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# Energy Consumption Optimization in Smart Factories Using AI-Based Analytics: Evidence from Automotive Plants

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**Abstract**

This chapter presents a review of the application of Artificial Intelligence-based Analytics in industry, followed by a discussion of the ongoing smart factory concepts in energy optimization, where AI is based on reinforcement learning and fed by smart metering data. Data from a use-case in a smart factory setting with a PV power generating facility is discussed, considering both shopfloor consumption and the microgrid. A conceptual setting for the use case with simulation support is shown. The optimization goals can vary and all contribute to reducing carbon footprints. Next, critical factors of acceptance in the production environment, and the type of community operations are discussed and final thoughts are given about future work.

At present, the industry is also driven by policies to reduce energy consumption below additionally pre-set limits. The special production structure of frequently small quantities in a shopfloor community linked to a microgrid cannot meet these requirements without assistance. Support is necessary to periodically adapt production plans triggered by e-mobility or e-housekeeping operations and regulations. As a result, time slots in production become concrete where energy optimizations or energy consumption optimizations must be implemented. The contribution discusses the impact of utilizing Artificial Intelligence, from smart meter data implemented in a reinforcement learning structure to find eco time slots. This contribution is based on the given conditions of a use-case situated in a smart factory for the boundaries of a microgrid with Photo Voltaic storage and connection to the DSO. Data structures from the smart metering implementation will be shown and supported with simulation. The discussion further focuses on acceptance prerequisites about community production resources, shifted eco time slots, etc. The goal of the contribution is to outline potential added values in the shopfloor community, aligned with bottom-up factors.

**Keywords:** Artificial Intelligence, AI-Based Analytics, Smart Factory, Reinforcement Learning, Smart Metering, PV Power Generation, Shopfloor Consumption, Microgrid, Energy Optimization, Carbon Footprint Reduction, E-Mobility, E-Housekeeping, Production Planning, Eco Time Slots, Simulation Support, Community Production, Smart Grid, Digital Grid, Energy Consumption Reduction, AI Acceptance Factors, Bottom-Up Optimization.

## 1. Introduction

Smart factories are increasingly integrating equipment, production systems, and business activities, collaborating seamlessly to produce extremely complex products at optimum prices and the quality demanded by customers. In this process, the Industry 4.0 paradigm is transforming modern factories into smart environments that take advantage of disruptive digitalization technologies, such as the Internet of Things, Cloud Computing, Cyber-Physical Systems, Big Data, and Artificial Intelligence, enhancing productivity, flexibility, efficiency, and effectiveness. Energy has a prominent role in this transformation. Energy costs can represent a significant share of total manufacturing costs. A modern factory consumes considerable amounts of energy in its many operations, including, among others, actuating tools; executing production activities, such as machining, finishing, and assembly; and, in many cases, shipping products to customers. However, the optimization of energy consumption is not usually incorporated into traditional Production Planning and Control. With the advent of smart factories, it is becoming possible to optimize the energy employed in production through dynamic responses to variable demand, featuring shorter lead times, additional changeovers, and changes in schedules. It is now possible to measure directly the energy consumed in the execution of production operations, enabling the real-time feedback necessary to meet production targets and efficiently utilize the energy base.

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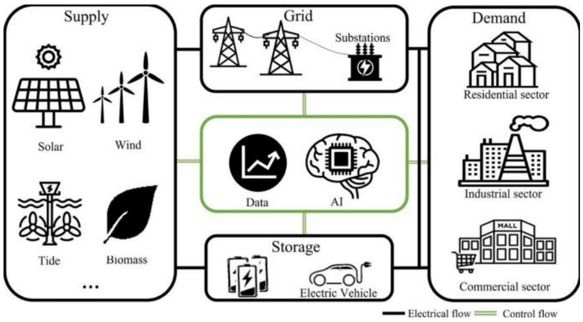


**Fig 1: AI-driven approaches for optimizing power consumption**

1. Purpose and Scope of the Study
In this paper, we explore how AI-based analytics can help improve energy consumption optimization in smart factories. To do so, we review the energy consumption optimization methods proposed in the literature and analyze how AI-based analytics, combined with dedicated IoT-oriented devices, can give new support to the processes through which energy consumption can be optimized, considering both the supply and demand sides and their interactions.

### 1.1. Purpose and Scope of the Study

Due to tightening global energy constraints, energy-aware technologies that improve energy efficiency in manufacturing are receiving increased attention and demand. Manufacturing currently accounts for around one-third of the global final energy consumption. Smart factories are expected to enable a drastic reduction in this size, thereby also decreasing the global carbon footprint. The goal of this study is to take advantage of the vast amounts of data generated in smart factories to produce valuable insights for energy decision-making and ultimately reduce energy consumption. It outlines a general Energy Analytics Framework that structures the required methodologies and applications and details important enabler concepts. This framework is then applied to different industrial sectors such as electromagnetic soft magnetic parts, pharmaceutical manufacturing, optical coatings, and wafer fabrication to develop and implement data-driven statistical analytics solutions to identify novel opportunities for energy efficiency improvements. Smart factories are characterized as fully connected, data-driven manufacturing and logistics ecosystems that can use artificial intelligence and other advanced digital technologies to optimize the efficiency, productivity, and flexibility of the manufacturing network. These factories generate big data measurable on a real-time basis along the entire value-added chain. Energy is one of the most important cost drivers for manufacturing companies but is still a side subject in many analytics and optimization applications within the Industry 4.0 framework. Artificial intelligence methods have achieved great results in visual inspection and defect detection. However, the majority of Industry 4.0 solutions have not focused on identifying further efficiency improvements in producing devices or products. In this contribution, we will show how to apply data-driven analytics to this immense pool of information produced in smart factories to develop solutions that allow for energy efficiency improvements.

## 2. Background on Smart Factories

1. Definition and Characteristics
Smart factories, as a crucial component of Industry 4.0, are an innovative and disruptive paradigm intended to optimize production processes. Despite not being unanimously defined, the expressive axial principle of a smart factory comprehends the production of mass-customized high-quality products being energy and resource-efficient, while providing a safe and pleasant work environment. The term smart factory can be understood as intelligent factories, where such a concept can express a factory intrinsically capable of making itself smarter. The notion of intelligent factories stands as a synonym for factor and involves a new paradigm for production and logistics systems where the individual entities seem to possess a certain degree of intelligence and act in a coordinated way to achieve pre-defined goals. Data-driven artificial intelligence methods for real-time processing of data generated by the device in factories are classified as enablers for an intelligent factory.
2. Importance of Energy Efficiency
Energy efficiency exposes technical and economic solutions to provide enough energy in every part of the production process while minimizing the investment and operating costs associated with energy delivery services for production. Efficient utilization of energy is beneficial both from an ecological and an economical point of view, even more in the perspective of the upcoming exhaustion of fossil energy sources and in the broader context of Climate Change. Unfortunately, energy-saving programs have been restrictedly adopted. Several barriers exist such as the energy bill can be effectively reduced, and the time of the factory is accompanied by correspondingly low energy use.
In the context of smart factories, industry digitalization using smart IoT, services, and digital twins, stimulate significant automation of the analysis, configuration, functioning, and management activities typically performed by factory

managers and operators. The smart factory environment becomes able to minimize the smart factory. A key enabling aspect to support the efficient energy utilization in smart factories consists of the capability of producing and sharing in a collaborative way, services and products.

**Equation 1: Total Energy Consumption**

$$E_{total} = \sum_{i=1}^{n} (P_i \cdot t_i \cdot \eta_i^{-1})$$

Where

$E_{total}$: Total Energy Consumed

$P_i$: Power of Machine $i$

$t_i$: Operating Time of Machine $i$

$\eta_i$: Efficiency of Machine $i$

### 2.1. Definition and Characteristics

A smart factory is defined as a digitalized and digitized factory with a cyber-physical networked connection between the whole factory equipment and systems with the support of machine learning, cloud and edge computing, devices, AI, augmented reality, and big data analytics. This system gives production engineers the enabling tools to realize a completely paperless factory, increase quality and flexibility, support mass customization, design and develop products based on fast change, utilize real-time production tracking and predictive maintenance, enable operating at sustainably lower cost and storage, facilitate remote monitoring and control, automate all the operations possible, enable data-driven decision-making, and drive a business model of servitization. Truly speaking, these characteristics of a smart factory are derived from the underlying enablers, but in practice cannot inadvertently be isolated. After all, the enabling technologies and the characteristics and functionalities of a smart factory are all interrelated and interdependent. In a digitalized factory, the workers are physically separated from the machines and automation systems and are instead heavily interconnected with information based on retrofitted capabilities that link together these devices with other activities in the supply chain and customers. We defined Factory 4.0 to be a “digitalized factory based on machine sensing through IoT, where the operations are monitored through the Cloud, while analytics support the decision making and the execution follows automation, where applicable".

### 2.2. Importance of Energy Efficiency

World energy consumption could rise by almost 50% by 2050. Thus, a more efficient use of energy is necessary not only because of its current price but also because of its future scarcity and related environmental problems. Indeed, energy efficiency constitutes a path to cope with the challenges imposed by high and volatile oil prices, energy dependency, and climate change. Moreover, energy efficiency is a necessary condition for achieving greater environmental sustainability and reducing the negative effects of economic growth. Efficiency investments also provide the means to a revival of the economy. Indeed, they can be undertaken quickly, involve relatively low capital amounts, generally have a low-risk premium, and generate more jobs per Euro invested.

In the last few decades, globalization spurred positive economic growth and an increase in the living standards of many groups around the world. However, pursuing such growth without scrupulous energy efficiency actions leads to an excessive use of energy resources with harmful consequences for the climate. To enhance the relationships among sustainable development, global warming, air pollution, energy efficiency, and national competitiveness, energy efficiency should be viewed and supported as an investment that has important macroeconomic effects as well as major microeconomic gains through improved industrial efficiency and reduced pollution. In this context, enterprises must become aware of the importance of the efficiency of energy consumption processes as a strategic lever for improving their competitiveness. Different motivations can drive companies towards an increasing involvement in the energy efficiency area. On one side, the increase and volatility of energy prices have an impact on the exposure to energy costs. Companies can forecast, analyze, and control energy costs to reduce their dependence on the volatility of energy prices.

## 3. AI-Based Analytics in Manufacturing

1. Overview of AI Technologies

For many years, industries have been ingesting increasing amounts of data from their machines and systems through sensors and measurement systems. Modern advanced technologies are capable of data collection at a very high speed and resolution. Consequently, a massive volume of diverse data is being generated. Big data technologies store and visualize this data, enabling humans to access it and derive insights from it. However, solely relying on human effort is not possible anymore due to the sheer volume of incoming data. And augmenting human capacity with computers is critical. In this context, the field of artificial intelligence (AI) has made enormous strides in the past decade. Many machine learning models have now reached such a performance level that they can uncover valuable patterns in big data autonomously. AI allows for automation of advanced analytics processes such as detecting anomalies, classifying objects, recommending actions, synthesizing models, or forecasting future developments. Furthermore, these intelligent systems are also able to assist humans in their decisions through context-dependent explanations and trust signals.

In recent years, industries have begun to rely on these capabilities for automating a wide range of processes. For example, in demand forecasting, an AI model inputs the historical demand for a product and predicts future demand. In predictive maintenance, equipment maintenance logs as well as sensor data indicating the equipment's health are processed by an AI model which then predicts the health of the equipment several days in the future. In quality control, a machine learning computer vision model analyzes camera images of produced items, classifying them as defective or non-defective, which informs the operator if the manufacturing process needs immediate correction. AI-powered capabilities are thus on the rise for all steps along industrial processes. Industrial production itself relies heavily on such enabling capabilities to achieve its largest goals: producing on time, producing at high quality, and producing at low costs. It is no surprise that many such capabilities improve the sustainability of the underlying processes as well.

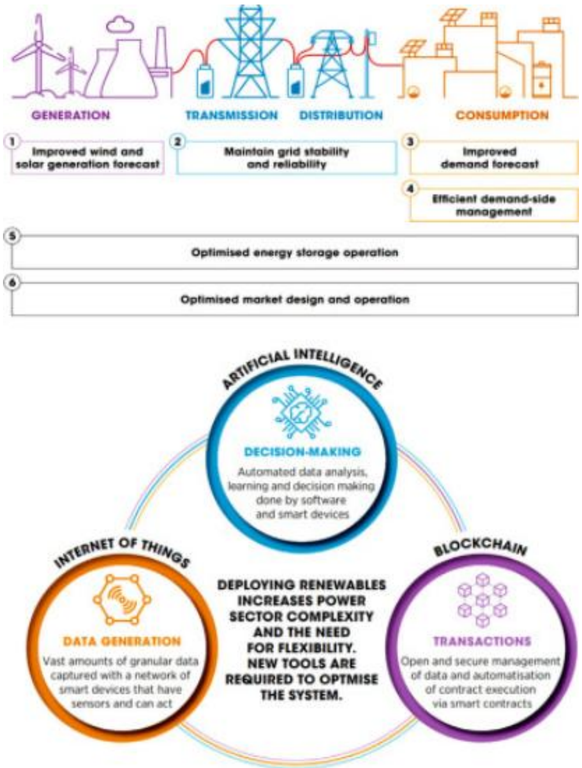


**Fig 2: Energetics Systems and artificial intelligence**

### 3.1. Overview of AI Technologies

Three areas of manufacturing are receiving attention from artificial intelligence technologies. The first is that data are often generated in abundance in production. Such data are descriptive. They can be in the form of images, audio, text, or numbers. Production resources also generate sensor data. Descriptive data can be analyzed to increase the fidelity of the digital twins of products and processes and to facilitate production planning and management, maintenance, and quality assurance. Process data typically stream without interruption. They can be summarized from descriptive data using features. Feature data can be analyzed for factory-level Intelligence, such as supply chain and logistics, production execution, and energy and emissions management, and to optimize product designs to facilitate production. The second area is that AI-based analytic methods are increasingly being developed to make better decisions, faster. The third area is industrial automation. Robotics and cyber-physical systems are increasingly designed to adopt AI methods to facilitate automation.

AI methods, tools, and techniques are diverse. Techniques from mathematical optimization, operations research, parallel computation on GPUs, robotic procedures, search tree search procedures, symbolic problem solving, and simulation are complemented by methods from modern AI, computer vision, deep learning, data mining, and natural language processing. What is new with modern AI is its ability to use large pools of descriptive data generated by users, either intentionally or unintentionally, to independently identify patterns to generalize from, project a problem situation onto, and use the identified patterns to make predictions for new situations for which limited data are available. Such predictions can augment human decision-making or be embedded into automated workflows.

### 3.2. Applications in Production Processes

AI technologies are widely used in manufacturing, especially in high-mix low-volume production environments since they can operate automatically and help humans make decisions more efficiently without compromising flexibility. Machine Learning methods are used in many stages of production processes, such as product design, process planning, and scheduling with a different focus, like product quality design, process time, resource allocation, production schedule, condition monitoring, product identification, resource management, and smart control loop.

Deep Learning technologies are used mainly in the earlier stage of production processes for product design and mockup development, such as photo enhancement and creation, and product features generation for configure-style products. Furthermore, in recent years, the Generative Design technology using Deep Learning was proposed to generate optimal design concepts. Active Learning and Reinforcement Learning methods with different focuses on Resource allocation, Process time, Production scheduling, and Smart control loop also have gained more interest in recent years. These methods emphasize fast and efficient solutions for time-consuming production planning and scheduling problems. The exploration-exploitation tradeoff is key to utilizing the solution spaces. Due to the importance of high-fidelity simulation in manufacturing, multi-fidelity Active Learning, Simulation itself configuration optimization, and Bandit compression optimization are necessary and important areas to be explored further. In addition, Probabilistic numerics or probabilistic implicit functions fusion of simulation with real data should be combined to fully exploit the synergy. These approaches will help to integrate AI-based solutions with traditional manufacturing planning and control systems.

## 4. Energy Consumption in Automotive Plants

1. Current Trends and Statistics

The industrial sector spends a significant amount of energy and emits CO2 into the atmosphere. In the UK, 22% of energy consumption comes from industry, and 24% of national carbon emissions come from industry. Primary industries, including the production of iron, steel, aluminum, cement, and fertilizers, are cemented as energy-consuming processes. Industrial processes consume around 70-80% of global electricity, of which 38-42% of electricity is consumed by motor-driven systems. Recently, businesses and industries have incorporated renewable energy technologies, as decarbonization also reduces reliance on imported fossil fuels. In automotive manufacturing, high energy-efficiency standards have resulted in a more stable energy-cost environment and a reduction in air pollution. Cars can be produced in a largely automated process. Due to relatively low labor costs, the majority of parts are produced by subcontractors. Car assembly is done in special factories called automotive plants. However, to achieve the energy efficiency provided by the components, car assembling must be realized in energy-efficient factories and automotive plants. The energy consumption of automotive plants greatly affects the total energy consumption of the automotive industry. Energy consumption, CO2 emissions, and emission regulations are very important issues not only in the automotive sector but for the whole economic sector. An analysis of the research literature showed that in automotive plants, the most main energy consumers are the energy used in press shall forming, the painting process, and logistics. Although the current trend is energy-saving optimization in all segments of the automotive plant, it must be quickly achieved and realized, as the world demand for automobiles is increasing.

2. Challenges Faced in Energy Management

As an automobile is generally regarded as a core product of the technological development of a country and a symbol of conveyance, it is anticipated that its demand will rise exponentially shortly. Regardless of its being developed as a high-performance, intelligent, high-safety, or environmentally-friendly product, energy is consumed throughout every phase of an automobile's life. Though a significant amount of energy is consumed during the lifetime of an automobile due to usage by the driver, energy is also consistently consumed during the production, shipping, distribution, sales, leasing, and maintenance stages.

### 4.1. Current Trends and Statistics

The automotive industry is at the forefront of the ongoing trend of comprehensive activities to reduce its impact on humans and the planet. It has been reported that the global energy consumption in the transport sector was about 29% of the total world’s energy consumption. Out of this, passenger road transport contributed to approximately 45%, freight road transport 25%, aviation and shipping 10% each, and rail transport 1%. On the other hand, over the last three decades, the global energy use in the transportation sector has increased by an average of 1.5% every year. One-fifth of this is related to the automotive manufacturing process. The rapid growth and globalization in automotive manufacturing technology are pushing traditional manufacturing production systems to shift toward the concept of smart factories. The global smart factory market size was valued at USD 76.56 billion in 2021 and is projected to grow from USD 88.5 billion in 2021 to USD 208.35 billion by 2029. Specifically, the automotive sector is forecasted to account for one-fifth share of the global smart factory market between 2022 and 2030. The Industry 4.0 technology-driven smart factories have the potential to help the automotive sector realize enhanced intelligence, efficiency, productivity, flexibility, and safety in its operations. Nevertheless, achieving all of these objectives in automotive smart factories, while focusing on energy consumption reduction is a delicate balance that automakers must strike and manage. The power usage effectiveness of traditional automotive plants has been reported to be more than double that of hospitals and data centers. This is because the diversity, complexity, and high consumption of power by the automotive manufacturing processes typically make it difficult to implement energy-efficient planning. Compared to other industries, automotive manufacturing facilities typically run 24 hours, 365 days a year; employ a large number of efficient lighting; have high-intensity heating, cooling, and ventilation demand; an intensive amount of diverse process exhaust; and a significant amount of water heating use.

### 4.2. Challenges Faced in Energy Management

Automation and control based on computer technologies have achieved great success in the development of the manufacturing industry, while with the improvement of process complexity of large scale and diverse production, the energy consumption cost of manufacturing becomes the major operational cost of enterprises and has clearly shown a greatly huge increase. In the manufacturing process, approximately 80% of the total energy consumption cost occurs at the fabrication and assembly phase, which makes the estimation, optimization, and prediction of energy consumption and cost become the main reasons of concern for manufacturers.

With the increase in production scale and increase in energy cost, it is predicted that the product yield, product selling price, manufacturing expected gain, and profit will be adversely affected. In addition, it has appeared that the variation of energy consumption during the fabrication and assembly operation can be an exciting, distinct expense that influences the final cost of products and the expected profit gain of manufacturers. Additionally, the rising energy demand in developing countries and the gradually improving ecological environmental awareness make people focus more on energy efficiency and CO2 emission during the manufacturing phase. Some economic sanctions create a need for considering alternative plants and equipment in the design and operation of a process; as a result, optimizing cost alone may not guarantee the most effective design. Thus, utilizing energy as a measure or assessment index may not only economically confine the estimated shop operation cost but also qualitatively reflect and justify the industry's eco-efficiency.

## 5. Optimization Techniques

1. Data-Driven Decision-Making Decision-making in the manufacturing domain often adopts a trial-and-error approach high in operational costs and low in utility, and a more formal approach to decision-making can enhance significantly the decision's expected utility. Unlike traditional decision analysis techniques based on expert judgments of probabilities and payoffs, MD utilizes statistical techniques that rely on data that can be collected or are available. DM applied to strategic decision-making allows for estimates of the critical uncertain parameters involved in a typical strategic decision problem, in particular those that capture unavoidable market uncertainties such as the size or growth rate of product markets or the underlying competition, to be derived from the observed market exploits of different products. Having data on how different products have exploited the market facilitates estimating the critical uncertain parameters. DM then enables strategic decision-making with confidence, which is a huge benefit since most of the information about market uncertainties is derived from the past and involves substantial uncertainty, resulting in fragile estimates.
2. Predictive Maintenance Strategies Resource consumption occurs in the production process and the operation and maintenance of the manufacturing resources such as machines and equipment. Energy-efficient strategies for optimizing production scheduling and for scheduling predictive maintenance in a specific time and/or action order are key to resource efficiency. While energy-efficient production scheduling is a classical problem in operations management, decision rules regarding the (de)activation of machines in the scheduling of predictive maintenance incur energy costs in addition to maintenance and opportunity costs. Nevertheless, the use of predictive maintenance strategies can yield a substantial reduction in the risk of costly resource failures and poor product quality and, thus, save postponable costs and enable energy-efficient production scheduling. Because the energy used for operating the machines cannot be directly reduced or turned off when they are idle, before a new planning strategy is developed the required machine downtimes, in particular the downtimes for maintenance and repair, have to be planned carefully and coordinated with the planning of maintenance activities to reduce their adverse economic and environmental impact.

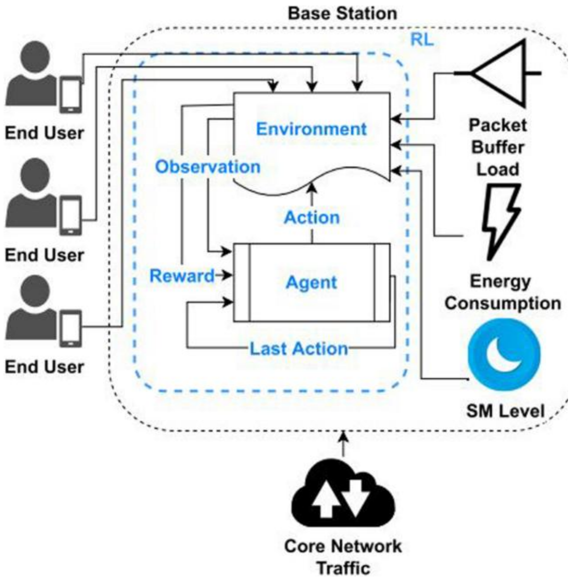


**Fig 3: Optimizing Power Consumption**

### 5.1. Data-Driven Decision Making

The ultimate goal for smart factories is to maximize the value of the collected data. However, from the available data, decision-makers face many challenges, e.g. the huge quantity, diverse formats and sources, and cyber-security threats. To facilitate data-driven decision-making process, data-driven methods can suggest the optimal approaches based on real-time monitored data. By implementing one of these decision-making methods, factories can become more intelligent, improving their operations and making their processes easier.

Data-driven decision-making is the process of making choices based on actual data rather than intuition. Thanks to the relatively recent advances in data-driven techniques such as data mining, machine learning, and predictive analytics, aided by the rapid, although uneven, development of hardware and software abilities, Data-Driven Decision Making is now possible. Data-driven decision-making can take various forms and can have numerous implementation and usage levels. The application of Data-Driven Decision Making creates value by increasing the performance of decisions or decision-making processes.

Some applications of Decision Making Models help managers to simulate, optimize and evaluate decisions offering some support. Such models try to imitate and help decision makers actually solve a decision problem or make a decision while sometimes reporting at what level Data-Driven Decision Making can be implemented. Data-driven decision-making combines advanced analytical techniques and algorithms with a business's existing data to facilitate faster and more precise decisions. Data-driven decision-making can take many different forms. For example, developing a forecasting model is not only a data-driven innovation.

**Equation 2: AI-Based Forecasted Energy Demand**

$$\hat{E}(t) = f(X_t;\theta)$$

Where

$\hat{E}(t)$: Predicted Energy at Time $t$

$X_t$: Input Feature Set (e.g., machine status, workload, weather)

$\theta$: Parameters Learned by AI Model

$f$: Predictive Function (e.g., neural network or regression)

### 5.2. Predictive Maintenance Strategies

The importance of “smartening” maintenance actions has been realized by many companies as well as academia in recent decades. Manufacturing companies use 15%–20% of their revenue to cover maintenance costs. 66% of middle-market manufacturers observed that reducing unplanned machine downtime has become a priority as they operate in an uncertain economy. Research has shown that more than 80% of the costs related to system failures can be avoided by maintaining the system on time. However, traditional maintenance actions fail to do so. The most common traditional maintenance strategy is the calendar-based strategy with the interval defined through historical experience and similar expertise. Such action can be disastrous as it may lead to over-maintenance or under-maintenance. Over-maintenance incurs additional operation costs and can even cause a temporary shutdown while under-maintenance can cause failures that lead to even suffering deaths. Therefore, it is essential to “predict” failures and maintain a system accordingly.

The goal of predictive maintenance is to "predict when in the future the failure will occur, enabling scheduled maintenance just in time to prevent the failure". The business opportunities related to predictive maintenance include reducing labor costs associated with excessive servicing of systems and equipment that are still operational and maximizing the availability of systems and equipment through the reduction of unscheduled service. However, due to the lack of good supporting data, most predictive maintenance systems only included simple analytical models from traditional preventive and condition-based approaches for failure prediction. Moreover, there were also challenges related to data management. After several years of research and development, now with the unprecedented amounts of data being collected by rapidly evolving information technologies and the support of new Managing and Analyzing Data technologies, there are novel Predictive Maintenance Models that have been developed that can systematically help manage these problems.

**5.3. Real-Time Monitoring Systems**

Real-time monitoring enables the detection of abnormal and abnormal conditions immediately. Therefore, an entire production line can continually be optimized. Sensory data collected from machines and electrical devices can give valuable insights to operators and managers. Based on the status of production lines, an optimal production schedule can be conducted to minimize energy consumption. Solutions can be provided via real-time alerts of managers and automatic control of machines and electrical devices, especially during the non-production run. For example, while an actual product is not being manufactured, machines should be operating in a sleep state to optimize energy consumption. However, machines and devices of the actual production line are not always being manufactured. In addition, to suggest valid solutions, other operational constraints should be considered besides energy consumption when notifying an abnormal condition. Other operational constraints are the production schedule, product sequence, and response time of the factory. To provide possible solutions to the operation of production lines, a decision-making and negotiation mechanism should be conducted in conjunction with other intelligent systems such as predictive maintenance and decision-making smart factory systems.

Several industrial manufacturers have made efforts to establish real-time monitoring and analytic systems. A cloud-based analytic solution for monitoring industrial operations in real-time collects operational data from on-premise systems and sends analyzed insights to the cloud. Then, analytical services notify factory users of operational alerts or exceptions. By leveraging a cloud-based infrastructure, manufacturers can access sophisticated analytic services with upfront costs at a much lower price point than traditional on-premises systems. This solution leverages a pre-built data warehouse populated from factory operational data to enable companies to convert large volumes of operational data into actionable information to support fewer resources dedicated to data analysis.

**6. Case Studies**

The proposed methodology is tested on three use cases related to energy consumption data modeling and anomaly detection. Data for the analyses was obtained from production areas within manufacturing facilities in collaboration with an industrial partner that operates in the apparel, electronics, and food industries. Data was collected from meters installed at the two production areas of Plant A, two production lines at Plant B, and the raw material preparation area in Plant C. The datasets were analyzed with the help of the Python programming language, different packages, and libraries including Pandas, Matplotlib, Seaborn, and sci-kit-learn, and software tools such as the Jupyter Notebook environment and Google Colab. The modeling process implemented in this chapter is based on previous work and refinement. The next subsections present the details of each model.

The first use case, concerned with Plant A, presents the application of a time-series modeling approach based on machine learning (ML) and statistical methods to energy consumption series. It exhibits a compressors' monitoring activity undertaken as part of testing wider system alarms to detect anomalies in energy consumption at Plant A. A decision tree classifier and a seasonal auto-regressive integrated moving average model were implemented within the study. The second use case, centered on Plant B, presents the application of an ML-based anomaly detection approach to the individual energy consumption series of two sewing production lines at Plant B. An isolation forest anomaly detection algorithm was employed to detect anomalies in the energy consumption of both lines simultaneously.

The third use case focused on Plant C, presents the application of the SARIMA statistical model to the energy consumption time series of the raw material preparation area at Plant C and the anomalies detected therein.

**6.1. Case Study 1: Plant A**

A smart factory with more than 20 machines working continuously on producing parts, sub-systems, and systems for automotive applications has been used for the presented case study. The studied energy system is composed of the electricity power system and production machines that produce heat as a secondary energy. Adopting a passive state-controlled concept for the heating operations of the machines during the weekends and unoccupied periods of the working days is diagnosed. The presented case reduces the annual consumption of electric energy without any reduction in the production volume. Moreover, the proposed energy optimization concept is designed for implementations that do not

require any additional investments or costs. Its general design idea is to change the year-round behavior of the factory energy system, achieved by conveniently selecting the heating regimes of the productive machines.
The involved data analysis and interpretation is based on the collected data from the electricity power system of the factory. The required data are processed and presented in the form of energy signatures that point out abnormal operations of the energy system element during the selected time interval. By careful analysis and interpretations of the signatures, it is possible to predict the abnormal operation of the energy system element, choosing suitable assumptions and explanations. The data collected from the factory are in the form of the real electric energy consumed by the plant, recorded with a sampling frequency of 30 min, from April 2019 through March 2020. The sensor was installed near the electricity meter. It comprises a Hall effect sensor with a special protection box containing a flash memory for data collection. The collected data show an increase in the time function on the weekends and during non-working days, when only space heating is done by secondary ones, to achieve a safe temperature inside the production halls.

**6.2. Case Study 2: Plant B**

In addition to the data analyzed in the first case study, a second dataset from Plant B was also explored. The data were collected from sensors and control systems for building electric installations and lighting, as well as for electric power supply to the equipment units in a Cluster of Quick Changeover Arrangements. The data operated in this work cover the period from November 01, 2022, to February 28, 2023. The sensors were located in all sub-units of the plant to track energy consumption by lighting (1 sensor), HVAC systems (3 sensors), and other electric-powered technological equipment used for the production and assembly of sensors (15 sensors). The sensors monitored the energy consumption for a total of 21 units. The environment parameters were recorded on the following ranges: December 02, 2022 – February 09, 2023 (for Lighting Control System); November 01, 2022 – January 12, 2023 (for HVAC Systems); and November 01, 2022 – February 28, 2023 (for other electric-powered technological equipment). The data sampling frequency was set at every 5 min.
The Cluster of CQ Arrangements includes 4 sub-units where sensor assembling is performed; 10 workstations of 2 types are located inside: 4 (for housing assemble – 2.5F) and 6 (for housing assemble – 2.2F). These workstations are for silicon-glass metalworks where capping and mounting are performed; the modules are encapsulated with a pouring resin, and curing is limed. The technical organizational illumination requirements are 200–300 Lux. The environmental parameters are monitored by the air temperature and humidity sensors. During the day and continuously for 48 h (for technological budget), the air temperature must not exceed 27 °C and the humidity – 70%.

**6.3. Case Study 3: Plant C**

Plant C is a glass bottle manufacturing plant. Its high-energy-consuming process consists of melting glass batch materials, blowing them into molds to produce bottles, heating the bottles until they reach a certain temperature, and subsequently transporting them to the warehouse. The anomalies are defined respectively by the glass melting, blowing, and thermal treatment processes. The purpose of the study was to use AI-based solutions to identify the anomalies of the specified three processes, that is, machine learning on time-series data, for monitoring the machines of the three processes and applying a proper automated action plan to reduce energy consumption and alarms. As a result, the machine learning models could effectively switch on/off the corresponding area lights and blowers to reduce power consumption and alarms in these areas of the factory.
In this case study, we collected the time-series data of the above-mentioned specific equipment of the three processes belonging to the same manufacturing line, during a five-week study period. The acquired data originated from a factory automation system that was designed and developed by the plant. The system enables the overall factory and relevant data collected to be monitored on a cloud server via the Local Area Network at the factory site. A data-collecting application has been implemented on the server. Various applications for the plant were developed to prove the data to guarantee the data quality and reliability and enhance the validation of the machine learning models. A preliminary descriptive analysis was conducted to understand the main data characteristics by transforming the industrial data and plotting graphical visualizations such as time-series data, contour images, and periodograms.

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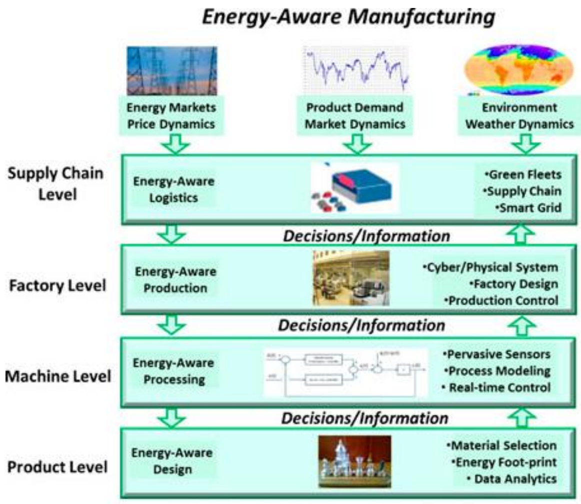


**Fig 4: Modeling Energy Consumption Using Machine Learning**

## 7. Evaluation Metrics

Performance indicators are important for the comparison of energy consumption optimization techniques and their practical implementations. So, it is important to properly define the metrics to measure potential energy savings, model and optimize energy usage, accurately observe actual performance improvements after energy consumption optimization actions, and justify the investments required for these actions. In particular, modeling, optimization, and evaluating are basic pillars of manufacturing systems simulation — a key stakeholder of smart factory analytics. We first list three important energy performance indicators that can be used in simple metrics to model and report on energy usage throughout the lifecycle of a manufacturing system. Then reporting on their models, metrics, and protocols to optimize and evaluate energy savings focuses on embedded energy analytics. Finally, embedded analytics optimizing the operating cost for energy should complement other optimizations, such as the generalized flow shop scheduling.
Different methods have been defined to evaluate factory design energy performance during the design or redesign of manufacturing systems. The design stage is a crucial and mandatory phase to obtain energy-efficient manufacturing systems because the most important choices by far in terms of overall energy consumption are made in this stage. In the operational phase of the life cycle, given the capital investment in the factory, facility, and equipment, the only variable costs are the utility bills. Thus, optimizing the operational phase is much more important than optimizing the design of the manufacturing system, as emphasized. Models, metrics, and protocols have also been defined to evaluate the energy impact of continuous incremental enhancements that have been proposed for discrete event simulation and agent-based modeling. Experimental results confirmed that cellular automata modeling for manufacturing systems is better at estimating energy consumption than discrete event simulation and agent-based models. However, CA modeling does not embed analytics, which means that using CA modeling does not clarify the originating causes of energy consumption.

### 7.1. Energy Performance Indicators

Energy management in a manufacturing system can hardly be evaluated by only considering the amount of energy consumed in the system. This is mainly because energy is not a product on its own; it is needed to operate machines for a specific purpose in the manufacturing system. When the production level is too low or too high, a large fraction of the total production cost can be attributed to energy consumption, such that the energy cost affects the profit of manufacturing companies in addition to productivity. However, the impact of energy consumption on the profit is different for different manufacturing operative conditions. Currently, two comprehensive energy metrics that quantify the impact of energy consumption on the total cost are focused on when measuring and analyzing the bound of energy audit: emissions in the factory and real industrial electricity cost. Therefore, some energy performance indicators under this economic aspect are proposed to enhance the programs of energy reduction: energy cost ratio, electricity consumption cost, cost of changing the electricity load, emissions cost ratio, emissions, total annual factory emissions, emissions in production, and variation in production cost. However, the econometric evaluation models for energy consumption, which make the energy metrics using advanced specific energy consumption or enhanced energy intensity, haven't pre-given any analytical form of those evaluation metrics in specific energy consumption or energy intensity.

### 7.2. Cost-Benefit Analysis

Compared to other industrial investments, the cost of an energy management solution is relatively small, but the potential benefits are huge, especially for energy-intensive industries. Therefore, before implementing an EMD system in the

factory, it is essential to estimate its potential costs and benefits. The evaluation of operational savings and costs of initial expenditure is essential for a serious approach to the feasibility and design of EMS, i.e., the cost-benefit analysis.
Cost-benefit analysis (CBA) is widely elaborated in the form of decision support tools. The general CBA framework distinguishes project cost categories: initial capital investments, replacement costs, operation and maintenance costs, and potential revenues and savings potential categories: generated revenues, reduced public government costs, reduced employer costs, and market sales. Calculation of the discount cash flow is a common valuation method. However, the literature is sparse on introducing risk into CBC and defining risk context. Benefits are essential on a government level, while on a company level, employers focus on costs. Cost estimations are mostly presented in the literature. Possible investment strategies are presented with rent strategy, ownership strategy, free utility strategy, auction strategy, lien strategy, consortium strategy, treaty strategy, leasing strategy, subscription strategy, and investing strategy. It is shown that the market conditions might have a huge impact on energy price reductions. The study findings support policymakers in stimulating more energy-efficient energy management in the industry sector. Moreover, the developed and presented cost-benefit model supports industries in long-term energy efficiency program planning.

## 8. Implementation Challenges

Optimization of various processes using machine learning is increasingly common in several real-world business cases. However, the use of such tools for optimizing energy consumption in the context of Smart Factories is still very much in its infancy. Therefore, there still lie several barriers that need to be addressed to facilitate a successful implementation.
1. Technological Barriers
These can mostly be outlined in three central aspects of a complete Smart Factory Energy Optimization System: data availability, potential systems’ interoperability, and the need for real-time constraints in algorithmic solutions. In a Smart Manufacturing context, energy consumption data availability at different levels can greatly vary from factory to factory. Factories with high levels of technology maturity and long-time efforts on energy data monitoring and management would surely present far more levels of detailed data availability than others without such effort. Data about factory energy consumption are obtained from systems through sensors connected to the power line on production machines. Many factories still do not have data collection systems in place that provide easily accessible interfaces for developers to read this energy-related data. The implementation of those collection systems and the required sensors in all machines and processes present significant efforts for companies that do not intend to make an extensive digital transformation of their production system.
2. Cultural Resistance
This barrier can materialize as resistance to change from any stakeholder in the factory process, from shop floor workers to management staff. Their cultural processes can hinder a successful project, so it is crucial to engage people in the entire energy efficiency process and show them the benefits to generate trust in new production processes and energy efficiency's positive impact on both financial performance and sustainability. Moreover, changes often come with the fear of losing jobs or fear of change since, for many employees on the shop floor, the new technologies are still a mystery. It is important to convey to workers that new technologies are there to help them and not to replace them.

### 8.1. Technological Barriers

Energy efficiency has received increasing attention in Industry 4.0, focusing mainly on production management problems and modeling, monitoring, and fuzzy decision-making systems, with less attention to AI-based energy-related technologies and design problems. Processes in manufacturing operations consume large quantities of energy in the form of electricity, gas, steam, oil, and water as well as in the form of embodied energy of other products. Energy efficiency improvement and emissions reduction have been major issues for researchers and practitioners, and energy is now included in the most important constraints in both design and operational phases. However, to create a circular economy it is important to reduce energy demand and valorize the local available energy sources. The smart factory is based on equipment and systems able to automatically monitor themselves and the surrounding environment, promoting energy consumption optimization, even at a global level that includes interconnected plants through the Internet of Things or the Internet of Services approach. Many discussions have addressed the role that Artificial Intelligence (AI) and AI-based models can play in this context. AI-based systems can assess the relations between process parameters and the relevant energy parameters, or even directly predict energy consumption and emissions, through various machine learning techniques. They can also combine predictive and prescriptive features. Deep Reinforcement Learning (DRL) agents can assess, based on their experience, which policy to adopt to limit energy demand. They can also be implemented to combine efficiency, flexibility, and quality, and to cover all phases of production and the entire production unit life cycle, thanks to transfer learning. Issues about the technological benefits and the possible risks of such approaches have been highlighted, taking into account the possibility of humans being displaced in their roles.

### 8.2. Cultural Resistance

Human nature is resistant to change, and one of the major causes of concern for the implementation of solutions focusing on the energy consumption patterns in SF is the refusal of the factory's managers or employees to apply the results regarding AI. Implementation of solutions or results regarding a solution solely based on the analyst fact findings without any input from the managers or employees would lead to cultural resistance. About that, at the starting point of a possible intervention in the Factory's process and consequent results, it is paramount that data is collected either through smart devices that allow for continuous collection without breaking the processes and incrementing costs or through well-coordinated auditing, in which employees and the facility manager actively participate. Failure to obtain representative data would likely lead to biased conclusions and consequently rejection of the implementation.

Once representative results are obtained and discussed, the implementation of energy consumption patterns optimization would be a lot easier if employees and managers were actively involved in the proposal and not simply presented with a "done" solution. Through involvement in the solution derivation, plant floor employees and managers are led to an awareness of energy consumer inefficiencies and energy waste related to process losses due to the adoption of suboptimal parameters. The usual employee's bottom-line thinking or the manager's partial awareness of the impact of his/her decisions in the factory process regarding energy efficiency will lead to a contribution towards a factory approach, with decisions taken having energy efficiency in mind.

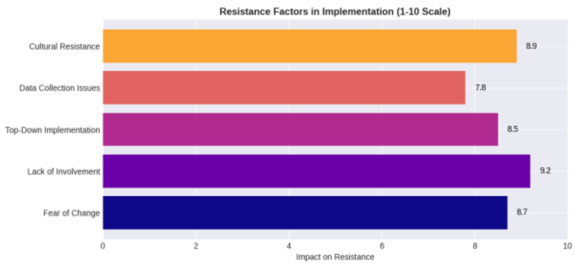


**Fig 5: Resistance Factors in Implementation (1-10 Scale)**

### 8.3. Financial Constraints

Energy optimization projects are typically not considered core businesses of manufacturing companies. These types of projects are often classified into auxiliary capital expenditures. However, it cannot be resolved without profits. As a result, due to financial pressure, it is not uncommon that investments in digital solutions are made with the aim of future returns which may be either tangible or intangible. Even though many digital solutions are available to find energy consumption problems and exploit recommendations, the threshold cost, amount of investments, difficulties in identifying possible benefits, and investment risk are still barriers to overcome for successful projects. The cloud offers an opportunity to mitigate the problems of companies with financial constraints. However, gaining insights from the cloud is largely limited to capital-intensive infrastructures. It should first be emphasized that the costs associated with these projects must be optimized before the energy consumption restrictions themselves.

In addition, investments in data-driven asset management tools are only slower from the start, and the financial impact over the entire life cycle may take a little longer to materialize. It is also important to understand that life prediction software and other new tools must rely on the credibility of expensive datasets and the benefits that can be derived from them before deploying them across large fleets of assets. Furthermore, investment costs should be taken into account during each step of the data-driven asset management process. For example, the setup of Phase 1 can represent significant costs if the goals stated above are not aligned with the investment budgets planned for this phase and the asset management process in general. In addition, key product performance indicators must be updated regularly throughout the life cycle of the assets. However, these updates can also present financial challenges if the costs associated with these updates are not carefully considered. Thus, proper allocation of investment, explained stepwise before implementing a data-driven solution, should mitigate expectation risk and allow for proper optimization of important company-wide decision factors, especially investment and management costs.

## 9. Future Directions

In the coming years, we will witness immense advancements in artificial intelligence and its technologies, which may ultimately lead to superior versions of today's AI-assisted data analysis for energy management in smart factories. Specifically, the white-box AI technologies forecasted to be seen in time horizons of weeks, months, and years will greatly augment the energy solutions described in this chapter. Such white-box AI technologies that will rapidly inject exponential power into energy solutions are expected to lead to: The exponential-influence intent-and-emotion analysis for designing revolutionary circular policy-development dashboards for neglecting factories' energy steering needs on grounds of meeting high-level intentions, motives, and purposes such as sustainability and conservativeness. White-box AI will

impact energy profile design by revolutionizing what data are considered, to ensure exploration of derivative energy profiles beyond those learnable merely from past data.
The powered-blueprint-generation white-box AI will revolutionize the generation of formal plans for factories' operations. The blueprints are practical and detailed instructions on what intended templates of work should be followed. The blueprints will follow high-level plans by formalizing the templates of work that promote sustainable practices while mitigating and removing ethically offenseable bias strains that jeopardize compliance with higher standards. Such factories will thus become vital both to their stakeholders, people, and society in general and also to the companies themselves for additive-pricing reasons as the added value is not measured only in monetary terms. Hence, both superlative business and ethical motivation will be witnessed, as also observed in recent years in industries.

**9.1. Emerging AI Technologies**
The previous chapters overviewed a series of AI-enabled optimization Methodologies that are being applied in the Industry 4.0 Context, to optimize Energy Efficiency in Smart factories. However, given the ever-growing amount of Data generated inside Factories, and their increasing Computational Availability, it becomes logical to see exponentiation in the Future of more Data-Driven and Bottom-Up Applied AI Transformations in Industry. A foreseen shift from a more Expert-Led Process-Driven Automation towards more Self-Led Data-Driven Automation can be seen. More methods, which up to now were applied through analyst work and expert knowledge, will have in their core Data-Driven methods that, through new Enabling Technologies, will allow easy plug-and-play applications. This visible tendency permits enabling the optimization of Industry in aspects still unexplored until now or economizing the work of analysts in Industries where the budgeting for such teams is high. At the same time, new Trends such as the Digital Twins applied to Energy Efficiency can offer at minimum cost, optimization ideas for Smart Factories, demanding a less closed relationship between Consultants and Companies and allowing smaller and medium-sized companies to also develop optimization projects. These AI Technologies will guarantee this shift in the mind of the People working in Smart Factories from a more closed vision of AI -being that only Analytical experts are responsible for processing the Data captured inside Companies and getting information that guides decision-making: People doing what AI can't -grow towards the opposite statement -AI does what People can't -People focused on Strategic implementation of Optimization Decisions in Labour and Process Flow.

**9.2. Sustainability Initiatives**
As demand for and pressure to curtail energy consumption increases, the role of advanced technologies in deriving efficiencies will necessarily broaden following the adoption and impact of Industry 4.0 and its components. Much of the above explores a digital transformation of manufacturing that leverages AI and lowers barriers to entry for its adoption. Beyond adoption's impact on individual factories, the questions of how digital transformation relates to sustainability initiatives require exploration. Sustainability initiatives can determine which technologies factories adopt, how those technologies are utilized, and the initiatives' tangible outcomes in improved energy sustainability. Following the adoption of and investment in Industry 4.0 components, initial approaches to sustainability indicate the effectiveness of improvements realized by other factories following adoption indicates the effects of synergy. Factories can achieve no deeper insights nor be motivated by better incentives than those provided by the lives lost; water, terra, and air damaged; and climate altered by unsustainable energy practices even where such measures appear distant. Combined, lessons learned from pursuing sustainability goals while using AI for energy optimization and consideration of how technological foundations shape sustainability policy and implementation can lay the foundation for future work.
Similar to the gap between realized functionalities of and announced projects around Industry 4.0 and energy optimization, the technologies used by factories that announce new sustainability initiatives do not leverage new approaches to create and use knowledge. But, unlike energy optimization, without demands inside the space shape functionality to transform how factories pursue sustainability management, technologies for sustainability management within factories also have adopted an approach and set of tools that appear frozen in time having to be used in an organization concerned with assuring compliance with existing regulations risking previous investments.

**10. Policy Implications**

Energy optimization represents a highly integrated aspect of a smart factory. However, the way a factory consumes energy is strongly influenced by the design of the regulatory frameworks affecting them. For instance, energy taxation can boost electrification of industry operations with renewables, and promote higher productivity and circularity by using energy in capital-intensive, instead of labor-intensive, manufacturing techniques. Emerging incentive schemes for energy efficiency such as models linking the price paid for the services delivered by an energy performance contract to the verified energy savings generated are being tested, with results that are still mixed but encouraging. In such a regulatory framework, it is possible to design a set of policies that can channel business energy data into a helpful support tool.
The recent trends, and direction, in energy regulation, signal that stark energy shifts for product manufacture will take place. Implementing energy management systems certified to can foster compliance with energy regulations focused on

production, and ensure guidance for a continuous review of energy performance. Integrating them into a smart industry information system can help manufacturers guide all automation systems to switch to a low-carbon solution, meeting differentiation objectives as sustainability hastily changes into a competitive battleground, where any opportunities for product valorization are welcome to help members of the supply chain cope with risks from this transition.
Industry cooperation for energy performance requirement definition, structural data explanation, and substantiation of the estimates of avoided damages, are essential prerequisites, along with a clarification of how to tackle the excess of uncertainty existing in some specific technological innovation in the product qualification process.

**10.1. Regulatory Frameworks**
For factories, a major element of their environment consists of the regulatory frameworks enforced by governments and institutions. These frameworks define the rules of the game for the many stakeholders involved in energy-related decision-making for the factory. Supervisory industries enforce standards at times and, in some cases, involve in factory audits. User companies that apply energy-intensive products are influenced in their decisions by reporting requirements, product selection criteria, and decision areas involving relationships with suppliers.
Energy taxes, trading schemes for emissions, efficiency grants, green technologies, and other policy segments represent mechanisms that align the stakeholders within the frameworks towards the intersection of regulatory prices and expected efficiency benefits. Of course, it stands to reason to ask whether the current policies lead factory indices sufficiently close to the efficiency optimum. For considering how energy price volatility influences corporate decisions, one may also address financial support for efficiency companies providing service packages that reduce efficiency uncertainty. Furthermore, other activities of energy efficiency companies may provide interpolation on costs, results, and implementation times to demonstrate the trustworthiness of efficiency projects for factories with little internal know-how, performance histories, and methods for evaluating project risks.
Such information management activities creating certainty about efficiency impacts are called “de-risking” in the field of financing and may involve the substitution of public and private budgets to offset the skepticism coming from the corporate skeptical side and thus encompass higher risk premiums on investments. For user policy segments, the provisioning of the reference infrastructure for communication and reliability may become important as well as actions that create efficiency awareness in energy uses of factories and involve mindful management and implementation of efficiency programs.

**Equation 3: Energy Optimization Objective**

$$\min_{S} \quad E_{total}(S) + \lambda \cdot C_d(S)$$

Where

$S$: Machine Scheduling Plan

$E_{total}(S)$: Energy Cost of Schedule $S$

$C_d(S)$: Delay Cost for Schedule $S$

$\lambda$: Weighting Factor Balancing Energy and Delay

**10.2. Incentives for Energy Efficiency**
Energy efficiency is a matter of much interest these days and energy-efficient technologies are readily available that could reduce energy consumption by 30-50% in current commercial buildings. Surprisingly, only a few building owners are currently pursuing these measures, even though the cost of energy should be creating a greater incentive for such investments. Furthermore, the few organizations pursuing these considerations appear to be motivated by concerns with user discomfort or a desire to provide philanthropic leadership in the area of sustainable development and not by long-term financial considerations. Yet, there are economic, financial, and behavioral barriers that inhibit the diffusion of presently available energy-efficient technologies.
The economic technical barrier refers to situations in which the cost of energy-efficient designs is larger than what may be economically justified even after considering the life-cycle savings from reduced energy costs. The financial barrier refers to the difference between the economic criteria for investment decisions and the risk-adjusted financial criteria applied by potential investors to decisions that depend upon long-term future predictions of operating costs. Because the user of a building does not pay the energy costs, the investor who receives reduced life-cycle costs is not the occupant who has the decision-making authority over energy investments. There is thus the potential for a disconnect and market failure. This can create a behavioral barrier, where it is the perceptions of both the investor and user that inhibit decisions to invest in energy efficiency choices.

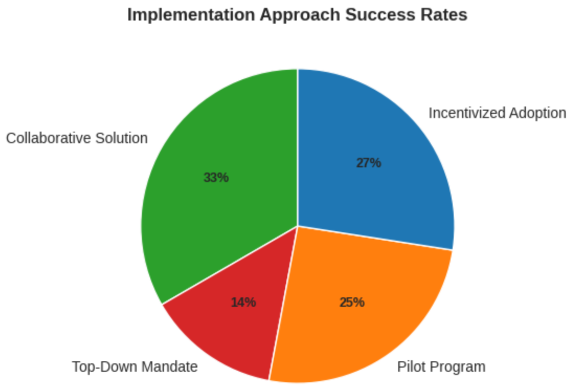


**Fig 6: Implementation Approach Success Rates**

## 11. Conclusion

In this research work, we reviewed the current trends for the optimization of energy consumption in Smart Factories using AI-based analytics. We provided an overview of the current state of the Art in Energy Systems and AI techniques, with several relevant examples of the implementation of these technologies in different types of Smart Factories. From all the collected information, we are led to the conclusion that the application of AI techniques in the optimization of energy consumption is still largely in an experimental phase, still very much linked to the solutions implemented in non-smart industry environments. Despite the lack of industrial applications, we found a niche market ready and open to the implementation of AI models, in the form of cloud-based services that can be tailored to the implementation of these models. From this perspective, we noticed that the adoption of AI techniques for the reduction of the high peaks regimes and the trained predictive models associated with the dynamic pricing schemas will be important drivers for the development of business models in the coming years.
On the other hand, it is still a long way to the complete automatization of the definition of AI models. To facilitate this process and to lower the required skills for its usage, the next generations of software tools will need to invest in the definition of more friendly user interfaces or dashboards. These support the whole process, from the data collection, and data sets treatment, up to the definition of AI models that can be used without the need of contacting experienced AI practitioners for the conduction of the whole AI model training process.

### 11.1. Summary and Key Takeaways

In an increasingly consumption-driven global economy, the efficiency of industrial production, as the backbone of the economy, is the key to a country's wealth. However, energy is wasted in many production processes without producing any useful work. Industry 4.0 introduces smart factories with AI capabilities where data are leveraged to optimize production and minimize waste. In this regard, we have contributed to fostering the growth of smart factories based on IIOT and AI. We successfully deployed a sustainable smart factory where the air-conditioning system –one of the two largest consumers of energy in an industrial production setting– was optimized with machine learning and computer vision to minimize energy waste while ensuring safe working conditions. The deployment was performed using an auto-machine learning framework that has the potential to alleviate the shortage of data scientists in the industry. Our simple AI algorithm together with our downloading procedure for training data achieved acceptable performance, comparable to that of complex solutions, without overfitting. The work has strong implications for the industry. The auto machine learning framework can be quickly adapted to any output that relies on visual data. With minimal investment, we can optimize many energy-consuming processes across sectors. In doing so, we can minimize companies' energy bills and, beyond that, contribute to reducing greenhouse gas emissions and climate change.
The work breaks new ground in the field of AI applied to supporting a just energy transition in several ways. First, using computer vision, we attempted to predict energy-consuming processes across industries based on visual data. Second, we provided a simple AI solution that matches the performance of complex solutions without overfitting and with an original downloading procedure for visual data that also has the potential to facilitate energy optimization in many real-life contexts with minimal investment. Third, due to the auto-machine learning framework, our simple solution can be quickly adapted to many functions that depend on visual data across the IIOT in industrial settings.

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