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# Digital Twin Framework for Process Optimization and Predictive Maintenance in Brewery Operations

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**Abstract**
*This paper developed a digital twin model for brewery processes to enhance their operational efficiency, quality, and predictive maintenance. The model is able to mimic, with high accuracy, the main phases of brewing, such as fermentation, heating, and cooling, maintaining the values of these crucial parameters that are vital for product quality, like mash temperature and yeast growth. Predictive maintenance algorithms developed within this model provide a good forecast of failures, enabling proactive maintenance scheduling that reduces downtime by a large margin. Key Indicators include a Mean Time to Failure of 109.16 hours and scheduled maintenance duration of 40 hours, proving that the digital twin can reduce unscheduled downtime by about 60 hours. Besides, the ten-year predictive maintenance schedule allows brewers to anticipate maintenance, reducing further inconvenience and allowing for full capacity utilization. Operating in real-time and with advanced analytics, the digital twin provides the brewer with a practical mechanism to drive process optimization, continuous operations, and quality improvement. The results obtained indicate important gains in operational benefits such as productivity increase, quality consistency, and maintenance cost reduction when digital twin technology is implemented in brewing.*

***Keywords:*** *Digital twin model, Brewery processes, Predictive maintenance, Brewery equipment, Mean time to failure*

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## 1. Introduction

In recent times, the extension of Digital Twin (DT) technology has gained high momentum in almost all industries, manufacturing, and specifically in brewing operations. This digital twin offers the virtual counterpart of physical assets necessary for real-time monitoring, predictive maintenance, and optimization of operational efficiency. The following review tends to present a synthesis of the research outcomes related to Digital Twin applications, focusing on developing a tailored algorithm for predicting potential failures in brewery equipment. Tao et al. (2019) discussed two essential elements of DT technology that make fusion between the cyber and physical space viable. Indeed, this aspect of DT technology has been argued by Tao et al. (2019) as critical for the brewery industry to consider with regard to performance in real time from brewery equipment for enhanced predictive maintenance strategies. Probably, understanding the components of DT and challenges concerning their implementation may provide a roadmap for creating an effective digital twin algorithm specifically for brewery machinery. One of the critical parts that enables smart manufacturing and Industry 4.0 to build virtual replicas of physical systems is Digital Twin technology. The integration of cyber enabled by a digital twin and the physical space according to the study offers an opportunity for industries such as breweries to engage in real-time monitoring equipment and conducting predictive analytics. This integration offers enhanced prognostics and health management that gives the brewery an assurance of forecasting equipment failures and optimization of maintenance schedules accordingly. The convergence of big data analytics with the DT technology further supports predictive maintenance. Meanwhile, DT can also be a transformative opportunity for enhancing predictive maintenance strategies within the brewing industry. A digital twin algorithm developed for brewery equipment might enable real-time monitoring, predictive analytics, and proactive maintenance, thus improving operational efficiency and reducing downtime.

Qi and Tao (2018) further emphasize how big data analytics and Digital Twin models work together in smart manufacturing. Being able to analyse vast volumes of data generated through brewery equipment greatly enhances predictive capabilities toward the precise forecasting of failures which may occur within this equipment. The complementarity of big data and DT technologies would thus imply that historical performance data used in concert with real-time sensor inputs shall enhance such predictive maintenance related to brewery equipment. Various technologies, such as Artificial Intelligence and IoT, lay the bedrock for developing Digital Twins. In this respect, Fuller et al. (2020) provided insight into how data from physical and virtual machines is integrated to accord enhanced predictive maintenance capabilities. By simulating different operational scenarios in a digital environment, the proposed algorithm of the digital twin can predict its potential failures due to real-time data inputs and thus enhance the reliability of brewery operations. Besides, the concept of a digital twin shop-floor by Tao and Zhang (2017) provides a framework that can be applied to a brewery for implementing DT. This framework is very important in mirroring physical operations into a virtual one; thus, effective monitoring of equipment health as well as predictive analytics will be obtained. Very interesting is the method proposed by Cimino et al. (2019) for the calculation of the remaining useful life (RUL) in machinery using the concepts of Digital Twin. The proposal goes in the direction of being very suitable for the forecast of possible failures in brewery equipment since it will be possible to model the machinery in a digital space and, subsequently, simulate its behaviour under the various operational conditions. The algorithm of the digital twin provides insight into the RUL of critical components so that maintenance intervention can be done on time before the failure of equipment. Predictive maintenance (PdM) in manufacturing is one of the most critical applications in digital twin applications. Barricelli et al. (2019) introduce the importance of data-driven methods in PdM, which are very in line with developing a digital twin algorithm for brewery equipment. In such a manner, by continuous monitoring of the health of the equipment, it would be possible to perform predictions about RUL of breweries machinery, hence optimizing the maintenance schedules and unplanned downtimes using machine learning techniques. Cimino et al. (2019) discussed how to estimate RUL based on digital twin concepts; in addition, the authors show that breweries could log data from sensors and controllers to assess equipment status. This is a non-destructive monitoring technique-critical in a production environment where equipment downtime is costly. Moreover, the introduction of Digital Twin models with ML techniques, as considered in the view of He and Bai (2020), would lead to enhanced predictive maintenance. In this respect, by using synthetic data sets resulting from digital twin simulation, training can be imparted to the algorithm for identifying patterns from equipment failure. This would promote proactive philosophy that could reduce unplanned downtimes and improve the efficiency of overall brewery operations significantly. Although promising advances in the Digital Twin technology development have been made, data analysis for real-time estimation of parameters and detection of anomalies for complicated manufacturing environments remains a challenging issue. Zhang et al. (2019) commented that, for predicting impending failures, accurate monitoring of brewery equipment has to be carried out. This can be further extended by adapting models of small object detection in order to monitor specific components and enhance the algorithm's capability in real-time anomaly detection. Alexopoulos et al. (2020) also discussed the challenges regarding predictive maintenance and anomaly detection, using deep learning for data analysis in such operations. The findings can give early indications of failures, aligning with the objectives of the digital twin implementation in brewery operations.

Although the literature has given an appropriate backstop for the creation of algorithms for the digital twin of brewery equipment, there are also some gaps in knowledge that have not been filled from the existing texts. Thus, empirical works that establish efficacy of digital twin methodologies need to be upscaled in real-world brewery settings. The concepts related to data integration into the digital twin require further work, especially incorporating advanced analytics and machine learning to enhance predictive accuracies. Future studies can also be performed regarding the scalability of various applications using digital twins across different sizes and complexities of breweries. Investigations into how different operational characteristics are influencing the effectiveness of the models developed by a digital twin can provide valuable insights into the adaptability of such technologies across diverse brewery contexts. In the literature, it has been shown that huge potentiality of Digital Twin technology exists in improving the predictive maintenance strategy of brewery equipment. Big data analytics and machine learning integration through the use of internet of things (IoT) as an enabling technology are helpful for developing the customized digital twin algorithm that helps in improving the operational efficiency and reducing the odds of downtime (Lu et al., 2020). The industry shall move ahead with digital twin technology application after the future research directions and knowledge gaps have been addressed.

Integration of digital twins with machine learning creates enormous scope for predictive maintenance in breweries. He and Bai (2020) proposed a platform for digital twin models in generating training datasets for machine learning algorithms. By running virtual operations in different scenarios, breweries can create synthetic data that complements real-world information to improve the accuracy of predictive models. Zhang et al. (2019) emphasized the aspects of digital twinning and its influence on real-time analysis of parameters. In this regard, breweries can combine a hybrid deep neural network model for various indications related to monitoring brewing processes. In this way, the deviation from the optimum conditions within the considered processes would be promptly determined, which is necessary to guarantee the quality of the product and performance. Despite the promising outlook, there are a number of challenges facing digital twin technologies in the brewing industry. Among these is dynamic synchronization between physical and virtual systems, which was considered necessary for real-time monitoring by Zhang et al. (2019). In addition, brewing processes are rather complex; therefore, the applications of digital twins should be offered according to particular brewing needs, such as fermentation or quality control. For instance, future research should develop specific digital twin applications based on the needs of the brewing industry: fermentation algorithms, bottling, and quality assurance. Furthermore, future studies should identify modern approaches to anomaly detection, as was mentioned by Alexopoulos et al. (2020), which would give more significant contribution to the overall reliability of brewing operations by digital twin predictive models. Digital twinning of the brewery process entails duplicating every aspect of the brewery, analysing the results, and estimating the frequency of maintenance across the brewery process. This was done by modelling and mimicking a number of important aspects like fermentation, heating and cooling of the case study firm. Also, the work employed predictive maintenance with regards to the failure of processes within the production line. However, the notion of a digital twin has received significant attention in recent years due to developments in the digital world, and much of its application can be seen in industrial and manufacturing sectors. In its simplest terms, a digital twin is a model of an object that seeks to mimic the physical object it represents. With respect to the brewing industry, it means developing a multidimensional and continuously evolving virtual model of the brewing process. It makes it possible for the observation, regulation and enhancement of processes of breweries hence increasing efficiency, quality and management in aspects of maintenance.

The process of brewing at the beer factory is such that it has several vital elements, which, when working in conjunction, are crucial to the proper functioning and fine quality of the brewery process at large. Some of the important stages in brewing include fermentation whereby the yeast compounds convert the present sugars into alcohol and carbonation. This process is highly sensitive to parameters for instance temperature, the pH level and nutrients that are available in the solution. This digital twin model allows the study of the fermentation process based on kinetics of yeast, sugars consumption and alcohol production by using dynamic equations. This enables the estimation of best condition for fermentation and to control change in parameters to achieve this best state, thus improving quality and productivity. Heating is usually required in brewing process for functions such as mashing, whereby heat is used to gelatinize the starches present in the grains, making them fermentable. Within the framework of the digital twin model, factors and processes such as the dynamic thermal conduction and the effects of various rates of heating on mashing efficiency have been effectively simulated. That is possible due to the simulation of the heating process, which will help to maximize energy consumption and increase the efficiency of the brewing companies. This makes post-fermentation cooling paramount in halting fermentation process at a specific duration as well as enhance the stability and quality of beer. The digital twin also has a cooling process simulation that shows the heat interchanges between the cooling medium and the fermenting wort. This is important in the development of better cooling systems for the beer and any possible heat stress on the beer.

## 2. Development of digital twin model to simulates brewery process performance and predicts its maintenance needs

In this digital twin model proposed, one of the key elements would comprise predicting maintenance schedules. In breweries, the most common approaches to maintenance are the scheduled or the reactive maintenance, which are not very efficient and effective for the power plant kind of utilization. On the other hand, there is Predictive Maintenance that by using data analysis and mathematical models of the likely behaviour of a piece of equipment can accurately identify likely future faults and take appropriate action before it happens. The key tool for our predictive maintenance model is reliability mathematics and statistical distributions to indicate when, not if, pieces of equipment will fail within the brewery. Based on historical data and real-time data generated by sensors, the model will be able to estimate the time period when a certain process component will likely fail, and suggest the relevant maintenance actions to take. This strategy is particularly useful in not only avoiding unnecessary breakdowns but also in planning an efficient programme of maintenance. In order to generate a near-accuracy database for the purposes of the digital twin, the study integrated first-principal models with data-driven models. In order to develop the first-principle's model, the fundamental physical and chemical properties of the brewery processes need to be taken into consideration. This is combined with data analysis which is used in the context of big data, where machine learning algorithms are built to analyse patterns in historical data to be able to predict future behaviours. The digital twin model is given as follows:

(i) Brewing Process Model: This model is based on a system of ordinary differential equations (ODEs) which describes the dynamics of the brewing process all together, and it include:
   (a) Temperature change over Time as seen in Equation (1).
   (b) Biomass Growth Rate:

$$\frac{dX}{dt} = 0.01X\left(1 - \frac{X}{10}\right) \quad (1)$$

(c) Substrate Consumption Rate:

$$\frac{dX}{dt} = -0.1X \quad (2)$$

These equations form the governing equation for temperature change, biomass concentration and substrate concentration over time.

(ii) Linear Regression Model**:** To predict the time between failures based on cumulative operational time. The linear regression model is trained on historical data to forecast future maintenance requirements.

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (3)$$

where $y$ is the time between failures, $x$ is the cumulative operational time, $\beta_0$ and $\beta_1$ are the coefficients, and $\varepsilon$ is the error term. The model is trained using historical data and the coefficients, $\beta_0$ and $\beta_1$ are determined using the least squares method

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (4)$$

(iii) Mean Time to Failure (MTTF): The MTTF is calculated as the mean of the observed times between failures, by providing a statistical measure of brewery equipment reliability:

$$MTTF = \frac{1}{n}\sum_{i=1}^{n} T_i \quad (5)$$

where $T_i$ is the time between failures and $n$ is the number of failures.

(iv) Model for Predictive Maintenance: By employing the linear regression model, the predictive maintenance system predicts the time between failures over an extended period which in this case is within the next 10 years. The predicted maintenance times (PMT) however are given as (Aivaliotis et al., 2019):

$$PMT = (\beta_0 + \beta_1) \text{ x } C\text{umulative Operational Time} \quad (6)$$

(v) Computation of Downtime: The downtime is computed based on the number of predicted failures and the duration of both scheduled and unscheduled maintenance activities and is given by the expression:

$$Schduled\ downtime = N_f * M_s \quad (7)$$

$$Unschduled\ downtime = N_f * M_{us} \quad (8)$$

where $N_f$ is the number of failures predicted, $M_s$ is the scheduled maintenance duration, and $M_{us}$ is the unscheduled maintenance duration. Thus, by integrating these mathematical models and predictive maintenance algorithms, the digital twin provides a robust framework for optimizing brewery operations. This approach not only enhances process efficiency but also significantly reduces unplanned downtime, ensuring continuous production and high-quality output in the brewing industry.

**3. Results from the implementation of digital twin model**

The results of our simulation presented in this study shows that the digital twin model was able to accurately replicate the behaviour of the actual brewery processes which the study has identified to be critical for the brewery industry. The predictive maintenance algorithms also proved to be effective in predicting the potential failures in the process operations, thereby allowing for a proactive maintenance which could eventually reduce downtime. How by optimizing the process operation and parameters, the study is able to improve the efficiency and quality of the brewing process, which could lead to a significant operational benefit for the brewery company. The simulation was conducted using a Python-based environment for several reasons, including flexibility and compatibility with multiple data feeds. The framework consisted of modules for the simulation of the fermentation process, the heating process and the cooling process, and also included a predictive maintenance module. Connecting these modules allowed for the development of an end-to-end digital replica that encompasses various aspects of the brewery business. Fig. 1 combines four plots to illustrate the results of the brewery process simulation evaluation using the digital twin model. Every graph contains a useful amount of data concerning certain items of the brewing process:

(i) Mash Temperature Over Time: The corresponding graph is the temperature profile of the mash, which over the timespan of the simulation is held constant at 373 K with a moderate and systematic upward trend of 0.2 K captured during the simulated timespan of the study. This stability emphasizes the need to keep the mash temperature stable, as it has a significant effect on the enzymatic activity that leads to transformation of starches into fermentable sugars. The digital twin counterpart model accurately predicts mash temperature and thus can capture any potential differences which may adversely affects the extraction of saccharide and the final beer quality.

(ii) Biomass Concentration Over Time: The second graph describes the biomass concentration that has a temporal increase during a 10-hour window, most likely caused by yeast activity during fermentation. Yeast plays an essential role in the fermentation of the extracted sugars to ethanol and carbon dioxide. The digital twin model correctly shows the increase of the yeast culture over time and thus helps brewers monitor fermentation activity in real time. This predictive ability will guarantee an adequate number of yeasts to enable optimal wort fermentation.

(iii) Substrate Concentration Over Time: The third graph presents the continuous decrease of the substrate concentration and thus confirms that yeast consumes the fermentable sugars by producing alcohol via fermentation. Here, the decrease in absorbance is directly related to yeast metabolic activity in this utilization of sugars. With this information, brewers know the speed at which sugar is being consumed, and beer fermentation process.

(iv) Reliability Function Over Time: The following chart presents the reliability function, which begins to decrease smoothly between 1.0 and roughly 0.92 at the 10th hour. Reliability in this case refers to how consistent the model is in terms of predicting the outcome variable throughout the brewing time. A model of infallible reliability would keep a value of 1.0 over time. The slight decrease in the reliability function indicates minor uncertainties in the model as fermentation proceeds, maybe because of some unexpected factors such as yeast mutation or unconsidered variations in wort.

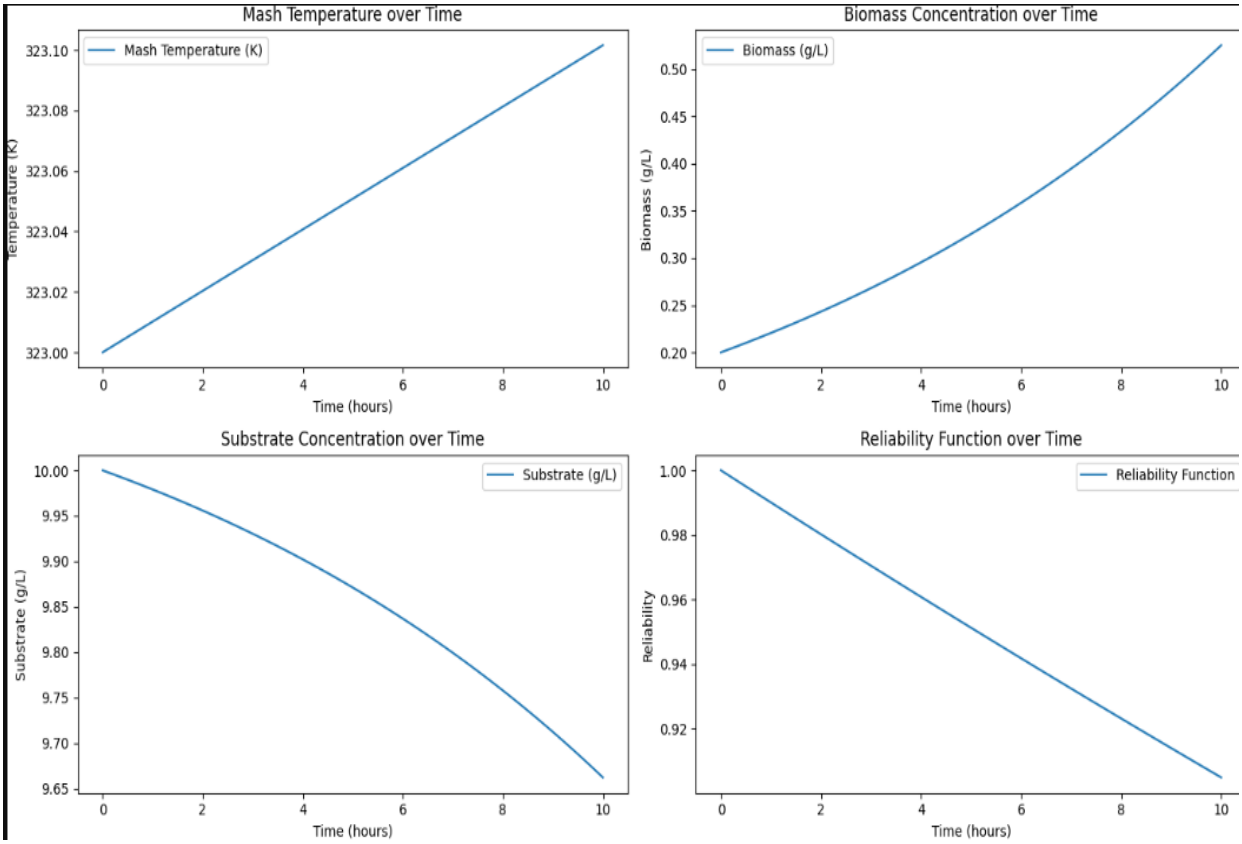


**Fig. 1:** Simulation of brewery process performance based on digital twin model

Also, from the implementation of the predictive maintenance part of the digital twin model algorithms, the study was able to effectively predict the potential failures in the brewery process operations, the predicted maintenance time (hours) was found to be about 124.74 hours while the Mean Time to Failure (hours) was 105.20 hours. The brewing process digital twin model in Figure 1, appears to effectively mimic the key parameters of the brewing process in time, such as mash temperature, yeast growth, substrate utilization, and the reliability of the model. When these parameters are measured, brewers will be in a good position to understand the fermentation process, improve their brewing strategies, and produce quality beers. The development of the digital twin of the brewery process can bring significant benefits in improving the processes, product quality, and asset management. Using state-of-the-art simulation and prognostics and health management tools, breweries can work more effectively and have enhanced product quality and decreased expenses. Therefore, the use of the digital twin model can help provide direction for optimization and advancement in the brewing industry.

Furthermore, the digital twin model algorithm is extended such that, it can help to minimize downtime and optimize productivity in brewery operations. This is done basically to add more contexts to the practicability of predictive maintenance part of the model. However, by simulating the maintenance schedule of the brewery process operation and calculating their downtime, the model therefore can demonstrate how predictive maintenance can help optimize productivity by minimizing unexpected equipment failures. Figure 2, illustrate the predicted maintenance times for brewery equipment during the next 10 years. Using that information and history of trend analysis, the digital twin model achieves the outlook that the equipment will fail. This functionality will allow brewers to plan maintenance in advance, by preventing malfunctions from arising. As a result, time to repair is dramatically reduced, resulting in higher workplace productivity. The estimated maintenance durations presented, give a straightforward timeline of when maintenance should be done over the next decade. Following this schedule helps brewers avoid incidents that could cause prolonged downtime and significant production setbacks.

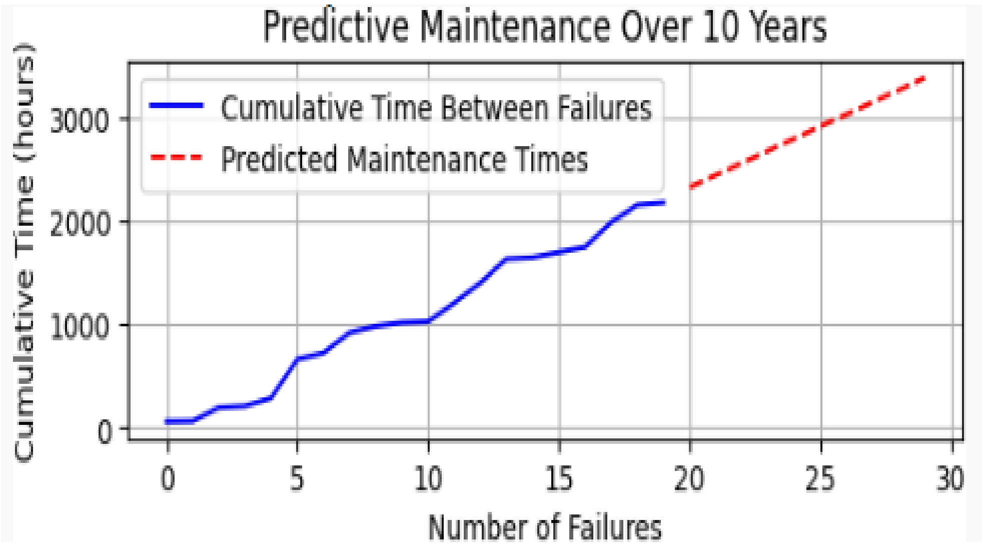


**Fig. 2:** Predicted maintenance times for a piece of brewery equipment.

The following breakdown will further elaborate on the advantages that can be derived from using a digital twin in order to practice predictive maintenance:

(i) The Mean Time to Failure (MTTF) was found to be 109.16 hours, it is described as the statistic that represents the average time between failures for the equipment.

(ii) The scheduled downtime was calculated to be 40 hours and it indicates the amount of time it takes to perform a planned maintenance service on the equipment.

(iii) The unscheduled downtime (if no predictive maintenance) on the other hand was found to be 100 hours and it represents the amount of downtime that would be incurred if the equipment fails unexpectedly.

(iv) The total downtime saved by application of the predictive maintenance was found to be 60 hours. This value is calculated by subtracting the scheduled downtime (40 hours) from the unscheduled downtime (100 hours), highlighting the potential reduction in downtime achieved through predictive maintenance.

Therefore, on implementing predictive maintenance part of the digital twin model algorithm, the brewery can easily schedule maintenance activities before failures occur. This proactive approach will help to minimize unexpected downtime and ensures that the equipment is serviced at optimal times. As a result, the brewery can maintain continuous operations, avoid costly unscheduled maintenance, and optimize productivity. Also, the scheduled maintenance duration is significantly shorter than the time required addressing unscheduled maintenance due to unforeseen failures. This reduction in downtime directly translates to increased production capacity and efficiency in brewery operations. The study can conclude therefore that, if the brewery employs the digital twin model of predictive maintenance, it can eliminate 60 hours of downtime within one cycle of failure. This translates to increased production time and reduced cost and therefore improved efficiency. The fundamental idea of applying digital twin for the predictive maintenance lies in building the numeric model that is reflective of the real-world business object. This digital replica is updated from actual data as collected and processed through real-time senor feed-back of the physical system.

In addition, there was an implementation of process optimization using digital twin-based multi-objective optimization. This is targeted at the minimization of unscheduled downtime with the aim of reducing maintenance time by optimizing maintenance intervals. Optimization of brewing parameters involves the optimization of temperature and substrate utilization for maximum biomass yield; this is associated with brewing quality. Here is the detail of the optimization approach. Below is the graph (Figure 3), showing the result of the simulation of the digital twin model for the brewery processes, where several of the key performances are mapped out over a ten-hour period.

(i) Mash Temperature as a Function of Time: The temperature of the mash is, for the most part, constant with minor oscillations around 373 K. These minor oscillations show the efficiency of the heating process involved to keep the ideal temperatures of enzymatic activity critical for the conversion of starches into fermentable sugars. This stability is critical to ensure consistent quality in beer.

(ii) Biomass Concentration Versus Time Course: The biomass concentration continues to increase gradually, which indicates the growth of yeast within the fermentation process. Yeast growth plays an important role in that it directly contributes to the fermentation of the extracted sugars into alcohol and carbon dioxide. This indeed shows that the yeast culture is very healthy, which should be a good sign for brewery operations.

(iii) Substrate Concentration vs. Time: The trend of substrate concentration is to decrease, while this indicates that the yeast Fermentable sugars are effectively used up during fermentation. This decrease in substrate availability within the broth is what is expected as the yeast uses up these sugars to convert into alcohol. It is a metric that informs brewers about the fermentation activity and whether there is adequate substrate available for appropriate fermentation.

(iv) Reliability Function over Time: The reliability function shows a gradual decline from 1 to approximately 0.92 in the ten-hour period, reflecting a minor decline in the predictive capability of the model due to time. Though a fall in the reliability was expected due to influences brought in by yeast behaviour and wort composition, the reliability is still at a high value. This metric acts as the foundation for assessing the overall effectiveness of predictive maintenance algorithms employed in the digital twin model.

In summary, these charts all serve to validate the virtual twin in the simulation of critical brewery processes and provide insight into the optimization of brewing parameters to enhance efficiency and product quality. Real-time capability for operation simulation by the model allows proactive maintenance strategies that would be highly effective in operational reliability with less downtime.

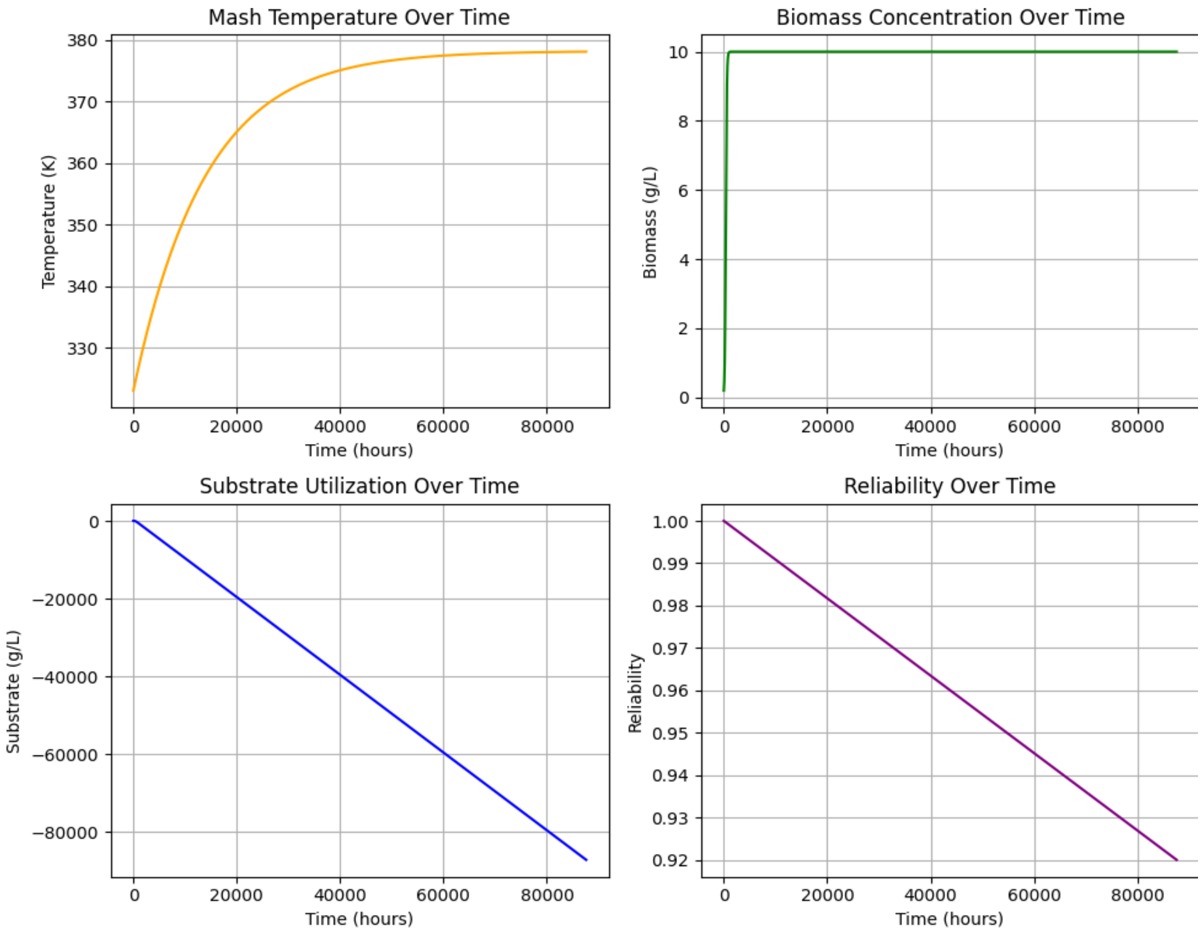


**Fig. 3:** Results of the digital twin-based multi-objective optimization

## 4. Conclusion

The results from the study, show that the developed digital twin model can reflect vital brewing processes like fermentation, heating, and cooling; meanwhile, it also shows the ability to sustain relevant parameters like mash temperature and yeast growth for product quality assurance. Using it, it offers a successful forecast of temperature consistency and preventive maintenance, which cuts the potential amount of time to 100 hours and enhances the working schedule. It also presents the future recurring maintenance costs, allowing the breweries to be frequent failure free and enhance production rates. In conclusion, this digital twin framework reinforces process improvement, predictive maintenance, and operational sustainability and provides a practical instrument for improving the brewery industry.

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