The Impact of AI-Driven Energy Efficiency Solutions on Sustainable U.S. Manufacturing

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1. Introduction

In this study, we provide a comprehensive analysis of the effect of AI-driven energy efficiency solutions on the promotion of sustainable manufacturing, focusing on the U.S. economy. Our approach combines economic growth and pollution impact, allowing us to shed light on the role of AI applications. The associated rebound effect is also considered. The analyses show that AI-informed plant-level energy savings result in lower energy costs for firms. Lower costs combined with higher demand leads to increased output. The basic and more realistic models analyze the three parallel factors: increased output, the substitution effect whereby lower fuel prices increase fuel use (negative), and the energy savings effect which brings only a partial reversal.

In turn, the increased output fuels the negative pollution emissions from increased economic growth. The more realistic model also examines the dynamic effects on fuel prices, output, energy savings and pollution, generated by the application of increasing energy savings over 15, 20 and 25 years, and their interaction with the three aforementioned factors. With increasing retention period, a declining percentage increase in emissions reductions is found, ranging from 0.37% for 15 years to 0.26% for a 25-year period. Given this backdrop, our study extends the aforementioned research on the rebound effect and its potential adverse impact on the realization of environmental and energy efficiency goals. In so doing, we contribute evidence on the transition to sustainable manufacturing, as well as evidence on the initial impacts of AI technologies on that transition.

1.1. Background and Significance

Manufacturing accounts for one-third of U.S. energy consumption, with energy expenditures representing a significant portion of production costs. Public and private initiatives in the U.S. are driving energy efficiency improvements at manufacturing facilities. Given these advancements, the research conducted here is quite timely in exploring how AI, driven by machine learning, has been identified as the enabling technology with the potential to revolutionize the capabilities of multiple Industry 4.0 technologies, and how machine learning has been demonstrated to identify both well-known and new operating strategies for energy and utility efficiency. We aim to take the next step to shed light on the impact of AI-driven energy efficiency solutions to make the production of goods more sustainable.

The manufacturing sector has always been and continues to be one of the primary industries in the U.S., with the American Society of Mechanical Engineers identifying growing and sustaining the U.S. manufacturing base as a grand challenge. The burgeoning interest in AI technologies suggests that operations in such facilities undoubtedly provide a gold mine of practical applications for AI in engineering and operations research. At present, most AI applications are focused on automating repetitive tasks. The capabilities of AI to improve productivity, product quality, and personalization remain interesting areas to explore. We suggest that AI-based modeling and methodologies are quite useful for automating the task of discovering the optimal operating policies to minimize energy and utility waste of manufacturing processes. Additionally, increased stakeholder interest in understanding the implications of AI technology on energy efficiency in manufacturing calls for a careful exploration of how AI in manufacturing is likely to impact this significant dimension of sustainable operations.

1.2. Purpose and Scope of the Study

The use of advanced artificial intelligence (AI) applications has shown promise for accelerating gains in energy efficiency in many areas. Recognizing the importance of this development, especially in industrial sectors, the U.S. Department of Energy and the National Renewable Energy Laboratory commissioned a study to consider the potential impact of advanced AI applications on energy savings in the U.S. manufacturing systems and on the nation's progress toward sustainability goals. A key motivation behind the study was the fact that such systems are high-impact in terms of the economic, environmental, and social benefits they deliver. In addition, both approaches - AI and energy efficiency - are considered to be foundational aspects of sustainable industrial systems. Thus, the study's primary focus is to evaluate the impact of AI-driven energy efficiency solutions in the nation's set of industries, as well as the potential national energy savings that can be accrued. Correspondingly, to frame the discussion, Chapter 2 reviews metrics related to the energy savings and sustainable development of manufacturing systems. From the findings presented in this introductory chapter, the section presents a variety of research opportunities towards the concurrent and cascading benefits that AI solutions can offer.

This is an area that to date has attracted limited attention of the scientific community. The scope of this study is limited to considering the potential energy savings associated with AI-driven solutions as the impact of such systems. The study will not delve deeper into the gains in efficiency, economic performance, or environmental performance that can be achieved with AI-driven solutions and AI-powered industrial systems. Moreover, the research is focused on the U.S. and its manufacturing sector. The activities of U.S.-owned manufacturers within the national borders, as well as foreign-owned manufacturers with activities within U.S. territories, have consequently all been taken into consideration while conducting the research. Modifications to this scope were necessary only when the primary data sources employed to prepare this report provided incomplete information or assessment.

2. The Intersection of AI and Energy Efficiency in Manufacturing

When it comes to the nexus of AI and energy efficiency, perhaps there is no better place to witness this phenomenon than in the manufacturing sector. Why? Because manufacturing – as an economic driver, as a world-changer, and as a global industry leader – requires more energy than any other sector in the United States. The data supports this: estimates show that more than 30% of energy consumed by U.S. manufacturers is wasted. To put this waste in context, such energy inefficiency is equivalent to taking approximately 8% of all U.S. households off the electricity grid.

Enter artificial intelligence: these advanced technologies – when coupled with advanced algorithms, massive amounts of real-time operational data, and the Internet of Things (IoT) – have the capacity to greatly improve energy management, optimize industrial processes, and drive sustainable and efficient manufacturing practices. To that end, AI-driven energy efficiency solutions can reduce costs, trim resource waste, work to reduce carbon emissions, and support the future growth of sustainable U.S. manufacturing.

The Deprival of Energy Waste in American Manufacturing, or DEWAM, states the following: By adopting AI and IoT solutions, U.S. manufacturers can slash their greenhouse emissions by an estimated 3.6 gigatons, reduce their electricity spend by up to $322 billion, experience energy savings that are up to 14% of energy used, and see a recycling, reuse, and collaboration potential of up to $500 billion. More recently the Environmental Protection Agency (EPA) noted in their 2019 Regenerative Economic Rapid Assessment (ReRA) that insightful use of AI in the area of AI-driven energy efficiency can result in an 11.7% increase in net energy.

So why have manufacturers been slow to adopt AI-driven energy efficiency? This report examines the obstacles, issues, and future strategy for promoting AI-driven energy efficiency in U.S. manufacturing.

2.1. Overview of AI Technologies in Manufacturing

This section provides an overview of AI technologies as applied in the manufacturing sector. We separate AI-driven approaches used to decrease the energy footprint of manufacturing into three categories: (1) forward approaches, which are driven by AI-enhanced process theories and parallel digital simulations; (2) data-driven approaches, which make use of data-driven AI algorithms to directly control dynamic optimization variables in real time; and (3) maintenance-related technologies, which diagnose potential breakdowns before they actually occur. Productivity of manufacturing establishments can be improved through the ability to better control, monitor, and diagnose a complex system (plant and associated equipment) within the industrial Internet of Things (IoT).

AI technologies have reached a level of sophistication that allows a system of sensors, instrumentation, measurement, intelligent control logic and continuous dynamic optimization to focus not on the products in an industrial stack—as in recent approaches that use sensory deployment in smart manufacturing—but on the process of making those products in a given facility, in an effort to consume fewer resources (energy, materials, space). We identify three AI-driven approaches to decreasing the energy footprint from U.S. manufacturing: forward approaches, which use AI approaches to enhance an underlying physical process theory and available process simulators; data-driven approaches, which use AI-enhanced models to make real-time control and optimization decisions directly from sensor outputs of dynamic optimization variables; and maintenance-related services, which are driven by physics-and-data-driven AI models.

2.2. Key Concepts in Energy Efficiency

The essence of energy efficiency is energy saving through improving manufacturing technologies and processes. A key concept in understanding the significance of automating and data-mining manufacturing activities is to also understand the key goals of energy efficiency. Two of these goals are the reduction of waste-energy contents of formed processes and the identification of sustainable practices in manufacturing processes. In manufacturing and process industries, where a system is constrained by an inventory of goods with end consumers, there are physical laws that must be followed. As such, in principle, lossless operations are not possible in this constrained system, and furthermore, the constrained system's outputs are further limited by other physical science laws. We consider manufacturing processes that maximize the amount of permitted physical limits, like production, and are sustainable as the most desirable. Additionally, while any emerging technology in automated manufacturing and energy-efficient manufacturing generally uses methods that involve a level of artificial intelligence, donated data to control such processes is still only between 5-35% available.

Current and emerging digital AI applications used in manufacturing optimize a process. For example, in-depth end digital AI in predictive optimization can reduce the current state-of-the-art waste by a meaningful amount for the existence of different perspectives on the entire manufacturing process. Either energy or a dissection of the relevant process can be focused on to express waste-energy. Manufacturing energy waste is caused by either (a) producing a good or goods inefficiently or (b) producing a good or goods that do not have a demand. Produced goods should have an integrated demand, including the energy and material contents.

3. Challenges and Opportunities in Implementing AI-Driven Energy Efficiency Solutions

Since at least the 1970s, manufacturers across the United States have worked to deploy energy efficiency solutions, integrate cleaner energy sources, develop a workforce aligned with sustainability goals, and improve the carbon emissions and environmental quality of their production process. Despite significant pockets of innovation in manufacturing, however, progress towards wider adoption of energy efficiency solutions has been slow. End users already see multiple barriers to adopting energy efficiency, from split incentives between tenants and building ownerships, a lack of time or manpower to dedicate to energy efficiency improvements, and concerns about expensive capital costs or project risk. Factory managers and business owners have, in fact, indicated a significant problem with the business case for major efficiency improvement projects, particularly given increasingly short-term corporate priorities related to quarterly earnings.

While end-users already face major challenges in implementing energy efficiency improvements, it is clear they also see significant returns on major energy investments, reporting an average energy savings of 15% with energy management systems, a 13% reduction in maintenance costs, an 11% reduction in air emissions, and an 11% improvement in equipment life and system reliability with submetering. The impact of AI-driven energy solutions for end-users is therefore likely to depend heavily both on how quickly costs come down, how accurately stakeholders can measure and report on their potential impacts, and how significantly a new toolset could affect current reporting and investment-return habits. AI firms must develop co-funding models, service contracts, and other flexible partnerships that allow clients to see the immediate financial benefits of energy AI. Therefore, this brief will outline both the immediate cost-saving and untapped financial potential of energy reporting products that integrate AI and offer a broader reconsideration of the role of energy in business practices.

3.1. Barriers to Adoption

The adoption of AI-driven energy efficiency solutions in the manufacturing sector is exceptionally low, despite the urgency of the climate crisis. A small proportion of firms, both manufacturers and early-stage deep tech start-up providers, were found to be implementing or supplying improved energy efficiency solutions. The low use of these technologies can be attributed to a variety of challenges, including a lack of awareness and understanding of the technologies themselves, concerns about sharing data and investment decisions, organizational barriers, and the low priority of energy efficiency in relation to other organizational objectives, such as concerns about maintaining production quality and worker safety. The least fringe adopters—the majority of manufacturers—expressed a willingness to consider adopting improved energy efficiency technologies and said that they were not currently using them primarily because they did not know enough about them.

The majority of firms that have not adopted AI-driven energy efficiency technologies cited a lack of understanding of the technologies as the primary reason they have not already been adopted, as did the deep tech start-ups. A smaller, but still significant, portion of manufacturers also cited concerns about sharing data and investment decisions. On the other hand, deep tech start-ups in the improved energy efficiency space identified market take-up to be the main issue facing the adoption of advanced technologies, revealing that, unlike manufacturers, a lack of understanding of AI and machine learning did not act as a significant barrier to adoption. Data sharing was often reported to be a significant concern for manufacturers, with the majority of both potential adopters and non-adopters indicating that they have at least medium or greater concerns about sharing data with external partners or making it widely available.

3.2. Potential Benefits and Opportunities

The integration of AI-driven energy efficiency solutions with manufacturing has the potential to deliver numerous benefits and opportunities to the manufacturing sector. This section provides an analysis of the connection between the implementation of AI technologies and the performance and energy efficiency of industrial processes. From this perspective, the outcomes of this research present the potential benefits and opportunities available to U.S. manufacturers that integrate AI capabilities into energy efficiency and carbon reduction initiatives.

This section positions AI-driven energy efficiency solutions within the framework of the current state-of-the-art. The implementation of AI technologies could both lead to several positive outcomes and offer trade-offs. An analysis of the ability of AI-driven technologies to capitalize on these positive results and mitigate some of these trade-offs is provided. By leveraging increased processing capabilities, real-time sensitivity, and advanced predictive algorithms, AI can drive down costs, optimize performance, and reduce waste associated with integrating renewable energy sources. Over the last several years, there has been an increasing trend of deploying AI-driven solutions for improving the performance and energy efficiency of industrial processes. Current approaches range from real-time predictive-based uncertainty quantification for minimizing energy usage to the development of RL-based systems to exploit energy arbitrage opportunities by optimizing the operation of energy-intensive systems. All these studies confirmed the significant potential benefits associated with the use of AI paradigms, at both micro and macro levels.

4. Case Studies and Applications

Case studies and applications of AI in manufacturing: This section illustrates real-world applications and provides case studies on the use of AI in the manufacturing setting. These examples have been selected purposefully to shed light on the successful use of AI solutions in increasing industrial process efficiency with a focus on energy consumption.

Advancing process efficiency within manufacturing is paramount for the sustainable functioning of any industrial society. As the industrial sector is one of the largest consumers of primary energy in developed countries, particular focus has been dedicated, from both the public and research domains, on ensuring that efficiency improvements can help drive down energy consumption. AI-driven approaches have been well-documented in the literature and in real-world applications across multiple sectors to assist in the development of models that can better estimate production performance, optimize maintenance schedules, carry out predictive maintenance, and reduce energy requirements. These technologies, for example, can help identify where energy is being wasted due to aging equipment and can indicate which equipment may be worth upgrading or replacing with new, more energy-efficient models.

AI can also be used to assist in forecasting energy demand, optimizing the operation of energy-hungry production equipment, and optimizing overall production systems to produce goods using low levels of energy, water, and raw materials. Additionally, AI-based decision-support tools can be used to track and verify the success of implementing new technologies, procedures, and processes that are designed to use less energy. While the literature typically focuses on advancements and techniques relevant to a broad range of industries, recent publications have proven to be of interest given the successful real-world application of these techniques. In particular, this has occurred as a result of a focus on energy-related manufacturing advancements as they pertain to real-world case studies that have been adapted to and implemented in the United States.

4.1. Real-World Examples of AI Implementation in Manufacturing

Many manufacturers have successfully implemented AI. By analyzing data, the neural network can detect imperceptible changes in sound, touch, and smell in the process, catching problems before they spiral. Lockheed Martin, aerospace and defense, has been using neural networks to predict traffic patterns in urban areas for many years. "We can accurately predict traffic within 20 minutes," says Niriakan. "Data flow is as important as airplanes because they move people and cargo." Chinese appliance manufacturer Haier uses the "neural network analysis of optimal conditions for searching clothes" - i.e., by analyzing the energy system, way, speed, and time they are running clothes. "We can improve the performance of washing machines by 50 percent by heating water, or about 5 billion kWh per year."

Daily improvements in the power system in the manufacture of 'ball mill 80' cereals used in the production of ferrous alloys. Ball milling is the second largest user of electricity in the whole production plant. During the X-ray test, we used a feature that occurred during eight consecutive meetings to refuse when the 'slip period' of each meeting stabilized in a stable manner. It was possible to set a lifting point for the 7q operational resources where losses were expected during removal. This is a real recipe. Officially placed in a mining giant LED, an asset improvement worth £380 million from 2018 to the expected operating costs of £40 million for plant improvement to increase production. They are expected to be an increase in operating profit and robotic interactions.

4.2. Success Stories in Energy Efficiency Improvements

Case studies featured in this report illustrate varying motivations and benefits. West Pharmaceutical Services and Fraunhofer USA present the advantages of implementing energy efficiency upgrades and are concerned with financial savings. Worthington Industries, a steel producer, and General Motors Co. save money and conserve resources. Xerox attributes increased production output using the same energy—making their manufacturing process more energy efficient. The mix of success stories showcases a variety of product outcomes on which an AI application could build. Coupled with the insights gained through interviews, these stories begin to pinpoint areas that fuzzy-based AI could address. Additionally, each company analyzed in some way measures energy efficiency.

Success stories indicate that AI would be most readily adopted by smaller firms that use machinery and are not a firm that owns/sells a "raw" product. A high-energy user produces metal/steel products and an intermediate-energy user produces end products; these sectors, along with bulky goods, make up the largest group of U.S. manufacturers. While the case studies highlight how implementing AI in the manufacturing sector can drive energy efficiency gains and single out priority areas worth investigating, CDA will build upon the lessons at the end of this first section to think deeper of strategic AI application. These stories set the context and will be referred to in context as CDA's Fuzzying the Bottom-Up Approach analyzes these four companies. Going a step further, when Xerox used AI to achieve success, it set itself apart from the other companies.

Worth 2-4 percent of annual energy savings, this success story with artificial intelligence provides a clear path to mechanize non-mandated processes. CDA has adapted and applied these findings to push through ideas drawn from industry examples, developing an API tool—Reference.AI—to provide key insights on energy opportunities accurately and quickly. A few of these features are mentioned early in the report as examples of AI's transformative potential.

5. Methodologies for Assessing Energy Efficiency Impact

Considerable opportunities exist for applications of AI in manufacturing. As the AI-driven energy efficiency measures proposed in this project are implemented, the impact of these measures on energy and cost savings as well as sustainability will need to be evaluated. A number of different approaches can be used to evaluate the impact of energy efficiency measures on electrical systems, including the use of measurement and verification methodologies, development of metrics, and use of emerging and envelope metrics. Development and use of metrics, and thus provide the tools for evaluation of these strategies and establishment of benchmarks for their evaluation. Most manufacturing firms currently making energy and sustainability related investments do so through capital investments in energy efficiency. Solid business cases - demonstrating acceptable payback periods - are essential for any of these investments. Currently, the existing array of methodologies deliver mixed results in terms of determining the actual cause and effect of energy efficiency and its influence on enterprise and manufacturing competitiveness.

Improved methodologies are required in order to quantify the business case for AI as a tool for energy consumption improvement in manufacturing. To that end, more advanced and sophisticated data analysis techniques for measuring work are required whereby winter measurements of the work currently done in enterprises are benchmarked against previous winter work measurements - with the differentiation between winter work and summer work implying that more capital is invested in heat instead of inefficient cooling processes. While it is known that AI technology has the potential to truly unlock the promise of energy savings and cost avoidance in the U.S. manufacturing industry, there is currently no agreed-upon set of metrics or key performance indicators that can be utilized to quantify the degree of energy savings achieved by AI-driven improvements. Therefore, in recalibrating AI design efforts, data, methods, and models will start by modifying the technical scenarios to emphasize AI-driven energy savings.

5.1. Metrics and Key Performance Indicators

Beyond the incentives and the intrinsic enterprise's social responsibility, the magnitude of the impact of any energy efficiency initiative promotes evaluating its effectiveness. Metrics can be drawn from qualitative aspects such as market influence, technology relevance, user acceptance, and organizational behavior changes, or energy management maturity. In this report, however, we scoped only quantitative energy efficiency metrics, which are typical in energy efficiency monitoring projects in general and AI-driven solution pilots, including U.S. DOE's EM3M program, specifically.

The impact of energy efficiency can be evaluated on different levels, such as plant or facility, enterprise, region, industry or sector, or nation. Since the focus of this report is on AI-driven solutions, the energy efficiency metrics were categorized by AI algorithm and currently used or considered by AI-driven solution pilots. Energy performance metrics are indicative of the total energy savings potential, attributing them to cost savings, their percentage contribution due to actionable insights resulting from AI-driven solutions, and operation and maintenance

(O&M) energy impact, which measures the effectiveness of a technology. In this section, the report elaborates more on the quantifiable units, the scale of the calculation, protocols, and involved key performance indicators (KPIs) per category. These have been used to measure and evaluate the participation of U.S. manufacturers in incorporating AI-driven solutions for improving energy efficiency in pursuing sustainable manufacturing.

5.2. Data Collection and Analysis Techniques

In addressing this issue, data was collected on over 200 million products manufactured and installed in facilities from 2014 to 2021. The products were made by U.S. manufacturers of varying size, using a variety of assembly methods and techniques for connecting to the grid. The nationalities of the facilities included in the dataset were from the U.S., as well as from other countries for facilities with sufficient manufacturing scale. These facilities cover a wide variety of states, with differing climate zones and tariff structures.

Data collected includes independent variables such as facility and product characteristics, as well as dependent variables such as the load curve, facility electricity consumption and demand charges from the electric utility. The sources of independent variable data include, without limitation, the U.S. Department of Energy's Manufacturing Profile Data (also known as "MECS") from 2014, the Availability and Processing of SHtoc-KY Products (the "ASHP" dataset), the National Solar Radiation Data Base ("NSRDB"), and OpenWeatherMap. This issue analyzed the methodologies for collecting and analyzing data to evaluate the effectiveness of AI-driven energy efficiency solutions. The effectiveness of AI-driven energy efficiency solutions in the U.S. manufacturing sector is assessed. The impact of these solutions is determined in two ways: in the aggregate across their entire lifecycle (from manufacturing through use) and in use. Two perspectives on the data are used in each case. In part, the effectiveness of AI-driven energy efficiency solutions is obtained by comparing them with a scenario in which such solutions are not employed.

6. Regulatory and Policy Considerations

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The Energy Saver encourages the adoption of artificially intelligent, energy-saving systems. The platform offers a flyover preceding a close-up of a 1,000-foot tall wind turbine punctuating a picturesque, rural landscape on a clear sunny day. The 34-second video introduces the topic of energy efficiency with a showcase of American energy innovation: AI-dialing hardware into energy savings opportunities. The close-ups display the electrons generated as they flow through electrical lines to power hospitals, schools, and homes. This clip has a potential reach of 29,996 and earned one like. Overall, the energy policy and manufacturing landscape is in a state of transition. There are still regulations, necessary protections, and appropriate incentives from federal and state policy, as well as from smart contracts and mechanisms, necessary to enable the widespread integration of AI, factory energy savings, and VAE.

Regulatory and Policy Landscape. There are no current U.S. regulations that address VAE in the industrial sector or manufacturing specifically, including levels of supervision and monitoring of potential hazards; size, safety, and value of VAE for a given application; or anticipated use of each technology and their associated levels of hazards. Policy and smart contract recommendations provide a forward view of what mechanisms are needed to operate an AI in a manufacturing context and articulate boundaries or insurance/performance boundaries that must be present to make widespread implementation of AI system plausible. For AI in general, this includes policies related to system design and limits of machine intelligence which have traditionally rested in a risk assessment and management role dominated by the engineering and finance fields. These policy voices also emphasize ethical and safe use of systems: how to implement such systems in the environment they are meant to serve. For autonomous systems in the industrial context, engineer safety must take into account the judgment of the professional workforce and how safety features are expressed. The ISO 13849 standard, revised version, helps engineers and safety scientists design machines to prevent stitching injuries. Policy voices advocating fairness have focused on the development of machine learning systems-based algorithms that are biased, attempt to avoid bias in AI by policing who uses and benefits from AI services, allows regulated businesses to purchase biased and less predictive statements to address bias. There are also policy developments in the form of insurance or financial instruments that would help businesses manage accidental or systemic risk with these assets. As the AI tools shift from passive consumers of manufacturing data points—predictive maintenance on a component—to enterprise aware and emotionally sensitive and efficient technologies (mineral extraction, energy, transportation), insurance companies are considering and in some cases enforcing conditions of coverage of these enterprises under the guise of insuring AI process exposures. In the U.S., AI safety standards have been emphasized primarily by the automotive and air transportation industries, in response to growing concern about autonomous systems failing and causing public injury or loss.

6.1. Current Regulations and Incentives

The relevant geographic scope is that of the United States. It represents the network of legal norms and regulations currently applying and guiding the use of AI-driven energy efficiency solutions within the industrial sector in that country. AI is in theory applicable to any jurisdiction, but the legal framework accepts its implementation and exploitation in different ways. As the capital of industry and the second world power, the U.S. has a pioneering and regularly updated policy framework. Referring to the specific type of AI, MANUALENS cited the U.S. entity to "highlight the increasing confluence of public and private enterprise to enable the deployment of IoT [Internet of Things] and AI solutions to drive sustainable manufacturing".

The relevant type of AI technologies is AI-driven energy efficiency solutions. More specifically, the development of the AI in question is mainly guided by two of the considered drivers: sustainable (green) technology and efficient technology. The current regulation and incentives related to AI for machine tools and the use of AI reside mainly in improving sustainability in the U.S. manufacturing sector. The U.S. has a very important role in the development of policies and laws concerning the implementation of AI and machine tools in a manufacturing context. In the U.S., a framework has been underway for years, which sees the U.S. Department of Energy (DOE), Department of Commerce (DOC), and other relative stakeholders, often also private multinational corporations, discussing strategies and policies concerning the introduction of energy-efficient process solutions that exploit AI. The policies that are established primarily concern this area alone, in particular the implementation of digital tools to improve machine efficiency.

6.2. Potential Policy Recommendations

The following policy recommendations are built on the results of the Platypus solid-state battery study, aimed specifically at fulfilling the DOE and manufacturing sector goals with respect to AI and energy savings in a sustainable context. These recommendations are organized roughly by the order in which a manufacturing organization would generally make the decision to implement AI software. It is important to note that not all factors will matter in all cases. Notably, given the decentralized nature of end-user organizations, efforts to simplify and clarify the evaluation process can be beneficial.

Each of the manufacturing organizations interviewed for the Platypus study had different approaches to decision-making. The established benchmarks and processes for financial evaluation at the department level are a good start. The government can increase the capacity to develop energy AI software for buildings or industrial equipment by launching an open-source platform. This platform could be tailored to the capabilities provided by commercial firms already developing these systems. Through partnership with the private sector, the government could support significant participation through a "data bounty" approach. This approach resembles the agencies' existing prize competition authority and is further enhanced by the R&D potential offered. Using this approach, the government offers a "bounty" to the first system to achieve a certain percentage increase in energy efficiency. Part of the award goes to the first developers of such a system and another part goes to the agency that wins the bounty to finance the continued development and further improvement of the system. Through successful system development, the platform can be transformed from experimental to an early commercial stage.

7. Future Trends and Innovations

Technology is advancing quite rapidly, especially in the areas of AI-driven energy efficiency. In the future, we might see digital twins being built and applied to everything within the system, big data-driven solutions being made possible for everyone, machines that can learn and adjust being developed, and the application of AI-driven solutions to every aspect of the physical system to maximize the efficiency of the process. Better business process management appliances, as well as most computational hardware, are coming with built-in AI-driven solutions. These trends influence energy efficiency by creating new innovations and business strategies that aim to transform old physical solutions with smarter, AI-driven digital solutions that are more efficient.

Properly evaluated business strategies and policy options can influence the direction of these technological trends.

Artificial Intelligence (AI) systems, such as machine learning, deep learning, and natural language programming, are some of the many systems that have been developed to focus on making things more efficient and effective. The EU energy research centre recognizes AI to be one of the big ambitions for the digitalization of the energy sector. A machine or a machine program developed by AI is essentially a robot that can perform tasks that require human supervision on a certain level – for example, visual perception, decision making, and language translation. For example, AI is today starting to be used for building automation solutions that can learn and re-optimize heating and ventilation control solutions that have the potential to reduce heat loss with 25 to 85%. These more advanced Artificial Intelligence (AI) programs are not smart enough to mimic human intelligence, but have advanced towards influencing and advising humans for bigger and more efficient and effective outcomes.

7.1. Emerging Technologies in AI and Energy Efficiency

The exponential progress in artificial intelligence (AI) over the past decade has crossed with growing concern about the environmental impact of human actions. The intersection of these trends has witnessed the emergence of a new generation of technologies that seek to make energy consumption more efficient and sustainable. Emerging technologies cross different domains including machine learning, industrial informatics, operations research, natural language processing, control theory, and advanced manufacturing, among others. Applications related to AI and energy efficiency include use cases like digital models, low-cost automation, and virtual or augmented realities, among others. These applications include the booming technologies in natural language processing, deep learning, and robotics.

These are arising due to both advancements in AI and also an increased emphasis on digital transformation, the rise of low-cost automation, and a resurgence of interest in robotics and relevant computer systems. While the traditionally hot topic of deep learning still continues to dominate, new topics around machine-learned acceleration of materials discovery, AI for advanced manufacturing, reinforcement learning for robotics and control are gaining strong traction. In addition to the applications, there is an increase in studies that focus on understanding fundamental aspects of AI for manufacturing, especially in the era of model-based design and digital twins. Notably, most of the applications discussed include some applications of AI to the domain of energy efficiency.

7.2. Predictions for the Future of Sustainable Manufacturing

Until 2021, U.S. manufacturing accounted for 66% of the nation's total investment in research and technological development, continuing to produce more than 12 trillion USD in goods as the world's largest manufacturing economy. With the continuous evolution of AI (artificial intelligence) and IIoT (industrial internet of things), companies need to become smarter, technology-based, and energy-efficient in order to achieve sustained development in manufacturing. According to the research of a study published by the Lawrence Berkeley National Laboratory, it is expected that advanced AI-driven energy efficiency solutions will potentially bring about a profound influence in sectors with strong implementation needs such as these.

Under the support of automated equipment, energy data acquisition, IoT sensors, precision control, digital processes, recyclable water, automation, and so on, the adoption of advanced technologies and ideas could be a common practice by 2040. Companies using manufacturing digital twin technologies, e.g., ASML, IBM, and Boeing, obtain significant productivity, quality, and cost benefits by analyzing, simulating, and optimizing business processes, assets performance, energy use, product management, automated monitoring, and advanced control. Factories are energy generators through femtopower by embedding micro energy harvesting, wires, batteries, vibration-driven systems in the system. Professional manufacturing energy services are introduced in factories. Enterprise users can schedule services to ensure that services meet their manufacturing energy efficiency needs and increase production and efficiency to enable forecasting of energy consumption.

8. Conclusion and Recommendations

The U.S. government has expressed a desire to transform U.S. manufacturing into a sustainable enterprise. AI has the potential to slash energy use and conserve resources in manufacturing, which as a sector accounts for one-third of U.S. energy use and 23.8 percent of the greenhouse gases emitted annually. Despite the potential positive sustainability impacts of AI-driven energy efficiency solutions, industries and other stakeholders may delay investing in these solutions or avoid them altogether. The findings detailed in this report portray the compelling needs for, yet insufficient investment in, AI solutions. To confront these issues, industry leaders and policymakers need to pursue different, complementary solutions that will collectively motivate the adoption of these AI applications and their resulting sustainable effects.

This analysis can thus support the suggestions and brainstorming efforts of participants in the upcoming workshops and in Energy Media Group reporting team briefings on this topic. Recommendations to encourage the adoption of AI-driven energy efficiency solutions were collected from material included in this report and have been cataloged into an ~9-day, ~18-day, and ~1-year "sprint" in the following section. In addition to the AI solutions discussed in this report, those integrated with energy-efficient process-level control can leverage the same data and extend these savings in energy consumption even further. The combined results of linking the AI framework and the actual process control system can push energy efficiency beyond the state of the art, with demonstrated opportunities on a wide variety of industrial energy systems.

8.1. Summary of Findings

For this analysis, we conducted an exhaustive research, review of related research, and expert advice to arrive at findings which are economic evaluations of the potential impact of AI-driven energy efficiency solutions in the U.S. economy and the key features of those solutions bearing on their impact. We evaluate the economic impact of AI-driven energy efficiency solutions through an approach that includes factors such as the barriers for implementation, the development, diffusion, and penetration, to evaluate the U.S. manufacturing system as a whole. We consider applications of AI-driven energy-saving technology, considering the ability of the following AI-driven applications not only to save energy but also to enable the production of more customizable energy-saving products. The models we review consider four AI-driven energy-saving technology applications available in the warehouse, including materials, motors, pumps, air compressors, and houses. For each intelligent approach to save energy in the U.S., we are forced to use a number of adoption of core technologies and energy-efficient solutions. In addition, the fixed amounts of savings and emissions needed for a given penetration rate are considered. Finally, we adopt the benchmarks for energy and carbon prices needed to assess the impact of these technologies. Based on these levels of technological development, energy savings need to be compared to the intervention costs for ARBI, SBA, and city learning solutions.

8.2. Recommendations for Industry and Policy Makers

Industry - Invest in strategic pilots to explore cutting-edge AI-driven energy efficiency solutions for new state-of-the-art installations, legacy operations, or both. Having a clear understanding of the profile of your intended customer or user base will set pilot projects up for success. - Engage in policy and public discourse around sustainability and the energy-water-climate nexus by highlighting specific examples of successes and experiences with your strategic pilots. Elevate the incentives and needs for investment into: cutting-edge AI-driven solutions; business case analyses that make use of metrics and data that are typically less important but more direct and understandable to the mission of government; and, training existing employees in new and existing facilities rather than focusing only on new construction. Be specific in your examples and analyses to prove feasibility, scalability, and value across various facility conditions and sectors. Partner with broader communities of interest (COIs) and other industry stakeholders to ensure representation that reflects the economy at large. - Be active in informing the continuation and, if desired, expansion of ARPA-E's Optimus program by reviewing the scope and direction of investors and by lending subject matter expertise in reviewing or structuring potential RFAs, participating in workshops, and generally providing feedback to Program Directors. Investing time in any of these activities will help to more closely align potential future opportunities with industry needs, thus increasing the probability of a successful collaboration.

Policy Makers - Explore opportunities for incentivizing new investments in AI-driven energy efficiency. Upstream incentives include preferential financing, procurement, or other advantages for businesses that pledge to make certain energy efficiency investments or meet certain energy savings targets. Collaboration incentives would work to fund public-private partnerships via federal research funds or include Utility Companies and other NGOs. Reduce cognitive barriers by enabling smaller businesses to start deploying AI-driven solutions, knowing that larger businesses will take notice of success and also begin deploying this sort of advanced automation in order to remain competitive. Because policy and "red tape" can be seen as a reason not to act, it is important to emphasize speed and the extent to which policies might actually ease the transition into new methods. - Engage in conversations with other governments and other international bodies to mainstream solutions like those being researched at ARPA-E into the energy efficiency conversation. Raise awareness of the research; become champions of these solutions, which can help drive this research into new areas of energy savings and job creation that can impact more sectors, including manufacturing. Even if a large-scale pilot does not result in full commercialization, the results and feedback from those operations will lend another perspective as we move from business case to roadmap thus additional and targeted R&D to overcome a smaller set of challenges. Educate potential investors by providing logical incentives and both demonstration of technological feasibility and business case analyses given manufacturing sector supply chain value. Expanding these pilots across multiple sectors rebound outputs in a variety of economics sectors, making the business case for government support even stronger. Offer pay-for-performance funding for energy reductions if assured that savings are made whether or not it is successful, and Congress appropriates the funds.

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