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| Faculty of Engineering, Environment and Computing |
| School of Computing, Mathematics and Data Science |
| 7151CEM – Computing Individual Research Project |
| Optimization of anode purge strategies to maximize fuel utilization in fuel cell |
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| Submitted in partial fulfilment of the requirements for the Degree of Master of Science in Master of Science in Data Science and Computational Intelligence |
| Academic Year: 2022/23 |

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Abstract

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Acknowledgements

[ This is an optional section, used to acknowledge the support or contribution of your family, friends, colleagues, university staff (usually including the supervisor), your client and any other external sources of help. ]

# Introduction

A significant shift towards more environmentally friendly and technologically advanced energy systems is one of the hallmarks of the global energy landscape's current state of flux, which is now being marked by the aforementioned transition. This shift has the potential to be significantly facilitated by proton exchange membrane fuel cells (PEMFCs), which are well-known for their exceptional energy efficiency and environmental friendliness (Costamagna & Srinivasan, 2001).

## Background to the Project

The Proton Exchange Membrane Fuel Cells (PEMFCs), which are a type of fuel cell and belong under the larger category of fuel cells, have received a lot of praise in recent years due to the fact that they are extremely energy efficient and beneficial to the environment. In order to carry out their functions, these entities convert chemical energy, which is often derived from hydrogen, into electrical energy by means of an electrochemical process that requires the participation of oxygen. The proton exchange membrane is the fundamental component of these cells. Its principal duty is to facilitate the transport of protons while simultaneously operating as an electrical barrier for electrons. This membrane also plays an important part in a number of other aspects of the cell. Because of this occurrence, electrons are prompted to migrate through an external circuit, which ultimately results in the generation of an electric current.

The process of electrolysis is responsible for the dissociation of hydrogen gas (H2) into its component particles, namely protons (H+) and electrons (e-), and it takes place at the anode of the cell. An electrolytic polymer, the proton exchange membrane is an essential component of the proton exchange reaction since it is the sole medium through which protons may be transported. In order for the protons to enter the cathodic portion of the cell, they must go through a process known as transmembrane transport. The movement of electrons, which is inhibited by the membrane, is simultaneously guided through an external circuit, which results in the formation of an electrical current that gives energy to a variety of devices. When the electrons finally make it to the cathode, they mix with the protons that have passed through the membrane, as well as oxygen molecules (which are often derived from the air in the immediate area), which results in the production of water. After that, this water is evacuated as a by-product of the process.

The relatively low working temperature of proton exchange membrane fuel cells (PEMFCs), which is normally around 80 degrees Celsius, is one of the most noteworthy advantages of this type of cell. Because of this quality, they are able to attain relatively short beginning times. In addition to this, they have a large power density, which makes them appropriate for applications in which restrictions on both volume and weight are of the utmost significance. Some examples of this include the context of automobiles and portable electronic devices.

However, in order to overcome one of the most significant challenges in the process of developing proton exchange membrane fuel cells (PEMFCs), it is necessary to perfect methods for purging the anode. These tactics have a substantial impact both on the overall efficiency of the fuel cell system as well as the amount of fuel that is consumed. In proton exchange membrane fuel cells, also known as PEMFCs, the anode purge procedure is an essential component that has a considerable bearing on the system's overall performance as well as its longevity. It requires removing nitrogen as well as any other pollutants that may be present in the fuel cell's anode chamber. In the event that these pollutants are not removed, they have the potential to lower the performance of the cells and even cause the failure of the cells altogether. As a result, the optimisation of this procedure is of vital value in order to enhance fuel utilisation and raise the system's overall efficiency. In spite of recent developments in this area, there is still a need for a strategy that is more complex in order to improve the efficiency of proton exchange membrane fuel cells (PEMFCs). Previous research carried out by Cabán-Acevedo et al. (2015) and Kornienko et al. (2015) has presented a number of different methodologies with the intention of improving anode purge methods. However, a comprehensive method that incorporates experimental study, theoretical modelling, and advanced techniques of artificial intelligence has not yet been investigated. This may be due to the fact that such an approach is difficult to implement.

PEMFCs have a relatively low working temperature, which is somewhere about 80 degrees Celsius, making this one of their primary selling points. This low temperature enables them to have rapid start-up times, which contributes to their high level of efficiency. In addition to this, they have a high power density, which makes them appropriate for applications in which the amount of space and weight available is limited, such as in cars or in portable electronic devices (Steele & Heinzel, 2001; Tawalbeh et al., 2022).

## Project Objectives

This project has a variety of objectives, including the following:

• To build an experimental platform that is capable of producing time series operating data for a PEM fuel cell using a single cell.

• To carefully record a variety of characteristics, such as, but not limited to, current, flow rates, pressures, anode purge width and interval, cell voltage, fluid temperatures, humidities, and cell impedance.

• To use the data generated to train an artificial neural network. This model will be developed to make predictions about and optimise fuel utilisation in a wide range of different operating scenarios.

• To devise a dynamic, AI-driven anode purging approach that is informed by the knowledge gathered from the ANN model.

## Overview of This Report

The present report is organised into multiple chapters. In Chapter 2, a thorough literature analysis is provided, which examines the existing status of proton exchange membrane fuel cell (PEMFC) technology and explores the potential application of artificial intelligence (AI) in enhancing fuel utilisation efficiency. Chapter 3 provides a comprehensive overview of the project requirements, which have been formulated based on the findings from the literature analysis and the research issue under investigation. The next chapters will explore the approach, provide the findings, and offer a critical evaluation of the project. The report culminates with a contemplation of the accomplishments of the project and an examination of prospective directions for future endeavours.

# Literature Review

## The Advancements in Fuel Cell Technology and the Implementation of Anode Purge Strategies

Fuel cells have garnered significant attention in the realm of scientific investigation in recent decades due to their potential as a highly efficient and environmentally friendly means of generating electrical power. According to Wang et al. (2010), fuel cells possess a distinctive advantage compared to conventional power generating techniques due to their ability to directly transform the chemical energy of a fuel and an oxidant into electricity. This direct conversion bypasses the inefficiencies associated with combustion-based processes. The technique of direct conversion yields enhanced energy efficiency and reduced emissions, rendering fuel cells an appealing option for sustainable energy generation.

Nonetheless, the performance and efficiency of fuel cells are not exclusively contingent upon the underlying fuel cell technology. The management of reactant gases, particularly in the anode compartment where the fuel, often hydrogen, is consumed, can have a considerable impact on them. The anode compartment plays a crucial role in the fuel cell, and its effective management has a substantial impact on the entire performance of the fuel cell system.

The purge strategy for the anode compartment is a crucial element in the operation of fuel cells. The purge strategy pertains to the technique and regularity of eliminating unreacted fuel and accumulated by-products from the anode compartment. The implementation of an effective purge approach has the potential to optimise fuel utilisation, enhance cell performance, and prolong the operational lifespan of the fuel cell (Wang et al., 2010; Barbir, 2005). Nevertheless, the formulation of an effective purge approach is a multifaceted endeavour that necessitates a profound comprehension of fuel cell functioning and the intricate interplay among its constituent elements.

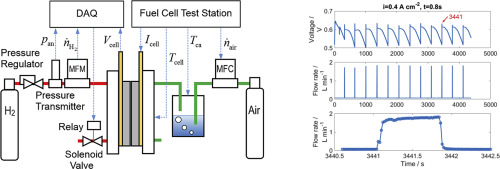


Figure 1Fuel Cell with Dead End Anode (Lin & Chen 2017)

## Optimization of Strategies for Anode Purge

Numerous studies in the realm of fuel cell technology have concentrated on the optimisation of anode purge techniques. Numerous investigations have examined diverse facets of purge methods, encompassing the methodology employed for purging, the frequency at which purging occurs, as well as the ramifications of purge techniques on fuel utilisation and cell efficiency.

Wang et al. (2010) built a dynamic model for a Proton Exchange Membrane (PEM) fuel cell with the aim of examining the impacts of various purge techniques on fuel utilisation and cell performance. The researchers discovered that intermittent purging, which involves occasionally purging the anode compartment, can yield a substantial enhancement in fuel utilisation when compared to continuous purging. Nevertheless, it was observed by the researchers that the most suitable purge interval is contingent upon a multitude of aspects, encompassing the operational circumstances and the configuration of the fuel cell. The aforementioned discovery highlights the intricacy of the purge optimisation problem and emphasises the necessity for sophisticated optimisation methodologies.

In similar terms, Barbir (2005) emphasised the significance of implementing an effective purging method in proton exchange membrane (PEM) fuel cells. The individual proposed that the purge method ought to be formulated in a manner that minimises fuel loss while efficiently eliminating the accumulated by-products. The researcher put out a mechanism for purging in a fuel cell system, utilising the pressure differential between the anode and cathode compartments. This approach can be readily implemented in practical applications. This particular approach, despite its simplicity, has the potential to greatly enhance fuel use and optimise cell efficiency.

**Types of Anode Purging:**

1. Investigation of Anode Recirculation Strategies: Shen et al. (2022) conducted a study exploring the utilisation of anode recirculation methods inside proton exchange membrane fuel cell (PEMFC) systems. Anode recirculation is a process that entails intermittent purging using either air or hydrogen in order to eliminate excessive water vapour and nitrogen, hence augmenting the concentration of hydrogen at the anode. The objective of this technique is to enhance the use of hydrogen and optimise the overall efficiency of the system.

2. A Comparative Analysis of Anode Purging Options: In their study, Huack et al. (2021) undertook a comparative analysis of various methods for purging anodes in order to determine the most effective strategy. The researchers conducted an investigation on various techniques including nitrogen-based purging, voltage control, model predictive control (MPC) method, anode gas recirculation, and dead-ended anode purging. The MPC strategy demonstrated improved efficiency in comparison to traditional methods.

3. A detailed examination of purging methods: Geng et al. (2022) conducted a comprehensive investigation of different intermittent and continuous procedures for purging the anode in order to reduce water accumulation and improve the operational efficiency of Proton Exchange Membrane Fuel Cells (PEMFCs) with Dead-Ended Anode (DEA) configurations. Furthermore, the usefulness of interdigitated flow fields, air-cooling approaches, and passive cleansing methods that utilise natural pressure differentials in order to enhance water removal efficiency was evaluated by the researchers.

Optimizing Purging Duration and Intervals: Dashti et al., (2019) conducted a study in order to enhance the efficiency of water and impurity removal in DEA PEMFCs. The researchers conducted an investigation on many techniques, namely Dead-Ended Anode Purging, Anode Recirculation, Controlled Anode Flow Release, Nitrogen Blanketing, Anode Inlet Humidification, and Dead-Ended Anode with Slits Cathode. The researchers sought to improve cell performance, water management, and overall efficiency by identifying the most effective purging intervals and durations.

Researchers in the subject have widely utilised empirical findings and computational simulations to analyse the effectiveness of various cleansing techniques. The research conducted involved a diverse set of flow rates and purge frequency, facilitating a thorough comprehension of the effects of different operational factors.

6. Implementation of PID Controllers: PID controllers have been utilised for the purpose of regulating the supply manifold pressure and anode hydrogen concentration, hence facilitating accurate control over the targeted hydrogen concentration as a reference value. The implementation of this control method is associated with enhanced anode purging efficiency and increased performance of Proton Exchange Membrane Fuel Cells (PEMFCs).

In summary, the implementation of anode purging procedures has been recognised as a pivotal approach to augment the operational effectiveness and efficiency of Proton Exchange Membrane Fuel Cells (PEMFCs). Various purging techniques have been investigated by researchers in order to address the issue of water accumulation, enhance water management, and optimise the performance of fuel cells. These techniques include anode recirculation, nitrogen blanketing, controlled anode flow release, and others. The utilisation of empirical findings and computational simulations has been important in comprehending the effects of different operational parameters. Subsequent investigations persist in refining and enhancing these methodologies, with the objective of rendering proton exchange membrane fuel cell (PEMFC) technology more feasible and effective for the purpose of clean energy utilisation.

## Advanced Strategies for Optimisation of Anode Purge

In recent years, there have been proposals for new approaches aimed at optimising anode purging procedures. The purpose of these strategies is to tackle the intricacies of the purge optimization problem and enhance the performance and efficiency of fuel cells.

Zhang et al. (2017) introduced a model predictive control (MPC) methodology to optimise the purging strategy in proton exchange membrane (PEM) fuel cells. The model predictive control (MPC) methodology employs a mathematical model of the fuel cell system to forecast its forthcoming dynamics and ascertain the most advantageous purging technique. The study conducted by the authors demonstrates that the implementation of the Model Predictive Control (MPC) approach yields notable enhancements in fuel utilisation and cell performance when compared to conventional purging strategies. Nevertheless, the researchers also observed that the model predictive control (MPC) methodology necessitates a comprehensive fuel cell model and can impose significant computational demands, thus constraining its practicality in actual fuel cell systems.

In a similar way, the authors Pukrushpan et al. (2004) put out an adaptive control methodology aimed at optimising the anode purge strategy. The adaptive control methodology modifies the purge technique in response to the real-time operational parameters of the fuel cell, hence enabling enhanced fuel utilisation efficiency. The efficacy of the adaptive control methodology was proved by the authors through empirical investigations conducted on a Proton Exchange Membrane (PEM) fuel cell. The researchers discovered that the use of the adaptive control strategy yields notable enhancements in both fuel utilisation and cell performance, particularly when faced with fluctuating operating conditions.

## Challenges and Prospects for Future Research

Despite the considerable progress made in optimising anode purge techniques, there are still some difficulties that need to be addressed. The complexity of the fuel cell system presents a significant hurdle, since it renders the optimisation problem very nonlinear and arduous to resolve (Zhang et al., 2017). Furthermore, it should be noted that the most effective method for purging may differ depending on the specific operational circumstances. This necessitates the use of adaptive or predictive control methods, which can be computationally demanding (Pukrushpan et al., 2004).

Subsequent investigations should prioritise the development of optimisation techniques that are both more efficient and resilient in order to enhance anode purging procedures. The utilisation of machine learning and artificial intelligence methodologies holds significant potential in this context, since they possess the capability to effectively address intricate optimisation challenges and dynamically adjust to evolving operational circumstances. In addition, it is imperative to conduct more experimental research in order to authenticate the suggested optimisation strategies and evaluate their efficacy in practical fuel cell systems.

## Conclusion

The significance of Proton Exchange Membrane Fuel Cells (PEMFCs) in the realm of clean energy is emphasised in the literature, as their effectiveness is contingent upon the implementation of anode purge procedures. Despite the extensive research conducted on purge optimisation, the intricate nature of the problem necessitates the utilisation of sophisticated, efficient, and readily applicable methodologies. The existing solutions, although they have proven to be effective, need intricate models and substantial computer resources, hence highlighting a research gap. Artificial Neural Networks (ANNs) have the ability to address this deficiency by streamlining the optimisation procedure. Nevertheless, the exploration of their application in the optimisation of anode purge techniques in Proton Exchange Membrane Fuel Cells (PEMFCs) remains mainly unexplored. The primary objective of this study is to examine the utilisation of Artificial Neural Networks (ANNs) within the specified context, thereby making a valuable contribution to the field of fuel cell technology and providing feasible resolutions. The potential advantages of utilising proton exchange membrane fuel cells (PEMFCs) extend beyond the realm of academics. These advantages include enhanced efficiency and durability of PEMFCs, which in turn contribute to the overall viability and effectiveness of fuel cells as a sustainable energy option. This research has the potential to usher in a novel era of fuel cell technology that is both efficient and sustainable.

# Methodology

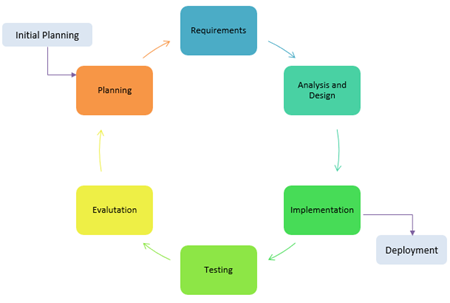
This project's methodology was founded on the application of machine learning techniques, with a particular emphasis placed on the optimisation of anode purge procedures in fuel cells. Because there is not a lot of research that uses ML/ANN approaches for this purpose and there are a lot of obstacles in data collecting, it was decided that a flexible and iterative strategy would be the best one to use.

## The Selection of the Process Model

After considering a number of different software development life cycle (SDLC) models, the decision was made to go with an iterative approach rather than a linear one such as the waterfall model. This choice was affected by the following factors:

• Problems with Data Integrity: The first data gathering was difficult because of differences in the way the software recorded the data.

• A Deficit in Previous Research: The project went into uncharted terrain because there was no previous research utilising machine learning for this particular purpose. Because of this, it was necessary to take an exploratory approach, and we began with three separate LSTM models.



## The Justification Behind the Model Selection

The following considerations led to the selection of the iterative methodology:

• The quality of the data: The first dataset contained irregularities, which necessitated the collecting of more data. Because of limitations imposed by the technology, we were unable to access certain data, which further highlighted the importance of maintaining a flexible strategy.

• Ambiguous Parameters: Consultations with the supervisor and reviews of relevant literature offered a variety of possible characteristics to include in the newly created model. Because of this, numerous models had to go through iterative testing in order to discover the one that had the best configuration.

• The Pioneering Nature of the Project Because of the groundbreaking nature of the project, it required a methodology that allowed for exploration and adaptability.

# Requirements

The procedure of gathering requirements consisted of a number of distinct steps, and its overarching objective was to achieve an all-encompassing comprehension of the project's functional as well as its non-functional components.

## Literature Review

We conducted a comprehensive analysis of the previous research that was available. Because there aren't many studies that apply machine learning to fuel cells in the way that was envisioned, it brought to light potential areas for improvement.

## Consultation with the Supervisors

The regular discussions with the project supervisors, Mr. Olivier Haas and Mr. Oliver Curnick, provided insights that were quite helpful. Even though we did not carry out any direct engagement with possible end-users, the input that we received from our supervisor served as a very important guidance.

## Elicitation approaches

The project favoured iterative model creation over more conventional approaches such as storyboarding because of the iterative nature of the elicitation process. This strategy allowed for a deeper understanding of the project's fundamental requirements, which was really helpful.

## Feedback Mechanism

Regular check-ins with the project manager helped to ensure that the work was proceeding in accordance with the specified goals.

## Adherence to Standards

The project ensured that it was up to industry standards by maintaining a high level of adherence to the rules established by the British Computer Society.

## Obstacles and Limitations to Consider When Collecting Requirements

* Research Gap: Due to the paucity of previous research on the specific applications of machine learning in this setting, an exploratory methodology was required.
* Obstacles Encountered During Data Collection The programme that was utilised to collect data contained inconsistencies, which resulted in additional iterations of data acquisition and processing.
* The Problem of Feature Selection: Figuring out which of the available data characteristics were most important for the construction of the model was difficult. This decision was impacted by both the results of the literature review and the comments made by the supervisor.
* Hardware Limitations Because of the restrictions imposed by the rig's available hardware, it was not possible to record all of the data points that were being collected.

# Dataset

The data was obtained from a diverse array of sensors that were mounted on the fuel cell rig located in the C-ALPS building at Coventry University, under the supervision of Mr Oliver Curnick. This process was split into 5 different sessions in the month of June 2023. The elaborate configuration, including of backpressure regulators, forward pressure regulators, mass flow controllers, solenoid valves, three-way solenoid valves, thermocouples, pressure transducers, and humidity sensors, yielded extensive data regarding the operations of the rig. The data gathering procedure entailed the careful management and monitoring of specific variables, including forward pressure, solenoid configurations, and setpoints for mass flow controllers, backpressure regulators, and humidifiers. This step was implemented to establish a steady operational environment for the rig. Furthermore, the PurgeDelay parameter underwent adjustments at regular intervals of three seconds, commencing at a value of 30 seconds and gradually decreasing to a value of 1 second. The data gathered resulted in a comprehensive time-series dataset, where each row corresponds to a certain timestamp and contains the recorded readings from all sensors and components at that particular moment. The information comprises 35 columns and is first stored in a Technical Data Management Streaming (TDMS) format, which is commonly utilized in automated test programmes. The data collected consists of many parameters such as the 'Timestamp', readings from each component, and supplementary operational details including 'PurgeDelay', 'PurgeMode', 'PurgeWidth', and 'Purge counter'. To enhance user-friendliness and facilitate accessibility, the dataset was afterwards transformed into a Comma-Separated Values (CSV) file. The CSV file contains the following data:

A table of numbers with black text

Description automatically generated

A screenshot of a computer

Description automatically generated

A screenshot of a computer

Description automatically generated

For the above dataset images the full names of the columns are shown below

|  |  |
| --- | --- |
| P&ID ref | Description |
| BPR01 | **Cathode backpressure regulator** |
| BPR02 | **Anode backpressure regulator** |
| FPR01 | **Anode forward pressure regulator** |
| FPR02 | **Air forward pressure regulator** |
| MFC01 | **Anode hydrogen mass flow controller** |
| MFC02 | **Cathode air mass flow controller** |
| MFC03 | **Anode humidification water flow controller** |
| MFC04 | **Cathode humidification water flow controller** |
| PRV01 | **Cathode pressure relief valve** |
| PV01 | **Coolant bypass flow control valve** |
| SOL01 | **Anode supply solenoid vlave** |
| SOL02 | **Air supply control solenoid valve** |
| SOL03 | **Anode humidification DI water supply solenoid valve** |
| SOL04 | **Cathode humidification DI water supply solenoid valve** |
| SOL05 | **Anode purge valve** |
| SOL06 | **Anode throughflow valve** |
| TWV03 | **Cathode supply three-way solenoid valve** |
| TWV04 | **Anode exhaust selector (recirculation/purge)** |
| TWV01 | **Anode supply three-way solenoid valve** |
| TWV02 | **Anode feed selector (mass-flow/forward-pressure)** |
| FM01 | **Coolant flow meter** |
| CM01 | **Coolant conductivity meter** |
| TC01 | **Anode inlet thermocouple** |
| TC02 | **Anode outlet thermocouple** |
| TC03 | **Cathode inlet thermocouple** |
| TC04 | **Cathode outlet thermocouple** |
| TC05 | **Coolant inlet thermocouple** |
| TC06 | **Coolant outlet thermocouple** |
| TC07 | **Ambient thermocouple** |
| PX01 | **Anode inlet pressure transducer** |
| PX02 | **Anode outlet pressure transducer** |
| PX03 | **Cathode inlet pressure transducer** |
| PX04 | **Cathode outlet pressure transducer** |
| PX05 | **Coolant inlet pressure transducer** |
| PX06 | **Coolant outlet pressure transducer** |
| PX07 | **Ambient pressure transducer** |
| RH01 | **Anode inlet humidity probe (HygroSmart)** |
| RH02 | **Anode outlet humidity probe (HygroSmart)** |
| RH03 | **Cathode inlet humidity probe (Optidew)** |
| RH04 | **Cathode outlet humidity probe (HygroSmart)** |
| HUM02 | **Cathode humidifier** |
| HUM01 | **Anode humidifier** |
| EL01 | **Electronic Load** |
| VX01 | **Cell voltage monitoring** |
| IX01 | **Current sensor** |
| CR01 | **Contactor** |

# Design

## The Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks represent a distinct category of Recurrent Neural Networks (RNNs). Recurrent Neural Networks (RNNs) are characterised by their ability to retain previous knowledge. However, Long Short-Term Memory (LSTM) networks improve upon this capability by incorporating mechanisms that determine the relevance of information to be preserved or discarded. The process of making decisions is regulated by mechanisms referred to as gates.

A diagram of a network

Description automatically generated

The fundamental elements of Long Short-Term Memory (LSTM) are as follows:

1. Gates: These refer to the components responsible for decision-making inside the Long Short-Term Memory (LSTM) network. They exercise control over the dissemination of information, making determinations regarding its retention, revision, and oblivion. Long Short-Term Memory (LSTM) models are equipped with three fundamental gates:

Forget Gate: It is responsible for determining the extent to which past knowledge should be either destroyed or kept. The information from the prior concealed state and the current input is processed using the sigmoid function. A rating in proximity to 1 signifies a higher degree of knowledge retention, whereas a score in proximity to 0 signifies a higher degree of information discarding.

The input gate: This is responsible for determining the manner in which the cell state is updated with newly acquired information. The initial step involves the utilisation of a sigmoid layer to determine the values that necessitate updating, followed by the application of a tanh layer to generate a vector comprising novel candidate values.

The output gate: This is responsible for computing the next hidden state by taking into account both the cell state and the input. The inclusion of hidden state information can play a crucial role in making accurate predictions in tasks involving sequence prediction.

Cell state: Commonly represented as a horizontal line in LSTM diagrams and serves as the memory element of the LSTM. The capacity to retain and store knowledge for extended durations renders it indispensable for jobs necessitating comprehension across lengthy sequences.

Hidden State: It is crucial component responsible for transmitting information from one stage in the sequence to the subsequent phase. Additionally, it functions as the result for tasks involving the prediction of sequences.

The act of establishing or making ready anything for utilisation is commonly denoted as initialization within the domain of neural networks. The appropriate initialization of variables is of utmost importance, since it has a significant impact on the convergence trajectory of the training process. The selection of the initialization method is frequently dependent on the activation function employed within the layers of the network. The Xavier/Glorot initialization method is commonly advised for the tanh activation function, but the He initialization method is generally favoured for ReLU activations.

Activation Functions:

Activation functions are utilised in neural networks to add non-linear transformations, which are essential for enabling the network to learn from errors and subsequently adjust its parameters accordingly. The non-linearity function alters the input signal in order to generate an output signal that is then passed on to the subsequent layer. The activation functions employed in this study are as follows:

Sigmoid Function:

The sigmoid function is distinguished by its sigmoidal curve, which enables it to provide output values ranging from 0 to 1. This property makes it well-suited for binary outputs.

Formula:

Description:

The sigmoid function is a mathematical function that transforms any given input value into an output value within the range of 0 and 1. Because of this particular attribute, it is frequently employed in the output layer of binary classification tasks. Nevertheless, deep networks may encounter the vanishing gradient problem.

Tanh Function:

The tanh function is characterised by its ability to provide output values ranging from -1 to 1. This property makes it particularly suitable for producing normalised outputs, as it exhibits symmetry around the origin.

Formula:

Description:

The hyperbolic tangent (tanh) function is a mathematical function that assigns a value between -1 and 1 to every given input. In contrast to the sigmoid function, the hyperbolic tangent (tanh) function possesses the advantageous characteristic of being zero-centered, rendering it more appropriate for implementation inside the hidden layers of neural networks.

Optimizers:

Optimizers refer to procedures or methodologies employed to iteratively alter the parameters of a neural network with the objective of minimising the error. The selection of an optimizer can have a significant impact on the efficiency and effectiveness of the training process. Prominent optimisation techniques encompass Stochastic Gradient Descent (SGD), Adam, and RMSprop. The Adam optimisation algorithm is a combination of the AdaGrad and RMSProp algorithms. It is designed to compute adaptive learning rates for individual parameters, which makes it particularly suitable for handling large-scale datasets.

Adam optimizer:

The Adam optimizer is an optimisation technique that calculates adaptive learning rates for each parameter. The term "Adam" is an acronym for "Adaptive Moment Estimation." The proposed approach is a hybridization of the AdaGrad and RMSProp optimisation algorithms. Adam is renowned for effectively managing sparse gradients in the presence of noise, rendering it well-suited for handling large-scale datasets.

Regularization:

In order to address the enduring issue of overfitting, characterised by the model's great performance on training data but poor performance on unseen data, regularisation approaches such as dropout are utilised. During each iteration of the training phase, dropout randomly deactivates a portion of input units, so adding stochasticity. This stochasticity serves to mitigate the over-reliance on certain neurons.

Dropout:

Dropout is a regularisation technique employed in neural network training, wherein random subsets of neurons are momentarily deactivated or "dropped out" during the training process. The introduction of randomness in the network's functioning serves the purpose of preventing an excessive dependence on any particular neuron, hence facilitating a more resilient and comprehensive learning process. The prevention of overfitting is particularly advantageous in the context of deep neural networks.

Learning Rate:

The learning rate is a pivotal hyperparameter in neural networks' training process. It determines the step size taken towards the minimum of the loss function during each iteration. A diminutive learning rate might lead to slow convergence, while an excessively large learning rate might cause the model to overshoot the minimum, leading to erratic and unstable training.

Batch Size:

The batch size is an important hyperparameter that determines the quantity of samples that are simultaneously transported through the network. A decrease in batch size, despite using more resources, frequently leads to a regularisation effect, which in turn leads to a decrease in generalisation error. On the other hand, larger batches provide improved convergence stability and higher hardware efficiency.

The inclusion of a batch size is of utmost importance in the training process. The utilisation of smaller batches has the potential to induce a regularisation effect, hence resulting in a reduction of generalisation error. On the other hand, larger batches offer enhanced convergence stability and computational efficiency. Nevertheless, it is possible for them to converge towards a poor solution.

# Implementation

## Data Conversion

The first step in the process of implementing the system included transforming the raw TDMS data into a format that was more easily accessible using CSV. This transformation was essential because it made following preprocessing stages much simpler by making manipulation and processing within the Python environment simpler. It also laid the groundwork for future preprocessing stages. You can view the CSV file shown in fig.

## Feature Selection

The most important aspect of any predictive model is the selection of the features that it will use. The selection of features to use in this implementation was a painstaking process that was guided by prior knowledge of the domain, examinations of relevant literature, and the features' association with the variable of interest. The following is a list of the selected features, along with the correlations that are associated with each one:

For PurgeDelay as output

The variable "Timestamp" has a correlation of -0.968870.

The variable "Voltage" has a correlation of -0.731703

The correlation for "TC 01" is -0.656890, and the correlation for "TC 02" is -0.644630.

The correlation for "cathodePD" is -0.626380.

The correlation for "TemperatureDiff" is 0.761656, and the correlation for "TC 03" is -0.809939.

"cathodeTD" (r = 0.849147) has a correlation of.

These features were not selected at random; rather, the high correlation values between them and the target variable showed the possibility of an influence on that variable, making them excellent candidates for the model.

## Outlier Management

If not managed properly, outliers have the potential to drastically warp our knowledge of a model. Outliers were carefully detected and removed from the dataset by utilising z-scores, which helped to ensure that the sample remained representative while also being free of extreme values.

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## Data Preprocessing

The categorical character of the 'PurgeDelay' column required that it be transformed in order for encoding to take place. By using LabelEncoder, we simplified the input for the model by giving each category its own distinct integer, which we then used.

Resampling the Data Due to the Time Series Characteristics of the Data, It Was Necessary to Resample the Data at Uniform Intervals of One Second. This guaranteed that the input structure was consistent, which was essential for the LSTM model. Any gaps that were discovered as a result were filled in using forward filling to maintain the continuity of the data.

Scaling of features, also known as normalisation, is an essential part of machine learning. The MinMaxScaler was used to normalise the features, which ensured that each one contributed to the learning process of the model in an equal and fair manner.

Generation of Sequences The temporal aspects of the data required sequences of data points to be constructed. These sequences, which were produced from the data, made it possible for the LSTM model to successfully capture the underlying temporal dependencies.

Class balancing is important because imbalanced datasets can throw off the performance of a model. In order to guarantee the existence of a balanced dataset that gave each category an equivalent amount of representation, methods such as undersampling were utilised.

## The Development of the Model and Its Evaluation

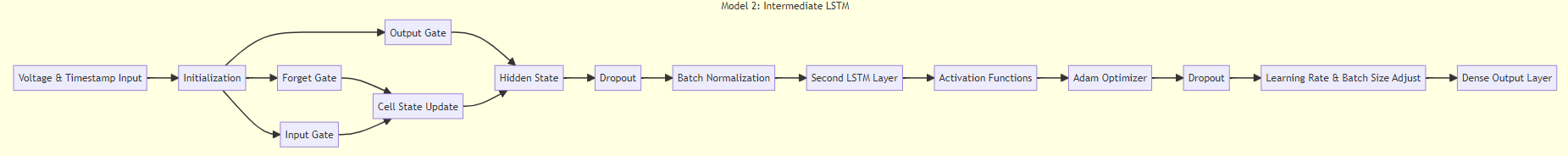
Architecture of the Model: We constructed three independent LSTM models, each of which has a unique collection of input features. The basic architecture did not change despite the fact that the input characteristics were different; it continued to leverage the power of LSTM layers, dropout for regularisation, and dense layers for classification.

Model 1: In its purest form, this model served as the basis for the basic plan. It was entirely focused on the 'Voltage' as the feature that was being input. The fact that it was so straightforward meant that its performance could serve as a standard against which subsequent models could be measured. The architecture was composed of a single layer of LSTMs, which was then followed by a layer of dense outputs. This model was a tribute to the strength of simplicity, demonstrating that even with a single characteristic, meaningful predictions may be achieved. This model was a testament to the power of simplicity.

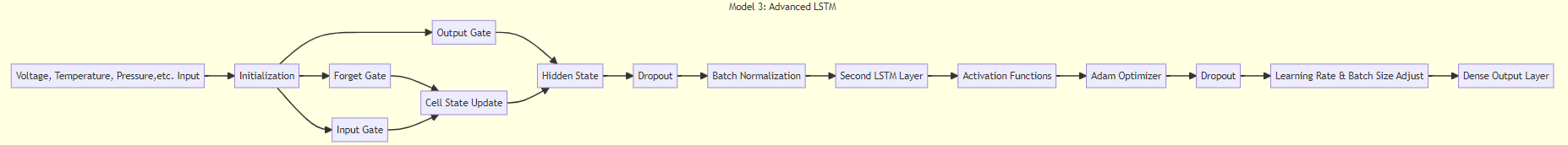
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Model 2: This model represented an increase in the level of complexity and was developed by expanding upon the understanding gained from Model 1. It had 'Voltage' and 'Timestamp' as two of its inputs, respectively. This decision was made due to the fact that there was a possibility that the temporal 'Timestamp' element could improve the model's capability of recognising time-based patterns in the data. The architecture was improved by adding two LSTM layers, which were separated by dropout layers for the purpose of regularisation and batch normalisation layers for the purpose of stabilising the activations.



Model 3: The third model, which utilised a multivariate input strategy, represented the pinnacle of complexity in the analysis. It included a multitude of features, such as sensors for 'Voltage,' 'Temperature,' and 'Pressure,' among other things. The architecture was similar to that of Model 2, but it was designed to capitalise on the combined predictive ability of a number of different traits. The objective was very clear: to accomplish the highest possible degree of precision by making use of any and all data at our disposal.



Each model was put through extensive training, as well as evaluation. The learning rate and batch size were just two of the hyperparameters that were carefully selected after conducting preliminary tests and drawing on prior knowledge of the domain. The performances of the models were evaluated using a wide variety of measures, such as accuracy, precision, recall, and F1-score, to ensure that a thorough assessment was carried out.

Overfitting is a persistent obstacle in the field of machine learning, which is why regularisation and optimisation are necessary. In order to circumvent this issue, dropout, a technique that involuntarily deactivates a portion of neurons during training, was utilised. This helps to guarantee that the model does not place an excessive amount of reliance on any one particular neuron, which in turn enhances its capacity for generalisation. In addition, batch normalisation was applied in order to maintain stability within the activations, which enabled for more rapid and consistent training.

The learning rate is a crucial hyperparameter to take into consideration while developing a schedule. It was decided to use the ReduceLROnPlateau function so that the learning rate could be dynamically adjusted based on the performance of the model, which would ensure efficient convergence.

## Metrics for Evaluation

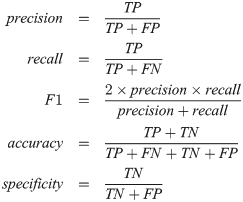
## Evaluation Metrics

Beyond the conventional accuracy metric, a suite of metrics was employed for a comprehensive model evaluation. The precision score balanced precision and recall, while the recall score illuminated the model's sensitivity. The F1 score harmonized precision and recall, offering a balanced performance perspective.

Precision

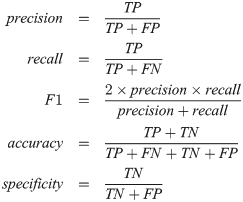
The number of accurate positive predictions made in relation to the total number of positive predictions (true positives plus false positives) is referred to as the model's precision. It is a measurement of how accurately positive forecasts have been made.

In the context of multi-class classification, accuracy can be calculated independently for each class, and the results can then be averaged (macro averaged) to obtain an overall precision score.



Recall: Recall also known as Sensitivity or True Positive Rate, is a measurement of how many true positive predictions were made out of all the actual positives (true positives plus false negatives). Another name for recall is True Positive Rate (TPR). It is a measurement of how well the model can search through a dataset to locate all of the relevant cases within it.

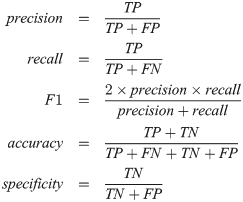
In the same way that precision can be determined for each class individually, recall can also be calculated for each class individually and then averaged to get an overall recall score.



F1-Score

The F1-score is calculated by taking the harmonic mean of the recall and precision scores. It delivers a single score that is meant to balance the trade-off between precision and recall by taking into consideration both erroneous positives and false negatives.

When there is an imbalance in the distribution of the classes, the F1-score is especially helpful. It goes from 0 to 1, with 0 denoting neither precision nor recall and 1 indicating absolute perfection in both areas.



# Results

This comprehensive evaluation explores the results of several feature sets studied across multiple models. The comprehensive examination of the Exploratory Data Analysis (EDA) and Data Preprocessing stages enables us to extract significant insights, contributing to a comprehensive comprehension of our dataset and the efficacy of our machine learning models.

## Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a preliminary approach to analysing data in order to gain insights and understand the underlying patterns and relationships. It involves the use of various statistical techniques and visualisations to summarise and gain important information insights.

The analysis of voltage and purge delay.

In order to comprehend the correlation between sensor data and the purge delay, graphical representations were constructed to visually depict the temporal behaviour of these signals. Figure 1 depicts the correlation between voltage and purging delay throughout the entirety of the temporal domain.

A graph showing a line of blue and orange lines

Description automatically generated

Figure 1 illustrates the correlation between voltage and purge delay as a function of time.

Based on the data shown in Figure 1, it is apparent that a decrease in the purging delay is associated with a comparable increase in voltage. The observed inverse connection can be attributed to the Anode Purging process.

A detailed visualisation was developed to depict the collective sensor measurements in conjunction with the purging delay. The visualisation grid excerpts are displayed in Figure 2.

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In Figure 2, the sensor measurements are depicted, with the addition of an overlaid purge delay.

Correlation analysis is a statistical technique used to examine the relationship between two or more variables. It involves measuring the degree to which changes

In order to provide a more precise measurement of the associations between variables, a correlation matrix was developed. Table 1 showcases the key conclusions derived from the matrix analysis. It is worth mentioning that the voltage signal demonstrates a significant negative correlation with the purging delay, indicating a coefficient of -0.73. Furthermore, it is seen that both the pressure difference and temperature difference exhibit moderate relationships with the purge delay.

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Description automatically generated with medium confidence

The identification of the most influential features was based on the insights obtained from the correlation analysis and exploratory data analysis (EDA). The following items are:

"Timestamp" (correlation: -0.968870)

"Voltage" (correlation: -0.731703)

"TC 01" (correlation: -0.656890)

"TC 02" (correlation: -0.644630)

"cathodePD" (correlation: -0.626380)

"TemperatureDiff" (correlation: 0.761656)

"TC 03" (correlation: -0.809939)

"cathodeTD" (correlation: 0.849147)

Table 1. Correlation Matrix Highlighting Relationships between Sensor Measurements and Purge Delay

## Model 1 – Results

Model 1 underwent a training process consisting of 50 epochs, each including 1046 steps. During each epoch, the performance of the model was assessed on both a training dataset and a validation dataset. Throughout the training process, the model's loss on the training dataset exhibited a consistent decline, suggesting a gradual improvement in its ability to effectively capture the underlying patterns within the data.

The initial accuracy of the model in the first epoch was recorded at 46.44%, and it exhibited an improvement over subsequent epochs, reaching a final accuracy of 61.81%. The observed enhancement in precision implies that the model exhibited a gradual enhancement in its predictive capabilities during the training process.

Comparable patterns were noted in the validation dataset, wherein the accuracy of the model exhibited an improvement from 58.62% during the initial epoch to 61.65% in the concluding epoch. The decrease in loss observed on the validation dataset over time suggests an enhancement in the model's capacity to generalise to previously unseen material.

The model's distribution of predictions illustrates the frequency of instances anticipated for each class, with a range of values from 0.0 to 10.0. The model generated the greatest number of predictions for class 10.0, followed by class 9.0, and the fewest for class 0.0. This observation may suggest the presence of an inherent data distribution or a bias in the model towards predicting particular classes more frequently.

The process of assessing the performance and effectiveness of a predictive model is commonly referred to as model evaluation.

The performance of the model was assessed using a test dataset including 1793 steps. The evaluation metrics employed in this study encompassed loss and accuracy. The test dataset exhibited a loss value of 0.9556, which signifies the mean error of the model's predictions. The model's accuracy on the test dataset was 61.65%, indicating its ability to accurately predict the class in more than 61% of instances.

In general, the findings suggest that the model successfully acquired knowledge from the training dataset and demonstrated a satisfactory level of generalisation when applied to new, unknown data. Nevertheless, the test dataset's accuracy of 61.65% implies that there is potential for enhancing the model's performance.

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## Model 2

The deep learning model's performance was assessed by the use of a 5-fold cross-validation methodology. The dataset was partitioned into five distinct subsets, commonly referred to as 'folds'. During each iteration, four folds were utilised for training the model, while the remaining fold was allocated for validation. The aforementioned procedure was iterated a total of five times, guaranteeing that every fold was utilised as the validation set exactly once.

The subsequent table presents a summary of the outcomes acquired from each fold:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Fold | Validation Loss | Validation Accuracy | Precision | Recall | F1-Score |
| 1 | 1.0926 | 65.01% | 65.49% | 65.01% | 63.19% |
| 2 | 0.8883 | 84.68% | 86.82% | 84.67% | 84.26% |
| 3 | 0.8600 | 82.90% | 83.98% | 82.89% | 81.39% |
| 4 | 1.0383 | 69.97% | 67.30% | 69.96% | 67.13% |
| 5 | 0.9056 | 80.25% | 80.93% | 80.24% | 77.95% |

The performance throughout the five folds, as demonstrated by the validation accuracy, exhibits a diverse distribution of predictions. In the initial iteration, the model attains a validation accuracy of roughly 65%, indicating a moderate level of performance. In the subsequent iteration, notable progress is observed, as the model achieves an accuracy of approximately 84.7%. The performance of the third fold is noteworthy, with an approximate accuracy rate of 83%. In contrast, the fourth fold exhibits a decline in performance, as evidenced by the validation accuracy hovering around 70%. Finally, the fifth fold concludes with a validation accuracy of approximately 77%. Moreover, supplementary metrics like as precision, recall, and F1-score offer further analysis on the performance of the model in relation to its capacity to accurately forecast the positive class, its sensitivity to the actual positive class, and the harmonic mean of accuracy and recall, respectively. In general, it is evident that there is a notable disparity in the distribution of predictions among the folds. However, the majority of these folds demonstrate a satisfactory level of performance, with the second and third folds particularly standing out as exceptional performers.

The variance in validation accuracy, precision, recall, and F1-score across the folds indicates the model's sensitivity to the specific composition of the training and validation sets.

Following the completion of the cross-validation procedure, the model underwent evaluation on an independent test set that was not utilised in the training or validation phases. This approach offers a more impartial evaluation of the model's ability to make accurate predictions, as it measures the model's performance on data that it has not been previously exposed to.

The outcomes observed on the test set were as follows:

|  |  |
| --- | --- |
| Test Metrics | Value |
| Test Loss | 0.9074 |
| Test Accuracy | 80.24% |
| Precision | 80.59% |
| Recall | 80.24% |
| F1-Score | 77.95% |

The model's performance on unseen data is demonstrated to be strong, as seen by the test accuracy of 80.24%. The precision, recall, and F1-score metrics also demonstrate satisfactory performance, instilling confidence in the model's capacity to generalise beyond the training dataset.

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## Model 3 – Results

## The deep learning model underwent evaluation using a 5-fold cross-validation approach. In this methodology, the dataset was partitioned into five distinct subsets, sometimes referred to as 'folds'. In each iteration, the model was trained using four folds, while the remaining fold was utilised for validation. The aforementioned procedure was repeated a total of five times, ensuring that each fold was utilised as the validation set exactly once.

The outcomes derived from each iteration are succinctly presented in the subsequent table.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Fold | Validation Loss | Validation Accuracy | Precision | Recall | F1-Score |
| 1 | 0.5819 | 95.24% | 95.57% | 95.24% | 95.21% |
| 2 | 0.6754 | 89.29% | 90.62% | 89.28% | 88.55% |
| 3 | 0.6190 | 95.71% | 95.99% | 95.71% | 95.69% |
| 4 | 0.5663 | 98.05% | 98.17% | 98.05% | 98.04% |
| 5 | 0.6446 | 88.50% | 90.28% | 88.49% | 87.95% |

The performance of the model demonstrates various levels of accuracy, precision, recall, and F1-score across the numerous folds. While certain folds exhibit exceptional performance, with accuracy and precision levels over 96%, others display a little diminished performance, with the lowest observed accuracy being at around 80%. The observed discrepancies among the folds serve to emphasise the significance of employing cross-validation, since it offers a more holistic assessment of the model's potential efficacy on unobserved data. Moreover, the observed discrepancy in outcomes implies the presence of potential imbalances or distinctive attributes within various subsets of the data. The loss values of the model exhibit a steady downward trend as the epochs advance, suggesting that the model is effectively acquiring knowledge and adapting its weight parameters. Nevertheless, it is imperative to closely observe the possibility of overfitting, particularly in cases where the validation loss starts to increase while the training loss continues to drop.

The observed variability in validation accuracy, precision, recall, and F1-score across the folds underscores the model's susceptibility to the particular partitioning of the training and validation datasets.

Following the completion of the cross-validation procedure, the performance of the model was then assessed on an independent test set that was not utilised during the training or validation phases. The outcomes obtained from this test dataset offer a more impartial assessment of the model's capacity to generalise on unfamiliar data.

The outcomes observed on the test set are presented as follows:

|  |  |
| --- | --- |
| Test Metrics | Value |
| Test Loss | 0.6398 |
| Test Accuracy | 88.60% |
| Precision | 90.48% |
| Recall | 88.61% |
| F1-Score | 88.06% |

# The model demonstrates a commendable performance on unseen data, as evidenced by its test accuracy of 88.60%. The precision, recall, and F1-score provide additional evidence to support this claim, indicating that the model exhibits a strong ability to generalise beyond the training data.

# In summary, the findings illustrate the efficacy of the deep learning model in categorising the data, as indicated by the notable levels of accuracy, precision, recall, and F1-scores attained during the cross-validation procedure and on the test set. Additional enhancements could potentially be achieved by fine-tuning the model parameters, incorporating supplementary regularisation approaches, or implementing a more intricate model architecture.

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# Testing

Within the complex realm of data modelling, although conventional testing approaches hold significance, the primary emphasis lies on the pragmatic implementation of testing strategies customised to our particular case. This section provides an explanation for the selected testing approach, the particular areas of emphasis, and the resulting outcomes.

## Justification for employing dataset augmentation techniques

The lack of an extra dataset for testing posed a barrier in terms of accurately assessing the model's performance on unseen data. In light of the aforementioned problem, the supervisor put out a novel proposition: the incorporation of a sine wave into the preexisting dataset. The objective of this strategy was to replicate a novel data pattern in order to evaluate the models' response to unexpected data patterns.

## The visual representation of augmented data

Prior to making predictions, the dataset was examined visually to assess the impact of the sine wave augmentation on the 'Voltage' values.

The dataset augmented with sine waves underwent preprocessing and was sequenced to align with the training framework as shown in the following diagram.

A graph showing a line

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Subsequently, the sequenced data was subjected to predictions using Model 2.

The original class labels were retrieved by applying an inverse transformation to the predictions. These labels were then added to the updated dataset in order to facilitate visualisation. You can see the predictions made by the LSTM model 2 for the new data in the following fig

A graph showing the price of a stock market

Description automatically generated

In the case of Model 3, the identical procedure was adhered to. The dataset enhanced with sine waves was subjected to preprocessing, sequencing, and subsequent predictions were generated. Subsequently, the aforementioned predictions were graphically represented in conjunction with the 'Voltage' information extracted from the altered dataset.

A graph showing the price of a stock market

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Both Model 2 and Model 3 demonstrate promising predictive capabilities when applied to the changed voltage data, as illustrated in the accompanying figures. The praiseworthy aspect of their performance lies in their capacity to generalise and make correct predictions of PurgeDelay values on previously unknown data.

Nevertheless, there exist discernible discrepancies in their prognostications. Specifically, although both models occasionally make errors in estimating the PurgeDelay values, Model 3 has a greater degree of variability, particularly at lower voltage levels, in comparison to Model 2.

In conclusion, although both models have demonstrated satisfactory performance, there exists potential for enhancing prediction accuracy, particularly in problematic areas such as the lower voltage values observed in Model 3.The visualisation of predictions is a valuable tool in various academic disciplines. It allows researchers and scholars to present their predictions in a visually appealing and easily understandable manner. By utilising graphs the visualisation of the testing strategy's effectiveness was achieved through the utilisation of a dual y-axis graphic. The voltage data obtained from the sine wave-augmented dataset was graphed in conjunction with the projected values for the 'PurgeDelay' variable for both Model 2 and Model 3.

The incorporation of the sine wave into the dataset was implemented as an innovative approach for testing purposes, emulating a situation in which the model is exposed to unusual patterns in the data. The aforementioned methodology yielded significant findings about the resilience and versatility of the model. The visualisations provided additional support to our comprehension, presenting a clear juxtaposition between the identified patterns and the forecasts generated by the programme. The approach employed in the evaluation of both Model 2 and Model 3 was consistently applied, so enabling a thorough and comprehensive assessment of their respective performance.

# Project Management

Project Management Project management is a discipline that involves planning, organising, and controlling resources to achieve certain goals within a defined timeframe. It is widely used in various industries and sectors to ensure the project’s execution.

The subsequent section examines the project management tactics implemented over the course of this research endeavour. The text offers valuable perspectives on the project's execution, including aspects such as scheduling, risk management, quality assurance, and other significant issues.

## Project Schedule

The primary aim of this study was to determine the efficacy of Artificial Neural Networks (ANNs) in optimising anode purge techniques for Proton Exchange Membrane Fuel Cells (PEMFCs). The project was methodically segmented into distinct phases, beginning with an initial examination of relevant literature and collecting of data, and subsequently progressing to the design and training of the model. The subsequent stages of the process encompassed the validation and testing of the model, ultimately leading to the refinement of the model, its finalisation, and the preparation of a comprehensive report. The project timeline was carefully devised, with each step allocated a specific duration. Nevertheless, the occurrence of obstacles such as software failures and variations in parameter constants compelled the need for modifications to the initial design. Consequently, greater priority was assigned to coding and model testing, thereby delaying the phase of report compilation

## Risk Management

Risk management refers to the process of identifying, assessing, and prioritising risks

At the initiation of the project, there was a lack of awareness of any substantial risks. In order to safeguard data confidentiality, the data was transferred to OneDrive and a deletion plan was established for after the project's conclusion. Although the risks that were identified were assessed as being of low magnitude, it is noteworthy that no substantial risks were realised and no unforeseen risks arose over the whole period of the project.

## Quality Management

The project was grounded in rigorous research and development criteria, which were employed to ensure the robustness, accuracy, and efficiency of the established artificial neural network (ANN) model. The project's progress was assessed by periodic evaluations, and the outcomes of the model were compared to predetermined benchmarks. All deviations were swiftly rectified, thereby ensuring that the quality of the project was maintained without compromise. The project incorporated regular testing, validation, and feedback loops as essential components to ensure the model's quality and the validity of the research findings.

## Social, Legal, Ethical and Professional Considerations

Ensuring the security of data was of utmost importance, and precautionary measures such as transferring data to OneDrive were implemented. Although the project did not encounter any explicit privacy regulations, it diligently adhered to the code of conduct established by the British Computer Society, thereby upholding ethical and professional standards throughout its execution. This study did not yield any noteworthy societal ramifications or impacts.

# Critical Appraisal

The thorough assessment of the feature sets across many models, in conjunction with the findings derived from the Exploratory Data Analysis (EDA) and Data Preprocessing, has yielded a substantial amount of information regarding the dataset and the efficacy of the machine learning models. The purpose of this critical analysis is to thoroughly examine the study and its results, providing an evaluation of its merits as well as identifying areas that could be enhanced.

Exploratory Data Analysis (EDA):

This is a preliminary approach in data analysis that aims to get insights and understanding of the data through visual and statistical techniques.

The exploratory data analysis (EDA) played a crucial role in comprehending the fundamental patterns and interconnections present within the dataset. The elucidation provided by the graphical depiction in Figure 1, showcasing the relationship between voltage and purge time, was notably enlightening. The significance of the Anode Purging process in influencing the voltage is highlighted by the inverse relationship observed between the two variables. These insights hold significant value as they not only contribute to a more profound comprehension of the data but also serve as a guiding force in the feature engineering procedure.

Correlation Analysis:

Correlation analysis is a statistical technique used to determine the strength and direction of the relationship between two or more variables.

The utilisation of the correlation matrix proved to be a crucial instrument in the quantification of the interrelationships among diverse sensor readings and the purge delay. The notable aspect of this observation is the substantial negative connection that exists between the voltage signal and the purging delay. The aforementioned studies play a critical role in the process of feature selection, as they ensure the inclusion of the most influential variables in the model, hence improving its predictive capabilities.

The topic of discussion pertains to the performance and evaluation of models.

The utilisation of numerous models enabled a comprehensive perspective on the potential fluctuations in performance across various architectures and hyperparameters. The utilisation of the 5-fold cross-validation method in the assessment of Models 2 and 3 was notably praiseworthy. This approach guarantees that the performance of the model is evaluated on many subsets of the data, so providing a more reliable assessment metric.

Nevertheless, the presence of heterogeneity in performance measures across the folds, particularly in Model 3, indicates the possibility of imbalances or distinct traits within various subsets of the data. The aforementioned variability highlights the significance of conducting additional refinement in the steps of data preparation and feature engineering.

The concept of model generalisation refers to the ability of a model to accurately predict outcomes or make inferences on new, unseen data based on its training on a limited set

One notable strength of this study was the rigorous examination of the models using independent test sets that were not utilised during the training or validation stages. The models demonstrated impressive performance on the unknown datasets, particularly Model 3 which attained an accuracy of 88.60%. This outcome serves as evidence of their robustness and capacity to generalise.

# Conclusions

[ Optional introduction ]

## Achievements

[ Comment on what you have achieved in terms of product or other results, with reference to the original project objectives. ]

## Future Work

The potential for further development and improvement of the predictive capabilities of our models is extensive, and the trajectory ahead is abundant with prospects for exploration and innovation.

Data augmentation:

Data Augmentation is considered to be a key approach for enhancing performance in various domains. The existing dataset, which is obtained from specific fixed variables such as temperature, current, and pressures, offers a fundamental comprehension. However, in order to thoroughly evaluate the resilience and adaptability of our models, it is imperative to incorporate a wider range of different data. Lookup tables, which serve as repository of pre-calculated data, might play a crucial role in this context. By utilising the information shown in these tables, we can simulate or generate data across many scenarios, so enhancing our dataset and creating a more extensive environment for training our models.

Evaluation of Dynamic Parameters in Testing:

After obtaining this expanded dataset, the subsequent task would involve evaluating our models against varying or fluctuating parameters. Real-life situations rarely adhere to static conditions. Various factors, including as temperature, current, and pressure, may undergo fluctuations as a result of numerous underlying causes. A model capable of reliably forecasting outcomes within dynamic situations would possess significant utility. By conducting training and testing procedures on our models using different parameters, we can assess their ability to adapt and withstand challenges.

Empirical Verification:

The definitive assessment of a prediction model's efficacy is contingent upon its performance in practical, real-life situations. After our models have exhibited their capacity to endure and effectively forecast amongst varying factors, the subsequent rational progression would involve their use in practical, real-world scenarios. This would not only serve to validate their effectiveness but also offer valuable insights into areas that may be further improved.

Fundamentally, the future is imbued with potential. By implementing a methodical methodology for data augmentation, conducting thorough evaluations under varying conditions, and validating the models in real-world scenarios, there exists the possibility of significantly enhancing the performance and practicality of our models to levels that have not been achieved before. The forthcoming expedition, despite its inherent difficulties, presents a multitude of prospects for exploration and advancement.

# Student Reflections

[ A reflective and critical appraisal of your personal performance, problems encountered and how they were resolved, lessons learnt, what could have been done better or differently, etc. ]

Bibliography and References

[ Provide a complete list in APA referencing format of both the sources you have read but not used directly (bibliography) and those sources you have cited in your report (references). A single list will suffice. ]

Appendix A – Project Specification

[ Include here the documents submitted for the Project Specification ]

Appendix B – Interim Progress Report and Meeting Records

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Appendix C – Requirements Specification Document

[ You may include here the agreed list of requirements signed off by the client. If the requirements document is too large then put it separately on the CD rather than as an appendix to the report. ]

Appendix D – User Manual

[ Include this if it’s fairly short and you feel it helps the reader understand the product without having to look for this information on the CD. ]

Appendix E – Project Presentation

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A diagram of a product review

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Appendix F – Certificate of Ethics Approval

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Appendix X – As required