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Research Article

Maintenance 4.0: Automation of Aircraft Maintenance Operational Processes

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Abstract

The advancement of technology is ramping up the pace of digitization and automation of aircraft maintenance activities, and with that, the stakeholders' interest in high-level technology has also increased over the past few years. Thus, to stay relevant in the market and capable of competing, Aircraft Maintenance and Overhaul (MRO) companies must reshape and adapt to newer methodologies to enhance and enrich the quality of aviation and after-sales services. Operational processes are essential to any successful business because it plays a vital role in the efficient and effective functioning of the organization and structure of the enterprise. Hence, this paper will focus on the possibilities of automation and data integration into the daily operational workflow, its contribution, and its influence on the industry. And since the initiation of Industry 4.0, newer opportunities and possibilities have arisen to investigate decision-making algorithms, their influence on overall job quality and precision as well as the synergy between humans and machines and their cooperation in the operational areas of the maintenance process.

Keywords

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Industry 4.0
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Operational process development
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1. Introduction

Technology has effectively changed how companies connect and interact with their consumers, allowed stakeholders to make more strategic choices, and create smoother workflows. Data analysis enables enterprises to take informed moves toward operational efficiency with more confidence. With the introduction of the 4th industrial revolution, it is now possible to integrate complete digitalization and a high level of automation into the operational and professional structure of every company. Hence, reducing the necessity for direct human intervention.

The increasing amount of data generated in Industry 3.0, together with enhanced computational abilities and the usage of Business Analytics (BA), paved the path for Artificial Intelligence (AI) to be employed during this period, allowing a substantial amount of information to be processed by machines and computers. The Internet of Things, Big Data analysis, and machine learning are the cornerstone technologies of Industry 4.0, this term applies to the implementation of advanced information technologies in industries and is often used for the digital revolution. In Industry 4.0, AI integrates numerous technologies that enable software and machines to sense, comprehend, act, and learn human operations.

Maintenance has carved out a large portion of the industry's research budget for the following development release. It can benefit from BA and data

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collection to lower the likelihood of a system or component failure and related costs.

AI was considered a potentially beneficial tool by many institutions, research centers, and even industries to address the obstacles and challenges that MRO firms confront. The large number of papers and publications on this subject reflect the high degree of interest in these applications in maintenance management, scheduling, and planning, as well as the notion of developing an intelligent maintenance optimization system.

Furthermore, it is clear that aviation technology is advancing toward more sustainable and environmentally friendly solutions, which means that maintenance operations must be able to satisfy those new standards accurately while being cost-effective.

MRO aims to preserve the aircraft's airworthiness and reliability to high levels, and as the number of flights has risen so did the need for aircraft availability. As a result, organizations in this industry must invest in their skills and experiences to assure high-quality work and market competitiveness. So, according to this fast and continuous development and growth in the aviation sector, the MRO model has matured to noticeable levels in the past few years, it evolved from being reactive and human-based to being more automated and sustainable, as it is illustrated in Fig. 1.

It is difficult to predict when complete automation and entirely computerized decision-support agents in MRO will be reached as it is dependent on several variables such as technical developments, legal frameworks, and industrial acceptance. However, it is more likely to see further development in this path over the next several decades. For example, the Federal Aviation Administration (FAA) set a target almost a decade ago to achieve the lowest possible aircraft accident rate caused by 2025 (FAA, 2011), this safety plan is still a goal today and will continually necessitate higher levels of automation and AI incorporation in MRO operations.

Currently, the technology in this field has reached level 3 of maintenance maturity, and with the assistance of huge data sets, trend recognition with high accuracy and efficiency will be realized and pave the way for full automation in decision-making without human intervention. Therefore, the results will be an increase in efficiency, preparedness for future events, and a decrease in delays and costs.

There are already ongoing effort attempts to create more sophisticated AI systems for MRO, such as the use of machine learning algorithms for predictive maintenance and problem diagnostics. However, regulatory obstacles, as well as worries about safety, reliability, and cybersecurity, may restrict the implementation of completely autonomous systems.

Predicting the duration of maintenance tasks is one area where AI could show great potential. Accurate scheduling and planning are critical in MRO operations because it helps to optimize aircraft Turn Around Time (TAT) and reduce delays and outages. However, determining the time length of maintenance tasks can be complex and difficult because it depends on many variables such as the task's complexity, the availability of tools and equipment the technician's experience and skill, and the unknown damages/problems. Hence, the purpose of this article is to investigate the use of AI for estimating the performance time of maintenance tasks, as well as to examine the current state of the art and find possibilities for further research and development.

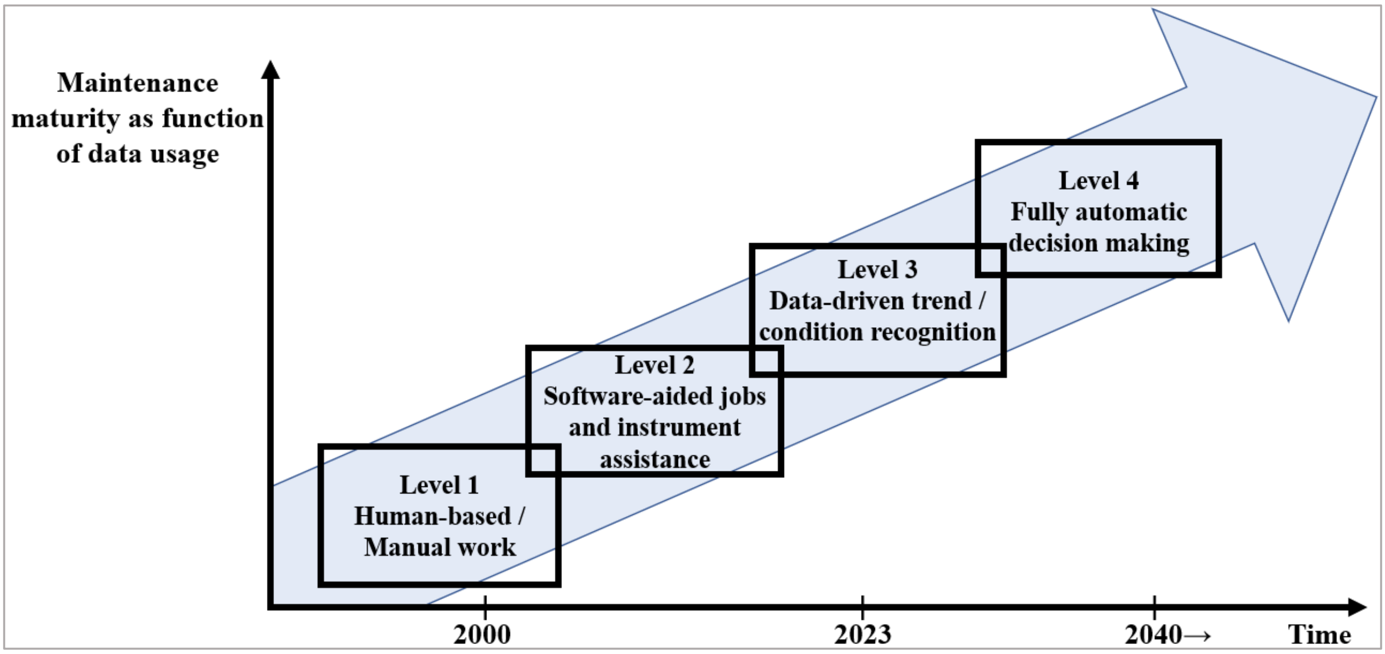

Fig. 1. The maturity of operational maintenance over time as a function of data utilization

This research will begin with a summary of the daily routine and current challenges facing MRO procedures, it will then go over the state of the art of AI integration in MRO processes, going over the different methods and algorithms that have been used to forecast and improve accuracy in MRO operations. Then a neural network module will be suggested to evaluate its ability to detect repeated patterns in task time prediction. Finally, the conclusion will highlight future research and development areas, examining how AI can be further incorporated into MRO operational workflow to enhance aircraft efficiency, safety, and dependability.

2. Method of automation and AI integration in MRO Operational Processes

2.1 Key Elements of MRO Operations

The goal of aircraft maintenance, repair, and overhaul services is to guarantee high reliability, safety, and airworthiness levels. Several maintenance actions are carried out to achieve these goals following the customer's customized Aircraft Maintenance Program (AMP) which is initially developed from the Maintenance Planning Document (MPD) in addition to any extra tasks needed by the aircraft manufacturers or aviation authorities. This can include Service Bulletins (SBs), Airworthiness Directives (ADs), or other requirements specific to the aircraft's configuration, model, or operation environment such as customer-specific additional jobs (FAA, 2016).

The scope of work performed when completing the related types of maintenance is set by the manufacturer's maintenance requirements, which are coordinated with national civil aviation authorities with a common target of restoring and maintaining the aircraft's ability to work, delaying aging of structure elements, preventing/correcting possible malfunctions, and upgrading software and computers ensuring that the highest amount of safety possible.

When a set of work orders or tasks are given to the MRO company to be performed on a specific aircraft, the MRO will give the operator/customer of the aircraft an estimated time for finishing the check and in accordance with that, the contracts will be signed. This time is called Turn Around Time (TAT) and it is extremely crucial for the entire maintenance process since the airlines strive to keep their planes in the sky, in other words, aircraft on the ground are not making a profit but on the contrary, they are costing money.

Therefore, keeping the agreement and delivering the aircraft back on time is one of the key elements of competitiveness in the market, the process of delivering the aircraft on time comprises of the proper coordination of all resources involved to ensure aircraft punctuality and keep operators waiting as little as needed. But a the same time performing excellent maintenance work in order to ensure that the aircraft is reliable and airworthy.

However, in an environment that is characterized by having a lot of uncertainties and emergency occurrences, it is quite challenging to accurately forecast the future manually without the help of data-generated modules and algorithms which is why it is easy to find a lot of research in the pipeline for such innovations.

2.2 The State of the Art in AI Integration for MRO Operations

Building correct modules and enhancing them by AI is not newly investigated for MRO, and when a work environment is known for having a lot of uncertainties, the focus was always focused on finding better ways to make correct predictions and developments in various fields of maintenance to make the work a bit more organized. With the help of Big Data, the Internet of Things (IoT), and AI techniques such developments surfaced and gain popularity. For example, Knowledge-Based Systems (KBS) were used in diagnostics decisions (Acosta et al., 2006), troubleshooting (Bello, 2016), HR management, and scheduling. The architecture of KBS systems is illustrated in Fig. 2.

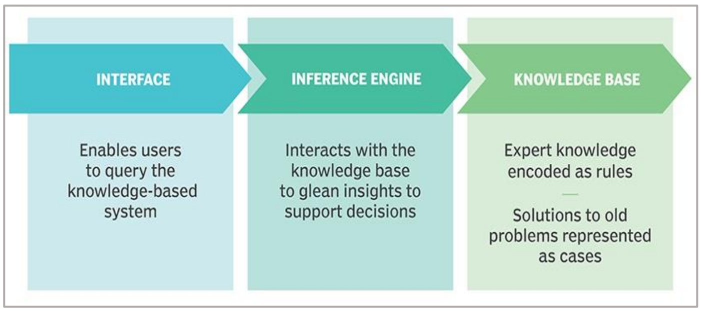

Fig. 2. The architecture of KBS system (Moore, 2019)

Case-Based Reasoning (CBR) is another famous sort of experience-based methodology that can effectively obtain knowledge from previous situations and solve new problems. Since this kind applies several human intelligence traits such as learning and memory, it is widely used for planning, problem-solving, and reliability analysis (Kolodner, 1992). Furthermore, until today this type of AI is still being explored lately it was used to not only give a diagnosis but also to give maintenance decisions according to historical data (Xie *et al.*, 2020). The CBR systems work process is illustrated in Fig. 3.

Fuzzy logic (FL) is also quite popular in MRO operational applications, is a developed form of Boolean logic, where the logic is either truth or fault (1 or 0) that today's computers are based on. The method uses "degrees of truth" in addition to extreme "yes or no" cases as illustrated in Fig. 4, it mimics how a person would make decisions, only much faster therefore this system is effective for engineering cases without precise data or for uncertain cases, such as natural language processing (Zhou et al., 2021), machine input, and output controls, maintenance modeling, and risk-based inspection programs (Djenadic et al., 2022).

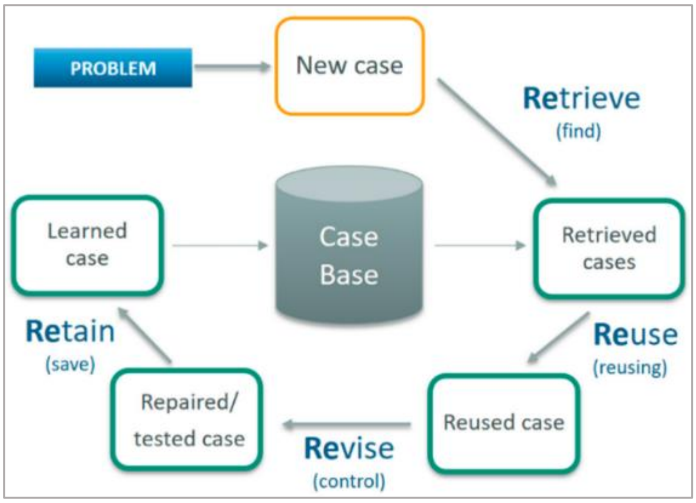

Fig. 3. CBR systems work process (Pusztová, et al., 2021)

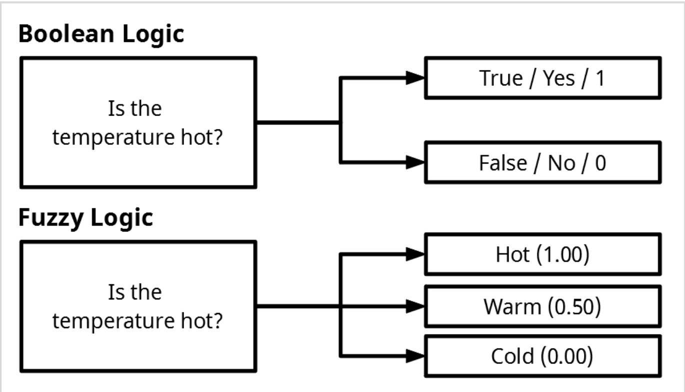

Fig. 4. Difference between Fuzzy and Boolean logic (Sioson, 2020)

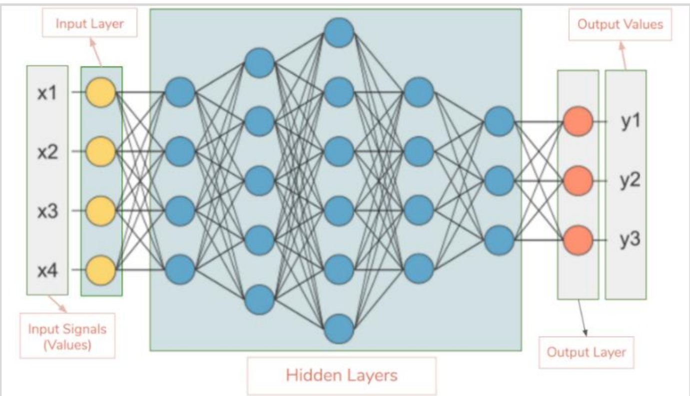

Fig. 5. Example of a simple ANN layout (Mate Labs, 2017)

The ANN system is made up of several parallel-connected processors that are organized into levels or classes. The first level of processors gets the raw inputted data, the second level receives the output data of the level before it (no longer raw data), and so on until the output data of the last level of processors is reached, which is the system's output (see Fig. 5). ANN are incredibly adaptive systems that learn from prior experience and training.

Of course, there are hybrid systems also, which are the combination of two or more AI types together to achieve optimum performance.

2.3 Improving Turn Around Time (TAT) Accuracy in Aircraft Maintenance with Artificial Intelligence (AI)

In the areas of predicting the correct time duration for performing maintenance tasks, AI deployment in the field of MRO processes is still not fully explored as much as it is in other industries. For example, in manufacturing and production processes, deep learning is frequently employed in predicting the time it will take to complete a certain product (Huang, Chang, and Arinez, 2020). But, in those investigations, the trend in human performance is not studied.

In aviation, the Original Equipment Manufacturers (OEMs) try to estimate the number of man-hours required to perform various maintenance tasks, usually, it is based on average values determining the time needed for a regular mechanic to perform the job with the correct tools, support, and equipment (Sasadmin, 2014). This estimation can be a bit over-optimistic for operators and MRO facilities because technicians' and mechanics' competency varies from one MRO to another, so every company will introduce a factor based on its team efficiency and it can be anywhere from 1.25 times to 4 times the recommended OEM recommendation.

The problem with that factor is that it is fixed, it doesn't take into consideration the aircraft's age, the experience of the technician, or the limitations and constraints that are facing the activities. The real performance time or the actual human man-hour of performing tasks can alter and change the original TAT and thus delay the release of the aircraft. So accurately predicting this value can be a game changer in MRO workflow.

MRO planners frequently anticipate the number of manhours needed for either scheduled or unplanned MRO duties resulting from historical inspection reports. Accurate forecasting can boost the productivity and revenue of MRO operations while also reducing turnaround time for aircraft operators. Hence, forecasting techniques and distribution functions were used to improve job time prediction with the help of data analytics (Pelt, Stamoulis, and Apostolidis, 2019) (Pelt and Stamoulis, 2018).

Another example from the scientific world is a time duration estimation for ship refit (deck painting task) that was forecasted using hybrid - historical data/human experts inputs – and the sklearn decision tree classification algorithms to train the prediction models. The results showed improvements in the estimation accuracy by 5 – 10% (Li and Lafond, 2023).

As indicated from the literature research accurate task duration prediction is an extremely important aspect of aircraft project management. Hence, keeping the agreement between the maintenance provider and the customer and for the scheduling and optimizing of maintenance planning.

2.4 Methodology and Data Generation

The precision of ANN will be tested in this paper by the usage of dummy data by utilizing a similar approach to the ones used in previous research with a special focus on the multi-layer perceptron regressor which belongs to the ANN.

The Multi-layer Perceptron (MLP) is a supervised learning method that learns the function:

$$f(.)\ :\ R^{m} \rightarrow R^{o} \qquad (1)$$

By training on a dataset, where "m" is the number of dimensions for input, and "o" is the number of dimensions for output, given of set of features (inputs X= x_1, x_2……,x_n) and a target (output y) it can learn a non-linear function approximator for regression problems (Scikit-learn, 2019).

To test the capability of the ANN "random dummy (synthetic) data" was generated according to Table 1.

All the values are manually generated values, structured in a way that will allow to test if the ANN is actually capable of noticing a trend in the performance time and accordingly predicting future events. For example, by looking at the employee's age, it is generated by giving one random employee a random age. Similarly, the task number is given a random number and each task number will have a random planned time.

When creating the data and to know the accuracy and precision of the module, a random function was defined to generate the value of the "actual man-hour" in Excel. These values were fed to the ANN module as a two-dimensional data frame in a CSV file form containing numbers. If the module understood the trend and was able to predict it correctly, it means that it could be used on real-life data.

The ANN module will be trained by the following data set (see Table 2), it consists of 6000 rows and 8 columns. The more columns we have in the dataset the more rows we need to train the neural module. The inputs should be defined based on the input data we want to analyze, so the ANN model that will be used will have 7 inputs. The actual time column is not counted in because it is the output of the prediction. Therefore, the output will consist of only one neuron which is the actual time. In other words, the module will base its actual man-hour prediction on task number, planned man-hour, the employee who performed the task, the employee experience, the employee's age, the aircraft age, and the aircraft Manufacturer's Serial Number (MSN).

The 6000 rows of data were divided into two parts, the first 99% of the set will be used for training, and the remaining 1% will be used as a test set for the trained module. Before training, pre-processing was done by means of standard scale which is a function in "scikit-learn" more known as "sklearn" inside a machine learning python package, because it improved the accuracy.

Table 1. Dummy data descriptions for the aircraft maintenance task

ID	Feature	Description	Type	Value Range
1	Task Number	Input	Integer	index [1007378, 9998413]
2	Planned Time	Input	Float	[0.01, 10]
3	Performed By	Input	Integer	[1, 50]
4	Actual Man-hour	Output	Float	[1.29, 101.5]
5	Employee Age	Input	Integer	[22, 50]

Table 2. The dummy data was used to train the ANN module

Task	Planned Man-Hour	Performed By	Actual Man-hour	Emp. Age	Emp. Experience	MSN	A/C Age
8139944	1.23	employee_3	1.68	45	22	200	23
8642378	0.06	employee_7	1.68	39	4	600	19
4105888	2.67	employee_9	3.41	29	8	600	19
…	…	…	…	…	…	…	…
2140896	0.19	employee_2	1.61	35	10	300	22

3. Results and Discussion

After training, and by using the test data set the results are as illustrated in Fig. 6, it is noticed that the neural network was able to predict accurately the actual man-hour needed for the task specified, and it noticed the trend for each employee/technician working on the tasks.

The aircraft age also played a role in defining the time needed for finishing the task. The module, based on the data given for training, presumed that the older the aircraft the more it would take to finish the job, which is not always the case in real life because not all tasks will have that effect. For example, servicing tasks such as lubrications and changing filters won't be affected by the age of the aircraft in general. So, this will need to be tested with different datasets to see if the module can recognize it.

Fig. 6 clearly shows the results of the predictions, by comparing the actual man-hour values with the predicted values. It is noticeable that the number of hidden layers in the ANN can contribute significantly to the efficiency and reliability of the module. The result got better by increasing the number of those layers. For each case and shape of the above-plotted ANNs the accuracy, of the rate was calculated as a function of the number of hidden layers, the results are shown in Fig. 7.

By increasing the number of hidden layers, the module is giving better results. However, the usage of computing resources will increase significantly, so more time will be needed for training. This can be solved by using advanced computational methods and higher computational resources. With the size of the data used, rows, and columns, increasing the number of hidden layers after 15 is impractical as the accuracy stayed almost the same after this point.

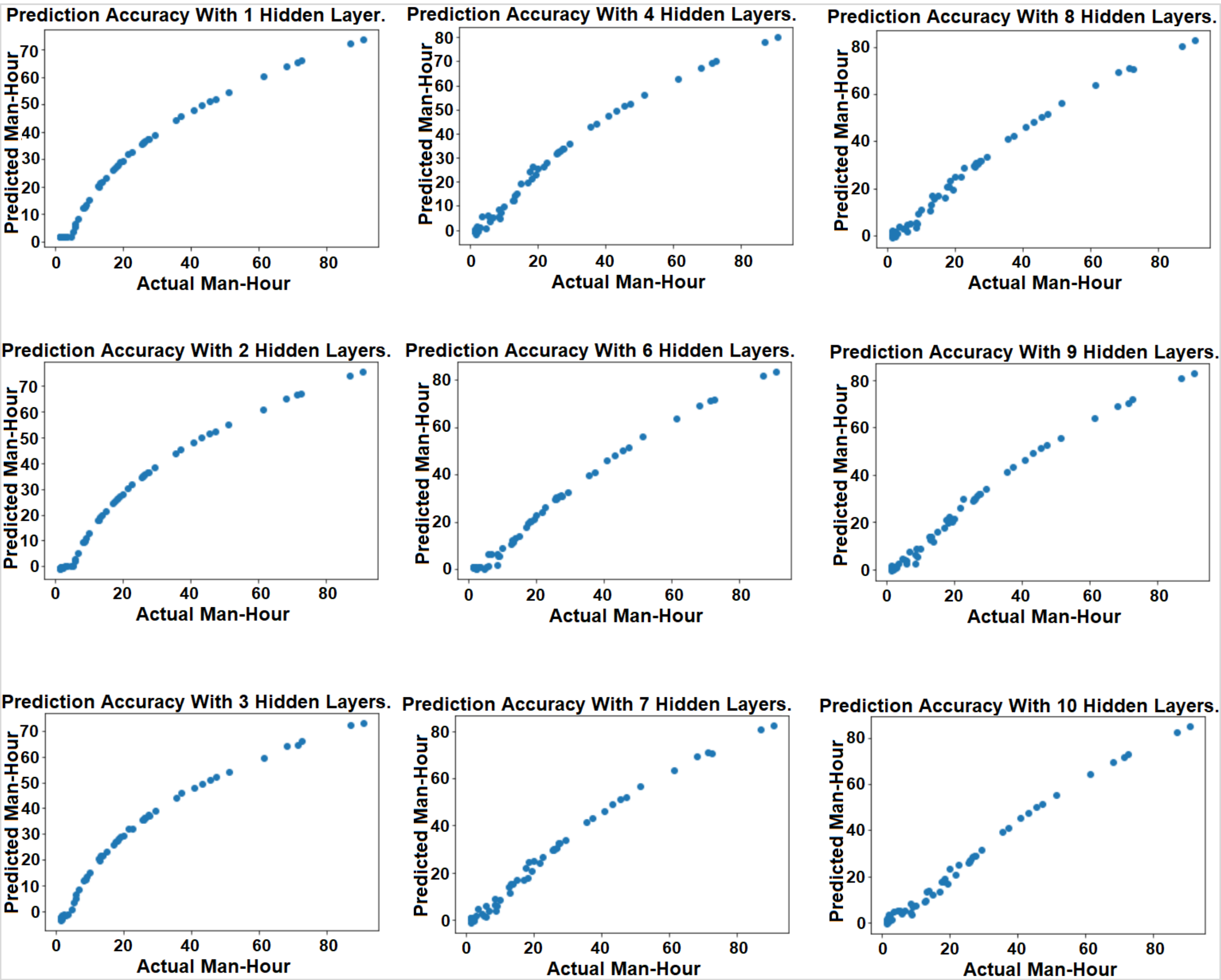

Fig. 6. Comparison between the actual man-hour and the predicted man-hour

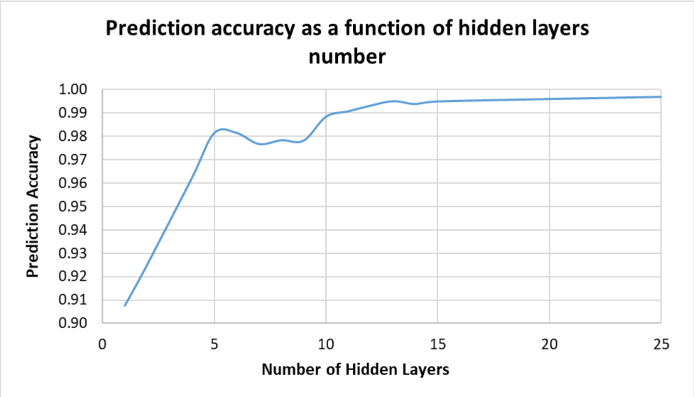

Fig. 7. Prediction accuracy as a function of hidden layers number

4. Conclusions and Future Research

Aircraft maintenance is a crucial factor in aircraft safety, reliability, and airworthiness. With the emergence of the Industry 4.0 revolution and the data era, it is logical to expect a more automated and digitalized future.

Automation and optimization of maintenance procedures go hand in hand with the advancement of AI technology. AI is the imitation of human intellectual thought processes and reasoning without the emotional aspect, which means that in the future, more and higher levels of human mistake elimination may be feasible.

Because AI comprises numerous layers and levels, it is critical to select the ideal type, form, and dimension of it to best serve the task at hand and provide value to these novel techniques.

The digitalization and the potential application of artificial intelligence in aircraft MRO processes will increase speed, improve reliability, and reduce costs by achieving predictable and consistent turnaround time (TAT). In this paper, the capabilities of neural networks for predicting the actual man hours were tested because accurate TATs lead to better aircraft release compliance and hence customer satisfaction.

The generated ANN module was capable of predicting precisely the actual tasks' man-hours for different employees and recognizing the trends based on the dummy data that we trained the ANN with. The results show that this method with minor modifications is ready to be tested on real-time data for verification and validation.

The utilization of AI in MRO operational activities will not only make planning more efficient and sustainable but also improves the utilization of company resources and enable economic operators to take on more tasks, thereby strengthening their market and competitive position and growth.

It is essential to mention that in this study, we trained and tested our ANN model for real man-hour prediction in aircraft maintenance using dummy-generated data. While dummy data allows for a controlled environment for testing and assessing model performance, it does not completely represent the complexity and variability of real maintenance duties.

We plan to use actual data in the future to verify the effectiveness of our ANN model. We can better catch nuances and variations in actual maintenance tasks, which improves the model's accuracy and generalizability.

For further work, firstly the weight of inputs will be introduced to give more accurate outputs. It assists the algorithm in determining which characteristics or factors are dominant to the job at hand. By assigning various weights to each input, the algorithm can prioritize characteristics that have a higher correlation with the intended outcome.

Another direction that could be explored is adding more input features to the module to help give more accurate results. Such features could be related to tasks such as type of the tasks (lubrication, operational test, inspection), and other features could be related to the human factor -since a lot of the inputs that are related to humans can have direct effects on the overall performance time- such features could be for example weather conditions, day or night shift, aircraft schedule (high/low season) and any other factor that could increase the model's efficiency.

For future research, the aim will be to create an interactive dashboard that integrates the appropriate AI system to aid in optimizing maintenance planning and scheduling which is going to help in visualizing the expected maintenance time length for various tasks. Future studies could include creating and testing a display like this in cooperation with maintenance specialists and end users which in return will reflect positively on the quality, cost, time, and accuracy of the MRO processes.

Nomenclature

A/C	: Aircraft
AD	: Airworthiness Directives
AI	: Artificial Intelligence
AMP	: Aircraft Maintenance Program
ANN	: Artificial Neural Network
BA	: Business Analytics
CBR	: Case-Based Reasoning
Emp	: Employee

FAA : Federal Aviation Administration
FL : Fuzzy Logic
IoT : Internet of Things
KBS : Knowledge-Based Systems
MLP : Multi-layer Perceptron
MPD : Maintenance Planning Document
MRO : Maintenance, Repair, and Overhaul
MSN : Manufacturer's Serial Number
OEM : Original Equipment Manufacturers
SB : Service Bulletins
TAT : Turn Around Time

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