Application of Data Analytics in Process Prediction, Analysis, Management & Visualization Using Microsoft Power BI

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Abstract

This research explores the application of data analytics, specifically Microsoft Power BI, to optimize processes within the chemical and manufacturing industries. By analyzing large volumes of production data from a PVC (polyvinyl chloride) manufacturing plant, it aimed to identify trends, anomalies, and opportunities for improvement.
The study involved collecting, cleaning, and transforming production data, including process temperature, flow rate, torque, tool wear, energy consumption, and failure types. This data was then loaded into Power BI, where it was analyzed and visualized to gain insights into the manufacturing process.
Through data-driven analysis, critical relationships between process variables and product quality were identified. For instance, it was observed that variations in voltage and temperature can significantly impact product quality and energy consumption. By monitoring these variables and making timely adjustments, it is possible to optimize production processes, reduce energy costs, and minimize product defects.
The findings of this research demonstrate the potential of data analytics to revolutionize industrial processes. By leveraging the power of Power BI, organizations can harness the value of their data to achieve significant improvements in efficiency, productivity, and overall performance.

Keywords: Data Analysis, Power BI, Data Visualization, Business Intelligence, Chemical Engineering, Process Control, Climate Change, Sustainability, Energy, Waste, Environmental Pollution.

Introduction

1.1 Background of This Study

The manufacturing industry today is dealing with various challenges. Uncertain shutdowns, increasing manufacturing costs, complexities in the supply chain, and machine operations and logistics are providing complications that must be addressed urgently. These challenges highlight the need for a solution to analyse the various types and large volumes of data that companies amass and visualize it in such a way that issues, trends, and opportunities can be readily identified. The process of transforming data into insights to improve business and operational decisions is referred to as big data analytics. Using this definition as a starting point, the community of chemical engineers embarked on using data-driven modelling approaches many decades ago.

Some of the most foundational data-driven modelling work has been done in the chemical process industry, which has proven to be a fruitful ground for such work. Though not efficient in the chemical engineering context, the collection and storage of process data for online monitoring and analysis were made possible by online instrumentation as well as centralized control systems. As a direct consequence of this, multivariate control, process monitoring, and inferential sensors have all enjoyed an exceptionally fast rate of adoption within the industry. Real-time model-based control, complex batch process monitoring, controller performance assessments, and integrated scheduling are some examples of new ways to use data that have more volume, variety, and speed because of recent advancements in computer hardware and numerical algorithms. These are all examples of new ways to use data. But despite the commendable improvements so far, chemical industries are still haunted by epileptic equipment breakdowns, faulty manufacturing, and high production costs.

The good news is business intelligence (BI) tools like Microsoft Power BI have the potential to solve many of these issues associated with the manufacturing sector. Power BI offers opportunities in multiple avenues to improve operations, including identifying top adopting trends and recognizing patterns for more accurate forecasting.

1.1.1 What Is Microsoft Power BI?

Power BI is a suite of business analytics and data visualization tools offered by Microsoft alongside Power Apps, Power Pages, Power Automate, and Power Virtual Agents collected in the Microsoft Power Platform suite. These desktop, cloud-based, self-service tools offer critical insights to business owners and engineers to assist them in making data-driven decisions. Power BI can enable companies, especially the chemical industries to seamlessly connect to and visualise any data using its unified, scalable platform for self-service and enterprise business intelligence (BI) which easily helps decision-makers gain deeper data insights.

Businesses in the manufacturing industry can now leverage Power BI for sourcing, compiling, transforming, and modelling data from cloud-based or on-premises data warehouses originating from manufacturing, sales, and marketing data. When data is captured, they are easily processed, stored, managed, and visualised using Power BI, further empowering decision-makers with the right insights. The Power BI dashboard provides intuitive and interactive reports using the sourced data, making it easy to comprehend and share within and outside the organisation.

1.2.2 Digital Transformations in The Manufacturing Industry

The manufacturing industry today stands apart in its drive towards digital transformation using Power BI. Focused on reducing the cost of energy, optimising productivity, forecasting production, controlling processes, managing resources, and customising manufacturing solutions to meet the needs of consumers, chemical industries are now looking to IT solutions to alleviate its growing challenges. Modern data analysis technologies and strategies have created immense opportunities to move away from the traditional manual approach, such as Microsoft Excel and other manual data processing tools, and automate key processes to understand which KPIs (key performance indicators) are influencing business revenue and profit. Even beyond ascertaining the profitability of manufacturing, industries are more concerned about maximising production by reducing energy costs, minimising waste, and forecasting trends both in production and sales.

Smart meters, weather forecasts, and other data sources are improving the energy industry's forecasting capabilities, which allows for a better understanding of the energy consumption behaviours of large populations as well as the energy consumption behaviours of local neighbourhoods. Electricity providers are also using these data sources to forecast demand surges, find faults and outages, and improve the reliability and efficiency of their systems. In several previous trials, utilizing gathered information from automated systems helped the semiconductor industry bring down its overall cost of production. Applications of real-time automatic process control are making efforts to locate errors, increase yields, and lessen product variability.

Methods of machine learning, dimensionality reduction, and visualization are being incorporated into research and development in the pharmaceutical industry to facilitate the analysis of complex data sets such as gene expression, protein interactions, and drug discovery information. Additionally, model-based control, real-time optimization, and real-time process monitoring contribute to an improvement in quality within the pharmaceutical manufacturing industry. The idea that the amount of data will continue to increase at an exponential rate is the defining characteristic of the era of big data. A speedy onslaught of information covering a diverse range of topics is expected.

Interestingly, digital transformation enabled by BI has resulted in improved efficiency, productivity, and profitability for manufacturing industries. By allowing innovation, it has also reduced the costs of data processing efforts by automating data capturing, analysis, and visualisation so that industrial leaders can focus on implementing the insights generated by Power BI. The clear impacts of Power BI on productivity have helped in the making of faster, data-driven decisions to better position companies to compete in today's fast-paced digital economy.

1.2 Problem Statement

The chemical industry, such as paint, plastics, pharmaceutical, metallurgy, cement, petrochemicals, and oil and gas sectors are continuously battling with numerous manufacturing setbacks, including pollution, uncertain machine shutdowns, increasing manufacturing costs, the inadequacy of raw materials, inflexible supply chains, and threatening climate change. These challenges are making the path harder for the manufacturing industries globally, reducing productivity across businesses and industries. Luckily, Power BI has the potential to solve many issues associated with manufacturing operations, from sourcing of raw materials and production of goods to marketing and sales by tracking production data, identifying KPIs and offering actionable insights to the company management, which empowers their decision-making. Power BI offers opportunities in multiple avenues to solve those challenges faced in today's process industries by improving operations, including identifying the top adopting trends and recognizing patterns for more accurate forecasting.

1.3 Aims and Objectives of This Study

1.3.1 General Objectives

This study explores the application of Microsoft Power BI to capture, process, manage, analyse, and visualise data to obtain actionable insights that empower manufacturing industries to make data-driven decisions.

1.3.2 Specific Objectives

The general objective of this research is to consider the possibilities of the application of data analytics in process predictions, analysis, management, and visualisations using Microsoft Power BI. The findings of this research will help reduce failures in the extrusion process of PVC production, optimise energy consumption and save manufacturing costs.

Furthermore, this study implements several data analytics and business intelligence strategies to design dashboards and digital pipelines to streamline the production chains of chemical industries from raw materials acquisition to manufacturing while elaborating the following:

- Application of Microsoft Power BI in the monitoring of the production processes of PVC extrusion
- Analysing manufacturing data with analytics tools to derive actionable process control and management insights.
- Management and automation of industrial processes using dynamic analytics dashboards.
- Process analysis, results visualization, and predictions of future outcomes using Microsoft Power BI.

1.4 Justification of This Study

The impact of integrating Power BI in large-scale industrial data analytics and visualizations is immense. At a high level, Power BI can help you visualize your business data, monitor overall performance, and make well-informed business decisions with critical KPIs derived from multiple data sources. Power BI dashboards allow chemical engineering industries to generate report metrics such as trends per product, production volumes, and underperforming products. It can also integrate the visual metrics in Power BI with other solutions, such as ERP (enterprise resource planning) systems. A Power BI dashboard shows significant connectivity with third-party systems while forecasting important trends. On the finance side of the business, users can view information for a current financial situation within a specific date range through real-time financial reports.

Literature Review

2.0 Introduction to Business Intelligence (BI)

Before now, decision support systems (DSS) were well-established types of information systems with the primary purpose of improving decision-making based on data and analysis (Troisi et al., 2020). However, some authors claim that the research field of DSS is no longer current or of interest and has been replaced by the newer fields of Business Intelligence and Analytics (BI&A) and Big Data tools such as Microsoft Power BI to enhance decision making (Soni et al., 2020). Others suggest that BI&A is a new kind of information system that originated from operations research and has been adopted mainly due to the more recent, ready access to large amounts of 'big data' for analysis, modelling, and predictions (Teng et al., 2021). In the early 1990s, the terms 'Business Intelligence', 'Business Analytics,' 'Big Data', and their variations were coined to describe a developing information technology that could take advantage of the growing amount of data, extensive interconnectedness, and significant advances in computing (Jiao et al., 2022). With the availability of data analytics, visualization, implementation and forecast technologies at the fingertips of industries, productivity can be maximized to cut costs.

According to Wang & Wang, there is a need to build concrete data analysis, visualizations, and results from prediction tools by IT professionals easily accessible for utilization by departments (Wang & Wang, 2020). Such technologies must possess the capability to seamlessly collect, analyse, and store the processed data with the ability to present the results in a simplified dashboard enabling the business to make predictions (Zhang et al., 2018). With this fact established, it's critical to analyse the trends in industrial data processing, and visualizations adopted a couple of decades ago, including the use of MATLAB, Python, Microsoft Excel, and other analytical tools (Fritzsche & Gölzer, 2021). Those technologies were interestingly helpful but can't offer the manufacturing industry the needed drive to survive in the current competitive economy. The ongoing industrial trend is swift, moving at the speed of light. Moreover, using sensors that collect different types of data at various stages of manufacturing and sales presents yet another ample opportunity avenues to utilize the obtained production and marketing data to further enhance future results (Jinil Persis et al., 2021).

It's these needs to quickly analyse and visualize data that opened opportunities for companies to also monitor their sales in a bid to understand their marketing trends. Beyond the demand for analytical tools to process manufacturing data, there's an even greater need to automate the data analysis and visualization processes (Kuo et al., 2021). Power BI, a part of the Microsoft Power Platform, provides the requisite technology that enables industries to access their data quickly. The ability to automate and simplify the cumbersome data collection, analysis, visualization and forecasting steps is a distinct feature and added advantage in Microsoft Power BI. Even nearly half a decade ago, production companies sparingly utilized the Power BI technology to collect and store datasets from multiple streams with inadequate expertise in further processing and digitalization to achieve an optimum result (Mohammadpoor & Torabi, 2020). However, the narratives in the overall adoption and implementation of BI capabilities have changed significantly with the geometrically rising population, inconsistent climate change, and global economic downtrends.

With an increase in population, the rate of production also increased. But how well can industries carefully withstand an economic decline yet enhance productivity to meet the demands of the populace? This is where the power of Power BI is most effective (Andersen et al., 2020). Because it enables industries to maximize their productivity by synthesizing manufacturing results to give insights to companies through understandable dashboards and reports. The obtained results further give stakeholders the much-needed insights to monitor and understand business trends.

Though Excel has traditionally been the most popular reporting tool for manufacturing businesses, Power BI offers more powerful analytics and reporting features leveraging near real-time data, available for even non-technical users in the manufacturing industry (Tiwari et al., 2018).

Data analysis expression (DAX) is one of the features that Power BI offers (Li et al., 2021). DAX functions will help you get the most value out of your visualizations and charts, helping you find and solve real business issues. Using DAX language functions allows manufacturers to get new insights and information from existing data. Using this capability, they can analyse growth for different ranges and categories for any product in the manufacturing sector (Yang et al., 2021). With DAX, Power BI offers an extension to Excel with functions like Excel formulas. With faster visualizations, and strategic functions and calculations across datasets, DAX provides the ability to obtain answers on the go and delivers far greater insight than Excel can (Zeiser et al., 2021; Phillips-Wren et al., 2021). Power BI tools help decision-makers visualize, analyse, and share large volumes of data collected from multiple sources to get more powerful insights to make informed business decisions (Zhang et al., 2018). It also enables them to collect and share insights extracted from the data sets with other departments of their organizations or companies. Hence, Power BI tools perform risk-free analysis while addressing critical issues like resources, shifts, locations, suppliers, and other factors that affect manufacturing processes.

2.1 The Position of Chemical Industries in The Era of Big Data

Big data analytics aim to provide valuable insights for making informed strategic and tactical decisions (Troisi et al., 2020). This journey becomes increasingly complex in terms of using the correct data and the proper tools (analytics) to make the right decisions in real time as the chemical engineering community receives more data (volume) from more sources (variety, velocity) (Banik & Bandyopadhyay, 2016). To take organizational success to the next level of multiplication, industries, government, academia, and business must collaborate on workforce development and innovation using Power BI (Knight et al., 2018). Thus, going forward, the concept of "big data" is still relatively new in the chemical industry, yet it already significantly impacts production efficiency. There is a social, economic, and technical revolution happening right now, and it is impacting all of us across sectors. Our daily lives—from talking to friends to playing video games to doing business—have all shifted online. In turn, the Internet has expanded to our mobile devices, the ubiquitous gadgetry of our homes and public spaces, and the industries that drive the global industrial economy (Ahmed et al., 2017). Because of this, there has been a boom of new information and discoveries enmeshed in data analysis and the visualization of generated information, which is changing our world.

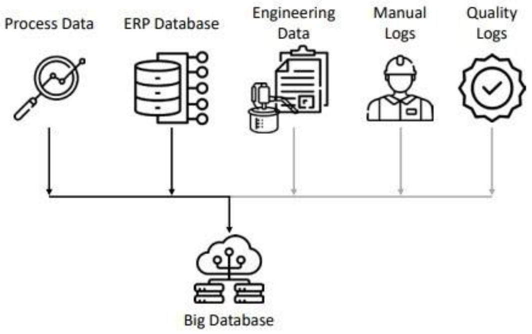

Figure 1-Figure 1-Origin, sources, and pipelines for data collection

Supporting Ahmed et al. (2017), Wang & Wang (2020) assert that the big data era is driven by new data generation (e.g., social media), new measurement capability (e.g., internet of things, smart digital devices), increased data storage power (e.g., cloud computing), and improved analytics computing technology (e.g., machine learning, artificial intelligence, cognitive computing). The mainstream media frequently discusses the business applications of big data. The Economist, McKinsey, Fortune, Forbes, the Financial Times, the Harvard Business Review, Newsweek, the New York Times, the Wall Street Journal, and the Washington Post are just a few of the significant business publications that have published articles covering everything from an introduction to big data to the technologies that make big data possible, from the benefits of big data to businesses to the challenges of using it to predict the future (Niu et al., 2021). Similarly, there has been an explosion in the number of papers devoted to using big data in the sciences and engineering, but a few have stemmed from the chemical engineering field. This shortage in research and resources also provides a viable avenue for further exploration (Duever, 2019).

Jinil Persis et al. (2021) noted that, in the context of the chemical process sector, first-principles techniques can be applied effectively to build mechanistic models for process operations, provided that the underlying chemical mechanisms are well known. Process data analytics are significant tools for gaining insights into process improvements for complicated processes whose initial principles are not well known (Zeiser et al., 2021). A new paradigm based on big data has the potential to improve data-driven operations and control in the process industries. Why (why you should care about big data), What (big data success stories from the process industries), How (getting started on the journey) and Future (challenges and future research directions) are critical questions stakeholders in process engineering are debating regarding the position of chemical and process in the data era (Teng et al., 2021). Given the prevalence of talk about big data across disciplines illustrated in (Teng et al., 2021), it may come as a surprise that a search of the literature using the terms "big data", and "chemical engineering" turns up relatively few results.

However, to describe the characteristics of data growth, which can be traced back to the earliest debates on big data today, Bandyopadhyay used the 3Vs of data (Banik & Bandyopadhyay, 2016).

Volume

In 2021 alone, 2.5 quintillion bytes of data were generated daily by humans (Hansen, 2019). A quintillion consists of 18 zeros. By 2025, it is estimated that 5 billion internet users around the globe will generate 463 exabytes of data. These statistics demonstrate the significance of the first V, namely data volume. Big data is dominated by volume (Khan et al., 2022). Using both current and historical data to derive insights, organizations can obtain a more comprehensive view of a product and customer due to the abundance of data. With such massive amounts of data, the need arises for the development of novel data processing and storage technologies (Fang et al., 2016). These datasets are simply too large to be processed on a simple lightweight desktop and mobile applications.

The sheer quantity of data available is what gives Big Data its name. This is reflected in the sheer volume of information obtained by recording enough variables at a sufficient frequency over a sufficiently long period (Abdulla et al., 2022). In the context of chemical engineering, "static" and "quasi-static" data from other data repositories, such as design data or internal transfer prices, can supplement the acquisition of real-time data for business intelligence analysis projects (Carlisle, 2018). Static or quasi-static data typically represent fewer data points but a greater number of variables. It’s important to note that not all massive data sets can be considered "big." Thus, according to Dubey et al. (2022), if the phenomenon of interest is rare, a large data set should contain enough occurrences to provide sufficient insight. The same is true of the depth, or rather the absence, of data.

Velocity

A faster update rate is often thought to be advantageous, but in the context of chemical operations, one may find two extremes of data in terms of the speed with which such data are generated (Hamid et al., 2022). The rate at which data is generated by process sensors is typically very high. Hence, the optimal rate of data production may depend on how long the process takes in terms of the smallest meaningful time constant (Haleem et al., 2021). In this regard, it may be preferable, concerning processing data, to forego some of the speed in exchange for greater precision. Quality logs and manual logs, on the other hand, are typically recorded at a relatively low velocity due to the time-consuming nature of the necessary tests and the fact that operators are typically preoccupied with managing the plant (Kabugo et al., 2020). The rate at which this kind of information becomes available can be greatly increased by automating the sampling and testing processes involved using streamlined data analysis and visualization tools. To meet this demand, researchers have created process analytical technologies (PAT) like soft sensors and inferential sensors, which feed operators with useful data (Cavallo et al., 2021). But despite the development of sensors to gather the data, the means of instant analysis and visualization of the generated data still create vacuums in the process.

Variety

As was previously mentioned, a chemical plant stores its process data in several different repositories according to their respective structural properties. ERP data, for instance, may include start and end times or datasets sorted by a batch number, while process data, for example, may include time stamps and other meta information (Dambros et al., 2021). However, ERP data does not necessarily indicate whether such settings are used, only the time spans during which they are valid. It's important to remember that ERP data can take on a wide variety of forms, often based on where in the company they're stored (business units, geography, etc.). Data sets for applications like BASF's Verbund-Simulation 36 require extensive pre-processing and validation in addition to the development of custom extractors. P&ID diagrams in process industries can show the "static" structural and, to some extent, spatial information of the process, while quality and manual logs are typically organized with batch numbers (Hamid et al., 2022). Therefore, extensive pre-processing is needed due to the heterogeneity of the data and the lack of cohesion and consistency in the data structures (Pistikopoulos et al., 2021). Instead, careful reconciliation and pre-processing are required to align data sets when there is variation in velocity within a single type of data (especially process data).

Veracity

Different data sets have varying degrees of veracity, which refers to how much you can trust the data (Lytras et al., 2020). Although there is a correlation between data volume and data veracity, it is still difficult to draw conclusions and make decisions based on low-quality data. Sensors in large-scale industrial petrochemical facilities need to be serviced and calibrated regularly if they play a role in the facility's ability to maintain its operating license. Systems with a high Safety Integrity Level (SIL) are rigorously documented, tested, and calibrated safety instruments. Traditional installations, on the other hand, rarely receive any kind of public interest, so they gradually lose reliability (Dubey et al., 2019). Consequently, conventional sensor readings are frequently of poor quality and provide only a qualitative insight into the process. Mechanistic models that have been verified could, however, be used to monitor sensor quality via data reconciliation and infer actual values (Kabugo et al., 2020). A company's culture also affects the reliability of manually recorded data, such as that found in enterprise resource planning (ERP) systems. Such data can only be harvested, and truly generalizable insights can be generated if the value of correct data is fully ingrained in the management and operational layers of an organization.

2.2 Applications and Advances of Big Data in Chemical Engineering

The Chemical Process Industry

The chemical process industry covers a broad range of products, including commodity chemicals, petrochemicals, refinery products, speciality chemicals, life sciences, and consumer goods (Beck et al., 2016). In favour of mass-produced goods for the life sciences and consumer goods, large-scale chemical and petrochemical production facilities have replaced smaller ones. In modern petrochemical and chemical complexes in (Dias et al., 2020) research, most of the manufacturing takes place in a relatively small area (Omar et al., 2019). That's because small changes in areas like energy efficiency, reliability, and safety would have a much larger impact at a larger scale due to economies of scale. Omar et al. surveyed executives in the chemical industry and found that 88% of respondents believe that data analytics will be very important for maintaining a competitive advantage in the next five years (Omar et al., 2019). As a result, big data analysis will be a booming industry.

When it comes to the widespread implementation of computerized control systems, the chemical process industry was an early pioneer (Jiao et al., 2022). But unfortunately, it has not kept the same pace with other industries over the years. Maintaining a plant's safety and efficiency calls for the constant tracking of countless process variables (Burggräf et al., 2021). The routine collection of process data for monitoring and control has paved the way for the investigation and development of data-driven techniques and programs. With the help of process-specific database servers like OSISoft PITM and AspenTech IP21TM, engineers and researchers now have quick and dependable access to process data which often requires further analysis and visualization (Sadat Lavasani et al., 2021).

Advances In Continuous Processes with Higher Data Volumes.

Univariate control charts have long been the gold standard for process monitoring, guaranteeing that all processes are running within acceptable parameters (Hamid et al., 2022). As more and more sensors and actuators are added to plants, the sheer volume of data generated can be daunting to plant staff.

Consequently, many data streams are typically ignored. With dashboards, Enterprise Manufacturing Intelligence (EMI) provides real-time visibility into the status of key performance indicators for manufacturing plants (Wang et al., 2022). Then, the EMI platform can be outfitted with a troubleshooting guideline based on the gleaned process expertise, allowing for more informed, data- and knowledge-based decision-making. At the Dow Chemical Company (hereafter referred to as Dow), the EMI platform has proven to be highly successful. Multivariate analysis is another method for putting a mountain of data into perspective (Wang et al., 2022).

Data streams produced by continuous processes tend to be dense (as opposed to sparse) and well-structured. Flow, mass transfer, energy transfer, and first-principles thermodynamics all contribute to the inherent correlation structures in these massive data sets, and this is where multivariate analysis comes in (Han & Trimi, 2022). When applied to process monitoring, these analysis techniques allow for the identification of faults and abnormalities in much higher-dimensional process data (Collier, 2023). Summary accounts of the most recent advances in fault-detection techniques can be found online. As a result of their superiority in characterizing large, complex data sets, projection-based methods like principal component analysis, partial least squares (PLS), independent component analysis (ICA), and canonical variate analysis (CVA) have dominated the literature on data-driven modelling (You & Chen, 2021; Sarlo et al., 2023).

Inferential sensors not only monitor processes but also make predictions about key variables by analyzing collected process data (Yu & Zhao, 2021). A lot of times, it's not practical or cost-effective to measure the crucial variables being predicted in an online setting. These forecasts help plants respond more quickly to process excursions, preventing substandard products, and are thus used in advanced control and quality monitoring. Dow, for example, relies heavily on inferential sensors for these applications. Numerous methods exist, but principal component analysis (PCA), multiple linear regression (MLR), artificial neural networks (ANNs), support vector regression (SVR), and Gaussian process regression (GPR) are the key ones (Ahmed et al., 2017). To account for nonlinearity, process drifts, and multiple modes, inferential sensors must balance the trade-off between model complexity and sensitivity. By focusing on the most important factors, feature selection helps reduce model complexity and yields more accurate predictions.

When compared to the conventional hierarchical PID-based control structure, the amount of process data needed for advanced control and control loop monitoring is enormous. New developments in advanced control, model predictive control, and plant-wide control have been summarized by (Chen et al., 2022). The effectiveness of plant operations can be evaluated with the help of strategies for monitoring control loop performance.

Advances In Data Variety.

Consistent and structured data sets are unusual outside of continuous processes. In batch processing, each batch may contain scalar, vector, matrix, or even tensor information (Yao & Ge, 2019). Due to factors such as inconsistent sampling rates, missing context, and inadequate instrumentation, the quality of the data is often subpar. Prior to applying the traditional methods used in continuous processes, data-driven models must first establish a consistent structure using dimensionality reduction and feature extraction techniques (Sandberg & Hultberg, 2021). Typical methods of pre-processing the data before modelling include unfolding, warping, and feature extraction. Inputs for multistage or multistep batch processes can be further categorized into phases or blocks to improve the results of the model's analysis. Inferential sensors for product quality in a batch sulphite pulping process and fault detection in a commercial fed-batch fermentation system are two examples of applications that make use of data from batch processes. Research and development in the chemical process industry have greatly benefited from the availability of large data sets thanks to the development of high-throughput experimental capabilities through laboratory automation (Di Vaio et al., 2020). Data from high-throughput imaging systems and online gas chromatography and spectroscopic analyzers are common components of these massive data sets. High-throughput experimentation, enabled by informatics methods, significantly quickens the rate of R&D (research and development) in many fields.

Business data (orders, sales, production, and customer demand) are generated in addition to the instrumental data from the manufacturing environment (Bascur & O'Rourke, 2020). Enterprise resource planning typically employs a hierarchical structure that partitions off sales, supply chain, production, and process control into their own distinct sub-functions. Improvements in numerical algorithms and processing speed have made it possible to quickly find solutions to problems of integrated scheduling and control that span multiple levels of the enterprise resource planning hierarchy (Božič & Dimovski, 2019). Minimizing the idle time between an upstream batch process and a continuous downstream process is the focus of research by (Torres et al., 2018). Data on future orders and how they will affect the plant's schedule is incorporated into the ongoing optimization of the process units further downstream. Timely transitions are achieved through the integration of scheduling, production forecasting, and real-time operational data (Ch'ng et al., 2021). It is also possible for the information to travel in the opposite direction, with a stochastic formulation of the planning and scheduling problem allowing for the incorporation of production uncertainty. In addition, Wright et al. suggest utilizing big data techniques to merge the planning and control phases of the steel manufacturing process (Wright et al., 2019).

When it comes to managing inventory and output, refinery operations follow a similar pattern (Moreno et al., 2020). Turnaround planning for large, complex chemical sites can be optimized with the help of maintenance data, such as equipment failure rates and reliability data when used within an optimization framework. Most of these uses can be traced back to elementary engineering and physics, as is evident from the reviewed literature. On the other hand, the operational teams have amassed a great deal of real-world, hands-on experience. Grey-box modelling, expert systems, heuristic systems, and fuzzy logic systems are just a few examples of the methods used to try to balance the data and the knowledge. A causal map built from plant process flow diagrams can aid in fault diagnosis, as shown by (Savage et al., 2021). For instance, (Kumar et al., 2017) modelled the temperature distribution of a methane reforming furnace using distributed temperature data to maximize the efficiency of the furnace. The information gleaned from this allowed for the development of a real-time optimization framework that has helped cut down on the furnace's temperature hotspots (Li et al., 2021).

2.3 Automatic Capturing of Manufacturing Data Using Smart IT Devices

Because of their widespread application in the measurement of energy consumption throughout the entirety of the manufacturing process, the benefits of the Internet of Things (IoT) technologies are coming into greater focus, especially across chemical industries (Kurniadi & Ryu, 2017; Yang et al., 2016). The monitoring of production processes in the manufacturing industry is becoming nearly more real-time because of IoT, and the seamless incorporation of Information Technology (IT) and data science (Cheng et al., 2018). The monitoring of energy consumption is one domain in which IoT technologies play significant roles. Some examples of such technologies include smart meters (Shah et al., 2020) and sensors (Li & Kara, 2017; Aruquipa & Diaz, 2022). To be more specific, smart meters collect data on electricity, gas, and water, while sensor technologies primarily capture data on energy consumption through the parameters of temperature, pressure, and so on. Still, the reality is that manufacturing presents several difficulties for energy management due to the complexity that results from the diverse ways in which energy is utilized across thousands of processes.

According to Chen et al. (2022), there are three levels of energy metering in factories. These three levels are the metering at the factory level, the metering at the level of the production line, and the metering at the level of the machine. (Velusamy et al., 2021) have developed a framework for IoT-based energy management to support the integration of gathered energy into the production management of an organization. This framework was developed based on the practices that are used in production management. In addition, an architecture for the real-time information capture of the Internet of Manufacturing Things (IoMT) has been developed to support better-informed workshop decisions (Cui et al., 2021). This was done to better inform workshop participants. In addition, Mourtzis et al. found that IoT can be applied in the energy management of products and that this application is currently taking place (Mourtzis et al., 2016). Because of this, the current real-time status of resources, as well as the data on the amount of energy consumed during the production process, can, in theory, be collected to improve energy-efficient decision-making (Parto et al., 2020).

Nevertheless, in contemporary manufacturing processes, measuring certain important variables in real time can be challenging due to the constraints imposed by either the process technology or the measurement technologies themselves (Yi, 2020; Gopal et al., 2023). Thankfully, soft sensors are utilized to find solutions to problems of this nature, while data analytics tools like Power BI can further be implemented to derive actionable insights. In contrast to conventional hardware sensors, a soft sensor is a combinatorial technology that consists of a mathematical model, data processing, and software techniques (Wang et al., 2016). The soft sensor model of a process that generates a virtual measurement to replace a real sensor measurement forms the basis of the soft sensor and is its most fundamental component (Tran et al., 2023).

Principally, there are two primary families of soft sensors, namely those based on a physical model and those driven by data. By applying the chemical and physical principles that underlie the process that lies between the key measure parameters and the easy-to-measure parameters, the physical model can be used to estimate these key measure parameters (Jamwal et al., 2022). However, a physical model is frequently unavailable due to the difficulty of the machining mechanism and the extensive amount of computational time required. Because of this, the data-driven model is an additional strategy for developing the soft sensor. A black-box model is known as a data-driven model, and it is based solely on measurements taken during an industrial process.

In the above modelling procedures, the relationship between the plant's inputs and outputs may be emphasized, while knowledge of certain complex processes may be ignored (Chan & Chen, 2021). This may be done at the expense of accuracy. A wide variety of artificial intelligence and machine learning techniques have provided some powerful modelling tools for the various data-driven models that have been developed in tandem with the development of more sophisticated analytical tools (Liu et al., 2022). Consequently, soft sensor methodologies are utilized to estimate these significant process variables. Despite this, most of the estimated variables are only used for controlling the product quality in an appropriate manner (Ammar et al., 2022). Rarely is there any research done about the analytical measuring and appropriate visualisation of the amount of energy consumed in extreme production conditions, an endemic manufacturing challenge that Power BI can improve when properly integrated

2.4 Enhancing Productivity by Saving Energy and Optimising Operational Efficiency

Energy savings and emission reduction are two important goals for manufacturing industries, particularly energy-intensive industries (EIIs), as they are under pressure from limited natural resources and growingly severe environmental problems (Ragab et al., 2022). EIIs are essential to the growth of the national economy and the global advancement of innovations and research. However, due to its massive energy consumption, energy stakeholders are seeking sustainable sources of energy, likewise, technologies that can monitor, measure, and regulate energy usage (Mendez-Alva et al., 2021).

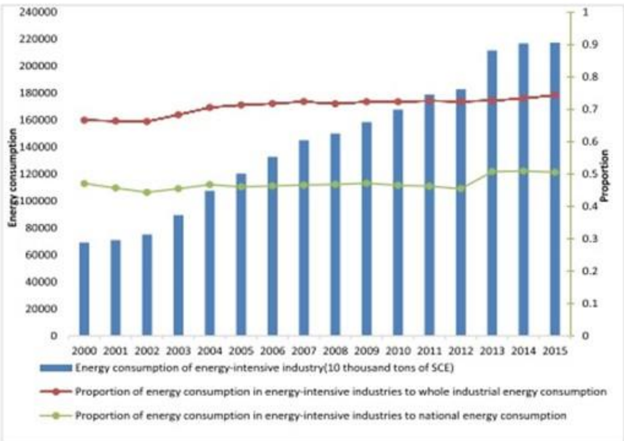

Figure 2-Increasing Rate of Energy Consumption over a 15-year period

In China for instance, industries that use a lot of energy are responsible for almost 51% of the country's total energy consumption (Zheng et al., 2022; Wang, 2022). It is essential for industries that rely heavily on energy to work toward continuously bettering their energy efficiency (Zuo et al., 2023). Production methods that are less harmful to the environment have been shown to be an efficient means of boosting energy efficiency and cutting energy use (Wang et al., 2022). However, studies by (Zhu et al., 2023) suggest that there is a lack of manufacturing data due to the difficult implementation of sensors in harsh production environments, such as high temperature, high pressure, high acidity, high alkalinity, and smoky environments, which hinders the implementation of the cleaner production strategy.

Improvements in productivity, dependability, and safety have been observed in the chemical processing industry as a direct result of the increased use of data (Artamonov et al., 2021). The goal of the energy industry going forward, therefore, is to meet the growing demand for power in a manner that is not only clean but also economical and environmentally friendly (Lena et al., 2022). Methods that are driven by data are utilized to improve the accuracy of estimating consumer demands, to enhance energy management, and lessen the negative impact on the environment. On the supply side of the energy industry, examples of applications for big data analytics include improving the efficiency of electricity generation, predicting plant outages, and forecasting energy consumption (Yan et al., 2023). When it comes to the demand for energy, understanding consumer patterns can provide useful information that can be used to influence consumer behaviour and, as a result, reduce energy consumption.

Fundamentally, big data analytics have been utilized in smart grid management, which also makes use of forecasting, real-time fault detection, load classification, and the identification of energy consumption patterns (Lin & Zhou, 2023). The sharing of information between power generation, transmission, distribution, and demand management is made easier by smart grids. Smart meters have a higher resolution, which allows them to collect real-time data such as device status and data regarding electricity consumption (Chen et al., 2022; Zheng et al., 2021). Customers can exert greater control over the amount of energy they consume because of the capabilities of smart meters, which include the ability to monitor and control household appliances, as well as the ability to communicate with other meters. Heat maps, 3D load graphs, and geographic information systems are useful for identifying issues in energy demand and play an important role in the role that visualization plays in identifying patterns and analysing information from large amounts of data, where visualization plays an important role (Ouchani et al., 2022).

In addition to gaining an understanding of consumption patterns, stochastic model predictive control has been shown in simulation to consider the unpredictability of the weather, to maintain occupant comfort while simultaneously lowering energy consumption (Zhang et al., 2022). Approaches from the field of machine learning have been utilized in the process of designing buildings that are powered by renewable energy sources to optimize the building's design parameters for thermal and visual comfort conditions (Toffolo & Ricardez-Sandoval, 2021; Psarommatis et al., 2022). As a result of their meteoric expansion, the proportion of the world's total electricity consumption that is accounted for by data centres has reached 1.5%. Computing resources (servers, storage devices, network hardware, and cooling systems), as well as physical resources, are among the factors that influence the amount of energy that a data centre consumes. In this regard, (Chai et al., 2022) a summary of the many different efforts that have been made to optimize the energy consumption of a particular data centre. (Şahin, 2022) proposes a method for managing the workload of data centres that is based on forecasting the amount of renewable energy that is available in addition to the cost of electricity.

Energy-intensive industries (EIIs) in manufacturing applications, also known as energy-intensive manufacturing industries (EIMIs), make use of expansive production facilities and machinery, and their energy consumption is significantly higher than that of any other industry (Wang et al., 2022). Both continuous flow and discrete flow manufacturing processes are included in EIMI's production chain. The interactions that occur between the two distinct types of processes make the modelling and analysis of energy consumption performance more difficult (Lee et al., 2022). Improving energy efficiency requires first gaining a comprehensive understanding of the patterns of energy consumption, which can range from a single process up to the entire production chain. However, gathering data on energy consumption can be challenging, particularly in the harsh production environments present in EIMIs (Starikov et al., 2021). Manufacturing industries may soon be able to use advanced information technologies such as radio frequency identification (RFID), smart sensors, and smart meters to collect data related to energy consumption, which will allow for energy savings and a reduction in product emissions (Zhu et al., 2021; Liu et al., 2022). This possibility presents a breakthrough in the development of new process control technologies and the enhancement of existing ones.

Modern-day EIMIs are characterized by the continuous generation of unprecedented volume and velocity of energy data from the process equipment, production process, and operation management. In Yu & Zhao (2021), the data consists of a combination of structured (for example, data on energy consumption that includes spatial, time, and energy dimensions) and semi-structured (for example, data exchanged between smart energy management platforms), and unstructured (for example, email notifications about energy use and interactions of consumers on social media about their energy use (Zhang et al., 2022; AlNuaimi et al., 2021). For example, energy consumption data includes spatial, time, and energy dimensions. These kinds of data pertain to the "big data" family in that they have a high volume, high velocity, wide variety, and high value. Additionally, such data on energy have a high volume (Che & Wang, 2022). Big data is a collection of data sets that are both too large and too complex to be managed and processed in an efficient manner using the technologies and tools that have been used traditionally (Nabeel M et al., 2020). A big data analytical architecture is proposed for cleaner production (CP) of complex products to conduct an in-depth investigation into the application of big data in manufacturing. This will allow for the creation of more complex products (Hirman et al., 2020).

According to the architecture, manufacturers are permitted to make use of sophisticated analytical tools to perfect the factors that have been demonstrated to have the most significant bearing on CP. The use of CP has been demonstrated to be an efficient method for achieving improved material utilization, decreased energy consumption, and decreased emission levels (Jin & Yu, 2022). Through the implementation of CP, the manufacturing industries have the potential to not only achieve the desired goal but also make significant headway in the areas of energy conservation and emission reduction by maximising its voluminous varieties of data (Majeed et al., 2021). CP has become an effective strategy that is resulting in the development of enterprise information processing, even though manufacturing industries are struggling to improve their sustainable competitive advantage (Khan et al., 2021).

Because of the vast amounts of data on energy consumption that are currently available, as well as the increasingly sophisticated techniques for analysing big data, a new field of research that draws from a variety of disciplines has recently emerged: the energy big data field. The increased research and development of energy big data analytics and its applications have brought about new opportunities for better comprehending EIMIs' energy utilization (Ma et al., 2022). Because energy, manufacturing, and big data all intersect, we now no longer consider them to be three distinct disciplines. This has led to the development of some new cross-disciplinary research fields.

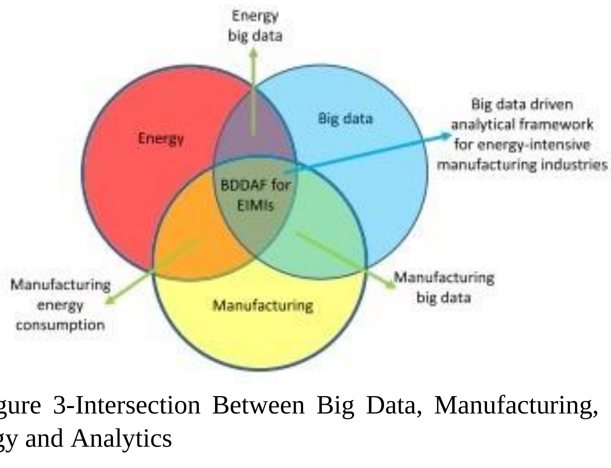

Figure 3-Intersection Between Big Data, Manufacturing, Energy and Analytics

The above visual illustrates the intersection of energy, manufacturing, and big data, as well as the positioning of interdisciplinary research areas. These areas include big energy data, manufacturing energy consumption, and manufacturing big data (Zhang et al., 2018). There hasn't been a lot of research done in the scientific community on the intersection of manufacturing, big data, and energy yet. A newly emerging area of research at the intersection of energy, big data, and manufacturing focuses on energy and big data analytics in manufacturing. As a result, within the scope of this study, we propose a big data-driven analytical framework (BDDAF) for EIMIs using Microsoft Power BI (Libby et al., 2022). This is to offer a theoretical and practical research direction within the academic and industrial fields. The following research questions are of particular interest because of the difficulty associated with the acquisition and mining of energy data.

How exactly does one go about establishing a BDDAF for EIMIs that takes a holistic, coordinated approach to the saving of energy and the reduction of emissions?

How can a framework for the overall perception and acquisition of big data in the energy sector be set up to sense multi-source and heterogeneous big data in the energy sector, particularly in harsh production environments characterized by high temperature, high pressure, high acidity, and high alkalinity, as well as smoky conditions?

How to mine large amounts of energy-related data for previously unknown insights to cut down on waste.

This research addresses these questions by proposing the large-scale application of Microsoft Power BI in analysing and visualizing material utilisation, product failure, and energy consumption in industries to improve management.

2.5 Improving Food Production with Data

The field of chemical engineering has been critically important in the development of various methods of disinfection (including pasteurization, food packaging systems, preservatives, and irradiation), as well as various types of reaction processes (brewing and fermentation) (Jeevanandam et al., 2022). The knowledge of unit operations, such as distillation, mixing, fluid and solid transfer, has also made it possible to scale up the production of food to an industrial level. Thus, according to (Hassoun et al., 2023), process automation and control have made it possible to produce food products and other consumables at a large scale while maintaining a high level of efficiency and quality. A new wave of computer-aided developments is becoming possible in the food industry due to recent advancements in high-throughput experimentation, new sensors, data-driven modelling, numerical solvers, and optimization algorithms (Kappelman & Sinha, 2021). This is all possible thanks to the era of big data. The types of data that have been encountered in industries that deal with food processing have been as varied as the industries themselves (Gupta et al., 2022). For instance, there is scientific data, such as genomic information on agricultural seeds and crops; engineering data in manufacturing plants and quality laboratories; and business data from suppliers, consumers, and the market (Morimura & Sakagawa, 2023)

Laboratory-scale research and development in the food industry, which is analogous to research and development in the chemical processing industry, is using data to develop better formulations, improve understanding of cause and effect, and speed up the product development cycle. In the process of formulating food, the use of techniques from the field of big data analytics enables the extraction of interactions and useful correlations from large data sets. For instance, Tamym et al. (2023) developed a bipartite network to model the relationship between ingredients that are commonly used in food recipes all over the world and 1,021 compounds that are known to introduce flavour in the known ingredients. This network was used to model the relationship between these two groups of ingredients. A bipartite network is a useful tool for quantitatively describing the qualitative aspects of differences between regional cuisines, such as flavour and nutritional content. Jain et al. (2022) later used this network model of food and recipes to computationally generate new recipes that satisfy existing preferences in nutrition and taste. These new recipes were created using the network model of food and recipes.

The analysis of large amounts of data also plays a part in the omics fields, which are becoming more prevalent in the evaluation of raw materials and finished products as well as the development of new processes in the field of food technology. Methods such as 2D electrophoresis, hyperspectral imaging, mass spectrometry, and various tailored chromatography techniques have all contributed to the generation of abundant high-dimensional data sets (Power et al., 2022). For these data sets to be effectively analysed, machine learning and multivariate data analysis are required (Ridzuan & Wan Zainon, 2022).

The development of Fourier transform infrared spectroscopy (FTIR) has resulted in the creation of numerous testing methods that are straightforward and non-destructive for a wide variety of chemical and physical components (Lucio & Ricardez-Sandoval, 2020; Wang et al., 2019). This work, in conjunction with the application of multivariate and chemometric models, has resulted in the widespread implementation of online analyzers throughout the chemical industry (van Kollenburg et al., 2020). Increases in the speed at which FTIR measurements are taken have resulted in an abundance of large spectra data that are abundant in process information. The use of FTIR in the field of food science enables the faster, more accurate, and better detection of contamination, adulteration, and food expiration on a large scale, which was previously uneconomical to perform. Because of these technological advancements, the scale of food quality monitoring and the speed at which it can detect potential hazards have both increased. In the field of food authentication, sensors based on spectroscopy can be combined with classification algorithms to determine the genuine country of origin of the food or product in question. For instance, using spectroscopy, (Power et al., 2022) analysed 200 different kinds of red and white wines sourced from 13 different regions across Australia. These regions include Tasmania, Victoria, New South Wales, and South Australia. To categorize their backgrounds, PLS discriminant analysis models were utilized (Saqline et al., 2021; Lucio & Ricardez-Sandoval, 2020).

Similarly, classification and regression techniques have been utilized in the detection of adulteration with lard in chocolate (Fernandes et al., 2022), adulteration with vegetable oil in extra-virgin olive oil, and the presence of high-density lipoprotein in hydrogenated products. A more exhaustive rundown of applications that make use of spectroscopy for detection and quantification can be found in the review that (Gordon et al., 2019) have written. Image data has become more widespread due to an increase in the accessibility of low-cost storage and computing resources. Because of this, quality control and evaluation procedures in the food industries have begun to incorporate image processing and machine learning techniques. Image processing techniques can be applied to data from charge-coupled device cameras, ultrasound, magnetic resonance imaging, near-infrared imaging, and electrical tomography in addition to optical images (Mourtzis et al., 2016). This is in addition to the fact that optical images can be processed. An image recognition system was used on an apple conveyor system in one of the studies, and it was able to sort apples into different grades based on the detection of surface defects. After pre-processing, the image is fed into a classifier based on neural networks (Velusamy et al., 2021).

2.6 Forecasting Customer Intents Through Power BI – powered Data Analytics

The manufacturing industry is under constant pressure to increase profitability in an international market that is becoming increasingly competitive (Zhang et al., 2022). Differentiation in this market is not tied to the products manufactured or the technologies utilized; rather, it is tied to the optimization of business processes. In this context, business analytics provides the opportunity to harness the knowledge edge and value hidden within enterprise information systems (Abbasi et al., 2016). This can be done to revolutionize innovation, improve supply chain management and production, accurately target marketing and sales efforts, and develop and manage profitable after-sales services. Even though the current body of academic research presents numerous specific applications in which business analytics techniques have been successfully implemented to improve specific business units, it is abundantly clear that an approach that encompasses the entire enterprise is lacking (Tamym et al., 2022). The current work outlines a method for achieving market leadership through the efficient application of business analytics. It suggests that attention should be focused on three obstacles that are becoming progressively more difficult to overcome (Omar et al., 2019).

The "standardization" of the data collection, aggregation, and storage processes is the first step that needs to be taken. Then, to create the ideal environment for business analytics to produce actionable results and recommendations, there must be an "organizational culture evolution" that moves beyond relying on one’s instincts and instead embraces making decisions based on empirical evidence (Rong et al., 2023). In turn, these must guide efforts to tackle new value creation and capture and secure market leadership through "business model innovation."

There has been a consistent pattern of continuing growth in the practice of basing current business decisions on the analysis of historical performance data. The term "business intelligence" (BI), which is frequently credited to Howard Dressner, but which was first coined by H. P. Luhn in 1958, refers to an objective understanding of significant business phenomena (Zerbino et al., 2021). It focused on capturing and querying data with a strong emphasis on reporting past events. It also provided managers with a fact-based comprehension of their organizations, allowing them to outgrow their reliance on intuition when making decisions. On the other hand, as time went on, the limitations of business intelligence started to become more apparent. It was designed to deal with relatively low volumes of static data that are typically segmented on older forms of information technology, which are now collectively referred to as legacy IT systems (Wang et al., 2022). In addition, it was a time-consuming process that focused on describing previous observations, but it did not offer any explanations regarding the causes of those observations, nor did it concern itself with the future of the company. As a result, business intelligence eventually grew to incorporate business analytics (BA), which is defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Phillips-Wren et al., 2021).

To put it another way, critical business data is analysed to assist businesses in developing a deeper comprehension of both their operations and the market in which they compete. In addition to answering "what happened," "how often," and "where," the focus shifted to providing explanations of "why," "what if this trend continues," "what will happen in the future," and "what is the ideal scenario" (ur Rehman et al., 2019). Previously, the focus had been on answering "what happened," "how often," and "where." These questions correspond to analytical tasks that are widely known as statistical analysis, forecasting, predictive modelling, and optimization. The terminology used here is specific to the topic being discussed. The deployment of these tools yields insights that are centred around business practices and methodologies, and those insights are used to make timely business decisions (He et al., 2022).

Within the non-financial business economy of the EU-28, nearly one-tenth of all enterprises can be found operating within the manufacturing sector (Lucena-Giraldo et al., 2022). In 2013, it was responsible for the employment of 29.7 million people and contributed 26.1% of the total value added that was produced by the non-financial business economy. In contrast to these optimistic figures, the manufacturing industry was described as having the second lowest level of profitability, with a gross operating rate of 7.9% (Fang et al., 2016). This rate is 1.6 percentage points lower than the average for the non-financial business economy. As a result of this, the industry is under constant pressure to lower costs and increase margins to compete with economies that are still in the process of developing. Because of this, manufacturing companies are making the transition to what is now commonly referred to as the "fourth industrial revolution," also known as "Industry 4.0" (Renugadevi et al., 2023). This revolution is characterized by the combination of automation with pervasive cyber-physical systems, which results on the Internet of Things (IoT) and massive data generation (Ma et al., 2022). After a report by McKinsey in 2011 indicated that the manufacturing sector had a competitive advantage over others regarding the availability of data and the talent to exploit it, stakeholders in the manufacturing sectors were encouraged to maximise the big data within their reach (Li et al., 2021; Rodrigues et al., 2022). The adoption of business analytics (BA), on the other hand, to derive insights and drive business decisions has been scant, which has opened a chasm between industry leaders and laggards.

Insights obtained through BA have the potential to raise an organization’s levels of productivity and competitiveness, as well as increase innovation and growth, and generate new ways for organizations to compete and capture value (Chai et al., 2022). By delivering information that is both timely and accurate, business analysis helps an organization become more agile (Dubey et al., 2022). In addition, the widespread utilization of data ensures transparency, helps in the discovery of market needs, reveals process or service variability, enhances performance, and contributes to the adoption of more environmentally friendly practices.

2.6.1 Research and Development

The current model of manufacturing emphasizes the use of global supply chains, in which an intricate network of suppliers provides the original equipment manufacturer (OEM) with the material resources necessary to bring a product to market (Akter et al., 2021). It is difficult to communicate effectively between the various parties involved in established value chains, and it is even more difficult to do so during the product development stages of new products. Therefore, research and development (R&D) and product design are the first areas in which BA may be able to assist the manufacturing industry (Lytras et al., 2020). In this context, the significance of the role played by technologies that promote interoperability along the value chain cannot be overstated. For instance, cross-enterprise Product Lifecycle Management (PLM)2 systems offer a platform for the co-creation of products by allowing numerous players along the supply chain to contribute ideas and designs (Han & Trimi, 2022).

This collaboration and experimentation shift the burden of innovation across the organizational boundaries of the OEM, which in turn helps with decision-making as well as the selection of appropriate suppliers while simultaneously reducing costs and the amount of time needed for prototyping. However, input from customers is essential to a fruitful design-to-value process (Heinen & Richards, 2020). Expanding the information pool regarding the requirements, applications, and solution technologies that would be most valued by a potential consumer and, in turn, are most important to securing success in the market is accomplished through open innovation, which is when customers take the lead in the design of new offerings (Ch’ng et al., 2021). The interaction between customers and businesses through social media is now being used in addition to traditional point-of-sale data and customer feedback. This has the effect of altering the relationship between market actors and increasing brand engagement.

2.6.2 Time-to-market

"Time-to-market" refers to the amount of time that elapses between the inception of a brand-new product and the point at which it can be purchased by consumers. In most cases, it is applied as a metric to determine a company’s level of competitiveness concerning product development [156]. The time-to-market (TTM) of new product offerings is something that the manufacturing industry is working on cutting down on for a variety of reasons. This is in response to the continuous shortening of product life cycles as well as the increased international competition. To begin, a shorter TTM not only extends the life of the sales cycle but also increases profitability as a direct result (Oakley et al., 2021). In addition, getting to the market before the competition allows the manufacturer to charge premium prices for their products, which results in increased revenues and a larger market share. It also provides the manufacturer with the opportunity to set industry standards and develop a technological advantage (Sumbal et al., 2017). In addition, a shorter TTM has been linked to increased flexibility in responding to shifting customer trends. This, in turn, results in higher levels of customer satisfaction and loyalty, which may lead to an increase in sales (Kleinaltenkamp et al., 2022). In addition to this, research has shown that a shorter TTM is associated with lower product development costs, a quicker break-even point, and improved operational and business performance.

2.6.3 Shortening product development through open innovation

Because between 80 and 90 percent of the TTM is consumed during the design phase, involving both suppliers and customers in the development of new product offerings has a significant impact on the TTM (Lamrhari et al., 2022). To achieve this goal, Chesbrough, in 2003, proposed a new model for research and development that he called "open innovation " (Lu & Chesbrough, 2022). It operates under the presumption that for businesses to advance their technology, they ought to utilize both internal and external ideas, as well as internal and external routes to market. Customers and vendors are two potential sources of ideas that come from the outside (Wu et al., 2022). Involvement of customers, also known as the “co-creation” of products by customers, provides businesses with access to a pool of information about consumer preferences and requirements, which is helpful during the decision-making process. After all, managers agree that analytics based on large amounts of data should be applied to gain insights about customers and to adjust, customize, and/or develop new service offerings (Chiu & Lin, 2022). Customers can voluntarily and freely provide feedback and information about the shortcomings of products through the process of customer co-creation (Aagaard & Rezac, 2022). The manufacturers can use this information to their advantage and make changes earlier on in the process of developing new products using this information. The participation of suppliers cuts down on the costs of development, helps with the standardization of components, ensures consistency between the design and the capabilities of the supplier, and reduces the number of engineering changes that are required (Yun et al., 2022).

By involving suppliers, the OEM gains access to knowledge and technical skills that are not housed within the company (Meyer-Waarden et al., 2023). This results in an increase in product quality and a decrease in the number of defects, as well as earlier identification of any technical issues and an increase in the number of potential solutions. However, it is essential to remember that businesses that embrace open innovation are likely to go through a learning phase before truly benefiting from faster development cycles (Scaliza et al., 2022). This is especially true when it comes to the process of structuring development agreements with organizations that are located outside of the company.

2.6.4 Supply Chain Management

Supply Chain Management (SCM) is another area in which Business Analytics can be applied to gain insights that will boost performance (Song et al., 2022). Promoting efficiency and reducing operating costs are two areas that are frequently cited as areas in which BA could be applied. This is true across the board for the manufacturing industry. According to the words of one of BA’s executives who was interviewed for this article, BA helps "build a stronger relationship with our suppliers as a means of shortening lead times and improving delivery reliability and certainty" (Dai & Liu, 2020). The unpredictability of consumer demand, combined with a lack of adaptability and responsiveness on the part of suppliers to meet ever-evolving requirements, constitutes one of the most significant challenges in supply chain management. The tendency for orders to suppliers to have a larger variance than sales is what’s known as the "bullwhip effect"(Malekinejad et al., 2022). This distortion tends to become more pronounced as it moves upstream, so it’s important to keep an eye out for it. A related effect, known as the "ripple effect," occurs when a disruption that cannot be localized spreads further downstream, affecting the SC’s performance and changing its structure (QU & RAFF, 2023). Given the "volume," "variety," "velocity," "value," and "veracity" levers that big data possesses, research has shown that business analytics has the potential to mitigate these effects (Hu et al., 2022).

2.6.5 Supply/demand match

A perfect matching of supply and demand requires accurate knowledge of customer preferences regarding the products and features that are perceived as the most valuable quantities that consumers would be willing to purchase (Bag et al., 2020). This is because perfect matching of supply and demand requires perfect knowledge of customer preferences regarding the products. In addition, the prices of products need to be set in a manner that strikes a balance between the costs of production and the prices that consumers are willing to pay (Vieira et al., 2020). This provides a clue about a few different tasks, including utilizing customers’ input to produce successful products, forecasting demand to manufacture the appropriate quantities, and setting appropriate prices. In the following paragraphs, a few examples of contemporary practices applicable to these fields will be presented (Nguyen et al., 2018). Using social media, market research can transition into customer co-creation. Traditionally, feedback from customers was gathered through market research, in which a representative sample of the population of the target customer would either respond to surveys, participate in focus groups, or interact with prototypes and describe their experiences (Sheng & Saide, 2021). Customers were considered an irrelevant third party during the product and innovation development process, which took place within the confines of the organization. These days, managers want to use BA to gain insights about their customers so that they can adjust, customize, or develop new products and service offerings (Tiwari et al., 2018). Numerous sectors are increasing their level of brand engagement by encouraging customer participation in product development by utilizing modern communication technologies (Wang et al., 2020).

Customers play an active role in the design of a new product or service through collaboration with manufacturers in an environment that is voluntary, creative, social, and occasionally competitive (Zhang et al., 2022). This term is used to describe the approach to product development that is referred to as "customer-driven innovation." The accumulation of a greater quantity of information in possession of the manufacturer relating to requirements, applications, and technical solutions constitutes the primary goal of an approach of this kind. This information is used by the producer to increase the "fit to market" of new offerings and their potential to capture monopolistic rents (Hader et al., 2022). In other words, the producer makes a profit. In this context, one thriving area of research examines the impact of social media on customer co-creation as a component of the innovation process (Karumanchi et al., 2022). The difficulty lies in gleaning useful information from the vast quantity of posts on social media, which are primarily made up of unstructured data in the form of text, audio, images, and video. Using social media analytics, which involves the collection, monitoring, analysis, summarization, and creation of visualizations of social media data, as well as the application of forward-thinking methods such as natural language processing and text mining, it is possible to extract intelligence that can be put into action from social media posts (He et al., 2020). These insights are a key source of information for the management of customer and stakeholder relations, product design, innovation, and marketing and are, therefore, an essential component of BA (Sundarakani et al., 2021).

2.6.6 Demand forecasting

The term "demand forecasting" refers to the process of making an accurate estimate of the number of units that will be sold (Wang et al., 2023). Demand forecasting is of utmost importance to produce items in sufficient quantities to maximize service levels while maintaining low capital investments on inventory. In addition, demand forecasting is used to support strategic decisions such as expanding capacity and transforming it, migrating technology, purchasing tools, and outsourcing (Doszyń, 2022). The likelihood of obsolescence, urgent orders, inefficient resource utilization, and the spread of the bullwhip effect along the supply chain is increased when forecasting is inadequate (Sun et al., 2022; Punia & Shankar, 2022). Demand forecasting, much like other aspects of the manufacturing industry, is highly variable across industry sectors and, therefore, cannot be easily standardized. This is the case for several reasons. For instance, the fast fashion industry manufactures products with short life cycles and brief selling seasons. These characteristics are characterized by impulsive purchase patterns, great demand volatility, and low predictability for a large variety of different items (Bag et al., 2022).

According to Omar et al. (2023) accurate demand forecasting can be challenging due to factors such as short selling seasons, high levels of uncertainty, and a lack of historical data (caused by continuous innovative product releases). Because of this, leaders in the industry found a compromise with the supply chain's responsiveness that enables them to complement forecasting and continue to function effectively despite high levels of uncertainty (Cillo et al., 2021). One good example is the Spanish company Zara, a retail chain (Bilińska-Reformat & Dewalska-Opitek, 2021). When figuring out how to distribute items among stores, they use shipment requests from managers and past historical sales to build demand forecasts. This helps them determine how to distribute items best. After that, these projections are entered into an optimization model, along with the assortment decisions and warehouse inventory levels, to determine shipment quantities while simultaneously increasing total sales worldwide. Therefore, agile supply chains (Omar et al., 2023) that are highly adaptable and interconnected, rely on information shared among all the partners in the supply chain and are closely connected to end-user trends have a competitive advantage. Under these circumstances, BA could extract previously unrealized predictive value from product and customer information and retailer sales and manufacturing orders (Gupta et al., 2022). This, in conjunction with vertical supply chain integration and a rapid response time, ensures that market leaders will turn a profit while simultaneously securing the shortest market lead times (Schoenherr, 2023).

2.6.7 Dynamic Pricing

Pricing a product or service is a challenging endeavour that requires careful consideration of several factors to maximize sales and profitability (Talón-Ballestero et al., 2022). These factors include a company's operating costs, supply availability, brand equity, and future demand forecasts. The use of dynamic pricing, in which the price of an item varies in real-time to account for fluctuations in market conditions such as demand, inventory levels, competitor offerings, and customer history, is a common practice that was initially introduced in industries where the short-term capacity (supply) is difficult to change (Li & Mizuno, 2022). Some examples of these industries include airlines, hotels, and sporting events.

According to (Prakash & Spann, 2022), dynamic pricing was initially introduced in industries where it took time to change the short-term capacity (supply). An increase in the availability of demand data, the emergence of new technologies that facilitate changing prices, and the availability of software for analysing demand data and dynamic pricing have all contributed to the proliferation of the adoption of dynamic pricing strategies (Dong et al., 2022).

These new technologies make it possible for retailers and manufacturers to combine information about sales with demographic data and the preferences of customers and then use this combined information to optimize pricing and markdowns and evaluate the effectiveness of promotions (Anton et al., 2023). Early adopters of dynamic pricing strategies have reported improved financial performance, a quick return on investment, and no negative impact on price image. This is because dynamic pricing strategies are more accurate in reflecting actual market conditions. However, it is of the utmost importance that pricing practices be completely transparent (Guizzardi et al., 2022). Although many customers are okay with dynamic pricing in response to changing market conditions, there has been pushback due to pricing based on the price elasticity of demand for individual customers (Yang et al., 2022; Keller et al., 2022).

2.7.1 Challenges in Implementing Data Analytics and Power BI in Chemical Engineering

Technical Challenges

It is important to remember that combining data and analytics is the secret ingredient for transforming raw data into actionable insights that can improve both business and operational decision-making (Yan & Wang, 2022). This section provides a concise summary of the technical challenges. The fact that not all data are created equal is the aspect of volume that presents the greatest challenge to users; users need skill sets in analysis to determine whether the data are meaningful. Users are required to filter out the noise to improve the signal when working with data sets that contain little information (Chang et al., 2021). Another important analytical skill is recognising when information is missing from data sets and designing experiments required to generate the correct data (Ma et al., 2022).

In terms of the variety of challenges that are presented, the chemical engineering community collects data in scalar quantities (such as temperature, pressure, flow, and concentration), one-way arrays (such as spectrum, chromatogram, and particle-size distribution curves), two-way arrays (such as image and gas chromatography with mass spectrometry), three-way and higher-order arrays (such as video and hyperspectral images), and text data (such as emails, operator log books, lab notebooks (Kamble et al., 2021; Dwivedi et al., 2022). The fact that all these data are stored in various sources, such as process historians, application and business databases, websites, email memoranda, and handwritten notes, makes the situation even more challenging to manage. It is not a simple task to combine all these different data sources to draw meaningful conclusions using analytics (Bag et al., 2021).

When it comes to the challenges posed by velocity, massive amounts of data are gathered in real-time at various time resolutions, ranging from milliseconds to hours, days, or even months. The first obstacle to overcome is choosing the appropriate level of real-time resolution for the analytics applications of interest (Chourasiya et al., 2022). A second challenge is to use real-time data to adapt the existing models so that they can incorporate new information and knowledge. This is necessary because most chemical processes are inherently dynamic.

The notion that erroneous patterns and correlations are more prevalent in the era of big data is one of the criticisms levelled against it the most frequently. This is often the case when analytics based on big data are applied to problems in chemical engineering in the absence of context and domain knowledge. First, principles are the guiding force behind chemistry’s processes. When developing a model with fundamental modelling approaches, domain knowledge is utilized, and the resulting model is frequently of a dynamic, nonlinear, and detailed nature (Chourasiya et al., 2022). The amount of money, time, and expertise necessary to develop such fundamental models can be substantial when dealing with complicated industrial processes. To generate insights, data-driven models can be used to complement domain knowledge; however, the literature has only reported a small number of these models’ successes (Corallo et al., 2022). Another one of the technical challenges that still needs to be overcome involves integrating the fundamental modelling and process knowledge with big data analytics tools.

Platform Challenges

The absence of a suitable software platform is a significant obstacle that must be surmounted to successfully implement and maintain big data analytics applications. To gather data, these applications require the use of multiple data sources, and to execute their algorithms, they require a computational engine that is fairly complex (Espinoza Pérez et al., 2022). When compared to the relative simplicity of conducting proof-of-concept demonstrations in an offline setting, the implementation of a tool online in such a way as to guarantee its reliability in an industrial setting is frequently more difficult (Azeem et al., 2022). Because of this, the business world needs to carefully weigh the trade-offs between buying standard generic software, which limits the use of advanced algorithms and making custom-made applications, which may be harder to maintain over time.

Culture Challenges

The papers surveyed in the five different industries all shared a common thread: the idea that there are multiple pockets of success in building a solid culture in the adoption of data-powered manufacturing (Eswaran & Bahubalendruni, 2022). When it comes to making use of big data analytics, each sector of the economy has its own set of benefits and drawbacks. Consider, for instance, the chemical processing industry in addition to the energy industry. The industry of chemical processing has a long-standing custom of relying on process data to control and monitor processes. Based on this foundation, recent developments in process control, real-time optimization, and integrated scheduling have further pushed the boundaries of efficiency and reliability (Mahmoodi et al., 2022). When contrasted with the energy industry, the chemical process industry is noticeably slower to react to real-time feedback provided by customers. For its part, the energy industry has demonstrated significant progress in estimating real-time electricity demands and the actions of consumers. In addition, the supply side has not yet found an effective way to use the information that was uncovered (Ma et al., 2022). There is a window of opportunity for different industries to work together and leverage one another on a more systematized level.

One of the more fundamental reasons for the observed pockets of success is the lack of a common driving force within and across industries designed to achieve success on an enterprise level. For instance, there is a scarcity of standard benchmark big data analytics problems that can be used to evaluate previously published works, and this is true even within the same research field (Fernández et al., 2022). This results in multiple approaches being published that show no significant differences in performance; in other words, it is a case of "reinventing the wheel." A good example of such a widespread motivating factor is the Netflix Prize, for which a benchmark problem was made public and could be solved by any interested participant (Valero et al., 2022). Because of this, an incentive and an environment were created to methodically benchmark the contributions of innovation in this field.

2.7.2 Solutions to the Challenges in Big Data and Power BI

The idea that the amount of data will continue to increase at an exponential rate is the defining characteristic of the era of big data (Li et al., 2022). There will be a wide variety of data coming in, and it will do so rapidly. Chemical engineers need to pay attention to both the growth of their workforce and the improvement of their analytics if they want their insights to grow exponentially.

Developing an Agile Workforce

It is becoming increasingly difficult for the community of chemical engineers to collect more data (volume) from a variety of sources (variety), and as a result, it is becoming increasingly difficult to use the appropriate data and tools (analytics) to make the appropriate decisions in real-time (velocity) (Tamym et al., 2022; Ma et al., 2020). This will necessitate the acquisition of additional skill sets in addition to the conventional education in chemical engineering. The field of data science is one of the most cutting-edge and rapidly expanding occupations of the twenty-first century (Azeem et al., 2022). A professional who possesses the technical skills (such as programming, statistics, mathematics, and model building) and the intellectual curiosity necessary to make unexpected discoveries in the era of big data is known as a data scientist.

Due to the worrisome insufficiency of data science professionals and Power BI experts assessed by (Smaldone et al., 2022), over 70 universities in the United States are offering master’s degree programs that range from one to two years in length in fields such as analytics, data science, data analytics, data engineering, predictive analytics, business analytics, and applied computational science. This is being done to meet the growing demand for data scientists (Viola et al., 2022). The training that graduates receive from these degree programs is necessary but not sufficient for them to address the opportunities presented by big data analytics in chemical engineering.

An interdisciplinary skill set is required, and it should not only include the approaches of big data analytics, but it should also include a traditional education in chemical engineering, which should include topics such as unit operations, thermodynamics, reaction kinetics, transport phenomena, and process control (Tian et al., 2022). It is recommended that data scientists receive their education in a bachelor’s or master’s degree program in chemical engineering that lasts for five years, with the fifth year focusing on topics related to big data analytics (Ardagna et al., 2021). This would prepare them to address implementation opportunities at the practitioner level. It is necessary to have training at the researcher level from a PhD program in chemical engineering to address the technical challenges in big data analytics that have been outlined. In addition, experienced professionals in the field of chemical engineering extraction who can incorporate Power BI at the industrial level are strongly encouraged to receive on-the-job training in big data analytics (Salvadorinho et al., 2020).

2.8 Literature Gap

The major difference between this research study and previous works is the integration of data analytics capabilities into Power BI to automate the processes of deriving profitable insights quickly and easily from production and sales data.

2.9 Definition of Concepts

Power BI

Power BI is a technology used in carrying out data analytics. It comprises the strategies and technologies used by enterprises for the data analysis and management of business information. Common functions of business intelligence technologies include reporting, online analytical processing, analytics, dashboard development, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics. BI technologies can handle large amounts of structured and sometimes unstructured data to help identify, develop, and otherwise create new strategic business opportunities. They aim to allow for the easy interpretation of these big data. Identifying new opportunities and implementing an effective strategy based on insights can provide businesses with a competitive market advantage and long-term stability.

Business intelligence can be used by enterprises to support a wide range of business decisions ranging from operational to strategic. Basic operating decisions include product positioning or pricing. Strategic business decisions involve priorities, goals, and directions at the broadest level. In all cases, BI is most effective when it combines data derived from the market in which a company operates (external data) with data from company sources internal to the business, such as financial and operations data (internal data). When combined, external and internal data can provide a complete picture which, in effect, creates an "intelligence" that cannot be derived from any singular set of data.

Among myriad uses, business intelligence tools empower organizations to gain insight into new markets, assess the demand and suitability of products and services for different market segments, and gauge the impact of marketing efforts.

BI applications use data gathered from a data warehouse (DW) or a data mart, and the concepts of BI and DW combine as "BI/DW" or as "BIDW". A data warehouse contains a copy of analytical data that facilitates decision support. Power BI technologies can be used to monitor the production process by placing the sensors at strategic points. For example, in a brewery, the sensors can be placed at the weighing machine to know the frequency at which the machine works, and the number of grains used, and another sensor can be placed at the bottling session to count the number of beers produced.

Power BI Data

Business operations can generate a very large amount of data in the form of e-mails, memos, notes from call centres, news, user groups, chats, reports, webpages, presentations, image files, video files, and marketing material. According to Merrill Lynch, more than 85% of all business information exists in these forms; a company might only use such a document once. Because of the way it is produced and stored, this information is either unstructured or semi-structured.

The management of semi-structured data is an unsolved problem in the information technology industry. According to projections from Gartner, white-collar workers spend 30–40% of their time searching, finding, and assessing unstructured data. BI uses both structured and unstructured data. The former is easy to search, and the latter contains a large quantity of information needed for analysis and decision-making. Because of the difficulty of properly searching, finding, and assessing unstructured or semi-structured data, organizations may not draw upon these vast reservoirs of information, which could influence a particular decision, task, or project. This can ultimately lead to poorly informed decision-making.

Therefore, when designing a business intelligence/DW solution, the specific problems associated with semi-structured and unstructured data must be accommodated as well as those for the structured data.

Automated Reports

Having a large amount of unprocessed data is as bad as not having enough data during your decision-making process. How can you take that data process it, and understand it correctly in your reporting processes? With Power BI, an organization can fully automate a company’s reporting needs to be done every week, hour, month, or year. This also allows you to filter your reports to as much as needed, allowing you to send specific insights for different recipients from a single dashboard without overwhelming them. You can prepare reports such as production performance analysis, trend analysis, comparisons for budgeted and actual volumes, sales forecasts, maintenance updates and production trackers. All you will need to do is tell your Power BI robots what information you need and when you need it. In this way, automated reporting can be an effective way of sharing insightful information with the right people at the right time.

Predictive Analytics

Predictive analytics holds significant value and has the potential to deliver great insights to manufacturing professionals. Because of this, many organizations in this sector are working hard to leverage analytics. The amount of data to be stored by organizations is increasing every minute, but beyond the collection or storage of the data lies the real challenge. It is to make good use of the stored data and process it to obtain insightful information that can be used for operational functions enabling a better decision-making process.

The adoption of a BI and analytics strategy enables manufacturing organizations to get timely and agile visibility through the production lifecycle, as well as drive flexibility in a fast-paced market. Power BI brings the predictive power of advanced analytic capabilities, including predictive analytics, data visualizations, integration, and data analysis expressions to allow users to get better results.

Power BI also helps an organization obtain insights into the daily business decision process of manufacturing companies by allowing users to get useful information from stored data to solve business issues. Users can create samples of predictive analytics from existing data to enable organizations to make data-driven decisions about their business.

Materials and Methodology

3.1 Materials

Data analysis and visualization in chemical and manufacturing industries can simplify complex facts and figures, transforming raw data into actionable business insights. The materials employed in this research project encompass all the equipment utilized, both the physical and non-physical ones. Because it’s a tech-based study, some of the tools used are non-material such as the major software and supporting application packages. The data sources and internet access required for the execution of this project are also non-tangible but remain core in the work. The primary physical and hardware materials used are the computers and their peripherals. Generally, the materials section will outline all the tools, equipment and facilities incorporated in this research which facilitated its completion and success. They are exhaustively discussed below:

1. Desktop computer, monitor and peripherals.
2. Laptop computer
3. Microsoft Power BI Desktop software
4. Data Source
5. Microsoft Office 365 applications
6. Microsoft Edge browser
7. Internet subscription

3.1.1 Desktop Computer, Monitor and Peripherals.

Desktop Computer

Figure 4-HP Compaq Desktop Computer

The desktop computer employed in this project is HP Compaq Elite 8300 SFF Intel Core i5 3rd Gen 4GB RAM 500GB HDD Windows 11 Pro Desktop. It’s a highly functional and super-fast computer running at 3.40GHz processor speed which facilitates faster processing of data. The efficient Intel HD Graphics 2500 card enabled a quicker rendering of visuals during the Power BI data visualization. The HP Compaq is a 64-bit operating system with an x64-based processor which implies that all the complimentary software and application packages to run must be 64-bit compatible including the Power BI desktop. Coupled with the updated Windows 11 Pro 21H2 OS (operating system) build of 22000.2360 which is the most current pack as of the time of this report, the computer had high performance and the ability to multi-task especially when it was necessary to open multiple tabs or applications at once. The 500GB hard drive provided adequate storage while the 4GB RAM was enough to support faster data processing. There were also multiple USB, HDMI, and VGA ports to which other peripherals like monitor, keyboard, mouse, Bluetooth, and Wi-Fi were connected.

Monitor

Figure 5-NEC MultiSync Computer Monitor

The NEC MultiSync EA273WMi system monitor was used as an output device in this project to provide a wider view and ease of data and information visualization. It’s a 27” extremely thin monitor with 1920 x 1080 resolution which aligns with its ultramodern design that enhances productivity during this project. Ambient lights and human sensors enforce a sustainable product concept while offering better ergonomics with 130 mm height adjustability. The ergonomic performance of the screen is further enhanced by the relatively large dot pitch for easy text readability and complements the excellent IPS image quality. The future-proof Display port, HDM, D-Sub and DVI-D.

3.1.2 Laptop Computer

Figure 6-HP Laptop 14-cf2xxx computer

As a backup tool for the research project especially for internet research and to gain a condensed view of the Power BI visuals, a small-screen laptop computer HP 14-cf2xxx was used. Laptop HP 14-cf2xxx is a 14-inch screen size PC (personal computer) popular for its powerful Intel ® Core™ i3 10110U CPU running 2.10GHz clock speed. It has 4.0GB RAM (random access memory) and 1TB storage and is powered by Windows 11 Pro Insider Preview (Evaluation copy, Build 23536 ni_prelease.230826-1546). Like the HP Compaq, it was paired with, this HP 14 is a 64-bit operating system with an x64-based processor. It comes with high-resolution graphics drivers for better graphics rendering and numerous ports for more connectivity.

3.1.3 Microsoft Power BI Desktop Software

Figure 7-Microsoft Power BI software

Power BI (Business Intelligence) is a Microsoft data modelling, analysis and visualization tool founded on the technological builds of Microsoft Excel spreadsheets, Structural Query Language (SQL) and PowerPoint applications. This is why users of Excel and PowerPoint find it more interesting as it combines the powerful and speedy calculations in Excel using (DAX-Data Analysis Expression) and PowerPoint's extensive visualization capabilities. The Power Query, Power Pivot, and SQL components also give Power BI its reliable analytical and data processing power. At its highest level, Power BI enables organizations and companies to pull raw data from numerous sources whether offline, on a database or cloud, and transform it into actionable insights that business owners, process engineers and project managers can implement, using a powerful, interactive, and easy-to-use user interface (UI). Generally, Power BI has direct connectivity to various data sources and types (CSV, Excel, Database, SQL, Azure, social media, etc.), the ability to compress data and extract only the necessary files and features, and varieties of visuals and report sharing features. Many users choose Power BI over other competitors like Tableau or Excel because it combines analytical, modelling and visualization capabilities found individually in others into one simple, powerful, and centralized dashboard (Model, Data and Report views). Microsoft Power BI come in Desktop, Mobile and cloud (Service) forms and can be downloaded through their website or on the Microsoft Store.

3.1.4 Data Source

The data files used in this research were obtained on Kaggle (Kaggle, 2024). Kaggle is a world-renowned data-sourcing community with millions of users globally. It collects, stores and shares datasets for data analysis, data science and machine learning projects freely. The data sources I used in this research are credited to Lemuel Adams (Adams, 2021) - plastic extrusion data, and Shivam (Shivam, 2021) - predictive maintenance data. Before being converted from CSV to Excel .xlsx, the PVC (polyvinyl chloride) extrusion and predictive maintenance data were 127 KB and 519 KB respectively.

3.1.5 Microsoft Office 365 Applications

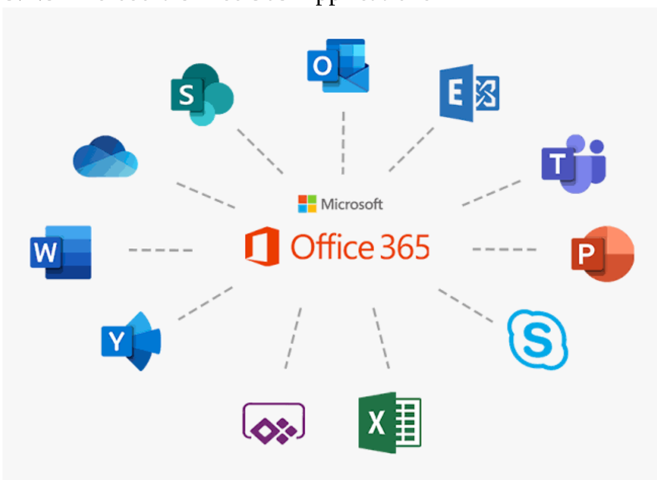

Figure 8-Microsoft Office 365 Suite

Microsoft Office 365 is a premium corporate version of Microsoft Office application packages. It's subscription-based (annual, monthly). Office 365 includes all the packages found in regular offices be it 2021, 2019, 2016 or lower versions. The 365 copy of Office has better features and capabilities that align with modern technological requirements in corporate and scientific settings. In this research, Microsoft Excel and Microsoft Word were used to review and inspect the data as well as compose this project report. Excel 365 provide the needed tool for the earlier analysis of the data before loading and transforming them with Power BI for further data modelling, analysis, and visualization. The Microsoft Word application was used in writing, editing, and formatting the research report as well as for citing and referencing sources using an add-in called Mendeley cite. With Word 365, it is easier to share the report and collaborate with editors and project contributors.

3.1.6 Microsoft Edge Browser

Figure 9-Edge, Microsoft's official browser

Microsoft Edge is the official browser developed and used by Microsoft. Before now, Windows OS ran on Internet Explorer browser until a few years ago when Microsoft released Edge and made it their standard browser across all their devices and OS especially Windows 10 and 11. Aside from the Desktop version, there a mobile and tablet versions of Microsoft Edge and all work seamlessly and can be synced across using a Microsoft account. It's powerful, fast, and powered by AI (artificial intelligence).

3.1.7 Internet Subscription

To gain access to information online, there was a need for browsing data. Throughout this research, internet subscriptions were used to access data online, from preliminary internet research and gathering of literature to downloading Power BI software and data sources. I also used an internet subscription to import other visuals that were not originally in the Power BI desktop such as the Scroller visual as will be seen later.

3.2 Methodology

The methodology will introduce and elaborate on the processes and methods incorporated in this project, detailing all the steps employed in the research, data analysis, and reporting which eventually produced the results obtained. In this project, both quantitative and qualitative methods (mixed) were applied in the sense that numerical data were used to derive actionable insights, with a qualitative analysis of the Power BI working principles. The data analyzed, modelled, and visualized were primary data sources obtained from Kaggle with a free license. The data sources were PVC pipes extrusion data set and predictive maintenance dataset respectively existing as CSV (comma-separated files) which were later inspected with Excel and converted to .xlsx (Excel workbook) format to avoid data loss and improve the table structure before loading into Power BI. Generally, this section will delve into and explain all the steps followed to arrive at the final results of this research. All the steps will be extensively discussed especially as it pertains to the actual data analysis, modelling, and visualization using Power BI. Therefore, the methodology will commence with data inspection, transformation, and modelling and proceed to analysis, visualization and finally reporting.

3.2.1 Data Inspection

Data analysis and visualization in Power BI often commence with a comprehensive study of the data source (file) even before defining the key objectives of the project. As part of the preliminary actions on the raw data, inspection plays a key role in ensuring the right type and form of data is used for the research. Therefore, data inspection is the meticulous survey and checks conducted on the data source to ascertain its veracity, size, authenticity, and usefulness to the project. During data inspection, the properties of the data such as the number of columns, rows, file size, measured quantities, variables, etc. are checked thoroughly before loading into Power BI. Most Power BI data analysts often skip this first and important step hurriedly to save time. However, because the key objective of this research is understanding how Power BI can be effectively utilized in process prediction, analysis, visualization and management, every detail and steps were considered and executed irrespective of their minuteness.

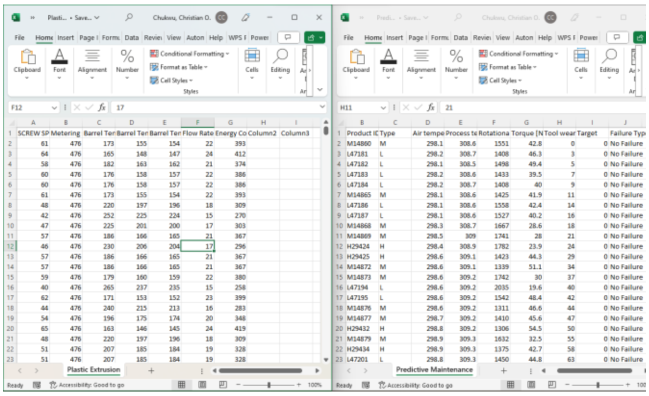

Figure 10-Data Inspection of the two CSV data sources

To commence with the inspection process, the two data files (PVC extrusion dataset and predictive maintenance dataset) were opened with the Microsoft Excel 365 desktop application. Afterwards, the csv file was “saved as” an Excel workbook in a data conversion process. This conversion is a recommended standard because, with the file existing in .xlsx format, it was easier to open, navigate and inspect the rows and columns. After the conversion, the file sizes for plastic extrusion and predictive maintenance increased from 127 KB and 519 KB to 179 KB and 565 KB respectively. The PVC extrusion file had 7 populated columns 2 empty columns, and 5001 rows total while the predictive maintenance file had 10 columns and 10001 rows. After the checks, it was confirmed that the data files contained the right columns and physical quantities required for a successful and accurate study of a typical PVC extrusion machine. They were therefore saved, and the spreadsheet closed.

3.2.2 Data Transformation

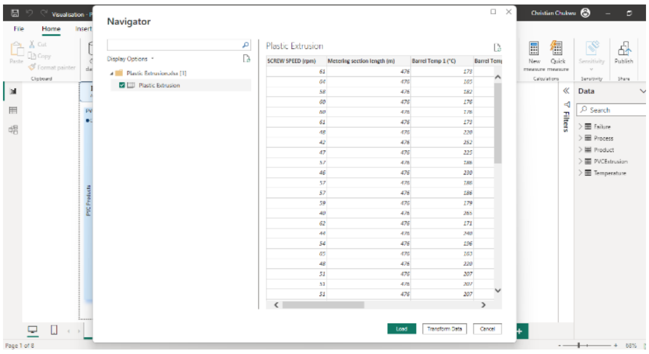

Figure 11-Data Loading and Transformation

The transformation of the raw data starts with opening the file into Microsoft Power BI after the previous inspection. Data transformation involves the process of changing the data source from its initial state and form to the required condition essential for efficient analysis and visualization. Power BI desktop application was launched before opening the extrusion and predictive maintenance Excel data in the application. To grab and upload the data files, the “Get Data” button was used. Get Data is located in the Home tab and allows you to upload data into Power BI from numerous sources such as Excel Workbook, Power BI datasets, folders, Dataflows, website URL, SQL server, text/csv, SharePoint, Azure, and many other channels.

In this project, the folder and Excel workbook options were used to introduce the data files. After bringing the data into Power BI, they’re neither yet saved nor loaded. At this stage, the files were reviewed for the last time to ensure they were the right files and data source for the project. After confirmation, they were either loaded or transformed. In my case, they were transformed before loading. Data transformation is recommended before loading because this enables the analyst to clean and shape the data before finally loading and saving them in Power BI.

The process of data cleaning entails removing unnecessary columns, duplicate and empty cells, and data with errors. This goes along with shaping and profiling in which the tables were properly checked for quality. The data types (date, whole number, decimal number, text, etc.) of each column were checked and corrected. It was also a stage in which the columns were renamed and formatted. The naming and renaming of columns during data transformation before data modelling and analysis is extremely important as it enhances efficiency and accuracy as well as ease of referring/calling tables while writing DAX (data analysis expression) codes.

During the data cleaning and shaping, it’s very easy to retrace steps by using the “applied steps” feature. With the applied steps, some steps can be undone if there are noticed errors. It also enables faster editing of steps for example If a column or query were wrongly deleted or renamed. While a column can be renamed during data transformation, queries and tables can also be renamed or deleted in this stage. Also, during data transformation, columns are split, sorted, filtered, or grouped. The two datasets used in this project underwent these processes to eradicate the empty columns, duplicates, and tables with errors. After the data transformation, the datasets were then loaded into Power BI, the changes were applied, and the project was finally saved.

3.2.3 Data Modelling

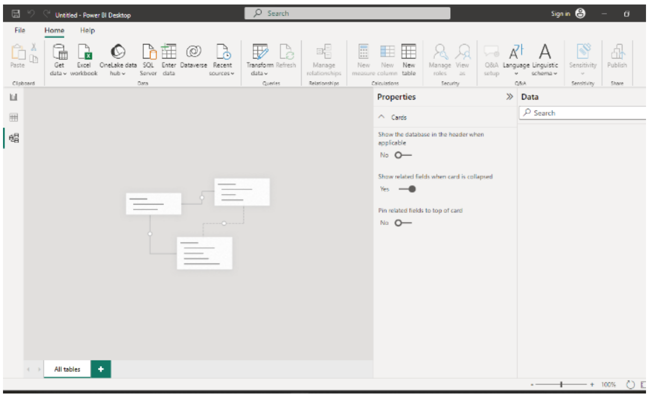

Figure 12-Power BI Model View

The modelling of the two datasets began after the transformation. Now that the cleaning, shaping, and profiling processes confirmed the veracity of the dataset as well as improved its quality, they were then modelled in the model view. Data modelling is making the data in Power BI as accurate, intentional, and purposeful as possible. During the data modelling, relationships were created across different fields and tables by merging and appending related tables and data types. It provided an opportunity to expand the field size of the dataset. The initial fields were plastic extrusion and predictive but after the modelling through query merge, the data set was expanded to obtain PVCExtrusion, Process, Temperature, Failure and Product fields respectively (see the Power BI modelled star schema in the results chapter)

PVCExtrusion here is the FACT table while Process, Temperature, Failure and Product fields represented the DIM (dimension) tables. During this project, it was unavoidable to break the dataset down into tables for better analysis and visualization. The FACT table is usually one and often keeps data that might be aggregated in the reporting visualization. In contrast, the DIM tables can be as many as possible. DIM tables store descriptive information that can slice and dice the data in the FACT table. The FACT tables usually contain key data that is compared against supporting data located in the DIM tables. The combination of the FACT and DIM tables forms a relationship. In my case, the star schema relationship was formed by placing the PVCExtrusion field (FACT table) at the centre of the DIM tables (Process, Temperature, Failure and Product fields).

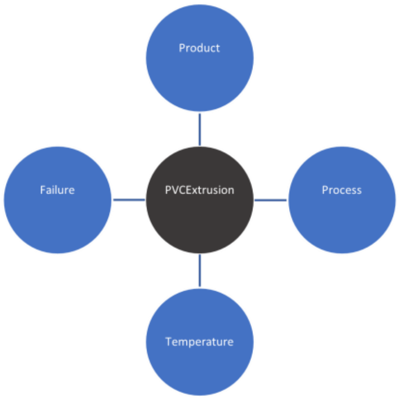

Figure 13-Star Schema of the Data Model

The essence of the DIM tables was to group similar and related columns into one or more tables using common keys. This process was possible using the merge feature. During column or table merge, one could merge two or more queries as new and different queries with a new name or simply merge into any of the existing ones without creating a new query. However, for merging to be possible, a common key was created in both the plastic extrusion data set and the predictive maintenance dataset. In power BI analysis and visualization, it’s a tradition that both tables ready for merge must have common keys. Specifically, the target columns must have the same data types even if not the same column titles. For example, a column with texts cannot be merged with another that contains whole numbers.

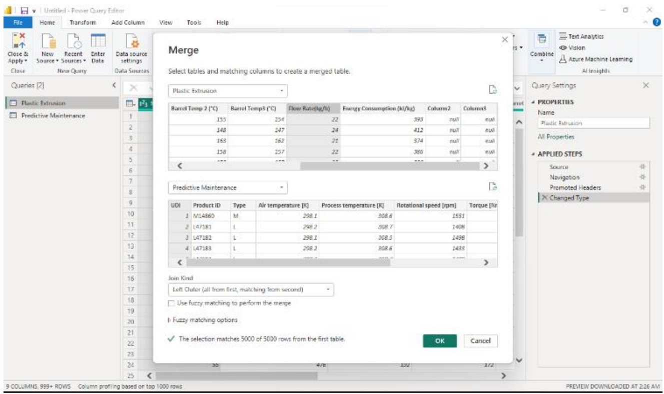

Figure 14-Merging Queries in Power BI using Key Columns Merging Queries in Power BI using Key Columns

Merging works perfectly when there are the same or very similar data or columns on one or more tables. Reiteratively, a key field is an important field that makes the data to be merged identically (it often appears as an ID or index number). Therefore, when a DIM table doesn’t have a key field, add one by going to the Add Colum tab and then add an index column counting from 1. Summarily, one of the golden rules of data modelling in Power BI observed during this stage of the project was not to have FACT and descriptive columns in the same field or table. Thus, by breaking and separating the tables into FACT and DIM, the performance of the dataset was optimized.

3.2.4 DAX – Data Analysis Expression

Data Analysis Expression (DAX) is an effective mathematical and analytical tool that provides the needed tool for statistical analysis and the addition of more tables and columns. is an elegant and easy-to-learn formula language used in Power BI, Power Pivot and SSAS Tabular to add analytical value to your data model. DAX improves data models by allowing users to extract more value from their data and make more informed business decisions. Microsoft specifically developed DAX to support a large user base. DAX is much easier to learn than traditional technical languages, making it an ideal language for users who don't come from a technical background but want to do their own Self-service Business Intelligence. DAX is often compared to an advanced version of Excel, having a high-end capability of managing and manipulating data. Many DAX functions are similar to Excel functions, which means new Power BI users can leverage their existing Excel knowledge to make an easy transition to writing and authoring DAX formulas. While there are similarities between DAX and Excel, the two languages are not interchangeable.

DAX is a functional language, which means formulas are constructed by applying and composing various functions. The functions can contain other nested functions, conditional statements, and value references. Execution starts from the innermost function, or parameter, and works outward, making formatting important. DAX works with data that is stored in a tabular data model. These models are comprised of one or more tables, each table containing columns and rows of data. There are two primary data types: Numeric and non-numeric or other. Numeric includes integers, decimals, dates, and currency, while other include strings and binary objects. If a function works on a number, it works for any numeric data type. While you can create Power BI reports that show valuable insights without using DAX formulas, creating effective DAX formulas will help you get the most out of your data, providing insight and solutions that might be missed with typical analysis.

Calculated Columns and Calculated Measures

Calculated columns are primarily used to add new columns to a table providing more ways to describe and break down the data. For example, you may add an age column to a customer table so that sales and profit margins can be analyzed and broken down by age demographic. Another common use case for creating calculated columns is to create a unique key on a table, which may be necessary to define a relationship between two tables. In this research, calculated columns were used to expand the measures, variables quantity and quality of the dataset by creating new columns to better understand the data. Some of the added columns were indexes and key columns throughout the PVCExtrusion, Product, Temperature and Process tables. Two extra and very important DAX calculated columns were added to the Failure table namely Alarm, Comments, and Action. These DAX-powered columns are intended to provide more clarity to the dataset and enable process controllers to monitor the production, receive feedback quickly and know the right actions to take.

Calculated Measures are dynamic calculations that recalculate depending on how a report is viewed or filtered. For example, if a user changes a time-range slider on a report, the measures on that report would be recalculated to reflect the time-range selected. Unlike calculated columns which are calculated during processing of the data model, measures are calculated at runtime when a report is opened or when a user interacts with the filters on a report. Therefore, the results of a measure are always changing and are not stored in your database. Calculated measures are different from columns in quite a few ways as shown in this table.

3.2.5 Data Visualization

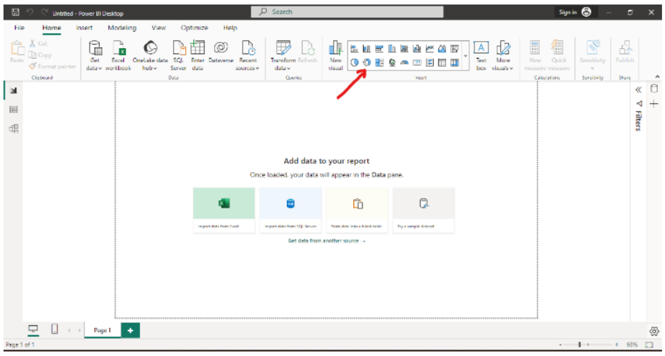

Figure 15-Advanced Home View of the Report View

The data visualization capability of Microsoft Power BI is a core and outstanding lure for most data analysts. It's the first feature that anyone would easily and quickly identify. Power BI has numerous kinds and forms of visuals for presenting data. When data is properly visualized, decision-makers and the audience can then easily understand the key outcomes of the data analysis and be able to make data-backed decisions. Since this project centred on the application of data analytics in process predictions, analysis, management, and visualization using Microsoft Power BI, favourable attention was allotted to the report view page. The right visuals such as line and stacked column charts, pie charts, line charts, scrollers, clustered column charts, card visuals and slicers were maximized in effectively visualizing the data.

Some of the key focus areas in analyses and visualizing the data were to understand the relationships between all the variables especially the impacts of other physical conditions such as process temperature, rotational speed, screw speed, flow rate and even metering length on the failure type of the

PVC materials and their energy consumption. Therefore, the right visuals were appropriately inserted to match the different measures. In the report view, there are eight pages of reports with each one focusing on a particular process condition and their impacts on the materials failure. As a matter of fact, with the right visuals, identifying the causes of the failure of the PVCs during the extrusion process was straightforward.

To create any report, various visuals are selected from the visuals pane and data is dragged from the data pane into the canvasses. Depending on the kind of visual selected, there are options to add aggregations, filter the visuals and format the columns and rows or the entire visualization. Power BI further offers the ability to switch between visuals at any stage of the visualization. The formatting feature facilitates the editing of visual size and style, title, callout values, category labels and cards. There is also a very helpful visual in the insert menu called Q&A that creates an interactive atmosphere between the report user/viewer and Power BI. With Q&A, anyone can ask questions regarding the entire data and receive detailed responses. This feature is essential, especially to a novice or an audience who wants to extract quick information from the visualization.

Similarly, another important visual that boosts the efficiency of Power BI reports is the slicers. Slicers facilitate a fast and efficient sorting and filtering of data by slicing through the visuals. When slicers are inserted and a particular data, variable, table, or measure is selected in the slicer, the entire report view is filtered to show only the information for the selected value. This is an essentially useful capability that enhances user accessibility to the results of the data analysis and visualization without sieving through the entire voluminous information.

3.2.6 Reporting, Insights Communication and Decision Making (Process Control)

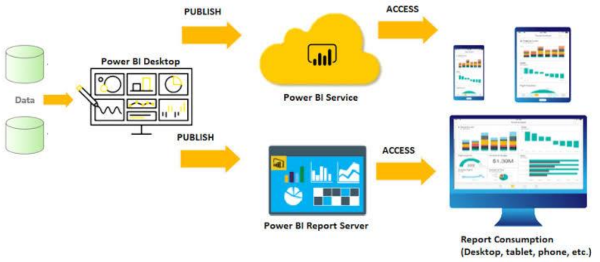

Figure 16-Publishing and Sharing of Power BI Reports

The last step in every Power BI project is always reporting and communicating the analysis and visualization findings to an audience. In business settings, Power BI developers and analysts communicate their findings to managers and directors who in turn translate them into decisions. Thus, the essence of any Power BI project is to help organizations, companies, and industries understand their data and use the findings to influence decision-making. Without properly sharing the outcome of the project, the entire lifecycle of the analysis and visualization becomes futile. Visualizations, Q&A, publishing and sharing of the published report demonstrate a completed BI project.

As process engineers, understanding the results of the Power BI project is critical in making core decisions. In this research, emphasis was placed on adopting the appropriate visualization that engineers can easily understand and implement. Instead of just one page of the report, 8 pages were built to detail each process measure and their contributions to the failure of the PVC pipes during extrusion. The pages are process summary, temperature, flow rate, torque, tool wear, energy consumption, PVC failure, and process control. They are elaborated and discussed in the results and discussion section of this report.

After completing a Power BI project, it’s either published to the Power BI service, saved as a Power BI project file, or converted into PDF (portable document format) for sharing. The essence of publishing and sharing BI reports is to reach more audiences who need the results to understand the production process. In my case, the reports were published, converted, and shared with the chief manager, directors, production engineers and other process control technicians. Afterwards, the concerned persons utilized the report in adjusting the process conditions as required to optimize production, minimize waste of the PVC raw materials, and save energy expended in the manufacturing of faulty/failed products.

Results and Discussion

4.1 Results

The result of this project cut across the data model, DAX calculations, and visualizations. These three components make up the findings of this project and each one is distinct in both methodology and impacts. They will be individually evaluated sequentially according to their order of execution during the actual data analysis and visualization in Power BI. The results of this project are extensive and inexhaustive, but the key findings shall be incorporated and highlighted to provide a comprehensive report to the audience and a potential user of this work.

4.1.1 Model building

Modelling in Power BI is a process of creating relationships between tables, queries, and fields to indicate connection and enhance further analysis and visualization. To create a clearer model structure, this project adopted the star schema approach in which the FACT table is centralized and surrounded by descriptive tables as seen below.

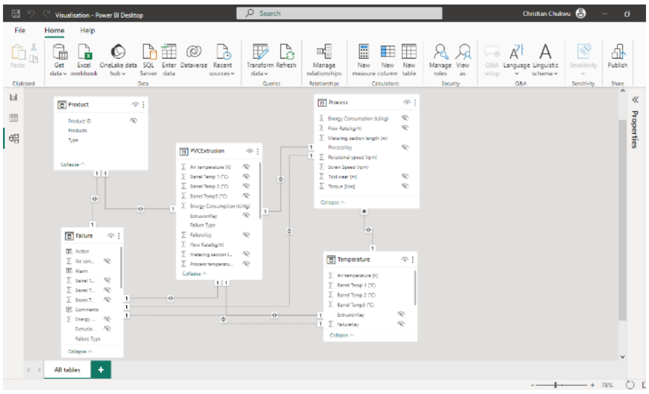

Figure 17-The Modelled PVC Extrusion and Predictive Maintenance Datasets

The PVCExtrusion field contains the FACT tables. These are numerical and primary data which contain key information required for an effective study of the PVC extrusion process. Some of the important tables contained therein include the material flow rate (kg/h), tool wear (m), torque (Nm), rotational speed (rpm), energy conversion (kJ/kg), failure type and product type. These are the fundamental measures of this research which are complimented by the DIM field values (air, process and barrel temperatures, product ID). As cited earlier in the methodology, the FACT and DIM tables serve varying purposes often during the visualization. Aside from improved dataset quality, breaking down the tables enhances data categorization and grouping.

During the visualization in the report view of Microsoft Power BI, the tables and variables in the FACT table are compared against those in the DIM tables. For instance, on the Temperature page of the Power BI report, failure types (No failure, overstrain failure, power failure, etc.) were compared alongside the process temperature to understand how the temperature gradient of the extruder influences the type of failure obtained at each temperature increase or decrease.

4.1.2 DAX Analysis

All the DAX calculations were performed within the Data View of Power BI. The Data View section of the Power BI dashboard is where major data analysis expressions and computations are made. It offers the ability to directly add new columns and tables. More importantly, DAX expressions (codes or programs) can be written here to calculate new columns and tables. Recall that DAX is to Power BI what MATLAB language is to the MATLAB application. DAX expressions make use of functions, operators, and constants to perform pure mathematical calculations and statistical analysis at the speed of light. During this project, more columns were added to various tables to expand the data set and build new measures essential in subsequent analysis and visualizations as shown below.

Comments =
IF(Failure[Failure Type]="No Failure", "Everything is perfect",
IF(Failure[Failure Type]="Power Failure", "The power is down",
IF(Failure[Failure Type]="Overstrain Failure", "Material under intense strain",
IF(Failure[Failure Type]="Tool Wear Failure", "Equipment wearing out",
IF(Failure[Failure Type]="Heat Dissipation Failure", "Heat supply is excessive",
"System automatically adjusting")))))
Alarm =
IF(Failure[Target] = 0, "Normal",
"Critical")
Action =
IF(Failure[Failure Type]="No Failure",
"No Action Required",
IF(Failure[Target]=0, "No Action Required",
IF(Failure[Target]=1,"Adjust System Condition",
"No Action Required")))

This DAX expression generated calculated columns for Alarm, Comments and Action respectively as shown in the table below.

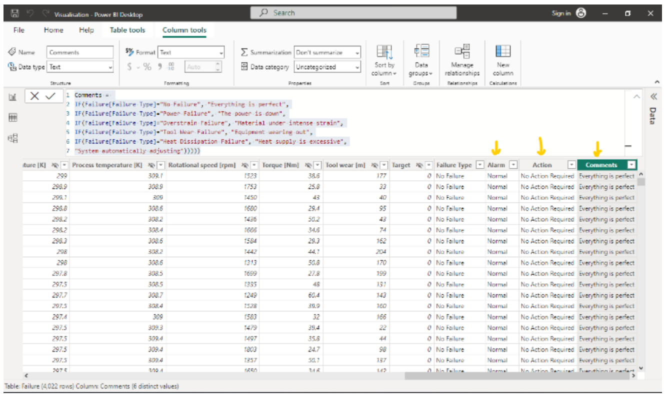

Figure 18-Calculated Columns for Alarm, Comments and Action

As shown above, some of the newly calculated columns include Alarm, Comments, and Action. They were added to the failure table to account for the technology systems that notify process controllers. Specifically, alarm sounds warnings if there is an impending material failure, the comments column returns feedback on the situation inside the extruder while an action is performed by an automated error tracer and corrector which is expected to fix the problem. If the system functions perfectly, an alarm technology powered by sensors is expected to notify control engineers who activate the actuators that immediately locate the problem in the system and fix it. For an AI (artificial intelligence) powered PVC extruder (as I propose), when an alarm sounds, the AI detects the source of the error and informs the controller. The controller then activates an error correction system that adjusts the process conditions whether it's temperature, flow rate, rotational speed, or screw speed.

4.1.3 Data Visualization

Data visualization was the last stage of this Power BI project. With several visuals available, the first task of this stage was choosing the most appropriate visual for each field or visualization. A line graph is best suited for data values that show gradients. Bar charts and clustered columns are alike. A pie chart also is recommended for tables that illustrate the percentage increase. To get started with the visualization, charts are picked from the visual column. You can simply click on it or drag and drop it into the canvas. Proceed to drag the appropriate data from the data page. You may also add more data to the various axes and slicers. Afterwards, proceed to add card visuals and specialized slicers that will enable you to sort the visuals.

Below are the 8 report pages of this research with each page accounting for a single measure, often compared to the failure type of the extrusion process. Further explanations on the relationships between the variables in each visualization is discussed in the discussion section.

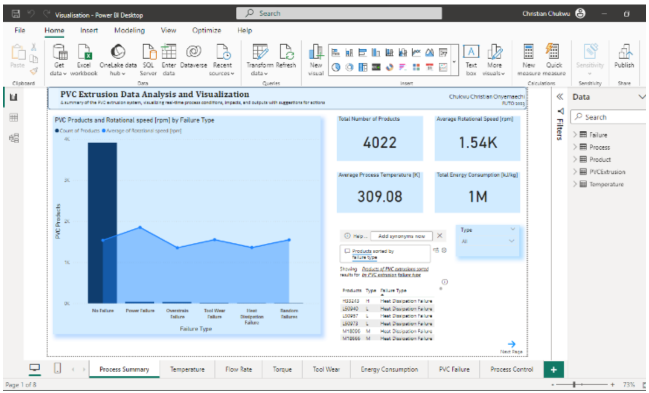

Figure 19-Process Summary Visualisation

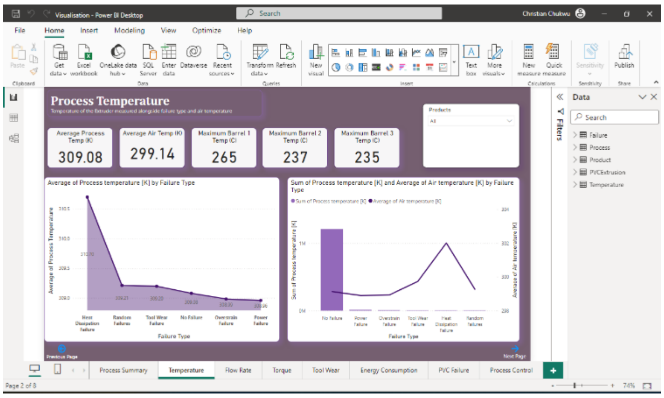

Figure 20-Temperature Visualisation

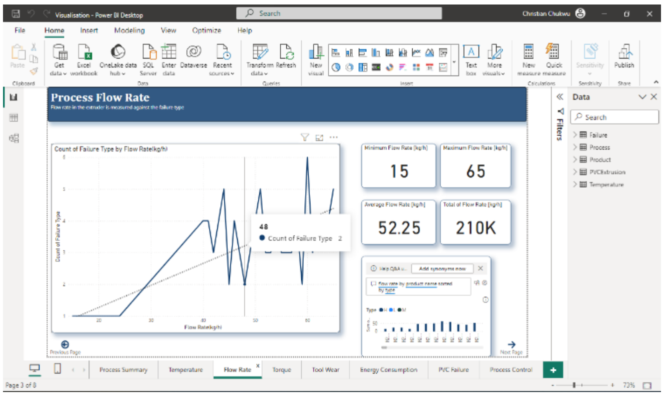

Figure 21-Flow Rate Visualisation

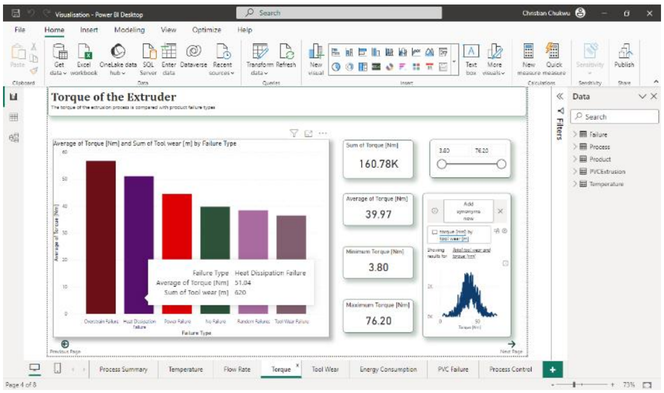

Figure 22-Torque Visualisation

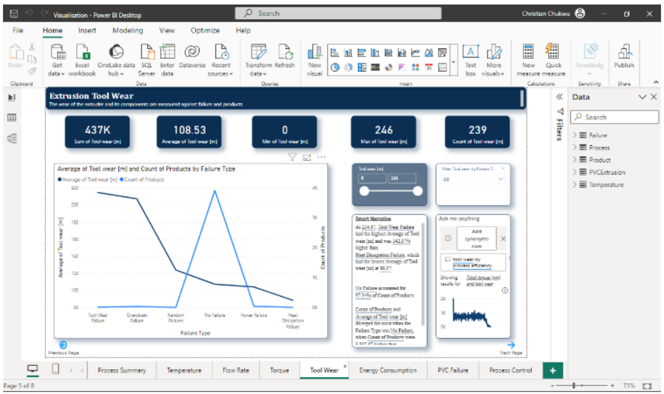

Figure 23-Tool Wear Visualisation

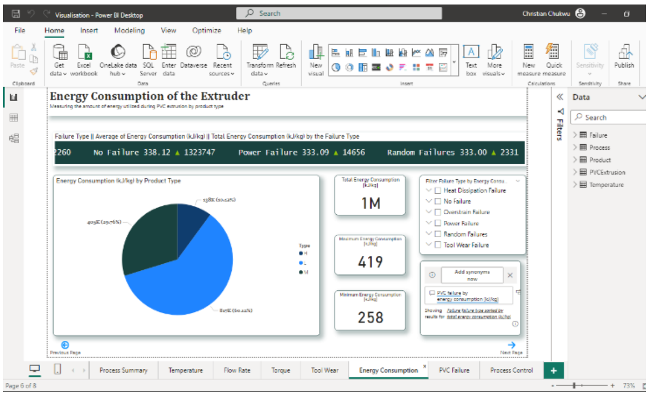

Figure 24-Energy Consumption Visualisation

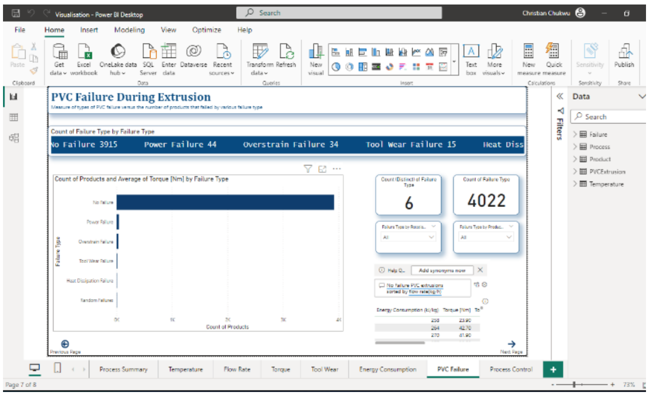

Figure 25-PVC Failure Visualisation

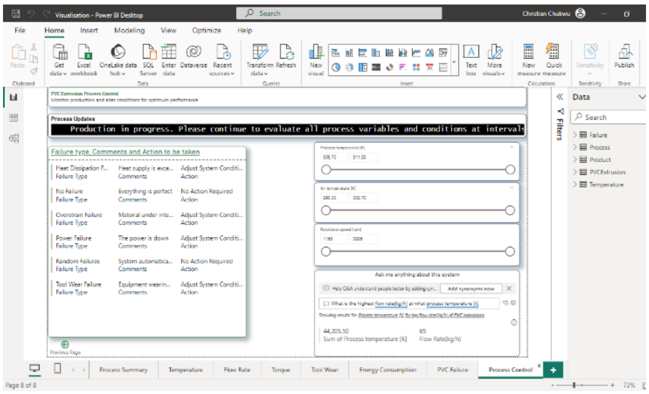

Figure 26-Process Control Visualisation

4.2 Discussion

4.2.1 Modelling

This section will elaborate on the findings of the results in detail and add more clarity to the points established in the methodology. The analysis, modelling and visualization of the raw extrusion and productive maintenance data produced three basic results: data model, calculated columns, and eight visualizations. The data model is a star schema showing active and inactive relationships between PVCExtrusion and Process, Temperature, Product and Failure tables. Each is connected by unique values. There's a one-to-one (1:1) relationship existing between the PVCExtrusion (FACT table) and Process table using the ProcessKey created in the Process table to match an existing key column in the PVCExtrusion table. Similarly, there are other one-to-one relationships between the PVCExtrusion table and the Temperature, Failure and Product tables respectively linked y unique identities which vary across the fields.

4.2.2 DAX

In the Data View, the DAX calculations were used to create new columns (alarm, comments, and action). With the help of DAX expression, lines of code were written in a matter of a few minutes in the DAX editor. Using the Comments column as an example, the expression writing began with naming the table (Comments) followed by the equality sign and the main statistical expression that computed and populated the DAX column. Because it's a conditional column, a conditional statement was used (IF). In the second line of the expression, IF (Failure [Failure Type] = "No Failure", "Everything is perfect", Power BI DAX goes to the Failure table/query to find the Failure Type column and locate the cells containing No Failure. It then returns and saves the answer before proceeding to the next line. On the 7th line where the expression was closed with five brackets, DAX finally returns the complete answers for all the lines and then populates the Comments column with the right responses. In a case where there is an error in the DAX expression, the table is either filled with the #ERROR or no computation is done at all. However, the Power BI error detection system will always return error messages and potential solutions. Notably, while writing DAX codes, IntelliSense, Power BI's resourceful suggestion system often guides one with suggestions and options to choose from while typing.

Generally, DAX expressions are very handy but note that while the calculated columns add the new columns to the table, calculated measures don't. instead, all calculated measures are viewable only in the report view and can be used in the visualization even though they won't be stored in the project. If there are columns and tables are not needed in the report and visualization, they are switched off or hidden. This is recommended especially if there are numerous datasets or unrequired data created earlier. The hidden tables and queries won't be loaded into the data model and visualization.

4.2.3 Visualization

The visualizations in the report view show all eight pages sequentially arranged. Each page presents unique measures, has different objectives, and serves varying purposes. They are individually discussed below:

1. Process Summary

The process summary page shows a comprehensive and condensed description of the entire extrusion visualization in one view. Here, the failure types (no failure, power failure, overstrain failure, tool wear failure, heat dissipation failure, and random failure) are plotted against the various PVC products. The values on the y-axis represent the average number of products that failed while the x-axis has all the failure types. Note that all the products had failure values, but not all failed. The “no failure” products are the only good ones that were extruded successfully. The remaining plastics had one fault, or another caused by either power failure, overstrain, tool wear, heat dissipation and random failures. The third line y-axis contains rotational speed (rpm) table values. From the visual, it’s noticeable that about 3,915 products did not fail which accounted for most of the products. Considering the lengths of the individual failure type columns, “no failure” is the tallest indicating that a huge number of the products were not faulty.

44 products failed due to power issues, 34 failed due to overstrain, 15 failed due to tool wear, 7 failed due to heat dissipation and only seven products failed due to random factors. The card visuals by the right of the visualization summarize key points of this page: there are 4022 total products, 309.08 K average temperature, 1540 rpm rotational speed and about 1,000,000 kJ/kg of energy consumed in the production most of which count as waste due to the failures. The slice by the right near the Q&A is used in filtering the entire visualization according to the product type. The Q&A card provides the needed support and assistance for asking questions directly on the visualizations and getting feedback. By simply typing in questions or selecting from the existing likely questions and FAQs (frequently asked questions), you can get instant answers and summaries about the data.

2. Temperature

The temperature report page places the average process temperature side by side with the failure type in the first leftward visualization. It also compares the failure type with the sum of process temperature. Above the visualization, the individual cards show that the average process temperature of the extruder is 309.08 K, average air temperature is 299.14 K with the barrel temperatures reading 2615, 237 and 235 Celsius maximum temperatures respectively. Across the extruder barrels, from barrel 1 to barrels 2 and 3, there is a noticeable temperature drop. This is expected because, throughout the extrusion process, the temperature gradient decreases along the extrusion line.

In the first temperature visualization, heat dissipation accounted for 310.70 K average temperature which is no surprise. This is followed by random failure and tool wear failure types. Coming fourth is No Failure while overstrain failure and power failure comes later. From this visualization, it’s empirically obvious that at high temperatures, heat dissipation causes lots of failures. Also, when the power supply was very low, there was a power failure. Therefore, to manufacture PVC products with no failure, an average temperature of 309.08 K should be maintained and regulated. Any temperature over or below this threshold would result in product failure.

3. Flow Rate

Flow rate measures the amount of plastic materials flowing through the extruder per unit time (kg/h). A line graph was used to compare the increase and decrease of material failure with the flow rate throughout the production. From the visualization, an increase in flow rate resulted in a higher number of failures. This could be due to a malfunctioning extruder component. Nevertheless, this anomaly accounts for the importance of flow rate in the production of PVC products. PVCs are plastic materials made from polyvinyl pellets which are plastic polymers. A variation in the heat supply and temperature of the extruder, surrounding air and barrels affect the flowability of the semi-solid materials flowing through the extruder. When not checked, a suddenly increased flow rate extrudes many failed products.

In this ideal extrusion system, the recommended average flow rate is 52.25 kg/h. At any flow rate slightly above or below this value could result in errors and failures which ultimately increase waste and production costs.

4. Torque

The torque (Nm) measured throughout the production process indicates that the higher the torque, the more failed PVC products are extruded. At a torque of 60 Nm, there were too many overstrain failures. The values decrease from heat dissipation failure, power failure, no failure and random failure down to tool wear failure where there was less torque and tool wear. This analysis indicates that an increased torque generates more faulty products and causes disastrous tool wear.

From the card visuals, an average torque of 39.97 Nm will be sufficient to yield products with no failure. At a minimum torque of 3.80 Nm and maximum torque of 76.20 Nm, there are bound to be faulty extrudates resulting in overstrain failure or tool wear failure. The slicer at the extreme upper right corner can be used to gauge the torque values and failure types by sliding it left or right.

5. Tool wear

Tool wear (m) is a measure of the amount of worn out in equipment often caused by friction or the agedness of the tools. Equipment wear in a PVC extrusion line can result in underperformance of the extruder and other components. In the tool wear visualization, the tool wear failure (214.67 m) was rampant with an increase in the average tool wear. It afterwards decreased down to heat dissipation at 88.57 m average tool wear. As can be seen on the visualization, the total tool wear is 437,000 m, 108.53 m average, and 246 m maximum tool wear. Generally, about 239 instances of tool wear were recorded during the production. On the tool wear report page is also a tool called smart narratives.

Smart narrative is an AI feature in Power BI that automatically summarizes the visualization on a page into texts, highlighting key metrics and trends. From the smart narrative analysis, at 214.67, Tool Wear Failure had the highest Average of Tool Wear (m) and 142.37% higher than Heat Dissipation Failure which had the lowest average tool wear of 88.57%. These insights from smart narratives confirm the values plotted on the chart. Smart narratives are very effective, especially for complicated graphs and charts. When enabled, it scans through the plotting and extracts concise summaries of the data.

6. Energy Consumption

Energy consumption is a major consideration in chemical engineering industries and PVC manufacturing companies aren't left out. With a rising cost of energy globally, every process industry today should pay attention to their energy consumption both the amount effectively utilized for useful production and the waste. In the extrusion dataset used in this research, a voluminous amount of energy was wasted due to the multiple failures. This energy consumption varies across product types and failure types.

From the energy consumption visualization, the product type was compared with the volume of energy consumption per product type. The L-type consumed 60.12% of the energy; H-type, 10.12%; and M-type, 29.76%. The total energy utilized in the manufacturing was 1,000,000 kJ/kg with a minimum consumption of 258 kJ/kg and a maximum of 419 kJ/kg. Summarily, L had the sum of energy consumption at 792313 kJ/kg, followed by product type M at 397112 kJ/kg and H at 134322 kJ/kg.

7. PVC Failure

Detecting the failure of the PVC products during extrusion has been part of the key objectives of this research. If failures could be predicted and identified before they occur through the analysis and visualization of the extrusion process, process engineers would have more leverage to manage the manufacturing process. On the failure page of the Power BI report, the number of products reading 'no failure' was highest compared to those that malfunctioned due to power failure and other failures. As shown in the visualization, approximately 3,915 PVC products were successfully extruded without any impairment. The remaining products were faulty due to several factors such as low or high temperature, flow rate, power supply, rotational speed, etc.

Generally, this extrusion not only produced faulty finished materials but also consumed a large volume of energy (1M kJ/kg) at high production and maintenance costs.

8. Process Control

The process control report page provides an effective system control mechanism that the control technologists can use to monitor the process and handle faults and breakdowns. A multi-row card was used to visualize the different fault types of failures, and their alarm, comments, and actions. When the production is running smoothly the automated process monitoring system reports that everything is perfect, and no further action is required. But in cases where there is heat dissipation failure or other failure types, the system reports the problem and takes action immediately to correct the problem. Fixing the faults in the extrusion process might involve altering the production conditions and variables such as air temperature, process temperature, flow rate, rotational speed, screw speed or the temperatures of the three barrels. In an ideal PVC plant, as I envision, an automated error corrector will be responsible for quickly troubleshooting and solving the issues to avoid further loss to the industry in the form of tool wear, energy waste or multiple failures.

Conclusions and Recommendations

This research project has duly studied the failure of PVC products in an extrusion process with key interest in how other internal and external conditions in the extruder such as process and air temperatures, flow rate, rotational speed, tool wear and torque affect production and influence rate of failure and energy consumption. The research commenced with the specification of project objectives, data collection, inspection, modelling, analysis, visualization, and reporting using Power BI. Microsoft Power BI is an effective tool for deriving insights from structured and unstructured data. Through a clear methodology, I performed an in-depth analysis and visualization to generate the results discussed in the results section.

Generally, my discovery in this research indicates that an uncontrolled PVC manufacturing system is bound to generate inconsistent yields in the form of failure and can consume more energy than supposed due to all the wasteful work done in extruding faulty products. Therefore, my research proposes that the PVC production process can be optimized by applying data analytics in process predictions, analysis, management, and visualization using Microsoft Power BI. This has been exhaustively demonstrated in this work, but future research is encouraged to explore several discrepancies and discover how best to deploy Power BI in process control effectively.

In the meantime, the following were threatening challenges to this project which inhibited both progress and success. On a personal level, they include the unavailability of free data sources online especially ones from manufacturing companies. Also, this type of research is time-intensive and requires an adequate timeframe of consistent research. Though IT-based research, this study was averagely costly and therefore requires enough financial backing to procure the perfect computer, subscribing to Power BI pro and regular internet subscription. More importantly, the field of data analytics using Microsoft Power BI in the chemical industries is yet to be explored. Thus, the ideal literature was scanty, making the literature review rely heavily on general data analytics, data science and machine learning resources. On the industrial scale, the challenges to the application of Power BI in process industries include the unavailability of advanced sensors to collect manufacturing data and inadequacy of the technological and technical know-how that can capture the massive and often wasted big data and transform them into useful decision-making tool as I did in this project.

To alleviate and eradicate the shortcomings mentioned above, I therefore recommend the following:

Manufacturing industries should make their production data available online for public use. This will cut down the search time spent in scavenging for the right dataset.

Universities should be able to sponsor students with financial assistance in future research of this nature. This will help cut costs so that the student can focus on carrying out successful research.

Educational institutions and stakeholders in the education system are encouraged to empower young people with Power BI data analysis, visualization, and reporting skills through free live and online training.

Chemical industries should begin to maximize their massive production data to generate useful insights. This can only be performed by experienced data analysts who should be properly renumerated and encouraged to deliver efficient results.

Lastly, local industries are encouraged to collaborate to develop analytical capabilities to start exploiting their data locally instead of depending on foreign partners.

Inarguably, the future of Power BI data analysis' role in chemical engineering is bright and promising if the recommendations above are implemented to the last. Nevertheless, the community of chemical engineers still has work to do to overcome upcoming technical, platform, and cultural challenges. Academic institutions, private businesses, and public agencies need to work together on workforce development and analytics innovation if they want to take advantage of the opportunities. The early adopters of big data technologies are responsible for motivating the rest of the community to embark on the big data journey and establishing a culture that emphasizes the ongoing pursuit of new opportunities. Power BI hold potentials for the chemical and allied industries. Therefore, to accelerate this journey of fully maximising the "big data", especially in process industries, stakeholders are encouraged to adopt Power BI to predict, analyse, visualise, and manage production processes optimally, thereby maximising energy and saving cost.

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