FINAL THESIS

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GÖDÖLLŐ
2024

Hungarian University of Agriculture and Life Sciences

Szent István Campus

Institute of Technology

MSc. Engineering Management

Enhancing Energy Efficiency in Production Lines Through Advanced Process Monitoring and Control System

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Gödöllő

2024

INSTITUTE OF TECHNOLOGY
ENGINEERING MANAGEMENT MASTER
Project Management Specialisation

FINAL THESIS

worksheet

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For

Title of the diploma thesis:

Enhancing Energy Efficiency in Production Lines Through Advanced Process Monitoring and Control System

Task reference:

- Explore technologies and solutions for enhancing energy efficiency in production lines.
- Develop and design a process monitoring and control system (PMCS).
- Apply optimization algorithms to real-life production line to schedule operations during low-energy cost periods for maximum efficiency.
- Assess economic and technical feasibility of applied optimizations.
- Identify the optimal scenario and design post-optimization procedures for long-term success.

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Deadline of thesis submission: April 29, 2024

Gödöllő, November 15, 2023

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1. Introduction

Energy in manufacturing sector, is a critical and pivotal resource, essential to the continuity of operations, as well as the ability to remain economically viable and environmentally responsible simultaneously. As the industry develops, the requirement of energy efficiency becomes more pronounced, triggered by the desire to cut operational costs, and reduce the environmental footprint of operations. Energy efficiency can be explained through the desire to reach the same results in terms of production with less energy spent. This implies the dedication to the sustainable principles of manufacturing since most of the world has already been involved in global initiatives of resource preservation and climate change.

The quest for energy efficiency improvement at industrial manufacturing goes in with the need for integrating advanced energy technologies and optimization of manufacturing processes. Conversely, making large energy usage reductions seems to be a challenge. It requires a lot of financial investment in new equipment, while adjustment of traditional production processes takes quite some time and effort. These investments and changes become pertinent since they help companies meet environmental policies, bring down operational expenses, and increase the market share through sustainability. Implementing such a massive change is, however, complex and requires detailed planning, coordination, a change in culture within organizations towards energy consciousness. Moreover, the transition not only needs technical knowledge but also a strategic change that may unsettle ongoing operations for some time.

The objective of this thesis is to provide a guide on the most efficient ways to improve energy efficiency in manufacturing. The focus is energy-intensive processes by means of Advanced Process Monitoring and Control Systems (PMCS) with optimization algorithms intended to link energy-intensive processes to the time of lower energy costs. This research seeks to demonstrate, through a detailed case study of a manufacturing company in Syria facing fluctuating energy prices, the potential of PMCS to drive energy efficiency gains and operational improvements. The research offers practical insight into the application of these strategies, their scalability, and their impact within the manufacturing industry. finally, the thesis will cover the technical and economic aspect of the feasibility of the developed project in detail.

2. Literature Review

2.1 Overview

Energy efficiency in manufacturing is one of the most crucial aspirations of the modern industry as it is an optimal combination of operational excellence and environmental responsibility. This literature review touches upon the various aspects of energy consumption on the levels of machines, the production line, and the entire factory. Each of these levels has unique challenges and opportunities for the enhancement of energy efficiency. The purpose of the literature review is to identify the challenges and benefits in applicable energy savings across three levels above using different technological innovations and process modifications. It aims to develop an understanding of existing and potential solutions and mitigation strategies to develop a thorough understanding of energy use and the possible pathways to efficient and economically feasible industrial applications. The literature review tries to cover the number of strategies applied to reduce energy use, from new control systems and the use of energy management systems to comprehensive process optimization. The review also covers the models for small businesses and the organizational approaches such as employee incentives and the adoption of the continuous improvement philosophy that allows maintaining savings achieved through energy optimization. Through the analysis of technical and managerial solutions.

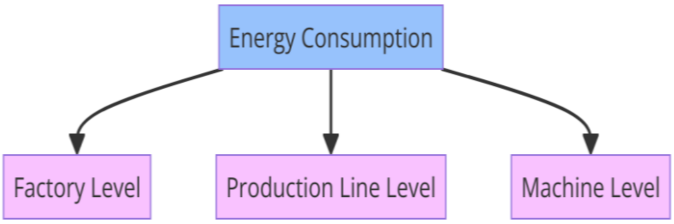
Finally, the literature review critically discusses process-level monitoring and control systems as an essential element of energy management. Specifically, the source provides in-depth evidence on how such systems can improve the operation of manufacturing processes through real-time data collection, condition-based and predictive maintenance, and optimal energy use. This part also considers the application of advanced sensors, data analysis techniques, and control algorithms, which help to minimize energy use, maximizing production output or efficiency. this literature review plans to offer insights into the implementation of energy savings in manufacturing as vital to achieving economic and environmental performance.

2.2 Levels of Manufacturing Energy Consumption

The energy consumption within industrial settings can be dissected into three primary tiers levels as it is illustrated in Figure 1: machine level, manufacturing line level, and factory level. Each of these levels presents unique challenges and opportunities for optimizing energy usage, ultimately contributing to cost savings and environmental sustainability.

Figure 1: Levels of manufacturing energy consumption

(Source: own work)



- Machine level energy consumption:

At the machine level, energy consumption is characterized by the operational energy use of individual machines during the production process. This level of consumption is divided into three main components: active energy (the theoretical energy required to perform a change of shape or manufacture a part), additional energy (energy required by the machine to operate beyond the active energy, including basic and idle power demands), and the energy demand of the process-periphery (energy used by ancillary equipment and services that support the machine's operation). The focus at this level is on optimizing the machine’s energy efficiency through technological improvements, component upgrades, and waste energy recovery strategies (Diaz et al., 2009).

- Production line energy consumption:

The production line level of energy consumption deals with the collective energy use of a series of machines and processes configured in a production line. This level examines how individual machines interact within the production process and how their energy use can be optimized. Energy efficiency at this level is achieved through operational methods designed to minimize the energy consumption of the entire manufacturing line, including the logical benchmarking of manufacturing lines and the utilization of energy flows between machines. The goal is to decrease energy costs while maintaining production quality and meeting environmental regulations. The energy efficiency improvements at this level emphasize the need for modelling frameworks that integrate energy consumption forecasting and optimization strategies for tool machines (Gungor & Gupta, 1999).

- Factory level energy consumption:

Energy consumption at the factory level encompasses the entire energy usage of a manufacturing facility, including both production and non-production related energy use. This holistic view considers the interactions between all components of a factory, including manufacturing processes, technical building services (such as heating, ventilation, and air conditioning), and the factory's layout and design (Herrmann et al., 2011). The emphasis is on creating an integrated energy management system that includes forecasting, simulation models, and strategies for reducing energy consumption across the entire factory. This level of analysis supports the identification and implementation of comprehensive energy efficiency measures that can lead to significant reductions in energy use and environmental impact (Müller et al., 2013).

2.3 Energy Efficiency in Manufacturing

Energy efficiency stands as a critical concern in contemporary manufacturing, yet often remains overshadowed by traditional performance metrics. While companies diligently track production outputs, quality, and costs, energy consumption receives insufficient attention, leading to missed opportunities for optimization. Energy balances offer a powerful analytical tool to illuminate energy usage patterns across various production levels, yet lack of comprehensive monitoring and understanding of energy requirements obscures potential optimizations. Both technical and organizational approaches are pivotal in energy efficiency optimization, involving deployment of energy-efficient equipment, integration of heat recovery systems, and strategic load management to minimize unnecessary energy consumption. Practical recommendations, including life cycle costing analysis, are essential for integrating energy efficiency into investment decisions, ensuring a holistic approach to energy management. In conclusion, by embracing proactive energy management strategies and leveraging energy balances, manufacturing enterprises can unveil hidden energy saving potentials, paving the way towards a more sustainable future (Römer, 2021).

Table 1: Energy efficiency levels and their optimization parameters

(Source: Römer, 2021)

Energy Level	*Optimization parameter*	*Effect on Energy efficiency*
Process level	– processing time/speed, – process parameters, – process interdependencies (e.g., cooling unit and process speed)	minor effect, as consumed energy on process level is rather small
(technical) Machine level	– correct dimensioning of machine parts (e.g., engines and drives) – replacement of single machine parts	high impact, as new more efficient technologies have entered the market
(organizational) Machine Level	– timing of operational machine states – decrease of peak demands – planned machine runtimes and shutdowns	major impact, as the behavior of main consumption centers is addressed and influenced
Line level	– machine scheduling (line internal) – line-internal dispatching rules – consumption profiles of idle machines	major impact, as the behavior of main consumption centers is addressed and influenced
Factory level	– electricity control policies – machine scheduling (cross-production line) – dispatching rules (cross-production line)	major impact, as the behavior of main consumption centers is addressed and influenced

2.4 Energy Efficiency in Production Lines

Energy efficiency in production lines can be understood as the practice of minimizing the amount of energy used in the manufacturing while maintaining or improving the productivity of the production process (Department of Energy, n.d.). This involves a comprehensive approach that includes optimizing production workflows, implementing energy-efficient technologies, and engaging in practices that reduce energy consumption and environmental impact. The Department of Energy provides numerous case studies, such as those of Alcoa, Eck Industries, Inc., and Volvo Trucks, illustrating various strategies companies have adopted to enhance their energy efficiency and operational performance.

2.4.1 Strategies and Approaches to Optimize Production Lines Energy Efficiency

Key strategies for improving energy efficiency in production lines include process optimization to eliminate waste and streamline operations, investment in energy-efficient machinery, heat recovery and cogeneration to make use of waste heat, and the implementation of smart systems and automation for energy management. Furthermore, employee engagement and the adoption of energy management systems are crucial for sustaining energy efficiency improvements over time (Department of Energy, n.d.). We can categorize the strategies into five parts according to their method of application:

- Equipment and technology upgrades:

upgrading of equipment and technology constitute a critical point of focus in the drive towards optimization in energy efficiency along the production line not only the adoption of more energy-efficient machinery but also the integration of advanced control systems that can significantly reduce energy consumption.

Accordingly, high-efficiency motors and drives have proved effective in reducing energy consumption across a series of industrial applications. So, the energy gains derived from the substitution of old equipment with high-efficient ones could be considerable in direct contribution to the efficacy of the production line (Bertoldi, De Almeida & Zoia 2002). The modernization of industrial machinery, including compressors and HVAC systems. This will aid in the reduction of the energy footprint left by the manufacturing processes to a very large extent (Reay, 2012).

The importance of advanced control systems in optimizing energy use cannot be overstated. This would involve smart control technologies, for instance, Advanced Process Control (APC) Systems and Programmable Logic Controllers (PLCs) to moderate the operation of machinery according to real-time demand, averting consumption of unnecessary energy. These control systems are very helpful in ensuring the reasonable operation efficiency of the equipment, therefore increasing the energy savings (Mehta & Thumann, 2021).

The energy recovery system plays a major contribution to the increment of the sustainability of industrial operations. The waste and energy recovery systems involve the capturing of waste heat, reuse, and reusing said waste heat and energy, respectively, to reduce the global consumption and energy of the production lines. Additionally, the technologies, when introduced, help in meeting the environmental sustainability goals; it helps in the reduction of operational costs related to energy usage (Rossiter & Jones, 2015).

- Energy Management Systems (EMS):

Energy management systems are very essential tools for industries and manufacturing entities, focusing on the best method for the optimization of energy use and minimizing cost. (Capehart et al., 2012) underlines the need for the systems in identification, analysis, and management of the energy consumption in a production environment. In other words, a well-structured EMS provides for the constant improvement of the system; hence, organizational units will be able to gain substantial energy savings and environmental benefits from the investment. Key steps in the implementation of EMS in production lines. The first one is a clear organizational commitment to energy efficiency. Systematic monitoring and analysis of energy data form an indispensable part of EMS. The further developing energy accounting, as described by Capehart et al., shows that information on energy use is collected, processed, and analysed so that energy wastage is laid bare, with specific areas for improvement being pointed out. Some of the performance indicators that would help in effective performance measurement and benchmarking of the organization's energy management include the Energy Utilization Index (EUI) and the Energy Cost Index (ECI) (Capehart et al., 2012).

Another very major perspective of EMS is training and education. Employees must be provided with knowledge and skills regarding energy efficiency. All these will be supportive to the organization in developing a culture of consciousness regarding energy. This, in effect, empowers employees at all levels to easily take part in energy-saving initiatives and thus increases overall the effectiveness of the EMS through targeted training programs (Kals, 2015).

- Predictive Maintenance Manufacturing (PDM):

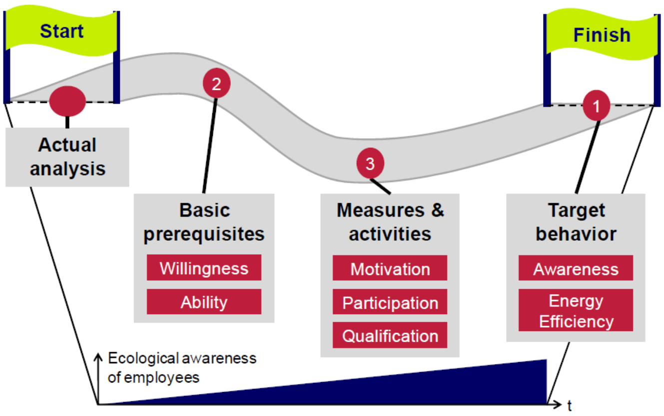
Predictive maintenance (PDM) uses predictive analysis in multi-sensor monitoring for predicting equipment failures, allowing more of proactive maintenance (Meddaoui et al., 2023). The system predicts potential problems before their appearance and, respectively, provides a possibility to take measures in time for not allowing sudden disturbances in the process of work. In terms of energy efficiency, PdM offers several notable benefits. First and foremost, there will be reduced downtime since the predictions of failure on the equipment will be perfect enough to avert the breakdown of production activities. The second element is based on the fact that continuous monitoring optimizes equipment performance, reducing linked energy wastages with inefficiencies (Meddaoui et al., 2023). The third is that timely maintenance implemented through PdM increases the life of equipment, and again, this saves on resources and lesser replacements of equipment are required (Hashemian & Bean, 2011). Finally, PDM does contribute to larger energy use, through the decrease of operational costs and carbon emissions (Mobley, 2002).

- Employee engagement:

Employee engagement has a significant impact on energy efficiency in factories. The approach "productive behaviour" mentioned in Figure 2, summarises all actions that support the organization's goals. Three categories of productive employee behaviour exist: the first one is characterized by workers who behave as outlined in their job descriptions. the second form states that workers collaborate and support one another. the third type of behaviour as inventive. It alludes to how creatively staff members assist the enterprise's competitive position (Dombrowski et al., 2013).

Figure 2:The approach to energy efficient employee behaviour

(Source: Dombrowski et al., 2013)



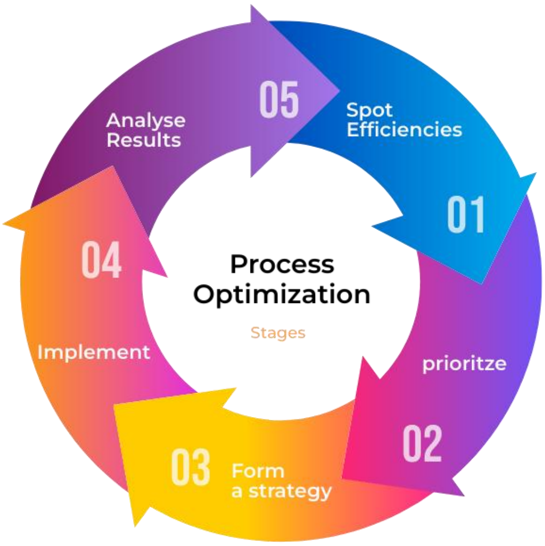
2.5 Focus on Manufacturing Process Optimization

Process optimization refers to a production management methodology that focusing on the removal of redundant stages from a particular process step in the production system. It's a product optimization meant to boost that step's or subprocess's efficiency in order to optimize production (Immerman, 2021).

As it shown in Figure 3, Process optimization can be applied consistently in small steps or all at once in a more radical leap. Continuous improvement involves analysing current procedures and optimizing them for efficiency by drawing on experience. This leads to a continuous optimization in small steps (Liu & Zhang, 2023).

Figure 3: Process optimization stages.

(Source: own work)



2.5.1 Manufacturing Process Optimization Approaches and Techniques

General review of current global research and development trends in modelling and optimizing a range of manufacturing processes. Based on the optimization technique, we can categorize strategies into four distinct groups:

- Workflow optimization:

Workflow Optimization focuses on the improvement of the sequence and organization of production processes, seeking to minimize waste and delays while generally improving efficiency in the total manufacturing operation. Therefore, such an approach is applied following the principles of Lean Manufacturing, where the value to the customer should be delivered with minimum waste (Womack et al., 1990). Common techniques of identifying waste in value-adding activities and synchronizing production processes with customer demand, thus reduction of levels of inventory and improvement of inventory turnover, include Value Stream Mapping and Just-In-Time (JIT) production (Liker, 2004).

Advanced scheduling algorithms and simulation models are the second important component of Workflow Optimization. They contribute to planning in detail and scheduling a variety of production activities under consideration of existing constraints, such as available machines, skills of labor, and material supply. Two successful instances are generally assumed: Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO), both of which have been successfully applied to the problem-solving environment of complex scheduling. Since then, the applications have more effective use of resources and shorter production cycles (Goldberg, 2012). Digital twin technology reflects one of the most advanced trends in workflow optimization. It allows the company to simulate, analyse, and optimize their workflow in an outwardly real-time mode through the establishment of a digital model reflecting the physical manufacturing process, with the objective of identifying eventual inefficiencies or opportunities of improvements, not perturbing the actual realization of the products (Tao et al., 2018).

In brief, Workflow Optimization is a comprehensive approach that aims at combining principles of lean manufacturing, advanced scheduling algorithms, and digital technologies in view of making flow in the production processes flawless. The goal of this approach is to attain perfect flow of activities that are required to be carried out in the organization from the suppliers to the customers of the organization.

- Equipment efficiency:

Equipment efficiency is very essential in the alignment of manufacturing processes to the sustainability goal, such that firms minimize their environmental impacts while at the same time ensuring economic performance in reduced energy costs. Furthermore, (Duflou et al., 2012) draw attention to the technological innovation and strategic operational changes for realizing remarkable energy saving; they hence propose a holistic approach in equipment efficiency. In so doing, they suggest a process of continuous assessment, measurement, implementation of measures on energy saving, and control, and consequently, development of a culture of sustainability and continuous improvement within the manufacturing sector (Pons et al., 2013).

One main advantage of improved efficiency equipment is that it is likely to lead to huge energy savings. Industrial companies that involve energy-efficient technologies and practices may make energy savings of between 10 to 20 percent. These will not only lead to savings in operational cost but are congenial in improving the sustainability profile of a company.

Siemens AG, a leader in electrical engineering and electronics, bringing an opportunity to demonstrate the practical application and benefits of enhancing equipment efficiency in manufacturing. For instance, Siemens has implemented the "Energy Efficiency Program" through equipment renewal and optimization in its factories all over the world in a bid to reduce energy consumption by developing technology and optimizing processes (Siemens AG, 2020). The approach of Siemens is ambitious, with a special focus on new motor systems that feature variable speed drives (VSDs), considering their critical role in adjusting energy production at actual consumption levels of the production line, a measure needed to be applied for operation but not also overindulgent in productivity.

Meaning, by this investment, it saves both energy and wear of the equipment, meaning that it has a much longer lifespan. The company uses smart sensors and technologies of automation in its manufacturing processes. This is the integral innovation that makes sure there is the ability to track energy consumption at all points in time and the adjustments that need to be made to machines and the production process, which would ensure the maintenance of optimal consumption.

- Resources optimization:

Resource optimisation refers to the method of resource used for both labour and non-labour resources to ensure that they are matching with the schedule. Resource optimisation is essential in the area of improving energy efficiency of the production lines. Strategies and techniques of the two-capacity planning and resource allocation remain very important aspects that will help the company to reduce the energy used and at the same time increase the amount of output from the available resources (APM, n.d.).

Capacity planning: A strategic approach under which a firm determines the production capacity required by an organization to remain in parity with changes in demand for its products (Heizer et al., 2017). This involves careful planning of equipment, labor, and production schedules against the goal to attain an optimum operational efficiency and reduction in energy wastage. Proper planning, such that production capacity is aligned with market demands, helps companies to avoid overproduction, hence saving significant energy and other resources. For example, a study by (Frazzon et al., 2014) on the simulation-based planning approaches in green supply chains highlights how strategic adjustments of the capacity shall hold potential to improve energy efficiency and, at the same time, sustainability.

Resource allocation: This is the major way in which an entity can distribute the available resources to the different activities and processes taking place within the production line to secure effectiveness in operation (Krajewski et al., 2015). It ensures effective resource allocations to make sure the machinery and equipment are run at an optimum level required, hence minimizing the use of energy. Often, such techniques as Lean Manufacturing and Six Sigma are being implemented to eliminate wastage from the processes, including the waste of energy (Pyzdek & Keller, 2018). For example, "Kaizen" or continuous improvement principle may be used to detect and clear all those processes that take in superfluous energy, with the aim of optimizing the whole energy efficiency of the production line.

Integrating these with strategies of capacity planning and resource allocation, and using cutting-edge technology such as IoT and AI, makes an overall approach to optimize energy efficiency in their use. End Thus, it can be assumed that IoT devices enable monitoring the work of machinery and further adjusting it at current time in order to reach peak efficiency, while AI algorithms can predict and plan for the best distribution of resources in accordance with production forecasting (Song et al., 2017).

In conclusion, the strategies of capacity planning and resource allocation becomes a very essential strategy in an organization that wants to optimize the use of resources while increasing efficiency in the resource, which is of energy. It will enable companies to ensure that minimal consumption is done with the involvement of energy costs, and the environment is sustained, thus making it a must to plan and allocate resources perfectly.

- Process monitoring and control:

Process monitoring and control are increasingly recognized as being among some of the pivotal elements in the advancement and sustainability of manufacturing industries. Such recognition was done on the verge of the critical roles that they play toward enhancing efficiency, tool life, and product quality within the manufacturing operations. Monitoring involves the analysis of sensor measurements to deduce the state of the manufacturing processes. From the simplest and characteristic tasks of the machine operators, like the visual check of the integrity of the tool, to the use of very complex and unmanned algorithms, which use advanced signal processing of the sensor data. On the other hand, control means the manipulation of process variables in such a way that provides regulation and optimization of the process. This may generally be done by on-line or off-line adjustments affecting an operator or automated system (Stavropoulos et al., 2013).

Here is a comprehensive overview of the key components of process-level monitoring and control for energy efficiency:

1. **Monitoring System**:

Establishing a monitoring system within manufacturing operations among the ways furthering progress in energy efficiency by increasing the level of optimization in process performance. This system comprises many major components that all play vital roles within the effective process of monitoring and management in relation to energy used and process parameters (Stavropoulos et al., 2013).

Sensor networks: are installed for this process, which can include temperature, pressure, flow, and power measuring sensors. These networks form a very good base for monitoring in that they, in real time data, reveal the variation of several process parameters and are thus able to guide in respect to process inefficiency and to pinpoint places for possible energy saving (Deshmukh & Shaligram, 2013).

Data acquisition: devices are designed to collect real-time data from sensors and meters, placed at every relevant point within the manufacturing facility. The data acquisition forms the central part that is allowed for processing to operate in an energy-efficient manner through effective monitoring, capturing accurately, and transmitting real-time operation data from the field (Patel & Thakkar, 2015).

Monitoring software: Applications are used for the collection, processing, and storage of data received from monitoring devices. It plays an important role in enabling the analysis of data coming from any cyber-physical system with the aim of increasing manufacturing efficiency. They are used to process and analyse big datasets in a bid to identify patterns and make insights into energy consumption and process efficiency (Lee et al., 2015).

Network infrastructure takes care that data is transported from the sensors to the data-collecting hardware and further to the monitoring software, supporting the seamless data flow over the manufacturing facility. This leaves ample time for remedial adjustments in the quest to improve efficiency in energy, including the setting up of infrastructure for data transmission and communication for the sensors to monitoring systems (Xu et al., 2014).

2. **Data Analysis and Visualization:**

play very key activities for the day-to-day operations of manufacturing companies, with reference to energy optimization. In today's advanced scenario, through advanced analytics and data visualization tools, companies can dissect heaps of data collected to find out inefficiencies and pointing toward better opportunities for their energy efficiency. It facilitates the process through which the realization of well-informed decisions, which will drive improvements of operations, may be aided through improved understanding of complex datasets.

Advanced data Analytics: Techniques involve the use of statistical analysis, machine learning, and pattern recognition in the analysis of data collected to be able to derive insights from this data. For example, (Kusiak & Verma, 2012) researched how machine learning algorithms could possibly help in enhancing the performance of wind farms and concluded that advanced analytics were able to significantly improve energy efficiency. (Smith et al., 2015) further point out statistical analysis as a way through which the patterns and anomalies of energy consumption data are indicated to give way for the successful execution of directed measures towards conserving energy. Usually, in manufacturing advanced data analytics can be handled through cloud platform systems platform is usually a suite of services from cloud computing that provides consumers with a wide range of computing resources and services via the Internet. Cloud platforms provide modern digital operations with support that is broad enough to accommodate all kinds of applications: from applications requiring data storage and processing, applications for enterprise resource planning, customer relationship management, and so many other applications.

Types of Cloud Platform:

IaaS (Infrastructure as a Service): virtualized computing services that are provided over the internet to a paying customer. This means that users can pay under a pay-as-you-go scheme to hire but not to buy virtual machines, storage, and networks instead of physical hardware. For instance, some big players in the field include Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP) (Mell & Grance, 2011).

Platform as a Service (PaaS): Offers the cloud environment provided with facilities for developing, testing, deploying, managing, and updating applications. "PaaS is a service-providing platform to web or mobile apps developers without losing time on baseline infrastructure setup and management." Examples of PaaS are Heroku, Google App Engine, and Microsoft Azure App Services (Lawton, 2008).

Software as a Service (SaaS): delivers software applications on a subscription, internet-delivered basis, which allows users to access and use cloud-based apps via the internet without worrying about installation, maintenance, or coding. Examples include Salesforce, Google Workspace, and Microsoft 365 (Turner et al., 2003).

Benefits of cloud platforms:

- Scalability: Cloud platforms provide businesses with scalable resources, which are dynamically adjustable with demand, to manage the fluctuations of workloads effectively (Marston et al., 2011).

- Cost-effective: it assists to reduce expenditure costs such as purchase, maintenance, and updating of both software and hardware that an organization must incur if installed within (Armbrust et al., 2010).

- Accessibility: Cloud services are globally accessible via an internet connection, meaning they can be accessed from any part of the world. This effectively supports the implementation of remote work, which increases global Labor productivity (Qian et al., 2009).

<u>Data Visualization:</u> Visualization is an approach to placing data in a graphic form. The diversity of techniques utilized in this includes charts, graphs, and maps. Visualization can aid the making of data more understandable and accessible while being used to bring out the identification of trends, patterns, and outliers (Few, 2009). Visualization software able to generate information in the form of graphs, charts, dashboards, etc., that help in the representation of the analysed data graphically, so that complicated information can be easily understood by various stakeholders. (Tufte 2001) underscores that effective data visualization is a critical approach to making formidable data sets more accessible and actionable. In the field of energy management, the tools for visualization would allow clearly showing facts of energy consumption tendencies, existing inefficiencies, and potential fields for optimization, which can help decision-makers in the identification and prioritization of energy-saving projects.

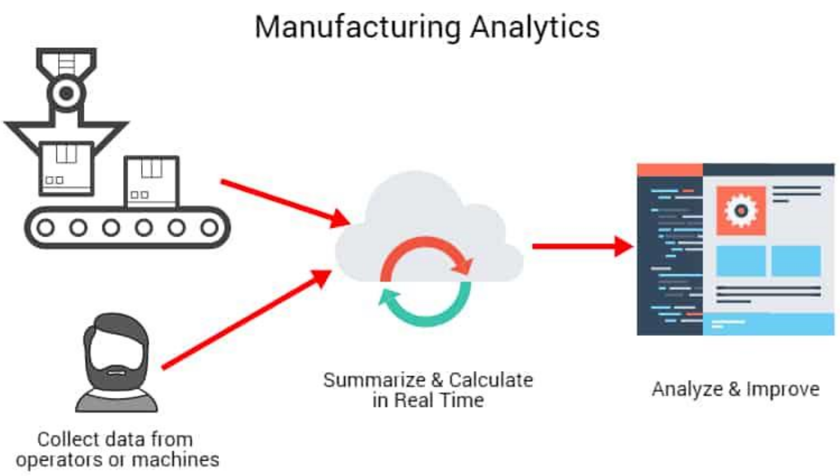
(Keller & Tergan, 2005) highlights the key benefits of visualization:

- Makes data more understandable and accessible.
- Helps to identify trends, patterns, and outliers.
- Supports decision-making.
- Can be used to track progress and measure the impact of initiatives.

Insights generation: data analysis and visualization should give the room for insights that guide strategies in place for energy optimization. Advanced analytical methodologies find inefficiencies and opportunities, while clear data visualization effectively communicates such findings for organizations to reduce energy consumption and improve their operational efficiency through the right target interventions. The ability to translate data into insights and actions will be very vital in the ability to derive improvements and gain sustainable energy efficiency in contrast to (Kahneman, 2011).

Figure 4: Manufacturing analytics

(Source: Mingo Smart Factory, n.d.)



3. Control Algorithms:

The manufacturing system of today will necessarily require control algorithms that can optimize best the efficiency in their processes and consumption of energy. These are the Model Predictive Control (MPC), Adaptive Control, etc., that can guarantee that the operation of processes remains within some specific required limits, therefore allowing an enhancement of general efficiency and sustainability.

Model predictive control (MPC): An MPC uses a prediction of the mathematical model to predict future process behaviours and adjust the control actions for optimum outcomes. (Camacho & Bordons, 2007) gives various industrial applications in which MPC has been used—with the above case being among them, showing the effectiveness in dealing with dynamic systems of a complex nature involving predicting future states and changing control actions beforehand so as to optimize process efficiency and energy usage, respectively.

Proportional-Integral-Derivative (PID) control: PID control is the most used feedback control mechanism that ensures the process variable is held to the required setpoint. (Åström & Hägglund, 2006) gives a full account of the PID controllers, particularly how they are applied in feedback loops, to make the correction from target values automatically. This method is pivotal in maintaining process stability and efficiency, directly impacting energy consumption.

Advanced optimization algorithms: Designed for finding optimum process parameters in real-time to minimize energy consumption while ensuring meeting the production targets. Going further, (Bequette, 2003) provides more insights about the advanced optimization techniques used in process control: all those algorithms presented herein allow great improvements in energy efficiency by dynamically adjusting process parameters in view of changing conditions or objectives. such as cross-correlation, heuristic optimization algorithms, ant colony optimization (ACO), and linear programming (LP) which are designed to dynamically adjust process parameters in real-time.

Adaptive control: The control techniques in which the control parameters automatically change with the change occurring in the process conditions or any of their surroundings' environmental factors. (Ioannou & Sun, 2012) focus on an adaptive control methodology that offers the capacity to manage uncertainties, and hence variations in process dynamics, for assured optimal performance and energy efficiency, even under continuously changing conditions.

4. Integration with automation systems:

The approach integrates the process-level monitoring and control systems into the currently existing automation systems (like the Supervisory Control and Data Acquisition (SCADA) and Distributed Control Systems (DCS)) of manufacturing operations. Integration of this system, therefore, helps in the communication and coordinated actions of the monitoring and control systems to other manufacturing equipment, to aid in optimization of the use of energy from input of production through to the end of the production process.

SCADA systems integration: It integrates with SCADA systems for a centralized supervision and control of process execution, presenting real-time process data to enable capabilities for the operator to control energy consumption and process efficiency. (Boyer, 2009) centralizes on the role of SCADA in industrial automation, bringing out a discussion of the need for operational efficiency and emphasis on energy optimization.

DCS integration: DCS is a must to be able to control the distributed process, not only of the process variables, from various manufacturing units, but also from the distributed set of units to manage energy usage in the best possible manner. (Singh, 2012) notes that the importance of merging DCS with process-level monitoring systems underpins how such synergy allows improved quality in maintaining optimal energy efficiency across several parts of the manufacturing process.

Interoperability: The success of integration efforts largely depends on the establishment of robust communication protocols and ensuring interoperability among different systems. On the same line, (Gungor & Hancke, 2009) describe the importance of communication protocols in industrial automation, setting the necessity of standards that will ensure the smooth process of incorporation and data exchange between monitoring and control systems and automation equipment.

5. Continuous improvement:

Continuous improvement of the control and monitoring at process level are the basic cornerstones to enhance energy efficiency at manufacturing operations. In this iterated process or cycle, it becomes critically essential for a keep at constant monitoring, which would result in optimizing continually to identify the underlying inefficiencies and opportunity areas for better energy savings.

Continuous improvement philosophy: This concept of continuous improvement, otherwise referred to as Kaizen, holds that continuous small improvements accrue to be big values incrementally (Imai, 1986). This philosophy is very instrumental in enhancing efficiency in the manufacturing process, including energy management. This means it nurtures an environment in which continuous assessment and adjustment are part and parcel of organizational culture that, in turn, leads to sustained improvements. The role of data in continuous improvement cannot be overstated. In addition, through the above, an analysis of systematically presenting production analysis data on energy consumption and performance offers manufacturing the possibility of how to localize areas for optimization and readjusting control strategies. (Suzaki, 1987). This is therefore purely dependent on strong data, analysis, and action frameworks, which advocate sophisticated monitoring technologies and analytics tools that are integrated into the manufacturing operations (Womack et al., 1990).

Advanced analytics for deeper insights: Use advanced analytics and machine-learning algorithms that help users receive deeper and accurate analytic insights into energy consumption and process efficiency. These technologies enable the recognition of some patterns and even optimization opportunities that would be hard to recognize when using traditional analysis methods, thusly supported by more informed decision-making and an improvement of the strategy (Davenport & Harris, 2007).

The Implementation for the ‘’ Process Monitoring and Control system’’ need an accurate work starting from collecting the data and visualizing it ending with optimizing the input (energy consumption) by using the advanced optimization algorithms and finally the continuous improvement and monitoring.

Table 2 summarize the key components of the ‘’Process Monitoring and Control system’’ and its implementation tools and benefits for each:

Table 2A: key components of the PMCS

(Source: own work, based on the previous study)

Key Component	Implementation tools	Benefit
1 **Monitoring System**	**Sensor Networks:** Measure process parameters (e.g., temperature, pressure, flow,energy). **Data Acquisition:** Collects real-time data from sensors. **Monitoring Software:** Processes and analyses data for insights. **Network Infrastructure:** Transmits data from sensors to monitoring systems.	➢ Identification of inefficiencies. ➢ Identification of energy-saving opportunities.
2 **Data Analysis and Visualization**	**Advanced Analytics:** Uses statistical analysis, machine learning, and pattern recognition to derive insights from data. **Data Visualization Tools:** Graphically represents analysed data for easy understanding. **Insights Generation:** Guides energy optimization strategies based on data analysis and visualization.	➢ Improve decision making. ➢ identify energy consumption patterns and anomalies. ➢ prioritization of energy-saving projects.
3 **Control Algorithms**	**Model Predictive Control (MPC):** Predicts future process behaviours and adjusts control actions for optimal outcomes. **Proportional-Integral-Derivative (PID) Control:** Maintains process stability and efficiency. **Advanced Optimization Algorithms:** Finds optimal process parameters in real-time**.** **Adaptive Control:** Adjusts control parameters based on changing process conditions	➢ Enhance process efficiency. ➢ reduced energy consumption. ➢ improved process stability.

Table 2B: key components of the PMCS

(Source: own work, based on the previous study)

Key Component	Implementation tools	Benefit
4 **Integration with Automation Systems**	**SCADA Systems Integration:** Centralized supervision and control of process execution. **DCS Integration**: Controls distributed process variables and energy usage. **Interoperability:** Robust communication protocols to ensure seamless data exchange between monitoring and control systems and automation equipment.	• Improve energy optimization. • Coordinate actions between monitoring and control systems. • Enhance communication efficiency.
5 **Continuous Improvement**	**Continuous Improvement Philosophy:** Iterative process of monitoring, optimizing, and identifying inefficiencies. **Advanced Analytics for Deeper Insights:** Uses advanced analytics and machine learning for deeper insights and improved decision-making.	• Sustained energy efficiency improvements • data-driven optimization • informed strategy adjustments.

3. Research Methodology

3.1 Overview

As mentioned in the literature review, there are three levels of energy consumption in manufacturing. Therefore, to increase energy efficiency (reduce energy consumption and electricity costs), optimization is necessary. Energy consumption in manufacturing businesses occurs at three levels: machine level, production line level (comprising multiple interconnected processes), and factory level. Given that the production line is the primary source of energy consumption, we choose to focus on this level. Various strategies for optimizing energy efficiency in the production line are covered. Estimated effectiveness percentages for each strategy in increasing energy efficiency:

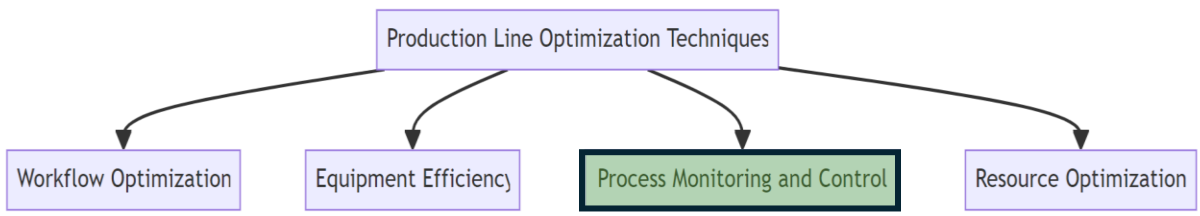
- Workflow Optimization: 10% - 20%
- Equipment Efficiency: 20% - 30%
- Process Monitoring and Control: 25% - 35%
- Resource Optimization: 15% - 25%

<u>We will choose the ‘’Process monitoring and control’’ for the optimization as it is the most effective method for increasing energy efficiency in production lines for these reasons:</u>

1) enables real-time identification of energy wastage.
2) continuous improvement.
3) adaptability to variability.
4) seamless integration with automation.
5) offers a comprehensive approach to optimization.

Figure 5: Production line proposed optimization techniques

(Source: own work)



3.2 Case Study

This case study delves into the company's development approach with the reduction of electricity usage in a paper recycling production line, which is a big operation expense and an environmental consideration, through implementing a monitoring and control system following a technical analysis and feasibility study. The approach adopted in this section were developed with guidance from feedback provided by an expert in the relevant field, ensuring practical relevance and accuracy in the assumed parameters.

Problem Description:

The company facing a high cost due to rising electricity prices for manufacturing in Syria, which has been increasing steadily during the ongoing war. This is primarily due to a nationwide fuel shortage, where they must find a continuous and flexible solution for this problem. Implementing a monitoring and control system on the production line is critical in this context. At this stage we will cover the comprehensive study of the optimization to find the optimal processes schedule. This will enable the company to operate all processes during periods when electricity prices are at their lowest, considering all constraints and preferences.

Table 3: Company details
(Source: own work)

Company Details	
Company Name	X for recycling solutions
Industry	Paper recycling
Location	Damascus, Syria
Products	Recycled printing paper, craft paper
Annual Production Capacity	730 metric tons
Operational Hours	12 hours
Number of Employees	25 employees
Daily Electricity Consumption	1980 KW
Raw Material	Collected wastepaper from local recycling programs
Key Environmental Initiatives	Closed-loop water system, solar power for non-manufacturing operations

Figure 6: Production line daily scheduling

(Source: own work)

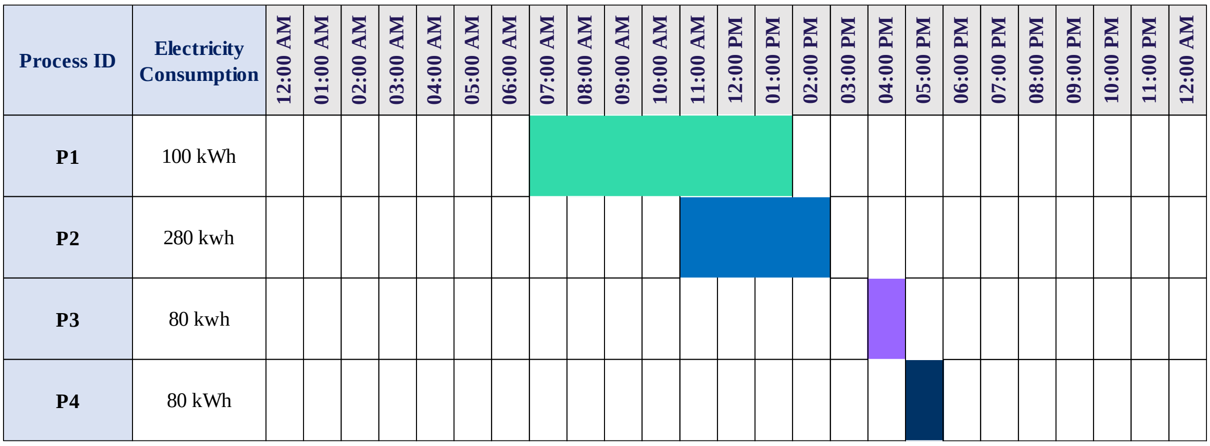


Table 4: Production line details

(Source: own work, based on the company provided data)

Production Line Details				
Process ID	**Process Name**	**Operation Hours**	**Electricity Consumption**	**Machines**
P1	Collection and Pulping	7 AM - 2 PM (7 hours)	100 kWh	Pulping Tank, High-Density Cleaners
P2	Paper Making	11 AM – 3 PM (4 hours)	280 kWh	Paper machine (including forming, pressing, and initial drying sections)
P3	Paper Cutting	4 PM - 5 PM (1 hour)	80 kWh	Automated cutting machines
P4	Packaging	5 PM - 6 PM (1 hour)	80 kWh	automated packaging line

<u>Processes description:</u>

Collection and Pulping (P1): First stage, where the wastepaper is collected and mixed with water and chemicals in the pulper, and mechanically broken down into fibres. In this stage Low energy consumption suggest efficient mixing and cleaning machinery.

Paper Making (P2): The wet pulp is laid on wire screens to form sheets and pressed, then dried. This stage takes the most energy, whereby the pulp must be heated and dehydrated.

Paper Cutting (P3): The continuous paper sheet is cut into the required sizes. Such an operation is short and consumes a moderate amount of energy reflects a mechanical nature of cutting without extreme heating.

Packaging (P4): The final products are counted, stacked, and packaged. The low energy consumption in this stage accounts for the automated packaging machinery.

3.3 Technical Methodology

3.3.1 Process Monitoring and Control System Infrastructure

The Implementation for the ‘’ Process Monitoring and Control system’’ need an accurate work starting from collecting the data and visualizing it ending with optimizing the input (energy consumption) by using the advanced optimization algorithms and finally the continuous improvement and monitoring. Therefore, we need to establish a specialized infrastructure within factory for the ideal implementation of the Process Monitoring and Control system.

The methodology proposed will cover the latest and most used methods and tools for implementing PMCS in the manufacturing industry. The components of the PMCS infrastructure:

1. IoT sensor infrastructure
2. Cloud platform
3. Data model
4. Optimization algorithm
5. Visualisation

3.3.2 Optimization Workflow

<u>Step 1: Data Collection</u>

- Install IoT sensors on machines and throughout the production environment.
- Configure sensors to collect data on machine status, production rate, and energy consumption.
- Connect sensors wirelessly to the cloud platform.

<u>Step 2: Data storage and processing</u>

- Create a data model that defines the structure of the data collected from the sensors.
- Establish a cloud platform to store and process the data.

- Configure the cloud platform to receive data from the sensors and store it according to the data model.

Step 3: Optimization algorithm execution

- Select an optimization algorithm that is suitable for the specific production line and optimization goals.
- Configure the optimization algorithm with the necessary parameters and constraints.
- Execute the optimization algorithm on the data stored in the cloud platform.

Step 4: Schedule deployment

- Receive the optimal schedule from the optimization algorithm.
- Send the schedule to the production line.
- Configure machines to follow the optimal schedule.

Step 5: Energy consumption monitoring

- Continue to collect energy consumption data from the IoT sensors.
- Transmit the data to the cloud platform for analysis.

Step 6: Optimization algorithm feedback

- Analyse the energy consumption data to identify any deviations from the optimal schedule.
- Adjust the optimization algorithm parameters based on the analysis results.

Step 7: Visualization

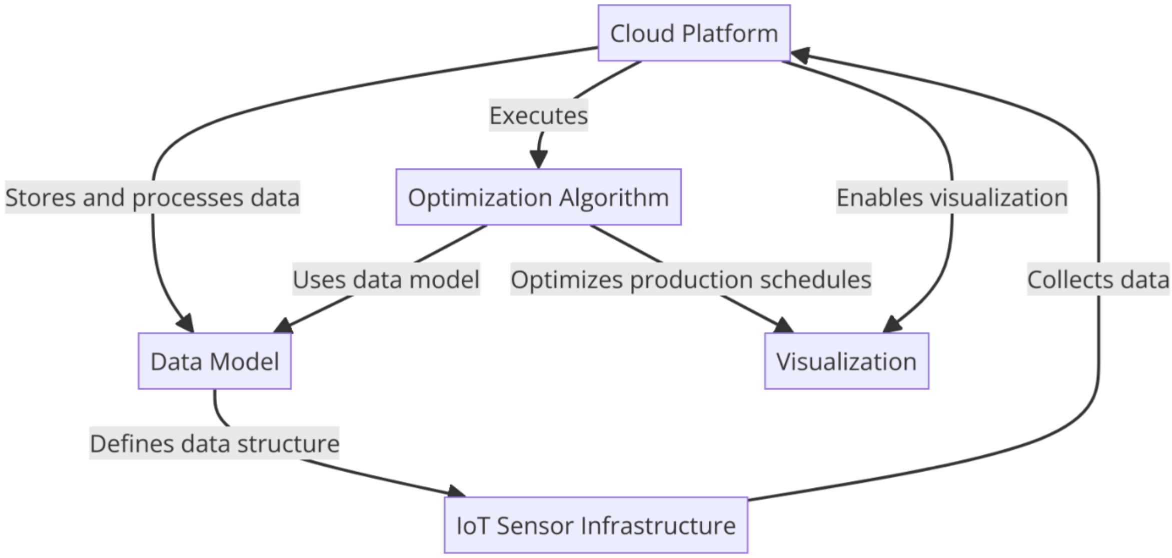
- Create a user interface that displays the optimal schedule, energy savings realized, and production rate impact.
- Allow users to monitor the system's performance and adjust as needed.

Step 8: Continuous optimization

- Regularly collect data from the IoT sensors and execute the optimization algorithm.
- Update the optimal schedule based on the latest data and analysis results.
- Continuously monitor the system's performance and adjust as needed.

Figure 7: Interaction between PMCS components

(Source: own work)



3.3.3 Optimization Goal and Strategy

The main part of our study and the key factor to increase the energy efficiency is the optimization which will be adopted by using optimization techniques which will utilize tools and optimization algorithms on the energy consumption data and processes constrains we have selected it collected, processed, and visualise it. After applying the optimization algorithms to the connected processes, we will have many possible scenarios of the optimization which will be visualized in the power BI and based on the company references, feasibility study and the production line constrains, the optimal solution of the scheduling will be selected.

<u>The optimization philosophy:</u>

Identify the optimal schedule for the processes, to save energy based on the hourly prices of the electricity during the day. Which means find the most adequate schedule for the processes. This is a very valid point since the 24-hour clock shows differences in electricity unit prices per hour. Then, the objective is to find the time through which the utilization of hours is maximized under minimum prices with respect to all the production constraints.

$$\text{Total Cost} = \sum_{\text{all processes}} \left(\sum_{t} C_i(t_i) \cdot P(t_i) \right)$$

$$\forall i, \quad t_{\text{start},i} \leq t_i \leq t_{\text{finish},i}$$

Discussing the equation:

Total Cost: Total electricity cost for the running processes within specific period.

$C_i(t_i)$: Electricity consumption of process *i* at time t_i.

$P(t_i)$: Stands for the price of electricity at time t_i. Varies over time.

Summation over t: Indicates that the cost is accumulated over different time intervals for each process, considering both the consumption and the price of electricity at those times.

Summation over Process: Indicates the cost across all processes in the production line, which means the total cost.

The equation aims to find the schedule t_i for each process to minimizes the total cost by adjusting the start times t_i within allowable constrains.

Time Constraints for Each Process:

t_i : Represents the actual start time for process *i*.

$t_{\text{start},i}$ and $t_{\text{finish},i}$: Earliest start time and the latest finish time for process i, respectively.

These constraints ensure that the optimization algorithm schedules each process within a feasible time window.

3.4 Economic Feasibility Methodology

This methodology offers a structured approach to assess costs, revenues, market dynamics, and regulatory landscapes, enabling informed decision-making and risk management. After applying the infrastructure of the PMCS into our production line and finding the possible scenarios, the comprehensive analysis will be applied to find the optimal scenario from the economical and feasible part. This process involves the following steps:

1. **Data collection:**

- Identification of relevant data sources
- Collection of financial, market, and operational data

2. **Cost estimation:**

- Breakdown of costs associated with the project
- Identification and calculation of initial investment costs
- Estimation of operational and maintenance costs

3. **Revenue projection:**

- Forecasting revenue streams from the project
- Analysis of market demand and pricing strategies
- Consideration of sales volume, pricing, and revenue growth potential

4. **Financial analysis:**

- Calculation of key financial metrics (e.g., NPV, IRR, payback period)
- Comparison with benchmark metrics and industry standards

4. Results and Evaluation

4.1 Overview

This section will cover the elaboration of the implementation of a Process Monitoring and Control System (PMCS) of our production line. The system will be prepared based on the preferences of the company and adapted to an already-existing working environment. We will discuss the elaboration of the implementation optimization of the schedule and take a closer look at this elaboration based on the proposed scenarios. This optimization targets the most cost-effective hours for electricity usage, enhancing energy efficiency and reducing overall energy costs.

The optimized schedule then will be analysed in depth in an economic feasibility way to assess the resultant financial and operational impacts of the changes. This will help us understand what cost benefits are obtained and support the decision-making regarding implementation of energy-efficient practices.

After optimization, we propose a continuous improvement routine and adaptation. Regular follow-up regarding the unfolding scenario requires adaptation of the production schedule for efficiency not to be lost in any way, problems to be avoided, and adaptation to changes in electricity pricing or altered production demands. All this is done with the aim of maintaining the beneficial state that has been initially reached through optimization as a key success factor in the long term.

4.2 Design of the Process Monitoring and Control System

The right of the PMCS needs accurate selecting of the best solutions for each component in this part we will check the available solutions which must fit with the current operational environment and choose the best.

<u>The proposed components of the PMCS infrastructure:</u>

1) IoT sensor infrastructure
2) Cloud platform
3) Data model
4) Optimization algorithm (Solver)
5) Visualisation

4.2.1 IOT Sensors

Selection of IoT sensors:

The Eaton's Power Xpert® IoT sensors will be selected due to their very broad electrical monitoring capability, measuring all the critical parameters like current, voltage, power quality, temperature, and energy consumption. Their very versatility and reliability render them ideal for our Predictive Maintenance and Condition Monitoring System.

Features and implementing core capabilities:

These can seamlessly be integrated into our production line infrastructure for wireless options such as Wi-Fi, Bluetooth, Zigbee, and LoRaWAN for easy rollout. Once installed, this facility would provide electrical data for monitoring and analysis in real time to enable proactive maintenance and optimization of equipment performance.

Figure 8: Eaton's Power Xpert® IoT sensors.

(Source: Eaton's official site)

4.2.2 Cloud Platform

Our solution will be choosing the Platform as a Service (PaaS) for theses reasons:

1) Flexibility and control over infrastructure.
2) Scalability to meet changing demands.
3) Customization of environments and applications.
4) Development and testing agility.
5) Simplified migration of existing workloads.
6) Cost control with pay-as-you-go pricing.
7) integration with existing systems and workflows.

There are many providers for the IaaS (Infrastructure as a Service):

1) Amazon Web Services (AWS)
2) Microsoft Azure
3) Google Cloud Platform (GCP)

We will go with Microsoft Azure since it is easier in utilization and excels in integration and security. aligning well with our company's requirements and preferences.

Figure 9: Microsoft Azure

(Source: Microsoft's official site)

<u>The proposed cloud platform includes:</u>

- Stream Analytics:

Processes real-time data from IoT devices, filtering, aggregating, and detecting patterns.

- Azure SQL Database:

Stores data from Stream Analytics, offering high availability, scalability, and security.

- Azure Machine Learning:

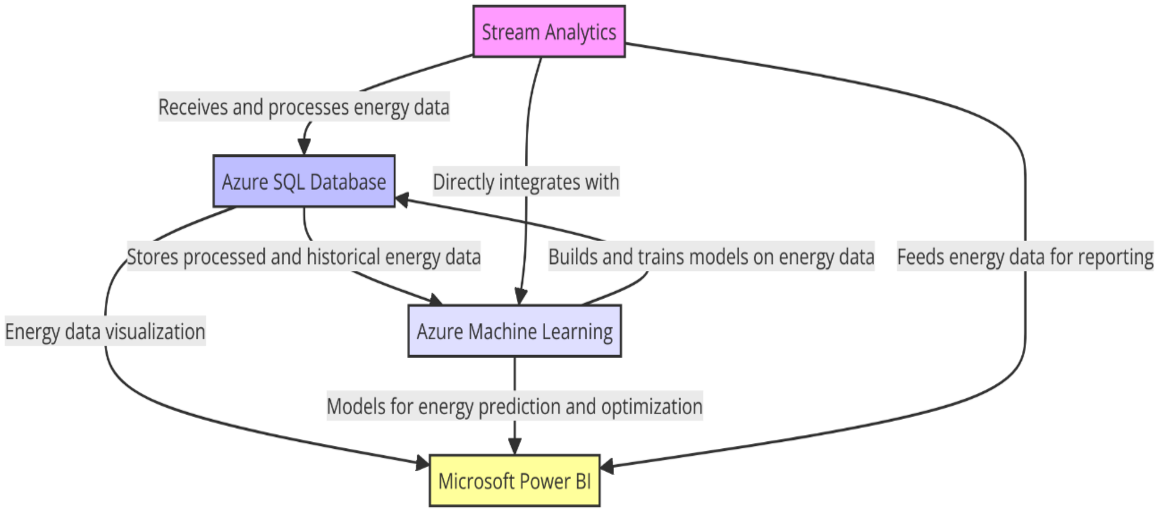
Builds, trains, and deploys ML models using data from Azure SQL Database.

- Microsoft Power BI:

  Creates interactive reports and dashboards from Azure SQL Database and Azure Machine Learning, aiding in tracking progress and enhancing energy efficiency.

Figure 10: Interaction between cloud platform components

(Source: own work)



4.2.3 Visualization

<u>Considerations for visualization:</u>

- Choose the right visualization method for the data and the audience.
- Use clear and concise labels and titles.
- Avoid cluttering the visualization with too much data.
- Make the visualization interactive to allow users to explore the data.

<u>Examples of visualizations that could be used for the optimization:</u>

Line chart: Shows the trend of energy consumption over time.

Bar chart: Compares the energy consumption of different machines or processes.

Pie chart: Shows the proportion of energy consumption by different areas of the factory Scatter plot: Shows the relationship between two variables, such as energy consumption and production rate.

Map: Shows the location of energy-intensive areas of the factor Many tools have been introduced into the market that fulfils this purpose. Possible solutions for the visualisation:

1) Microsoft Power BI
2) Tableau
3) Google Data Studio

we will choose Microsoft Power BI, since it stands out as the most comprehensive and powerful visualization tool, offering a wide range of features and capabilities. Furthermore, the cloud platform is from the same provider.

Figure 11: Microsoft Power BI

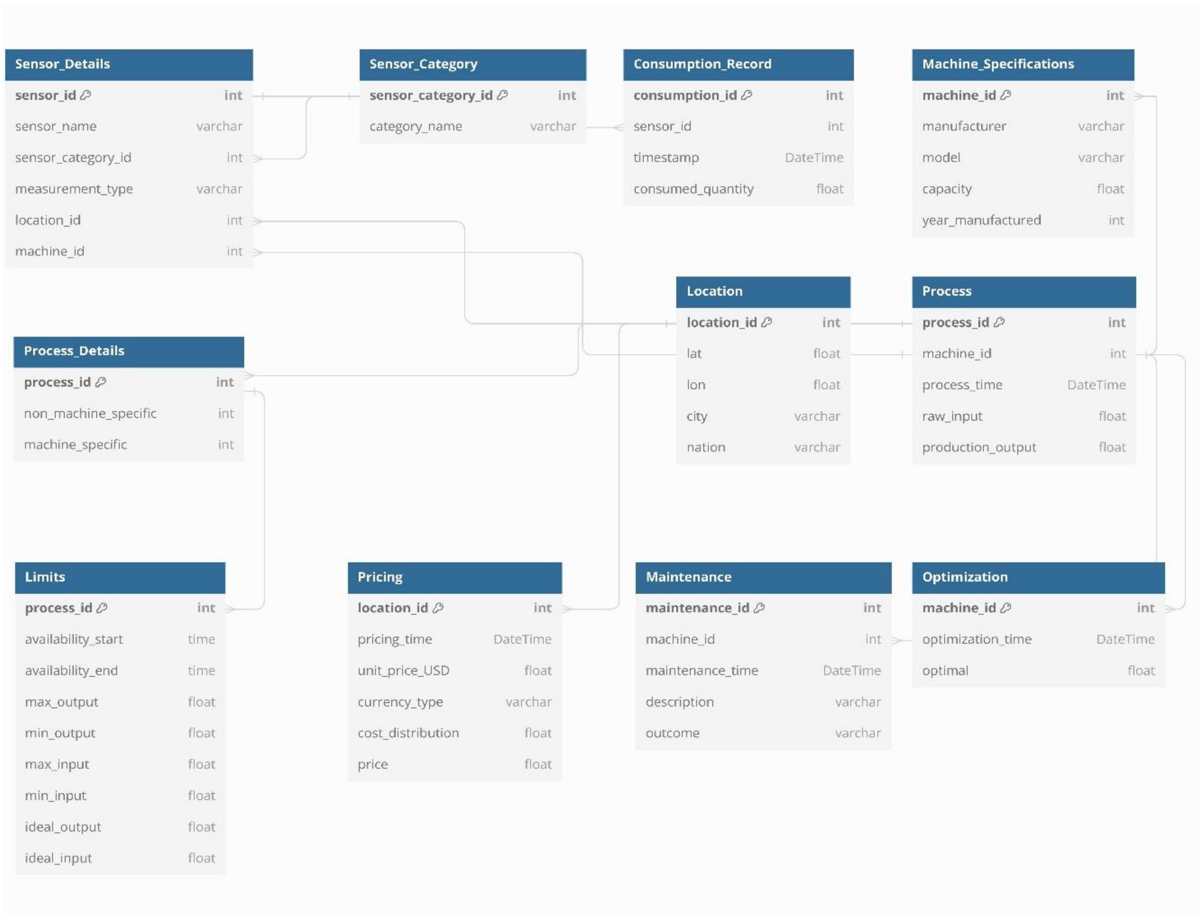
(Source: Microsoft's official site)

4.2.4 Data Model

The data model will be extracted from Azure Machine Learning in a .mod extension, which is sent to the optimization solver serve to derive the most energy-efficient operation schedules through the algorithm of linear programming.

Figure 12: Data model

(Source: own work)



4.2.5 Optimization Solver

Optimization solver acts as the engine that searches through the feasible solution space defined by the problem constraints. It systematically explores various combinations of decision variables to find the configuration that minimizes the objective function (in this case, minimizing electricity costs).

There are many solutions for this matter:

1) IBM ILOG CPLEX Studio
2) GLPK (GNU Linear Programming Kit)
3) Gurobi Optimizer

We will choose GLPK (GNU Linear Programming Kit), since it is open-source nature, making it both cost-effective and flexible for the optimization needs. Its user-friendly interface ensures ease of use, while its compatibility with cloud platforms streamlines deployment and scalability, aligning perfectly with the project requirements.

4.3 Optimization

4.3.1 Overview

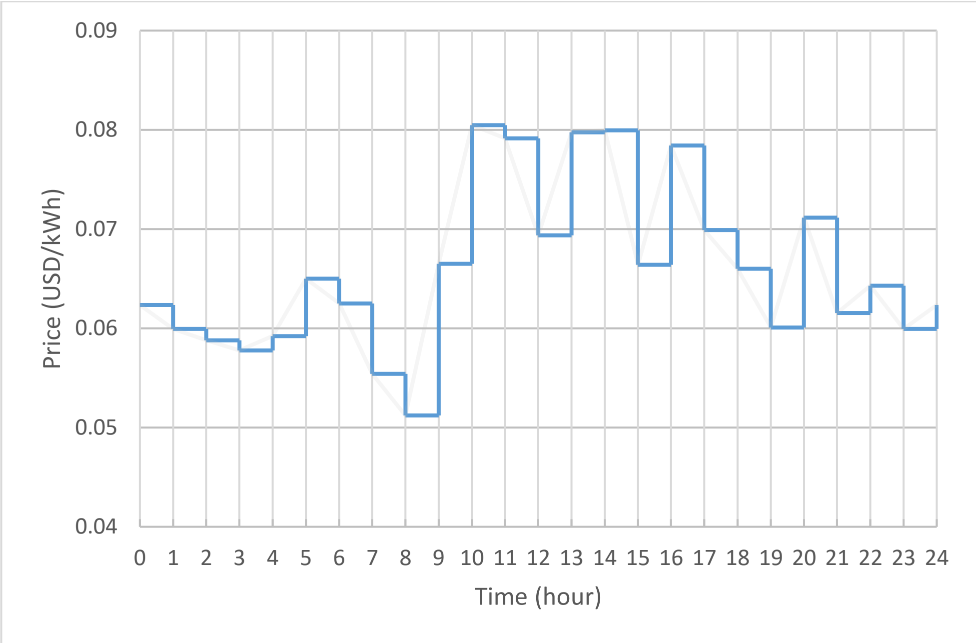
The optimization will be done based on the data of collected consumption rates, electricity prices, and process schedules according to the abilities of the linear programming optimization algorithm using GLPK (GNU Linear Programming Kit). In this approach, the LP algorithm used to minimize the electricity cost within the production schedule. The actual method and calculations are described and implemented in the accompanying code as detailed in the Appendix (Linear Programming (LP), Optimization Code).

before we start optimizing, let's look to the manufacturing electricity prices, these prices can significantly swing day by day due to fluctuations in the Syrian currency compared to the dollar. Thats why we need to implement the continuous monitoring and control system since the company has flexible working shifts.

The provided prices in Figure 13, reflect the average hourly prices during January 2024:

Figure 13: Electricity hourly prices

(Source: own work)

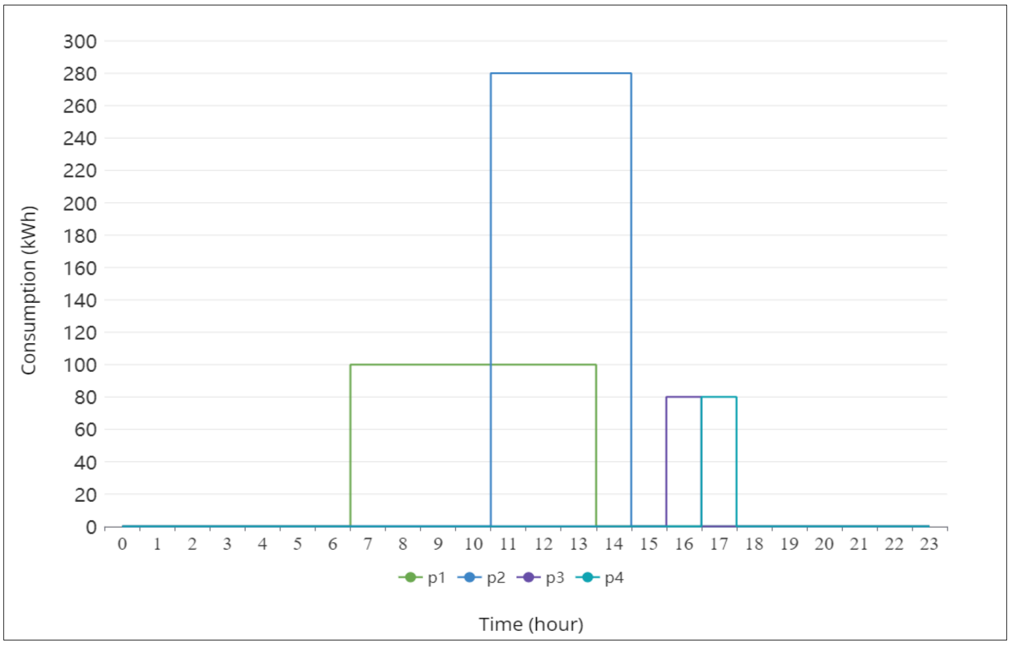


4.3.2 Optimization Scenarios

- **Original schedule:**

Figure 14: Processes schedule and consumption.

(Source: own work)



Based on the hourly electricity prices provide in Figure 14, the daily cost of electricity:

$$\text{Total Cost} = \sum_{\text{all processes}} \left(\sum_{t} C_i(t_i) \cdot P(t_i) \right)$$

Total daily Cost= 147 USD

- **Scenario A (Flexible - working hours):**

In this scenario, the company have the autonomy to operate their facilities and conduct business activities without being constrained by fixed or traditional working hour regulations.

<u>Constrains:</u>

1. Process duration: Time needed for the machinery and workers involved to carry out their respective tasks effectively:

$$t_1 = 7 \text{ hours}$$

$$t_2 = 4 \text{ hours}$$

$$t_3 = 1\ hour$$

$$t_4 = 1 \text{ hour}$$

2. Process start and finish time constraints: Logical constrain to ensure that Each process must start before it finishes:

$$t_{\text{start},1} < t_{\text{finish},1}$$

$$t_{\text{start},2} < t_{\text{finish},2}$$

$$t_{\text{start},3} < t_{\text{finish},3}$$

$$t_{\text{start},4} < t_{\text{finish},4}$$

3. Processes dependencies: Ensure sequential workflow, optimize resources, minimize downtime, assure quality, and reduce risks:

$$t_{\text{start},1} + 3 \leq t_{\text{start},2} \leq t_{\text{finish},1}$$

$$t_{\text{start},2} + 4 \leq t_{\text{start},3} \leq t_{\text{finish},2} + 1$$

$$t_{\text{start},4} = t_{\text{finish},3}$$

After analysing the current inputs and constraints in the solver. We will be able to find 59 possible solutions. However, we will choose the top effective solution:

Figure 15: Optimal solution for scenario A

(Source: own work)

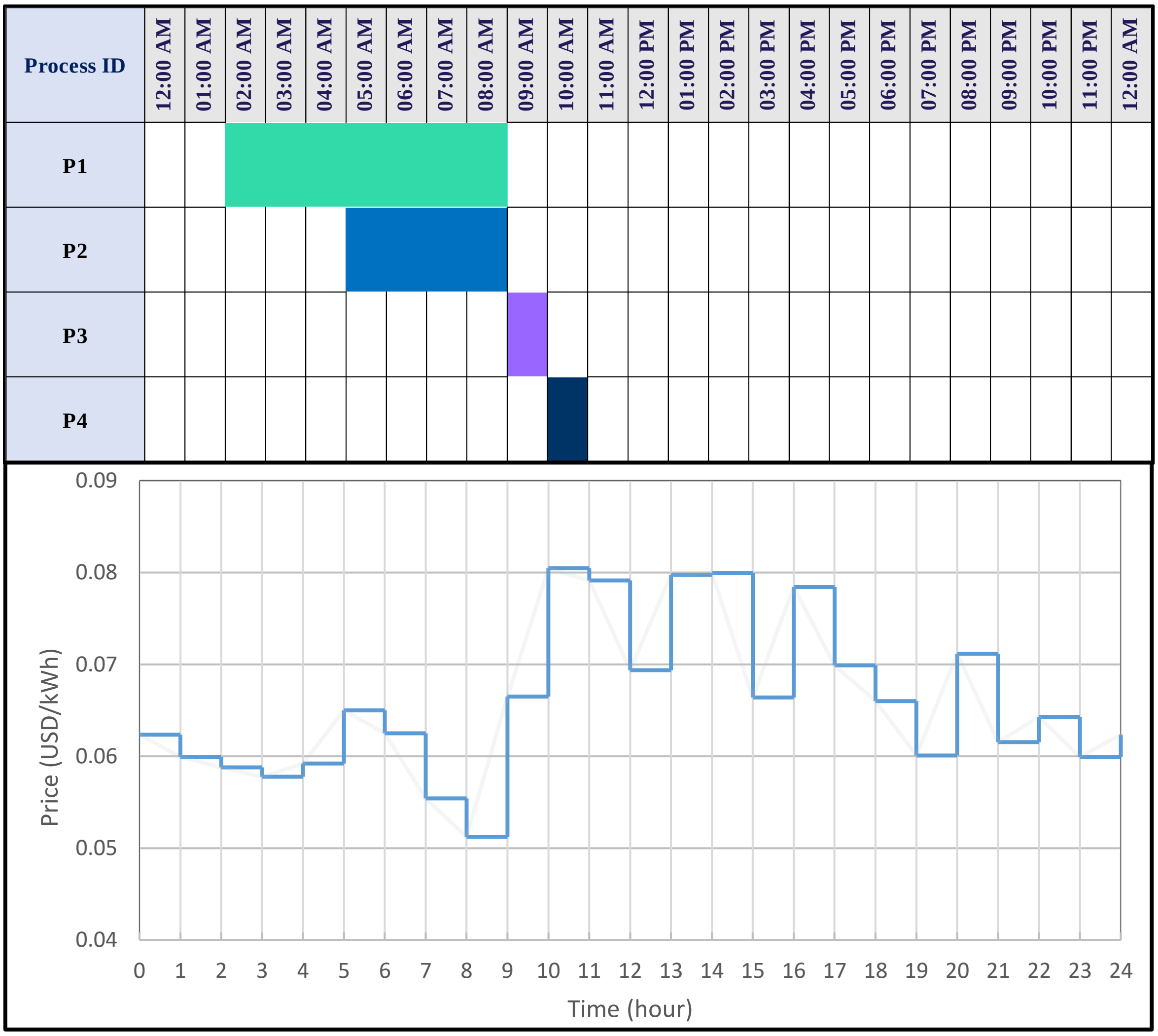


Table 5: Optimization result for scenario A

(Source: own work)

Optimization Result		
Daily cost before optimization	**Daily cost after optimization**	**Efficiency**
147 $	118.30 $	19.52%

- **Scenario B (Fixed - working hours):**

To ensure that the factory works efficiently and strictly during stipulated hours. The processes supposed to start not earlier than one hour after the factory has opened, and it is supposed to close not less than two hours before the factory closes. This basically means that no process is supposed to start before 4 a.m. because the factory opens at 3 a.m. Equally, all the processes should be winding up by 6 p.m. to accord two hours of shutting down before the factory is closed at 8 p.m. The following approach of scheduling to ensures that all operations are aligned with the factory working hours, ensuring they take place at the best usage of resources and conformance with operational guidelines.

<u>we can incorporate this into a clear mathematical constrain:</u>

Constraint for start time no earlier than 4 AM:

$$t_{\text{start},i} \leq 4$$

Constraint for finish time no later than 6 PM:

$$(t_{\text{finish},i} = t_{\text{start},i} + t_i) \leq 18$$

With remaining the same constrains:

$$t_{\text{start},1} + 3 \leq t_{\text{start},2} \leq t_{\text{finish},1}$$
$$t_{\text{start},2} + 4 \leq t_{\text{start},3} \leq t_{\text{finish},2} + 1$$
$$t_{\text{start},4} = t_{\text{finish},3}$$

$$t_{\text{start},1} < t_{\text{finish},1}$$
$$t_{\text{start},2} < t_{\text{finish},2}$$
$$t_{\text{start},3} < t_{\text{finish},3}$$
$$t_{\text{start},4} < t_{\text{finish},4}$$

$t_1 = 7$ hours

$t_2 = 4$ hours

$t_3 = 1\ hour$

$t_4 = 1$ hour

After analysing the current inputs and constraints in the solver. There are 19 possible solutions. However, we will choose the top effective solution:

Figure 16: Optimal solution for scenario B

(Source: own work)

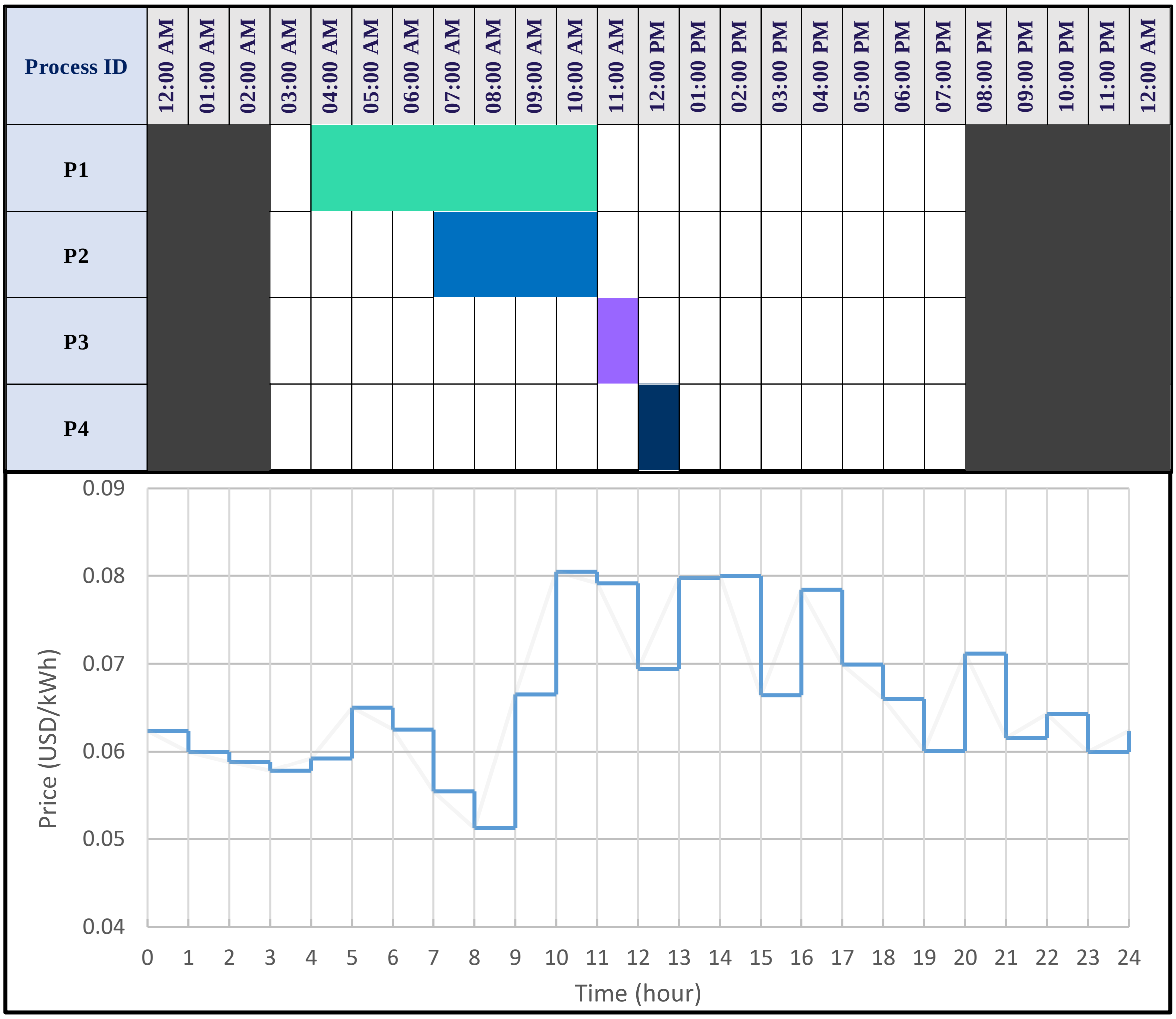


Table 6: Optimization result for scenario B

(Source: own work)

Optimization result		
Daily cost before optimization	Daily cost after optimization	Efficiency
147 $	126.92 $	13.66%

As a result, As predicted, since the lowest electricity prices occur during the times of lowest demand, which is the early morning, we may lower the costs of consumed electricity by optimizing under the given conditions. Table 5 shows that there have been savings of over 19%, which is a significant outcome. recognizing that total flexibility in terms of working hours would be necessary for it to be realized. This is only possible in production lines that are completely automated and if the final product doesn't need particular storage circumstances. Still, we need to make economic analysis for the two solutions to find the best scenario for our case.

4.4 Economic Feasibility Study

This section presents a comprehensive economic analysis of the two different scenarios, our analysis will quantify the financial outcomes of each scenario through careful revenue calculations, including assessment of long-term economic viability through net present value (NPV) analysis.

First, in this section, we present the revenue models for both flexible and fixed working hours since they were incorporated in the first set of optimized electricity consumption strategies presented. These models are very instrumental in elaborating the direct financial implications of operating efficiencies in strategic scheduling and resource management.

Second, the NPV calculation would be performed to determine the present value of the future cash flows which would be realized by every scenario. This will help in evaluating sustainability and profitability of the operational adjustments over a longer horizon, keeping in view the present value of future earnings in the background of continuous economic challenges.

The objective is to generate a clear financial perspective in the support of decision processes at the Company, ensuring that the operational strategy not only minimizes costs but also maximizes economic returns in a challenging market environment.

4.4.1 Expenses and Initial Capital Investment

We break out the labor costs for the platform development, or design and programming activities, in the definition of the cost of investment. Moreover, Table 7 shows that all currently in use measurement equipment has been accounted. This indicates that all project finance requirements are covered by the strategy.

Table 7: Initial capital investment

(Source: own work)

Initial Investment	
Labor hours invested	760
Hourly labor rate	USD 12.00
Licensing fee	USD 200.00
Miscellaneous development expenses	USD 1000.00
Total	**USD 12,000.00**

Table 7 outlines the various monthly expenses associated with implementing and maintaining the PMCS in the process manufacturing. It gives a cost breakdown regarding equipment, Labor, software, and any other relevant payments that need to be done for the efficient running of the PMCS.

Table 8: Monthly expenses

(Source: own work)

Monthly Expenses Breakdown	
Component	**Cost**
Subscription to Power BI Pro	USD 10.00
Azure SQL Database - Premium Tier	USD 120.00
Azure Inbound Data Transfer (1 GB/month)	USD 0.00
Azure Outbound Data Transfer (1 GB/month)	USD 0.00
VNET Peering within same Azure Region	USD 0.01
Azure Machine Learning Service Standard Tier	USD 0.00
GLPK (GNU Linear Programming Kit)	USD 0.00
Total	**USD 140**

From Table 8, the yearly expenses of this system will cost $1680.00, reflecting the investment needed to maintain a technologically updated and smoothly operating PMCS.

4.4.2 Revenue Calculation

In the process of revenue calculation, we derive the financial gains by leveraging the savings derived from the outlined scenarios earlier. This involves a detailed investigation of the costs involved solely for electricity consumption. And then apply savings on them. This approach brings an inclusive view of the revenue potential derived from optimized resource use, in particular, electricity usage efficiency. Table 9 shows the electricity cost of the production line processes and based on that and the efficiency, the revenue will be calculated.

In the economic analysis, for purposes of this discussion, we shall proceed on a simplifying assumption that efficiency across the year does not significantly change with respect to our monthly optimization efforts.

Table 9: Electricity cost

(Source: own work)

Electricity Cost	
Number of working days each month	22
Daily consumption (kWh)	1980
Monthly consumption (kWh)	43,560
Daily cost (USD)	147
Monthly cost (USD)	3,234
Yearly cost (USD)	38,808

Table 10A: Scenario A, revenue
(Source: own work)

Scenario A, Revenue	
Efficiency	19.52%
Monthly electricity cost (USD)	3,234
Yearly electricity cost (USD)	38,808
Monthly revenue (USD)	631.28
Yearly revenue (USD)	7575.36

Table 10B: Scenario B, revenue

(Source: own work)

Scenario B, revenue	
Efficiency	13.66%
Monthly electricity cost (USD)	3,234
Yearly electricity cost (USD)	38,808
Monthly revenue (USD)	441.76
Yearly revenue (USD)	5301.12

4.4.3 Net Present Value (NPV)

To provide an assessment of the project's economic feasibility, Net Present Value (NPV) must be computed. The application of NPV in this context serves as a robust analytical tool to ascertain the profitability of project in five years. Calculating the NPV makes it possible to put into a more comprehensible form the present value of inflows and outflows in the future, thereby making a decision based on the time value of money. Before calculating the Net Present Value (NPV), the following analysis should identify basic economic parameters important for assessing the financial outcome of a project. Each parameter has been chosen carefully to reflect the economic realities of a high-inflation environment and, therefore, provides the project with a basis for realistic financial evaluation. The analysis in table 11 presents a period of 5 years, reflecting the expected life cycle of the project's economic benefits. The estimated regional energy market price reflects an 11% increase in electricity. The raise in the price of the cloud by a margin of 3.70%, considered on a gradual technological adoption and readjustment in market demands. Moreover, in the economic instability and hyperinflation that Syria is facing, there is a 12% discount applied to make sure that future cash flows are justly valued in present terms.

Table 11: Economic Key Factors.

(Source: own work)

Key Economic Factors	
Projected period	5 years
Electricity price increase rate	11%
Cloud price increase rate	3.70%
Discount rate	12%

To calculate NPV by this formula:

$$NPV = \sum_{t=0}^{n} \frac{R_t}{(1+i)^t}$$

Where:

R_t: the net cash inflow-outflows during a single period t,

t: number of time periods

i: discount rate

In the financial framework of this project, the upfront investment of $12,000 shall be considered a capital expenditure (CapEx). Expanded investment in the first year is used to improve the production line. It consists of all expenditures incurred for purchasing and installing new machinery, equipment and any additions/alterations required in existing structures. A constant savings rate is assumed throughout the year for the sake of simplicity and smoothness in financial forecasting.

Table 12: NPV for scenario A

(Source: own work)

NPV for Scenario A					
Year	**Electricity Price**	**Revenue (savings)**	**Expenses**	**Net cash flow**	**Discounted cash flow**
0	-	-	-	-$12,000.00	-$12,000.00
1	$38,808.00	$7,575.32	$1,680.00	$5,895.32	$5,263.68
2	$43,076.88	$8,408.61	$1,742.16	$6,666.45	$5,314.45
3	$47,815.34	$9,333.55	$1,806.62	$7,526.93	$5,357.52
4	$53,075.02	$10,360.24	$1,873.46	$8,486.78	$5,393.50
5	$58,913.28	$11,499.87	$1,942.78	$9,557.09	$5,422.95
				NPV	**$14,752.10**
				IRR	**50.92%**

Table 13: NPV for scenario B

(Source: own work)

NPV for Scenario A					
Year	**Electricity Price**	**Revenue (savings)**	**Expenses**	**Net cash flow**	**Discounted cash flow**
0	-	-	-	-$12,000.00	-$12,000.00
1	$38,808.00	$5,301.17	$1,680.00	$3,621.17	$3,233.19
2	$43,076.88	$5,884.30	$1,742.16	$4,142.14	$3,302.09
3	$47,815.34	$6,531.58	$1,806.62	$4,724.96	$3,363.13
4	$53,075.02	$7,250.05	$1,873.46	$5,376.58	$3,416.92
5	$58,913.28	$8,047.55	$1,942.78	$6,104.77	$3,464.01
				NPV	**$4,779.34**
				IRR	**25.63%**

NPV for scenario A indicates higher net cash flows over the years, which also translates to higher discounted cash flows emanating from better efficiency savings. The NPV of this case is much higher, going ahead to show that Scenario A is more profitable in the long run. Therefore, this scenario A will be chosen as the solution proposed, considering that the company can work at any hour during the day, and the management of the work shifts needs to be more precisely conducted. This subject will also be discussed in this paper.

4.4.4 Profitability Index (PI)

PI gives an index of almost 2.23, from which a return on investment for each dollar spent on the project can be considered reasonable. Shows a very profitable venture under the assumptions placed in the financial model. It means that the project is feasible financially and can bring quite good returns compared to the investment.

$$\text{Profitability Index (PI)} = \frac{\text{NPV} + \text{Initial Investment}}{\text{Initial Investment}}$$

$$\text{Profitability Index (PI)} = 2.23$$

4.4.5 Pay-back Period

Table 14 shows that by the end of the second year, the cumulative cash flow exceeds the initial investment of $12,000, affirming that the Payback Period is 2 years.

Table 14: Payback Period

(Source: own work)

Payback Period		
Year	**Net cash Flow**	**Cumulative Cash Flow**
1	$5,895.32	$5,895.32
2	$6,666.45	$12,561.77
3	$7,526.93	$20,088.70
4	$8,486.78	$28,575.48
5	$9,557.09	$38,132.57

4.4.6 Benefit-Cost Ratio (BCR)

In the context of an economic feasibility study, as it is calculated in Table 15, BCR of 1.8 suggests that the project is expected to deliver a high return, with benefits nearly doubling the costs, indicating strong financial viability.

$$BCR = \frac{Total\ benefits}{Total\ costs}$$

$$BCR = \frac{PV(R)}{PV(C) + PV(I)}$$

Where:

PV(R): Present value of revenue

PV(C): Present value of expenses

PV(I): Present value of initial investment (INI)

Table 15: Benefit Cost Ratio

(Source: own work)

Benefit-Cost Ratio (BCR)						
Year	**Initial Investment**	**Revenue**	**Expenses**	**PV(R)**	**PV(C)**	**Present Value of INI PV(I)**
0	$12,000.00	-	-	-	-	$12,000.00
1	0	$7,575.32	$1,680.00	$6,763.68	$1,500.00	$0.00
2	0	$8,408.61	$1,742.16	$6,703.29	$1,388.84	$0.00
3	0	$9,333.55	$1,806.62	$6,643.44	$1,285.92	$0.00
4	0	$10,360.24	$1,873.46	$6,584.12	$1,190.62	$0.00
5	0	$11,499.87	$1,942.78	$6,525.34	$1,102.39	$0.00
			Total	**$33,219.87**	**$6,467.76**	**$12,000.00**
					BCR	**1.80**

4.4.7 Economic Feasibility Study Results

From the conducted full-scale economic analysis, it is evident that both examined scenarios prove to have a level of profitability in the long-term and significant impacts on saving energy cost. Meanwhile, Scenario A is preferable since for long-term indicators of economic efficiency, they are higher in this case. These are easily noticeable when the strong return on investment, improved efficiency, and drastic cost reduction in the period projected for this scenario are factored in. However, this latter implementation of Scenario A requires exact planning and execution, both in the short and long term. It requires systematic integration of intricate steps that allow smooth transitions and strict adherence to the set objectives. It will also require a more stringent focus on work schedule management, as this is adjusted every month according to the outcomes of the optimization plan. This may make scheduling of variables more difficult in workforce management and maintaining operational consistency, which calls for forethought and active management.

4.5 Operational Schedule

Total Operating Hours: 12 hours per day, with operations split into distinct processes:

- Setup: 1 hour (1 AM to 2 AM)
- Process P1: 7 hours (2 AM to 9 AM)
- Process P2: 4 hours (5 AM to 9 AM)
- Process P3: 1 hour (9 AM to 10 AM)
- Process P4: 1 hour (10 AM to 11 AM)
- Shutdown: 2 hours (11 AM to 1 PM)

Workforce management:

Three types of shifts: Night (12 AM to 8 AM), Evening (4 PM to 12 AM), and Day (8 AM to 4 PM) to handle the operating hours better. Due to the 12-hour working requirement, it could probably be configured as one shift of 8 hours plus an extra half shift of 4 hours.

Group work and rotation: There are 25 workers in the factory all of whom possess equal skills across various production phases. Because of group and daily rotation, the work can always be doled out equally. The rotation policy also ensures that no single worker spends more than 45 hours a week.

Flexibility: Employees are comfortable swapping work shifts, therefore supporting a dynamism in scheduling that can be flexible to change according to the needs of operations, together with the workers' preferences.

Schedule optimization:

Will be done every month at least five days before the end of each month, considering predictive analytics of electricity prices drawn from historical data and governmental sources. This will help one to be cost-effective in operations and effectively communicate the work schedules to employees.

Transportation plan:

Employee commute: This initiates the commencement of transportation planning, enabling an effective transportation mechanism for the employees to and from the factory. This will be done considering shift starting and ending times so that the transportation system can dovetail with the work schedule, availing maximum benefit in terms of convenience to the employees and guaranteed arrival and departure times.

Communication and deployment announcement:

Monthly schedule release: Employees will announce through an official communication channel their monthly schedules at 5 days in advance to enable them to make the necessary preparations. This will also include information on transportation arrangements corresponding to their shifts.

Feedback and adjustments: There will be open feedback elicitation of employee opinion in regard to the schedule and transportation arrangements made to continuously improve the plan of management.

Safety and compliance:

There will be regular safety training and audits to make sure that all operations are done with adherence to safety and legal requirements. This would also include preparedness for responses to emergencies, as well as regular safety drills in the workplace.

Plan for January:

Based on the optimization plan for January, the Total working hours is 12:

- Setup: 1 hour (1 AM to 2 AM)
- Process P1: 7 hours (2 AM to 9 AM)
- Process P2: 4 hours (5 AM to 9 AM)
- Process P3: 1 hour (9 AM to 10 AM)
- Process P4: 1 hour (10 AM to 11 AM)
- Shutdown: 2 hours (11 AM to 1 PM)

Therefore, there will be two types of shifts:

1. **Shift A (Full shift- 8 hours):** Nightshift (1 AM – 9 AM)
2. **Shift B: (Half shift- 4 hours):** Dayshift (9 AM – 1 PM)

There will be 5 groups (A, B, C, D, E) where each group has 5 employees, for the first shift, we will conduct 3 groups since it needs more workforce and 2 groups for the second shift, these groups will be rotated during the weekdays to ensure equal working hours per week for all the employees. Based on the schedule mentioned in Figure 17, each group will appear 3 times in shift A and 2 times in shift B weekly. Therefore, the total working hours for each employee per week equals 32 hours.

Figure 17: Weekly working schedule for January

(Source: own work)

MONDAY	Gourp A	Group B	Group C	Group D	Group E
SHIFT A: 1AM - 9PM	X	X	X		
SHIFT B: 9AM - 1PM				X	X

TUESDAY	Gourp A	Group B	Group C	Group D	Group E
SHIFT A: 1AM - 9PM		X	X	X	
SHIFT B: 9AM - 1PM	X				X

WEDNESDAY	Gourp A	Group B	Group C	Group D	Group E
SHIFT A: 1AM - 9PM			X	X	X
SHIFT B: 9AM - 1PM	X	X			

THURSDAY	Gourp A	Group B	Group C	Group D	Group E
SHIFT A: 1AM - 9PM	X			X	X
SHIFT B: 9AM - 1PM		X	X		

FRIDAY	Gourp A	Group B	Group C	Group D	Group E
SHIFT A: 1AM - 9PM	X	X			X
SHIFT B: 9AM - 1PM			X	X	

5. Conclusions and Proposals

5.1 Overview

Through this thesis, the reader has been provided with an overview of the project, which aimed to explore potential ways of optimizing production schedules in order to achieve electricity cost savings through the shifting of loads of particular operations within the production line. The thesis's secondary objectives were to look into the project's technical and financial viability and to provide suggestions for potential applications for the created algorithms.

The crucial aspect of the journey was the study and design of the Process Monitoring and Control System that enlightened path for more efficient process through other systems. Alongside, a thorough comparison of various systems and technologies was conducted, with focus on monitoring process and control systems.

The methodology was selected, and the problem was addressed, with the system of PMCS proposed as a solution and the practical insights into companies. Operating within a real-world company environment added a unique layer of complexity to this research, yet, despite those, PMCS demonstrated real benefits for the manufacturing company due to load shifting opportunities.

As a result, the thesis met the objectives and offered a feasible way of production schedule optimization for energy efficiency. The insights, especially from the PMCS implementation, formed a basis for sustainable manufacturing processes and added to the companies' economically suitable performance.

5.2 Design of Process Monitoring and Control System

The design of the PMCS Model has become part of an amazing effort in improving the effectiveness of industrial operations and optimizing energy consumption. Selection and integration of advanced technologies into the conceptual model have been strategic; each has been selected with unique capabilities and relevance to the objectives of the model.

Very importantly in the development of the conceptual model was the careful selection of the IoT sensors deployment to offer superior electrical monitoring, which in this case would be provided by the Power Xpert® sensors from Eaton. The sensors provided real-time data about energy consumption in relation to other production parameters, thereby ensuring the current systems were compatible.

For the handling and analysis of big data sets, the service of Microsoft Azure was employed as a cloud computing platform for its wide range of services, capacity for scaling, and strong security features. All these features of Azure, putting the processing and analysis of data into effect, have supported the development of machine learning models for predictive maintenance.

The PMCS optimization solver, facilitated by the GNU Linear Programming Kit (GLPK), effectively solved complex linear programming challenges, identifying efficient operational strategies considering fluctuating electricity prices and production requirements. For data visualization Microsoft Power Bi integrated to convert complex data sets into clear, actionable insights.

In a nutshell, the PMCS Conceptual Model integrates state-of-the-art technologies to significantly improve energy efficiency and operational performance.

5.3 Optimization Algorithm

The adoption of linear programming (LP) for scheduling optimization in this project was driven by high level of reliability in accurately finding an optimal solution. This implies a solid foundation for further development, considering the fact that heuristic methods are unable to provide a guaranteed accurate solution.

The LP algorithm developed in R with AMPL language segments performed well in a local and in cloud instances for many models with both simple and complex systems. While LP is primarily aimed at cost minimization, its reliable performance proves its value for time optimization. Integrating LP in the strategy of the project has set a benchmark for exploring heuristic algorithms, which in the near future attests to the utmost importance of LP in delivering accurate optimization solutions and has been a stepping stone in the advancement of algorithms.

5.4 Technical Feasibility

The technical feasibility study, focusing on the optimization of the production line through the application of linear programming (LP) by the solver. This section describes the optimal solutions of each scenario after taking place practical optimization and the potential increase in efficiency with respect to energy use.

The optimization process, using the GNU Linear Programming Kit (GLPK), was carried out to find the hours of most cost-effective electricity usage. This was a part of our work toward improved energy efficiency and overall energy cost reduction. The solver took account of consumption rates as well as electricity pricing and process schedules, and strategically reduced electricity costs in the production schedule through LP techniques.

The two central scenarios were studied:

Scenario A (Flexible Working Hours): This scenario allows the company in its operational hours to make adjustments flexibly, and so minimizes power usage. Constraints such as process duration, start and finish times, and inter-process dependencies were built into it for guaranteeing a seamless flow of efficient operations. Out of 59 potential solutions, the most effective one was selected for an efficiency increase of 19.52%. This optimization reduced daily electricity costs from $147 to $118.30, reflecting the advantages of a flexible scheduling approach.

Scenario B (Fixed Working Hours): In this scenario on the contrary, within the factory's time of operations prescribed and strictly followed without deviation. The optimization allowed for constraints on process initiation or conclusion times in order to dovetail with each stage in the factory's schedule and produce cost minimization. Of the 19 promising solutions, the optimal choice yielded a 13.66% increase in efficiency, with daily electricity costs falling from $147 to $126.92.

The results of the optimization scenarios show how careful operational planning and optimization can bring huge energy cost savings. All scenarios analysed; Scenario A emerges as a superior choice due to higher efficiency in reducing electricity costs. This scenario makes full use of flexibility in operational hours, thus offering a notable benefit for countries with varied electric tariffs. Implementing such a scenario requires a dynamic approach to workforce management, one that has carefully scheduled personnel complements and operations in order to fit the optimized schedule. That might mean the development of complex scheduling software or systems that can react to surges in demand and currency rate fluctuations with virtually no delay. Moreover, it is essential to establish firm communication channels among all concerned parties so that any change in timetable can be relayed immediately up and down the production line, at every node and point of blockage.

5.5 Economic Feasibility

The economic feasibility study delves into the financial analysis of two scenarios and tries to quantify financial outcomes, with an assessment of long-term economic viability. The study begins with proposed revenue models for flexible and fixed working hours, which can be understood as operational efficiencies that one can realize through strategic scheduling and resource management. In each of the scenarios, the NPV calculations found the present value of future cash inflows and outflows, which is important in determining over time the sustainability and profitability of the undertaking. The expenses and initial capital investment of the undertaking are broken down in detail to ensure that there is the fulfillment of all needs in project finance. This is to bring out a clear indication of expenses that will be incurred in the implementation and maintenance of the system on a monthly and annual basis. It is this revenue calculation that is expected to apply the saving from the optimization scenarios, especially in the cost of electricity consumption. The NPV appraisal would base on a very strong analytical framework to determine profitably over five years based on key economic parameters. Scenario A with the higher efficiency savings rate indicates superior net cash flows and discounted cash flows that demonstrate higher profitability in the long run. Both calculations on the Profitability Index and Pay-Back Period, however, have confirmed further evaluation on the financial soundness of Scenario A. From the above analysis, it becomes clear that both scenarios score reasonably well in terms of long-run profitability and saving of energy costs. The research establishes that while both the cases are economically efficient in the long run with energy cost savings, the Scenario A is more preferable in economic terms. However, the critical success factor is the ability to plan and execute, which is best done with meticulous work-schedule management and proactive operational management.

5.6 Proposals for Current Situation

These recommendations outline strategic measures for implementing the Process Monitoring and Control System (PMCS) with flexible working hours to optimize current operations.

1. **Phased implementation:**

- Before the fully implementation of the system Launch a small-scale pilot of the Process Monitoring and Control System (PMCS) with flexible hours (make the optimization on small part of the production line) to evaluate and minimize risks.
- Early engagement of the department heads and staff to allow for easy integration of PMCS and adjustment based on feedback.

2. **Training and support:**

- Develop specialized training on functionality of PMCS and flexibility in use.
- Provide a help desk and workshops to put a support system in place that will make it quick to resolve issues and provide ongoing feedback.

3. **Data and system integration:**

- Develop a strategy to interface legacy data in PMCS in such a way that data integrity is maintained.
- Ensure compatibility for PMCS with enterprise systems to enhance data exchange and monitoring.

4. **Performance monitoring:**

- Develop and monitor key performance indicators in order to improve efficiency.
- Regularly review performance with stakeholders to assess impacts and adjust based on data.

5. **Change management:**

- Develop a change management plan for the implementation of PMCS and flexible hours overcoming resistance and encouraging adaptability.
- Maintain open communication to keep all levels informed and engaged.

6. **Workforce and efficiency:**

- Implement a flexible scheduling framework responsive to both operational and energy cost changes.
- Providing employees with strong self scheduling tools, thorough training, and support.
- Make periodic scheduling updates based on price predictions of energy to ensure efficiency.
- Establish feedback loops for continuous learning and adaptation, align transport flexibly with shifts, ensure compliance with safety norms, and make any change in policy clear in communications.

5.7 Proposals for Future Developments

Here, we will introduce the potential future developments and strategic advancements essential for optimizing industrial operations via process monitoring and control system:

1. Strategic automation with industry 4.0 technologies:

Use Industry 4.0 technologies like IoT, robotics, and smart sensors. The use of these technologies at the case of flexible working hours where the production line schedule and workforce schedules varying between month and another and does not have fixed schedule, therefore the partly or fully atomization of the production line will integrate effectively with the PMCS aim of optimization and flexibility at the same time it will reduce the cost of human workforces.

2. Integration of AI and optimization algorithms

Enhance the efficiency and decision-making in a process by implementing integration of AI and optimization algorithms. It involves predictive analytics that provides optimization to scheduling, resources, and energy in order to minimize costs and enhance operations.

3. **Renewable energy integration:**

Blend renewable energy sources, like solar and wind, to meet the energy composition that aligns consumption with its availability. At the same time, reduce the dependence on non-renewable sources. Manage this through the PMCS.

4. Licensing and service model for optimization systems:

The PMCS can be developed as a licensable service or product, so that it can be shared (share the platform and the optimization system with more than production line which indeed needs its own sensors system) or sold to other facilities. This opens up more revenue streams and drives efficiency, sustainability, and productivity across the industry by collaborating.

6. Summary

This thesis research examines the possibilities to improve energy efficiency in production lines by creating and developing a Process Monitoring and Control System (PMCS). The principal aim of the project is to develop the schedule of production's processes, according to which it will be possible to perform all the operations at the time of the lowest prices for energy with the help of a complex monitoring and control system that can optimize energy consumption immediately.

The literature review evaluates current practices and technological advances in energy efficiency within the manufacturing sector. reviewing hierarchical nature of energy consumption, from individual machines through to the factory level, and underscores the potential for transformations made possible through the integration of systems for real-time monitoring and control. The paper has laid a very strong foundation toward the need to adopt highly advanced systems, which are able to change dynamically in the reflection of demand for energy and changes in operational conditions for maximum efficiency.

The study is performed based on a structured methodology with the central emphasis on the development, and effectiveness of the PMCS in real industrial settings. The development of the Process Monitoring System Infrastructure and the Optimization Workflow are key addressed points in this. An in-depth explanation of these two components shows how the PMCS harvests, processes, and uses data in making energy use in manufacturing activities efficient. This approach has emphasized the capability of the system to analyze real-time data and the strategic application of optimization algorithms with the aim of improving overall energy management.

The thesis's results introduced a holistic design and effective implementation of a PMCS that is configured to perform the continuous monitoring of energy usage along a production line. The system is engineered to process and analyze this data in order for it to make well-informed decisions in its energy usage and production scheduling. In doing so, the system can be integrated into the present infrastructural setup for production, which adds to its features, adaptability, and functions, and hence, a sharp reduction in energy consumed and operating costs. Analysis of economic feasibility is in strong support of the financial feasibility of the system through analyses like Net Present Value (NPV) and Return on Investment (ROI), thus enabling it to produce more sustainable manufacturing operations.

Overall, the integration of PMCS resulted in an evident improvement in reducing energy consumption among the manufacturing production lines. Given the innovative design of the system and its application of real-time data, more industries worldwide should integrate it. The promising outcomes from the above case and already integrated systems indicate that PMCS would be integral in enhancing sustainability and cost-effectiveness in global manufacturing.

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List of Abbreviations

AI -Artificial Intelligence

AMPL - A Modelling Language for Mathematical Programming

APC - Advanced Process Control

APM - Advanced Process Management

AWS - Amazon Web Services

BCR - Benefit-Cost Ratio

BI - Business Intelligence

DCS - Distributed Control Systems

ECI - Energy Cost Index

EMS - Energy Management Systems

EUI - Energy Utilization Index

GAs - Genetic Algorithms

GCP - Google Cloud Platform

GLPK - GNU Linear Programming Kit

IoT - Internet of Things

IaaS - Infrastructure as a Service

IRR - Internal Rate of Return

JIT - Just-In-Time

LP - Linear Programming

MPC - Model Predictive Control

NPV - Net Present Value

PaaS - Platform as a Service

PID - Proportional-Integral-Derivative

PI - Profitability Index

PLCs - Programmable Logic Controllers

PDM - Predictive Maintenance Manufacturing

PMCS - Process Monitoring and Control System

PSO - Particle Swarm Optimization

ROI - Return on Investment

SaaS - Software as a Service

SCADA - Supervisory Control and Data Acquisition

VSDs - Variable Speed Drives

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Appendix

Linear Programming (LP), Optimization Code

```
import pulp as lp

# Define the problem
model = lp.LpProblem("Minimize_Electricity_Costs", lp.LpMinimize)

# Constants
DURATIONS = {'P1': 7, 'P2': 4, 'P3': 1, 'P4': 1}
CONSUMPTION = {'P1': 100, 'P2': 280, 'P3': 80, 'P4': 80}
HOUR_RATES = [
   0.06235, 0.05994, 0.05879, 0.05777,
   0.05921, 0.065,   0.0625,  0.05541,
   0.05122, 0.0665,  0.08047, 0.07914,
   0.06937, 0.07975, 0.07995, 0.0664,
   0.07842, 0.0699,  0.066,   0.06008,
   0.07115, 0.06154, 0.06429, 0.05994
]
MAX_HOURS = 24
WORKING_HOURS_START = 0# Effective working hours start (after startup operation)
WORKING_HOURS_END = 24# Effective working hours end (before factory close)
ORIGINAL_COST = 147

# Decision variables
start_vars = {(p, h): lp.LpVariable(f'start_{p}_{h}', cat='Binary') for p in DURATIONS for h in
range(WORKING_HOURS_START, WORKING_HOURS_END)}

# Constraints
for p in DURATIONS:
   model += lp.lpSum(start_vars[p, h] for h in range(WORKING_HOURS_START,
WORKING_HOURS_END)) == 1
   for h in range(WORKING_HOURS_START, WORKING_HOURS_END):
      if h + DURATIONS[p] > WORKING_HOURS_END:
         model += start_vars[p, h] == 0

# Process start dependencies
for h in range(WORKING_HOURS_START, WORKING_HOURS_END):
   model += lp.lpSum(start_vars['P2', h2] for h2 in range(h + 3, min(WORKING_HOURS_END, h +
DURATIONS['P1']))) >= start_vars['P1', h]
   model += lp.lpSum(start_vars['P3', h3] for h3 in range(h + 4, min(WORKING_HOURS_END, h +
DURATIONS['P2'] + 1))) >= start_vars['P2', h]
for h in range(WORKING_HOURS_START + 1, WORKING_HOURS_END):
   model += start_vars['P4', h] == start_vars['P3', h - 1]

# Objective function
model += lp.lpSum(CONSUMPTION[p] * lp.lpSum(HOUR_RATES[(h + hour) % 24] * start_vars[p, h]
            for hour in range(DURATIONS[p])) for h in range(WORKING_HOURS_START,
WORKING_HOURS_END)) for p in DURATIONS)
```

```
# Solver settings and solving
solver = lp.PULP_CBC_CMD(timeLimit=120)
solutions = []
while True:
   model.solve(solver)
   if lp.LpStatus[model.status] != "Optimal":
      break
   cost = lp.value(model.objective)
   if cost >= ORIGINAL_COST:
      break
   solution_details = [(p, h, DURATIONS[p], cost) for p in DURATIONS for h in
range(WORKING_HOURS_START, WORKING_HOURS_END) if lp.value(start_vars[p, h]) == 1]
   solutions.append(solution_details)
   # Constraint to forbid the current solution
   model += lp.lpSum(start_vars[p, h] * lp.value(start_vars[p, h]) for p in DURATIONS for h in
range(WORKING_HOURS_START, WORKING_HOURS_END)) <= \
         sum(lp.value(start_vars[p, h]) for p in DURATIONS for h in
range(WORKING_HOURS_START, WORKING_HOURS_END)) - 1

# Calculate the number of solutions
num_solutions = len(solutions)
print("Number of possible solutions:", num_solutions)

# Sort solutions by cost and display top two
solutions.sort(key=lambda x: x[-1][3])
for i, solution in enumerate(solutions[:2]):
   efficiency = ((ORIGINAL_COST - solution[-1][3]) / ORIGINAL_COST) * 100
   print(f"Solution {i + 1} (cost: ${solution[-1][3]:.2f}, efficiency: {efficiency:.2f}%):")
   for p, h, duration, _ in solution:
      print(f"{p} starts at hour {h}, runs for {duration} hours.")
      print('Schedule:', ' '.join(['_' * h + '▓' * duration + '_' * (MAX_HOURS - h - duration)]))
```

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