

PROFESSIONAL TRAINING REPORT

AT

Sathyabama Institute of Science and Technology

(Deemed to be University)

Submitted in partial fulfillment of the requirements for the award
Of Bachelor of Technology Degree in Information Technology

By

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**DEPARTMENT OF INFORMATION TECHNOLOGY
SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC

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APRIL-2023



SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **VELAN S ,40120103** who carried out the project entitled "**NSIC COURSE "MILK TEMPERATURE ANALYSIS"**" under my supervision from January 2023 to April 2023.

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Submitted for Viva voce Examination held on 29.04.2023

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DECLARATION

I velan s hereby declare that the Project Report entitled “**MILK TEMPERATURE ANALYSIS**” in **power bi** done by me under the guidance of **DR.P.AJITHA** At Sathyabama Institute of Science and Technology (Deemed to be University),Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600119 is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Information Technology

DATE: 29.04.2023



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I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

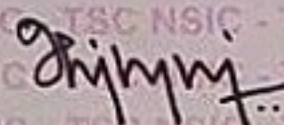
I convey my thanks to **Dr.T.SASIKALA M.E.,Ph.D, Dean**, School of Computing **Dr.R.Subhashini** Head of the Department of Information Technology for providing me necessary support and details at the right time during the progressive reviews.

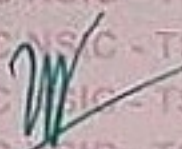
I would like to express my sincere and deep sense of gratitude to my Project Guide **DR.P.AJITHA** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Information Technology** who were helpful in many ways for the completion of the project

This is to certify that Mr. **VELAN S.** S/o. Shri. **SENTHIL KUMAR P. N.** student of III year B.Tech. (IT), Sathyabama Institute of Science and Technology has undergone "**SKILL DEVELOPMENT PROGRAM ON DATA ANALYTICS**" conducted by us for a period of one week (30 Hours) from 09.03.2023 to 14.03.2023.




HEAD OF TRAINING


HEAD OF CENTRE

ABSTRACT

Ensuring stringent temperature control parameters and efficient cooling mechanisms are maintained at a dairy plant are critical to downstream processing capabilities and product quality. This study examined the temperature of incoming raw milk across three production months (June, July, August 2018), to capture peak season processing at one dairy manufacturing plant. A total of $n=4,236$ data points across three milk intake bays were analysed. Across the study area, the average temperature of incoming milk was 6.18°C (1.54 Standard Deviation (SD)). After the initial cooling step in the dairy facility, the average temperature of stored raw milk was 4.74°C (0.77 SD), with an average cooling performance of -1.44°C (SD 1.34). This research highlights for the first time, the analysis of a narrow but important quality step in a milk processing plant, namely the critical criteria of temperature monitoring and flow rate management at a dairy processing facility.

Keywords: *Cold-chain; Dairy; Quality; Processing; Temperature*

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1.INTRODUCTION

Temperature management of the raw milk supply chain is a key performance indicator at dairy processing plants. European Union legislation [1], allows a milk processing plant to collect milk on farm up to 10°C and it requires milk to be cooled and stored to a temperature of no more than 6°C until further processing. Milk is virtually sterile once synthesised in the mammary gland of a healthy cow and sterility is diminished once the animal has been milked. Daily milk collection is not sustainable for large dairy plants and as the temperature of milk leaving the udder at 35°C is highly favourable for bacterial growth [2], cooling and maintaining the temperature of raw milk thereafter is essential in avoiding an increase in microbial load.

After raw bulk milk arrives at a manufacturing plant it must undergo a suite of legislative and quality tests [3] before it is pumped through Plate Heat Exchange (PHE) units and stored in silos until further processing. A composite sample from each lorry compartment is tested for Somatic Cell Counts (SCC), Total Bacterial Counts (TBC), acidity and antibiotics [4]. SCC levels in milk are correlated with herd health and can rise with temperature increases. Uncontrolled SCC levels in milk can considerably reduce protein and fat recovery and ultimately reduce yields, particularly in cheese production [5]. It is estimated that Gram-negative microflora accounts for more than 90% of the total psychrotrophic raw milk microflora [6]. Thermophilic bacteria can also be detrimental to the production of dairy products [7,8] claimed temperature plays an important role in the formation of biofilm, a microbial population that adheres to a solid surface. Biofilm build up can be difficult to eliminate even with stringent cleaning in place programs [9]. If bacterial growth is not arrested early on in the production chain, it may result in special-cause variation in a manufacturing process and final product quality will be compromised.

Time/temperature storage parameters for intake silos have significant importance on the raw milk cold supply chain. A review of the literature demonstrated that the optimum temperature of stored raw milk is 4°C [10-12]. A higher temperature of the incoming raw milk supply greatly reduces storage time of the product.

AIM AND SCOPE

1.1 AIM

Milk protein content is an important component of milk, especially from a nutritional point of view and also for payment purposes. The aim of work was to draw up an overview on reference and routine methods for protein determination. Reference methods perform accurate analyses comply according to the International Standard ISO whereas routine methods perform analyses using routine instrumental techniques for faster and cheaper results with acceptable accuracy and a large number of processed samples. In most of cases, using of routine indirect methods for milk protein analysis requires their specific calibrations according to biological kind of measured milk (cow's, goat's or sheep's milk) or specific conditions of milk technology treatment. Also, the quality control measures have a significant role for result determination reliability.

Physical properties are measures of the bulk behavior of milk and of how milk interacts with energy, while physico-chemical properties are measures of how the bulk behavior and energy interactions depend on milk's constituent colloidal particles, molecules, atoms, and ions.

In this article the more important physical and physico-chemical properties are quantitatively defined, and their significance with respect to milk analysis, and to the design and control of milk processes, is described. Recognizably physical properties – rheological properties, density, and thermal properties – are discussed first. Then, properties that fall within the realms of both physics and physical chemistry are discussed: surface tension, acoustic properties, electrical and dielectric properties, and optical properties. Finally, recognizably physico-chemical properties – the colligative properties, and acid–base and oxidation–reduction equilibria – are discussed.

Representative numerical values of properties are given for whole milk and, in some cases, also for skim milk and cream. The dependence of properties on such factors as temperature, product composition, and product treatment is also described.

1.2 SCOPE

They aim to ensure that the safety and quality of their raw milk will satisfy the highest expectations of the food industry and consumers. On-farm practices should also ensure that milk is produced by healthy animals under acceptable conditions for the animals and in balance with the local environment.

The overarching principles applying to the production, processing and handling of all milk and milk products are:

From raw material production to the point of consumption, all dairy products should be subject to a combination of control measures. Together, these measures (good agricultural practice - GAP and good manufacturing practice - GMP) should meet the appropriate level of public health protection.

Good hygienic practices should be applied throughout the production and processing chain so that milk and milk products are safe and suitable for their intended use.

Wherever appropriate, hygienic practices for milk and milk products should be implemented following the Annex to the Codex Recommended International Code of Practice - General Principles of Food Hygiene.

GAP/GMP together should be effective.

All dairy farmers, suppliers to dairy farmers, milk carriers and hauliers, dairy product and food manufacturers, distributors and retailers should be part of an integrated food safety and quality assurance management system. Good farming practices underpin the marketing of safe, quality-assured milk-based products.

The role of dairy farmers is to ensure that good agricultural, hygienic and animal husbandry practices are employed at the farm level. The focus should be on preventing a problem (including animal diseases) rather than solving it after it has occurred.

Good dairy farming practices should contribute to ensuring milk and milk products are safe and suitable for their intended use.

3.SYSTEM REQUIREMENTS

Windows

- Microsoft® Windows® 7/8/10 64-bit
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum,
- 4 GB Recommended 500 MB for IDE + 1.5 GB for Android SDK and emulator systemimage
- 1280 x 800 minimum screen resolution

Mac

- Mac® OS X® 10.10 Yosemite or higher, up to 10.14 macOS Mojave
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum,
- 4 GB Recommended 500 MB for IDE + 1.5 GB for Android SDK and emulator systemimage
- 1280 x 800 minimum screen resolution

Linux

- GNOME or KDE desktop - Tested on gLinux based on Debian.
- 64-bit distribution capable of running 32-bit applications
- GNU C Library glibc 2.19 or later 17
- 4 GB RAM minimum, 8 GB RAM recommended
- 2 GB of available disk space minimum

4 METHODOLOGY

4.1 SITE STUDY DESCRIPTION

The temperatures of incoming raw bulk milk were analysed across a three-month period (June, July, August 2018) at a large dairy manufacturing plant. The milk reception area consists of three reception bays where 39 milk lorries pump milk to one of two raw milk storage silos. Milk is cooled via Plate Heat Exchangers (PHE) as it is pumped from a lorry to a raw milk-holding silo. Every minute, as pumping takes place, a manufacturing execution system (MES) automatically records the temperature of milk flow with inline sensors located before and after the PHE. The company processes over 300million litres of milk annually in accordance with EU legislation [1] protocols and manufactures a range of food ingredients including fats and powders. Company-identifiable information was removed to preserve confidentiality.

To uphold product quality and optimise processing capabilities, it is imperative that best practice guidelines for temperature management of raw milk at dairy manufacturing plants are followed. To our knowledge, there is minimal research focusing on the management of raw milk at dairy plants. The approach of this study was to evaluate incoming raw milk temperatures and logistical functions at one dairy manufacturing plant across three production months during high season processing times

4.2 PARETO ANALYSIS

The data are presented in Pareto charts, which are widely used in quality control settings to identify critical factors leading to failure or defects in a process [16].

Data were scored in a standard scale and arranged in descending order. The percentage of each item in relationship to the total measurement of all items was calculated. Once it is assured that the combined percentages equal 100%, a bar graph with elements for each individual item was created. Superimposed on this bar graph is a line graph that represents the cumulative percentage. Noting the highest score and working through the items to the 20 per cent point in the line graph, the changes represented in this area of the graph will have the biggest benefit. Conversely, the items with the lowest scores (as we get closer to 100% in the line graph) will have the least amount of benefit [17].

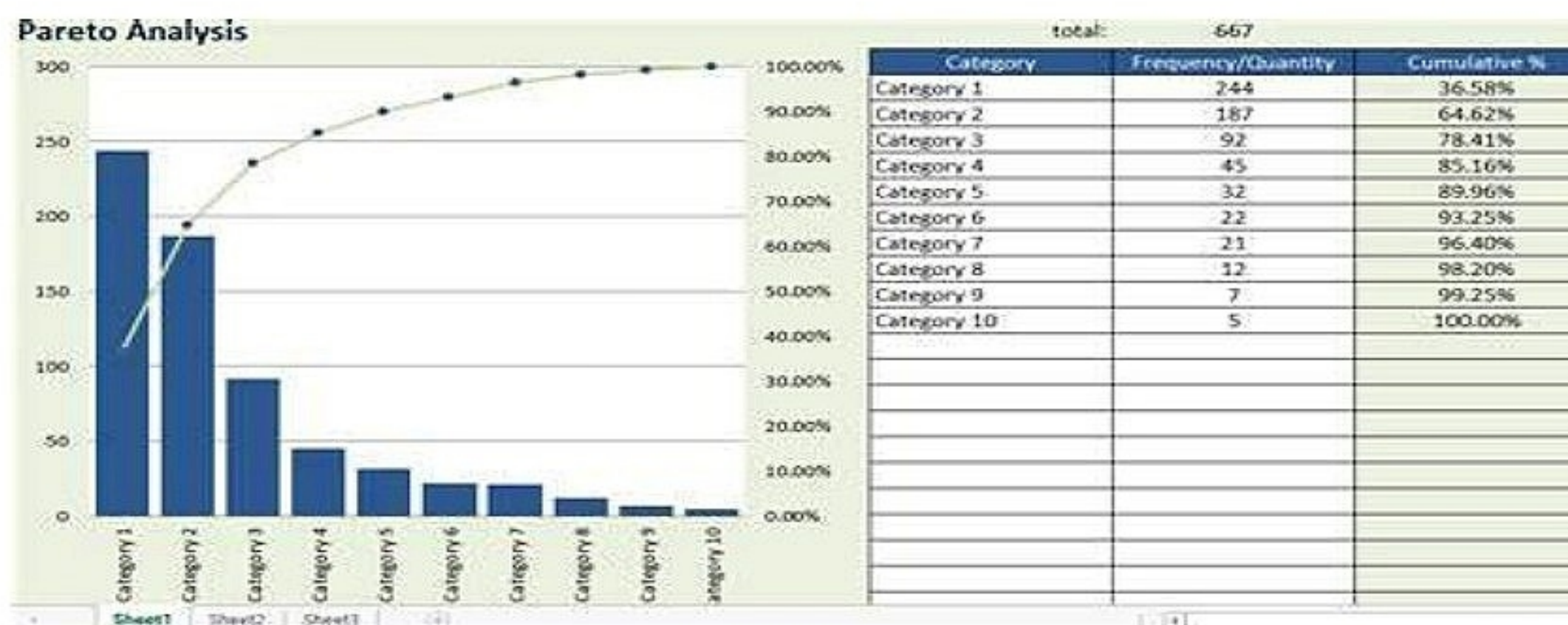


Figure 4.1 PARETO ANALYSIS

4.3 DATA ANALYSIS

The process of data analysis, or alternately, data analysis steps, involves gathering all the information, processing it, exploring the data, and using it to find patterns and other insights. The process of data analysis consists of: Data Requirement Gathering: Ask yourself why you're doing this analysis, what type of data you want to use, and what data you plan to analyze.

Data Collection: Guided by your identified requirements, it's time to collect the data from your sources. Sources include case studies, surveys, interviews, questionnaires, direct observation, and focus groups. Make sure to organize the collected data for analysis. Data Cleaning: Not all the data you collect will be useful, so it's time to clean it up. This process is where you remove white spaces, duplicate records, and basic errors. Data cleaning is mandatory before sending the information on for analysis.

Data Analysis: Here is where you use data analysis software and other tools to help you interpret and understand the data and arrive at conclusions. Data analysis tools include Excel, Python, R, Looker, Rapid Miner, Charito, Meta base, Rehash, and Microsoft Power BI. Data Interpretation: Now that you have your results, you need to interpret them and come up with the best courses of action based on your findings.

Prior to analysis, data cleaning was implemented to detect and correct corrupt records. Of the total data set, 105 outliers and 7 corrupt data points were removed; therefore, 4,236 data points were assessed. Data were extracted from a Laboratory Information Management System (LIMS)

4.4 TYPES OF DATA ANALYSIS

The four types of data analysis are:

- Descriptive Analysis
- Diagnostic Analysis
- Predictive Analysis
- Prescriptive Analysis

4.4.1 DESCRIPTIVE ANALYSIS

Descriptive analytics answer the question, “What happened?”. This type of analytics is by far the most commonly used by customers, providing reporting and analysis centered on past events. It helps companies understand things such as:

- How much did we sell as a company?
- What was our overall productivity?
- How many customers churned in the last quarter?

Descriptive analytics is used to understand the overall performance at an aggregate level and is by far the easiest place for a company to start as data tends to be readily available to build reports and applications. It's extremely important to build core competencies first in descriptive analytics before attempting to advance upward in the data analytics maturity model. Core competencies include things such as data modeling fundamentals, communicating data with right visualization and basic dashboard skills.

All data were analysed using the statistical analysis software package IBM SPSS Statistics 26 and Microsoft Excel 2016®. Statistical significance was set at the 95% confidence level ($p < 0.05$) by convention.

4.4.2DIAGNOSTIC ANALYSIS

Diagnostic analytics, just like descriptive analytics, uses historical data to answer a question. But instead of focusing on “what”, diagnostic analytics addresses the critical question of why an occurrence or anomaly occurred within your data. Diagnostic analytics also happens to be the most overlooked and skipped step within the analytics maturity model. Anecdotally, I see most customers attempting to go from “what happened” to “what will happen” without ever taking the time to address the “why did it happen” step. This type of analytics helps companies answer questions such as:

- Why did our company sales decrease in the previous quarter?
- Why are we seeing an increase in customer churn?
- Why is a specific basket of products vastly outperforming their prior year sales figures?

Diagnostic analytics tends to be more accessible and fit a wider range of use cases than machine learning/predictive analytics. You might even find that it solves some business problems you earmarked for predictive analytics use cases. Being at the diagnostic analytics phase likely means you’ve adopted a modern analytics tool. Most modern analytics tools contain a variety of search-based, or lightweight artificial intelligence capabilities.

These features allow for detailed insights a layer deeper (for example: the Key Drivers visualization in Power BI, or Qlik’s search-based insight functionality). To be clear, these are an effective lightweight means to address diagnostic analytics use cases but are not a means to a full-scale implementation. .

4.4.3 PREDICTIVE ANALYSIS

Predictive analytics is a form of advanced analytics that determines what is likely to happen based on historical data using machine learning. Historical data that comprises the bulk of descriptive and diagnostic analytics is used as the basis of building predictive analytics models. Predictive analytics helps companies address use cases such as:

- Predicting maintenance issues and part breakdown in machines.
- Determining credit risk and identifying potential fraud.
- Predict and avoid customer churn by identifying signs of customer dissatisfaction.

At the outset of any predictive analytics build, three core elements need to be established:

- Identify a problem to solve,
- Define what you want to predict, and
- State what you will achieve by doing so.

To start you should collect existing data, organize data in a useful way to allow for data modeling, cleanse your data and review overall quality, and finally determine your modeling objective.

While modeling takes up the spotlight in predictive analytics, data prep is a crucial step that needs to happen first. This is why organizations with a rock-solid foundation in descriptive and diagnostic analytics are better equipped to handle predictive analytics. Simply put, the time and effort to prep, transform, and ensure data quality for retrospective reporting has already taken place.

4.4.4 PRESCRIPTIVE ANALYSIS

Prescriptive analytics is the fourth and final pillar of modern analytics. Prescriptive analytics pertains to true guided analytics where your analytics is prescribing or guiding you toward a specific action to take. It is effectively the merging of descriptive, diagnostic, and predictive analytics to drive decision making. Existing scenarios or conditions (think your current fleet of freight trains) and the ramifications of a decision or occurrence (parts breakdown on the freight trains) are applied to create a guided decision or action for the user to take (proactively buy more parts for preventative maintenance).

Prescriptive analytics requires strong competencies in descriptive, diagnostic, and predictive analytics which is why it tends to be found in highly specialized industries (oil and gas, clinical healthcare, finance, and insurance to name a few) where use cases are well defined. Prescriptive analytics help to address use cases such as:

- Automatic adjustment of product pricing based on anticipated customer demand and external factors.
- Flagging select employees for additional training based on incident reports in the field.

Prescriptive analytics' primary aim is to take the educated guess or assessment out of data analytics and streamline the decision-making process. Prescriptive analytics is commonly considered the merging of descriptive, diagnostic, and predictive analytics. Getting started isn't so much a step-by-step list but rather the time and effort up front to build your competencies within the analytics maturity curve.

4.5 POWER BI

Microsoft Power BI is a business intelligence (BI) platform that provides nontechnical business users with tools for aggregating, analyzing, visualizing and sharing data. Power BI's user interface is fairly intuitive for users familiar with Excel, and its deep integration with other Microsoft products makes it a versatile self-service tool that requires little upfront training.

Users can download an application for Windows 10, called Power BI Desktop, and native mobile apps for Windows, Android and iOS devices.

5.5.1 USES OF POWER BI

Microsoft Power BI is used to find insights within an organization's data. PowerBI can help connect disparate data sets, transform and clean the data into a data model and create charts or graphs to provide visuals of the data. All of this can be shared with other Power BI users within the organization.

The data models created from Power BI can be used in several ways for organizations, including the following:

- telling stories through charts and data visualizations;
- examining "what if" scenarios within the data; and
- creating reports that can answer questions in real time and help with forecasting to make sure departments meet business metrics

5.5.2 FEATURES OF POWER BI

Microsoft has added a number of data analytics features to Power BI since its inception and continues to do so. Some of the most important features are the following:

Artificial intelligence. Users can access image recognition and text analytics in PowerBI, create machine learning models using automated ML capabilities and integrate with Azure Machine Learning.

Hybrid deployment support. This feature provides built-in connectors that allow PowerBI tools to connect with a number of different data sources from Microsoft, Salesforce and other vendors.

Quick Insights. This feature allows users to create subsets of data and automatically apply analytics to that information.

Common data model support. Power BI's support for the common data model allows the use of a standardized and extensible collection of data schemas (entities, attributes and relationships).

Cortana integration. This feature, which is especially popular on mobile devices, allows users to verbally query data using natural language and access results using Cortana, Microsoft's digital assistant.

Customization. This feature allows developers to change the appearance of default visualization and reporting tools and import new tools into the platform.

APIs for integration. This feature provides developers with sample code and application program interfaces (APIs) for embedding the Power BI dashboard in other software products.



Analysis of milk



4.7 PROJECT IMPLEMENTATION

- In this section, there is an overview of the process of data mining and data modeling, from collecting the data, through the data preparation and finally the data modeling.
 - Data cleaning and formatting can be considered as the most critical part of the whole project according to several data scientists .
 - Once the project undertaking is completely comprehended, our subsequent stage is to gather the information that is required for future model building.
 - The information accumulation was an issue as data was not situated at a single source.
 - The data was kept in unique information design.
 - To achieve the end goal, it requires a clear understanding of the correct location of the data.
-
- Next one is the main objective of the project that is outcome of milk analysis
 - The analysis of milk depends on various factor namely:
 1. Milk analysis processing
 2. Density
 3. Fat content
 4. Acidity
 5. Total dry extract (TDE)
 - Now collect the dataset of these milk analysis
 - Import to the excel sheet.
-
- The project is implemented in Microsoft excel and Microsoft power Bi
 - Power BI is an interactive [data visualization](#) software product developed by [Microsoft](#) with a primary focus on [business intelligence](#). It is part of the [Microsoft Power Platform](#).
 - Power BI is a collection of software services, apps, and connectors that work together to turn unrelated sources of data into coherent, visually immersive, and interactive insights.
 - Data may be input by reading directly from a [database](#), webpage, or structured files such as spreadsheets, [CSV](#), [XML](#), and [JSON](#).

The following diagram shows the datasets taken

DATE	BRAND	QUANTITY	LOCATION	PRICE	TEMPERATURE	PH	CATEGORY WISE SALES(COLOR)	SHIFT	UNSOLD	TYPES OF DELIVERY
01-Jan-22	AAVIN	11	CHENNAI	330	35	5.6	YELLOW	MORNING	1	ONLINE
01-Jan-22	AROKYA	11	CHENNAI	396	36	8.6	BLUE	EVENING	1	OFFLINE
02-Jan-22	AAVIN	12	MADURAI	360	70	7.4	ORANGE	MORNING	2	ONLINE
02-Jan-22	AROKYA	12	MADURAI	432	34	6.8	PINK	EVENING	2	OFFLINE
03-Jan-22	AAVIN	13	TRICHY	390	37	6.5	BROWN	MORNING	3	ONLINE
03-Jan-22	AROKYA	13	TRICHY	468	37	4.7	VIOLET	EVENING	3	OFFLINE
04-Jan-22	AAVIN	14	CHENNAI	420	45	3	YELLOW	MORNING	4	ONLINE
04-Jan-22	AROKYA	14	CHENNAI	504	60	9	BLUE	EVENING	4	OFFLINE
05-Jan-22	AAVIN	15	MADURAI	450	66	6.8	ORANGE	MORNING	5	ONLINE
05-Jan-22	AROKYA	15	MADURAI	540	45	6.6	PINK	EVENING	5	OFFLINE
06-Jan-22	AAVIN	16	TRICHY	480	45	6.5	BROWN	MORNING	6	ONLINE
06-Jan-22	AROKYA	16	TRICHY	576	50	4.5	VIOLET	EVENING	6	OFFLINE
07-Jan-22	AAVIN	17	CHENNAI	510	55	6.6	YELLOW	MORNING	7	ONLINE
07-Jan-22	AROKYA	17	CHENNAI	612	90	6.8	BLUE	EVENING	7	OFFLINE
08-Jan-22	AAVIN	18	MADURAI	540	45	6.5	ORANGE	MORNING	8	ONLINE
08-Jan-22	AROKYA	18	MADURAI	648	38	6.6	PINK	EVENING	8	OFFLINE
09-Jan-22	AAVIN	19	TRICHY	570	38	6.5	BROWN	MORNING	9	ONLINE
09-Jan-22	AROKYA	19	TRICHY	684	40	6.6	VIOLET	EVENING	9	OFFLINE
10-Jan-22	AAVIN	20	CHENNAI	600	43	6.4	YELLOW	MORNING	10	ONLINE
10-Jan-22	AROKYA	20	CHENNAI	720	40	6.5	BLUE	EVENING	10	OFFLINE

FIGURE 4.3 : DATASET 1

Date	Month	Week	Time	Weight	Price/kg	Departure	Type of Food Waste	Reasons of Waste	Cost	Kg CO ₂ emissions
07/02/2018	Feb	6	08:00	50 kg	1.88		Tomato	Quality	£69.00	190
07/02/2018	Feb	6	09:00	28 kg	5.28		Tomato Puree	Quality	£147.84	106.4
07/02/2018	Feb	6	10:00	23 kg	2.71		Chicken	Misorder	£62.33	87.4
07/02/2018	Feb	6	11:00	4 kg	2.39		Single Cream	Misorder	£9.56	15.2
07/02/2018	Feb	6	12:00	8 kg	2		Onion	Trim Waste	£6.00	11.4
07/02/2018	Feb	6	13:00	3 kg	1.09		Yogurt	Trim Waste	£2.73	9.5
07/02/2018	Feb	6	14:00	4 kg	1.38		Tomato	Quality	£5.52	15.2
08/02/2018	Feb	6	07:00	43 kg	5.28		Tomato Puree	Expired	£227.04	163.4
08/02/2018	Feb	6	08:00	51 kg	2.71		Chicken	Misorder	£147.78	199.5
08/02/2018	Feb	6	09:00	54 kg	2.39		Single Cream	Misorder	£129.06	205.2
08/02/2018	Feb	6	10:00	53 kg	2		Onion	Trim Waste	£106.00	201.4
08/02/2018	Feb	6	11:00	8 kg	1.09		Yogurt	Quality	£2.73	9.5
08/02/2018	Feb	6	12:00	3 kg	1.38		Tomato	Trim Waste	£4.14	11.4
08/02/2018	Feb	6	13:00	5 kg	5.28		Tomato Puree	Spoilage	£26.40	19
09/02/2018	Feb	6	07:00	20 kg	2.71		Chicken	Quality	£54.20	76
09/02/2018	Feb	6	08:00	1 kg	2.39		Single Cream	Vendor Trial	£1.79	2.85
09/02/2018	Feb	6	09:00	10 kg	2		Onion	Equipment Failure	£20.00	38
09/02/2018	Feb	6	10:00	50 kg	1.09		Yogurt	Trim Waste	£54.50	190
09/02/2018	Feb	6	11:00	60 kg	1.38		Tomato	Trim Waste	£82.80	228
09/02/2018	Feb	6	12:00	33 kg	5.28		Tomato Puree	Quality	£174.24	125.4
09/02/2018	Feb	6	13:00	13 kg	1.09		Yogurt	Misorder	£14.17	49.4
09/02/2018	Feb	6	14:00	8 kg	1.38		Tomato	Equipment Failure	£11.04	30.4
09/02/2018	Feb	6	15:00	6 kg	5.28		Tomato Puree	Quality	£31.68	22.8
10/02/2018	Feb	6	07:00	78 kg	2.71		Chicken	Quality	£211.38	296.4
10/02/2018	Feb	6	08:00	42 kg	2.39		Single Cream	Misorder	£100.38	159.6
10/02/2018	Feb	6	09:00	10 kg	2		Onion	Trim Waste	£20.00	38
10/02/2018	Feb	6	10:00	33 kg	1.09		Yogurt	Misorder	£35.97	125.4
10/02/2018	Feb	6	11:00	40 kg	1.38		Tomato	Quality	£55.20	152
10/02/2018	Feb	6	12:00	2 kg	5.28		Tomato Puree	Misorder	£10.56	7.6
11/02/2018	Feb	6	07:00	21 kg	2.71		Chicken	Equipment Failure	£56.91	79.8
11/02/2018	Feb	6	08:00	4 kg	2.39		Single Cream	Quality	£9.56	15.2
11/02/2018	Feb	6	09:00	30 kg	2		Onion	Handling	£60.00	114
11/02/2018	Feb	6	10:00	7 kg	1.09		Yogurt	Misorder	£7.63	26.6
11/02/2018	Feb	6	11:00	30 kg	1.38		Tomato	Handling	£41.40	114
11/02/2018	Feb	6	12:00	1 kg	2.71		Chicken	Misorder	£1.90	2.66
11/02/2018	Feb	6	13:00	50 kg	2.39		Single Cream	Misorder	£119.50	190

FIGURE 4.4 : DATASET 2

5 RESULTS AND DISCUSSION

As a first exploratory examination, we consider the watched likelihood of deferral in minutes on the whole dataset. The best path is through a histogram and graphs.

5.1 PREDICTION

Although its primary purpose is data visualization, Power BI contains surprisingly powerful predictive forecasting options, specifically in the area of time series forecasting. Time series forecasting is defined as taking a model that is fit to historical data.

There are many different statistical models and methods that can be applied in this use case, but with Power BI, the end user doesn't have to worry about the behind-the-scenes math going on. Instead, they can use one of Power BI's preexisting visualization tools to quickly build a forecast model and visualize the results.

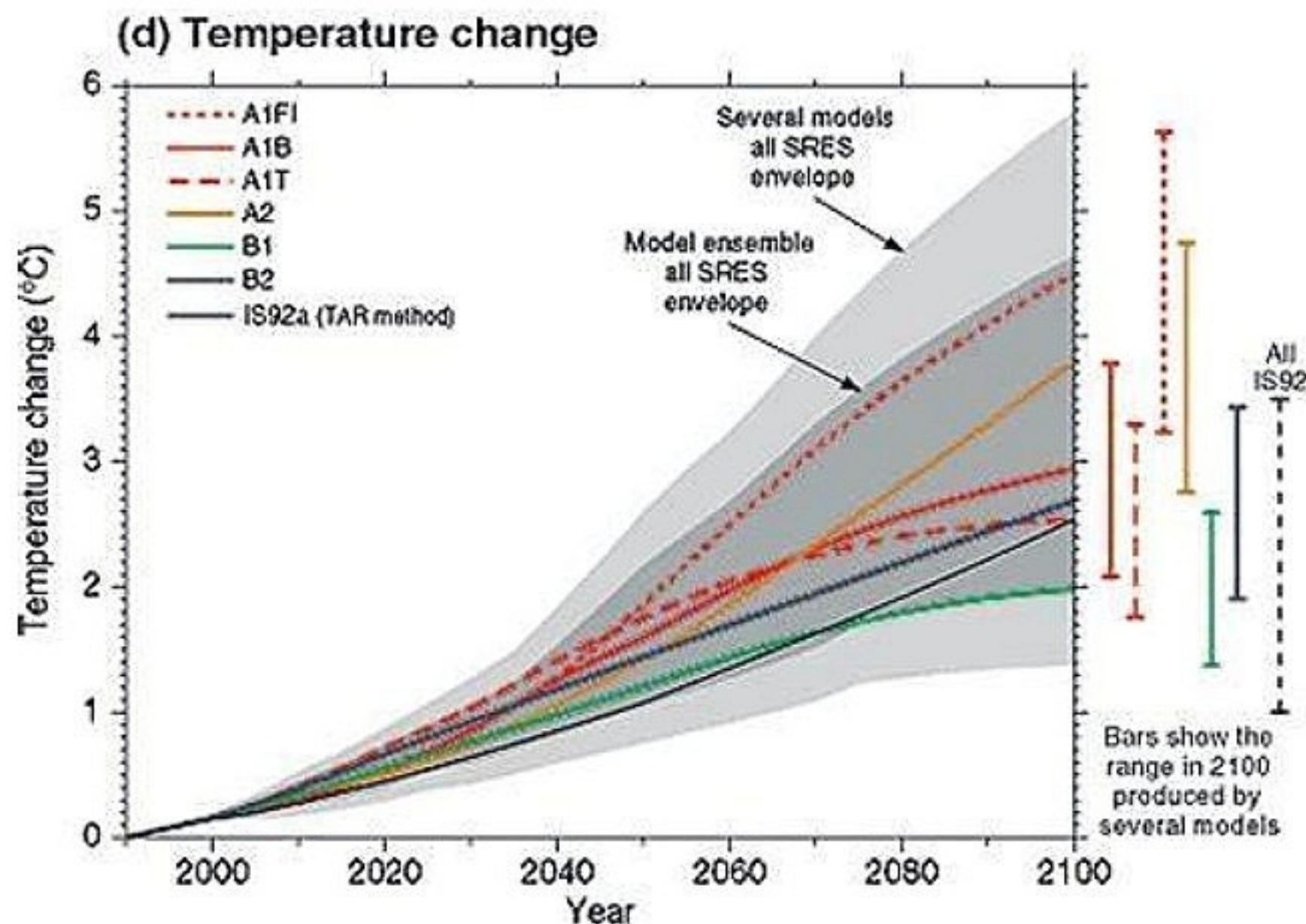


FIGURE 5.1 : PREDICTION TABLE

5.2 Q & A:

A report designer can add a specific type of interactive visual called the Q&A visual. Power BI report end users can ask natural language questions and create a new report visual that represents the answer to the question. The Q&A visual behaves like any other visual in a report. Cross-filter, cross-highlight, bookmarks, and comments are enabled.

Q&A visuals have a question box across the top of the visual. You type your question into the question box and Q&A responds with a visual. The Q&A visual can be used over and over again to ask questions about your data. When you leave the report, the Q&A visual resets to its default.



FIGURE 5.2 : Q&A

- Q&A feature lets you explore your data or query your data in your own words
- The smart narrative visualization helps you provide a quick text summary of visuals & reports

The Q&A feature in Power BI lets you explore your data in your own words by using natural language. Q&A is interactive, even fun. Often, one question leads to others as the visualization.

5.3 SMART NARRATIVE:

The smart narrative visualization helps you provide a quick text summary of visuals and reports. It provides relevant innovative insights that you can customize. Use smart narrative summaries in your reports to address key takeaways, to point out trends, and to edit the language and format for a specific audience.



FIGURE 5.3 : SMART NARRATIVE

- Q&A feature lets you explore your data or query your data in your own words
- The smart narrative visualization helps you provide a quick text summary of visuals & reports

You see a narrative that's based on all of the visuals on the page. For example, in the sample file, smart narratives can automatically generate a summary of the report's visuals that address revenue, website visits, and sales. Power BI automatically analyzes trends to show that revenue and visits have both grown. It even calculates growth, which in this case is 72 percent. Sometimes a hidden-summary symbol appears in the smart narrative.

5.4 MILK ANALYSIS PREDICTION

This dataset is manually collected from observations. It helps us to build machine learning models to predict quality of milk. This dataset consists of 7 independent variables ie pH, Temperature, Taste, Odor, Fat, Turbidity, Color. Generally, Grade or Quality of the milk depends on these parameters. These parameters plays a vital role in predictive analysis of the milk.

Generally, Grade or Quality of the milk depends on these parameters. These parameters plays a vital role in predictive analysis of the milk. Usage. Target variable is nothing but Grade of the milk . It can be if Taste , Odor, Fat, Turbidity are satisfies optimal conditions then they will assign 1 otherwise 0.

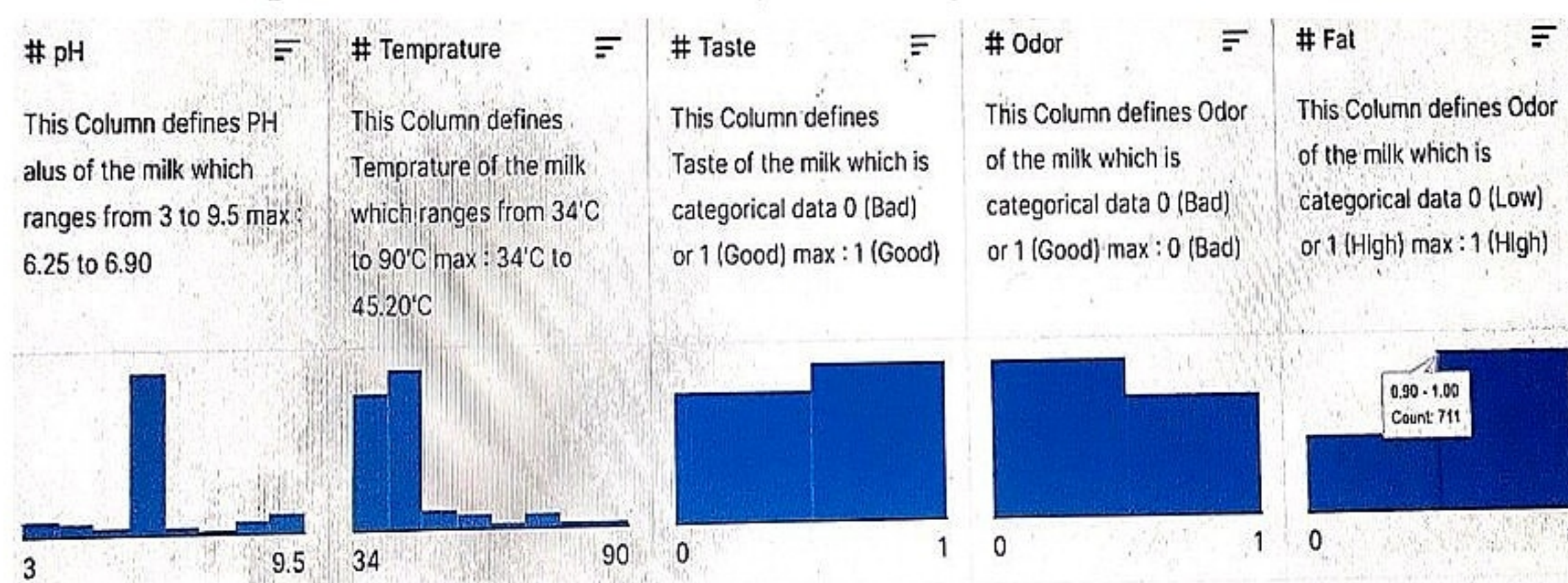


FIGURE 5.4 : MILK ANALYSIS PREDICTION

Numerous statistical machine learning methods suitable for application to highly correlated features, as those that exist for spectral data, could potentially improve prediction performance over the commonly used partial least squares approach. Milk samples from 622 individual cows with known detailed protein composition and technological trait data accompanied by mid-infrared spectra were available to assess the predictive ability of different regression and classification algorithms. The regression-based approaches were partial least squares regression(PLSR),

5.5 AVERAGE MILK ANALYSIS

The average milk procurement through 19 District Co-operative Milk Producers Unions during the year 2018-19 stood at 33.23 LLPD. **On 29.10.2018, procurement stood at an all time high level of 37.03 lakh litres.** Aavin stands at fourth position among the state cooperatives across the country. In order to maintain the initial quality of milk and to improve the keeping quality of milk by avoiding long time transportation to Chilling Centres/Dairies, Bulk Milk Coolers (BMC) have been installed at village level for immediate chilling of milk. At present, there are 356 BMCs with a chilling capacity of 15.94 llpd.

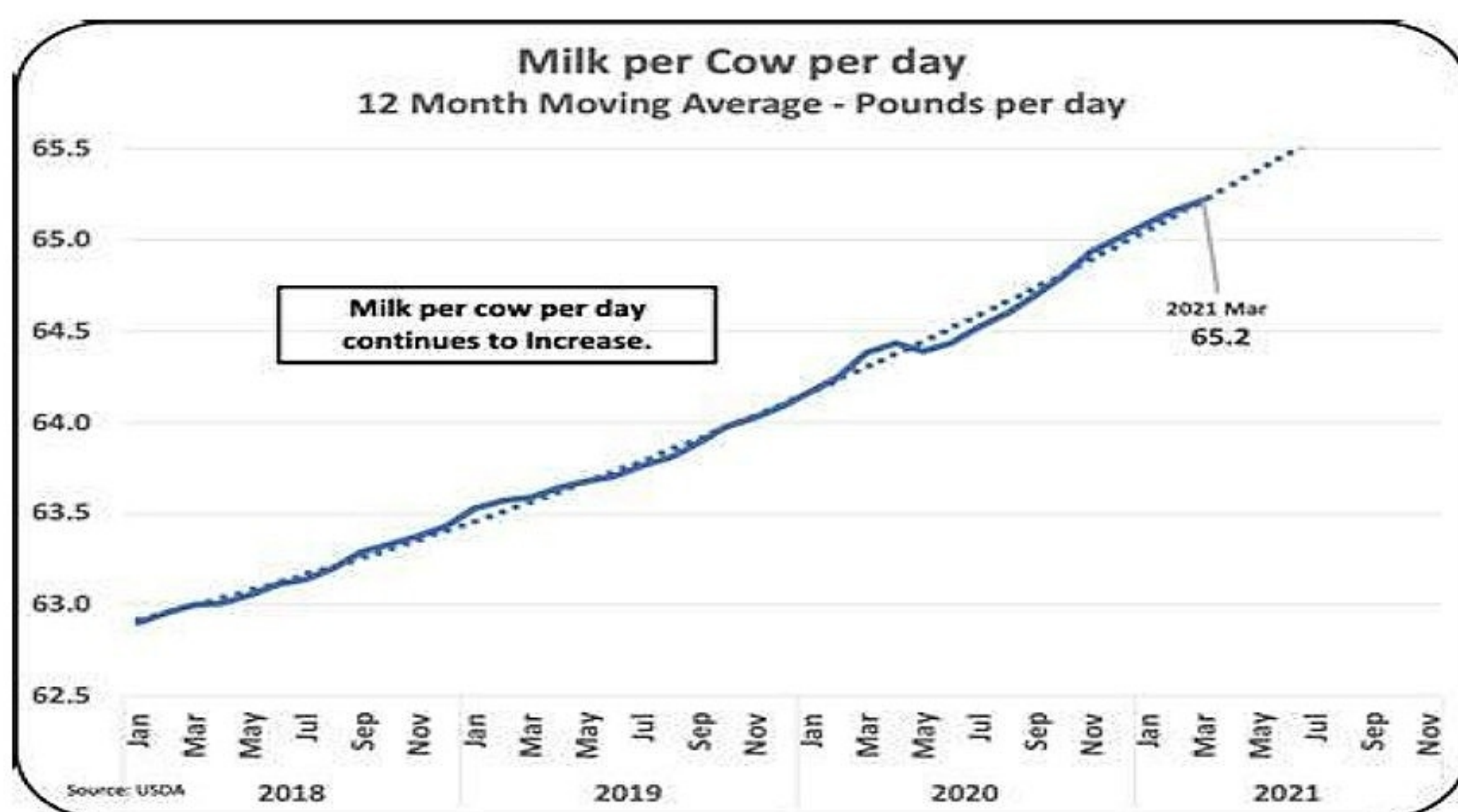


FIGURE 5.5 : AVERAGE MILK PER DAY

5.6 6 PH

The pH of a glass of cow milk ranges from 6.4 to 6.8. Milk fresh from the cow typically has a pH between 6.5 and 6.7. The pH of milk changes over time. As milk goes sour, it becomes more acidic and the pH gets lower.

PASTEURISED, HOMOGENISED STANDARDISED MILK

500 ml

Arokyt®

STANDARDISED MILK

4.5% Fat



5.8 AVERAGE MILK TEMPERATURE ANALYSIS

Analysis of the data shows 1.58% ($n = 67$) milk intake loads demonstrated a temperature greater than 10°C (Figure 2 outlined in black bar), while 60.22% of milk intake loads ($n = 2,551$) were between 5°C and 7°C (Figure 2 outlined in clear bars). Although raw milk on farms should be stored at 6°C , if not collected daily, EU legislation (EU 2004) allows milk to be at 10°C on delivery to the milk processing plant. Nevertheless, the temperatures need to be monitored more closely and interventions undertaken to lower the temperature presenting at milk intake.

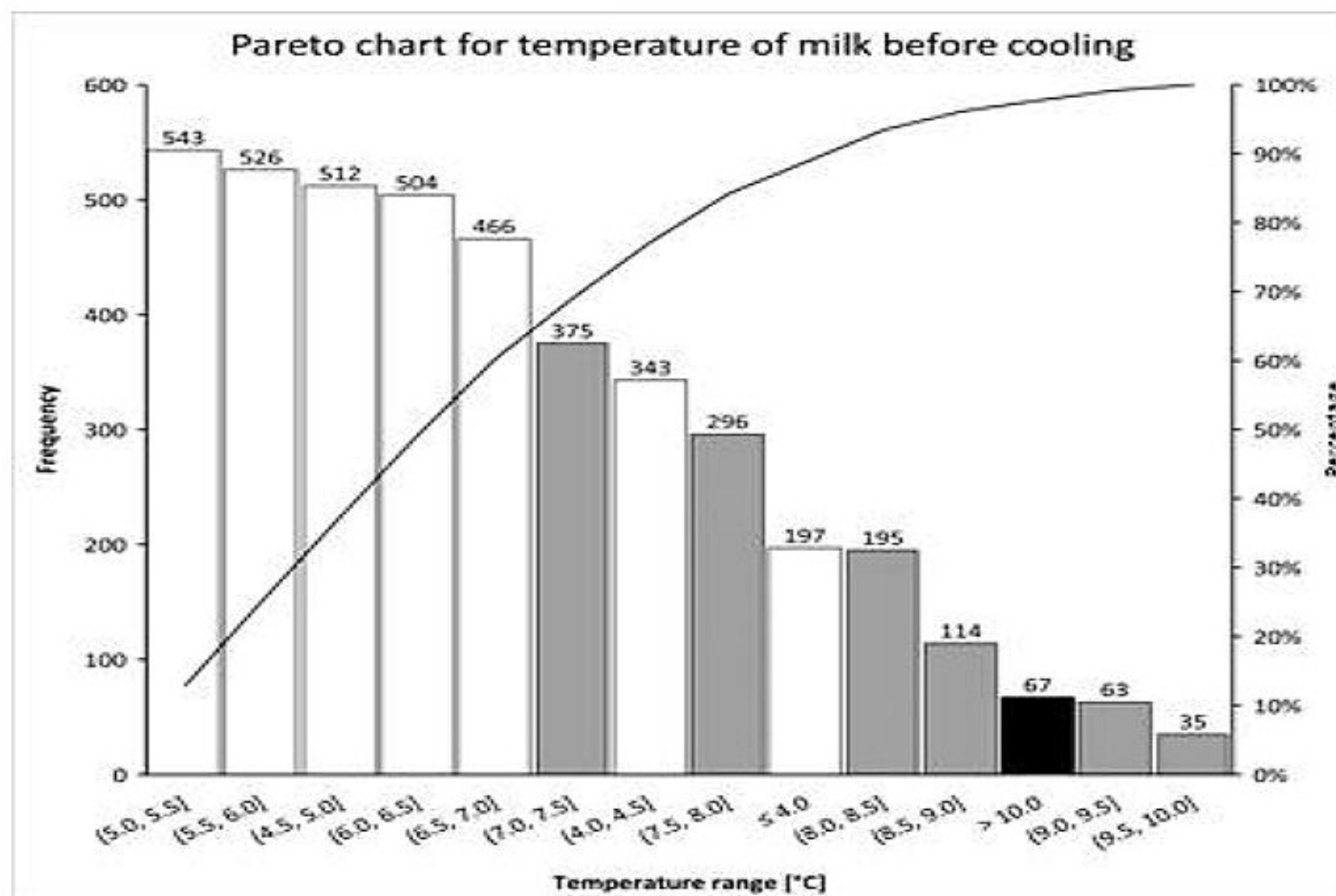


FIGURE 5.8 : AVERAGE MILK TEMPERATURE

5.9 AAROKYA VS AAVIN ANALYSIS BY YEAR

The effects of raw milk quality on processing capabilities and finished product quality have been widely researched [18-20]. The bacterial load prior to pasteurisation for example, affects the efficacy of pasteurisation [21]. With the temperature of raw milk being one of the biggest influencing factors on product quality [14], little research has focused on the impacts and benefits of temperature control of raw milk once it has reached the dairy processing plant. Legislative requirements are in place to regulate the collection and handling of raw milk from farm level to the processing plant. Therefore, it is in the interest of the processor to uphold the quality of raw milk once collected at the farm. Oftentimes however, particularly during peak season, temperature control may be diminished. Uncontrolled temperature variation, combined with inefficient CIP's (cleaning in place programs) and non-optimal hygienic design of equipment, can lead to a larger energy demand including heat and water, required to sufficiently clean processing equipment and uphold the quality of product [22,23].

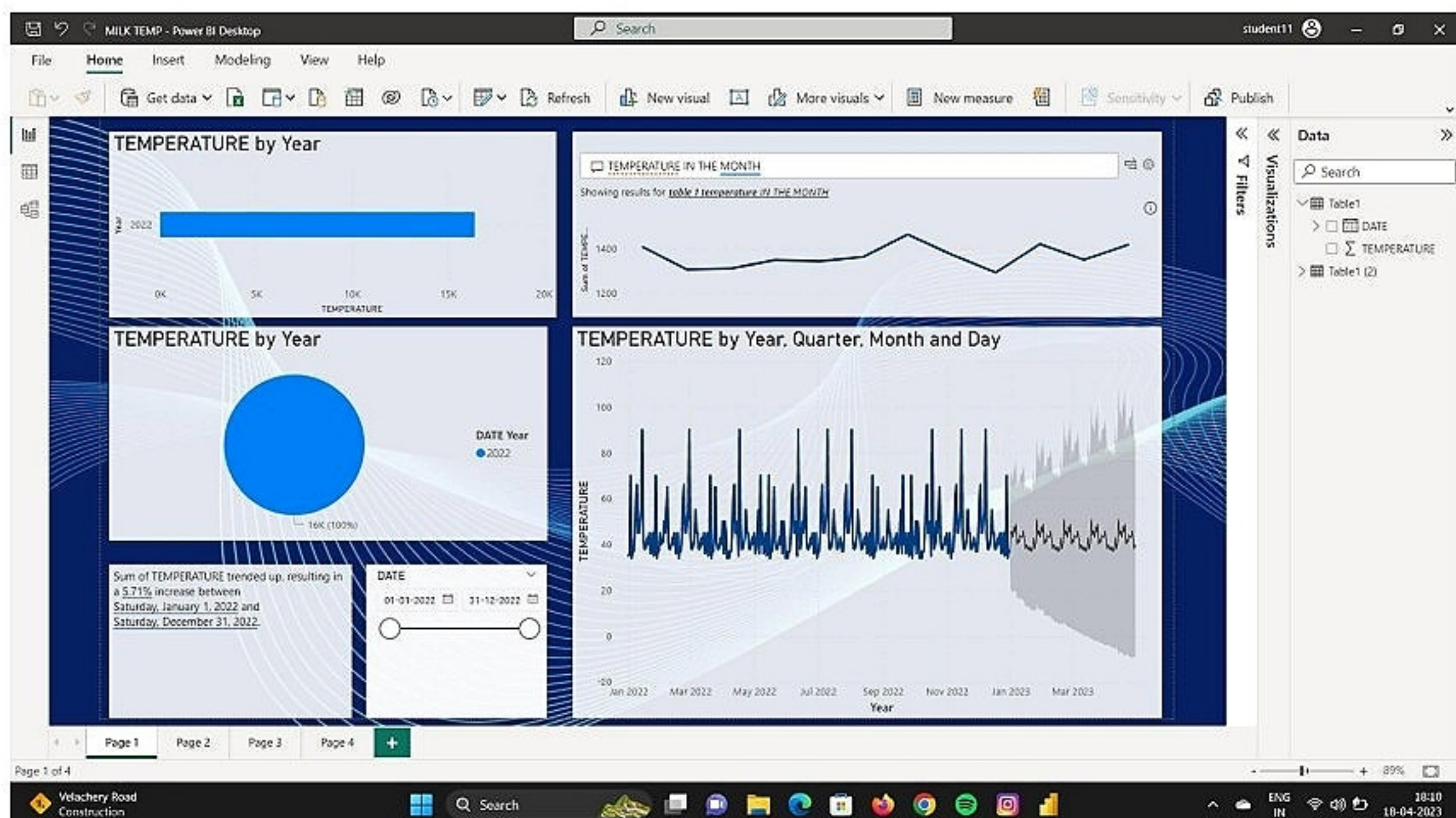


FIGURE 5.10 : AAVIN VS AAROKYA ANALYSIS

5.10 TEMPERATURE OF MILK AFTER COOLING

23 loads of milk exhibited a temperature greater than 10°C after cooling, while 49% of loads were chilled to between 4.5°C and 5°C ($n = 2,086$). Furthermore, analysis of the data shows 9.82% of milk intake loads were heated rather than cooled after pumping, i.e., 416 loads were heated by up to 1°C increments (Figure 4). While 31 loads were heated by more than 1°C increments

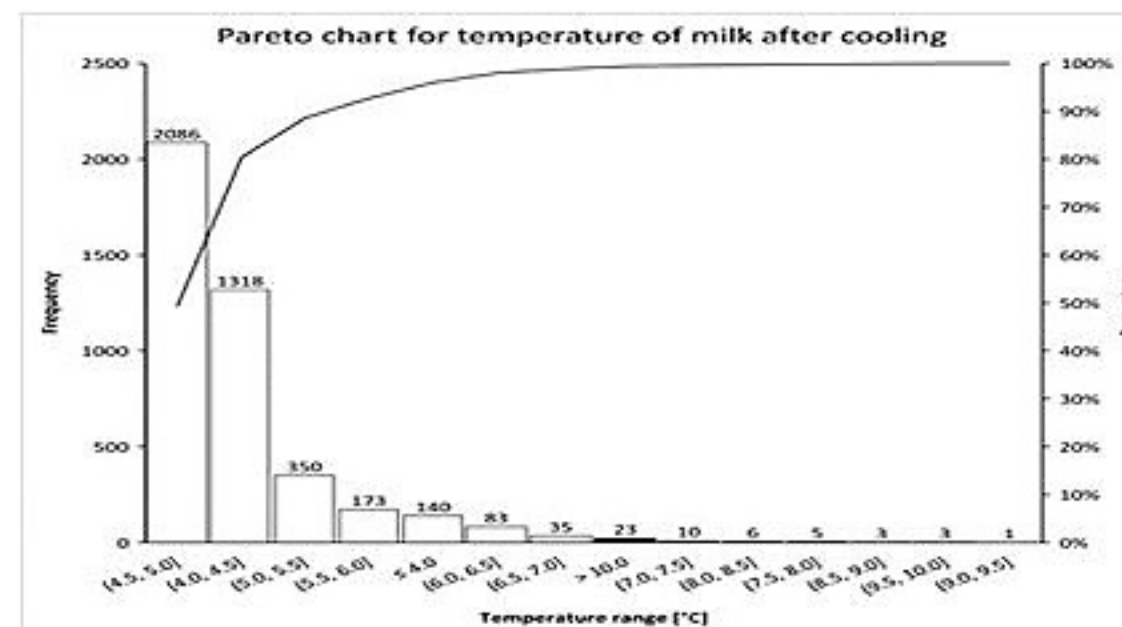


FIGURE 5.11 : MILK TEMPERATURE AFTER COOLING

5.11 OUTSIDE MILK AIR TEMPERATURE

Finally, all temperature data were compared with local air temperatures recorded by a weather observing station located near the dairy plant (Met Éireann 2020), to determine whether statistical significance existed between the temperatures of milk and outside air temperatures for the period analysed. The findings showed that there were significant positive correlations between the temperatures of loads in, the temperatures of loads after cooling and the temperatures of outside air ($P = +0.299$ and $+0.036$ respectively).

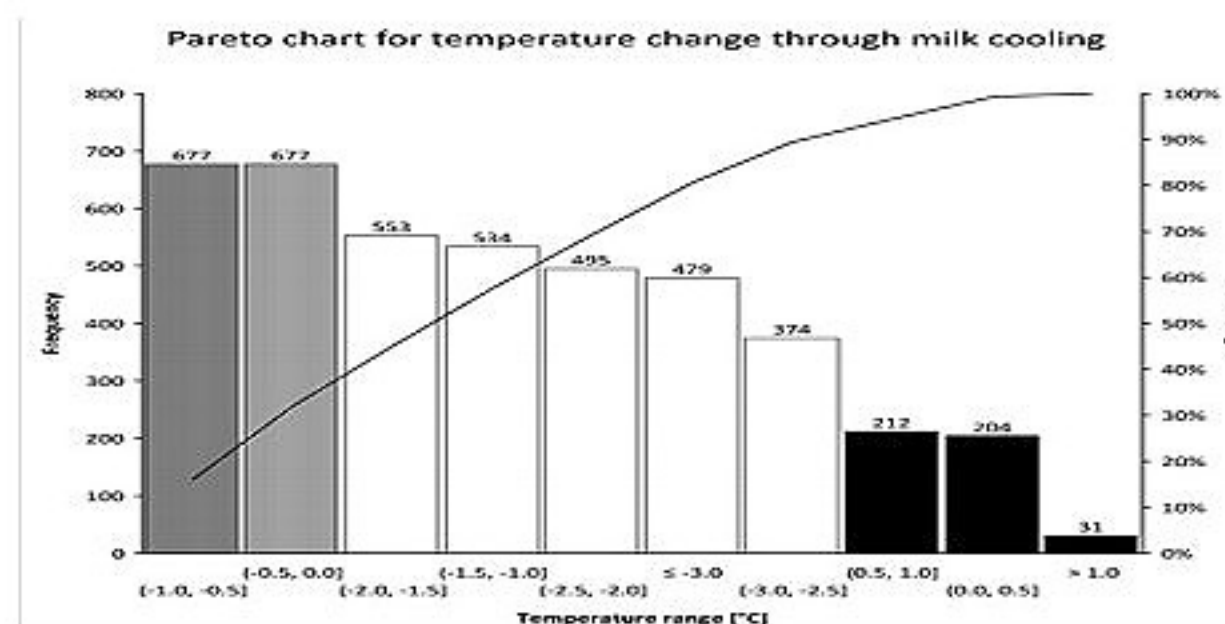


FIGURE 5.12: OUTSIDE AIR TEMPERATURE

5.12 MILK PRICE

milk represents cow's milk used mainly to make cheddar cheese. One contract contains 200,000 lbs of class III milk. The Milk prices displayed in Trading Economics are based on over-the-counter (OTC) and contract for difference (CFD) financial instruments. Our market prices are intended to provide you with a reference only, rather than as a basis for making trading decisions. Trading Economics does not verify any data and disclaims any obligation to do so.

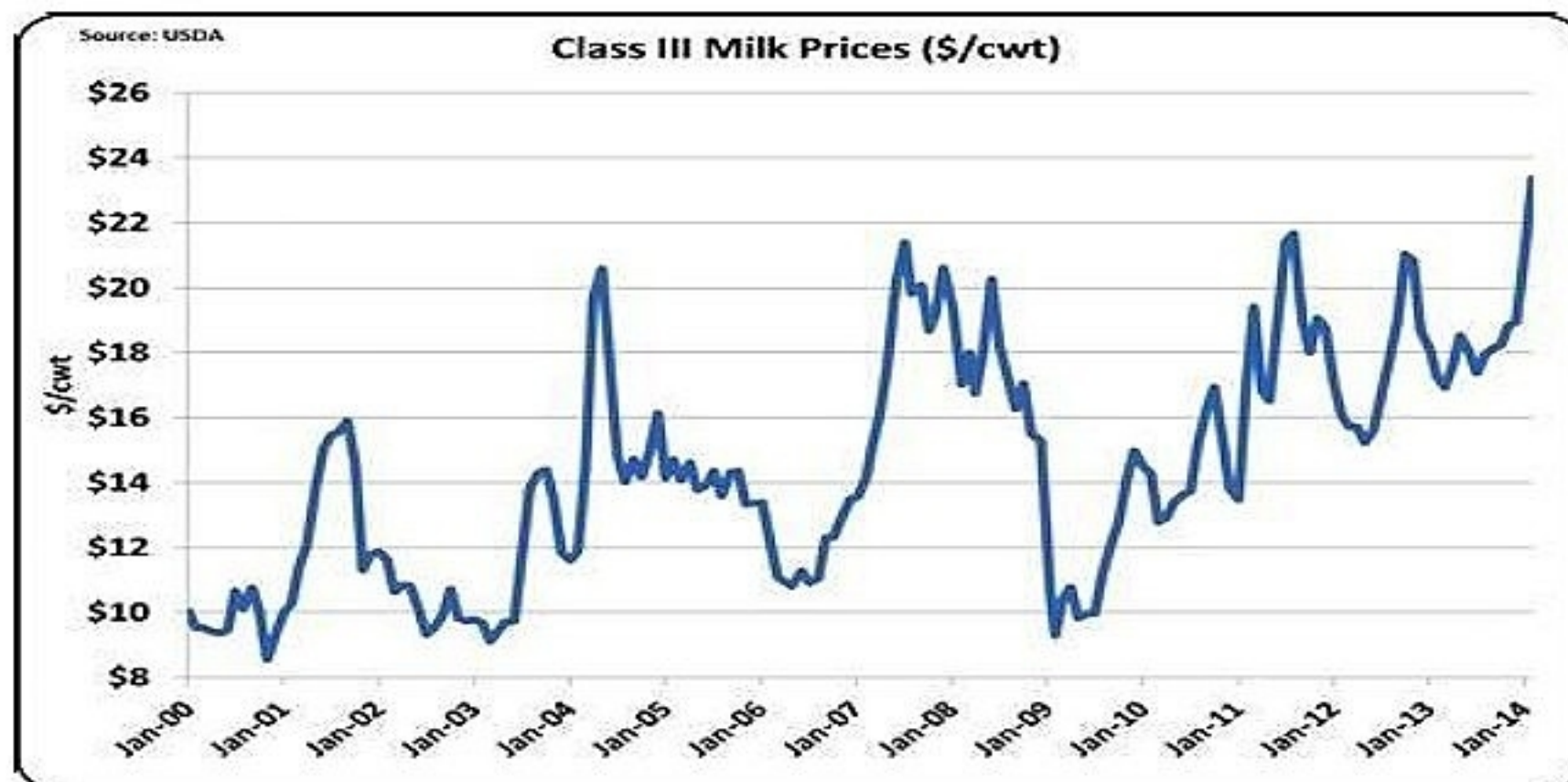


FIGURE 5.13 : MILK PRICE

5.13 GROWTH RATE IN MILK ANALYSIS

Between 2000 and 2016, the largest dairy operations (those with more than 1,000 milk cows) experienced a TFP growth rate of 2.993 percent per year. Meanwhile, TFP growth for the smallest operations (those with fewer than 100 milk cows) increased at an annual rate of 0.639 percent.

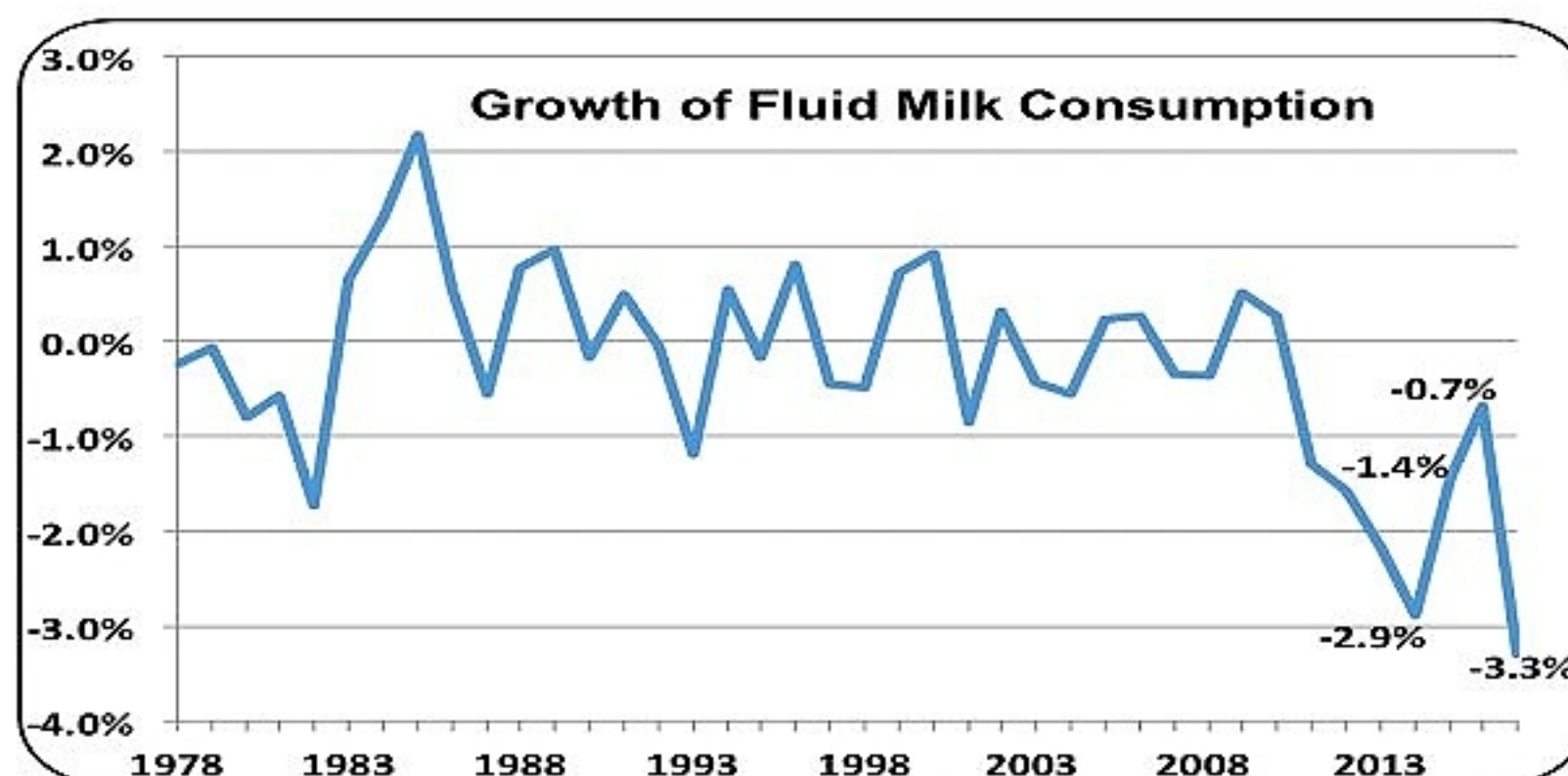


FIGURE 5.14 GROWTH RATE IN MILK

5.14 AAVIN AND AAROKYA PREDICTION

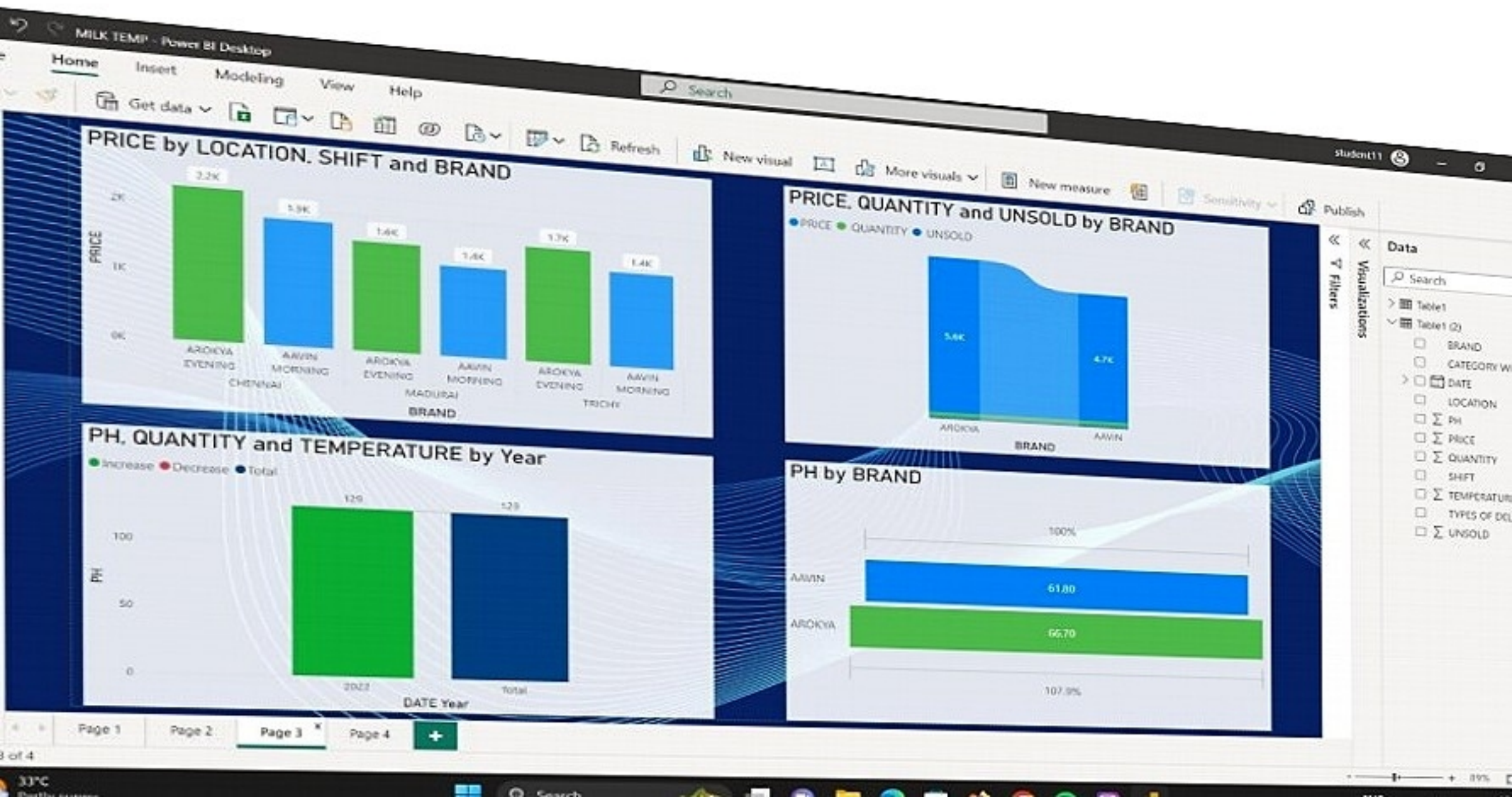


FIGURE 5.15: AAVIN AND AAROKYA PREDICTION

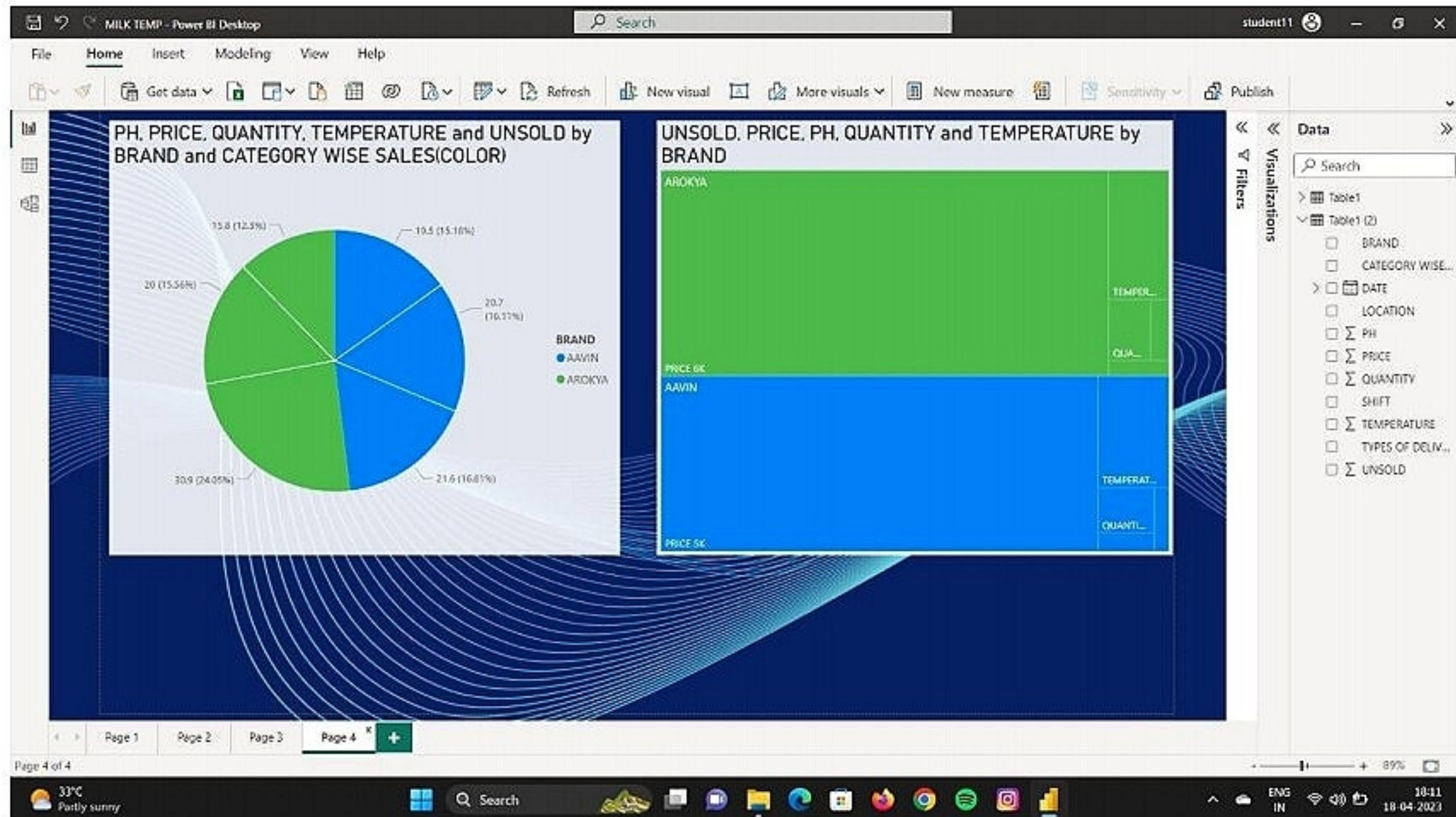


FIGURE 5.15: AAVIN AND AAROKYA PREDICTION

The objective of this research was to evaluate the temperature of incoming raw bulk milk loads at one large dairy manufacturing site. Data were collected and collated for a three month peak season period (June, July and August 2018). Temperature records for 4,236 data points, across three milk intake bays were analysed. The aim was to trend temperature information and provides recommendations for optimisation at the milk intake step.

The effects of raw milk quality on processing capabilities and finished product quality have been widely researched [18-20]. The bacterial load prior to pasteurisation for example, affects the efficacy of pasteurisation [21]. With the temperature of raw milk being one of the biggest influencing factors on product quality [14], little research has focused on the impacts and benefits of temperature control of raw milk once it has reached the dairy processing plant. Legislative requirements are in place to regulate the collection and handling of raw milk from farm level to the processing plant.

5.15 DISCUSSION

The objective of this research was to evaluate the temperature of incoming raw bulk milk loads at one large dairy manufacturing site. Data were collected and collated for a three month peak season period (June, July and August 2018). Temperature records for 4,236 data points, across three milk intake bays were analysed. The aim was to trend temperature information and provides recommendations for optimisation at the milk intake step.

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6.CONCLUSION

This study quantitatively assessed the incoming raw milk temperatures and cooling performance across three milk intake bays at one dairy manufacturing site for a three-month period (June, July, August 2018). The outcomes of this study provided the dairy manufacturer with the capability to reassess their pumping schedules with regards to usage frequency on individual pumps to optimise both flow and chilling performance. This research should encourage any dairy manufacturer to investigate their onsite chilling performance and pumping frequencies at all intake bays.

The maximum temperature recorded for the three-month period was 17.17°C (Table 3). A total of 1.6% loads in were warmer than 10°C however, the majority of loads received were between 5°C and 7°C (Figure 2). Legislation states that once milk is received it must be cooled to and stored at 6°C or below until further processing. With an average site chilling performance of -1.44°C (SD 1.34), it is essential that stringent temperature parameters at intake are followed. Where chilling capacity is inefficient, milk must be processed as quickly as possible to uphold its quality. Milk processing plants capability to cool incoming raw milk is crucial to upholding quality. The most significant outcome of this investigation was the fact that some loads of milk (10.55%) had a greater temperature after being pumped through the PHE. There were 416 loads heated to less than 1°C increments while 31 loads were heated by >1°C increments (Figure 4). Of these loads, only 0.54% data points show a temperature >10°C, however it was recommended to the processing plant to carry out a full investigation on their pumps and PHE at each intake bay.

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