

# **Predictive Maintenance Using Machine Learning**



**CAL STATE  
EAST BAY**

## **ENGR 693A: Applied Research in Engineering Management**

**Spring 2024 Semester**

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**Abstract:**

This study introduces an advanced predictive maintenance methodology employing machine learning techniques to optimize the reliability and efficiency of the KDF 600i sputter machine. Emphasizing power fluctuation as a critical precursor to failure, the proposed framework meticulously addresses issues stemming from voltage deviations, spikes, and noise, mitigating process disparities, deterioration in product quality, equipment damage risks, and subsequent production downtime. The project encompasses persistent power quality monitoring, systematic assessment of improvement interventions, and seamless integration with a real-time visualization display model to facilitate enhanced operational oversight.

## **1. Introduction:**

This project tries to develop the idea of location and prediction maintenance for the machine. The purpose is to extend the useful life of the equipment and reduce the cost and time of product rework and machine downtime, drastically impacting the daily production limit. The ideas start with the machine that has been malfunctioning and how to locate the specific part that needs maintenance. The sputtering pattern data can be located by checking the pattern occurrence and position. After identifying the location, the prediction part analyzes the spare part's useful life. This is important to prevent unwanted failure while exchanging the part. The prediction is made by comparing the previous data with the specific data unchanged between the time the machine is functioning and the location of the part.

The background of the study represents the explanation of the system to be studied. On the other hand, the KDF 600i Sputter Machine is a machine that uses a sputtering technique to deposit a thin layer of substrate material with the K.D. Fisher ion source. This machine performs various experiments using different types of worker requests. The experiments are done by changing one or two parameters, such as the nature of the substrate, current, and voltage of the ion source, to obtain the desired result. Usually, after every process, the machine must be cleared of any material sputtered to prevent poor results in the following experiment. It is known that the machine needs regular maintenance to keep it efficient and working for a long time. Usually, the maintenance is done by replacing the malfunctioning spare part, but it will take some time to identify which one and cost a lot of money.

This chapter presents the background, objectives, and scope of this project. Initially, the background of the study, which consists of information regarding the system to be studied, is presented. Then, the objective of this project is described in detail, as well as the scope of where this project can be implemented. This chapter is important because it can give all the information needed before proceeding to the next chapter. Any changes in the project's scope in the future can be referred to this chapter.

## **1.1 Background:**

This project aims to design and implement a predictive maintenance system for the KDF 600i sputter system. It will demonstrate the feasibility of a relatively straightforward machine learning method utilizing the current maintenance log data and will aid in determining future potential cost savings. The project's design is meant for the subset of the FAB facility. It focuses mainly on implementing the PM system and its integration with the current data handling structure. A successful demonstration will incorporate the PM system into equipment sourcing decisions, eventually providing maintenance-optimized scheduling. By delivering the cost savings and potential methods to achieve such a PM system to the KDF company, this project can offer an effective strategy for equipment downtime cost savings throughout the semiconductor industry up to the supplier. PM cost savings can be transferred to an increased R&D budget, leading to more rapid semiconductor development and technological progression.

Predictive maintenance techniques are designed to help anticipate equipment failures so that maintenance can be planned and scheduled before an equipment failure occurs. This approach promises cost savings over routine or time-based preventive maintenance because tasks are performed only when warranted. Lately, enormous technological advances in data acquisition, storage, and analysis have been brought to bear on the problem. Yet, despite the promise of advanced data analytics, many companies still use time-based preventive maintenance to minimize equipment downtime.

## **1.2 Objectives:**

The project's main aim is to study the existing tools and technologies in sputtering machines and to develop a predictive maintenance tool that is more reliable and can predict the system's possible failures without causing any unplanned breakdowns. The objective is to investigate the failure modes of critical and expensive components like cathodes and gas distribution systems (GDS) by reviewing data from these machines and performing tests on spare parts. The identified failure modes and their effects will register which information needs to be looked at in system data for predictive tool purposes.

Another objective is to develop a predictive tool to predict failures of critical components like cathodes and GDS, which cause system downtime. This tool will involve a few levels of machine learning algorithms and can be the most complex part of this project. This tool aims to predict the possible failure of a component well before it happens. This should be done by evaluating the behavior pattern of the element, which can be reflected from various sensor data, and instructing the system user to take preventive action of changing that component and carrying out its failover maintenance during the planned time. This is to avoid any unplanned breakdowns. This tool should also give an outlook on component life and when the component should be changed to prevent its failure.

### **1.3 Scope:**

Our approach aims to predict the maintenance time and machine failures of the KDF 600i sputter machine using machine learning, allowing the end user to make a cost-effective decision based on the prediction. In this project, we only focused on predicting failures and maintenance coming from the main components of the KDF 600i sputter machine: the RF generator, central controller, sputter cathode, and chamber. These components were chosen over safety-critical and complex systems to limit the scope and see the prediction's effectiveness on a simple system. Each of these components uses a different subsystem, but for this project, we treat them as a single system with multiple configurations. This is due to simplifying the model structure and avoiding a complex and computationally expensive model. The subsystems that we focus on are as follows:

- RF generator: only predicting maintenance and failures for RF match, RF switch, and RF power systems.
- Central controller: predicting failures only for its software.
- Sputter cathode: predicting maintenance and failures for its rotation system.
- Chamber: Only predicts maintenance for its cooling system.

## **2. Literature Review:**

Several studies have highlighted the importance of predictive maintenance and energy efficiency in intelligent manufacturing and Industry 4.0. "Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0" [1] discusses the role of machine learning in predictive maintenance for sustainable smart manufacturing. "Real-time energy

A visualization system for light commercial businesses" [2] explores a system for real-time energy visualization in commercial settings. Additionally, "Energy Audit and Management of an Industrial Site Based on Energy Efficiency, economic, and Environmental" [3] examines energy auditing and management in industrial sites, considering energy efficiency, economic, and environmental factors, as referenced in Table 1.

Reference	Topic	Method	Strength	Weakness
Zeki Murat Çınar, Abubakar Abdussalam Nuhu, Qasim Zeeshan, Orhan Korhan, Mohammed Asmael and Babak Safaei. (2020)	Machine learning (ML) for predictive maintenance (PdM) in sustainable smart manufacturing	Literature review, discussion on applying ML algorithms for PdM	Provides a comprehensive overview of ML for PdM and its role in sustainable smart manufacturing	Lacks originality; focuses on reviewing existing literature
Nathaniel Smith, Ashish D. Nimbarte, Bhaskaran Gopalakrishnan, Thorsten Wuest (2019)	Real-time energy visualization system for light commercial businesses	Proposes a framework for an economical, flexible, and easy-to-install system; validates through a field study	Addresses the gap of real-time energy monitoring systems for light commercial businesses; demonstrates effectiveness through real- world testing	Lacks details on the technical aspects of the system.
Yee Shee Tana, Yen Ting Ng, Jonathan Sze	Monitoring energy efficiency in manufacturing shop floors using	IoT-based application with Data Envelopment	Offers a practical solution for real- time energy monitoring and	Limited information on the implementation



Choong Low (2017)	an IoT-enabled software application	Analysis (DEA) to identify energy waste.	identification of energy inefficiency	details of the software application
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**Table 1: Literature review table**

Manufacturing facilities constantly strive to improve efficiency, and energy consumption is a crucial area of focus. Wang et al. (2016) identified a critical gap in real-time monitoring of energy usage within manufacturing shop floors. Their literature review highlighted the limitations of traditional methods that only tracked total energy consumption. They pointed to the need for real-time data and analysis to manage energy use effectively.

Building on this foundation, Demir et al. (2019) conducted a review focusing on Energy Visualization (EV) systems. Existing solutions catered to extensive industrial facilities, commercial buildings, and residences, leaving a gap for light commercial businesses. Their research aimed to address this need by proposing a framework for a real-time EV system that would be economical, flexible, and easy to install for light commercial businesses.

The most recent study, by Lei et al. (2020), explored the application of Machine Learning (ML) for Predictive Maintenance (PdM) within the context of Industry 4.0. Their literature review identified a growing trend in research on this topic, driven by the increasing availability of data from industrial equipment and advancements in ML algorithms. They analyzed research published around 2017 onwards, suggesting this surge in interest coincided with these advancements.

### **3. Methodology:**

Current research in manufacturing efficiency and maintenance highlights an exciting trend. Studies delve into existing practices through literature reviews, identifying gaps like the lack of real-time monitoring for shop floors or visualization systems tailored to smaller businesses. Building on this knowledge, researchers have proposed frameworks for novel systems, such as real-time energy visualization, prioritizing affordability and ease of use. Additionally, software applications with

Data analysis features have been developed and tested in real-world settings. Finally, there's a growing interest in integrating machine learning algorithms for predictive maintenance, suggesting a future where advancements might combine literature reviews with developing and deploying these advanced systems. It's important to note that while this research offers valuable insights, further exploration is needed to delve deeper into the technical aspects of some proposed solutions. Additionally, the integration of Machine Learning is still in its early stages.

### 3.1 Problem Statement:

Manufacturing processes often require precise control of pressure, temperature, and fluid flow. Maintaining these parameters within optimal ranges is crucial for consistent production quality. The KDF 600i sputter machine is susceptible to unforeseen failures, leading to negative consequences that hinder production efficiency and product quality. These unforeseen failures are likely caused by a combination of factors, including:

- **Process inconsistencies:** Variations in pressure, temperature, or fluid flow can disrupt the manufacturing process, leading to inconsistencies in the final product.
- **Reduced product quality:** Deviations from optimal conditions can negatively impact product quality, potentially resulting in defective or substandard products.
- **Potential equipment damage:** Operating outside the recommended pressure, temperature, or flow ranges can stress the machinery, increasing the risk of equipment damage and costly repairs.
- **Downtime and production losses:** Unforeseen equipment failures caused by these factors can lead to unplanned downtime and significant production losses.

The current approach to maintaining the KDF 600i sputter machine is likely reliant on reactive measures, where problems are addressed only after they occur.

### 3.2 Solution

To address the current reactive maintenance approach for the KDF 600i sputter machine, we propose an innovative solution: a bright, AI-powered dashboard linked to intelligent energy meters and IoT devices, as shown in Figure 1.

This system continuously monitors the machine's energy usage in real-time, as shown in Figure 3. By analyzing deviations from standard power consumption patterns, the system can predict potential equipment failures before they occur. This proactive approach allows for early intervention, minimizing downtime and production losses.

The integrated AI assistant within the dashboard takes this solution a step further. It leverages knowledge of the machine's specific OEM (Original Equipment Manufacturer), expected failure rates, and current usage patterns. This allows the AI assistant to prioritize potential issues and guide maintenance personnel toward the most likely cause of abnormal energy consumption, as shown in Figures 7, 8 & 9. This targeted approach streamlines troubleshooting and repairs, saving valuable time and resources.

This intelligent dashboard empowers a proactive maintenance strategy for the KDF 600i sputter machine. The system helps ensure consistent product quality, minimize downtime, and optimize production efficiency by predicting potential failures and guiding targeted interventions.

### 3.2.1 UI for the AI-powered dashboard

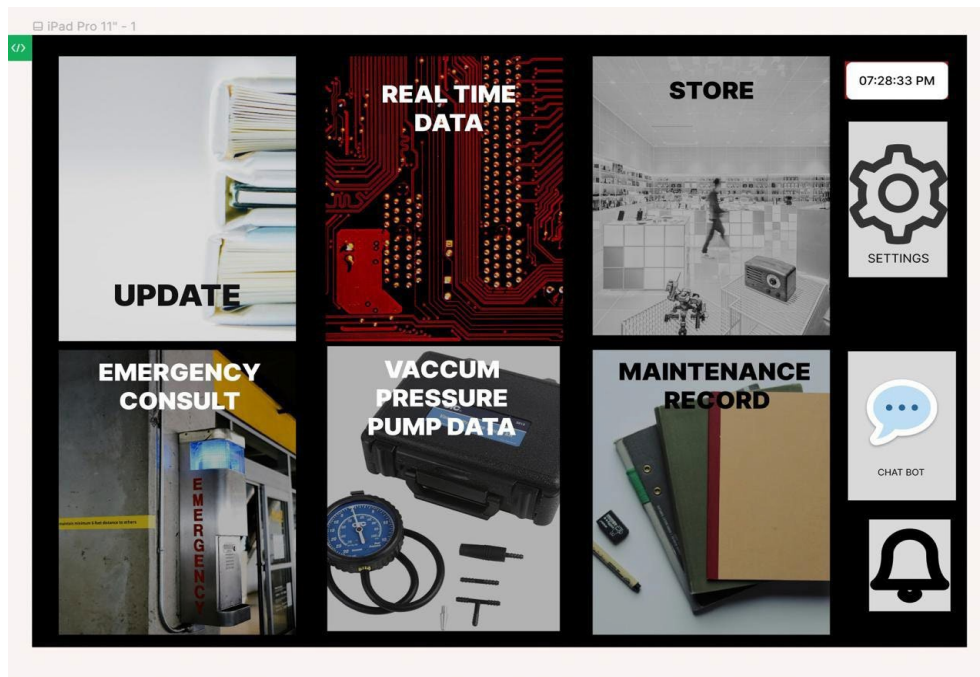


Figure 1: UI for the AI-powered dashboard

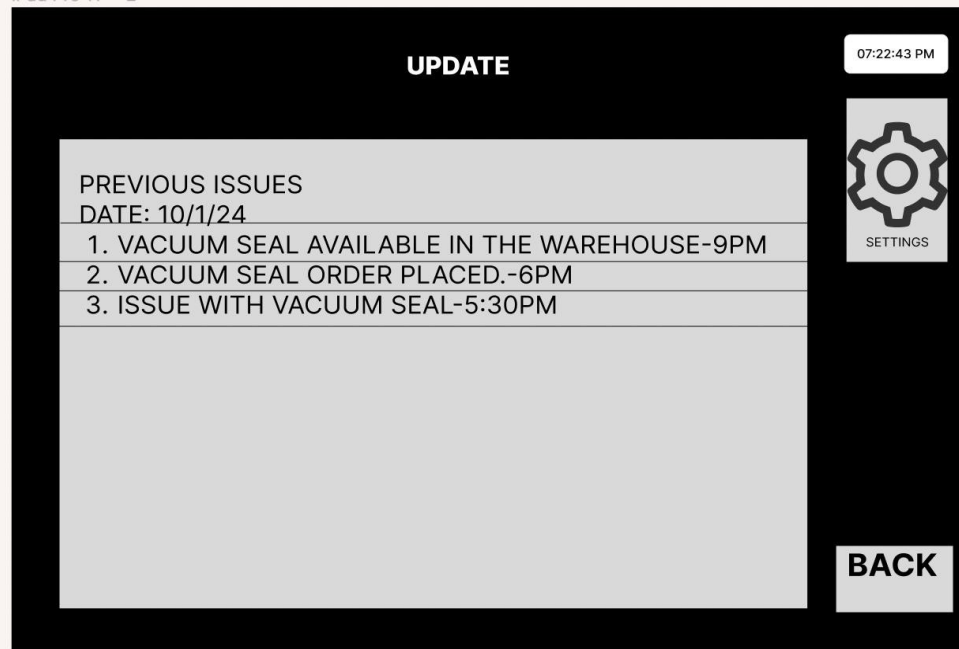


Figure 2: Update tab

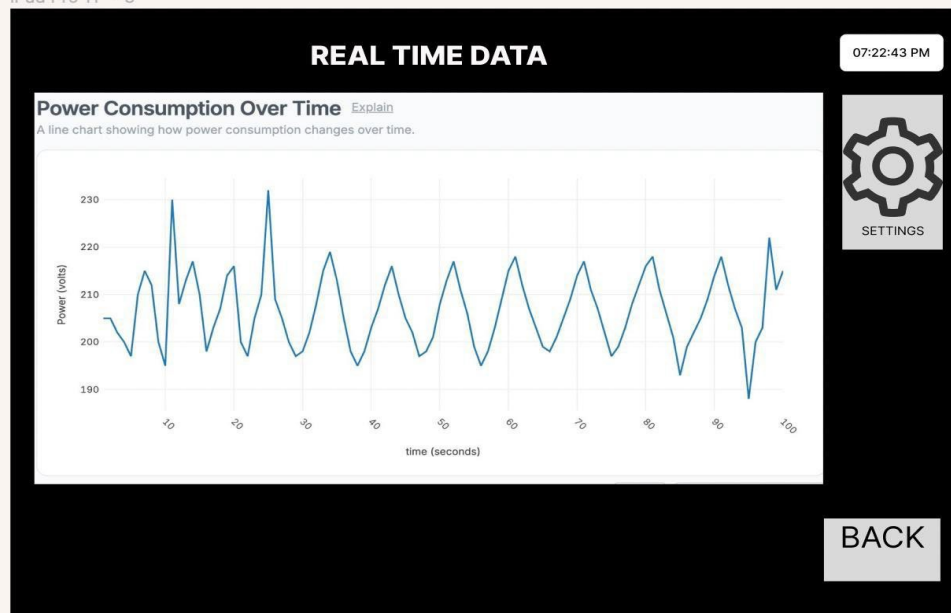


Figure 3: Real-time data tab

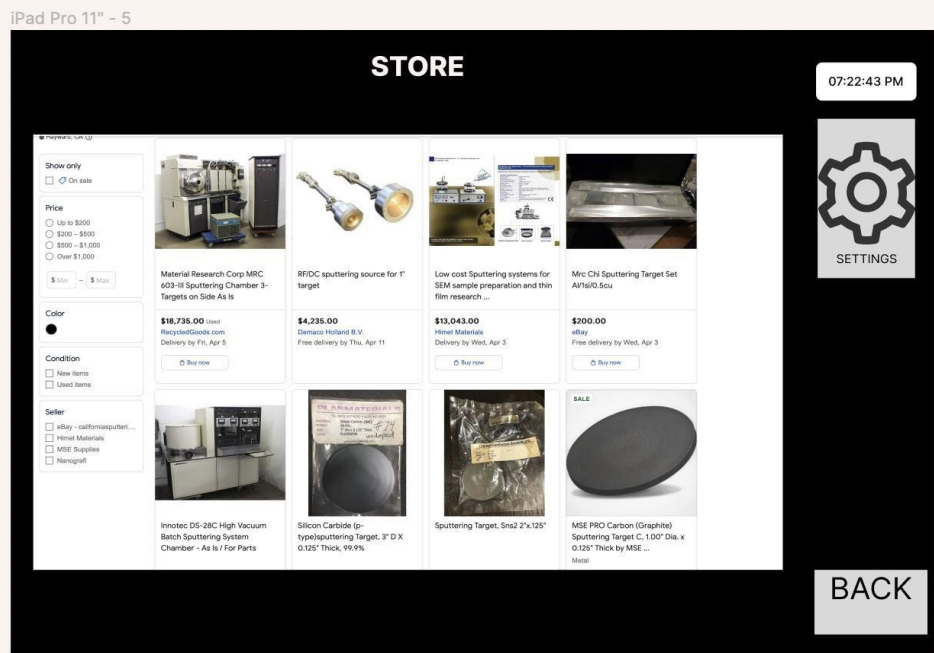


Figure 4: Inventory/Store tab

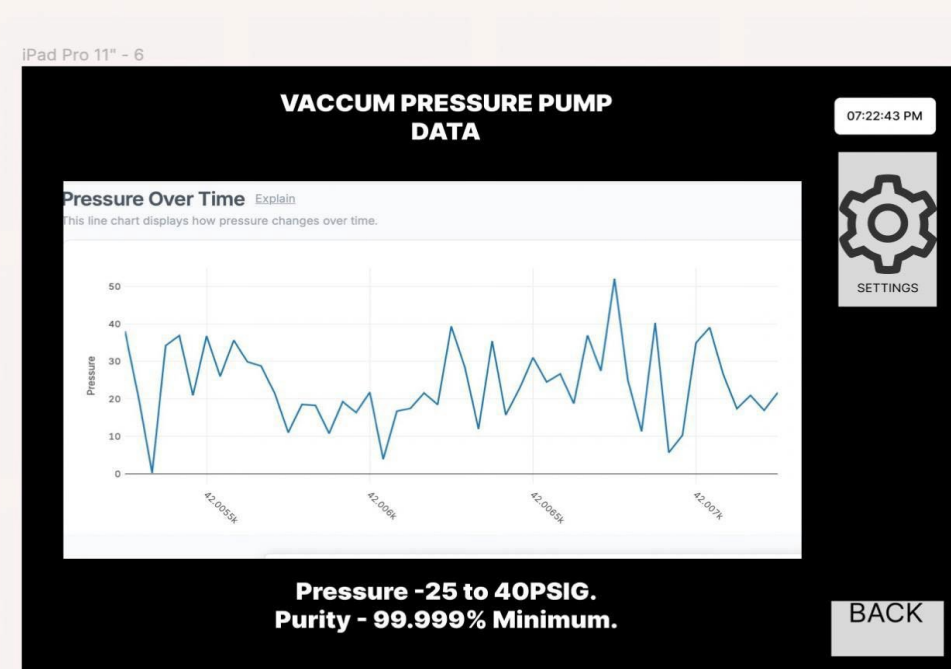


Figure 5: Vacuum pressure pump data tab



Figure 6: Maintenance record tab

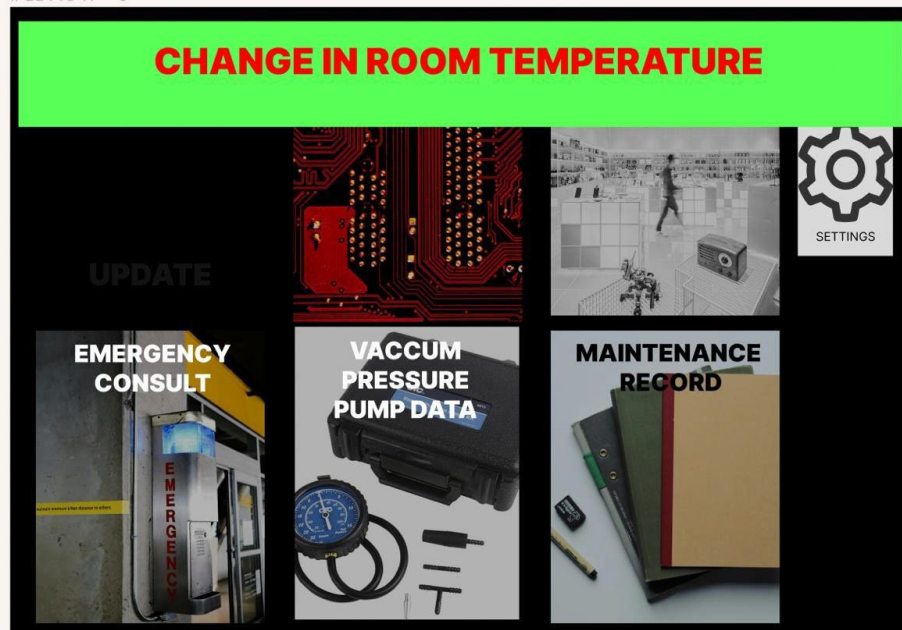


Figure 7: Green (low priority) notification alert

iPad Pro 11" - 10



Figure 8: Red (critical) notification alert

iPad Pro 11" - 8

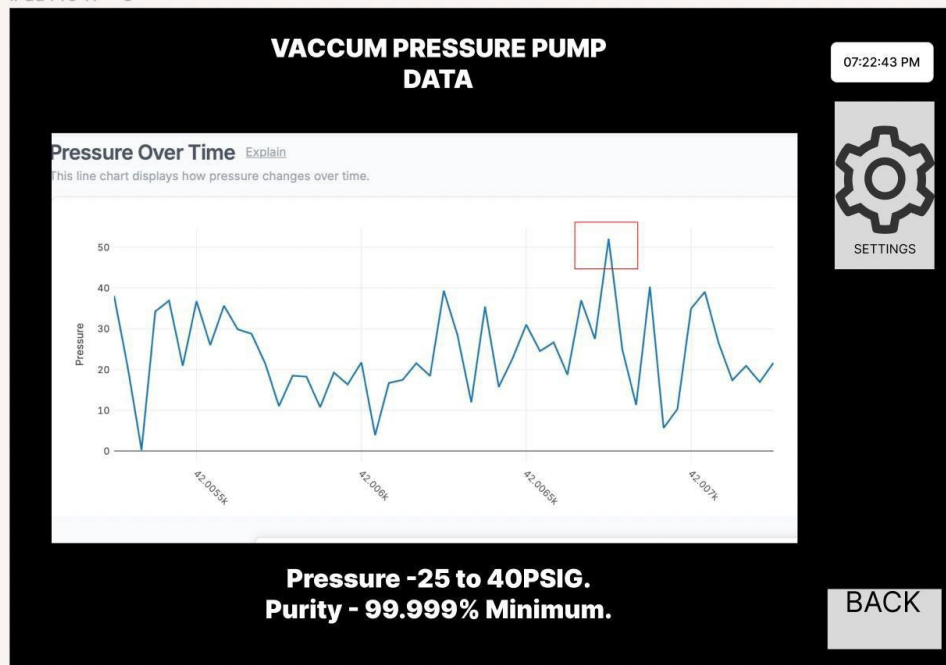


Figure 9: High-pressure warning alert

### **3.2.2 AI-powered Chat-Bot:**

In a groundbreaking convergence of cutting-edge technologies, we have pioneered the development of an intelligent chatbot utilizing Langchain and OpenAI's Key to revolutionize predictive maintenance and streamline repair processes in the context of sputtering machines. This innovative system represents a paradigm shift in industrial maintenance strategies, harnessing the power of artificial intelligence and natural language processing to predict and mitigate machine failures before they occur.

By integrating Langchain's advanced predictive analytics capabilities with the sophisticated language understanding of OpenAI's Key, the chatbot possesses a profound understanding of the intricacies of sputtering machine operation and maintenance. Through meticulous training with bespoke data tailored to the specific nuances of the sputtering process, the chatbot has acquired a comprehensive knowledge base encompassing the machine's history of errors, standard failure modes, and optimal repair procedures.

This wealth of information enables the chatbot to provide real-time assistance to technicians, guiding them through troubleshooting processes, interpreting error codes, and offering tailored solutions to mitigate potential issues, as shown in Figures 10 & 11.

Moreover, the chatbot is a proactive safeguard against unplanned downtime, leveraging predictive analytics to anticipate impending failures based on subtle indicators and historical trends. The chatbot empowers proactive maintenance strategies by alerting technicians to potential issues before they escalate into full-blown malfunctions, optimizing machine uptime and productivity. In the event of a breakdown, the chatbot becomes an invaluable resource for rapid recovery, offering step-by-step guidance through the repair process, identifying the root cause of the problem, and recommending the most effective course of action to expedite resolution. Through its seamless integration into the workflow of maintenance technicians, the chatbot enhances operational efficiency, reduces downtime, and minimizes costly disruptions to production schedules.



Furthermore, by continuously learning from interactions and feedback, the chatbot evolves, refining its predictive capabilities and expanding its knowledge base to adapt to changing maintenance requirements and emerging challenges.

The intelligent chatbot represents a transformative leap forward in industrial maintenance practices, empowering technicians with unprecedented insights and assistance to ensure sputtering machines' smooth and uninterrupted operation. With its ability to predict failures, assist with troubleshooting, and expedite repairs, the chatbot enhances operational efficiency and drives significant cost savings by minimizing downtime and maximizing asset utilization. As organizations embrace the era of Industry 4.0, the intelligent chatbot is a beacon of innovation, heralding a new era of predictive maintenance excellence in sputtering technology.

### 3.2.3 Chat-Bot Operation:

```
Prompt: what are the most occurring errors?
The most occurring errors for the Sputter Machine are:

1. Computer error
2. Chamber vacuum not in-spec
3. Pallet travel error
4. Other
5. Gas level low
6. Heat lamps not turning on
7. Target 3 low
8. Pallet not sensed

These errors appear multiple times throughout the log.
Prompt: what is the vacuum pressure?
The vacuum pressure for the 600i Series is specified as follows:
- Chamber ultimate:  $\leq 1 \times 10^{-7}$  torr
- Chamber leak rate: 20 minutes to  $1 \times 10^{-4}$  torr
- High vacuum dome ultimate:  $\leq 1 \times 10^{-7}$  torr
- High vacuum dome leak rate: 15 minutes to  $1 \times 10^{-4}$  torr
- Pump down from atmosphere: 110 minutes or less to  $1 \times 10^{-6}$  torr or  $2 \times 10^{-7}$  torr overnight
```

Figure 10: Chat-Bot Operation 1

```
Prompt: get me the contact details
The contact details for KDF Electronic & Vacuum Services Inc. are as follows:

Address: 10 Volvo Drive, Rockleigh, NJ 07647
Telephone: 201-784-5005
Fax: 201-784-0202
Website: www.kdf.com
```

Figure 11: Chat-Bot Operation 2

### 3.2.4 Code for the Chat-Bot:

```
import os

import sys


import openai

from langchain.chains import ConversationalRetrievalChain, RetrievalQA

from langchain.chat_models import ChatOpenAI

from langchain.document_loaders import DirectoryLoader, TextLoader

from langchain.embeddings import OpenAIEmbeddings

from langchain.indexes import VectorstoreIndexCreator

from langchain.indexes.vectorstore import VectorStoreIndexWrapper

from langchain.llms import OpenAI

from langchain.vectorstores import Chroma


import constants


os.environ["OPENAI_API_KEY"] = 'Key'


# Enable to save to disk & reuse the model (for repeated queries on the same data)

PERSIST = False
```

```

query = None

if len(sys.argv) > 1:

    query = sys.argv[1]


if PERSIST and os.path.exists("persist"):

    print("Reusing index...\n")

    vectorstore = Chroma(persist_directory="persist", embedding_function=OpenAIEmbeddings())

    index = VectorStoreIndexWrapper(vectorstore=vectorstore)

else:

    #loader = TextLoader("data/data.txt") # Use this line if you only need data.txt

    loader = DirectoryLoader("data/")

    if PERSIST:

        index = VectorStoreIndexCreator(vectorstore_kwargs={"persist_directory": "persist"}).from_loaders([loader])

    else:

        index = VectorStoreIndexCreator().from_loaders([loader])


chain = ConversationalRetrievalChain.from_llm(

    llm=ChatOpenAI(model="gpt-3.5-turbo"),

    retriever=index.vectorstore.as_retriever(search_kwargs={"k": 1}),

)

```

```
chat_history = []

while True:

    if not query:

        query = input("Prompt: ")

    if query in ['quit', 'q', 'exit']:

        sys.exit()

    # result = chain({"question": query, "chat_history": chat_history})

    # print(result['answer'])

    print(index.query(query, llm=ChatOpenAI()))

    # chat_history.append((query, result['answer']))

    query = None
```

## **4. Conclusion:**

The proposed predictive maintenance approach using machine learning techniques addresses the challenges of maintaining consistent power quality in the KDF 600i sputter machine. The project seeks to enhance process consistency, product quality, equipment reliability, and overall production efficiency by continuously monitoring power quality data, identifying issues, and implementing mitigation measures.

### **4.1 Cost Analysis:**

Number of shifts per day = 3

Each shift has 8 hrs., with 24 hrs. in total.

The number of wafers per shift is 50, or 6.25 wafers/hr.

The total number of wafers produced per day is 150.

The cost of one wafer is \$300.

The cost for 150 wafers is  $= 150 * \$300 = \$45000/\text{day}$  ----- (1)

The range of machine downtime varies from 0.50 hrs. to 24 hrs.

Wafer production loss per 30 mins = \$975

Wafer production loss per 1 hr. = \$1950

Labor cost per hour = \$25 (approx.)

Total loss in 1 hr. = labor cost/hr. + production cost/hr. = \$1950 ----- (2)

Approx. Loss in 1 hr. \$1950 to \$2000

Therefore, for the range of machine, time (30 min to 24 hrs.), the loss can vary from \$1950 (from eq. 2) to \$46000,

Technician minimum Analysis or diagnosis time for the error varies from 30 minutes to 4 hrs. (depending on the diagnosis and type of error the machine is facing)

By implementing our innovative dashboard with alerts and AI failure prediction, we predict that we can reduce the reaction and diagnosis from 4 hrs. to 1 hr. by predicting the possible error and where to focus on repairs on these complicated machines.

Example: Power management PCB error causes improper heating of the target material and low plasma, leading to improper metal deposition over the substrate and uneven deposition.

With the alert system, we can alert the technician of power fluctuations as they occur. The technician must go through the entire machine without an alert system for diagnosis.

3hrs. of wafer production =  $18.75 \text{ wafers} * \$300/\text{wafer} + \text{labor cost } (\$25 * 3 \text{ hrs.}) = \$5700$ ----- (3)

We can save up to 3 hrs., translating to \$5700 in costs (from eq. 3).

Considering the one-year machine downtimes and diagnosis period in the historical data, we can estimate that the company can save \$57,500 to \$60,000 & up to 25 hours by predicting and targeting the problem.

Based on the historical data of the sputtering machine, \$57,500 to \$60,000 is the minimum cost savings that can be saved by reducing the overall machine diagnosis by up to 30 hours cumulative. These values are based on theoretical calculations and not tested in real life. The savings might increase if the company prepares the necessary inventory and technicians for more downtimes and accurate failure predictions. Precise predictions can be made by adding more relevant information and failure data to the dashboard and fine-tuning the predictive failure rate to predict downtimes.

## **5. Acknowledgement:**

We acknowledge our professor, Dr. Farnaz Ganjeizadeh, for her support and guidance during the project and presentations and Professor Eric Olivar's support in obtaining real-world data and sharing his knowledge of the predictive maintenance topic.

## **6. References:**

1. Zeki Murat Çınar, Abubakar Abdussalam Nuhu, Qasim Zeeshan, Orhan Korhan, Mohammed Asmael and Babak Safaei, (2020). Machine Learning in Predictive Maintenance Towards Sustainable Smart Manufacturing in Industry 4.0. Sustainability 2020, 12(19), 8211.
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