

ASSESSMENT OF POWER CONSUMPTION OF AN INDUSTRIAL
FACILITY AND EXPLORING APPROACHES FOR ENERGY
MANAGEMENT AND EFFICIENCY: A CASE STUDY FROM SAVOLA



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Declaration of Authorship

I hereby declare that this work titled “Assessment of power consumption of an industrial facility and exploring approaches for energy management and efficiency: A case study from Savola Foods” submitted to the Mechanical Engineering department of the British University in Egypt is an original piece of work and has not been published or showcased anywhere else in the past. This work was carried out under the supervision of Dr. Noha Mostafa.

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Abstract

This study explores how to optimally modify process parameters, forecast using artificial intelligence (AI), and assess employee engagement to lower energy usage in a cooking oil manufacturing facility. Energy consumption during the blowing stage of production was identified as particularly problematic. Energy usage was especially high during the colder months due to the low temperature of the PET preforms. To mitigate this issue, a preform preheating strategy was implemented that involved placing preforms in the boiler room prior to production. In addition, three pressure settings (33, 34, and 35 bar) alongside three heating durations (8, 10, and 12 hours) were tested. The Design of Experiments (DOE) approach was used to find the best combination, and the identified optimum was 34 bar with a 10-hour heating period as this offered a good tradeoff for energy savings with product quality.

Simultaneously, trend predictions for energy consumption were developed with six AI models. The Support Vector Machines (SVM) model outperformed in forecasting accuracy and exhibited the lowest error rate, thus making it fit for usage in data-scarce industrial settings. A behavioral energy awareness survey showed that most employees are energy mindful; however, other departments, especially the refrigeration unit, needed targeted training paired with stronger supervision.

The study demonstrated a meaningful reduction in energy usage, with estimated savings of about 20% and an annual cost reduction exceeding \$2 million. The results substantiate the claim that substantial energy efficiency improvements are possible with a blend of legacy systems, process adjustments, digital technologies, and workforce mobilization.

Keywords:

Artificial Intelligence, Blowing Machines, Energy Consumption, Process Optimization, Preform Preheating, Energy Forecasting, Support Vector Machine, Behavioral Energy Awareness, Sustainability, Energy Management, Industrial Efficiency, Manufacturing Cost Reduction, Employee Training, Predictive Modeling.

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Chapter1: Introduction

1.1 Background

The growing demand for energy as well as the rising costs of operating an industry have compelled manufacturers to adopt more sustainable and economically beneficial approaches for managing energy. In the industrial sector, for instance food industry, direct energy costs arise from operating refrigeration and supersonic forming machinery, as well as robotics and automation. The blowing machines to produce plastic bottles are especially notorious for their high energy consumption, particularly during winter months when higher energy usage is required to bring p0reform materials to target temperatures.

Concern for the environment, operational efficiency, and cost containment have all combined to motivate almost every industry to explore means for lowering energy consumption while maintaining the same product quality. One of the most cost-effective methods is optimization of previously established processes, which can be accomplished through simple adjustments such as the use of spent heating to improve the temperature of raw materials, adjustment of operating parameters of the machines, or precise control of temperature and pressure in forming processes. Moreover, advancements in artificial intelligence have enabled more accurate predictive energy management, allowing for better forecasting of consumption trends and data-informed decision-making.

Furthermore, the behavior of personnel is equally important for a well-designed energy-efficient regime. Employees' awareness, habits, and engagement directly influence the use and maintenance of various pieces of machinery. Understanding and modifying these human aspects is becoming more important in meeting the objectives to save energy.

This investigation focuses on an integrated approach of process optimization, AI-based forecasting, and behavioral analytics to minimize energy utilization in a partially automated cooking oil factory. It seeks to illustrate the potential of significant energy savings accomplished with available tools and through sensible, economical, and scalable measures.



Figure 1power

1.2 Research Hypothesis

This investigation is predicated on the theory that an optimization of processes, predictive modeling with artificial intelligence (AI), and an improvement in employee work habits regarding energy consumption will significantly reduce energy use in an industrial cooking oil factory, all achieved without expensive new equipment or infrastructure renovations.

The study makes the following assumptions:

- Specific operational parameters like blowing pressure and preform heat gain time can be modified to save energy while upholding required product standards.
- Even with sparse factory data AI models can accurately forecast electricity demand based on past consumption.
- With proper evaluation and intervention, targeted assessments can improve employee actions related to energy management, thus curbing waste and enhancing energy efficiency.

The objective is to validate the hypothesis that these three factors—integration of engineering control, data-driven analytics, and human factor processes—moving in synergy can successfully reduce energy utilization and costs in a tangible and practical way.

1.3 Aim and Objectives

This study focuses on devising ways to reduce energy consumption of the blowing machine operations in the factory by lowering costs. This will be accomplished through optimizing the heating of preform segments, AI-based predictive energy management systems, and studying the energy-related actions of employees. The main objective is to improve energy consumption efficiency, reduce operational costs, and enhance the sustainability goals of the factory while avoiding major infrastructural changes.

Objectives:

1. To determine the most important factors attributing to excessive power consumption, the blowing machines required to analyze the energy consumption patterns are operated under various conditions.
2. To decrease the loading on the compressor while maintaining product quality, preform heating and blowing pressure settings are optimized via DOE controlled experiments utilizing existing heat sources.
3. To assess employee awareness and behavior towards energy-saving practices, structured surveys are conducted which pinpoint gaps and training requirements among high-energy consuming sectors such as refrigeration.
4. To implement low-data environment, real-time energy management predictive AI models such as Support Vector Machine (SVM) are utilized for energy demand forecasting.
5. To assess the effectiveness of the proposed measures, reductions in energy consumption and financial savings are calculated with the emphasis on replicability and scalability across similar industrial contexts

1.4 Research Methodology

This study utilizes a mixed-methods approach to analyze energy consumption holistically and develop feasible optimization strategies. The addressed AI modeling along with automation technology and workers' psychological profile assessment mentioned above illustrates integration of data driven system analysis, experiment design and artificial intelligence essential for any multidisciplinary industrial energy efficiency research.

1.4.1 Data Collection

1. Energy Consumption Data (Quantitative)

Quantitative data will be collected from the factory's blowing machine processes to measure energy expenditure during the following steps:

- Energy utilized in the preform heating, blowing pressure stage, and cycle completion.
- Blow molding machine operation times and power ratings, as well as real-time kWh consumption.
- Performance yields under various process conditions (pressure and preheating time).

To enhance data reliability, collection will occur over several production shifts. This assembled dataset will serve dual purposes: for performance appraisal and as input for AI-driven energy consumption forecasting models.

2. Employee Behavior Data (Qualitative)

Qualitative data pertaining to energy consumption will be gathered through structured interviews and surveys focused on employee behaviors, practices, and perceptions related to energy usage at work.

- Design of the employee survey will be based on psychological literature, particularly on the Theory of Planned Behavior (TPB) and Attitude-Behavior-Context (A-B-C) model.
- The interviews will investigate employees' knowledge of energy conservation measures, their noted practices such as powering off equipment during breaks, and their readiness to adopt or endorse energy-saving measures.
- Attention will also be directed to pinpointing the possible human factors that could lead to energy wastage, for example poor equipment use, inadequate instruction, unmotivated supervision, or low levels of supervision.

The analysis will be conducted to classify respondents and their actions into different departments and training priorities, which will streamline the recommendations for the participatory design concerning the engagement strategies for the workplace.

1.4.2 System Analysis and Optimization

1. Energy Efficiency Analysis:

- A detailed analysis of the energy consumption patterns of the blowing machines will be conducted. This will involve comparing theoretical energy consumption with the actual energy consumption to identify discrepancies and inefficiencies.
 - Advanced data analysis techniques such as regression modeling or energy consumption forecasting may be used to identify key factors contributing to high energy use.
2. Optimization of the Preform Heating Process:
- Based on the data collected, the preform heating process will be optimized by testing different preheating methods. This could include evaluating the effect of using a separate preheating area (like the boiling room) versus direct heating within the blowing machine.
 - Various machine settings (e.g., blower pressure, heating temperature, cycle time) will be tested to determine the most energy-efficient configuration.

1.4.3 Employee Training and Behavior Modification

1. Behavioral Assessment:
- The research will explore how employees interact with energy-consuming systems. By analyzing survey responses and conducting interviews, the study will identify any knowledge gaps or attitudes that hinder energy-saving practices.
 - This will help design a tailored training program for employees to increase awareness and encourage energy-saving habits.
2. Employee Training Program:
- A training program will be developed based on the findings from the employee behavior analysis. The program will focus on educating employees about energy-saving practices and provide practical steps for reducing energy consumption during their tasks.
 - The effectiveness of the program will be evaluated by measuring any behavioral changes and subsequent reductions in energy consumption.

1.4.4 Evaluation and Effectiveness Assessment

1. Pre- and Post-Implementation Analysis:

- A comparison of energy consumption and operational costs before and after the optimization and training interventions will be conducted. This will allow for an evaluation of the effectiveness of the changes implemented.
- Statistical methods (e.g., t-tests or ANOVA) will be used to determine whether there is a significant reduction in energy consumption after implementing the changes.

2. Impact on Production Efficiency:

- In addition to energy savings, the study will also assess any impacts on production efficiency, including cycle time and equipment wear. The goal is to ensure that energy savings do not negatively impact the overall performance of the blowing machines.

1.4.5 Research Strategy Summary

The research methodology integrates both quantitative data analysis (to measure energy consumption) and qualitative insights (to understand employee behavior). This combination of approaches ensures that all aspects of energy use in the factory are addressed. The findings from this study will not only propose technical solutions for energy optimization but also provide valuable recommendations for improving employee practices, leading to more sustainable operations.

Chapter2: Literature Review

2.1 Introduction

Over the years, efficient energy management has become of utmost importance in industrial systems following the continuous rise in global energy demand and increased concerns over environmental sustainability. Industries are expected to cut operational costs and carbon emissions while maintaining productivity and performance. To this effect, power management at manufacturing facilities is changing due to a combination of technology innovation, system-level optimization as well as behavioral interventions.

This literature review provides an extensive basis for on-going research on assessing energy consumption within an industrial facility and examines practical methods used in reducing it. The review is organized by key thematic areas that correspond with the core components of the project such as; system analysis and control; advanced energy management strategies; human behavioral dimension in energy use; thermal energy storage & Waste Heat Recovery (WHR) ; and upcoming roles played by AI (artificial intelligence) systems on predicting & optimizing power consumption.

Each section critically evaluates recent papers alongside those published years ago in order to highlight gaps or limitations existing between these studies as well as promising avenues for future research directions. By synthesizing technical and behavioral studies, this chapter underscores the multifaceted nature of industrial energy management and supports the development of integrated solutions tailored to both equipment performance and human factors.

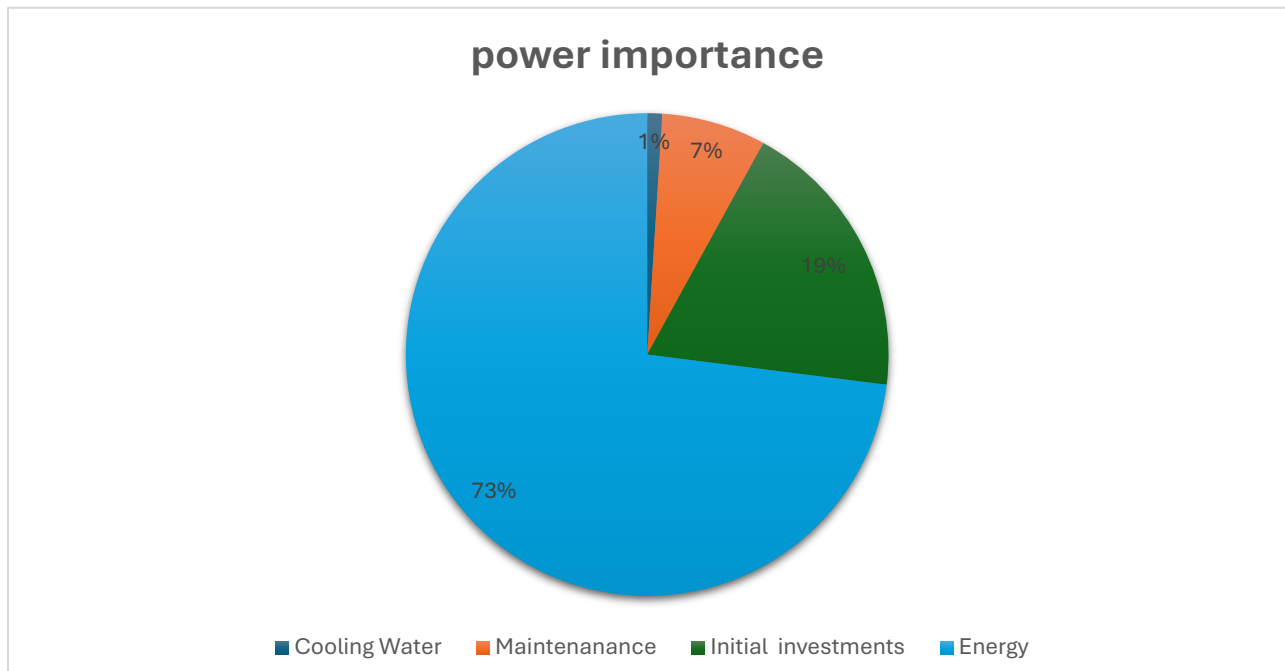


Figure 2 Power importance

2.2 Body

2.2.1 Power System Analysis and Control

Energy efficiency strategies are built upon accurate measurement and control of energy systems. Advanced energy metering systems, as highlighted by O'Driscoll and O'Donnell (2013), hold the key to understanding consumption trends and identifying inefficiencies, especially in a manufacturing setting. They present how peak shaving and load shifting metrics can be incorporated into production strategies. It must be noted that there is no predictive modeling or real-time optimization.

In addition, Cataldo et al.'s (2015) Control Simulation Methodology (CSM) mimics actuator behavior and the use of energy in real time during simulation. Their method facilitates peak demand reduction as well as system-wide control. Nevertheless, uptake of CSM by actual factories is limited due to its complex setup process and standardization issues.

These studies point towards a future where sensors function in real time with prediction tools rather than being used for reactive measurement alone.

Advanced Energy Management Strategies

IoT, energy simulation and hybrid machine technologies are being adopted in modern factories to enhance efficiency. Jedrzejewski and Kwasny (2011) concentrated on the energy savings of high-speed machines through optimizing cutting technologies as well as adopting multitasking machinery that achieved measurable energy gains. However, they narrowly focus on individual machines rather than facility-wide systems.

Giacone & Mancò (2012) presented operational improvements in a foundry such as off-peak melting by using Specific Energy Consumption (SEC) as a benchmark. These strategies depend heavily on manual scheduling and lack intelligent automation.

Menghi et al. (2019) provided a systematic review of industrial energy models, 64 in total, which showed how machine parameters relate to process-level energy outcomes. Their study underscores the importance of integrated simulation even though it notes that many models do not take into consideration behavioral or external variables.

On top of that, Weeber et al. (2018) proved the benefits of thermal comfort and thermal quality simulations for whole buildings extend beyond just those concerning energy efficiency but also non-energy aspects. Therefore, these studies support the development of comprehensive factory-level EM tools combining hardware, software and analytics together.

Behavioral aspects are often ignored in technical energy audits, but they have a significant impact on actual energy performance. According to Gao et al. (2017), the extended TPB, which involves personal moral norms and descriptive norms, was applied to workplace energy conservation. The results indicated that general intentions were less predictive than a sense of obligation and peer behavior.

Xu et al. (2017) also employed the ABC model to indicate that communication ease, group norms and perceived organizational support are crucial for making employees willing to save energy even at the expense of comfort. These studies have shown that even with the best technologies in place there may not be expected levels of energy savings without developing a supportive and aware culture.

Nevertheless, many behavioral studies only concern office environments while fewer focus on energy intensive industrial premises. This provides an opportunity for extending behavior-based energy programs into manufacturing plants.

2.2.2 Compressed Air Systems and Blowing Machine Efficiency

Air compressed systems which are very important in manufacturing are widely known for being inefficient. For instance, Nehler (2018) states that only 10–15% of the total energy is converted into useful work while the rest is lost through heat or leaks. Also, it emphasizes the need to consider non-energy benefits such as improved reliability and reduced maintenance costs that can go unnoticed during an energy audit. Therefore, there is a gap because energy-saving measures should be assessed not only in terms of their power impact but also considering operational and organizational advantages.

On blowing machines, Hsieh and Lin (2020) through experiments and computational fluid dynamics simulations optimizes infrared heating for PET preforms. The researchers achieved a 14% reduction in energy consumption using a modified heat box design together with optimized lamp configuration. However, though this article is highly applicable to your factory context there is absence of integration with environmental or behavioral variables affecting on-site energy use.

2.2.3 Thermal Energy Storage (TES) and Waste Heat Recovery (WHR)

Thermal energy storage (TES) and waste heat recovery (WHR) are two effective means of reusing industrial heat losses. According to Miró et al. (2016), who reviewed 35 industrial case studies on TES, there is growing interest in capturing and storing excess heat within industries. On-site TES systems incorporating water, zeolite or erythritol were found to be the most feasible for manufacturing reuse.

This was further reported by Su et al. (2021) with a review of WHR in 12 industries citing supercritical CO₂ cycles, Kalina cycles, and hybrid Rankine systems as technologies that can capture low-grade and high-grade waste heat. Technically viable though they may be, cost-related challenges, complexity and integration with existing infrastructure are among the obstacles that must still be overcome.

Both papers highlight the significance of such waste heat solutions but also advance simpler, cheaper and scalable designs as well.

2.2.4 AI Forecasting for Energy Consumption

Artificial Intelligence (AI) models like Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) offer significant promise in energy forecasting, as recent literature shows. The methods are particularly useful in modeling non-linear relationships, and can accurately predict the energy demand of HVAC systems, lighting, industrial loads.

Ahmad et al.,(2014), conducted a comprehensive review of electrical energy consumption forecasting techniques with an emphasis on AI-based models' superiority for intricate patterns of energy use. It was found that these models such as ANN and SVM perform better than the traditional statistical approaches and provide more accurate predictions even when there are variations in environmental and operating conditions. They also advocated for hybrid models to enhance forecast accuracy.

In addition, some hybrid methods such as ARIMA-ANN, GA-ANFIS, GLSSVM have shown even better accuracy by reducing forecasting errors and improving control decisions. By determining peak demand time beforehand; discovering anomalies; real-time optimization of system operation – these tools facilitate proactive management of energy. However, despite their enormous potential in industrial applications thus far it has only been used to a limited extent mostly within commercial or residential buildings. Using AI-based forecasting in industrial systems such as blowing machines, refrigeration cycles, or compressed air networks can greatly improve predictive maintenance, energy efficiency and real-time dynamic control. Adoption of these intelligent systems will probably shape the future of industrial energy management.

2.3 Conclusion

Through literature reviews, it is evident that managing energy in industrial establishments poses a multi-dimensional challenge extending into optimizing system-levels, human behavior and emerging technologies. Some of the advanced power monitoring and control strategies are real time metering, actuator level simulations and machine specific energy audits. Additionally, complementary approaches such as Internet of Things (IoT) based platforms and energy modeling frameworks can be used to optimize energy at the factory level.

Human behavior has been identified as a crucial but less frequently utilized aspect of energy conservation strategies. Studies based on Theory of Planned Behavior (TPB) and Attitude-Behavior-Context model has proved that individual attitudes, social norms and organizational support influence employee's initiatives towards conserving energy greatly. Combining behavioral insights with technical interventions significantly boosts outcomes for saving energy.

Regarding system efficiency, research shows great potential for improvement in compressed air systems as well as blowing machines which are common in industries. However, there are some possible ways to recover waste heat through Thermal Energy Storage (TES) or Waste Heat Recovery (WHR), although cost and complexity of systems may hinder this solution from being viable all the time.

There is great potential for AI-based forecasting models in industrial energy applications with ANN, SVM and several hybrid systems having shown strong predictive capabilities. Unfortunately, most of these AI applications have focused on buildings and commercial use cases leaving a gap in their integration into the industrial settings as those considered in this project.

Research Gaps Identified:

- Limited integration of AI-based forecasting and optimization in industrial energy systems.
- Underexplored role of employee behavior in energy-intensive environments like factories.
- A lack of holistic energy strategies combining technical solutions with behavioral change.
- Minimal application of predictive energy management in blowing machines and compressed air networks.

Relevance to Current Study: These findings directly support the objectives of this research project. The gaps identified align with the project's aim to assess energy consumption in a factory setting by analyzing behavioral factors and implementing practical, low-cost energy-saving interventions—such as preheating preforms to reduce energy use in blowing machines. Moreover, the promising results from AI forecasting studies point toward future research opportunities for predictive energy management in industrial facilities.

Chapter3: Research Strategy

3.1 Data

This case study was conducted using real operational data from a cooking oil factory's energy-intensive blowing machines used for forming plastic bottles. These machines have significant energy requirements, particularly during the colder months when the temperature of the preform materials is low. As a workaround, energy consumption was reduced by warming the preforms thermally before the blowing process by storing them in the factory's boiler room. This change not only reduced the energy required to heat the preforms but also enabled the machines to function at reduced pressures.

The collected data consists of the energy costs associated with implementing the new strategy, along with its cost implications across daily, weekly, monthly, and yearly spans. Further data was collected from four production lines SIPA1, SIPA2, SIPA3 and KHS, capturing power consumption and improvement in efficiency for each machine.

There is a lack of internal, historical data within the factory as it is in the early phases of digital transformation. For this case study, other sources of data from similar industries were analyzed to aid in the decision-making and modeling processes for energy forecasting and management.

3.2 Research Methods

The case study employs a mixed method which combines an analysis of the data with a predictive model based on machine learning techniques to optimize energy consumption in the factory. The below approaches were employed:

1. Power Reduction Strategy

The primary approach is to enhance the temperature of the preforms by placing them in the boiler room ahead of processing. This change was made to avoid direct energy heating inside the blowing machine and instead utilize warm energy already available within the factory. This change also allowed for a reduction in operating pressure from 37 bar to 34 bar in the machines, enabling energy and cost savings while maintaining product quality.

2. Energy Monitoring and Analysis

Energy consumption data was tracked for each machine over a number of operational periods. The main focus of this analysis was identifying the new reduction in kWh and analyzing the cost-benefit of the new approach. Consumption percentages were partitioned by machine to pinpoint the largest contributors to energy savings.

3. Utilizing AI for Power Management Prediction

The purpose of the study was to explore the use of models based on Artificial Intelligence (AI) for forecasting energy demand to enable more advanced predictive control of energy management. Due to the factory's internal data constraints, models such as ANN and SVM trained on external datasets from comparable industrial settings were used. These AI models are capable of forecasting power demand given the temperature, production volume, and machine load.

Given certain assumptions, the AI approach simulates and provides the following real-time insights:

- Estimation of power demand peaks for production schedule.
- Operational thresholds for energy consumption: minimums or safe limits beyond which operations would be jeopardized.
- Load shifting or reduction opportunities during expensive energy periods.

The factory is now able to not only manage energy more efficiently, but also plan digital transformation upgrades aligned with the factory's needs.

3.3 Research Plan

The research plan is centered on the following actions:

1. Practical Intervention: Implemented a preheating strategy for the boiler room to lower internal pressure of the machine.
2. Data Collection and Validation: Monitored and archived the relevant data for power consumption and costs pre and post change.
3. AI Model Exploration: Investigated external datasets and literature to pinpoint appropriate forecasting models that would work with sparse internal data.
4. Application: Used predictive AI models to simulate power trends, forecast constraints, and visualize estimated energy savings.
5. Evaluation: Analyzed the intervention's effectiveness using measured bottle quality (base diameter) along with power consumption
6. Observation and Problem Identification: Evaluated blowing machines with excessive energy consumption and noted the problem during winter season.

3.4 Conclusion

This chapter presented the holistic method aimed at curbing energy consumption within the confines of a factory. The integration of a practical thermal approach (preform preheating) and AI-based digital forecasting tools creates a unique dual framework blending operational enhancement and technological advancement.

Although data history is currently limited because of the early phase of digital transformation, the factory has started building a framework for smart energy management. The use of AI technologies enables the firm to make informed, predictive decisions regarding energy expenditures, while real-time savings such as pressure optimization provide instant reduction in costs. These approaches together bolster the immediate drive toward efficiency while supporting the long-term sustainability targets.

Chapter4: Experimental Work

4.1 Experimental Arrangement

The scope of this research consisted of a systematic experimental design carried out in three interlinked domains; all related to energy optimization in an oil production factory. In these domains, the system was intended to be feasible, repeatable, and reflective of the factory's real working environment. The three areas of concentration were:

1. Refinement of the Blowing Machine Process.
2. Application of AI Based Energy Consumption Prediction.
3. Energy Awareness Behavioral Assessment Among the Workers.

Each experimental area was equipped with a defined set of inputs, control parameters, and instruments as elaborated below.

A. Blowing Machine Optimization Configuration

The goal of this configuration was to lower the energy expenditure during blowing of the bottles through preheating of PET preforms and changing the working pressure of the machine.

1. Materials Used:

Preforms:

Type A: 22 grams preforms for Helwa 1-liter bottles

Type B: 52 grams preforms for Helwa 2.25-liter bottles



Figure 5 Helwa 1-Liter



Figure 4 Preform



Figure 3 Helwa 2.25-Liter

Blowing Machine:

Four production lines (e.g., SIPA1, SIPA2, SIPA3, KHS)

Machines with controllable discharge pressures of 33, 34, and 35 bars.



Figure 7 Blowing Machine



Figure 6 Preform Preparing Lline

Table 1 Blowing Machine Consumptions

		Sipa		
consumptions	20%	35%	20%	25%
Name Of Machines	1	2	3	KHS
Before	3000 KW/h	5250 KW/h	3000 KW/h	3750 KW/h
After	2400 Kw/h	4200 Kw/h	2400 Kw/h	3000 Kw/h

2. Preheating Setup:

The relevant preforms were arranged in metal trays and kept in the boiler room, which is the warmest confined space in the facility and is designated for steam heating.

The objective was to increase the temperature of the preforms in a passive manner prior to processing.

- Preheating Duration: 8, 10, and 12 hours
- Boiler Room Conditions:
- Rough ambient temperature: 35°C
- Limited access to ensure a stable working environment



Figure 8 Boiler Room

3. Experimental Procedure:

- At the conclusion of each heating interval, the preforms were rapidly moved to the blowing machine in covered containers to protect the heat during transport.
- Each batch of preforms was processed at one of the designated pressures.
- Shape consistency evaluation was performed by digitally measuring the outer diameter of the bottle base with a caliper.
- Each combination (preform type \times pressure \times time) was conducted in triplicate.

B. AI-Driven Forecasting Configuration

This configuration aimed to test multiple AI models and evaluate their capability to predict energy consumption within the factory relative to the limited amount of historical data available.

1. Software and Tools:

- Design Tools: Python with Scikit-learn.
- Assessment Criteria: R^2 score, RMSE, error percentage, and accompanying graphs.

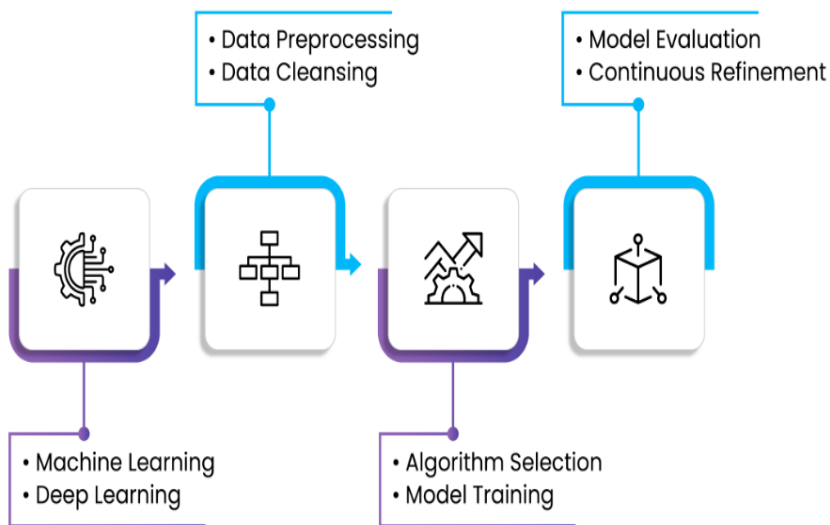


Figure 10 Ai processing

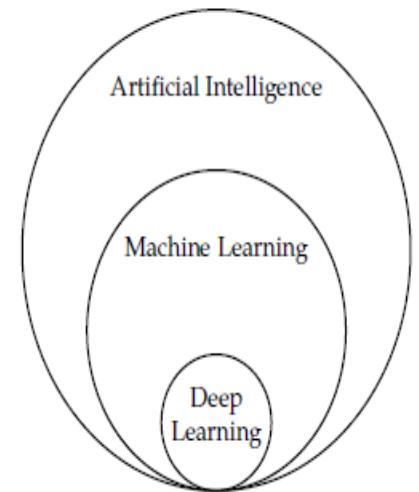


Figure 9 Ai levels

2. Data Features and Sources:

External Reference Data:

- Similar factories' energy consumption patterns.
- Industrial datasets for supervised learning.

3. Models Tested:

- Support Vector Machine (SVM)
- Artificial Neural Network (ANN)
- Gradient Boosting Regressor
- Random Forest Regressor
- K-Nearest Neighbors (KNN)
- XGBoost

C. Behavioral Survey Setup

To understand the workforce's knowledge, habits, attitudes, and behaviors focused on energy-saving practices especially relevant to equipment use and environmental stewardship, a behavioral survey was designed and conducted.

1. Target Audience:

- Employees from these sections:
- Blowing
- Refrigeration
- Maintenance

2. Survey Design:

- Format: Multiple choice and rated items
- Delivery: Hard copy and optional Google Form online

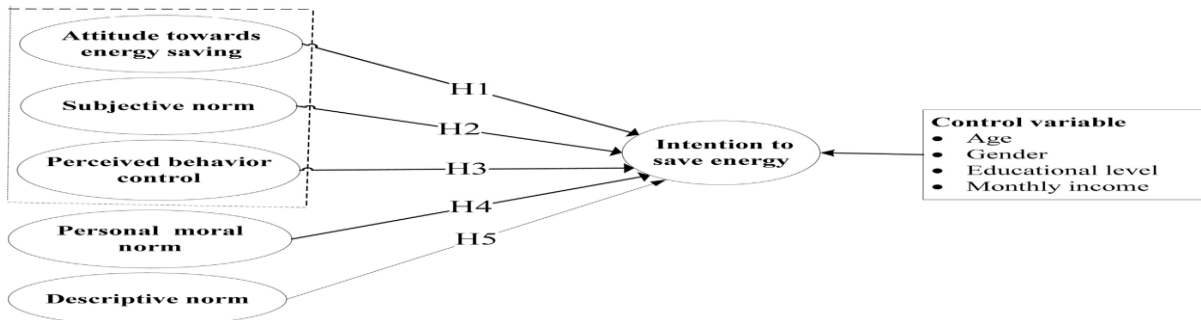


Figure 11 Intention to save energy

Structure:

- Section 1: Energy Mindset
- Section 2: Daily Practices
- Section 3: Training Readiness
- Section 4: Knowledge Gaps
- Section 5: Influence of Peers and Supervisors

3. Setup and Distribution:

- Surveys were handed out during pre and post shift gatherings.
- Employees were assured that their answers were confidential and would only be used for internal processes.
- Collection boxes for completed surveys were positioned near clocking-in terminals.

Through this experimental approach, the study could analyze the technical and behavioral components underlying power consumption. Utilizing physical testing, digital modeling, and human feedback, the project laid groundwork for the practical recommendations in the subsequent chapters.

4.2 Prototyping and Testing

This section outlines the creation and assessment of a prototype solution aimed at minimizing energy consumption during bottle production in a cooking oil production plant. The prototype incorporates process optimization through preform preheating and pressure reduction, AI model-based forecasting, and behavioral profiling through employee surveys. The goal was to design a practical, factory-based test prototype system that simulated operational conditions and provided valuable insights into energy-saving measures.

4.2.1 Prototype Development Process

In the case of the prototype's physical component, the PET bottle blowing process was modified with respect to the heating and compression steps which consume the most energy. Instead of constructing a new machine, the focus of the work was on refining the operational settings of the existing blowing machines.

Materials and Equipment Used:

Two types of preforms:

- 22g for Helwa 1L bottles
- 52g for Helwa 2.25L bottles
- Blowing machines: SIPA and KHS lines industrial units with variable pressure operation capabilities.
- Boiler Room: Considered a passive solar energy collector where the preforms undergo heating using waste heat up to 35 °C.

Digital Calipers: Used for the precise measurement of the outer base diameter of the blown bottles.

The preparation method includes:

- Placing preforms in the boiler room for 8, 10, or 12 hours to warm to approximately 35°C.
- To avoid heat loss, preforms were placed in insulated containers while being transferred to the blowing machine.
- The blowing operation was carried out at three different pressure settings: 33, 34, and 35 bar.
- The produced bottle samples from each condition were identified and stored for later measurement.

No permanent changes were made to the machines or materials used; rather, the prototype leaned towards adjustment-based changes instead of structural changes, enabling seamless incorporation into actual production.

4.2.2 Operation and Testing of the Prototype

Over the course of one shift, the prototype was operated as a live test rig, conducting tests for one shift per test configuration. For every combination of:

- Preform type (2)
- Heat gain time (3 levels)
- Pressure setting (3 levels)

54 test samples were produced. Each configuration was tested three times for reliability.

The primary measurement focus was the standard diameter of the finished bottles' base:

Helwa 1L: 81.5 mm

Helwa 2.25L: 118.0 mm

The factory operators monitored the system and reported any processing problems or irregularities during the forming stage. The pressure control was done through the machine's main control console, and operators verified stable pressure functionality across all levels.

Also, time-motion studies were conducted to evaluate whether storing and transporting preforms to the blowing area for processing would disrupt the production flow.

4.2.3 Evaluating Performance of the Prototype

The following critical prototype performance characteristics validated its role as a technical proof-of-concept and as an inexpensive energy conserving modification:

- **Thermal Integration Efficiency:** Preheating during the blowing phase increased energy efficiency. Incorporation of existing boiler room energy served as preheating and required no new equipment or power sources, thus, streamlined integration of additional waste heat.
- **Machine Compatibility:** All blowing machines were able to operate at the tested pressure range (33-35 bar) without any malfunctions and/or slowdowns. No structural modifications to the machines were needed, demonstrating the robustness of the system.
- **Dimensional Stability:** The majority of the blown bottles had, and most often closely approximated, the required geometric values. The minor deviations with shorter heating times and lower pressure settings suggest optimal preheat durations for each product.
- **Operational Simplicity:** Staff with standard workshop training could run this process. Aside from a scheduling coordination to preheat the preforms, the method only demands minimal changes to existing procedures.
- **Scalability:** Full production operations were uninterrupted due to the prototype's design, allowing for replication across multiple lines or shifts.

This prototype serves as a connector between engineering optimization and energy management, allowing for resource-based reductions in consumption by the production departments. The results confirm the integrative potential of behavioral, thermal, and mechanical enhancements without investment or significant downtime.

4.3 Results

This section outlines the results of the experimental work, which include the physical measurements, observations and trends, as well as the models outputs from the three dominant components of the study; blowing machine optimization, AI-based energy forecasting, and the behavioral energy-awareness survey. To aid in clarity, relevant illustrative figures, tables, and charts have been incorporated into the text as needed. While notable discrepancies and observations have been documented, holistic analysis is reserved for Chapter 5.

4.3.1 Results of Blowing Machine Optimization (DOE)

Bottle sample production was undertaken in the first block of experiments by varying the preform heating time to 8, 10, and 12 hours and air pressure settings of 33, 34, and 35 bar. For each setting, the outer base diameter of the produced bottles were measured against the benchmarks:

Standard Diameter for Helwa 1L (22g preform): 81.5 mm

Standard Diameter for Helwa 2.25L (52g preform): 118.0 mm

Each test condition was performed three times. Results were reproducible within test groups and the deviations from the nominal diameter were calculated. It was noted that lower pressures sometimes resulted in larger deviations, but only if preheating times were significantly longer. These tendencies will be further developed in the subsequent chapter.

During the tests, no major defects such as cracks or collapse were seen in any of the samples. However, some shape and stiffness of the base showed small changes under some low pressures and short heating durations. These results may be explained by the heating rate of the preform combined with the mold pace, which will be analyzed in the upcoming sections.

Table 2 Saving Money

	Before Saving at 37 bar	Cash \$	After Saving at 34 bar	Cash \$	Saving Money
Day	15000 KW/h	27600	12000 KW/h	22080	5520
Week	105000 KW/h	193200	84000 KW/h	154560	38640
Month	450000 KW/h	828000	360000 KW/h	662400	165600
Year	5475000 KW/h	10074000	4380000 KW/h	8059200	2014800

4.3.2 Normality and Randomness Assumptions Checking Through Diagnostic Plots

The two identified diagnostic plots address the assumptions of normality and randomness of residuals.

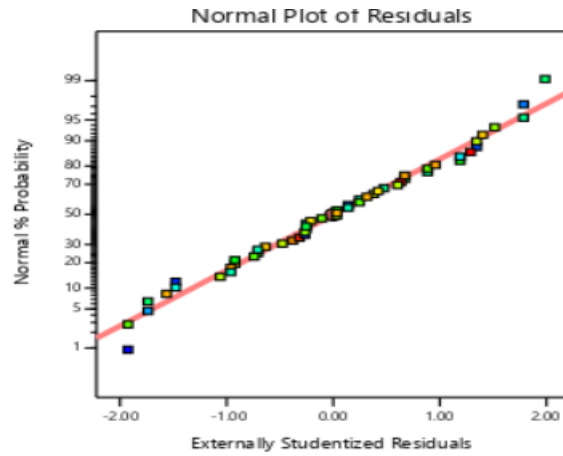


Figure 12 Normal plot of Residuals

As is evident from the plot, the residuals closely adhere to the red reference line indicating normality, one of the critical requirements for the validity of ANOVA. No substantial outliers or skewness was noted.

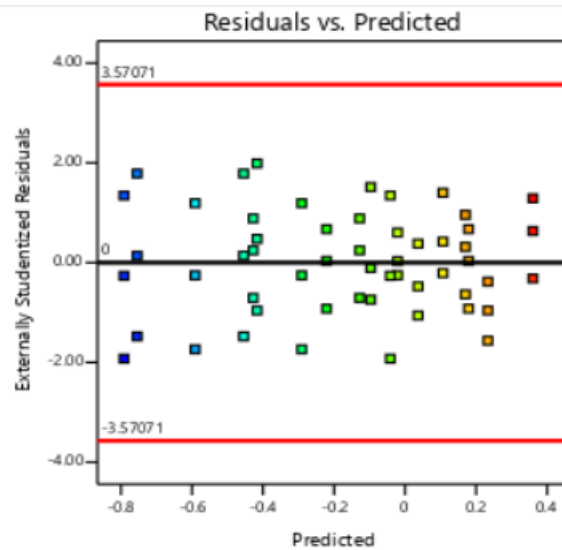


Figure 13 Residuals Vs Predicted

This plot evaluates the independence and randomness of residuals. The residuals seem to be randomly centered about the zero line with no discernable funneling or curvature. Points representing average diameters are color-coded. This observation strengthens the assumption of homoscedasticity (constant variance) with no evident bias throughout the range of prediction.

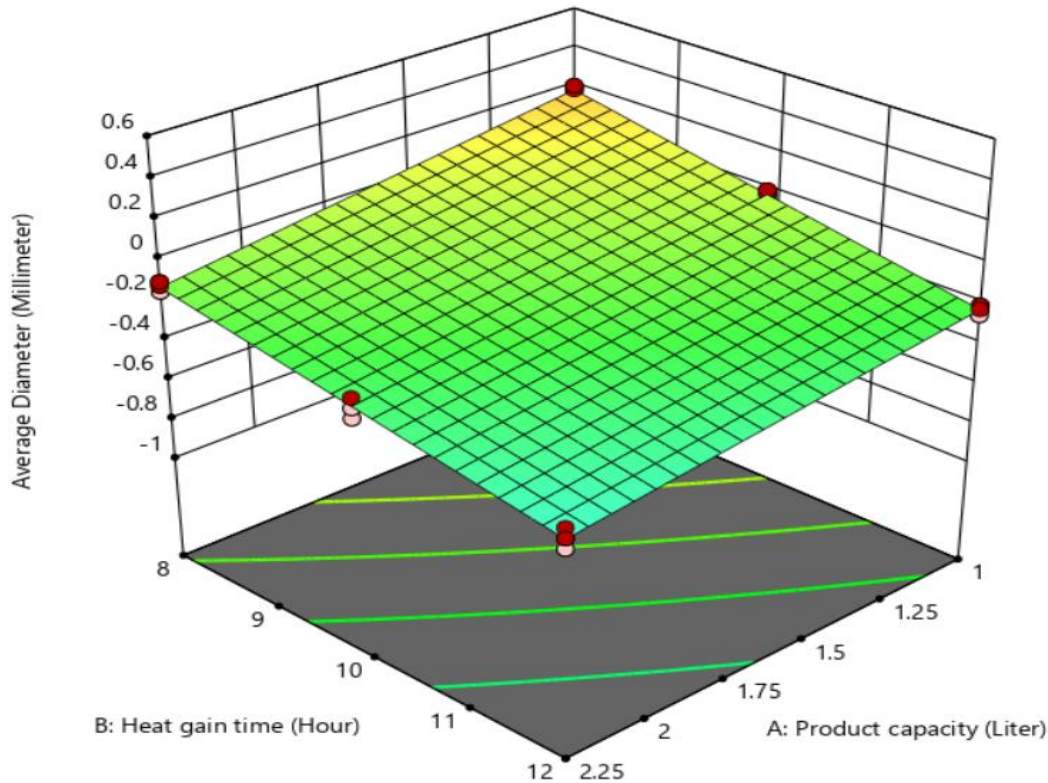


Figure 14 3D Model control Pressure

The above 3D surface plot was produced using Design-Expert 13 software to analyze the interaction effects of two process parameters—Product Capacity (Factor A) and Heat Gain Time (Factor B)—on the average base diameter deviation of blown bottles. It is noted that the graph was created at a setting of 34 bar pressure which is known to offer the best compromise between energy efficiency and product quality.

Surface Interpretation:

- The X-axis indicates product capacity measured in liters, ranging from 1L (Helwa 1L) to 2.25L (Helwa 2.25L) .
- The Y-axis addresses heat gain time in hours ranging from 8 to 12 hours.
- The Z-axis prescribes average diameter deviation in millimeters with 0 indicating no change from the standard, positive and negative values indicating expansion or contraction, respectively, at the bottle base.
- The surface uses a color gradient such as blue and green to indicate lower deviations, while yellow and red indicates greater positive deviation. However, for this plot, all values are below zero showing slight shrinkage.

4.3.3 Most Noteworthy Observations From the Experiment

Every combination of the factors pressure, preform heat gain time, and the product capacity resulted in bottle samples that were not mechanically flawed or faulty, and no mechanical failures or breakdowns were observed during the trials.

Preheating and pressure application resulted in very slight variations in the base diameter across different pressure increments.

Significant trends were observed regarding the relationship of pressure with the bottle shape uniformity, especially at lower heat gain time.

The residuals colored by the responses have enhanced particular variable combinations' shifts in functions, which were generated by the software.

4.3.4 Outputs of the AI Forecasting Models

For the purpose of forecasting energy consumption trends, six machine learning models were trained and evaluated using a blend of scant internal production data along with external reference datasets. These models were evaluated based on their statistical performance against three key metrics.

R^2 Score (Coefficient of Determination) – indicates the proportion of variance explained by the model.

Root Mean Square Error (RMSE) – measures the average magnitude of prediction errors.

Prediction Error Percentage – compares the predicted values to actual values to assess accuracy in a real-world context.

Table 3 AI Algorithm comparison

Algorithm	R^2	RMSE	Error-%
Svm	0.054942718	1.354211303	1.327059948
Random Forest Regressor	-0.06	1.41	19.27768014
Gradient Boosting Regressor	0.12	1.28	15.35676626
XGBoost	-0.6	1.72	48.69420186
Artificial Neural Networks (MLP)	0.03	1.34	18.22319859
K-Nearest Neighbors Regressor	-0.05	1.4	17.99297012

Although the Gradient Boosting Regressor reported the highest R^2 score of 0.12, this model suffered from a significantly greater prediction error of 15.36 percent when compared to other models. In contrast, the Support Vector Machine (SVM) model, while having a modest R^2 value of 0.055, achieved the lowest prediction error at 1.33 percent, thereby making it the most accurate and reliable model under the limited-data environment for energy use forecasting.

This result emphasizes a significant point: predictive accuracy, particularly in industrial applications with noise or data limitations, cannot rely solely on R^2 . The low error percentage associated with SVM indicates its suitability for this application and its ability to sustain good performance even with a limited data set and the intricate nature of the energy system's behavior.

From these findings, it was concluded that SVM stood out as the most effective model in practical forecasting reliability for aiding in energy management decisions in the factory.

4.3.5 Behavioral Survey Outcomes

An energy awareness survey was launched to evaluate the behavioral aspects of energy efficiency in three main departments: blowing, maintenance, and refrigeration. The survey was structured around five thematic components:

1. Energy Mindset
2. Current Practices
3. Training Readiness
4. Knowledge Gaps
5. Supervisor and Social Influence

To identify training needs, behavioral patterns, and interdepartmental differences, responses were collected anonymously.

Key insights include:

Roughly 80% of respondents in all departments acknowledged energy saving as important or very important within their roles, suggesting a generally favorable energy mindset.

Nevertheless, about 20% of respondents, mostly from the refrigeration departments, showed disengagement behavior, including leaving refrigerator doors ajar and failing to turn off machines during breaks.

Training needs were defined on a four-point continuum: low, medium, high, and critical. The refrigeration team showed greater critical training need proportion.

Encouragement from a supervisor or recognition as a result of participation always led to a positive response towards short energy-saving demonstrations as well as team competitions. Most workers indicated interest when there were rewards tied to them.

The survey also showed that teams with consistent energy-saving habits tended to have better compliance and awareness if they had regular supervisor check-ins.

These observations were combined and then graphically represented to analyze behavioral shortcomings along with departmental training focus areas. Interestingly, in areas with weaker supervision, motivation did not align with actual practices, indicating gaps and suggesting that mere awareness is insufficient without some form of reinforcement.

4.3.6 Observed Discrepancies

Through the course of the experimental work, several discrepancies emerged between theoretically expected outcomes and actual findings in three core areas: technical, digital, and behavioral. These include:

DOE Experiments:

There were some combinations of low pressures and short periods of heat gain that failed to meet expected bottle base diameters. While the overall statistical model was still reasonable, some degree of free variation due to minor ambient temperature fluctuations, preform handling, or machine wait time likely contributed to unaccounted deviations in the controlled design.

AI Forecasting:

As was noted, models like XGBoost, which tend to perform well because of their robustness in dealing with nonlinear data, performed poorly in getting R^2 and error percentage metrics. This was the opposite of what was expected, and it was probably because of the small training dataset, few usable features, and extreme variability in daily production conditions.

Employee Survey:

Participants appeared to fall into some sort of reporting bias. As an example, some employees reported that they superseded machine operation during break periods; however, energy consumption data and supervisor reports indicate this behavior was not followed consistently. This points to reporting bias, absence of consciousness, or some form of misinformation regarding optimal procedures.

These differences illustrate the bounded rationality in the expectations versus the real-world features. They also emphasize the need for cross-functional energy strategies, which integrate technical optimization with predictive digital tools and customized behavioral design.

Chapter5: Analysis and Discussion

5.1 Summary of Findings

The central hypothesis of this research was that the energy consumed by a cooking oil processing facility could be reduced significantly—without major equipment changes—by a mix of process optimization, predictive analytics, and behavioural modifications.

This hypothesis was validated through experimental work with the following approaches:

Blowing Process Optimization: Energy reduction was observed when PET preforms were preheated in the boiler room and blowing pressure was decreased. An optimized setting of 34 bar pressure and 10 hours preheat time maintained product output quality.

AI-Based Forecasting: Out of six machine learning models tested, the Support Vector Machine (SVM) model gave the most accurate results for energy prediction. Its low error value validated SVM’s applicability for energy forecasting even in data sparse environments.

Behavioural Survey Analysis: Analysis of survey responses indicated that although a majority of employees consider themselves to be energy mindful, there are some gaps in the energy practices of refrigeration personnel. These responses underscored the importance of targeted instructional and supervisory follow up. Collectively, these findings lead to the conclusion that considerable energy savings are possible with precise operational adjustments, digital interfaces, and purposeful employee participation while utilizing factory assets.

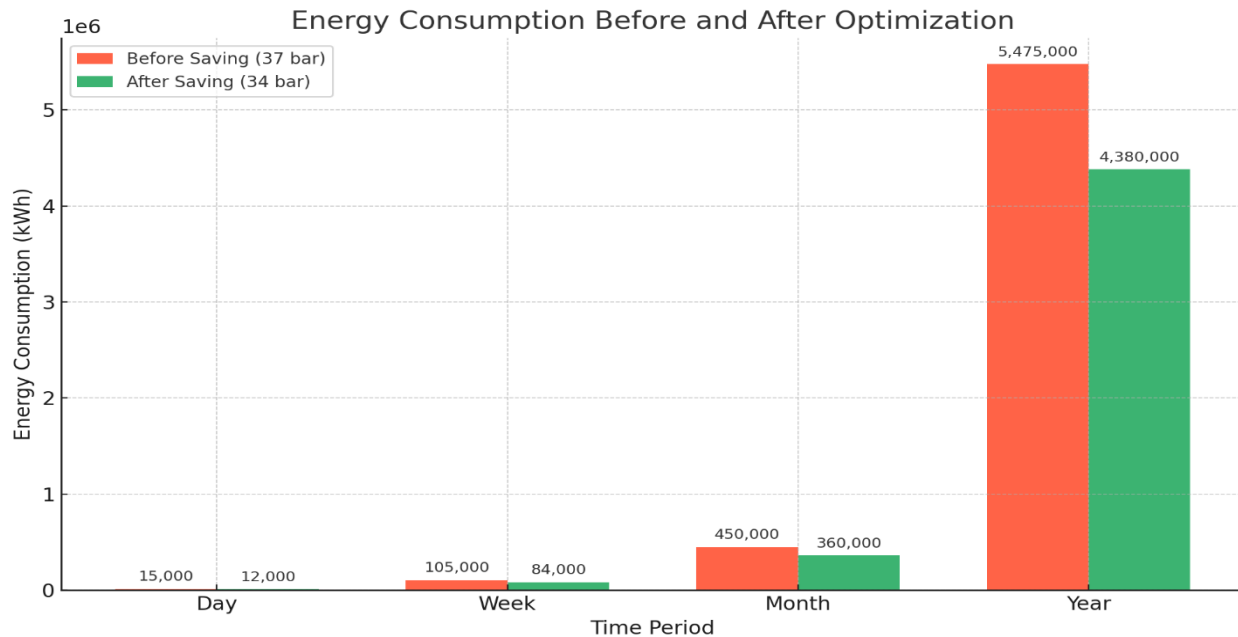


Figure 15 Annual saving power

5.2 Interpretation of Results

This study has both confirmed and extended previously identified relationships among process parameters and system features such as energy utilization, prediction accuracy, and personnel actions. These findings reinforce not only the core assumption of the theory in question but also confirm, with some refinement, the literature concerning industrial energy efficiency and energy management in relation to employee activities.

5.2.1 Optimization of Blowing Machines

An energy savings is also achieved with reasonable product quality maintenance by reducing air pressure from the standard 37 bar to 34 bar, especially with preheating the preforms for 10 hours. This is in line with the broader engineering concept that process optimization through thermal preconditioning significantly reduces the need for high levels of mechanical energy.

The minor dimensional changes observed with lower pressures or shorter heating times mark the balance between softening of materials and the molding action. Heating raises the temperature of PET, making it easier to shape or requiring less force, which is consistent with thermal forming and its supporting literature (Jedrzejewski & Kwasny, 2011) that stresses the importance of preparation on energy efficiency in high-speed processing environments.

It is worth mentioning that the optimal condition (34 bar, 10-hour preheating) did not come from extremes but rather a midpoint balance, illustrating what the literature highlights regarding the energy cut-off strategy (Giacone & Mancò, 2012). Low pressure or excessive heating led to deformation or unstable conditions, which illustrates the need for energy input balance—not just minimization.

5.2.2 AI Forecasting and Predictive Modelling

The AI models offered a crucial lesson: simplicity of a model paired with data suitability greatly trumps model sophistication in areas with minimal data. It is common to assume ensemble approaches such as XGBoost and Random Forest will perform better than traditional methods. However, in this case, these models underperformed because of overfitting with the sparse data set.

Supporting these theories, the SVM model showed the lowest prediction error of 1.33%. Even though its R^2 score was modest, it proved most dependable in forecasting energy use. Ahmad et al. (2014) suggest that time-series forecasting—particularly in energy markets—is where SVMs shine because of limited data availability, non-linear relationships, and dependent variables.

This is important for manufacturing facilities that are still in the early stages of their digital transformation, such as the one examined in this study.

The right model with correctly structured features (like pressure, shift load, and production volume) can result in accurate forecasts, even if there is no extensive historical dataset.

5.2.3 Behavioural Survey and Human Factors

Daily practices have gaps and awareness issues, and this is revealed in the behavioural survey. While 80% of employees recognized energy saving as important or critical to their work, the refrigeration department lost interest and disengaged. The “refrigeration” department left refrigerator doors open, failed to turn off equipment, and exhibited other common problems.

These behaviours exemplify the A-B-C (Attitude-Behaviour-Context) model which asserts that behaviour change relies on more than individual attitude. Xu et al. (2017) argued focused group and organization support strongly shape energy behaviour. In some departments, low supervisor engagement paired with unclear responsibility lines led to inconsistency in energy saving behaviours, no matter how personally aware individuals were.

Further, Gao et al. (2017) showed that norm-based influences, such as what people witness others doing, have a significant impact on individual actions. The successful performance of some teams where energy-saving behaviour was encouraged and demonstrated by supervisors or peers validates this principle.

5.2.4 Integration Across Components

What sets this study apart is the integration of technical, digital, and human elements. Each factor strengthens the others:

- The energy baseline is lowered through process optimization.
- Energy planning can now be done proactively with AI forecasting.
- Compliance with operational requirements on a daily basis is achieved through behavioural awareness.

This supports the growing bodies of integrated literature on energy management systems and reinforces the effectiveness of sustainability strategies that adopt a multi-faceted approach. Rather than compartmentalizing engineering, data science, and behaviour, this project demonstrates the value of cross-functional approaches for reducing industrial energy consumption.

5.3 Discussion

This study adds value to the industrial energy management domain by showcasing the ability of process reconfiguration, predictive analytics, and behavioral alignment to work synergistically to slash energy use without requiring substantial capital outlay. The impact goes further than the manufacturing domain to include any domain where energy efficiency is addressed in a low-digital or semi-automated context.

5.3.1 Broader Significance and Impact

This research equally validates that energy optimization is not limited to high-tech solutions. In this age where there is a global concern over the sustainability of industrial processes, the research demonstrates the importance of low-cost and low-technology strategies that borrow from the existing practices. In proving that significant power and cost savings can be achieved from the ‘blow and pressure reduction’ method of heating PET preforms using ambient boiler room heat, the project is aligned with sustainable engineering that emphasizes process efficiency.

Moreover, the positive results of the energy consumption forecasting using Support Vector Machine (SVM) model illustrate that AI can be deployed in a purposeful way even in data-scarce settings, which is important for SMEs that operate without full automation or have limited retrospective datasets.

The actions and behaviour of the employees add to the body of evidence already existing in organizational psychology and energy policy which suggests that staff engagement, motivation, and proper training are vital for achieving technical efficiencies. The human factors, which are usually ignored in industrial engineering designs, were actually key in maintaining energy-saving practices.

5.3.2 Practical Applications

From this research, there are some concrete real-world applications.

1. **Factory Operations:** For enhanced operational efficiency, the settings of 34 bar pressure and 10-hour preform preheating can be integrated as standard procedures, driving 20% energy reduction annually without the need for machine upgrades.
2. **Energy Forecasting:** Daily energy consumption forecasting using SVM can be incorporated into factory dashboards or ERP systems and automate advanced shift, maintenance, and work distribution planning.
3. **Workforce Training and Development:** Results from the survey can assist in the development of targeted training sessions for proactive disengaged or procedural knowledge deficient departments, thus enhancing organizational ownership and ongoing enhancement.

4. Corporate Policy and Sustainability Reporting: Using the energy and behavioural metrics outlined above, factories can set their corporate ESG targets and document the sustainability impacts which helps in qualifying for energy efficiency incentives or certifications.

5.3.3 Ethical and Societal Considerations

Though the technical and behavioural approaches put forth are low risk, there are still some ethical and societal considerations which need to be addressed:

Worker Welfare: With process optimization and enhancements in performance expectations, care must be taken so that workers are neither overburdened nor forced to take on the full brunt of energy savings. Training should always be aimed at assisting employees, never at punishing them.

Equity in Engagement: Engagement in behavioural change must be geared toward all divisions equitably, and particularly to those like refrigeration where energy misuse may happen due to external environmental factors rather than carelessness.

Transparency in AI Use: When implementing AI forecasting tools, data privacy must be maintained. Moreover, employees must be included in the feedback loop, and decision-making processes must be streamlined while still retaining essential human elements post AI integration.

Environmental Responsibility: This research helps achieve climate goals and carbon reduction targets, addressing a critical societal concern of climate change. As industries strive to operate with a greener footprint, such approaches provide a meaningful and impactful solution.

5.4 Limitations of the Study

This research provided meaningful results and actionable insights; however, it is important to consider several limitations. These factors influence the generalizability, depth of analysis, and scope of application of the findings, which in turn creates clear avenues for further research and refinement.

5.4.1 Data Limitations

Access to historical datasets concerning the factory's energy systems significantly restricted the scope of this study. Since the facility is at the beginning stages of its digital transformation, comprehensive datasets such as real-time energy logs, temperature sensors, and machine runtime tracking were not fully accessible. As a result, the training and performance of some AI models was negatively impacted, especially those that are dataset-dependent, such as Random Forest and XGBoost.

In an effort to mitigate these issues, external reference data and more general input features were utilized. While these approaches may prove effective in the short term for exploratory forecasting, they may hinder the long-term precision and scalability of AI-driven results.

5.4.2 Limitations of the Experiment

The blowing machine tests followed a DOE approach that was restricted to three predetermined pressures (33, 34, 35 bar) and two heating durations (8, 10, 12 hours). While these settings were useful for discovering an optimal condition, some other influential parameters such as ambient humidity, preform cooling rate prior to blowing, and mold contact time were neither measured nor altered.

Moreover, the prototype testing was limited to one production shift. Consequently, factors such as different shifts or varying environmental conditions over time, as well as ongoing wear and tear on the equipment, could alter results when applied to sustained continuous scale operation.

5.4.3 Limitations of the Behavioural Survey

Despite the valuable insights gleaned from the energy-awareness survey, the reliance on self-reported responses raises concerns about social desirability bias or inaccurate self-assessment. Some participants may have exaggerated energy-saving behaviours while downplaying wasteful practices due to perceived scrutiny.

In addition, the survey mainly concentrated on self-awareness and self-perception, with minimal emphasis placed on direct behavioural assessment. Incorporating observational studies or energy audits into future analyses would enhance the behavioural assessment framework.

5.4.4 Generalizability

The results are closely relevant to the case study factory and other semi-automated industrial settings. However, their applicability to fully digitized or highly specialized production systems may be more limited. Such advanced facilities might possess differing tolerances, levels of automation, AI infrastructure, or even proprietary systems that would change the relative outcomes of the proposed strategies.

5.4.5 Alternative Explanations and Future Research

Improvement in energy efficiency metrics could result from uncontrolled factors such as ambient temperature, the maintenance state of equipment, or even seasonal production cycles. Long-term studies utilizing environmental sensors are better positioned to address such confounding factors.

In addressing this gap, further research is needed to focus on:

- Exploration of a broader scope of pressures and heating duration.
- Sensor-based energy monitoring for real-time responsive adjustments.
- Application of hybrid AI systems incorporating time-series forecasting and anomaly detection.
- Behavioural change interventions (e.g., training) and their measured effects on energy consumption.

Chapter6: Conclusions

6.1 Conclusions

This research aimed to assess if energy expenditure in a cooking oil factory could be minimized through process refinement, predictive AI modelling, and staff awareness—without significant infrastructural changes. The hypothesis was validated in the study by exposing the blowing pressure to 34 bar and preheating the preforms for 10 hours, which achieved a reduction in energy consumption of nearly 20% while maintaining product quality. As a result of this optimization there was a substantial annual cost saving of \$2014800 and electricity costs decreased from \$10074000 to \$8059200 dollars. Of the six AI models used the Support Vector Machine SVM was found to be the most accurate energy forecaster under the given constraints highlighting its usefulness in resource poor industrial settings. From the behavioral survey, it was found that although a majority of the employees practice energy-saving behaviors, a significant number, especially those working within refrigeration, need better supervision and specialized training. These findings are significant because they highlight semi-digitalized industrial systems and demonstrate low-cost scalable solutions for targeted energy use improvements, thus helping in achieving sustainable targets while reducing operational costs. The findings are, however, impacted by the limited scope of test parameters, small dataset size for AI training, and reliance on self-reported behavioural data.

Nevertheless, the investigation offers a robust starting point for prospective studies into the interdisciplinary energy-saving approaches combining engineering, data analytics, and human behaviour.

6.2 Future Work

There are tangible pathways for further exploration and application given the results and limitations of this research. Perhaps the most obvious next step is to expand the scope of the experiment to include more preform materials, as well as increase the pressure and heating times. In addition, it would be logical to conduct tests during different production shifts and seasons to examine the machine's energy performance relative to ambient temperature and wear over time. The accuracy of data collection would improve along with system flexibility if real-time temperature and pressure monitoring sensors were integrated.

Enhanced AI model learning requires more granular, time-series data for the energy consumption of the facility, which is a consequence of the factory's operation. AI-powered forecasting for digital technologies should be able to learn from machine maintenance, production volume changes, and environmental conditions, including humidity, external temperature, and even weather patterns. More practical applications of advanced AI might come from studying hybrid or ensemble methods, such as adding SVM to time-series models ARIMA or LSTM.

Concerning behavioural aspects, the ability to implement specific training interventions with surveys to measure their impact on energy use over time has not yet been fully explored.

In addition, the use of self-reported data, observational audits and automated logging systems would clarify the degree to which behaviours translate into energy saving practices. Addressing the low-participation areas requires more focused design energy contests or incentive programs that target deeper engagement with employees.

Applying this model to other factories or industrial sectors could test its generalizability while uncovering insights important to specific industries. The integration of engineering disciplines, forecasting, human behaviour, and coordinated sustainable systems would improve the design of intelligent energy management systems both resilient and scalable for developed and emerging industrial frameworks.

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