9996	449.44	554.77	...	8.9057	315
1	7	0.0019	518.67	641.83	...	23.4578	314
1	8	41.9981	445.00	549.05	...	6.2787	313
1	9	42.0016	445.00	549.55	...	6.3055	312
1	10	25.0019	462.54	536.35	...	8.6119	311

RUL is a crucial indicator, telling us how much time an industrial machine has left before it stops working effectively. In our study, we assume that when RUL reaches zero, the machine stops completely. Understanding this timeframe allows us to take preventive actions in advance, reducing the risk of unexpected downtime and disruptions in industrial operations. While our dataset doesn't directly provide RUL information, we acknowledge its importance in our predictive modeling. Therefore, we calculate and derive RUL information from the dataset. This calculated RUL becomes a key factor in our analysis, helping us assess how well our predictive model anticipates the remaining operational lifespan of industrial machinery. The RUL information extracted from our dataset is a crucial metric for evaluating our predictive model's effectiveness. By comparing predicted RUL values with calculated RUL values, we measure the model's accuracy in

Test Engine Number	248
Test Data Number	41,213
Min Cycle	19
Max Cycle	486
Average Cycle	166.18

TABLE III: Testing Data Summary Table

Attribute	Symbol	Description	Unit
Sensor 1	T2	Total temperature at fan inlet	oR
Sensor 2	T24	Total temperature at LPC outlet	oR
Sensor 3	T30	Total temperature at HPC outlet	oR
Sensor 4	T50	Total temperature at LPT outlet	oR
Sensor 5	P2	Pressure at fan inlet	psia
Sensor 6	P15	Total pressure in bypass-duct	psia
Sensor 7	P30	Total pressure at HPC outlet	psia
Sensor 8	Nf	Physical fan speed	rpm
Sensor 9	Nc	Physical core speed	rpm
Sensor 10	Epr	Engine pressure ratio	-
Sensor 11	Ps30	Static pressure at HPC outlet	psia
Sensor 12	Phi	Ratio of fuel flow to Ps30	pps/psi
Sensor 13	NRf	Corrected fan speed	rpm
Sensor 14	NRc	Corrected core speed	rpm
Sensor 15	BPR	Bypass ratio	-
Sensor 16	farB	Burner fuel-air ratio	-
Sensor 17	htBleed	Bleed Enthalpy	-
Sensor 18	Nf-dmd	Demanded fan speed	rpm
Sensor 19	PCNfR-dmd	Demanded corrected fan speed	rpm
Sensor 20	W31	HPT coolant bleed	lbm/s
Sensor 21	W32	LPT coolant bleed	lbm/s

TABLE IV: Sensor Data Description

forecasting machinery failure time. This assessment validates the reliability of our predictive model and guides decisions on maintenance schedules and resource allocation, improving operational efficiency.

The dataset employed for training our LSTM and BiLSTM models consists of a total of 102,461 instances. The training data in this dataset consists of 61,248 entries, which accounts for approximately 60% of the total dataset. In addition, a portion of 10% of these training data is set aside for the purpose of model validation.

The data acquired from the Data Preprocessing module is utilized for the purposes of both model training and validation. The manner in which data is divided into partitions might exhibit variability depending on the specific procedures and techniques employed, as well as the properties of the dataset. In the present study, a partitioning scheme is employed wherein 60% of the data in the utilized dataset is allotted for the purpose of training, while the remaining 40% is designated for the purpose of testing.

B. Model Design

LSTM belongs to the Recurrent Neural Network (RNN) family and is explicitly designed to process sequential data. Standard RNNs struggle to capture long-term dependencies as they tend to compress information over time. To address

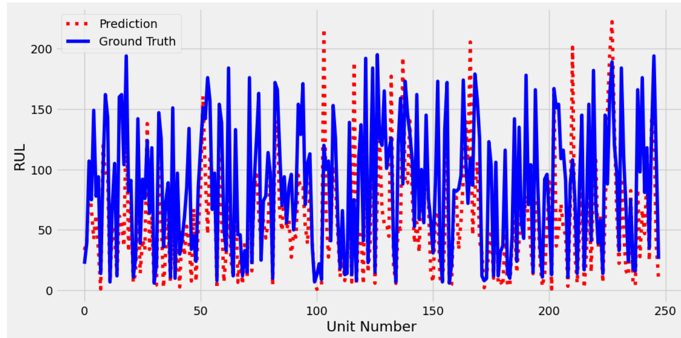

Fig. 2: Comparison of Predicted RUL values with True RUL values using LSTM. The graph illustrates the accuracy and deviation of the prediction model over time

this issue, LSTM introduces a specialized cell structure that considers input data, previous cell states, and information from the previous time step. This cell structure enables LSTMs to capture short-term dependencies while also maintaining long-term dependencies.

We explored the impact of various parameters on the results within the study. The finalized model was tested using the test data. The data employed in this study is derived from IoT devices operating on the Contiki NG operating system. We utilized Cooja, a network simulator, to emulate the system. Contiki NG is particularly crafted for wireless sensor networks. Docker containers were employed to host the Contiki NG operating system, while NodeJS and REST architectural services were instrumental in presenting data to the external environment. We stored the NASA Turbofan Jet Engine data in a PostgreSQL database as if emanating from this system. The application extracts this data from the database and dispatches it to the model in the form of streaming data.

C. Evaluation Result and Discussion

We have implemented the proposed business process. In this section, we show the results of our empirical review, which looked at how well the Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) models could predict how much useful life an industrial machine had left. Our analysis is based on a set of metrics, including MSE, RMSE, MAE, MAPE, and R-squared. Each of these gives us information about a different part of how accurate our predictions are and how stable our models are. The results described in the earlier sections not only show how well each model can estimate RUL, but they also show that the suggested business process can be used in real life. After a careful discussion, we figure out what these results mean and how LSTM and BiLSTM work differently. We also think about how these results could be used in the bigger picture of IoT and CPS-enhanced predictive maintenance. The goal of this collection of evaluations and discussions is to give a full picture of the models' abilities and show how predictive analytics methods can be improved in the future.

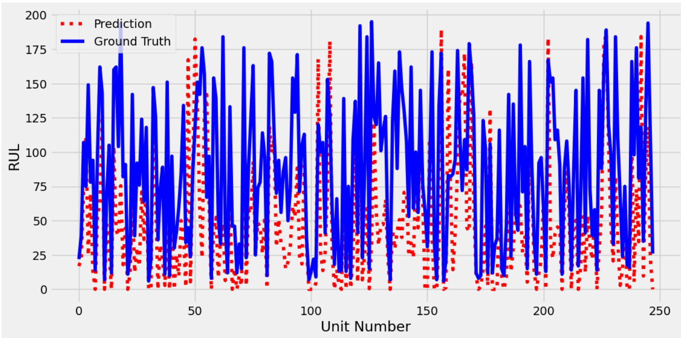

Fig. 3: Comparison of Predicted RUL values with True RUL values using BiLSTM. The graph illustrates the accuracy and deviation of the prediction model over time

The **MSE** measures the average squared difference between the estimated values and the actual value. A lower MSE indicates a model that predicts with fewer errors. The LSTM's MSE of 1885.77 is significantly lower than the BiLSTM's 3082.83, suggesting that LSTM is more accurate in its predictions.

The **RMSE** is the square root of MSE, representing the standard deviation of the residuals. Lower values of RMSE indicate a better fit. The LSTM's RMSE of 43.43 is preferable to the BiLSTM's 55.52, signifying a closer fit to the actual data by LSTM.

The **MAE** quantifies the average absolute difference between predicted and observed values. With an MAE of 32.09, the LSTM model outperforms the BiLSTM's MAE of 42.74, indicating that LSTM has a more precise predictive capability.

The **MAPE** expresses the prediction accuracy as a percentage. The LSTM model's MAPE of 38.73% is lower than the BiLSTM's 56.24%, demonstrating that LSTM's predictions are proportionally closer to the actual values.

The **R-squared** statistic indicates the proportion of the variance for the dependent variable that's predicted from the independent variables. The LSTM model's R^2 of 0.365, though not near 1, is positive, which is an indication of some predictive power. In contrast, the BiLSTM's negative R^2 of -0.037 suggests that it is not suitable for predicting RUL in this context.

In summary, the LSTM outperforms the BiLSTM across all considered metrics, indicating that it is more suited for the prediction of the RUL of industrial machinery.

The Figures 2 and 3 make it easy to see how accurate our LSTM and BiLSTM models are at making predictions. The predicted RUL values for both models are very close to the real RUL values. This shows that the models are good at capturing the underlying patterns of wear and degradation in the industrial machinery. This close alignment is especially important because it shows that the models can correctly predict how long it will be until maintenance or replacement is needed, which lets steps be taken ahead of time. The fact that the real and predicted lines are similar also shows that both models are well-tuned, though the LSTM model might be closer to the real values. One reason for this finding is that the LSTM naturally remembers long-term dependencies, which is very important in time-series prediction tasks like RUL estimation. The BiLSTM model might show some differences because it can look at data from both the past and the future. This can give it a full picture of the situation, but it might also make things more complicated, which might not lead to better predictions in this case. Also, the fact that the real and predicted values in the figures are similar shows how DL techniques could change predictive maintenance strategies. In spite of the noise and variation that come with real-world operations, this experimental study shows how well these models have learned from the sensor data.

Metric	LSTM	BiLSTM
MSE	1885.77	3082.83
RMSE	43.43	55.52
MAE	32.09	42.74
MAPE	38.73%	56.24%
R-squared	0.365	-0.037

TABLE V: Evaluation Metrics for Time Series Predictions using LSTM and BiLSTM. This table presents key metrics assessing the accuracy and fit of the predicted values against the true observed values.

VI. CONCLUSION AND FUTURE WORK

This study looked into predictive maintenance in the IoT and CPS frameworks, focusing on figuring out how much useful life an industrial machine still has. We created and put into action a business method that uses sensor data to help with preventative maintenance. We used LSTM and BiLSTM models on real-world sensor data as part of our research. This showed that these DL methods could be used to correctly predict RUL. The results of our comparison showed that LSTM models are better at this task, as they were more accurate in matching real RUL values and did better on a number of statistical measures.

The amount of knowledge in predictive maintenance is growing, and our work adds to it by creating a methodological framework that can be used in many different industrial fields. It also shows how important IoT is for making machines more reliable, which has big effects on how well they work and how safe they are.

Looking ahead, there are a number of possible directions for further study. In one area, researchers are looking into more DL frameworks and hybrid models that might make the models more accurate and use less computing power. Adding more complicated datasets, such as those with more dimensions and different types of sensors, is another possibility. This would make our suggested models even more difficult and help them get better. The business process could also be made bigger by adding real-time adaptive learning, in which models' settings are changed all the time as new data comes in. Finally, because predictive maintenance has bigger effects, future research could look at the financial and environmental effects of putting these IoT and CPS-enhanced systems into large-scale use. The next steps in this study will continue to change the way industrial maintenance is done and how IoT devices are used in businesses.

REFERENCES

[1] J. Nagy, J. Oláh, E. Erdei, D. Máté, and J. Popp, "The Role and Impact of Industry 4.0 and the Internet of Things on the Business Strategy of the Value Chain—The Case of Hungary," Sustainability, vol. 10, no. 10, p. 3491, Sep. 2018, doi: 10.3390/su10103491.

[2] W. Wang, R. D. Plante, and J. Tang, "Minimum cost allocation of quality improvement targets under supplier process disruption," European Journal of Operational Research, vol. 228, no. 2, pp. 388–396, Jul. 2013, doi: https://doi.org/10.1016/j.ejor.2013.01.048.

[3] T. Kalsoom, N. Ramzan and S. Ahmed, "Societal Impact of IoT-Lead Smart Factory in the Context of Industry 4.0," 2020 International Conference on UK-China Emerging Technologies (UCET), Glasgow, UK, 2020, pp. 1-5, doi: 10.1109/UCET51115.2020.9205484.

[4] J. Mohd, H. Abid, P. S. Ravi, R. Shanay, S. Rajiv,"Significance of sensors for industry 4.0: Roles, capabilities, and applications",Sensors International, vol. 2, 2021,100110, ISSN 2666-3511, doi:10.1016/j.sintl.2021.100110.

[5] S.-Y. Chuang, N. Sahoo, H.-W. Lin, and Y.-H. Chang, "Predictive Maintenance with Sensor Data Analytics on a Raspberry Pi-Based Experimental Platform," Sensors, vol. 19, no. 18, p. 3884, Sep. 2019, doi: 10.3390/s19183884.

[6] Y. Haoran ,Q. Yi, X. Sheng, W. Yi, C. Haizhou, "Long-term gear life prediction based on ordered neurons LSTM neural networks", Measurement, vol. 165,2020,108205,ISSN 0263-2241, doi:10.1016/j.measurement.2020.108205.

[7] C. Okoh, R. Roy, J. Mehnen, and L. Redding, "Overview of Remaining Useful Life Prediction Techniques in Through-life Engineering Services," Procedia CIRP, vol. 16, pp. 158–163, 2014, doi: https://doi.org/10.1016/j.procir.2014.02.006.

[8] C. Han, K. Xianguang, W. Qibin, M. Hongbo, Y. Shengkang, X. Kun,"Remaining useful life prediction combined dynamic model with transfer learning under insufficient degradation data", Reliability Engineering and System Safety, vol. 236, 2023, 109292, ISSN 0951-8320, doi:10.1016/j.ress.2023.109292.

[9] I. H. Sarker, "Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective", SN COMPUT. SCI. 2, 377 (2021). doi:10.1007/s42979-021-00765-8

[10] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, and B. Qureshi, "An Overview of IoT Sensor Data Processing, Fusion, and Analysis Techniques," Sensors, vol. 20, no. 21, p. 6076, Oct. 2020, doi: 10.3390/s20216076.

[11] P. Morella, M. P. Lambán, J. A. Royo, and J. C. Sánchez, "The Importance of Implementing Cyber Physical Systems to Acquire Real-Time Data and Indicators," J, vol. 4, no. 2, pp. 147–153, May 2021, doi: 10.3390/j4020012.

[12] G. Aydemir and B. Acar, "Anomaly monitoring improves remaining useful life estimation of industrial machinery," Journal of Manufacturing Systems, vol. 56, pp. 463–469, Jul. 2020, doi: https://doi.org/10.1016/j.jmsy.2020.06.014.

[13] H. Zhang, S. Liu, H. Lu, Y. Zhang, and Y. Hu, "Remanufacturing and Remaining Useful Life Assessment," Handbook of Manufacturing Engineering and Technology, pp. 3137–3193, Sep. 2014, doi: https://doi.org/10.1007/978-1-4471-4670-4_112.

[14] Y. Hu, S. Liu, H. Lu, and H. Zhang, "Remaining Useful Life Model and Assessment of Mechanical Products: A Brief Review and a Note on the State Space Model Method," vol. 32, no. 1, Feb. 2019, doi: https://doi.org/10.1186/s10033-019-0317-y.

[15] O. Serradilla, E. Zugasti, C. Cernuda, A. Aranburu, J. R. de Okariz and U. Zurutuza, "Interpreting Remaining Useful Life estimations combining Explainable Artificial Intelligence and domain knowledge in industrial machinery," 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Glasgow, UK, 2020, pp. 1-8, doi: 10.1109/FUZZ48607.2020.9177537.

[16] Z. Song, A. R. Mishra, and S. P. Saeidi, "Technological capabilities in the era of the digital economy for integration into cyber-physical systems and the IoT using decision-making approach," Journal of Innovation & Knowledge, vol. 8, no. 2, Apr. 2023, doi: https://doi.org/10.1016/j.jik.2023.100356.

[17] I. S. Khan, M. O. Ahmad, and J. Majava, "Industry 4.0 innovations and their implications: An evaluation from sustainable development perspective," Journal of Cleaner Production, p. 137006, Mar. 2023, doi: https://doi.org/10.1016/j.jclepro.2023.137006.

[18] Z. Kang, C. Catal, and B. Tekinerdogan, "Remaining Useful Life (RUL) Prediction of Equipment in Production Lines Using Artificial Neural Networks," Sensors, vol. 21, no. 3, p. 932, Jan. 2021, doi: 10.3390/s21030932.

[19] D. Zhong, Z. Xia, Y. Zhu, and J. Duan, "Overview of predictive maintenance based on digital twin technology," Heliyon, vol. 9, no. 4, p. e14534, Mar. 2023, doi: https://doi.org/10.1016/j.heliyon.2023.e14534.

[20] G. Liang, L. Naipeng , J. Feng, L. Yaguo, L. Jing 2017. A recurrent neural network based health indicator for remaining useful life prediction of bearings. Neurocomput. 240, C (May 2017), 98–109. https://doi.org/10.1016/j.neucom.2017.02.045

[21] A. Akbar, A. Khan, F. Carrez, et al., "Predictive Analytics for Complex IoT Data Streams". IEEE Internet of Things Journal. PP. 1-1., 2017, doi:10.1109/JIOT.2017.2712672.

[22] A. Dimara, V.-G. Vasilopoulos, A. Papaioannou, S. Angelis, K. Kotis, C.-N. Anagnostopoulos, S. Krinidis, D. Ioannidis, D. Tzovaras, Self-Healing of Semantically Interoperable Smart and Prescriptive Edge Devices in IoT. Appl. Sci. 2022, 12, 11650. https://doi.org/10.3390/app122211650

[23] B. Dundar, et al., "A Big Data Processing Framework for Self-Healing Internet of Things Applications," 2016 12th International Conference on Semantics, Knowledge and Grids (SKG), Beijing, China, 2016, pp. 62-68, doi: 10.1109/SKG.2016.017.

[24] J. Li, F. Huang, H. Qin, and J. Pan, "Research on Remaining Useful Life Prediction of Bearings Based on MBCNN-BiLSTM," Applied Sciences, vol. 13, no. 13, p. 7706, Jun. 2023, doi: 10.3390/app13137706.

[25] M. Hou, D. Pi, and B. Li, "Similarity-Based Deep Learning Approach for Remaining Useful Life Prediction," Measurement, p. 107788, Apr. 2020, doi: https://doi.org/10.1016/j.measurement.2020.107788.

[26] H. Wang, D. Li, D. Li, C. Liu, X Yang, G. Zhu, Remaining Useful Life Prediction of Aircraft Turbofan Engine Based on Random Forest Feature Selection and Multi-Layer Perceptron. Appl. Sci. 2023, 13, 7186. https://doi.org/10.3390/app13127186

[27] C. Peng, Y. Chen, W. Gui, et al. Remaining useful life prognosis of turbofan engines based on deep feature extraction and fusion. Sci Rep 12, 6491 (2022). https://doi.org/10.1038/s41598-022-10191-2

[28] S. Zheng, K. Ristovski, A. Farahat and C. Gupta, "Long Short-Term Memory Network for Remaining Useful Life estimation," 2017 IEEE International Conference on Prognostics and Health Management (ICPHM), Dallas, TX, USA, 2017, pp. 88-95, doi: 10.1109/ICPHM.2017.7998311.

[29] Y. Lei, N. Li, S. Gontarz, J. Lin, S. Radkowski and J. Dybala, "A Model-Based Method for Remaining Useful Life Prediction of Machinery," in IEEE Transactions on Reliability, vol. 65, no. 3, pp. 1314-1326, Sept. 2016, doi: 10.1109/TR.2016.2570568.

[30] M. Ma and Z. Mao, "Deep-Convolution-Based LSTM Network for Remaining Useful Life Prediction," in IEEE Transactions on Industrial Informatics, vol. 17, no. 3, pp. 1658-1667, March 2021, doi: 10.1109/TII.2020.2991796.

[31] B. Yang, R. Liu and E. Zio, "Remaining Useful Life Prediction Based on a Double-Convolutional Neural Network Architecture," in IEEE Transactions on Industrial Electronics, vol. 66, no. 12, pp. 9521-9530, Dec. 2019, doi: 10.1109/TIE.2019.2924605.

[32] C. Ordonez, F. S. Lasheras, J. Roca-Pardinas, F. J. de Cos Juez, A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines, Journal of Computational and Applied Mathematics, Volume 346, 2019, Pages 184-191, ISSN 0377-0427, https://doi.org/10.1016/j.cam.2018.07.008

[33] O. Asif, S. A. Haider, S. R. Naqvi, J. F. W. Zaki, K. -S. Kwak and S. M. R. Islam, "A Deep Learning Model for Remaining Useful Life Prediction of Aircraft Turbofan Engine on C-MAPSS Dataset," in IEEE Access, vol. 10, pp. 95425-95440, 2022, doi: 10.1109/ACCESS.2022.3203406.

[34] M.S. Aktas, et al., "XML Metadata Services", Concurrency Computat.: Pract. Exper., 20: 801-823. https://doi.org/10.1002/cpe.1276, 2008.

[35] M.S. Aktas, et al., ”High-performance hybrid information service architecture”, Concurrency Computat.: Pract. Exper., 22: 2095-2123. https://doi.org/10.1002/cpe.1557, 2010.
[36] G.C. Fox, et al., ”Real time streaming Data grid applications”, Distributed Cooperative Laboratories: Networking, Instrumentation, and Measurements, 253-267, 2006, Springer, Boston, MA. https://doi.org/10.1007/0-387-30394-4_17, 2006.
[37] A. Tufek, et al., ”Provenance Collection Platform for the Weather Research and Forecasting Model”, 2018 14th International Conference on Semantics, Knowledge and Grids (SKG), Guangzhou, China, 2018, pp. 17-24, doi: 10.1109/SKG.2018.00009.
[38] M.J. Baeth, et al., ”An approach to custom privacy policy violation detection problems using big social provenance data”, Concurrency Computat Pract Exper. 2018; 30:e4690. https://doi.org/10.1002/cpe.4690
[39] M.S. Aktas, et al., ”Fault tolerant high performance Information Services for dynamic collections of Grid and Web services”, Future Generation Computer Systems 23 (3), 317-337, 2007, https://doi.org/10.1016/j.future.2006.05.009.
[40] G. Aydin, et al., ”Building and applying geographical information system Grids”, Concurrency Computat.: Pract. Exper., 20: 1653-1695. https://doi.org/10.1002/cpe.1312, 2008.
[41] G.C. Fox, et al., ”Algorithms and the Grid”, Comput. Visual Sci. 12, 115–124 (2009). https://doi.org/10.1007/s00791-007-0083-8
[42] M.S. Aktas, et al., ”iSERVO: Implementing the International Solid Earth Research Virtual Observatory by Integrating Computational Grid and Geographical Information Web Services”, Pure appl. geophys. 163, 2281–2296 (2006). https://doi.org/10.1007/s00024-006-0137-8
[43] G. Aydin, et al., ”SERVOGrid complexity computational environments (CCE) integrated performance analysis”, The 6th IEEE/ACM International Workshop on Grid Computing, 2005., Seattle, WA, USA, 2005, pp. 6 pp.-, doi: 10.1109/GRID.2005.1542750.
[44] M.E. Pierce, et al., ”The QuakeSim Project: Web Services for Managing Geophysical Data and Applications”, In: Tiampo, K.F., Weatherley, D.K., Weinstein, S.A. (eds) Earthquakes: Simulations, Sources and Tsunamis . Pageoph Topical Volumes. Birkhäuser Basel, 2008. https://doi.org/10.1007/978-3-7643-8757-0_11
[45] M.A. Nacar, et al., ”VLab: collaborative Grid services and portals to support computational material science”, Concurrency Computat.: Pract. Exper., 19: 1717-1728, 2007. https://doi.org/10.1002/cpe.1199
[46] B. Dundar, et al., ”A Big Data Processing Framework for Self-Healing Internet of Things Applications”, 2016 12th International Conference on Semantics, Knowledge and Grids (SKG), Beijing, China, 2016, pp. 62-68, doi: 10.1109/SKG.2016.017.
[47] M.S. Aktas, et al., ”Implementing geographical information system grid services to support computational geophysics in a service-oriented environment”, NASA Earth-Sun System Technology Conference, University of Maryland, Adelphi, Maryland, 2005.
[48] B. Yildiz, ”Optimizing bitmap index encoding for high performance queries.” Concurrency and Computation: Practice and Experience 33, no. 18 (2021): e5943. https://doi.org/10.1002/cpe.5943
[49] B. Yildiz, et al., A. “Parallel membership queries on very large scientific data sets using bitmap indexes,” Concurrency and Computation: Practice and Experience, 31(15), e5157, 2019. DOI: 10.1002/cpe.5157
[50] B. Yildiz, G.C. Fox, “Toward a modular and efficient distribution for web service handlers,” Concurrency and Computation: Practice and Experience, 25(2), pp. 410-426, 2013. DOI: 10.1002/cpe.2854.
[51] B. Yildiz, ”Reinforcement learning using fully connected, attention, and transformer models in knapsack problem solving.” Concurrency and Computation: Practice and Experience 34, no. 9 (2022): e6509. DOI: 10.1002/cpe.6509
[52] B. Yildiz, and M. Tezgider “Improving word embedding quality with innovative automated approaches to hyperparameters,” Concurrency and Computation: Practice and Experience, 33(18), e6091, 2021. DOI: 10.1002/cpe.6091.
[53] B. Yildiz, 2022, September. Enhancing Image Resolution with Generative Adversarial Networks. In 2022 7th International Conference on Computer Science and Engineering (UBMK) (pp. 104-109). IEEE.
[54] Y. Uygun, et al., ”On the Large-scale Graph Data Processing for User Interface Testing in Big Data Science Projects”, 2020 IEEE International Conference on Big Data (Big Data), Atlanta, GA, USA, 2020, pp. 2049-2056, doi: 10.1109/BigData50022.2020.9378153.
[55] E. Olmezogullari, et al., ”Representation of Click-Stream DataSequences for Learning User Navigational Behavior by Using Embeddings”, 2020 IEEE International Conference on Big Data (Big Data), Atlanta, GA, USA, 2020, pp. 3173-3179, doi: 10.1109/BigData50022.2020.9378437.
[56] E. Olmezogullari, et al., ”Pattern2Vec: Representation of clickstream data sequences for learning user navigational behavior”, Concurrency Computat Pract Exper. 2022; 34(9):e6546. https://doi.org/10.1002/cpe.6546
[57] M.J. Baeth, et al., ”Detecting Misinformation in Social Networks Using Provenance Data”, 2017 13th International Conference on Semantics, Knowledge and Grids (SKG), Beijing, China, 2017, pp. 85-89, doi: 10.1109/SKG.2017.00022.
[58] M. Sahinoglu, et al., ”Mobile Application Verification: A Systematic Mapping Study”, In: , et al. Computational Science and Its Applications – ICCSA 2015. ICCSA 2015. Lecture Notes in Computer Science(), vol 9159. Springer, Cham, 2015. https://doi.org/10.1007/978-3-319-21413-9_11
[59] M. Kapdan, et al., ”On the Structural Code Clone Detection Problem: A Survey and Software Metric Based Approach”, In: , et al. Computational Science and Its Applications – ICCSA 2014. ICCSA 2014. Lecture Notes in Computer Science, vol 8583. Springer, Cham, 2014. https://doi.org/10.1007/978-3-319-09156-3_35
[60] A. Saxena, K. Goebel, D. Simon and N. Eklund, ”Damage propagation modeling for aircraft engine run-to-failure simulation,” 2008 International Conference on Prognostics and Health Management, Denver, CO, USA, 2008, pp. 1-9, doi: 10.1109/PHM.2008.4711414.
[61] A. Muneer, S.M. Taib, S.M.Fati, Alhussian H., Deep-Learning Based Prognosis Approach for Remaining Useful Life Prediction of Turbofan Engine. Symmetry 2021, 13, 1861. https://doi.org/10.3390/sym13101861