

An AI predictive model for drifts detection in dialysis machines components

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Abstract—Renal insufficiency affects millions of people worldwide, for whom hemodialysis is the only long-term maintenance therapy. Dialysis machines include alarm systems to detect malfunctions, but these provide alerts only after an issue has occurred, limiting proactive intervention. This study proposes an Artificial Intelligence model to anticipate failures of the system and its critical components, such as sensors and actuators. Results from real-case complaints demonstrated the model’s ability to predict their drifts in advance, enabling timely intervention and reducing machine downtime. Future works will focus on integrating this model into home dialysis systems, fostering preventive maintenance and improving treatment quality.

Keywords—dialysis, machine learning, equipment, prediction.

I. INTRODUCTION

RENAL insufficiency causes a reduction in kidney function that affects between ~4.9 and ~7.1 million people worldwide [1], for whom haemodialysis or kidney transplantation are the only life-saving options.

Haemodialysis (HD) is a treatment that uses a semipermeable membrane to separate two fluids: blood, which contains toxins that the kidneys can no longer eliminate, and a fluid rich in electrolytes and glucose, called dialysate. Such membrane allows toxins and waste products to be removed by a process of diffusion, while retaining proteins and blood cells. The process takes place in hemodialyzers, cylindrical modules filled with hollow polymeric fibers. These modules are installed inside dialysis machines, which are complex devices operated by trained personnel in a hospital environment for regulating and monitoring the HD process through the presence of many sensors and pumps [2].

Notwithstanding, numerous risks can be incurred during a treatment, such as technical malfunctions or alterations in the patient’s health status. To mitigate this problem, dialysis machines are equipped with alarm systems that can alert the operator and stop the procedure if necessary. Considering their complexity, regular maintenance and troubleshooting is required to identify and prevent potential issues.

Since the last century, the use of *Artificial Intelligence* (AI) techniques has interested an increasing number of fields, in order to provide powerful tools for predicting the behaviour of complex systems [3]. AI is a discipline that uses mathematical algorithms to perform tasks normally done by humans. There are several subcategories included under the common name of “Artificial Intelligence”, but in recent years the so-called *Machine Learning* (ML) has become particularly popular among them. ML focuses specifically on the ability of machines to learn from data and improve their performance over time without being explicitly programmed. Thus, the so-

called “training” is the basis of machine learning. Specifically, to train a ML model, it needs a dataset containing examples of the problem to be solved. Once trained, the model can be used to make predictions on similar, but new data, called “testing data”.

Applications of ML in the renal field have grown more and more over the years. The most recent works will be here discussed, with an analysis of the progress achieved and the remaining gaps, some of which this paper aims to explore and fill. The application of AI models in the dialysis field has focused primarily on developing predictive and non-invasive solutions to problems arising during or after dialysis treatment, with the goal of reducing the risk of further deterioration in already compromised patients. An example is given by Ota *et al.* [4], who developed a novel AI model to analyze the sounds generated by arteriovenous fistula and detect early signs of stenosis in hemodialysis patients, a complication caused by narrowing of the fistulized vessel. Interesting is also the development of AI models done by Tan *et al.* [5], aimed at studying fluid overload, responsible for various lung pathologies, in hemodialysis patients.

Despite the extensive research on AI models, few studies have specifically focused on dialysis equipment [6] and its critical role in managing the entire dialysis process.

Other biomedical devices have been studied, and AI models implemented to prevent their failures have shown good results. For example, Raboshchuk *et al.* [7] developed an AI model aimed to enhance alarm detection from biomedical devices in noisy environments as that of a neonatal intensive care unit. Similarly, Rahman *et al.* [8] proposed a predictive maintenance AI model for critical medical devices to optimise their utilisation and minimise downtime.

Building on these approaches, this study aims to make a novel contribution to the field of dialysis equipment through the implementation of an AI predictive model to monitor the behaviour of the system and its critical components, such as sensors and actuators, in order to predict and anticipate any anomaly or performance loss that require a technical intervention. Moreover, thanks to its ability to easily adapt to different types of signals once retrained, this approach could represent a scalable solution suitable for various monitoring contexts, both within and beyond the medical field.

II. MATERIALS AND METHODS

A. Dialysis machine

Dialysis equipment is designed with an internal hydraulic circuit, composed by actuators and sensors that control and monitor essential system parameters as illustrated in **Figure 1**.

Some of these components can be affected by drifts over time and require to be calibrated or replaced in case of malfunctions. Internal hydraulic pressures can be used to detect and identify a potential component drift or other anomalies that can lead to an equipment failure.

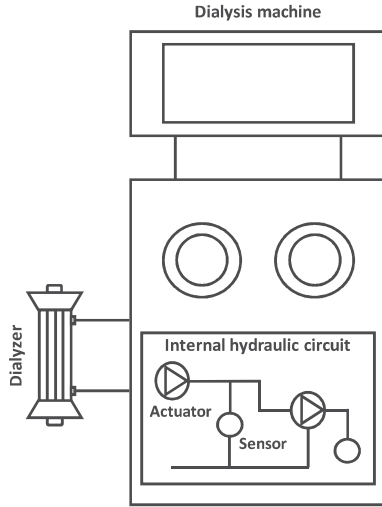


Fig. 1: Scheme of a dialysis machine with a focus on the hydraulic circuit.

B. Dataset pre-processing and ML model

In this work, a ML model able to identify in advance anomalous patterns that can lead to equipment potential issues and failures was developed. This predictive tool could be useful to detect in advance deviations that allow to identify the root cause and intervene early. Hydraulic pressure data recorded during specific machine phases were used to train and test the model. A total of 123 pressure-time signals were considered, all exhibiting normal behaviour, without drifts or anomalies. These conditions were chosen to allow the model to learn and generalize the correct pressure trends under proper operating conditions. Out of the 123 signals, 103 (~80%) were used for training, following standard practice in machine learning [9], while the remaining were used for testing. All signals were filtered to exclude any transition phases that could affect the learning and testing procedure.

The overall shape of these signals is illustrated in Figure 2.

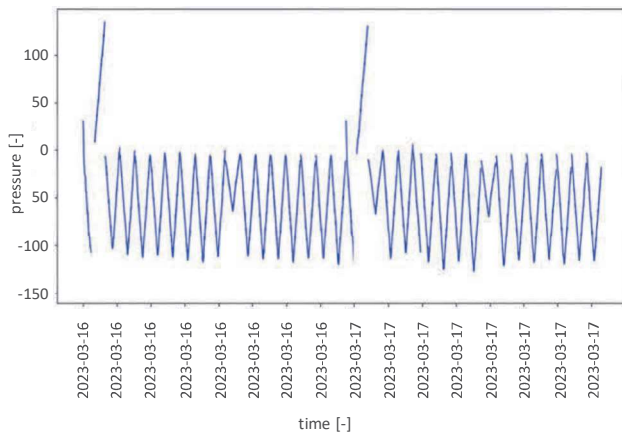


Fig. 2: Pressure-time signals filtered to include only their actual phases.

Subsequently, the signals were normalized to a range between 0 and 1 to ensure alignment on a unified scale.

After this pre-processing process, the final dataset took the shape of the signals shown in Figure 3.

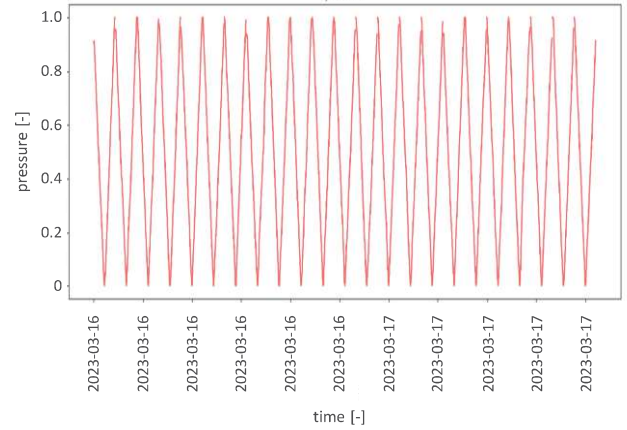


Fig. 3: Portion of the normalized dataset used to train the AI model.

C. LSTM model

A *Long-Short Term Memory* (LSTM) was used, a neural network model that can learn sequential data to predict future values based on past. A LSTM model well trained and tested for reconstructing normal data has difficulty reconstructing anomalous data, resulting in high reconstruction errors.

In this work, absolute errors were used as reconstruction errors, defined as $|x - \hat{x}|$, where \hat{x} is the predicted value and x the real value. Here, absolute errors between 0 and 1 were possible, since data were normalized in this interval.

Through the training on *clean* data, the minimization of the absolute errors and a good reconstruction of the training sequence was obtained. This permitted to have a model capable of predicting anomalous trends on new data sequences, based on the learning of the training phase.

Figure 4 shows the basic working principle of the LSTM model for this application.

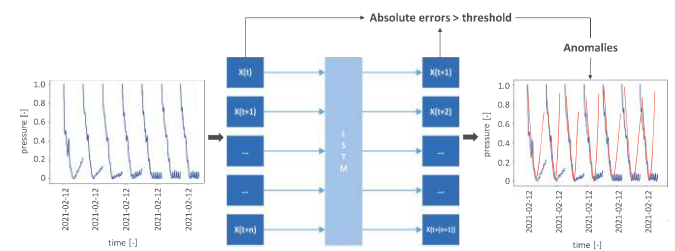


Fig. 4: LSTM application as tool for anomalies detection.

For a good training, it was necessary to calculate the absolute errors for all the samples of the *clean* data and verify that they were close to 0. To detect anomalies in the analyzed sequence, it was then appropriate to recalculate the absolute errors for all the samples and apply one of the criteria used to assess what to consider an anomaly in the signal reconstruction.

The chosen criterion considers the exceeding of a threshold: once all absolute errors have been sorted and a threshold limit set, any point with an absolute error above this threshold is an

anomaly. After testing the model to assess its generalization capability, several trials were conducted using data containing anomalies. Anomalies with a maximum threshold of 1 were identified, and various ranges of potential anomalies were set. These ranges were then categorized by significance and severity levels based on a comparison between what the model identified and what was found by the technicians who had investigated the problem at the complaint stage.

III. RESULTS

The results of the training phase are presented in **Figure 5**, which shows maximum reconstruction errors of ~ 0.08 . A very high-quality reconstruction of the signals was achieved, as evidenced by the accurate reconstruction of all points, the majority of which showed a maximum absolute error of ~ 0.02 .

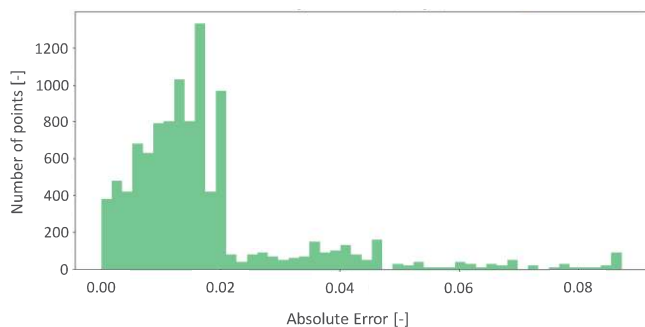


Fig. 5: Histogram of absolute errors distribution for the training phase.

Model testing conducted on the remaining $\sim 20\%$ of the entire dataset consistently demonstrated a maximum reconstruction error of ~ 0.08 . This confirmed that the previously found threshold is the limit of the model's reconstructive capacity, which cannot be further reduced during training. As a result, reconstruction errors larger than 0.08 were used for identifying anomalies in signals containing irregularities.

Specifically, the trials of the model were conducted using data derived from complaints submitted by hospitals to the company regarding malfunctions occurring during treatments.

Twelve cases belonging to three different categories were analysed, including the reported incident and approximately one month of treatment data leading up to it.

Table I summarizes these three categories.

TABLE I: CASES ANALYZED WITH THE LSTM MODEL, CATEGORIZED BY DIFFERENT COMPLAINT REASONS

Number of cases	Reason of complaint
4	Machine out of use linked to a component critical drift or malfunction
4	Machine not out of use but performance loss linked to a component drift or malfunction
4	Issues not linked to component critical drift or malfunction

Two cases belonging to the first two categories will be presented and discussed here. Beyond space constraints, the decision to omit cases from the third category was driven by their limited relevance. Specifically, since the reported problems did not concern data from the critical component on which the model was trained, it did not detect anomalies. As a

result, the model merely confirmed the technicians' assessment of the component's proper functioning, without providing any additional insight or useful detail.

The first case involves a complaint about a machine failure and out of use due to a component critical drift or malfunction, followed by another failure a few days later, despite an attempt to calibrate the component after the first failure. This provided clear evidence that the component needed to be replaced rather than simply recalibrated after the first failure. **Figure 6** shows the anomalies magnitude obtained in the reconstruction of the signals under investigation, ranging from 0.08 to 1.

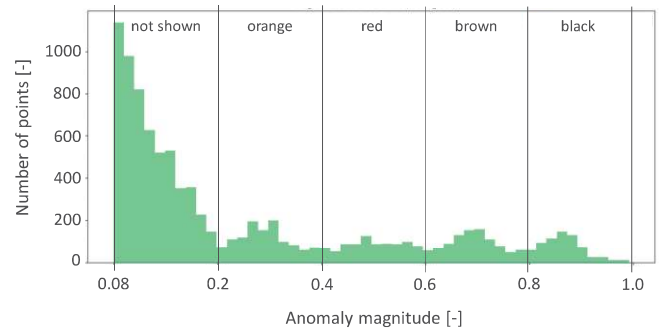


Fig. 6: Histogram of anomalies distributed according to their magnitude.

Five ranges of anomalies severity were established, as shown in the figure, each of them associated to different colours for facilitating the visualization of the results. Being the most represented, the first interval was excluded from the following graph, to make the distribution of the other intervals clearer.

Figure 7 shows the reconstructed signal (green line) overlapped with the original one (blue line), and the events of machine failure circled in red along the temporal x-axis.

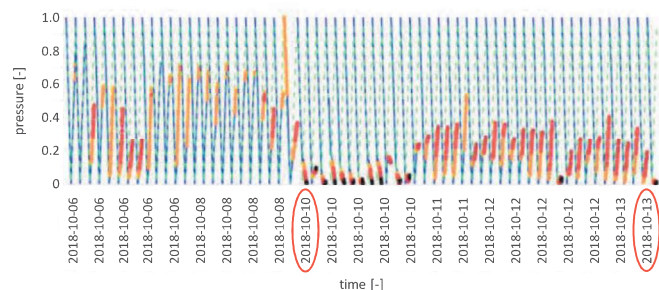


Fig. 7: Results of the first case where component malfunction resulted in machine failure.

The signal reconstructed by the model confirmed the machine failure, as evidenced by the brown and black marked points. In addition, it can also be identified the potential failure five days in advance as noticeable from the reported orange, red, and brown markers at the anomalous points.

Furthermore, the model showed another component malfunction immediately after recalibration, thus indicating a potential risk of subsequent failure, as in fact happened only four days after the first machine failure.

The second case involves a complaint of potential component malfunctions that had not resulted in machine failures but a performance loss has been complained by the hospital. This trial case aims to assess the model's true predictive capability, even in detecting anomalies not

identified by the machine. **Figure 8** illustrates the results of the model's reconstruction superimposed on the original signal, using the same shape and color legend as in **Figure 7**.

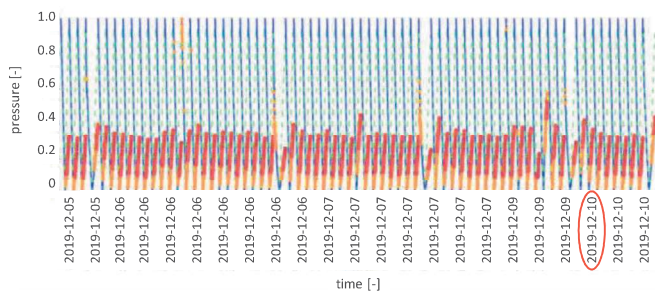


Fig. 8: Results of the second case where component malfunction not resulted in machine failure.

The signal reconstructed by the model (green line) verified the presence of actual component drift on the day the complaint was filed (red circle), identifying it as early as five days before the hospital reported the issue.

Once again, these findings highlight the predictive ability of the model, not only in anticipating possible future machine failures, but also less pronounced component drift. Based on these results, and following consultations with technical experts on component drift, **Table II** associates the anomalies magnitude found in this analysis to the potential issues, broken down by their severity.

TABLE II: CLASSIFICATION OF ANOMALIES MAGNITUDE FOR THEIR EARLY DETECTION

Anomaly magnitude (AM)	Severity of the issue
$0.08 \leq AM < 0.20$	Slight anomalies due to minor external disturbances and system inaccuracies
$0.20 \leq AM < 0.40$	More significant anomalies due to a small component drift
$0.40 \leq AM < 0.60$	Very significant anomalies due to a significant component drift, indicative of possible upcoming machine failures
$0.60 \leq AM < 0.80$	Serious anomalies indicating a forthcoming machine failure
$0.80 \leq AM \leq 1.00$	Very serious anomalies indicative of ongoing machine failure

This approach not only facilitates faster decision making but also enables targeted interventions to reduce risk.

Furthermore, the classification presented above highlights the model's potential to prioritize anomalies based on their severity, assisting clinicians in planning preventive maintenance to avoid the machine failure and, as consequence, its downtime.

IV. CONCLUSIONS

In this work, a LSTM model able to identify in advance anomalies that can lead to equipment issues was implemented, with focus on the drifts of machine components.

The model was trained on a dataset of normal systems trend logged by the dialysis equipment. After the training, the model well reconstructed new signals potentially influenced by

anomalous patterns, highlighting in advance deviations that enable the identification of root causes and early intervention.

Although the signal analysed in this work was relatively simple, making linear regression or even visual analysis sufficient to identify drift on normalized data, the decision to use an AI model proved advantageous. Indeed, unlike manual investigations, which are only feasible during the post-processing stage and after anomalies have occurred, a LSTM model offers a proactive approach, capable of anticipating anomaly detection earlier than traditional troubleshooting. Furthermore, a LSTM model is not confined to the specific signal analyzed but is capable of adapting to various scenarios and signal types through a straightforward adjustment of the training data, an advantage that simple linear regression models cannot provide. These capabilities not only demonstrate the model's effectiveness but also underline its potential benefits, such as optimized maintenance strategies, and improved system reliability.

Future perspectives will focus on integrating this model into home dialysis settings, where timely patient support and preventive machine maintenance could play a crucial role in enhancing the quality of remote treatment and promoting more sustainable healthcare practices.

V. ACKNOWLEDGEMENT

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