Software Development for Implementing New Features for Prediction and Impact Analysis of Key Parameters of Biogas Plant Operations for anessa

by

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Abstract

Biogas plants are configured with diverse plant specifications. Software exists to provide users with the ability to simulate, optimize, store and monitor data pertaining to the biogas plants. The purpose of this research was to implement two new features. We implemented the digester temperature-based prediction, leveraging an artificial intelligence-based model. This enables the user to predict the impact of temperature on the production of biogas and other products. We used Angular, Java and MongoDB for implementing this feature and the matrix computations were done using the ND4J library. We implemented another new feature, the Catalog, that would be used to build a model in the future, to predict the undesirable working conditions of the plant and unfavorable conditions for the micro-organisms to thrive. The implementation of this feature can be used to warn and alert the users of such conditions to avoid damages to the infrastructure. The report provides a comprehensive summary on the evaluation of the implementations and this was based on the prediction impact and the characteristics of the data collected.

Dedication:

I would like to offer prayers to god and elders of the family for having showered their blessings upon me all the time. I would like to dedicate this report to my cute and adorable daughter Srinidhi and my husband Paramesh who had been proud of my work consistently. I thank my sister Vasavee and her family who had been inspiring me to upskill myself. I thank my parents whose role has been significant in helping me achieve what I wanted to. I thank my in-laws who had been motivating me by being a great support during my Research.

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List of Symbols, Nomenclature or Abbreviations

$UJMP$	*Universal Java Matrix Package*
AI	*Artificial Intelligence*
$^{\circ}$	*Degree*
AD	*Anaerobic Digestion*
UI	*User Interface*
$CAPEX$	*Capital Expenditure*
$OPEX$	*Operational Expenditure*
JS	*Java Script*
$JSON$	*JavaScript Object Notation*
BMP	*Bio Methane Potential*

Chapter 1

Introduction

The process of generation of biogas in plants and biogas stations is an amalgamation of diverse complex sub processes. A complete end-to-end process requires optimal suggestions on the various parameters that aid in the production of biogas. The complete monitoring of the entire system is crucial to identify and predict the optimal conditions for a high yield of production [22]. One such factor is the digester temperature that plays a vital role in the biogas production especially in the case of plants that involve anaerobic digestion. The greater the temperature (until the optimal value is reached), the better the production would be. The traditional approach of biogas has been devoid of any technique for monitoring and predicting the temperatures that would obstruct the faster breakdown process of the waste and materials by the bacteria involved in the process of biogas production. Thus, prediction of the digester temperature using artificial intelligence would be critical towards identifying and maintaining temperatures that are optimal for the production of biogas [22]. Anaerobic digestion [11] is a process of several sub processes where micro-organisms work upon the material but do not use oxygen for the process. It is hence important to have a tool leveraging data collection and artificial intelligence. The tool would be essential to identify the conditions that are sub-optimal. This could then be used to

warn users of such conditions to bring about awareness that could avert any damages to the plants / micro-organisms / bacteria and to scale up the performance of the system.

1.1 Contribution

I developed a digester temperature-based AI feature implementation using Java that is trained using a neural networks methodology. The model computations produces a numerical value called the biogas factor, which is applied to the key parameters impacted by the change in temperature. Bio-methane potential is the component based on which all the simulation results of the plant are produced. Thus, this factor is applied on the bio-methane potential to understand the impact of it on the extraction efficiency and to calculate the actual and the theoretical biogas outcomes. The computations for the model are performed using the ND4J matrix library. This is done specifically for the mesophilic systems (temperature ranging between 20°C and 40°C) not thermophilic reactors (temperature greater than 40°C). I developed a data collection system to build a model that would be trained to predict the conditions that the clients might have to change to avert any damage to the system or to the micro organism. The data collection framework is built using Angular. This tool is configured to make computations on the data the user uploads on the data monitoring system and to alert the user of any data outside of the acceptable range. This alert helps to get rid of any damage that could otherwise have happened if the clients were not aware of the same. The collected data, of the conditions that led to the alert and the number of times the same had happened, are used to identify trends or pattern of operations of the biogas plants maintained by the clients. Upon this, a model would later be built and trained to predict any forthcoming conditions unsuitable for an optimal biogas plant operation.

1.2 Development Evaluation Scope

The digester temperature is already pushed to live. Testing had been extensively performed on plants that were manually created with different configurations and plants that were downloaded from live client plants and uploaded on lower environments. The feature is enabled on the AD•A platform, which is a platform for checking the feasibility of the plant. Hence, the results were from the configurations of a plant intended to be converted into a live plant if the same were feasible. Catalog has been developed using plant configurations similar to the live plants. Catalog has not been pushed to live yet and the characteristics of data were used to test the effectiveness of the development.

The remainder of the report is organized as below. Chapter 2 provides necessary background and terminology to understand the concepts presented in this work. Chapter 3 provides an overview of all the research work across different sections of the biogas domain. Chapter 4 describes the tools developed on top of the existing platform. Chapter 5 summarises the impact of the features developed by analyzing the technical and financial aspects and by understanding the characteristics of the data under consideration. Chapter 6 provides insight into the future works planned and the limitations of the current developments.

Chapter 2

Background

According to Hannah et. al, the search for alternate sources of energy has been increasing [38]. Fossil fuels and other sources of energy need to be replaced to meet the demands of the world. However, they are not abundantly available and they also expel a large amount of pollutants. Thus, biogas has already been looked at as the most reliable alternate by many countries such as Germany. Biogas plant operations are now integrated with software components to monitor the data, parameters and the plant conditions periodically. The use of AI to predict the ideal working environment for a biogas plant is under research. This chapter provides an overview of the process leading to biogas generation, key parameters of the biogas plants, an overview of an existing biogas software solution and a brief insight into the AI algorithms used for prediction purposes.

2.1 Anaerobic Digestion

The process of converting organic raw material (biodegradable throw away, manure [animal], waste from household, unused parts of plants) into useful biogas and residues is known as anaerobic digestion [36]. A small overview of anaerobic digestion is shown in Figure 2.1. There are multiple stages involved in such a complicated

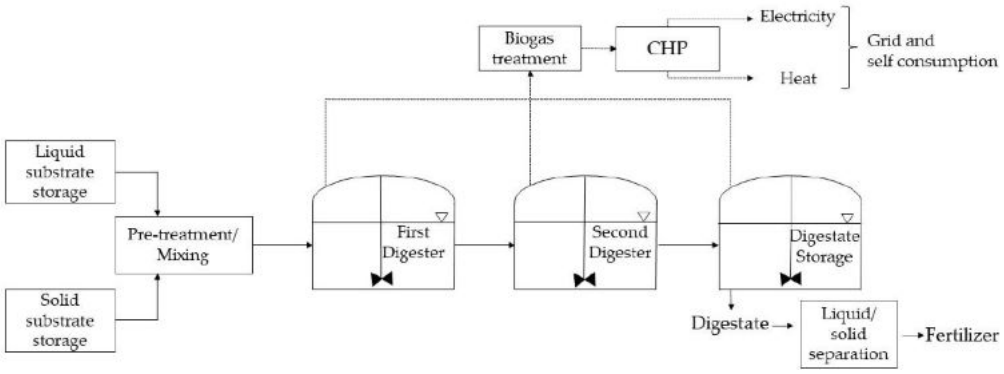


Figure 2.1: Anaerobic Digestion Overview
[22]

process. The environment under which the process of conversion happens is divergent and it depends on the kind of participating bacteria, that aids in anaerobic digestion [21]. There are a number of factors impacting the generation of biogas from the above process [46]. A small overview into the parameters influencing the production of biogas is provided in Section 2.2.

2.2 Insight into Biogas Parameters

Diversified research activities have been carried out to identify the most influencing parameters that could be used to improve the production of biogas [20].

2.2.1 pH

pH defines how acidic is the chemical composition that forms the baseline of the anaerobic digestion process [24]. The pH levels vary widely and are dependent on the bacteria operating upon the raw material during the anaerobic digestion process. Optimality of pH depends upon the stage of the anaerobic digestion and the kind of bacteria involved. An optimal pH is ideal for greater biogas production and identifying road blocks to achieving the optimal biogas production [50] [22].

Table 2.1: Temperature Classifications [22] [21]

Type Name	Range
psychrophilic	$\leq 20°C$
mesophilic	$20 - 40°C$
thermophilic	$\geq 40°C$

2.2.2 Temperature

Temperature is another crucial factor that has a great influence over the maintenance of optimal conditions within a biogas plant. An inhibitor is any compound that is responsible for termination of the anaerobic digestion process. Temperature is pivotal in averting extermination of the process owing to increased levels of inhibitors such as ammonia since with increase in temperature, specifically in the thermophilic range, the rate of ammonia inhibition was also higher [41] [32]. As shown in Table 2.1, temperature is classified into three ranges: psychrophilic, mesophilic and thermophilic [22] [21] .

2.2.3 Hydraulic Retention Time

Hydraulic Retention Time (HRT) is a measure of how long water and other solubles resides in the biogas plant. According to Bedoic et al. [20] and Sreevidhya and Balamurugan [21], the greater the HRT, the greater the yield of the biogas.

2.2.4 Total Solids

There are different kinds of anaerobic digestion methodologies and this is based on the solid content of the material used as input for the digestion process [39]. Total solid content is used to make clear decisions on the kind of digestion [22] as briefed here.

- *Wet Digestion-* A biogas plant consists of feedstock that is comprised of total

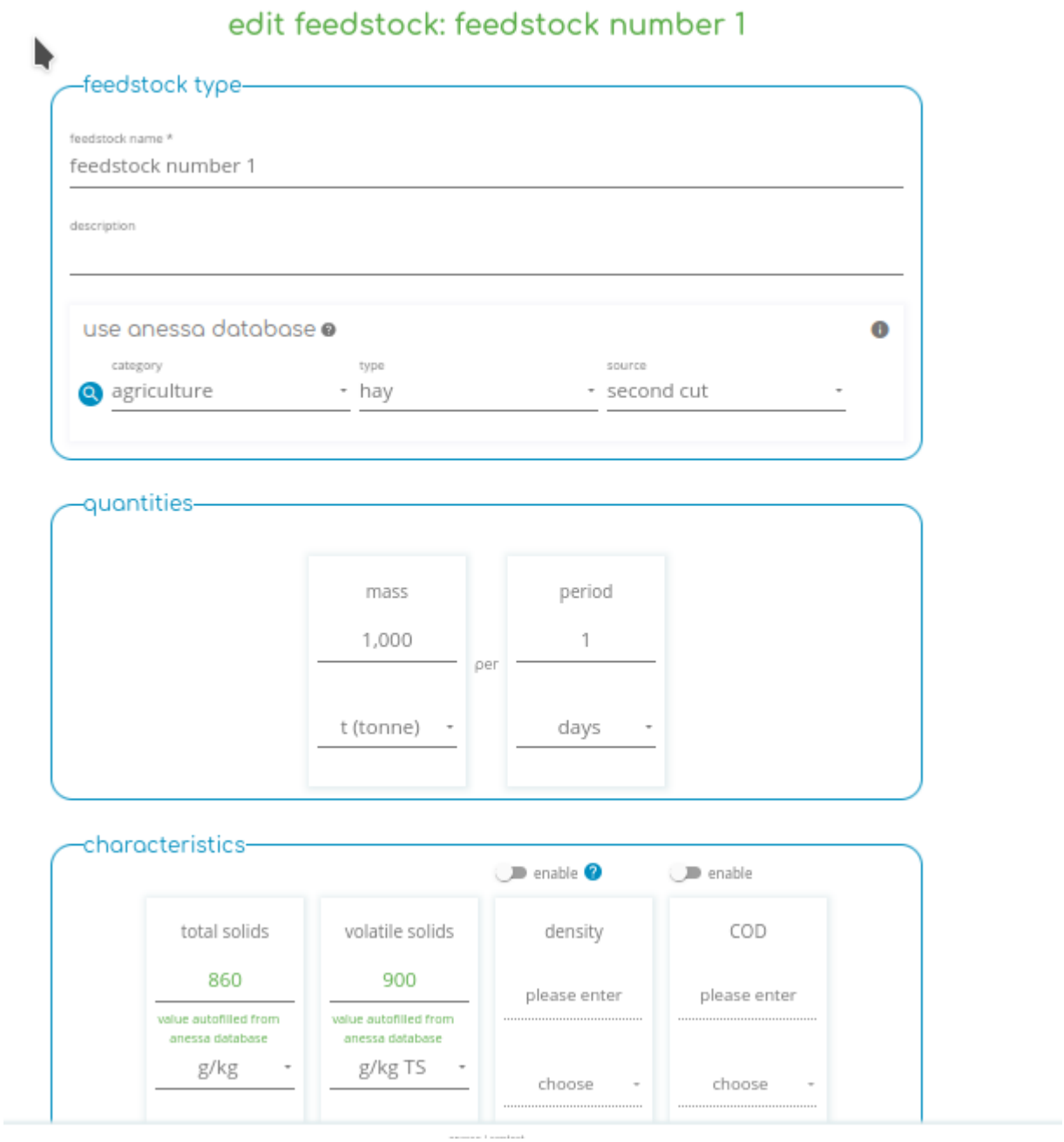


Figure 2.2: Feedstock Composition [2] [16]

and volatile solids as shown in Figure 2.2. Wet digestion is the kind of anaerobic digestion when the total solid content is lesser in the feedstock (less than 20% solid content of the feedstock) [34].

- *Dry Digestion-* Dry digestion is the anaerobic digestion when the total solid content is greater in the feedstock (between 20% to 40% solid content of the feedstock) [34].

2.2.5 Volatile Solids

Volatile Solids represent the organic portion of the total solid. According to the *American Biogas Council* [23], biogas plants should receive feedstocks with greater volatile solids, since the potential to produce biogas is greater in feedstocks with higher volatile solids.

2.2.6 Organic Loading Rate

Organic Loading Rate (OLR) is a measure of the quantity of the volatile solids provided to the digester and is the ratio of the quantity to time and volume of the volatile solids [22] [48]. The greater the OLR, the greater the biogas production since the solid input is greater.

2.3 Significance of Biogas

The need and demand for energy resources that are devoid of harmful emissions has been rapidly increasing everyday throughout the world [14]. The quest to identify such resources led to the increased study, research and use of biogas as an energy resource alternative to the current non-renewable sources of energy. The available non-renewable resources for many countries, for instance, Indonesia, is expected to be depleted, and hence the need to find an alternate is important [28]. From the

Year	Total, %	Municipal waste,%	Industrial waste,%	Solid biomass,%	Biogas,%
2000	100	100	100	100	100
2005	136	135	77	140	160
2010	224	176	131	230	355
2014	301	200	162	307	611

Figure 2.3: Growth Ratio based on Electricity Generated from Biogas in the World [45]

perspective of an economy that would profit from using energy resources such as biogas, Germany has been successful and has been running a large number of biogas plants [47]. Figure 2.3 substantiates the growth rate of biogas and the increased reliability owing to substantial availability of resources unlike non-renewable resources that have limited availability [45] .

2.4 Process Overview of Biogas Plant Operation

Biogas plants are those that are created specifically for carrying out the process of anaerobic digestion in supervised environments. The end product of the anaerobic digestion process is biogas that is methane rich and other additional products that could be used as manure such as solid residues [33]. In general, biogas plant operation is broken down into series of steps [5] [10] [6] [30] [8].

- Processing the raw materials (such as waste from food) and feeding the digester (one or many digesters depending on the complexity and the size of the plant) with the raw materials.
- Heating the materials inside the digester to different temperatures and thus enabling the bacteria to initiate the anaerobic digestion process by breaking

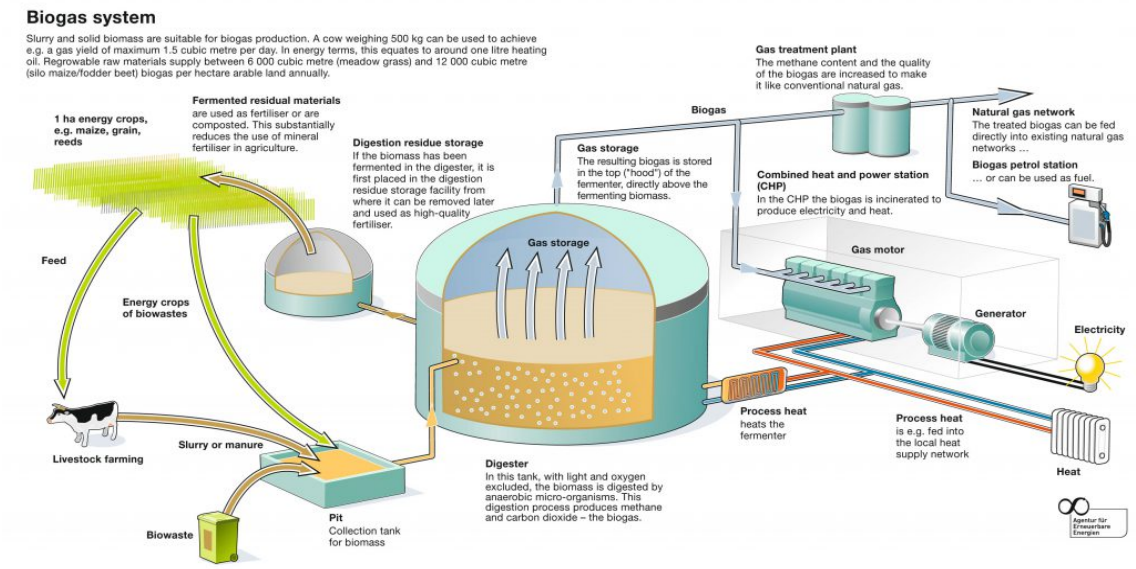


Figure 2.4: Biogas Plant Operation [8]

down the materials.

- Once the AD process is complete, biogas is produced, which consists of methane and other gases such as carbon dioxide.
- The residues are seperated from the other products, which is later used as fertilizers [10].
- The impure residues are further processed to generate useful products such as heat. This is to ensure the produced biogas is cleaned from such residues.

Detailed biogas plant operation is shown in Figure 2.4.

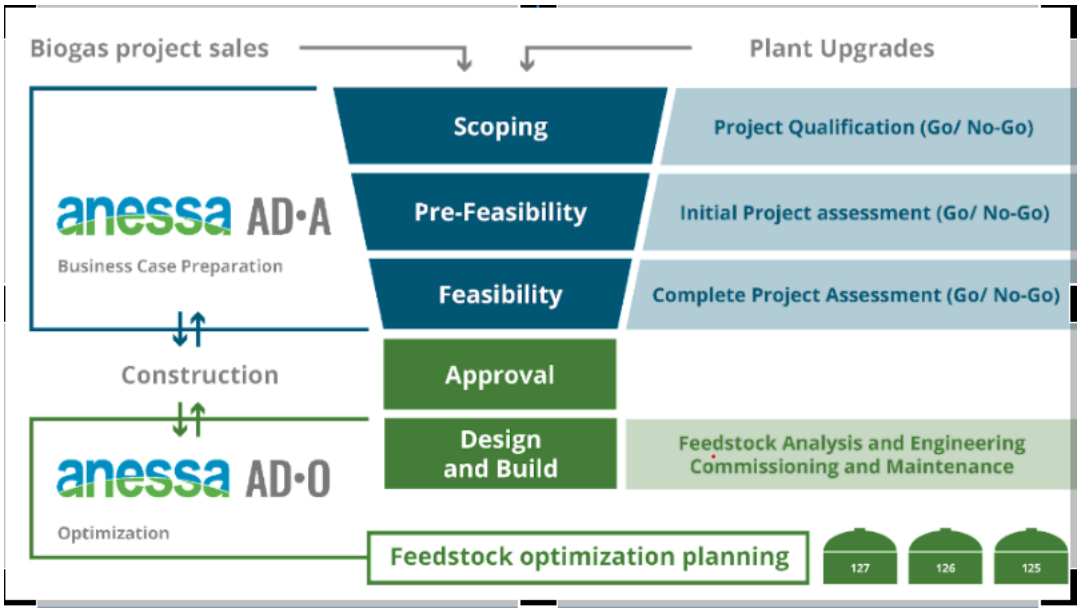


Figure 2.5: anessa AD•A (Source: anessa)

2.5 anessa Biogas—An Overview

anessa is driven by the value of bringing more reliability to the developers, operators and consultants of anaerobic digestion projects. The platform adds value to clients by providing them with computational outcomes processed by optimizing the plants or simulating the plants on the respective platforms. The plants are built based on the feedstock and specifications made by the clients. A brief overview of the different platforms of anessa is provided in the following subsections. Figure 2.5 was provided by anessa and details the basic operational principles behind anessa AD•A and AD•O [1] [16].

anessa AD•A, AD•O and AD•M platforms are used by clients for optimization and assessment purposes. These clients are users having different business needs for which they look toward the platform. For instance, a developer of an anaerobic digestion plant might use AD•A for examining the feasibility of the proposed project prior to building the plant while a financier or an investor is more interested in the financial outcomes of a plant upon it being optimized.

2.5.1 anessa AD•A

Prior to building a plant based on anaerobic digestion, it would be vital to study the feasibility of building the plant based on different aspects. anessa AD•A [1] [2] [16] is a platform developed for the above mentioned purpose. The platform provides users with an opportunity to look into the financial, technical and operational aspects if the proposed project were converted into a plant.

2.5.2 anessa AD•O

AD•O [1] [4] [16] is a platform built for optimizing existing biogas plants. Users of the platform benefit by obtaining feedstock suggestions based upon simulation of the plant. Artificial intelligence is incorporated in this platform to predict the most optimal suggestion that could help users generate the maximum profit out of the suggestion made.

2.5.3 anessa AD•M

AD•M [1] [3] [16] is a platform specific for monitoring the data of the various plants. The values from different sources such as sensors attached to biogas plants are displayed as a table in this platform. The platform has also been used for collecting data for the catalog to be discussed later in the report.

2.6 Importance of Monitoring the Parameters for anessa Clients

It is essential to identify the key parameter that would play a role in the operation of the plant and predict the optimal conditions for the plant to reach the highest success level. The key idea is create a suitable environment for any kind of bacteria to thrive

and aid in the maximum production of biogas. As discussed above, every parameter that has an impact on this process would need to be monitored periodically to avert any damage to the plant, the micro-organisms and the environment. Parameters such as temperature play a vital role in determining the infrastructure required for maximising the biogas production. The efficiency of biogas extraction would be greatly impacted based on such key parameters. Thus, monitoring of such parameters would help in identifying conditions suitable for the appropriate bacteria and predict the biogas extraction efficiency under such conditions.

2.7 Data Collection and Artificial Intelligence as a Tool

The role of a biogas plant operator is to ensure a consistent anaerobic digestion process. Operators would hence monitor the key parameters of the biogas plant such as the temperature [6]. The monitoring process is difficult yet important. Predictions, in this regard, would help save efforts spent on monitoring. Predicting the temperature, pH and other key parameters based on the past trend would help prevent the plant parameters from reaching improper values and hence assist the operator. Artificial intelligence is hence looked at as a tool by researchers to aid in better prediction. This section describes the machine learning model used for the digester temperature model for prediction. This section also provides insight into the library used for matrix computation for implementing the digester temperature model. Finally, a brief explanation on predictive analytics and data collection is provided here.

2.7.1 Matrix Computations

The performance of arithmetic operations on one or more matrices could either be done by writing logic to iterate through the matrix and perform computations or by making use of a pre-built library. The former method is highly inefficient since it takes a longer time to compute, thus resulting in a longer response time and page load times. The latter method has a variety of options to choose from such as ND4J [43], Colt [53] [7] and Apache [9]. According to Francois Dupire [25], ND4J, Colt and Apache Common Math are Java libraries used for matrix computation purposes. For smaller matrices, Colt and Apache outperformed ND4J. However, with the increase in size of the matrix, ND4J emerged the leader. Since real-time matrix computations would grow with increases in data from different sources, for digester temperature model, ND4J has been used for computations.

2.7.2 Neural Networks-based Model For Digester Temperature

The development and training of the model for the digester temperature-based prediction by the team at anessa was based on neural networks. Their model was a feed forward neural network with no hidden layers [19]. Feed forward neural network is an artificial neural network with absence of cycles between the nodes of the network. In creating their model, anessa collected data from different sources, such as literature, lab data sets, and data from actual plants (customer data). The input and the output was temperature and the biogas production efficiency. The collected data was processed to remove noisy data. However, the data from every single plant was large. Hence, the data was first generalized so that the model built could be comprehensive to incorporate different varieties of data sets. Previous work created a model with four layers without any hidden layer after experimenting with the data.

The size of the network decides the complexity of the model. A model with more layers is a model of a greater network size. This model, however, takes time to learn despite the fact that the model could produce more generic results. George et al. [19] had demonstrated in their research that the size is most often determined by trial and error. Likewise, owing to limited availability of data, building a large complex model did not seem a possible solution. Hence, through experimentation, the conclusion was that the number of layers should be four. The model produced a co-efficient value of 0.97 and this was most optimal for the prediction. The model was built using the second version of the TensorFlow library [12] and was developed making use of the Python language.

2.7.3 Predictive Analytics

Predictive analytics [51] is foreseeing future based on data collected from the past. Data is collected from the platform and a model is built using the collected data. The model thus constructed is used to predict the future. This prediction is then used to avert any untoward incident and to increase the optimality of the platform on which the model is built. The digester temperature model was built after the data collected from different sources were analyzed and the relationship between the temperature and biogas production were derived from the collected data.

2.7.4 Data Collection

Data collection is the first step towards building an AI model. The collected data would be pre-processed to remove noisy data and outliers, the model would be built, trained using the data processed and testing the model by splitting the data into training and testing and evaluating the performance of the model. The software development for implementing the data collection solution for anessa, also known as Catalog, is the initial step of collecting metrics and conditions of the plant specific

parameters. This is later used to predict the plant specific conditions after the model is built.

2.8 Summary

This chapters discusses the anaerobic digestion process and provides an overview of the key parameters of biogas and an outline of the significance. This chapter introduces an existing biogas platform for customizing, optimizing and monitoring the biogas plants. Finally, the chapter provides details on how AI, data collection and predictive analytics could benefit the operators of a biogas plant. The next chapter briefly describes the on-going research works in the biogas industry.

Chapter 3

Related Work

Research works focusing on biogas plant operations, the current state of production and integrating of artificial intelligence into the biogas industry are in progress and many recommendations have set the path way for future implementations that could benefit from the model proposed. This chapter provides relevant details about the process overview and the state of production. The chapter briefly explains the parameters that have an impact on the biogas plant operation and the works pertaining to the same. This is followed by a summary on the current monitoring systems. A small overview of the research on AI and biogas is also provided.

3.1 Biogas Process — An Overview

Anaerobic digestion has been the heart of biogas plants and hence been of greater interest to researchers and countries looking for renewable sources of energy as an alternative to the non-renewable ones. Figure 3.1 [35] shows the methane emissions based on different sources in the US. To re-iterate the key factors behind anaerobic digestion, Meegoda et al. [35] have provided an extensive overview of the parameters influencing the AD process and the methodologies that could aid in improving the efficiency of the same.

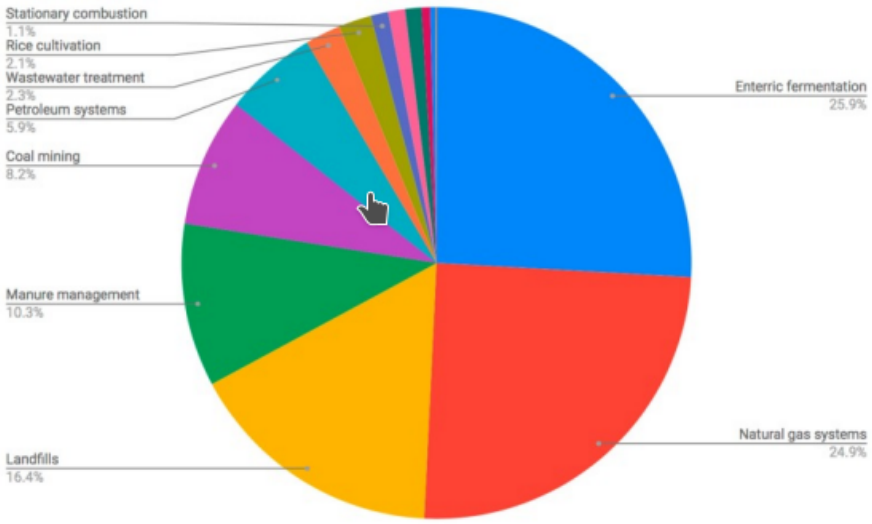


Figure 3.1: Methane Emissions in US(2015))
[35]

3.2 State of Biogas Production

The awareness of the current state of biogas production is crucial to foresee the trend the industry is expected to attain. Figure 3.2 summarizes all Europe and Figure 3.3 looks at specific countries in Europe (which are included in the total in 3.2). Thus, Europe has seen a significant increase in the production of biogas from different sources [45]. The current available models and the comparison between these models could help structure a model that could overcome the drawbacks of the existing ones. Datsun et al. [45] have studied the existing models, made a comparison and provided the outcome of the comparison.

3.3 Parameters Influencing Biogas Production

The research work in the field of biogas to identify the key parameters that would contribute to enhanced biogas production have been extensive. Sreevidhya and Balamurugan [21] contributed towards establishing the significance of the parameters

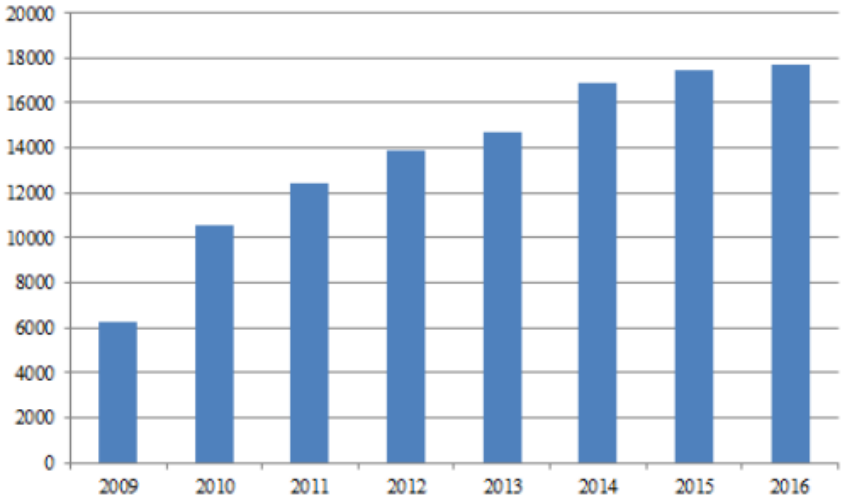


Figure 3.2: Growth of Biogas Plants in Europe
[45]

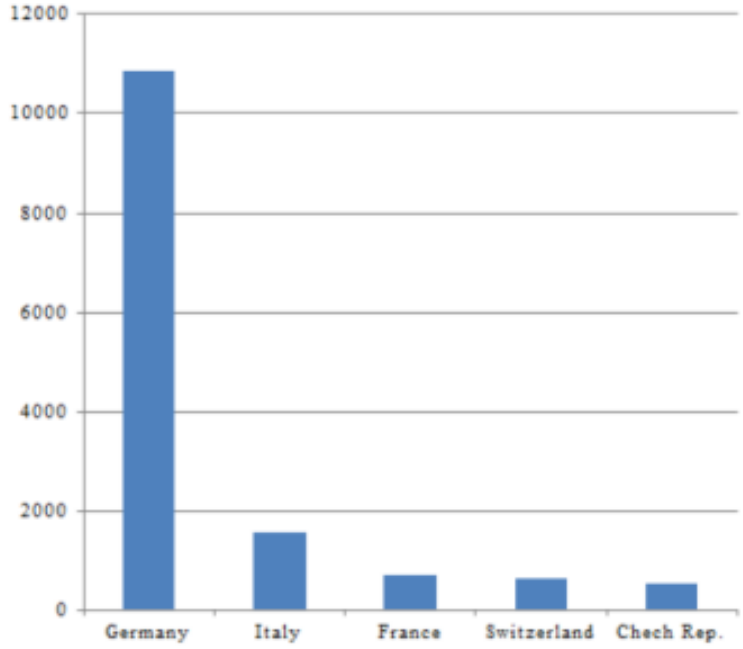


Figure 3.3: Count of Plants (Biogas) in European Countries (2016)
[45]

temperature and HRT for the production of methane. Methane is extremely crucial since it helps recognise the consistency of the anaerobic digestion process. The micro-organisms that aid in the production of biogas are different based on the temperature at which the process is carried out. Temperature is a key factor for optimal biogas production in the anaerobic digestion process. Thus, the authors of the paper [21] chose different locations with varying temperatures to identify the type of bacteria at the specific temperature and the impact on methane production. The results indicate that the mesophilic bacteria at temperatures ranging from 30°C to 34°C aid in the maximum production of biogas and the production of methane decreased substantially for temperatures less than 20°C.

The industrial considerations required to furnish an optimal plant recipe is essential for gaining deeper insight into the various factors that would influence the AD process. Dekhtiar et al. [24] identified pH as a chemical factor and temperature as a physical factor that has a significant influence on the activity of digestion carried out by the micro-organisms.

Many biogas research works were focused on establishing the significance of pH and temperature and elaborating on their role towards maximising the production of biogas. Dupade et al. [46] studied these on a biogas whose source of generation was household waste. The results of their studies have strongly demonstrated that increasing the temperature increases the production of biogas and this was specific to thermophilic range.

3.4 Current Biogas Monitoring Systems

Monitoring is the process by which the system under consideration is monitored for a prolonged period of time to collect data from the system periodically [13]. The collected data is instrumental in identifying the efficiency of the system. The data

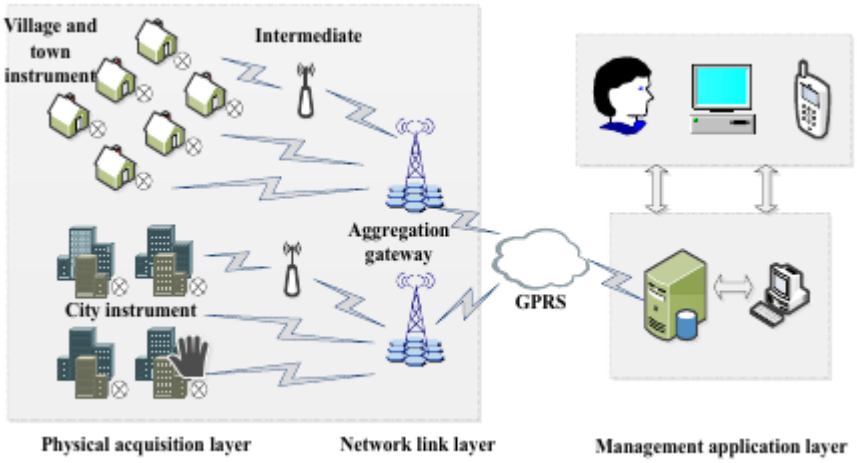


Figure 3.4: LORA Architecture
[50]

is also crucial to help modify the system to make it more efficient. Predicting the future behaviour of the system is feasible only when data from the past is analyzed and is another reason why the data is important.

To re-emphasize the significance of multiple parameters influencing the biogas production, Ogbonna et al. [36] derived the association between the input parameters and the output biogas production. A "black box model" was used since the model was found more effective towards carving the relationship between the factors and the output based on the generated data. The study however was limited to four parameters (temperature, pH, speed and pressure).

The construction of the most optimal system that monitors the biogas plants is under research and many solutions have been provided by various researchers. Xu et al. [50] constructed a monitoring system (Figure 3.4) that was based on long range technology. This was proposed to overcome the shortfalls of current monitoring systems that lacked high quality data, owing to the absence of appropriate infrastructure in obtaining automated data from the sensors attached to the plants. However, the solution proposed might not work when the data management involves users located at different locations.

Figure 3.5: Instrument to Monitor Biogas
[37]

Methane is a dominant component of biogas and the amount of methane is significant since methane is greatly flammable and is not so healthy to inhale. Thus, Helmy et al. [37] built an instrument to monitor the biogas (Figure 3.5) and to measure the concentration of methane. However, this instrument was directly connected to a personal computer where data was stored for use later. The direct connection posed a greater risk of losing data at any time.

Work in the area of monitoring the output of a biogas plant is ongoing and many researchers have made contributions towards the same. Asep et al. [13] constructed a monitoring system that embraced the concept of "Internet Of Things" to help with remote monitoring process in addition to the live monitoring. The flow of data started from the sensors attached to the plant. The data was then passed to the micro-controller for the refinement of the data. The micro-controller acted as an intermediate passing the data further to the IOT device.

3.5 Data Storage Solutions

The amount of data collected from a biogas monitoring systems is quite huge for any database to handle. Sensors attached to the biogas plants send data periodically (ev-

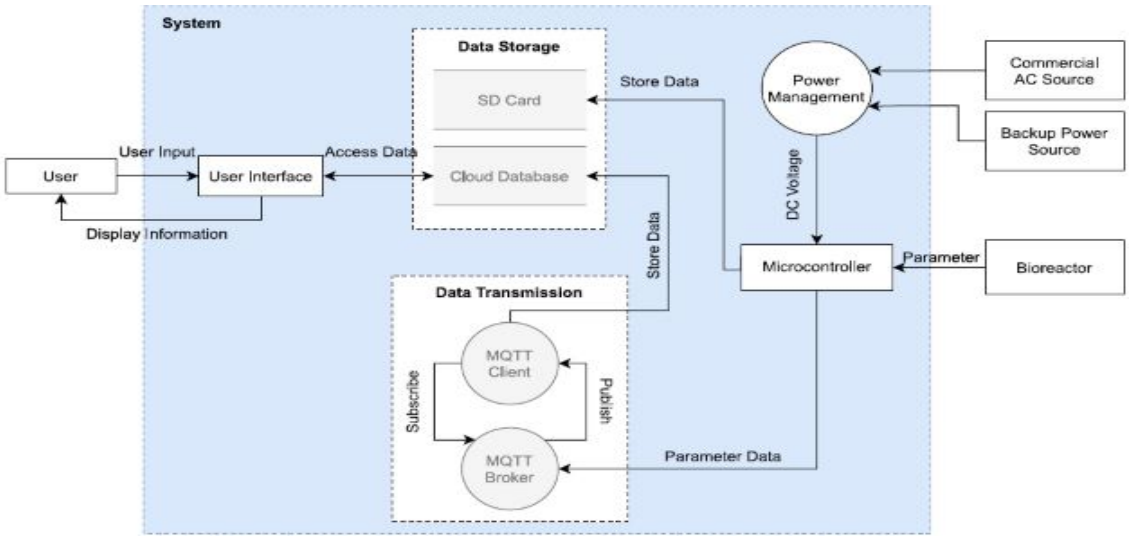


Figure 3.6: Data Flow Diagram
[28]

ery day) and hence database storage and retrieval may not offer optimal performance and may not be sufficient from the storage perspective. It is imperative to have a system built to handle data storage effectively. Matthew et al. [28] constructed such a system. The system proposed was a multi-component system as shown in Figure 3.6. Initially, collected data was gathered locally and then was sent online to cloud storage with the assistance of a micro-controller. However, the local data was stored on a microSD card. Reading data from a microSD card could be herculian if the online system crashes for any given reason since a card reader is required to read data from the card.

3.6 AI and Biogas

The parameters of the biogas plants are important to determine the efficiency of the plant. The values of these parameters are dependent on the specifics of biogas plants such as the feedstock, bio-methane yield type and amount. If these values are predicted and improper conditions are identified ahead of the plant attaining those

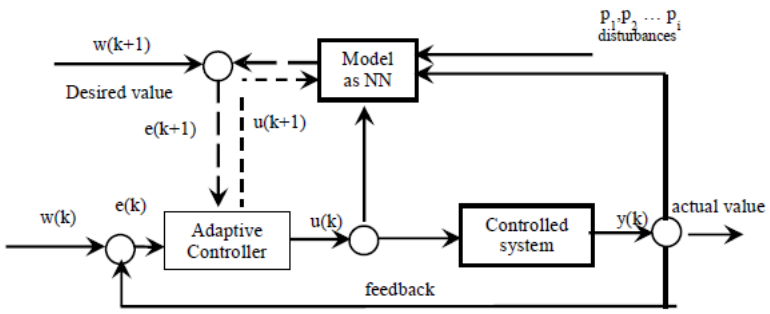


Figure 3.7: Neural Networks Predictive Controller [47]

values, it is possible to prevent damages to the plant by changing the unfavorable conditions. Artificial intelligence is an evolving field and AI for biogas would mean simplifying the world of prediction from the perspective of the user. The concept of biogas monitoring may be useful as long as the parameters to monitor are easy to recognise when monitored. However, uncertainty is higher in the case of identifying the parameters that defines the characteristics of all plants. Hence, to combat this ambiguity, Christine et al. [47] developed a specialised controller based on neural networks in combination with fuzzy logic as shown in Figure 3.7. The controller is a blend of a neural network-based model and a controller. The user who would specifically benefit from the controller would be the industrial scale biogas plant operator since the number of parameters to monitor and predict on an industrial scale is huge.

An overview of the prevalent conditions with respect to AI and biogas integration could help with better understanding of what could be improved over the existing ones and how could a more optimal solution be reached. Samet et al. [22] did extensive research on current trends in the integration of AI into biogas. The parameters that have a key influence on the process were identified and outlined as shown in Figure 3.8. The study was comprehensive to outline the differences between different models created curatively for the purpose of biogas plants. This included establishing

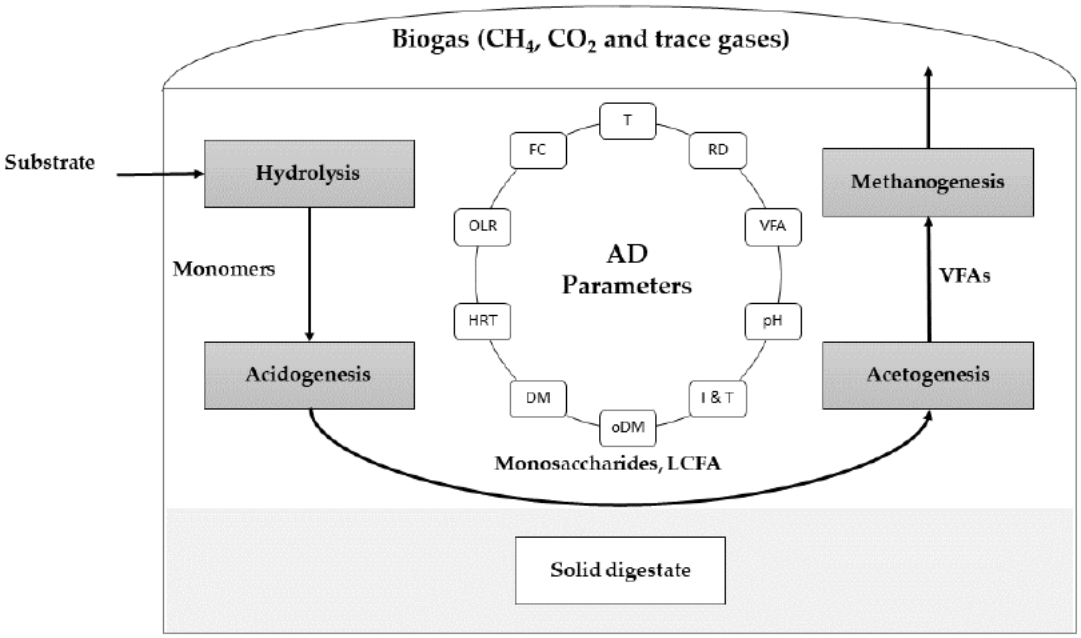


Figure 3.8: Parameters
[22]

the difference between first, second and third generation models and the statistical model. The integration of AI into biogas was thoroughly evaluated from the existing works. Various methodologies such as the fuzzy logic model, genetic algorithms and most updated artificial techniques were analyzed. Artificial neural networks seemed to outperform any other methodology and hence was recommended by the authors. An amalgamation of predictive analytics for predicting based on gathered data [42] [22], machine learning for training the data and an optimized sensor to perform with greater efficiency could prove to be a game changer when integrating AI into the biogas domain.

Prediction is an important aspect of AI for which the data is gathered initially. The accuracy of prediction depends highly on the model used to train the data, the accuracy of the data, the quantity of noisy data and their impact on the model. Models such as random forest and artificial neural networks are popular for prediction. However, efforts are underway to improve this accuracy and hence the extreme

machine learning model [52] is under study by researchers since it has more prediction accuracy. The model developed by Yi et al. [52] was a combination of ELM and the synthetic minority oversampling technique for regression (SMOTER), which was used to compensate for loss of adequate data for training and testing owing to hinderances from the infrastructure and environments such as being devoid of a good operating sensor. This combination proved highly efficient with a greater R^2 value.

3.7 Libraries for Matrix Computations

A matrix is a data structure used to store data in a multi-dimensional format. Matrices are especially useful when the volume of data is huge and when dimensionality reduction and computational performance are of concern. Many libraries to support matrix computations are currently available that could be used with Java. There has also been research on providing a library that best fits a requirement. For instance, extensibility is one factor where the matrix library COLT has surpassed the expectations and has outnumbered other libraries such as Apache Commons. Thus, Holger et al. [44] provided recommendations based on research in this regard. Their primary focus was on the UJMP library and the comparison of UJMP (Universal Java Matrix Package) with the other libraries is shown in Figure 3.9 and Figure 3.10. In summary, UJMP is highly extensible, available in various modes, has great features to support diverse visualization modes and is licensed. However, there are certain drawbacks such as the lack of standardised implementations and unavailability of documentation. Research from Antonela et al. [18] showed their development of the SmartOp (Sparse Matrix Library for Arithmetic Operations) library for sparse matrices. This was found to be useful in reducing the amount of storage and memory required. This also brought reduction in computation times. A performance comparison is shown in Figure 3.11. This library was found to be highly flexible and

	UJMP	Jama	Colt	MTJ	commons-math	vecmath
extendable	+	−	+	+	⊙	−
dense matrices	+	+	+	+	+	+
sparse matrices	+	−	+	+	−	−
2D matrices	+	+	+	+	+	+
3D matrices	+	−	+	−	−	+
4D matrices	+	−	−	−	−	+
matrices >4D	+	−	−	−	−	−
$> 2^{31}$ rows/columns	+	−	−	−	−	−
object entries	+	−	+	−	−	−
generic cell entries	+	−	−	−	−	−
matrices > RAM	+	−	−	−	−	−
entry iterators	+	−	+	+	−	−
advanced operators	+	−	+	−	−	−
import/export filters	+	−	−	+	−	−
visualization methods	+	−	−	−	−	−

Figure 3.9: Matrix Library Features
[44]

Library	Data type	Matrix type	Execution type
PCOLT MKL	Double, float, long, integer	Dense, sparse	Multi-threaded
JAMPACK la4j COLT JAMA JBLAS Apache common maths	Double	Dense	Sequential
oj! Algorithms	Number, bigdecimal	Dense	Multi-threaded
UJMP	BigDecimal, Boolean, byte, double, float, int, long, object, short, string	Dense, sparse	Sequential
ND4J	Float	Dense	BLAS dependent, GPU parallel
CupSparse	Float, double	Dense, sparse	GPU parallel
numpy/scipy	Int boolean float double long complex	Dense/sparse	BLAS dependent
PETSc	Double complex float long int	Dense, sparse	Sequential, multi-threaded, multi-process

Figure 3.10: Java Matrix Libraries Comparison
[44]

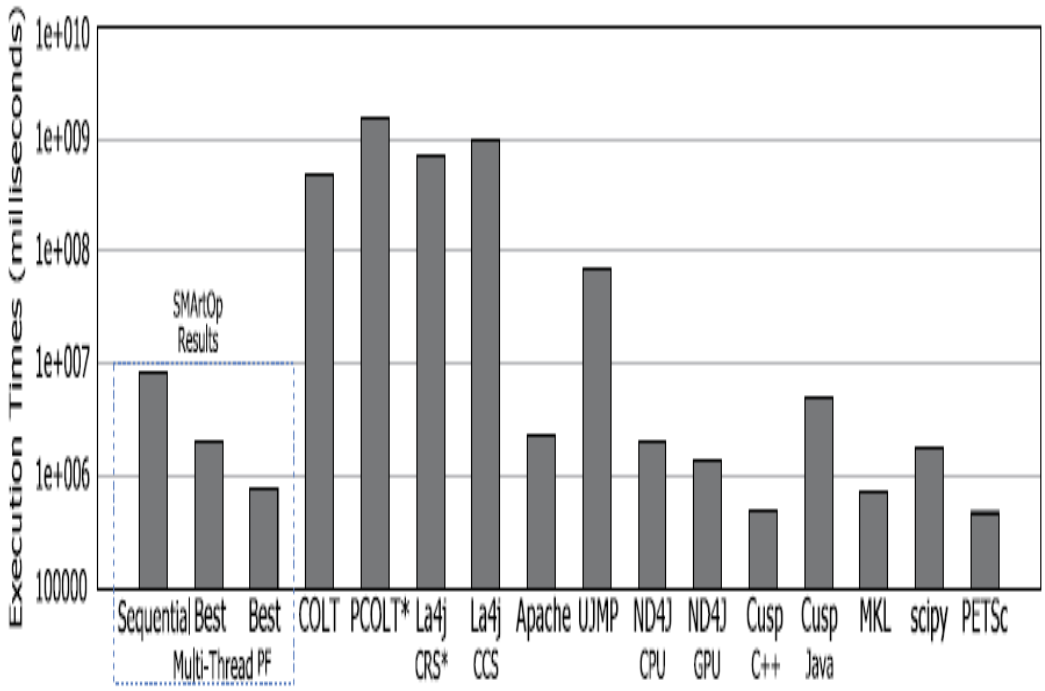


Figure 3.11: SmartOp Versus Other Libraries [18]

did not require customized hardware to support increased storage.

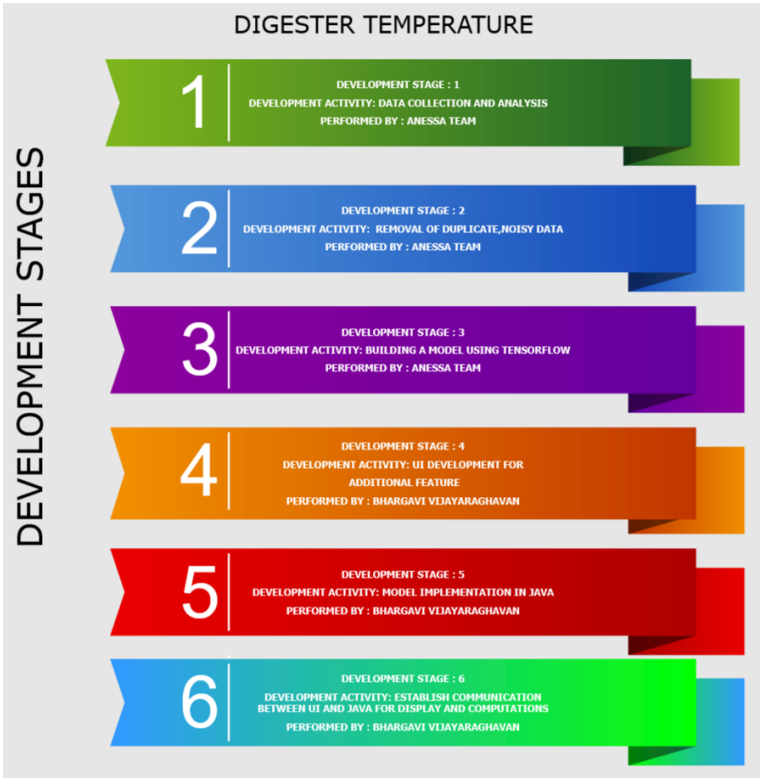
Chapter 4

Products Developed

As described in Chapter 1, we developed two features for anessa. We implemented the digester temperature-based prediction to enhance the experience of the users using anessa products and the catalog data collection using Angular and Java. This chapter describes the tools built on top of the anessa platform. They were built for different purposes at different stages of the implementation of artificial intelligence methodologies. Overall, two factors were considered while developing the software. A platform to collect the data that could later serve as the baseline for building an artificial-intelligence-based model. Another software development leveraged the previously built artificial intelligence-based model. The software was built to implement the model and predict the impact of temperature on the biogas plant. This was done by integrating the model with the AD•A platform [2] [16]. The development stages are shown in Figure 4.1 and a detailed description of the stages of development is provided in this chapter.

4.1 Digester Temperature Development Overview

The significance of temperature on the anaerobic digestion process was discussed in Section 2. To re-iterate, digester temperature is a portentous parameter that



(a) Development Stages of Digester Temperature

(b) Development Stages of Catalog

Figure 4.1: Development Stages

has a significant role in achieving the optimum biogas production. Therefore, it is essential to monitor and collect the data pertaining to digester temperature to be able to predict and analyze the impact of the temperature on various outcomes, for instance, digester efficiency.

4.2 Digester Temperature Prediction

The anessa AI digester temperature model helps foresee the operations of a plant but this is specific to the mesophilic range. The working methodology of the model is that if the feature is disabled by the user, the operations of the plant are unaltered. If the feature is enabled, the user is expected to key in a specific digester temperature in the mesophilic range. Based on the temperature entered, a biogas factor is determined by the model developed and the biogas factor is applied to the various results that would be impacted by this change in temperature. This helps the user foresee the impact of temperature on the plant and hence consider operating the biogas plant based on the produced results.

4.3 Development Stages For Digester Temperature

The stages of development are broken down into different user stories [26] such as building the model and building the platform for implementing the model.

4.3.1 Data Collection, Analysis and Building a Model

The first phase of building the model was previously completed and part of the existing platform. As described in Chapter 2, the information about the model is provided in this section. Neural networks-based prediction with a feed forward neural

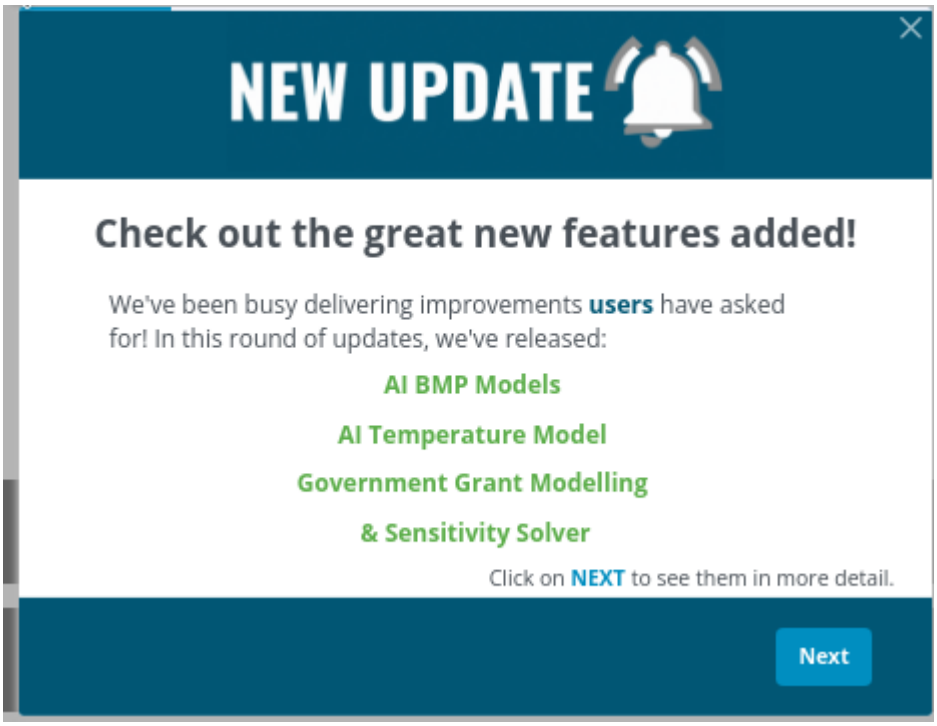


Figure 4.2: Notifications on Login Page

network model and absence of any hidden layers was used by anessa for building the digester temperature AI model. Different data sources were used for understanding and analysing the characteristics of the data. The data included data from labs and data from actual plants. anessa derived the correlation between temperature (input) and the biogas efficiency (output) through the analysis of the data sets. To construct a model that could be used to predict any given input, the data was generalized and then finally the model was derived based upon the above study. The language used for the model development was Python and the library was TensorFlow. A notification to the users of anessa platform was created to notify the users of the new feature and to bring about awareness of how the new feature would help the users. Figure 4.2 shows the notifications of the feature on the web page when the user logs in.

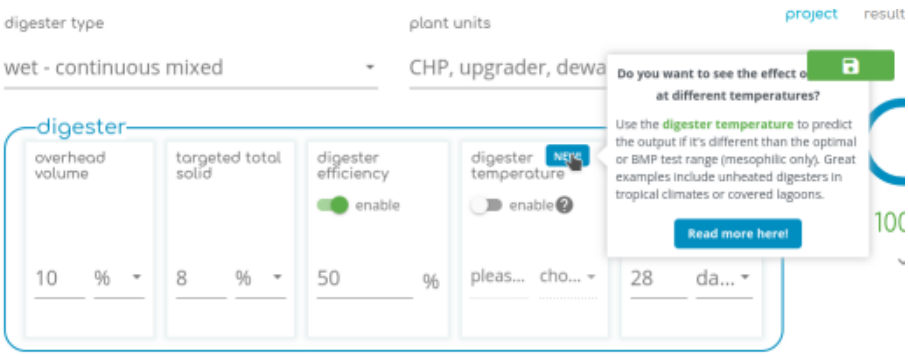


Figure 4.3: Digester Temperature

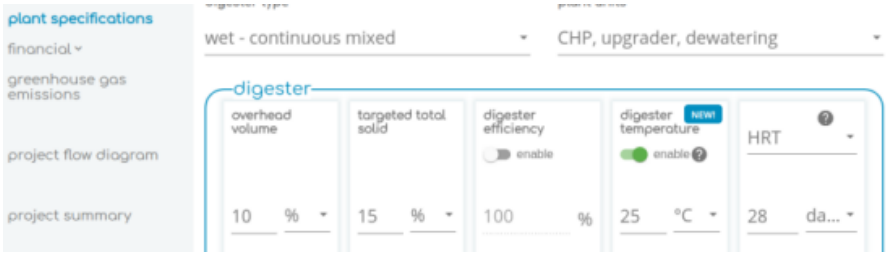


Figure 4.4: User Input Screen

4.3.2 Implementation of the Model

The anessa team developed a prototype of the model using Python language and TensorFlow library. We implemented the model using Angular and Java and integrated the model into the anessa AD•A platform. This was made available as a feature that the user could leverage.

4.3.3 UI Development

A new feature was added to the plant specifications as shown in Figure 4.3. The feature could be enabled or disabled using a radio button. When the feature is enabled, input combinations such as the digester temperature and the corresponding units are made available for the user to choose, as shown in Figure 4.4. The plant is then simulated by the user for calculating the biogas factor and for having a glimpse of the implications of digester temperature on financial and technical results after the factor is applied.

4.3.4 Artificial Intelligence-based Model Implementation and Calculation of Biogas Factor

The biogas factor is instrumental in understanding the working methodology of the AI Model built. The data entered by the user is passed via a protocol to the Java server where the AI based computations are performed and the values are returned via a controller as a JSON response. This object is obtained by Angular for showing it to the user on screen.

4.4 Catalog Development Overview

Catalog is the software used to collect data that would later be used for building an artificial intelligence-based model. The purpose behind the development of the software is multi-fold. The software intends to alert the user of a condition not suitable for ideal biogas plant operation. The user is alerted when the parameters influencing the biogas production reaches a level not desired for the bacteria. The alert is to warn the user to change the conditions proactively. The other purpose behind the software development is to collect the data pertaining to various parameters and their non-ideal operating conditions and the frequency of such operations. The intent of the data collection is to use the same for predictive analytics purposes. The collected data would be used for analysis after the data is processed and is ready for building an AI model. This model would be used to predict such conditions based on the current and the historical operational methodology of a plant under consideration.

4.5 Catalog Data Collection

The collected data is a combination of different parameters. The data that are captured as part of the data collection are described below.

- The parameters that were configured for current monitoring purposes.
- The frequency of the data and the exact values that were outside of the desired range.
- The plant specific configurations.
- The solution proposed by the software platform.
- The date the user was warned by the software platform.

The significance of each of these data are as elaborated below.

4.5.1 Significance of Data Collection

1. *Values of Data Outside the Desired Range* This determines the frequency with which a plant reaches the undesirable state. It is required to avert any major damage to the micro-organisms. This parameter would also help to understand the biogas plant feature responsible for such inconsistent conditions and help predict the next time the condition would become inappropriate.

2. *Plant Specific Configurations* The configuration of a plant is significant in identifying the parameters that would influence the operation of the plant. Analysis of plant specific configurations in combination with the values outside the desired range could help provide a more generic model to predict the conditions across all the plants.

3. *Solutions Proposed by the Software Platform* The alert to the user would indicate an ideal solution to the warning message displayed. This is to assist the user in corrective actions that could be adopted to turn the conditions favorable for maximised biogas production. The data of what solution was proposed is essential to understand if the corrective actions need to be restructured based

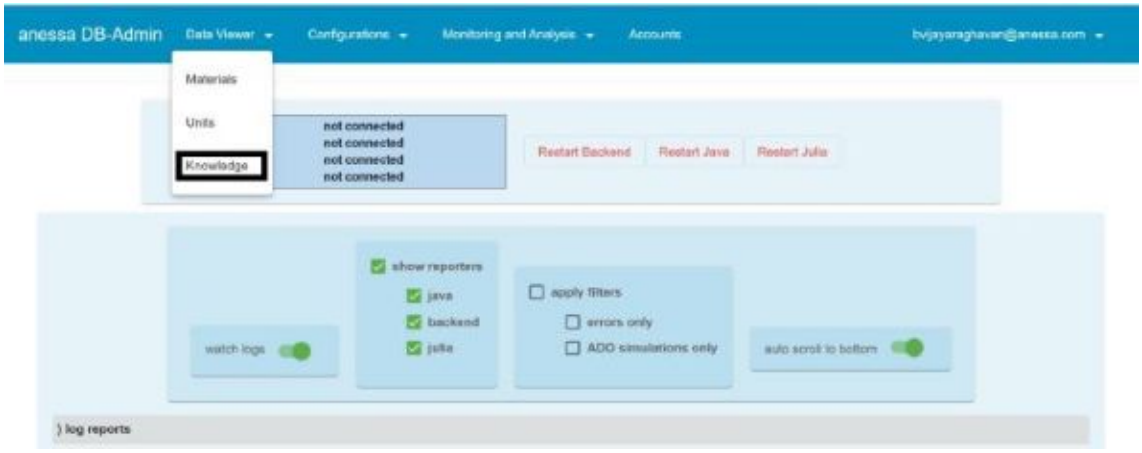


Figure 4.5: Knowledge DropDown

on the adaptability of the micro-organisms and thus make the solutions more versatile.

4. *The date the user was alerted* This metric is important to reconcile the values of the date and the warned solutions to predict the behaviour of the plant within a period from the date the user was warned.

4.6 Development Stages For Catalog

The stages of development are elaborated in the subsections that follow.

4.6.1 User Interface Development on DB Admin

The portal designed for the internal users of anessa is called the DB Admin. This portal is specifically for administrative purposes. To configure the catalog data collection, the first step of the development is to add a new dropdown that would navigate to the page where the Catalog related configurations are updated. The screen reference of the same is as shown in Figure 4.5.

The configurations page is shown in Figure 4.6. These configurations are uploaded and maintained by the anessa team. The configurations are updated periodically

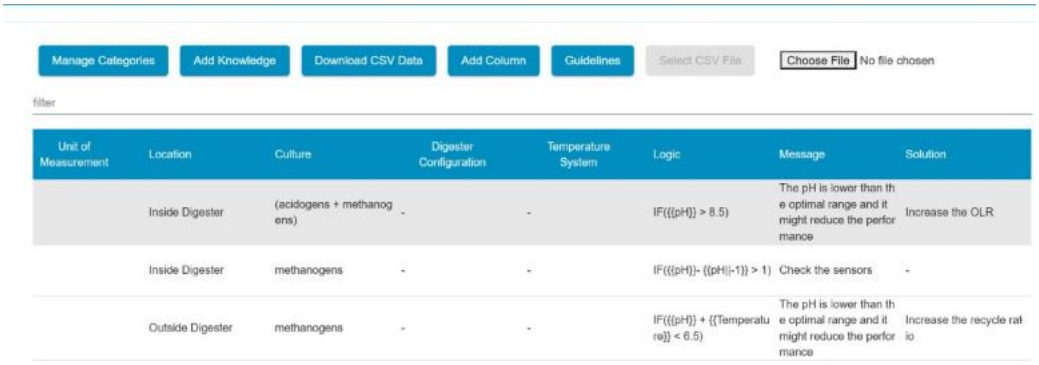


Figure 4.6: Knowledge Configurations Page

based on the observations made from the working model and conditions of different biogas plants. These include the parameters to monitor, the configuration and the location to look for, the message to be displayed when the logic evaluates to true and the solution to be displayed alongside the message. The message represents the warning displayed to the user and the solution is the suggested corrective action. Various other features developed as part of the UI development for Catalog on the DB Admin are detailed below.

1. *Manage Categories* Parent categories to which the child configurations are mapped are first created using the manage categories feature. Thus, the created category would be mapped to multiple child configurations pertaining to this category. The feature developed is as shown in Figure 4.7.

2. *Add Knowledge* Upon creating the parent category, the child categories to be mapped to the parent are added and these form the baseline of the configuration. A single parent category can have multiple configurations. The purpose behind mapping is to enable the user to delete all the configurations pertaining to a parent at once when the parameter is no longer required to be monitored. The page developed for adding the child categories is as shown in Figure 4.8.

3. *Add Column* The catalog configurations have default columns that are populated whenever no prior configurations exist. However, more dynamicity is

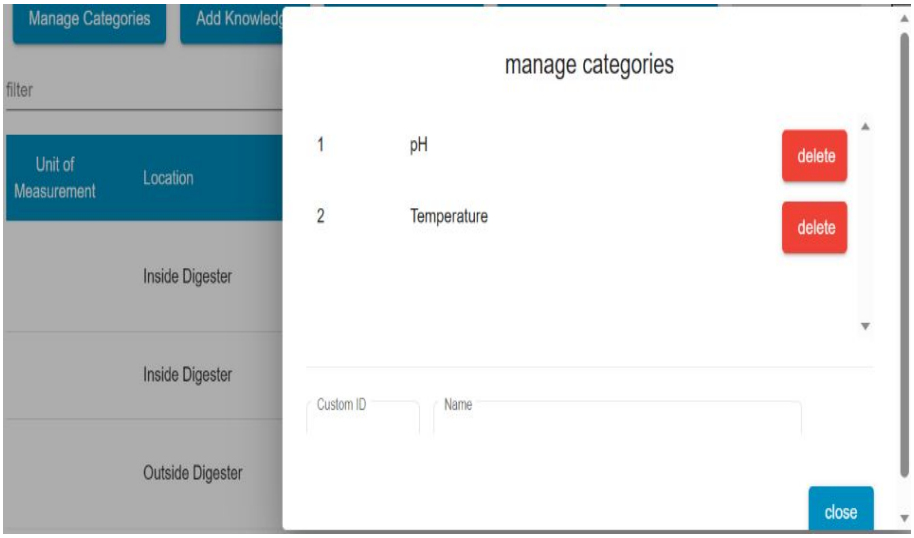


Figure 4.7: Manage Categories

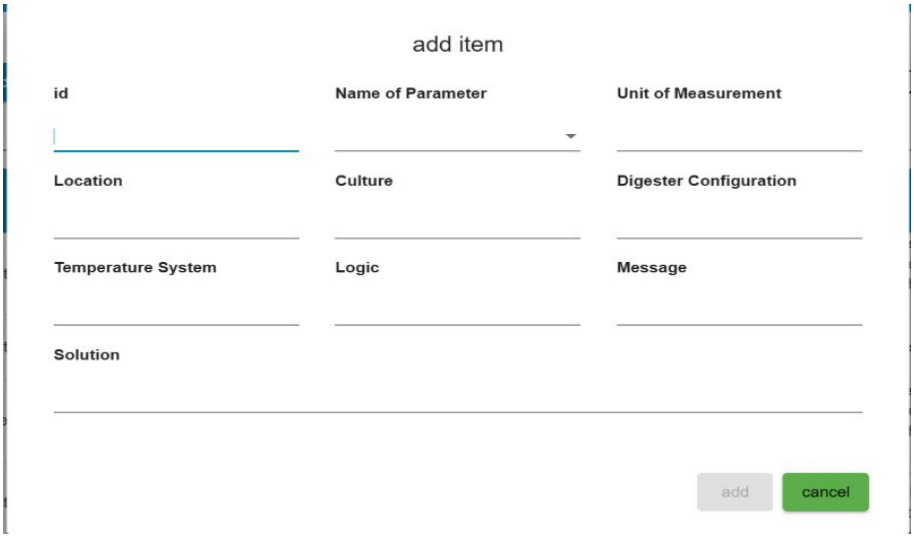


Figure 4.8: Adding Individual Knowledge

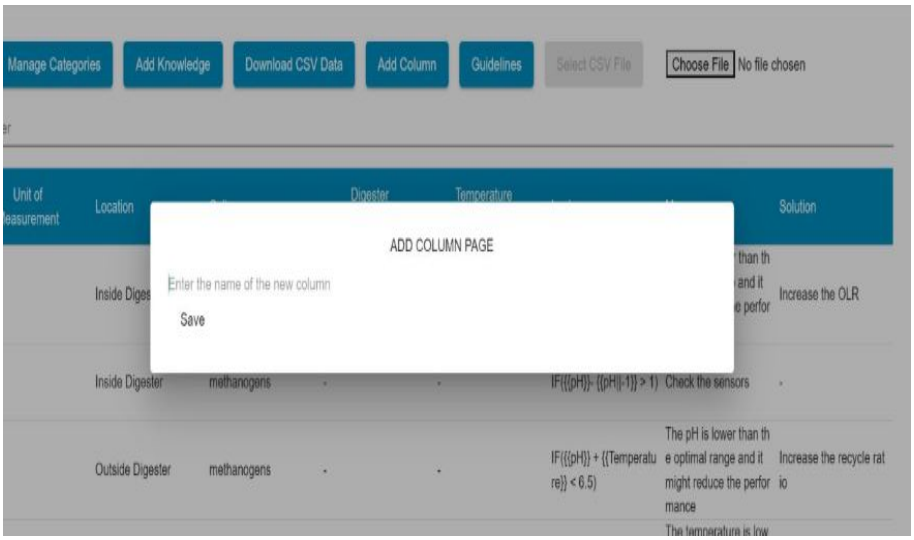


Figure 4.9: Add Column

provided by the "Add Column" feature that lets the user add more columns that could aid in more appropriate data collection. The feature developed is shown in Figure 4.9.

4. *Upload CSV Data* The creation of parent categories, adding child categories and mapping the child to the created parent category require manual inputs from the user. These are repetitive monotonous processes that requires that the user key in every individual input to be added to the configuration. However, the effort of such tasks is greatly reduced through the "Upload" functionality that lets the user upload a single file. The file is then converted into categories and child configurations after the upload is complete. The converted values are also stored onto the database. The file upload feature is shown in Figure 4.10.

5. *Download CSV Data* The data that is presented on the screen in the form of a table could be downloaded as a CSV by the user. This feature lets the user upload the same file again by using the upload CSV feature described above. The download CSV functionality enables the user to download the most recent

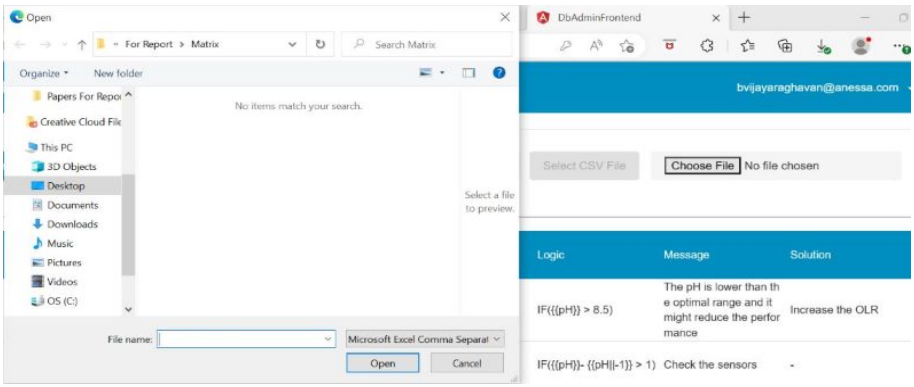


Figure 4.10: Upload CSV

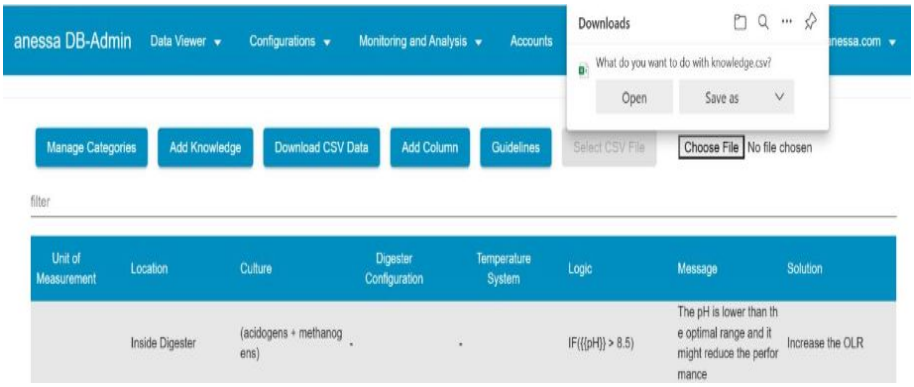


Figure 4.11: Download CSV Data

data with any changes made to the default configuration. The feature is shown in Figure 4.11.

4.6.2 Database Table Development

New database tables were created to store the parent and the child configurations from the DB Admin perspective. Routes were created on Angular to ensure the flow of data from the frontend to the database table. A detailed flow diagram for the DB Admin is shown in Appendix B.

4.6.3 User Interface Development on AD•M FrontEnd

AD•M is the platform for monitoring and storing the data. The configurations made on the DB Admin would be validated using the plants uploaded on the AD•M

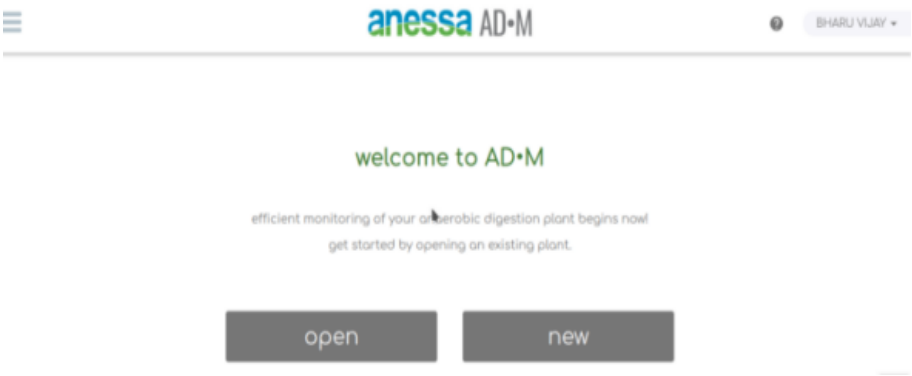


Figure 4.12: AD•M Home Screen

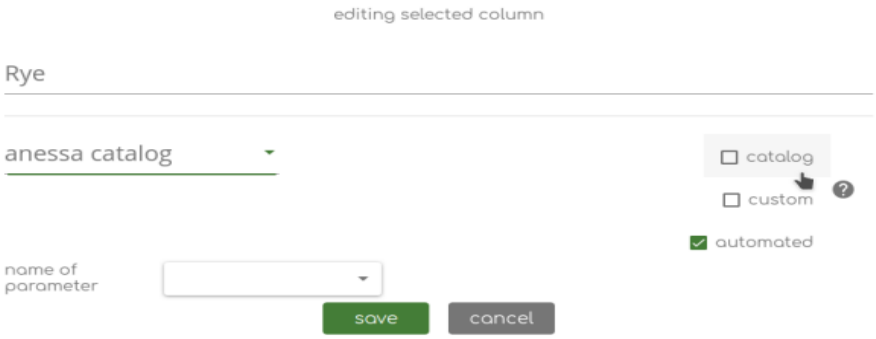


Figure 4.13: anessa Catalog Added to the DropDown

platform.

- Figure 4.12 shows the home screen of the AD•M platform. The catalog configurations of AD•M requires that a catalog be added to the drop down of every column of all the data-log of the plants. A catalog is added only to the numerical and the formula column types.

- Text columns do not have components to be validated or stored and hence are not configured with the catalog. Figure 4.13 shows the anessa catalog being added to the column of a data-log of one specific plant on AD•M.

- The parent parameters configured on the DB Admin under the parent category are shown once the anessa catalog is chosen as the type by the user as shown in Figure 4.14.

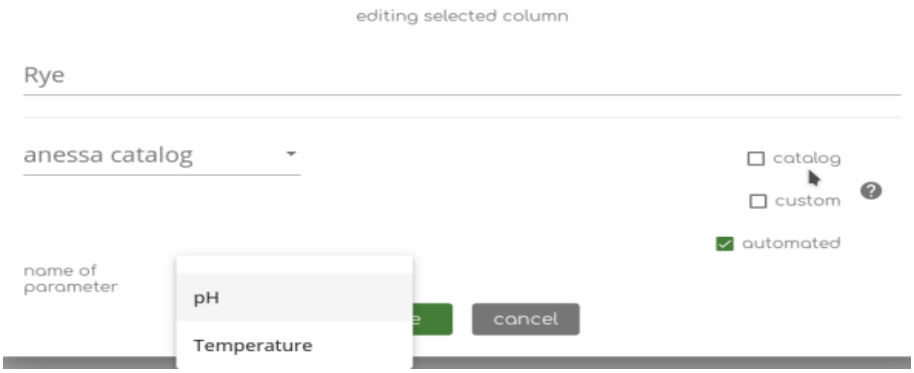


Figure 4.14: Parent Parameters on AD•M

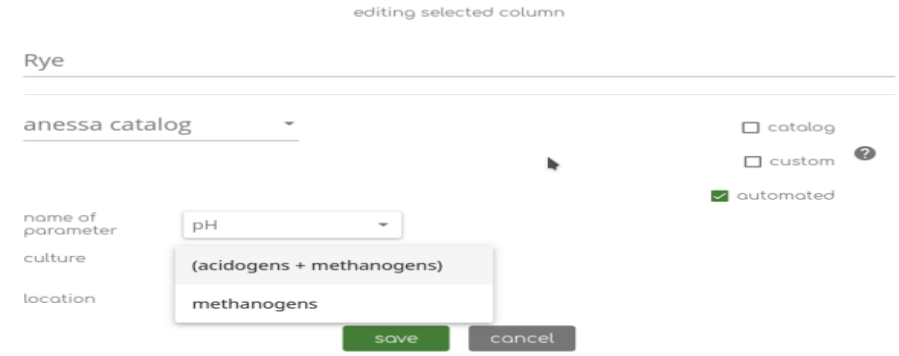


Figure 4.15: Selection of "Culture" Child Parameter on AD•M

- This parameter has various child parameters. For instance, the parameter pH has location and culture as the child parameters configured. Location, however, can have any number of distinct values and the same is the case for culture. Hence, all distinct values from DB Admin for a specific parameter are grouped together and shown as a single drop down once the parent parameter is chosen. This is shown in Figure 4.15 and Figure 4.16.

- After these values are chosen and saved by the user, the "logic" from the DB Admin is obtained. The logic formula is executed across all the rows of the column on which the catalog was configured. The values that meets the conditions of the logic are validated and an alert is displayed to the user with the "solution" and the "message" obtained from the configurations made for the particular logic. A sample warning message and solution is shown in Figure

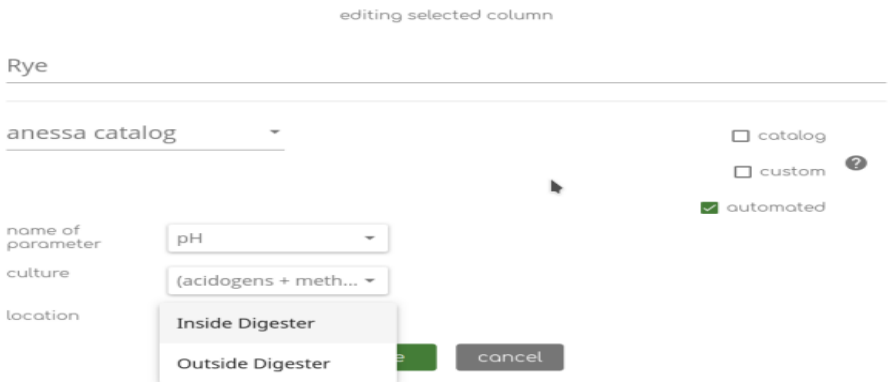


Figure 4.16: Selection of "Location" Child Parameter on AD•M

4.17.

4.6.4 Database Table Changes and Development on AD•M

Tables developed as part of the data collection process includes a table to store the catalog configurations made on a specific column and a table to store the values, the alert message displayed and the date and time of the alerts.

- **Column Specific Catalog Configurations**

  Figure 4.18 shows the configurations being saved to the database for a specific column. The column catalog information is stored in order to pre-populate the information already chosen by the user when the anessa catalog is chosen again on the same column. Any changes made to the catalog parameters overwrites the data already saved for the column.

- **Tables for Data Collection - First step towards AI Model**

  The AI model that would be developed for predicting the conditions not favourable for the biogas plant to operate requires collection of data from the past. This data would serve as the baseline for building the model. Figure 4.19 shows the parameters collected as part of this process. Figure 4.20 shows the collection of data for all the rows that triggered this process.

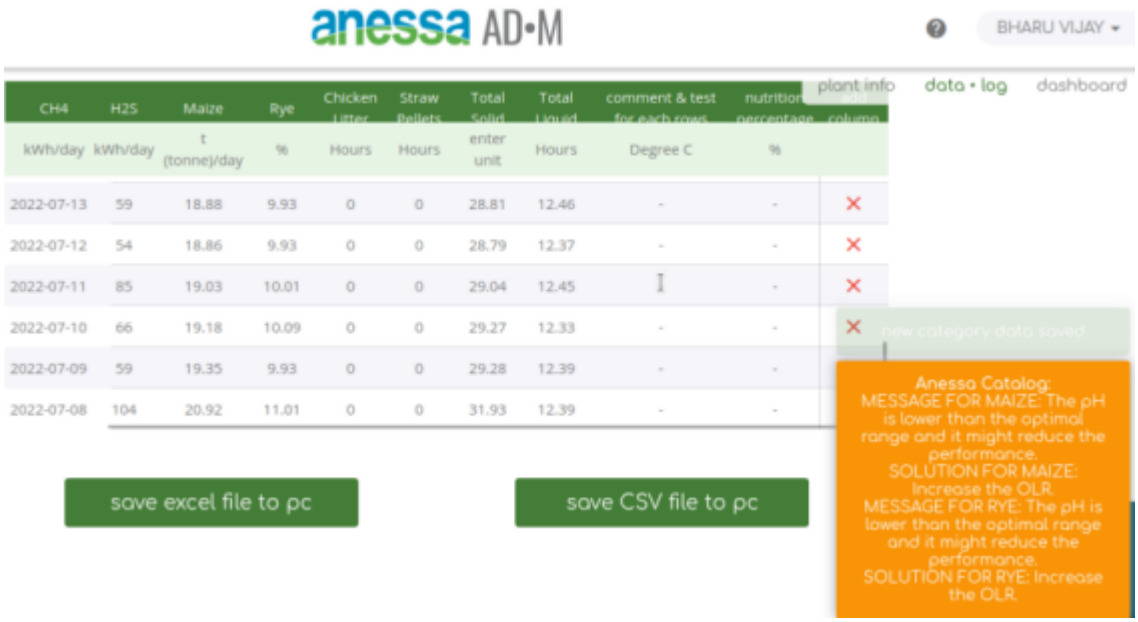


Figure 4.17: Warnings Displayed to the User

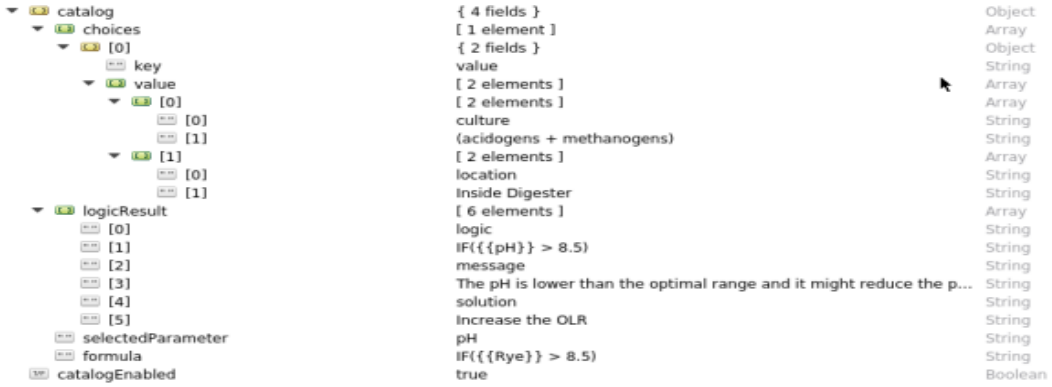


Figure 4.18: Database Table for Catalog Configurations

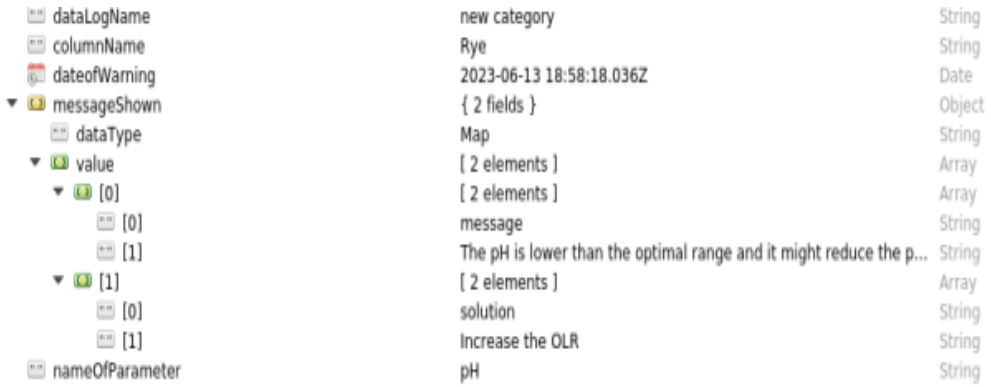


Figure 4.19: Database Table for data collection

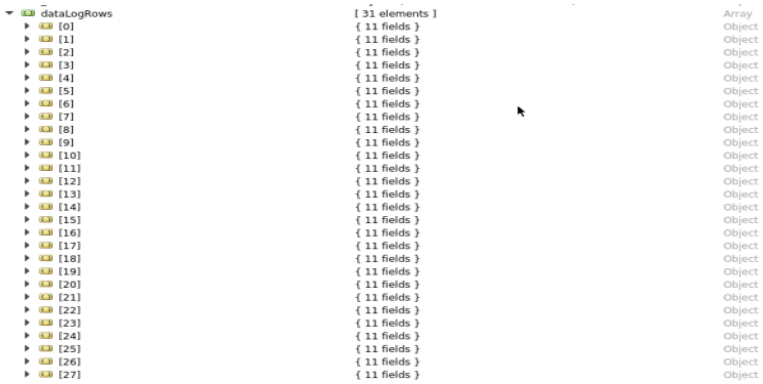


Figure 4.20: Database Table for data collection - Rows outside the desired range

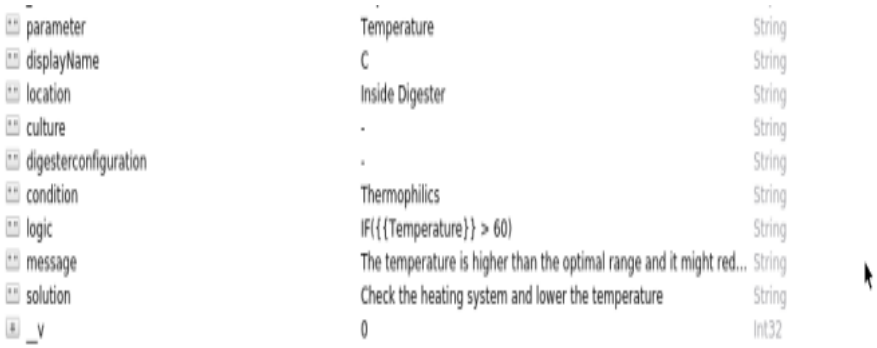


Figure 4.21: Database Table for Knowledge Configuration

- **Knowledge Configuration**

  New tables were created for the parent and child configurations storage and retrieval when the values are created in the DB Admin, either manually or when the same is uploaded via a CSV. Figure 4.21 shows the database table with the sample configuration for a child.

4.6.5 Formula Handler: The Core of Catalog

The original formula handler was developed using the Angular typescript language. We customized the formula handler and developed a more enhanced formula handler for catalog to make it more dynamic. The formula handler is responsible for obtaining the formula (logic) from the DB Admin for the parameters chosen by the user and processing the formula to obtain computed values for the corresponding row and

column. The formula is first processed to obtain a string in the format required by the computational method. This method has specific logic written for returning the values based on the type of formula invoked. The input to the method would be the entries on which the formula needs to be applied upon and the formula itself. The output is the processed result or a flag indicating if the conditions of the formula are met. The value is saved if the conditions are met since that signifies that the value might need to change. The message and the solution are then saved since they need to be shown on screen to the user. The screen entries are unaltered since the formula does not have any relevance to the entries on the screen.

4.6.6 Routes and Navigations on Angular

The developed code also includes the code for adding new routes for the following purposes.

1. Routes for navigating to the catalog page on click of "anessa Catalog".
2. Routes for connecting to the DB Admin models to obtain the data for parent and child parameters configured.
3. Routes for saving the catalog configurations onto the column.
4. Routes for saving the key process metrics collection for using it later for building the AI model.

4.6.7 Reading the Data and Calculating the Values

The catalog parameters chosen by the user are read, stored and used as query parameters to obtain the logic, message and solution corresponding to the values chosen. Formula handler is used to apply the logic on every row and calculate and identify values that are of concern for every column that has a catalog configured upon it.

4.6.8 Display of Warning Messages

Warning messages are displayed as small pop-up messages as shown in Figure 4.17. The messages indicate what went wrong and what is the most suitable method to overcome the fault. There is one pop-up notification displayed cumulatively for all the columns that have a catalog configured and for all rows whose values were a concern. Each column name, message and solution is displayed on separate lines on the same pop-up.

4.7 Summary

To summarize, the model for digester temperature was trained by the anessa team. The model implementation technologies and methodologies were elaborated in this chapter. This was deployed to production and clients were notified of the new feature. Catalog development is phased and the first phase of development to warn the users based on admin configurations and to collect the data has been completed. The stages of catalog development are detailed in this chapter. The further phase of development in the future would leverage upon the collected data and a model would be built to predict the plant feedstock parameters. In the next chapter, impact analysis of the developments and an overview on the financial and technical implications based on the predictions are provided.

Chapter 5

Analysis of Results

This chapter elaborates on the analysis of results. Results are based on the experiments performed on live plant data sets from multiple clients of anessa. The experimental set up for testing and evaluating the results are highlighted in this chapter. The digester temperature model is already pushed to live and the results are hence analyzed based on the impact the model brings on every plant. The data collection software is tested based on the characteristics of the data and a brief overview is provided about the same in the corresponding section.

5.1 Digester Temperature Results

In general, temperature is a direct measure of pace with which the micro-organisms disintegrates the waste materials. The lower the temperature, lesser is the movement of the bacteria and hence lesser is the conversion to biogas. The major areas of impact are seen to be on the technical and the financial results when the digester temperature AI model is enabled.

Figure 5.1: Initial Set Up

5.1.1 Experimental Set Up

The initial set up when the digester temperature is disabled is shown in Figure 5.1. For analysing the results, the sample experimental setup includes the following features:

1. *Digester Temperature Enabled:* Yes
2. *Digester Temperature Value:* 28
3. *Digester Temperature Unit:* °Celcius
4. *FeedStock:* 80,000 tonne/year
5. *HRT (Hydraulic Retention Time):* 28 Days

The experimental setup with the digester temperature enabled is shown in Figure 5.2 and the feedstock setup is shown in Figure 5.3. The intent of the experiment was to analyze prediction of the financial and technical results based on the digester temperature value and to compare the same with optimal plant conditions.

The evaluation of the technical and financial results to understand the impact of digester temperature on the biogas production and other products is discussed below.

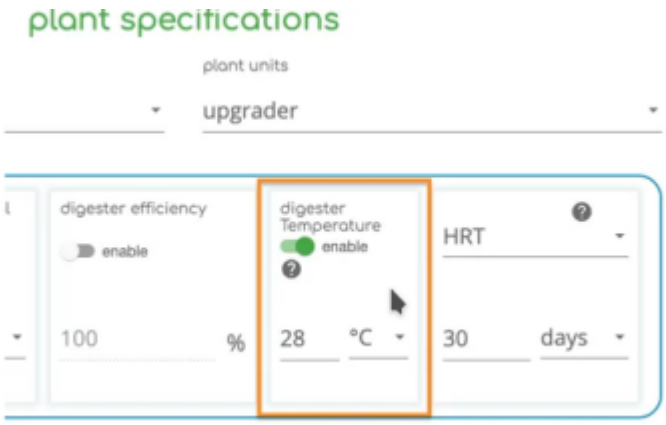


Figure 5.2: Digester Temperature Experimental Set Up

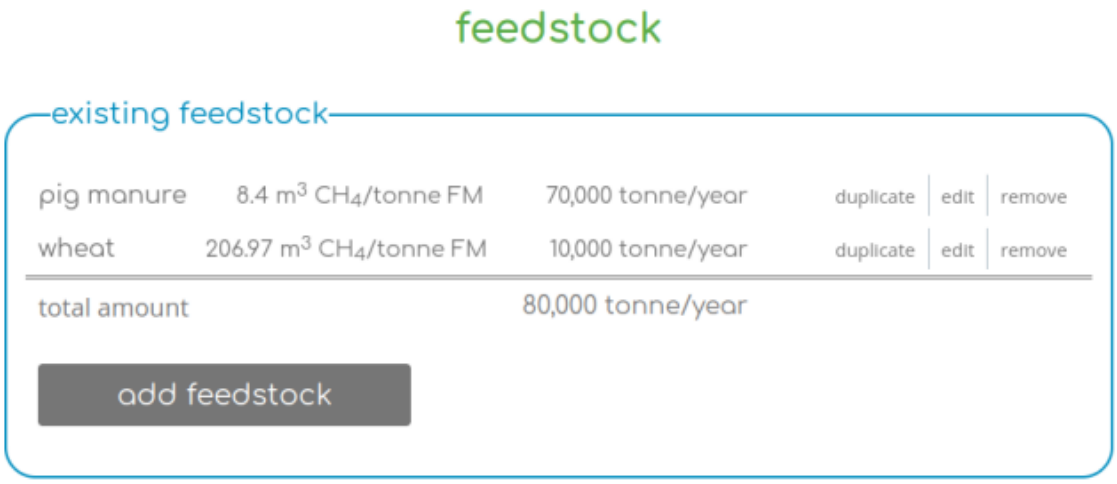


Figure 5.3: FeedStock Set Up

5.1.2 Technical Results

1. *Operational Parameters*

   When the digester temperature is enabled within the AD•A platform and a value for digester temperature is entered by the user, the biogas factor is computed and applied to the bio-methane potential. The values are applied irrespective of the type of the biogas yield estimation configured on the feedstock of the biogas plant. In the case of the yield type being a bio-methane potential curve, the biogas factor is applied to every value of the curve. Biogas extraction efficiency is a direct measure of the impact of the digester temperature AI model. The value of the biogas extraction efficiency reduces with a decrease in temperature. The suitable condition for the operation of any biogas plant is 37°C and any value lesser than this temperature would slow down the bacteria thereby bringing down lower predicted biogas extraction efficiency. Thus, the biogas extraction efficiency greatly reduces with decreasing the biogas factor value. The comparison between a plant configured with the AI model and the same plant that does not have the AI model configured is shown in Figure 5.4. Since the same plant is used for comparison, the plant configuration and the parameters are unaltered. The ratio of the extraction efficiency from the two configurations gives the biogas factor value at the set temperature.

2. *Input Flows*

   Minor impact is seen on the "digester input flows" as shown in Figure 5.5. Mass flow of the whole digestate is inversely dependent on the mass flow of the biogas and the recycled digestate is directly dependent on the mass flow of the whole digestate. Thus, when the digester temperature is enabled and is set to a value lesser than the ideal condition (37°C), the theoretical and the actual biogas production are different since actual value is predicted based on the factor from the AI model. Actual value is reduced by the application of the

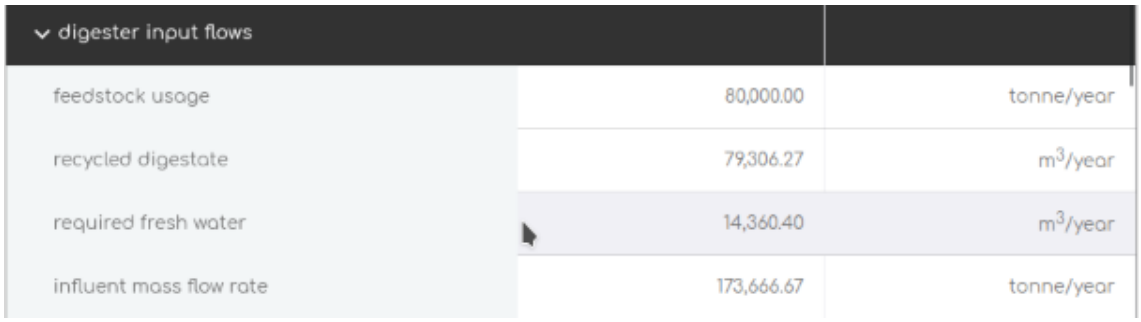
	value	unit
operational and performance parameter		
HRT (hydraulic retention time)	28.00	days
OLR (organic loading rate)	1.59	kg VS/m^3/day
digester working volume	13,322.37	m^3
digester total volume	14,023.55	m^3
biogas extraction efficiency	93.33	%
amount of methane flared	0.00	Nm^3 CH_4/year
amount of biogas flared	0.00	Nm^3/year

(a) Before AI Model

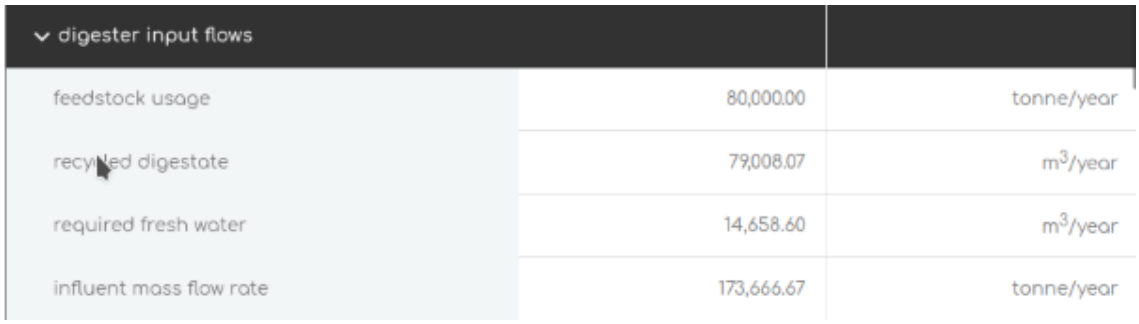
operational and performance parameter		
HRT (hydraulic retention time)	28.00	days
OLR (organic loading rate)	1.59	kg VS/m^3/day
digester working volume	13,322.37	m^3
digester total volume	14,023.55	m^3
biogas extraction efficiency	69.26	%
amount of methane flared	0.00	Nm^3 CH_4/year
amount of biogas flared	0.00	Nm^3/year

(b) After AI Model

Figure 5.4: Comparison of Operational Parameters



(a) Before AI Model



(b) After AI Model

Figure 5.5: Comparison of Input Parameters

biogas factor and hence is the reduction in the biogas mass flow. This brings forth an increase in the mass flow of the whole digestate. However, the total solids on the whole digestate increases with an increase in the mass flow. In other words, change in the recycled digestate of the input flow is because of the changes in the digestate of the previous output flow. The difference is thus very minimal on the the overall recycled digestate.

3. *Output Flows*

   Significant impact on the output flow is seen on the biogas production. This is because the predicted value is when the temperature is adjusted to conditions lesser than the optimal working conditions. This brings forth a reduction in the amount of biogas generated. The reduction factor is measured by the amount of decrease in the temperature and hence on the decrease in the biogas factor value. Biogas production is accompanied by production of other products that

digester output flows		
digestate flow rate	170,197.87	m^3/year
biogas production	3,989,116.05	Nm^3/year
methane production (fraction of biogas)	2,480,529.71	Nm^3/year
carbon dioxide production (fraction of biogas)	1,508,586.34	Nm^3/year

(a) Before AI Model

digester output flows		
digestate flow rate	171,092.47	m^3/year
biogas production	2,960,326.56	Nm^3/year
methane production (fraction of biogas)	1,840,803.30	Nm^3/year
carbon dioxide production (fraction of biogas)	1,119,523.26	Nm^3/year

(b) After AI Model

Figure 5.6: Comparison of Output Parameters

forms a portion of the biogas produced such as methane and carbon dioxide. Thus, when there is a change in the temperature, impact upon the above mentioned is directly related to the factor predicted by the AI model. When the digester temperature is enabled, the amount of gas produced is proportional to the reduction in the temperature from the ideal value. The comparison before and after the model was enabled, is shown in Figure 5.6.

4. *Sold Products*

   The products that are related to biogas or are linked to the quantities of various products being produced is expected to have an impact when the AI feature is enabled. This is evident from Figure 5.7 that shows an outlined comparison of the sold Products prior to and after enabling the feature. The "Renewable Natural Gas" is an improvised form of biogas and hence is directly changed by the change in temperature. Thus, the amount of the same produced is reduced

sold products		
renewable natural gas production	2,356,503.22	Nm^3/year
renewable natural gas production (GJ)	88,863.74	GJ/year
renewable natural gas production (GWh)	24.68	GWh/year
renewable natural gas production (kWh)	24,684,473.07	kWh/year
renewable natural gas production (Sm^3)	2,486,110.90	Sm^3/year
thin digestate biofertilizer	79,306.27	m^3/year
solid digestate biofertilizer	11,585.34	tonne/year

(a) Before AI Model

sold products		
renewable natural gas production	1,748,763.13	Nm^3/year
renewable natural gas production (GJ)	65,945.86	GJ/year
renewable natural gas production (GWh)	18.32	GWh/year
renewable natural gas production (kWh)	18,318,369.37	kWh/year
renewable natural gas production (Sm^3)	1,844,945.10	Sm^3/year
thin digestate biofertilizer	79,008.07	m^3/year
solid digestate biofertilizer	13,076.34	tonne/year

(b) After AI Model

Figure 5.7: Comparison of Sold Products

by the factor predicted by the AI model when the digester temperature is set. The impact on the "thin and solid digestate fertilizers" are not as significant as seen on the "RNG" since the biofertilizers are made from residual components and hence is lesser impacted.

5. *Solid and Thin Digestate*

   Total solids play a pivotal role in the amount of biogas produced [31]. Research works have proven that an increased amount of total solids (upto a maximum of 8 percent) in combination with the value of a temperature lesser than 40°

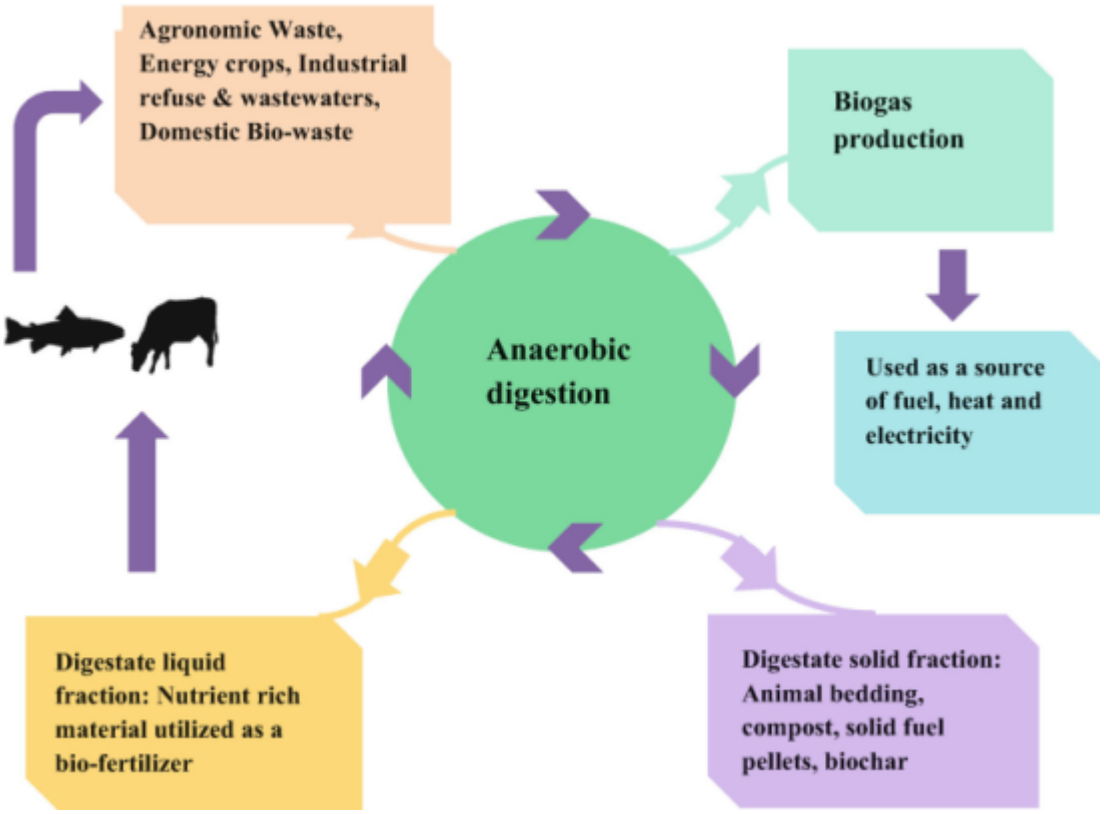


Figure 5.8: Anaerobic Digestion
[15]

Celcius is a great way of enhancing the production of biogas. However, total solids are also impacted by the mass flow of the digestate which in turn depends on the digester temperature. The solid and thin digestate bio-fertilizers are generated from the solid and liquid fractions [15] of the digestate. This depends on the total solids generated by the AD process (the process is shown in Figure 5.8) and hence has a minor change compared to the biogas produced when the temperature is varied. Thus, the predicted values show a minor change as shown in Figure 5.9.

5.1.3 Financial Results

1. *Capex Re-Estimation*

   Expenditures towards maintenance, storage, digester and digester tanks are all

solid digestate biofertilizer		
mass flow rate	11,585.34	tonne/year
total solid	30.00	%
thin digestate biofertilizer		
mass flow rate	79,306.27	tonne/year
total solid	2.19	%

(a) Before AI Model

solid digestate biofertilizer		
mass flow rate	13,076.34	tonne/year
total solid	30.00	%
thin digestate biofertilizer		
mass flow rate	79,008.07	tonne/year
total solid	2.48	%

(b) After AI Model

Figure 5.9: Comparison of Solid and Thin Digestate Parameters

Table 5.1: CAPEX Re-Estimations Comparison

Digester Temperature Value	*Default Lifetime*	*Name of Item*	*Value*
28 Celcius	20 Years	*biogas upgrading*	1140848.25
		digester	1301347.81
		biomass storage and preparation	867565.21
		buildings and logistic infrastructure	1301347.81
		installations	1518239.11
		digestate closed-storage tank	520539.12
		transport means	173513.04
		other	1084456.51
		TOTAL CAPEX	7907856.86
41 Celcius	20 Years	*biogas upgrading*	1298316.26
		digester	1480969.12
		biomass storage and preparation	987312.74
		buildings and logistic infrastructure	1480969.12
		installations	1727797.3
		digestate closed-storage tank	592387.65
		transport means	197462.55
		other	1234140.93
		TOTAL CAPEX	8999355.67
12 Celcius	20 Years	*biogas upgrading*	625707.89
		digester	713735.24
		biomass storage and preparation	475823.49
		buildings and logistic infrastructure	713735.24
		installations	832691.11
		digestate closed-storage tank	285494.1
		transport means	95164.7
		other	594779.37
		TOTAL CAPEX	4337131.14
Set OFF	20 Years	*biogas upgrading*	1312533.19
		digester	1497186.14
		biomass storage and preparation	998124.1
		buildings and logistic infrastructure	1497186.14
		installations	1746717.17
		digestate closed-storage tank	598874.46
		transport means	199624.82
		other	1247655.12
		TOTAL CAPEX	9097901.14

impacted with the change in amount of biogas and other products produced owing to change in the digester temperature. Table 5.1 shows the variations in the capital expenditures when the digester temperature is disabled or when the digester temperature is enabled and is increased from 12° Celcius to 41° Celcius. The predicted expediture values are seen to be increasing with an increase in the digester temperature owing to an increase in the amount of biogas produced and thus increased storage capacity required and infrastructure to support the process. For instance, the "digester and biogas expense" is minimal when the temperature is 12° Celcius and maximum at 41° Celcius.

2. *Opex Re-Estimation*

Table 5.2 shows the operational expenditure comparisons. The predicted operational expenditures are based on the digester temperature values and the corresponding capital expenditures. For instance, an increase in the temperature is predicted to have an increased biogas upgrading cost owing to the increased production and hence increased labor and upgrading unit costs. Thus, the prediction is made based on all linked costs and the comparison reveal that with an increase in temperature, the overall CAPEX increases and so does OPEX. However, this is smaller when compared to the cost when the digester temperature is disabled.

3. *Economic Metrics*

   Net present value and rate of return are altered when there is a change in amount of biogas produced and so does the profitability index. The biogas factor predicted by the model is applied to the BMP. BMP is decisive in determining the impact of temperature on the financial results. Figure 5.10 shows the economic metrics comparison prior to and after the digester temperature configuration is appended to the plant configuration.

4. *Other Finances*

   Digester temperature is disabled by the user when the plant operates outside of the mesophilic range (15° Celcius - 45° Celcius). The prediction is to determine the impact non-ideal temperatures would have on the biogas production. The ideal temperature is considered to be 37° Celcius. However, this varies greatly with the lab temperature of the plant. Hence, when temperatures are set to values lesser than this, biogas production is predicted to lessen and hence associated cost, investment, return on equity and the net income is reduced. This is shown in Figure 5.11.

Table 5.2: OPEX Re-Estimations Comparison

Digester Temperature Value	Name of Item	Value
	feedstock expenses	300000
	digestate expenses	0
	consumed fuel/utilities expenses	0
	Labor	41525.72
	Upgrading Unit	41525.72
12 Celcius	*Services*	12919.12
	Insurance	12919.12
	Taxes	10150.73
	pH Control	1845.59
	Other	9227.94
	Total	430113.94
	feedstock expenses	300000
	digestate expenses	0
	consumed fuel/utilities expenses	0
	Labor	86164.04
	Upgrading Unit	86164.04
41 Celcius	*Services*	26806.59
	Insurance	26806.59
	Taxes	21062.32
	pH Control	3829.52
	Other	19147.57
	Total	569980.67
	feedstock expenses	300000
	digestate expenses	0
	consumed fuel/utilities expenses	0
	Labor	75713.52
	Upgrading Unit	75713.52
28 Celcius	*Services*	23555.32
	Insurance	23555.32
	Taxes	18507.75
	pH Control	3365.05
	Other	16825.23
	Total	537235.69
	feedstock expenses	300000
	digestate expenses	0
	consumed fuel/utilities expenses	0
	Labor	87107.56
	Upgrading Unit	87107.56
SET OFF	*Services*	27100.13
	Insurance	27100.13
	Taxes	21292.96
	pH Control	3871.45
	Other	19357.24
	Total	572937.04

economic metrics		
NPV (net present value)	28,157,235.43	EUR
levered IRR (internal rate of return)	13.82	%
unlevered IRR (internal rate of return)	14.50	%
simple payback period	8.28	years
discounted payback period	8.28	years
profitability index	4.09	-

(a) Before AI Model

economic metrics		
NPV (net present value)	17,460,349.31	EUR
levered IRR (internal rate of return)	10.75	%
unlevered IRR (internal rate of return)	11.34	%
simple payback period	9.98	years
discounted payback period	9.98	years
profitability index	3.21	-

(b) After AI Model

Figure 5.10: Comparison of Economic Metrics

partner: initial owner		
investment	9,097,901.14	EUR
average net income	1,960,796.66	EUR/Year
individual ROE	21.55	%

(a) Before AI Model

partner: initial owner		
investment	7,907,856.86	EUR
average net income	1,335,168.75	EUR/Year
individual ROE	16.88	%

(b) After AI Model

Figure 5.11: Comparison of Finances

5.1.4 Overall Analysis of Results: Digester Temperature

A summary of the technical results comparison is provided in Table 5.3 and a summary of the financial results is provided in Table 5.4. In summary, prediction of the impact based on the digester temperature is on par with the findings of various research works [27]. The feature had an impact both of the technical and financial parameters of the plant and each of these parameters used to analyse the results outlined in Table 5.3 and Table 5.4. The predominant impact of prediction was seen to be on the amount of biogas, carbon dioxide and methane production and the conclusion from the prediction based model is that the increase in temperature brings forth an increase in the amount of biogas produced (when the digester temperature prediction is enabled and increased from lower to higher temperatures). The maximum value of the biogas factor is lesser than one. This is because the maximum temperature is the same as the ideal operating temperature for the plant. The operating temperature of

the plant is derived from the lab and is hence different for various varieties of plants. The prediction results were consistent in all such plant varieties. The method of biogas yield estimation, at anessa, is based on the type of biogas yield of the feedstock. The types are specified either as a measure of methane produced or the amount of biogas produced per volatile solid. For instance, the same prediction was used to determine the impact when the type of biogas yield varied from bio-methane potential to bio-methane potential curve. The prediction was not influenced by the type of biogas yield. The increase in expenditures, from the financial perspective, when the temperature was increased from the lowest value, signified that the higher the temperature, the more biogas produced and the more expected storage size of the plant. This was pivotal in determining the size of the plant and hence was crucial to understand the increased costs linked to the increased production of biogas and other products.

5.2 Catalog Results

Several prior research works have specified various algorithms for collection of data [40] [49] [29]. However, the collection mechanisms were either for structured data or from a specific source. Catalog is a software used to collect as much data, irrespective of data origin or the data being noisy or a replicate of already existing data. This is to assist in building a more generic AI model for prediction. The data collection happens as a result of the trigger of alerts on the AD•M. Another important evaluation criteria of the software is the configured alert to the user so that the values are changed to avert any damage to the working conditions of the plant. The process of data collection for the Catalog has been analyzed from two perspectives.

Table 5.3: Technical Results Comparison

The Digester Temperature being 28 and the unit is Celcius				
Parameters operational and performance parameter	**Unit of Measurement**	**Overall Observation**	**Without Digester Temperature**	**After Digester Temperature**
HRT (hydraulic retention time)	days	No change	28	28
OLR (organic loading rate)	kg VS/m^3/day	No change	1.59	1.59
digester working volume	m^3	No change	13322.37	13322.37
digester total volume	m^3	No change	14023.55	14023.55
biogas extraction efficiency	%	x AI Predicted Biogas Factor	93.33	69.26
digester input flows				
feedstock usage	tonne/year	No change	80000	80000
recycled digestate	m^3/year	very little	79306.27	79008.87
required fresh water	m3/year	very little	14360.4	14658.6
influent mass flow rate	tonne/year	No change	173666.67	173666.67
digester output flows				
digestate flow rate	m^3/year	very little	170197.87	171092.47
biogas production	Nm^3/year	x AI Predicted Biogas Factor	3989116.05	2960326.56
methane production (fraction of biogas)	Nm^3/year	x AI Predicted Biogas Factor	2480529.71	1840803.3
Carbon Di Oxide production (fraction of biogas)	Nm^3/year	x AI Predicted Biogas Factor	1508586.34	1119523.26
sold products				
renewable natural gas production	Nm^3/year	x AI Predicted Biogas Factor	**2356503.22**	**1748763.13**
thin digestate biofertilizer	m^3/year	very little	79306.27	79008.07
solid digestate biofertilizer	tonne/year	very little	11585.34	13076.34
solid digestate biofertilizer				
mass flow rate	tonne/year	very little	11585.34	13036.34
total solid	%		30	30
thin digestate biofertilizer				
mass flow rate	tonne/year	very little	79306.27	79008.07
total solid	%	very little	2.19	2.48
Gross Products				
thin digestate biofertilizer	m3/year	very little	79306.27	79008.07
solid digestate biofertilizer	tonne/year	very little	11585.34	13076.34
Whole Digestate biofertilizer				
mass flow rate	tonne/year	very little	170197.87	171092.47
total solid	%	very little	4.08	4.59

Table 5.4: Financial Results Comparison

The Digester Temperature being 28 and the unit is Celcius					
Parameters		Unit of Measurement	Overall Observation	Without Digester Temperature	After Digester Temperature
Economic Metrics					
NPV (net present value)	28	EUR	Moderate Change	28157235.43	17460349.31
levered IRR (internal rate of return)	0.1539	%	very little	13.82	10.75
unlevered IRR (internal rate of return)	86,438.67	%	very little	14.5	11.34
simple payback period	96,042.97	Years	very little	8.28	9.98
discounted payback period	93.3333	Years	very little	8.28	9.98
profitability index		None	very little	4.09	3.21
return ratios					
ROE (return on equity)	25,481.76	%	very little	21.55	16.88
ROIC (return on invested capital)	300,627.54	%	very little	22.63	17.73
	9,803.61				
margin ratios					
EBITDA margin	1,109,189.65	%	very little	72.44	65.1
operating profit margin	20,240,249.67	%	very little	72.44	65.1
net profit margin	11,788,357.79	%	very little	60.85	54.68
partner: initial owner					
investment	9,242,072.50	EUR	Moderate Change	9097901.14	7907856.86
average net income	662,417.23	EUR/year	Moderate Change	1960796.66	1335168.75
individual ROE	2,264.35	%	very little	21.55	16.88

- *Performance*
- *Variety of Data*

5.2.1 Catalog Performance

Performance is the baseline for analysing how efficient is the data collection mechanism especially when the data to be analyzed is quite huge. Performance is classified further based on the use case.

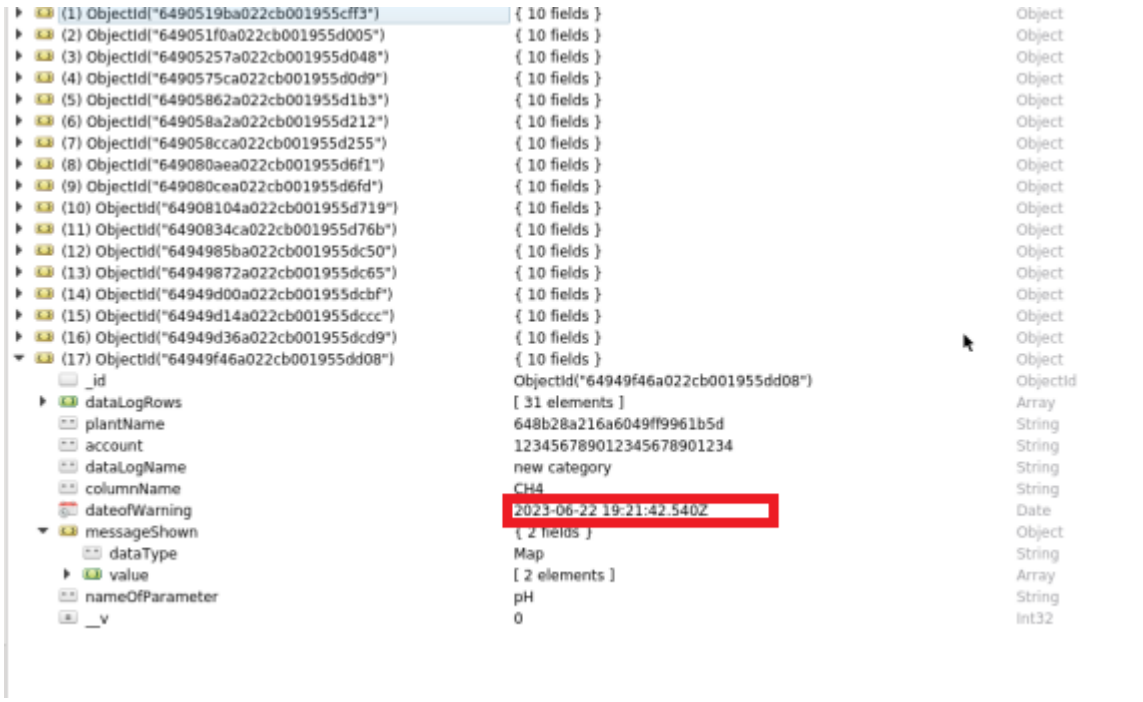
(a) *The Pace of Data Collection*

The collection of data is evaluated with respect to the speed with which data is stored into the database. It is also evaluated with the frequency of the data being stored. In the future, the sources of data for the data log would include the data from the sensors, the data from the mobile application. The current source of data is the data from the lab configured plants. The amount of data flowing would be huge and hence it is important that the computations happens at a rapid pace. Figure 5.12 shows the time taken to store the data per column of the data log. The data collection happens in less than a second for any number of rows having values that are not optimal. This is for a specific column. When multiple columns are configured with Catalog, the data collection happens at the same pace and the amount of time required to collect the data is a fraction of a second.

(b) *The Pace with which the Users are Alerted*

The alert to the user of the AD•M is dependent on the configurations made on DB Admin. As soon as the configurations are uploaded to the DB Admin, evaluation of the formula happens on click of "save" on the "anessa Catalog" on a specific column. It is hence the time used by the

(a) System Time when the alert was generated in PDT/PST



(b) Stored Time in ADT/AST

Figure 5.12: Pace of Storing the Data

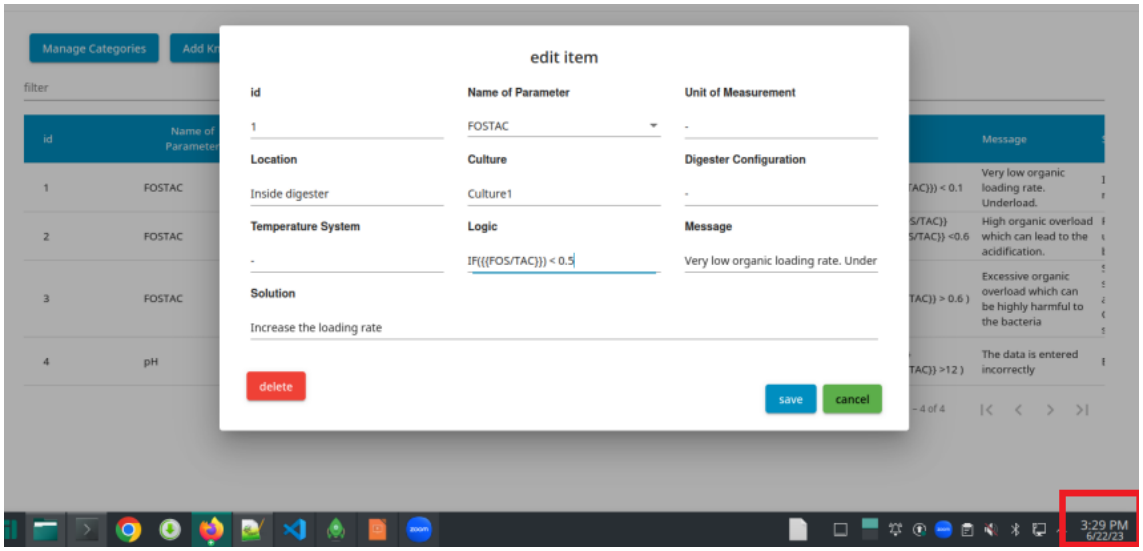
user to configure the column with the catalog. After the configuration is successful, the alert messages are shown at the same instant as the save button is clicked. Hence, time required for formula computations is as short as the time required to click a button. Figure 5.13 shows the system time when the alert was configured and the system time when the alert was displayed on screen.

(c) *Storage optimizations*

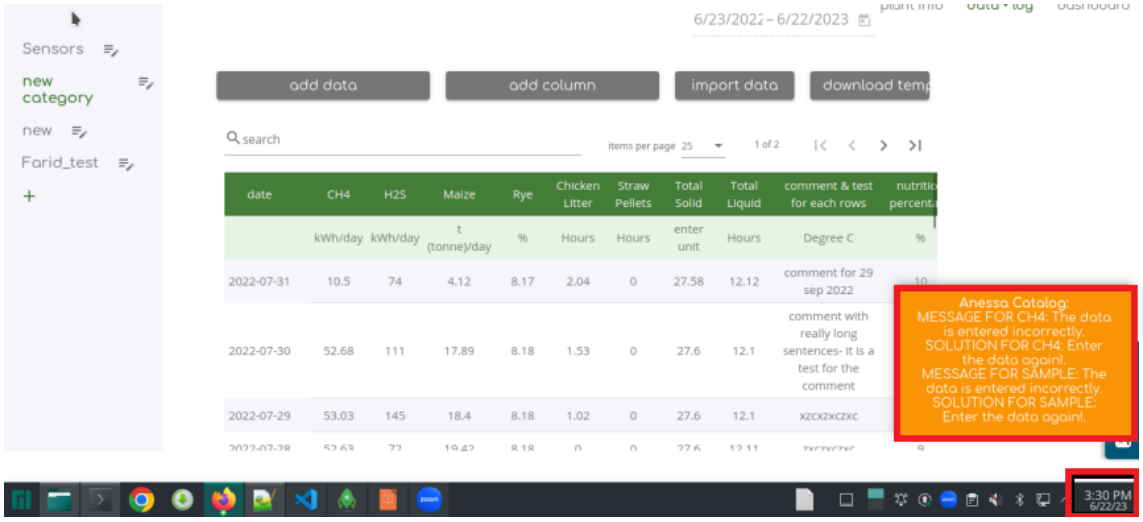
Storage optimizations are an indicator of the efficiency of the Catalog persistence mechanism since this is critical in determining how well data would be handled when the inflow of the data increases rapidly. Catalog uses a mechanism to group data and store only the values that do not meet the optimal required value for a specific parameter and by the time of warning. All the values pertaining to the same time of warning, to the same parameter or to the same column are stored as a single entry to have efficient storage for easy retrieval. Hence, when the data flow would increase in the future, the storage pace is unaltered by the increase in the number of rows since only the problematic rows are stored ignoring the rest of the data not required for building an AI model. This is also filtering out irrelevant data during the persistence step instead of reworking on the collected data.

5.2.2 Variety of Data

Data that is being persisted with respect to Catalog is not structured or uniform in nature. A column could be of any type upon which Catalog could be configured. Hence, it is a requirement that Catalog persistence is not impacted by the type of data stored although ensuring a uniform storage mechanism is crucial for any kind of data. Thus, the Catalog storage is dynamic. A sample



(a) DB Admin Configured System Time in AST



(b) System Time when the alert was generated in AST

Figure 5.13: Pace of Alerting the User

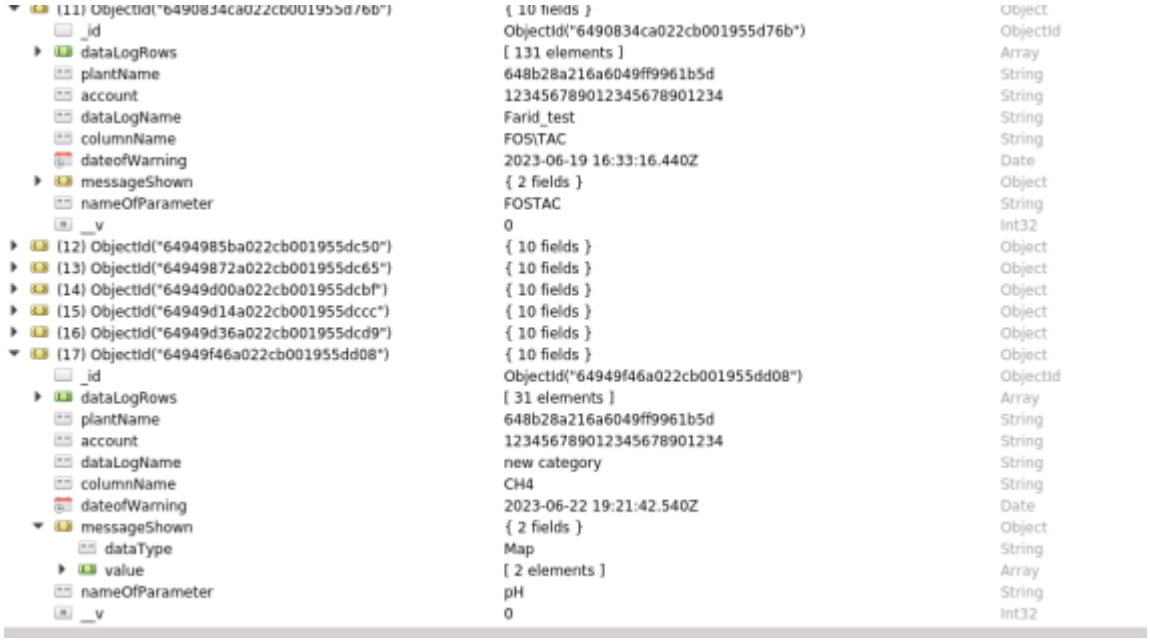


Figure 5.14: Variety of Data

of multi-column storage is as shown in Figure 5.14. Upon integration with real-time data such as data from sensors, mobile app and lab plants, collected data would have a variety of types required for building a model more reliable and consistent with different kinds of data sources and plants.

5.2.3 Overall Analysis of Results: Catalog

Catalog data collection is rapid and is a compilation of diverse data. The data collection is independent of source of data and does not require a structured platform to be stored. The collection of data is reliable and efficient and the data stored is permanent until it is intentionally erased. This cached data is used after the column has been configured with the Catalog unless the configuration on DB Admin has been changed and the catalog configurations on AD•M are saved again. The database used to store the data is Mongo. The data flow is orchestrated through Angular and persisted into Mongo. Flow of data is shown in Appendix A. Sources of data for the datalog are multitudinous.

Data management and security would be a focus in future developments.

5.3 Summary

Overall, the digester temperature-based prediction is accurate. In the mesophilic range, when the predicted temperature increases from the lowest value to the maximum value, the predicted biogas production increases and so does the extraction efficiency of the biogas. These results are also seen to impact the predicted technical and financial computations such as the CAPEX and the OPEX. Catalog software development has been collecting data from live plants to which the data is currently uploaded manually. The increase in the data from the sensors and the mobile application would soon result in data surge. Catalog, however, is efficient and is proven to be fast paced while collecting data (owing to minimal absolute time taken to collect data once the warning is shown to the user).

Chapter 6

Conclusion

The artificial intelligence-based software development for the anessa platform has proven to be a great start towards transforming the platform of simulation and optimisation to a platform coupled with the ability to predict and prevent loss owing to undesirable working conditions, damages to the plant or infrastructure and micro-organisms. The digester temperature-based prediction is already deployed live and is used by clients of anessa. The feature has been effective at predicting the plant conditions, as well as the financial and technical impact when the plant would operate on non-optimal range. This is crucial since the production of biogas, carbon dioxide and methane are all directly dependent on the digester temperature and is hence significant in determining the plant conditions when the same is varied. Our analysis has shown that when the prediction feature is disabled, the plant is anticipated to operate at optimal temperatures and is hence at a lab configured temperature that changes widely with different plants. When the prediction is enabled and is increased from lower to higher temperatures, the amount of biogas produced increases with increased cost expenditures since more storage capacity is required and hence associated labor and maintenance cost increases. Data collection via

catalog has been efficient in collecting data, frequency and optimal working conditions of different plants and is hence instrumental towards building an AI model that would predict in the future the non-ideal conditions for a biogas plant to operate. The data collection has been fast paced with adequate optimizations adhered to in order to facilitate efficient data storage.

6.1 Limitations

Limitations or potential challenges towards getting the analysis done are categorised according to dimensions such as persistence and UI readability.

- *Unavailability of Wide Data Sources*

  Data pertaining to biogas plants are confidential in most cases and are hence considered restricted for public use. This potentially had put forth limitations on the quantity of available data for building a generic AI model especially in the case of a digester temperature AI model construction. Literature data and lab data sets that are available for the public are much limited compared to the data required for research.

- *Trial-and-Error Based AI Model*

  The anessa team had built the digester temperature model using neural networks feed forward algorithm with 4 layers and no hidden layers. They had arrived at the dimension of the layers, the weights and the biases when the optimal R^2 value was reached. However, this was done by trial and error.

- *Data Security and Reliability*

  Current development pertaining to data collection has not been bundled with any security solutions for the data stored.

- *Catalog Alert Toaster is Larger with More Columns*

  The Catalog alert message shown as a toaster message to the user currently is a single toaster for all the columns configured with Catalog. This gets longer and difficult to read when the message and the solution for a specific column gets longer or when more columns are configured with Catalog.

6.2 Future Work

Multiple improvements are planned as part of continued research and for future explorations. They are focused on, but not limited to, enhancing the user experience of using the feature and storing the data with added security and more efficiently. These are outlined below.

- *More Customised Formula Computations*

  The current logic for computations are configured on the DB Admin web page and are specific to the parameter chosen by the user. These parameters are configured with a single formula that works taking in as input a single column. More work is underway to improve the ability to compute based on multiple columns and using complex formula logic that would be a replacement for multiple single line configurations on the DB Admin.

- *Genetic Algorithms under Research*

  As described above, the current algorithm to determine the biogas factor has been employed by the anessa team based on a trial and error approach to obtain the weights and biases that produces the maximum R^2 value. However, this approach may not be as effective with growing dimensions and scale of the data. Thus, the team is currently focusing on a research to replace the trial and error approach by genetic algorithms [17].

- *More Useful Alert Mechanisms under Development*

  Current methodology to display alerts to the user is using a toaster message to warn the users in the Catalog when the value from the sensor or any other source is undesirable for optimal plant operation. However, toasters stay on the screen for a very short time and disappear shortly after they are displayed. This may hence be missed by the user and the intent of warning the user might be lost. Hence a more useful mechanism of warning the user is under construction and this includes email notification of the alert message and displaying the notifications separately using a separate icon that stays until corrective measures are adapted.

- *Integration with Multiple Sources of Data*

  Current testing has been done on plants configured by the users that have lab measurements. The anessa platform would soon start receiving data from sensors automatically which would be displayed on the AD•M platform [3] [16]. The integration with the mobile application is also a plan for the future to be able to diversify the sources of data and build a more robust dataset that the biogas industry is currently devoid of.

- *Adding Layers of Security and Reliable Storage Solutions*

  The data collection mechanism currently has not employed any specific security solution although the data collected does not contain any sensitive data. Future focus and research is also intended at exploring more possible options for storing the catalog data with strong security so that the data is not compromised or lost.

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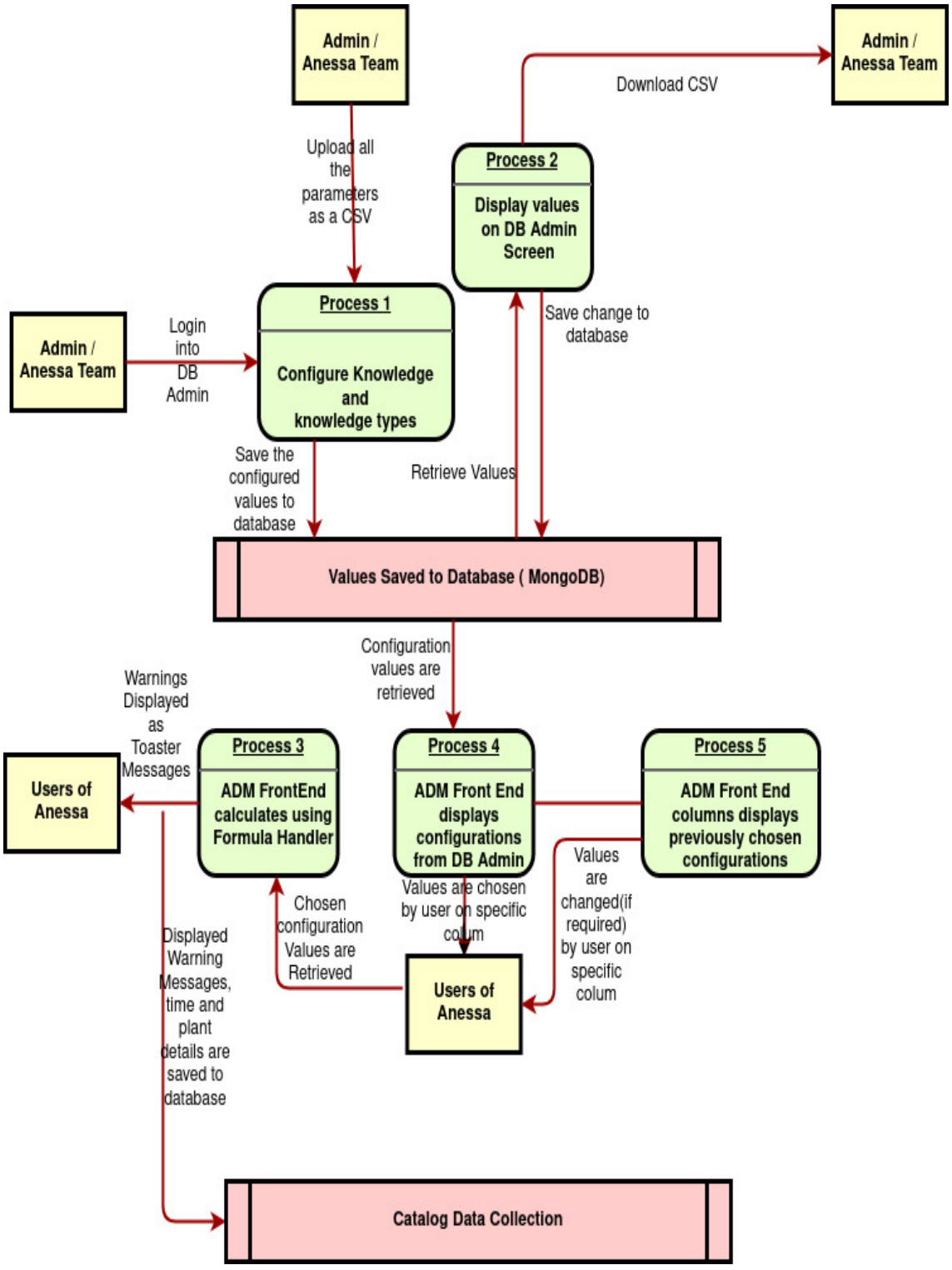
Appendices

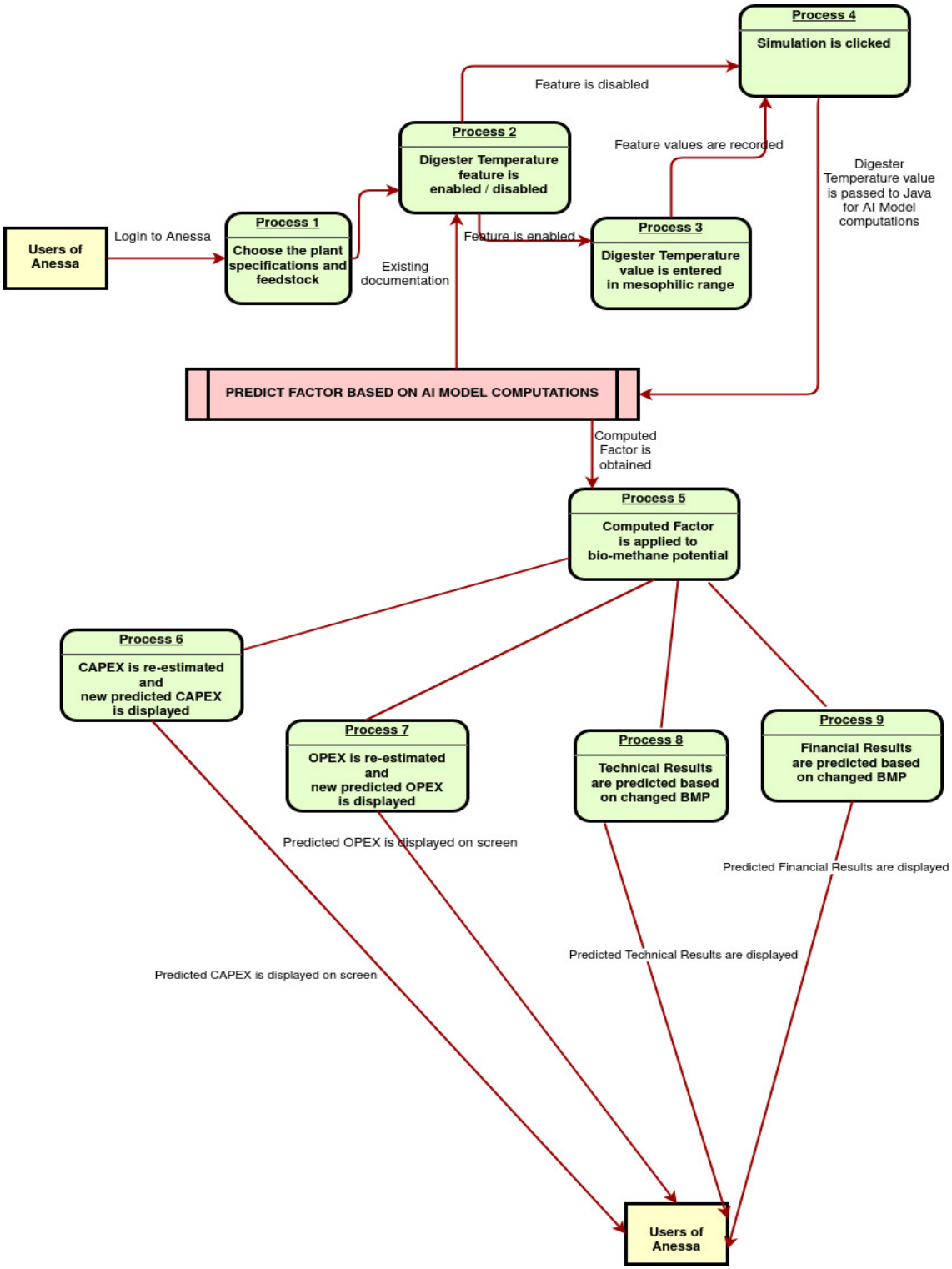
A. Catalog Flow Diagram

B. Digester Temperature Flow Diagram

Appendix A: Catalog Flow Diagram



Appendix B: Digester Temperature Flow Diagram



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