

Assessment of AI Impact on Energy Utilization in Robotics

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Abstract

This review presents an up-to-date summary of AI impacts on energy utilization in a broad spectrum of modern robotic platforms, solutions in the scope of AI employment in different robotics areas, and the crucial role AI plays in energy requirements of robotic stations. Notably, among the multitude of references devoted to robotics, energy, and AI technologies, most of the “early AI” approaches are either excluded from examination or serve as auxiliary components of the full-fledged AI robotic systems. Instead, this research reveals solutions for stationary and mobile robotics, the competent application of which can make the greatest impact on energy savings. The work reveals two interconnected directions contributing to reducing losses and improving energy recovery. The first one concerns platforms for AI-assistive process-level design and programming of robotic cells. The second way covers so-called AI robots, whose behavior is not only fully controlled by AI but also results in an obvious energy-saving effect. Thus, the study demonstrates how AI can provide robot management, thereby unlocking their potential to decline energy consumption in industry, agriculture, transport, household and other areas of vital activity.

Keywords: AI; robotics; energy consumption; power loss; energy recovery; efficiency

1. Introduction

According to the International Federation of Robotics (IFR), over five million robots work at factories, hospitals, farms, offices, and households around the world. Since the real boom in increasing the intelligence of robotics has occurred in the last five years [1], it seems reasonable to expect their further growth in the next few years, at least at the same pace. Figure 1 presents our forecast of annual installations of industrial and collaborative robots (cobots) for the coming years, made by combining the data published in [1–3] along with their polynomial extrapolation. These plots demonstrate the accelerated growth of robotics and a clear trend towards its further advancement.

Success of robotics is largely determined by energy management techniques and methods used in order to effectively employ robots.

Alternating current (AC) and direct current (DC) sources supply the robotic cells with electricity [4]. Power electronic converters (PECs) of different configurations link DC and AC energy consumers to ensure decoupled control and power adjustment (Figure 2). They distribute energy in such a way as to realize the functions of locomotion, manipulation, and management of robots that utilize various consumers, including motors, servos, interfaces, controllers, and computer frameworks.



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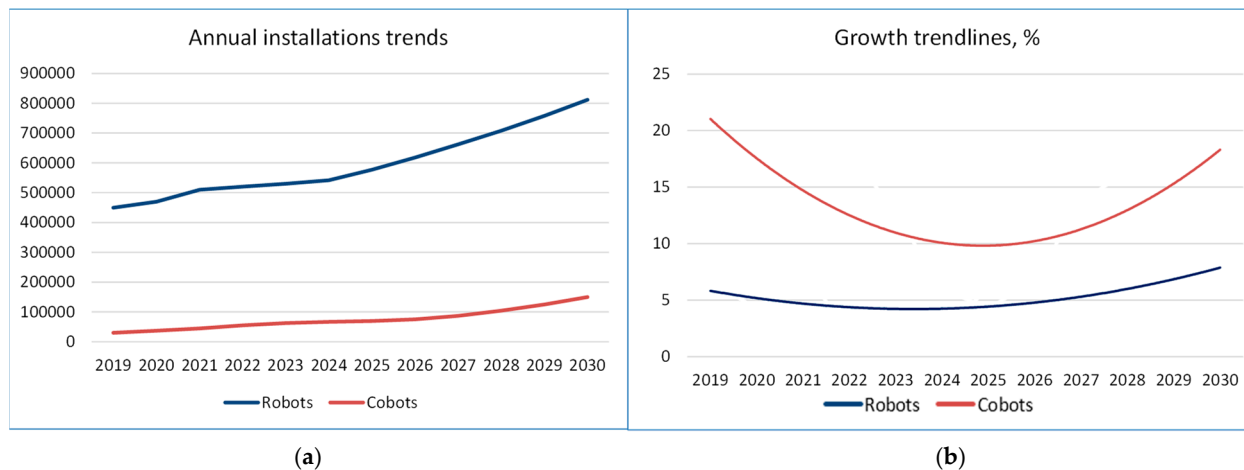


Figure 1. Trends in the annual robots and cobots installations (a) and their growth trendlines (b), compiled by combining and polynomial extrapolation of data published in [1–3].

All PECs are traditionally divided into four basic classes [5–8]:

- AC/DC converters, called rectifiers, which turn input AC to output DC voltage;
- DC/AC converters, called inverters, which reshape input DC to output AC voltage of adjustable frequency and amplitude;
- AC/AC converters, which adjust the AC shape, frequency, phase and amplitude;
- DC/DC converters, which change the DC levels.

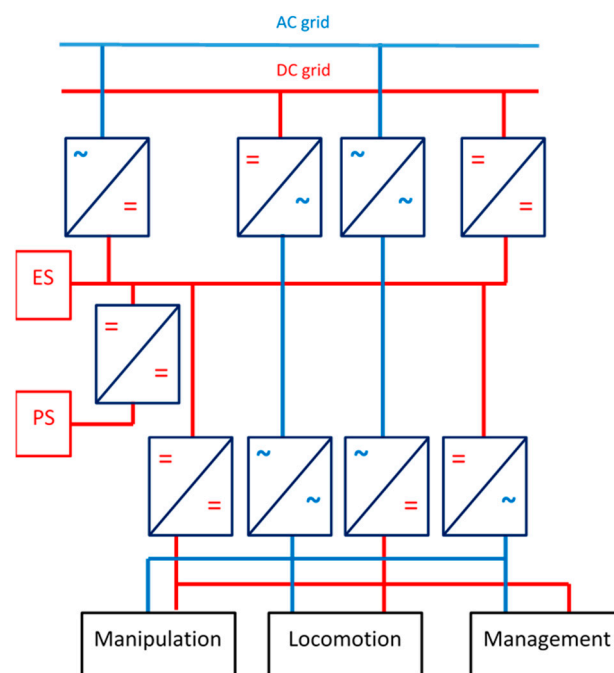


Figure 2. Generic energy conversion scheme between AC and DC grids, power and energy sources, and energy consumers of robotic cells (adapted from [7,8]).

The DC bus of stationary and, especially, mobile robots is supported by hybrid storage devices consisting of a battery (accumulators) and/or fuel cell energy sources (ESs), as well as additional power sources (PSs) such as supercapacitors and/or flywheels.

All storage units have limited power and energy capacity depending on their type, cooling method, and whether just a separate stack or the entire system is measuring (Figure 3). ESs usually have higher specific energy at smaller specific power, rate of charge,

and self-discharge capacity. From the other side, PSs exhibit less specific energy at more specific power, faster charging, and bigger self-discharge rate [9]. In [10,11] and other publications, there can be found many examples associated with energy exchange between AC and DC grids, ESs and PSs.

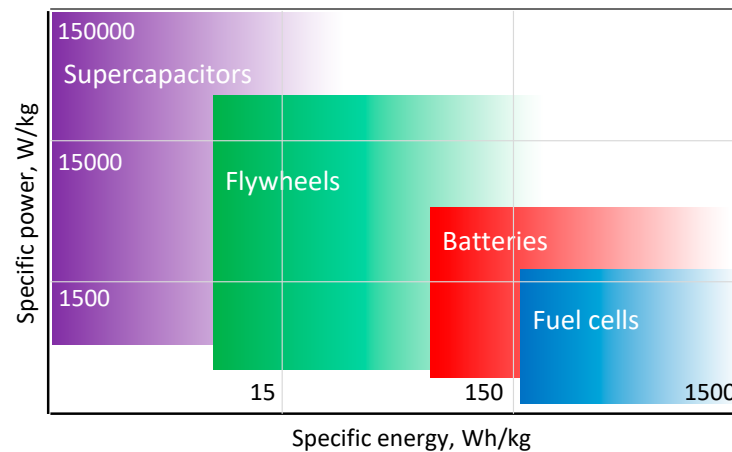


Figure 3. DC energy and power sources used in robotics.

ES and PS capacity and operating time maintain complex movements of robots, especially the legged ones that require much more energy to balance in three-dimensional space than stationary and wheeled robots. Most commercial humanoids consume from 0.5 to 3.75 kW/h, which provides them with 2 to 5 h of battery life. For instance, Tesla Optimus, powered by a battery with a capacity of about 2.3 kWh, consumes about 0.5 kW, enabling it to function for several hours [12].

High-speed, independent geared and gearless motors ensure accurate and safe adjustable locomotion and operation of robots [13–15].

In addition to the motors, a certain amount of energy is consumed by other parts of the robotic cells, including sensors, controllers, and similar units. Some of these consumers are power-hungry, while others work periodically. In either case, an ability to deliver electricity quickly, cleanly and inexpensively is required [16–19].

Herewith, networking of station parts is usually complicated due to different requirements for their supply characteristics. Voltage and current conversion between ESs, PSs and consumers is very important for robotics.

Given the growing challenges in energy production, this review is devoted to energy-efficient robotics (EER) and focuses on the ability of robotic systems to utilize minimal energy while performing useful work. In addition to decreased energy generation and transmitting requirements, ERR promises many benefits such as:

- Elongated operating time (especially for mobile and battery-fed robots);
- Lowered energy costs;
- Reduced heat generation leading to increased reliability;
- Environmentally friendly operation;
- Reduced energy storage and lightened designs.

While evaluating efficiency, authors of most studies and manufacturers usually consider robotic cells as isolated mechanical systems based on their energy capacity to perform the required useful work (E_{work}). According to the conservation law [20], the total energy remains constant over time t for all isolated systems, including robotic stations and their parts shown in Figure 4:

$$P_{supply} = P_{work} - P_{loss} \quad (1)$$

$$E_{supply} = \int P_{supply} dt \quad (2)$$

$$\eta = \frac{P_{work}}{P_{supply}} \quad (3)$$

where

η —efficiency;

P_{supply} —input supply power;

P_{work} —output active power;

P_{loss} —system loss;

E_{supply} —supply energy;

dt —time interval.

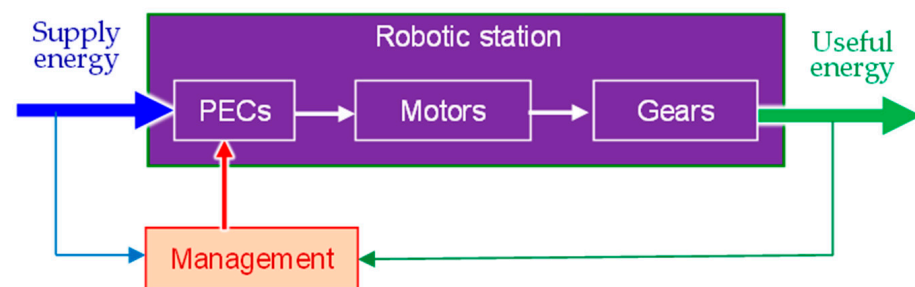


Figure 4. Functional diagram of a robotic cell.

Figure 5 visualizes the model (1)–(3).

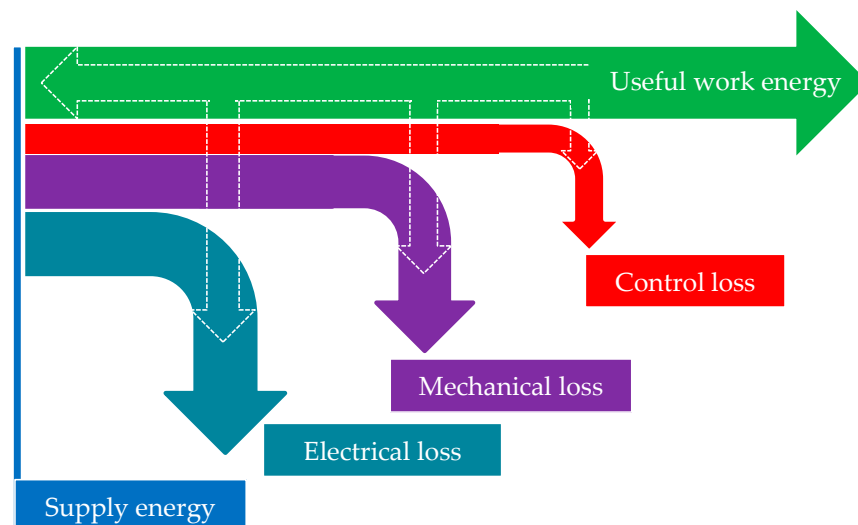


Figure 5. Energy distribution diagram of a robotic cell.

Most of electrical losses originate from PECs, electrical wires, and motor windings. Mechanical losses occur in gears, as well as in hydraulic and pneumatic parts of the station. In addition, control processes are also accompanied by corresponding losses [21–23].

As follows from (1)–(3) and Figure 5, there are several general ways to reduce energy consumption [24–26], namely:

- By prompt and timely planning and programming robotic cells;
- By purposeful machine configuration and force allocation;
- By optimal management of locomotion and routing;
- By decreasing electrical, mechanical, and control power waste;
- By organization of efficient power distribution and energy recovery.

Thanks to artificial intelligence (AI), robotics has been enriched with additional remarkable abilities for perception, learning and reasoning. By transforming robots from hard-coded automata into intelligent adaptive systems, AI delivers new advantages for manufacturing, transportation, logistics, healthcare, and other fields where robots are used:

- Real-time adaptability. Unlike traditional robots that operate according to rigid, preset programs, AI robots use sensor fusion and computer vision to analyze their environment in real time. This allows them to adapt to changes, such as moving obstacles or misaligned parts, without the need for human-fed reprogramming [27,28].
- Model Predictive Control (MPC). Intelligent predictive management algorithms provide data analysis from sensors to identify potential mechanical failures before they occur. This proactive capability helps reduce unexpected robot downtime [29–36].
- Increased speed and precision. According to [37], AI robots and robotic cells demonstrate a 50% or more reduction in operational errors and increased processing speed by 50% when completing tasks.
- Enhanced Human-Robot Interaction (HRI). AI helps cobots to “see” and perceive human movements, enabling them to work alongside people safely. HRI also allows robotic AI assistants to apply Large Language Models (LLMs) and Natural Language Processing (NLP) to comprehend and mimic human writing and speech. This increases productivity of robotic cells by combining human dexterity with robot endurance [38–40].
- Reduced deployment time. Using Machine Learning (ML), developers and robots themselves can master new tasks in virtual, mixed and augmented reality (AR) before being deployed thereby speeding up integration and reducing implementation time by up to 40% [41–44].

However, AI not only brings benefits, but also causes negative issues:

- Increased system design requirements;
- More expensive advanced components (efficient motors, sensors, materials, etc.);
- Need for trade-offs between efficiency and other quality factors;
- Complicated control algorithms and programs;
- Additional energy consumption of AI-empowered robot “brains”.

The last one is very important in terms of EER since AI itself does not save energy, being very energy-intensive. The energy required for the full-fledged operation of a robotic cell now depends not only on the machine’s weight, velocity, tasks, and other physical capabilities, but also on the additional computing power required by the AI.

In other words, the adoption of AI changes the relationship between the work performed and the energy spent for control, which has previously been considered negligible. This is especially true when it comes to the energy-hungry AI resources that place massive demand on energy supply. According to [45], with the development of AI data centers, projected electricity needs are growing at an alarming rate and are already reaching 1 MW per rack. In some countries, cloud and edge computing, as well as real-time optimization, will account for up to 10% of the total workload by 2035.

Thanks to cloud connectivity, robotic cells can utilize powerful computation, storage, and networking resources of modern data centers that successfully share information between various agents, including machines, smart objects, humans, etc. [46]. Using networks, users can also remotely delegate tasks to robots. Thus, cloud technologies provide robots with extensive capabilities, thereby creating the conditions for developing lightweight, low-cost smart robots with an intelligent cloud “brain”.

In contrast to clouds, edge computing provides processing data near its source. Such on-device processing minimizes latency, allowing for instant adaptation to changing condi-

tions without the need for continuous cloud communication, ensuring safety in high-density environments. By decentralizing computation, this technology ensures swift data analysis, enhancing robot autonomy.

Real-time optimization enables robotic cells to adapt to changing conditions, such as, for example, self-repairing or modifying gains. Their key functions are as follows:

- Self-modeling with dynamic internal simulations of robot arms to test and select optimal movements;
- Evolutionary strategies that allow robots, particularly the modular ones, to optimize their structural configuration for specific tasks or terrains;
- Homeostatic adaptation for adjusting internal control parameters to maintain operational stability across changing environments.

With all these, both cloud and edge computing, as well as real-time optimization, suffer from significantly raised energy requirements and increased power dissipation associated with new resources such as:

- Powerful computational equipment (data centers, knowledge bases, task planners, information processors, environment models, communication support) [47];
- Global libraries (images, maps, object data, expert systems, knowledge base) [48,49];
- Massively parallel servers for robot collaboration and coordination on demand [50];
- Digital twins (virtual replicas of physical robots continuously updated with live data from real sensors) [51,52].

Therefore, the development and deployment of such resources negate many benefits that AI brings. According to the analysis of [53], the three main stages of the AI lifecycle that consume most of the energy are the following:

- Data preprocessing, including cleaning, augmenting, and conversion of raw data into usable formats;
- Model training, which is the most time-consuming in terms of calculation stage, especially for deep Artificial Neural Networks (ANNs);
- Model inference, during which trained models are used for real-time or batch forecasting.

As a rule, ANN model training requires the most energy, since it may need thousands of processor hours to configure the model parameters and perform a hyperparameter search. In some AI robots, especially drones and humanoids, ANNs may consume even more energy than mechanical “brawns” [54].

This issue of energy utilization is complicated by the fact that developers and consumers often overlook it. Although many studies show promising prospects of applying AI across various fields of robotics, a key gap exists in clearly addressing the limitations associated with EER. In most of research, energy efficiency either remains in the shadows, or it appears as a side effect of the introduction of one or another AI technology. The number of studies specifically aimed at AI-supported EER remains small, despite its great potential. In particular, in refs. [15,55], the typical downsides of many AI-related studies are listed, such as uncertainties in energy usage, ignoring the implications of integrating renewable energy sources, lack of proper explanation regarding energy consumption, failure to consider power losses, energy recovery, and system efficiency during diverse working conditions, and others. The authors of [19] also point to this fact, summarizing the problems related to energy efficiency of onboard AI systems. Unfortunately, they do not concern either stationary robotics or AI assistants.

The goal and significance of the current research are to present an up-to-date summary of AI impacts on energy utilization in the broad spectrum of cutting-edge robotic platforms and solutions found in the scope of the AI employment in different robotics areas. The

work identifies the positive and negative role AI systems play in energy requirements of robotic stations across diverse stationary and mobile applications and explains how the AI-empowered solutions affect energy utilization. Consequently, this review objects to encourage researchers, designers, and engineering staff to involve AI to make the best energy-efficient decisions while boosting robot productivity in specific spheres of HRI.

The following parts of the review are devoted to AI-empowered systems of contemporary robotics, novel tools, and advanced techniques relevant for EER. After describing their development from non-AI through “early AI” to full-fledged AI solutions, examples of the most exciting practical applications of AI-enabled ERR in human life are provided, without delving into the complex algorithmic details behind the presented methods.

2. Materials and Methods

Inclusion and exclusion criteria for references of this review are essential for ensuring their quality and relevance, thereby helping maintain work integrity. The four distinct stages of materials and methods selection may be presented as follows:

2.1. Identification

To assess how AI impacts energy utilization in robotics, the authors appeal to three groups of references. The first one is robotics, the science and technology dealing with the design, construction, work, and application of robots. The second group covers energy utilization in robotics. And the third cluster includes intelligent technologies, primarily AI, which allows computers and machines to mimic human thinking owing to their ability to learn, make decisions, tackle problems, understand concepts, infer, and transform them into actions without human intervention. Considering that the authors have been working in the field of EER for several decades, their collection on such keywords as “AI in robotics”, “ANN in robotics”, “intelligent robotics”, “intelligent energy consumption”, “power loss in robotics”, “energy recovery in robotics”, “efficiency in robotics” exceeds 5000 publications.

During the identification, preference was given to peer-reviewed works from reputable books, journals, and academic publications to ensure the reliability of the information. The literature search was carried out over the latest decade using academic databases like IEEE Xplore, Web of Science, ScienceDirect, and Scopus. At the same time, given the delays caused by registration in the databases, on the one hand, and the rapidly changing landscape of AI adoption, on the other, the authors could not ignore company materials, industry reports, and websites. Thus, the scientifically technological character is a specific feature of the proposed review, which is an attempt to reflect not only the current state of AI impact on energy utilization in robotics, but also a kind of its time derivative in connection with the global trends in annual installations of robotic stations shown in Figure 1. In our case, the initial number of records obtained as a result of databases search and those found in other sources (technical documentation, company advertising materials, and websites) practically did not differ.

2.2. Screening

About 20% of records were removed as duplicates. But the problem of filtering out titles/annotations to exclude irrelevant materials turned out to be more challenging. As a rule, industrial claims cannot be treated as equivalent in evidentiary value to validated, peer-reviewed scientific results. However, when it comes to big, world-renowned companies such as ABB, KUKA, Yaskawa, Tesla, Ford, or GM, it is quite difficult to determine which side—scientific or technological—is more valuable in terms of relevance and trustworthiness for a potential reader and user. Any technology is based on science, and this study attempts to trace such a connection and evaluate the type of evidence obtained

through laboratory experiments, simulations, or industrial research in order to separate it from the manufacturer's declarations and advertisements.

Finally, about 70% of manufacturer records were excluded as irrelevant. Among them, websites that announced and reported on new AI-enabled solutions and developments, but often these were just some of the tools used in intelligent systems, rather than AI per se.

2.3. Eligibility

The next step was to distinguish between sources that fit and do not fit the inclusion criteria.

It is noteworthy that while the understanding of robotics and energy efficiency is more or less clear, the current problem for reviewers is the ambiguity in AI interpretation by various authors. The companies usually indicate the technological benefits of AI, but rarely analyze boundary conditions such as implementation costs, scalability, safety, latency, model reliability, dependence on training data, battery degradation, risk of errors in dynamic environments, and maintenance costs of computational infrastructure. From the other side, many scholars overlook limitations in generalizing their theoretical and simulation results to real robots.

In this study, only those systems are definitely considered as AI platforms that meet the following requirements:

1. They are based on deep ANNs;
2. They enable unsupervised ML from inputs (sensor data or experience);
3. They are capable of predicting the consequences of their behavior under uncertain conditions beyond the fixed, explicit rules;
4. They can independently generate outputs (actions, reasoning, adaptation, or inference).

This definition fits into the standards and regulations issued by authoritative sources and widely cited in policy and academia, such as OECD (AI principles) [56], ISO/IEC 22989:2022 (AI concepts and terminology) [57], and EU Artificial Intelligence Act (2024) [58].

Such an approach is more rigorous than in the reviews, where AI is understood as any kind of intelligent control. For example, in [19] MPC, Fuzzy Logic Controllers (FLCs), dynamic programming controllers, and intelligent hybrid energy storage controllers are called AI controllers. In [59], six intelligent control strategies are evaluated separately, namely, FLC, ANN, MPC, Sliding-Mode Control (SMC), adaptive control, and ML-supported control.

In [60], FLC, MPC, SMC, and Genetic Algorithms (GAs) were called "early AI" methods because they either focus only on supervised learning or do not support ML at all. In the current review, most of the "early AI" methods that do not meet the four above requirements are either excluded from consideration or serve as auxiliary components of full-fledged AI platforms. This does not mean that other intelligent methods are unable to provide high-quality EER. It is just that this review has a different purpose, which is an attempt to assess how justified is the use of powerful AI tools in terms of EER. For that purpose, among the multitude of functionalities described in [61–65], this study examines only those solutions for stationary and mobile robots that promise measurable energy savings, namely:

- AI-assisted process planning and programming suites;
- Technological improvements resulting from elimination of unnecessary movements based on the best configurations of joints and force allocation;
- Management of time-saving tool and vehicle pathing and routing with smart velocity, acceleration and jerk profiles;

- Reduced power waste thanks to the selection of advanced electronics and low-loss PECs, cost-effective motors and gears, and sensing systems [13,55,66];
- Organization of efficient power distribution and energy recovery.

Definitely, the time period of publications has a great influence on the filtering quality of AI-related entries. In fact, the real boom in the use of AI has been in the last five years, and there is no reason to talk about any serious adoption of AI in robotics at an earlier time. Alongside this, in some cases, it is useful to trace the timelines of robot intelligence development using examples of companies that have achieved undoubted success in the field of AI-supported EER.

2.4. Inclusion

As a result, 200 entries that meet all the requirements remain and they are included in this review. A total of 83% of them are younger than 5 years old, and 90% were extracted from peer-reviewed databases. All the filtered references directly relate to the AI impact on energy utilization in robotics. As a rule, these are the latest studies providing recent information, with reliable methodologies and clear, reproducible results, while older sources that have lost relevance, as well as dubious and unverified online advertisements and slogans from some robotics-related companies, have been excluded.

Based on included references, this study explores the impact on energy utilization in two areas of robotics through four types of AI resources (Figure 6).

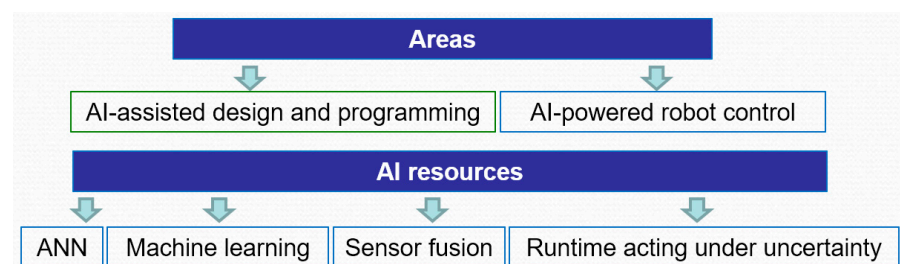


Figure 6. Areas and resources of AI-enabled robotics.

The first area encompasses platforms for AI-assisted process-level design and programming of robotic cells. As opposed to conventional, non-AI toolkits that rely on human-written, rule-based instructions for predictable outcomes, these AI assistants presume the presence of data-driven models capable of learning and adapting their patterns under unknown conditions. To operate, such AI suites use dynamic knowledge bases and perform all corrections of the system behavior in a changing environment through ML and adaptation. These instruments do not assume the completeness of their knowledge; therefore, they can order data, expertise them, learn from positive and negative examples, and adapt to changes in facts and data, while the role of a human tends to be reduced to the formulation of tasks. Since the AI platforms are capable of either solving tasks that humans cannot tackle in real time or finding solutions faster than humans, they should meet all of the above requirements necessary to reduce energy consumption.

The second area covers the so-called AI robots, whose functioning is not only completely controlled by AI, but also demonstrates an obvious energy-saving effect from AI usage. Unlike a conventional control system in which a physical–mathematical model-based regulator manages a known process workspace, an ML-enabled MPC-based AI controller responds to setpoint signals by generating training references to unknown environments. Feedback signals are used to improve both the model and the AI controller. The program code of AI robots includes three additional parts: data-driven model for object detection, a part for learning, and a part for adjusting movement through the model

outputs in new conditions. If the processed object misplaces, this code detects the new position and adjusts its path and velocity automatically. According to our research, most autonomous unmanned vehicles and some stationary robots belong the AI robot category.

In both areas, the material is presented in this review in the identical order. First, the problems identified are in non-AI situations assessed, then the advances in the adoption of “early AI” are demonstrated, and next the outcomes achieved thanks to AI are presented.

3. AI Assistants for Planning and Programming Robot Operation

Today, the market continues to be dominated by conventional non-AI robotic toolkits, which contain the desktop engineering and simulation software aimed at developing robotic cell operation as fixed instructions, under which robots act as explicitly programmed by the designer. However, if the object being processed is slightly displaced or the work environment changes, the operation planned using the conventional toolbox fails [67].

AI has led to a significant expansion and improvement of process planning and programming. As conventional toolkits have improved, prominent robotics institutions have begun to introduce various virtual, mixed and AR resources [68,69], with a gradual transition to AI-enriched suites that provide numerous benefits when compared with traditional toolkits. These benefits are primarily appear in their ability to generate program codes composed of the three mandatory parts:

- A data-driven model of object and environment;
- A part intended for ML;
- A part for process change in response to other inputs in new conditions.

As a result, if the object is misplaced, or the work environment changed, or the developer alters the task, an AI assisted toolkit detects the new situation and automatically proceeds to another brunch of the code, thereby initializing a new behavior.

This is confirmed by several robotics companies including ABB, KUKA, Yaskawa, Festo, Mitsubishi, and others.

As a first step in the development of the desktop RobotStudio toolkit [70], ABB has launched on the market the RobotStudio AR Viewer [71], which helps designers familiarize themselves with the ABB robot portfolio and estimate robot behavior in AR and 3D. AR Viewer shows the expected effects of a change in size or scale and also demonstrates how the robotic cell can be deployed on a factory floor to fit around any existing production equipment. Another ABB technology—RobotStudio HyperReality—helps create photo-realistic and physically accurate digital twins, reducing the “sim-to-real” gap with high accuracy. On the next stage, the generative AI assistant has been implemented, which allows developers to improve their productivity and programming skills, offering deep technical understanding. Now, it is suitable more easily perform complex tasks and get ahead faster in programming using step-by-step instructions and hints. AI assistant in the renewed RobotStudio Suit answers questions in real time, solves various tasks by providing simple recommendations, supports preferred languages based on the ABB LLM, and scans the ABB Document Library to obtain information and context based on the ABB Retrieval-Augmented Generation (RAG) system. In that way, an integrated AI assistant helps users reduce their process planning and programming time by up to 90%, compared to other solutions [48]. At the same time, although this RobotStudio AI assistant improves the station’s performance, it cannot entirely plan the process and program a robot without the developer’s input.

KUKA has implemented a set of integrated AI assistants in the iiQWorks modeling platform [72]. Under the iiQWorks.Copilot brand, they help developers generate robot control code using natural language prompts, thereby reducing the need for specialized programming knowledge. KUKA’s Predictive Maintenance Assistant analyzes data to

anticipate maintenance requirements, thereby reducing unplanned downtime. KUKA's Intelligent Item Picking Assistant optimizes the location of pickups in warehouses and logistics, ensuring accurate sorting of products such as food or pharmaceuticals. KUKA's Digital Twins Assistant simulates complex, delicate tasks in a virtual environment before deployment, enhancing safety and speeding up the setup process.

The latest Yaskawa's AI-powered robotic platform MOTOMAN NEXT [73] combines traditional industrial control (OT) with AI-driven software (IT) to create adaptive, autonomous automation. Thanks to intelligent adaptation, dexterity, and reasoning, this system enables robots to detect, understand, and react to changing conditions and work-piece variations using cameras. Its Autonomous Control Unit (ACU) allows for on-board, high-speed data processing. Advanced software stack includes automatic, collision-free path planning, AI-based image processing, and force sensing. MOTOMAN NEXT supports adaptive sorting and placing of items, vision-guided assembly with precise positioning and defect detection, and flexible loading/unloading of machinery.

In addition to the well-known programming platforms Festo Configuration Tool and Festo Ciro Studio [74], the AI-assisted software GripperAI was launched for mixed-product robotic picking processes. It can be used for operations such as mounting and aligning cameras, checking the suitability of the lighting, calibrating the robot base to the camera's frame, configuring parameters, calculation of a gripping point, tool selection when multiple tools are available, the robot's path control and recalculation of picking operations rather than stopping for reprogramming. GripperAI is compatible with most robot-agnostic software for robots, cobots, and Cartesian systems that perform motion specified by software.

Mitsubishi's MELFA FR series is now equipped with AI-powered MELFA Smart Plus Maisart functionality, which allows for ML and real-time adaptation to environmental changes. Mitsubishi's Predictive Maintenance warns about potential failures before they happen. Force Sensor Control optimizes force sensor settings for delicate tasks, reducing setup time and enhancing accuracy. 3D Vision Sensors allow for faster, more accurate object recognition. Thermal Compensation functions compensate for heat-induced deformation in robot arms, increasing accuracy.

Rather than conventional platforms, Universal Robots (UR) increasingly adopts task-specific AI applications built for a single process like welding, sanding, inspection, or assembly, once considered too variable or complex. Welding robots can now be equipped with vision-guided seam tracking and ML-assisted parameter optimization. In assembly robots, AI enables the management of variability in parts and processes. In service robotics, AI tackles tasks like packaging, sorting, and delicate material handling. In logistics, AI-powered robotic systems can efficiently perform complex picking, stacking, and touching operations.

With FANUC's robotic toolkits [75], users are informed of any deviations found on a machine equipped with a FANUC CNC utilizing reach data collections and analyses. Powered by AI, this system can predict possible failures of servo motors.

Toshiba provides a wide range of AI technologies and toolkits focused on robotics, data analysis, and edge computing portfolios designed for AI-enriched HRI technology that prioritizes explainability and works alongside human operators, particularly in manufacturing and infrastructure [49]. TSAssist-Next Generation Robot Programming Tool presents comprehensive package from TM Robotics for programming, simulating, and maintaining Toshiba Machine robots. Toshiba Machine Robotics Library for LabVIEW is a dedicated toolkit that enables graphical commanding and control of Toshiba Machine robots within the National Instruments LabVIEW environment. AI Image Inspection Technology uses "no-defects learning" that requires data from acceptable products to train the

model, allowing for rapid deployment of AI-powered vision systems in manufacturing. Another AI technology, Hybrid Action Recognition, combines skeletal motion data and image analysis to recognize actions involving tools with low computational load. Toshiba BRIL Regenerative AI focuses on creating self-healing AI models that can extend the life of AI systems.

The XRoboToolkit cross-platform framework for robot teleoperation based on extended reality [76] features low-latency stereoscopic visual feedback and diverse tracking. Its modular architecture ensures smooth integration of robotic platforms and simulators, including precision and dexterous manipulators and mobile robots. As a result, many EER design options currently appear on the market.

In households, advanced AI vacuum robots can be programmed to navigate autonomously around the rooms, including furniture, and avoiding conflicts with humans, pets, stairs, flowers, cookware, etc. In agricultural industry, AI robots replace humans in picking soft fruits without crushing them, while also learning via demonstration and analyze data for possible quality issues. They can provide each plant with the optimal amount of sunlight, water, and nutrients needed for growth. In healthcare, AI robotic cells can free up medics' time by administering taking medications and transporting patients. Some of them successfully vaccinate without the need for human supervision and help reduce the social isolation of the elderly.

4. AI Impact on Energy Consumption in Stationary Robotics

Properly organized operation of workstations can reduce the workload of stationary robots and, consequently, the energy consumed by them. In the literature, EER engineering solutions can be found that have been developed for a long time without involving AI. Many of them relate to both homogeneous and non-homogeneous serial and parallel robots that pick and place (PnP) processed objects, such as IRB1600 (ABB), UR5 (UR), 1500 MM (KUKA), or RV1 (Mitsubishi). The results of these studies have been applied to a wide range of industrial and domestic applications, often without making changes to the cell structure, upgrading equipment, or redesigning the robot's movements or routes in areas such as assembly, welding, packaging, quality control, loading, and wrapping.

In [77], an optimization procedure has been designed to reduce energy by up to 30% and peak power by up to 60%. To move the tool along the trajectories, various cost functions and algorithms were developed for a variety of scenarios. The energy-optimal trajectory design and initial pick point search problem are studied in [78] for a heavy high-speed palletizing robot, in which both the pick point and the place point are fixed to a desired location for each separate task. The article [79] demonstrates the possibility of optimizing energy consumption for cramped robotic cells with minor power dissipation. The authors of [80] present a method for optimizing the motion trajectories of robots with six degrees of freedom (DOF). At that, energy consumption is minimized, considering the robot kinematics and dynamics. The study [81] describes an approach to plan the trajectory of the robot motion, which minimizes energy consumption, while taking into account the durability of the most important mechanical components during the interaction of the robot with mobile platforms. A method for simulation and generating low-energy movements was offered in [82] using quantum computing technology. Based on the total torque required for movement as an objective function, the task was formulated as a search for changes in the robot's position in terms of minimal workspace and working time. In [83], trajectories with minimal energy consumption are planned using the improved sparrow search algorithm.

Unfortunately, due to the complexity of the design, most of the above-mentioned physical and mathematical models were focused on separate solving problems of kinemat-

ics, statics or dynamics and cannot reach sufficient completeness necessary to minimize energy consumed by the entire system as a whole. Consequently, there appeared a demand for new computer models to support the simultaneous solution of forward and inverse kinematics problems (for route optimization), statics (for minimal power requirements) and dynamics (for minimal energy consumption) of robotic cells.

Among the recent works related to ML in searching the movement trajectories that meet the EER needs, some studies may be highlighted such as [84–87]. Following their outcomes, it is not enough to be satisfied with solving classical tasks of searching for the shortest tool or vehicle paths, even with optimal speeds, accelerations, and jerks. Advanced resources are required to reduce energy consumption of a robot in these circumstances.

In contrast to other approaches such as [88,89], the introduction of data-driven AI models can provide broad opportunities for learning from the preliminary measurements made on real machines.

One of the design features that directly affects energy consumption is the robot joint configuration (JC), i.e., a set of locations that robot joints can occupy when the tool is placed in a target position. In Figure 7, four JCs that may be occupied to reach the target are adapted from [90] as an example where the IRB1600 robot has been studied. Comparison of permissible JCs demonstrates that the differences in their torques could reach 53 Nm (25%) while the difference in consumed electrical power at various JCs is 50 W (18% of the total consumption).

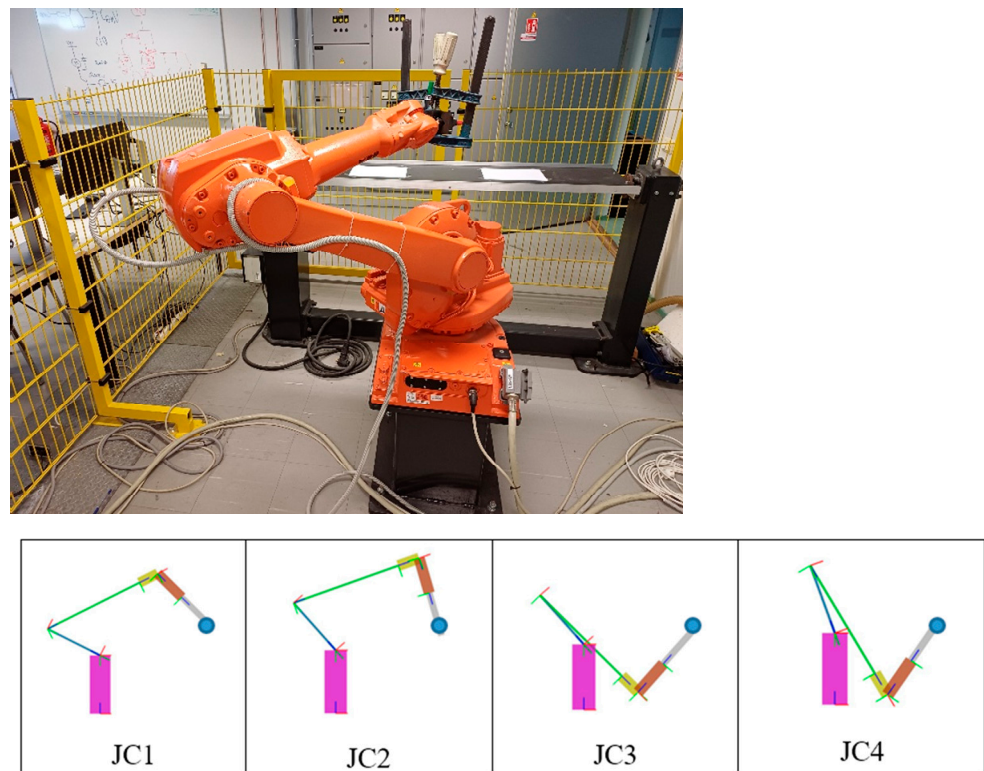


Figure 7. Laboratory setup and four JCs that can be used to reach the target position (adapted from [90]).

Notably, the JCs chosen by manufacturers are primarily designed to solve the inverse kinematic problem rather than being used as an energy management method [91]. The paper [92] can be considered as the earliest work on finding the best JCs, given the lowest power requirements. In [93], a similar task was set to solve the problem of PnP operation. Some other studies are also aimed at minimizing the energy consumption of robots when

they move along predefined trajectories [94,95]. In all these works, physical–mathematical models are developed based on expert knowledge and theoretical assumptions.

At that, solutions to two research problems are presumed, both of which focus on energy accumulation for PnP operations. The first way to save energy is to minimize robot power consumed in a given tool position. The goal is to search for the JC for each position that requires lowest supply power in statics. This problem is topical for quality control, welding, packaging, or wrapping, when the steady state placing and holding phases of the PnP cycle are much longer than picking. A goal of the second problem is to find out the route through all targets considering all possible JCs at which the minimal overall energy is consumed as a result of the time reduction for the PnP process. This problem is actual for the systems needed in the fastest picking and placing cycles at relatively stable power consumption, like loading, assembling, or painting.

The study [90] presents an AI-supported method for reduction in power consumed by robots during the PnP operations with long-term placing and short-term picking time intervals. This approach represents the mutual solution of the forward kinematics, inverse kinematics, inverse statics, and reinforcement learning (RL) robotic problems [96]. As an outcome, several MATLAB/Simulink™ (MathWorks, Inc., Natick, MA, USA) models and simulation methods are shown. To manage robot efficiently, an original ANN-based controller is developed. A study conducted on the IRB1600 robot proves the possibility of saving up to 18% of power consumption with an optimally selected JCs.

In [97], the multilayer feedforward fitting ANN is presented capable of selection of the best robot JC. Due to its purely data-driven nature, this model dispenses with full knowledge of all geometric and mass properties of the robot and its environment. Additionally, it adapts well to the changes in robot architecture that occur over time according to regular industry updates. Practicability and suitability of the proposed ANN-based methodology were confirmed by experimental tests on the Festo EXPT-45-E1 robot (Festo Co., Esslingen am Neckar, Germany) with energy saving of 9.5% resulted from path optimization.

5. AI Impact on Thrifty Movement of Mobile Robots

Energy demands constrain the scale of mobile robots' deployment. The role these limitations play for wheeling and, especially, battery-powered legged robots is much more significant than for stationary robots of the same dimensions and workload. The same concerns many specialized service robots, such as snow plows, lawn mowers, vacuum cleaners, etc., that randomly travel during their operation and repeatedly return to the same processed areas. Such chaotic motions lead to significant energy overruns.

These issues encourage the search for new solutions in mobile robotics related to traffic management, route planning, and allocation of transportation tasks that contribute to reducing overall energy consumption mainly by shortening the mission duration.

In structured environments with predefined path representations, such as warehouses and road maps, classical graph-based search algorithms are still widely used. The most common of them are the Floyd–Warshall algorithm [98] and different variants of Dijkstra and A* algorithms [99].

AI enables autonomous navigation in complex, dynamic indoor, outdoor, as well as air, water, underwater, and space environments. ML promotes finding optimal, obstacle-free paths in real time beyond the predefined routes for all types of mobile robots, including Unmanned Ground Vehicles (UGVs), Unmanned Aerial Vehicles (UAVs), Unmanned Surface Vessels (USVs), and Unmanned Underwater Vessels (UUVs). ANN models, supported by ML and RL, computer vision, LiDARs and 3D cameras, allow autonomous vehicles

to identify, interpret, and react to unpredictable obstacles like people or other vehicles, optimizing their paths and increasing overall throughput.

In accordance with [100,101], in service robotics, AI controllers decrease the demand for service power due to their ability to simultaneously consider many interrelated settings. Through ML, it is possible to significantly reduce energy losses everywhere, the total power and energy produced by robotic joints are badly predictable, since they are dependent on many factors.

To enable dynamic navigation, several advanced AI-enabled techniques are employed such as Simultaneous Localization and Mapping (SLAM), Intelligent Path Planning (IPP), Predictive Motion Control, and MPC.

By applying SLAM, a robot can estimate its location online. Before the era of AI and in its absence, it was a challenge for a mobile robot to navigate an unknown environment without a consistent map of this area and simultaneously determine its location within this map. Under such conditions, the problems of camera-based visual servoing, sonar navigation, laser-LiDAR-ultrasonic sensor, and Kalman filter-type algorithmization have generated many inspiring ideas. Multiple uncertainty measures for path search and active exploration were provided for UGVs and UAVs in [102–111].

One of the first solutions of the SLAM problem has been proposed in [112] based on fuzzy and neuro-fuzzy “early AI” controllers. In [113,114], the initial ANN-enriched solutions were described.

Nowadays, AI supports this technique to enabling robots to build and update maps on-the-fly by distinguishing between movable (e.g., pallets, people) and immovable obstacles in real time, thereby improving mapping accuracy.

Various combinations of ML techniques shown in [115–118] gradually improved the robustness of SLAM, bringing positive significance for intelligent navigation from the point of path following accuracy and obstacle avoidance.

With the development of the Deep Learning (DL) technology, SLAM is making further progress. The results published in [119–127] demonstrate that most of DL algorithms outperform other methods in terms of real-time object recognition accuracy of building the maps and estimating the robot’s position within dynamic and unstructured environments.

Similarly to SLAM, the IPP technology has also gone through several stages in its development, starting with classical non-AI mathematical algorithms, through “early AI” to modern RL platforms.

As evidenced from a comparative study [128], many path planning algorithms have been successfully applied for static environment such as Particle Swarm Optimization (PSO) [129–131], and Butterfly Optimization Algorithms (BOAs) [132]. The Ant Colony Optimization (ACO) algorithms were used to realize fast path planning of UGVs in complex environment [133]. In 3D path planning scenarios, Gray Wolf Optimization (GWO) [134] has demonstrated superior efficacy compared to PSO. Whale Optimization Algorithm (WOA) designed in [135] outperforms both the Cuckoo search algorithm (CSA) [136] and PSO in 2D path planning tasks.

Instead of relying on static maps, dynamic mapping encapsulates classical algorithms like A*, D* Lite for route calculation with optimal, obstacle-free pathing in real time, demonstrating the fastest speed along the path at the lowest traveling cost of UGVs and UAVs [41,137].

The article [138] discusses many “early AI” methods that have proven effective in solving more advanced IPP tasks related to minimizing energy consumption. GA was used in [139] to navigate UGV in unknown clustered environments. For greater safety, the fuzzy reasoning capturing the human expert knowledge was applied in [140] to make decisions on the best routes. The authors of [141–143] applied Rapidly exploring Random Trees

(RRTs) and GA with ACO, thereby obtaining a 30% and more reduction in average path length. In [144], the Timed Elastic Band (TEB) algorithm was used to model an UGV's path as a series of sequential locations (positions and orientations) connected by time intervals, optimizing this "elastic band" in real-time to avoid obstacles while respecting motion limits. However, both the GA and the fuzzy systems have rather poor real-time abilities and are inconvenient for navigation.

As the next step, Adaptive Neuro-Fuzzy Inference Systems (ANFISs), such as [145], have served as a bridge between "early AI" and full-fledged AI systems able to autonomously improve obstacle avoidance in local path planning. Implementation of ANNs has helped surpass the above-mentioned methods in modeling complex relationships and identifying patterns. To better bypass dynamic obstacles and avoid speed jitters caused by excessive acceleration, a set of recurrent ANNs was proposed in [146–148] that make the obtained trajectory smoother and more acceptable for intelligent UGV navigation.

Now the time has come to apply AI for EER problems tackling. In [149], the RL technique was perfectly used to save energy of the UAV in the conditions when wind velocity and direction can change at any time. In [150], the RL approach was applied to observe underwater environment and search targets by the UUV in intelligent ocean applications. In [151], a novel routing framework was involved to improve UGV pathing by integrating adaptive modular RL components.

Predictive Motion Control, which gradually evolved into MPC, have also followed an entertaining path in its development.

These techniques allow self-driving vehicles to predict the behavior of other travel participants. The data in [152] show that, compared to traditional PID control, predictive motion and MPC can improve system energy efficiency by approximately 20% and extend battery life by 15%. Nevertheless, the complexity of nonlinear modeling, parameter inaccuracies, and the high computational cost associated with high-order nonlinear control systems significantly hinder improvements in control stability and performance. Initial solutions for UGVs encountered problems at cruise control, cornering, reallocating the driving or braking torques and in emergency situations due to the complex nonlinear dynamics, impossibility to consider the future movement of moving obstacles, and safety critical constraints [29,153,154]. Similar issues have been noted with UAVs [31–34,155].

To address these challenges, the innovative data-driven MPC systems were introduced in [84,156]. Applying such adaptive models for ML helps to ensure safer and faster trajectory following under the MPC, bypassing collisions and respecting actuator constraints and complex nonlinear dynamics.

AI-supported MPC enables more flexible control over circumstances and measurements and safely prevents hazardous conditions [157,158]. The cost functions designed in [159] incorporate energy efficiency along with traditional MPC factors such as the longitudinal velocity, yaw rate, and lateral displacement. After training an ANN model on a history of states and controls, it became possible in [160] to predict electric vehicle (EV) dynamics under changing and complex operating conditions. To reliably act under extreme operating conditions, a hierarchical ANN architecture is proposed in [161], in which the upper-level Deep Learning-based MPC determines the front wheel steering angle, longitudinal force, and additional yaw moment, whereas the lower-level torque distributor ensures the stability of the vehicle by minimizing the impact of tire adhesion. Using the similar approach, the lower-level MPC designed in [162] regulates motor torques, providing accurate tracking of the desired tire slip factors. In [163], the ANN-based MPC successfully allocates energy among multiple PS and ES units of hybrid EVs.

A DL-enabled hybrid controller in [164] incorporates the nonlinear MPC, the FLC, and the feedforward ANN to exclude dangerous situations while maintaining accurate robot

tracking. In [165], AI-driven fleet coordination prevents congestion by enabling UGVs to communicate and re-route independently, thereby minimizing traffic jams and idle time and reducing downtime and bottlenecks. KUKA's UGV Fleet Control optimizes operations through real-time traffic management, route planning, and allocation of transportation tasks in challenging production environments [72].

Thanks to RL, unmanned vehicles can learn from past mistakes and improve their navigation strategies over time, resulting in faster and smoother operation. AI enables self-driving vehicles to operate seamlessly in unstructured or changing environments, such as warehouses or hospitals, without requiring significant infrastructure changes like magnetic strips or fixed guidance.

On the roads, mobile AI robots equipped with sensory navigation systems are successfully programmed to determine the best routes of movement avoiding dangers, making decisions at intersections, and acquiring new skills over time.

As an example, the authors of [166] provide the RL for humanoid's robust lower-body locomotion and precise upper-body manipulation. "Artificial Captains" [167,168] use AI-powered software for autonomous USV piloting, managing navigation, collision avoidance, and situational awareness without human intervention. These EER systems enhance maritime safety and enable unmanned operations for tasks such as environmental research and offshore surveys.

In aerospace, AI satellite repair robots are used, as well as the robots that help astronauts with their daily tasks and reduce stress through original LLMs, as well as serve as an early warning system to detect energy leaks and learn from the data.

Space rovers equipped with tools for sampling and imaging are capable of moving to collect soil and rock samples, analyze them on-site, and communicate data back to base stations on Earth. A significant part of their research focuses on autonomous navigation, robotic manipulation, and mobility systems for planetary exploration with AI-driven power management and path planning. IEEE Xplore Digital Library contains numerous papers on planetary rovers and field testing. NASA Technical Reports Server collects publications regarding rover design and energy-effective mission concepts. Efficient learning and pathfinding methods of space rovers can be found in [169–173], as well as in Nature Scientific Reports that cover data analysis from recent Moon and Mars missions.

6. AI Impact on Energy Recovery

Since power dissipation is crucial for the practical application of robots and their further development, manufacturing is taking measures to diminish power waste. Deployment of highly efficient energy converters, improved electromechanical brakes, renewed high-efficient motors, optimization of their capacity, gearless design, and applying novel light materials for making robot parts are the most popular methods used in robotics to lessen consumed power.

Energy recovery is another important way to avoid excessive power consumption. The choice of recovery approach vastly depends on energy management requirements, PEC topology and connectivity [174].

A review of multiple scientific papers and company's records reveals the presence of all PEC classes in stationary and mobile robotic stations [4,5,175]. They usually serve as voltage, current, and impedance sources that decrease (buck) or increase (boost, buck-boost) voltage level, with uncontrolled (diode-based) or fully controlled (transistor-based) electronic devices. Any of them can have a direct, indirect (multilevel) or isolated architecture, as well as their combinations. Depending on the energy flow direction, the unidirectional (energy flows only from the supply to the load) and bidirectional (energy may flow either from the supply to the load or from the load to the supply) PECs are represented on the market.

Advanced PECs not only facilitate faster and smarter operation but also support the integration of robotic cells into the broader energy ecosystem, paving the way for a more dynamic and interactive relationship between robots, energy storage units, and electrical rails. Each solution involves the use of advanced electronics capable of changing the shapes, magnitudes, or other electrical parameters [176,177].

The integration of new technologies cannot be possible without progress in power electronics. Advanced Wide Bandgap (WBG) devices allow to convert energy with minimal losses, thereby introducing new features to increase efficiency and productivity, as well as reduce power waste [178]. To operate at the highest voltages, frequencies, and temperatures, WBG components are based on the two most prominent materials, silicon carbide (SiC) and gallium nitride (GaN).

Taking into account that AI systems have a great demand for electricity, they, in turn, open up new opportunities for improving the design and implementation of energy systems [54,179–181].

According to [7,182,183], the following forward-looking AI-powered solutions most significantly enhance the efficiency of PECs and revolutionize robotics nowadays:

- Combination of WBG electronic components with AI technologies considering the great prospects of WBG devices, especially SiC transistors and bidirectional GaN switches [16];
- Development of AI-supported advanced control methods of synchronous rectifiers, such as adaptive control and MPC [184];
- Integration of AI into Wireless Power Transfer (WPT) to provide smarter energy distribution, diminished power waste, and prolonged battery life of unmanned vehicles [185].

Adoption of WBG electronics and bidirectional PECs encourages the development of energy recovery systems without excessive power consumption.

From 20% of the energy of stationary robots to 70% of the EV energy can be lost during deceleration [84]. This is why, for a relatively long time, many advanced braking methods have been proposed for automobiles [186] and aircrafts [187] to convert excess kinetic energy and return it to the ES and PS of the DC-powered robots, or to the grid in the case of AC supply. Since the problem of energy recovery at deceleration is currently of high importance in terms of EER, previous findings, such as GA [14] and FLC [188] algorithms, are being successfully applied and improved in modern robotics.

Regenerative braking (RB) has made the greatest contribution to mobile robotics, and EVs with RB are showing increasingly high efficiency every year [189]. Unlike the rule-based platforms that struggle to handle unforeseen situations, AI systems have great advantages in RB. They can continuously learn from external factors by analyzing the data about road conditions and speed and dynamically adjust braking force and refine their deceleration strategy in real-time. The best RB solutions blend regenerative and frictional braking to return a maximal amount of energy within a safe battery reserve, which can be autonomously learned by AI agents. Such systems ensure ES safety and lifespan optimization critical due to numerous spike-like charge braking currents. As a result, AI enables superior energy capture—up to 59–63% [190] and even up to 98% [60] of the total braking energy—thereby optimizing the split between regenerative and friction braking and increasing vehicle range and braking reliability [191,192]. To ensure enhanced safety and stability, ML can also be integrated into antilock braking systems (ABSs), particularly when decelerating on unpredictable or slippery surfaces [84].

Ford Motor Company, a prominent American automaker, currently offers an AI assistant BlueCruise, available on selective models, like Mustang Mach-E, F-150, and Expedition. It is equipped with cameras, radars, and sensors for hands-free, feet-free

driving on pre-qualified highways with Lane Change Assist enabling secure lane change and In-Lane Repositioning, which shifts the EV away from adjacent traffic. Ford is also developing in-house “eyes-off” Level 3 technology, targeting 2028 for its debut on new EVs, focusing on enhanced LiDAR sensors and improved software control. Both systems contain an AI-enhanced RB unit with a combination of supervised and RL algorithms to optimize energy recovery. The system analyzes real-time signals from various sensors, including the Global Positioning System (GPS), accelerometers, and wheel speed sensors, to predict upcoming braking events. Ford’s algorithms adjust the RB force based on these predictions, thereby maximizing energy recovery while maintaining passengers’ comfort. The system also considers passengers’ feedback to personalize the braking experience over time. Additionally, this technology incorporates a feature that learns from traffic patterns and road topography to further improve energy recuperation in urban environments [193].

General Motors (GM), an American automotive manufacturing corporation, is pivoting its self-driving strategy from robotaxis to personal unmanned EVs, aiming to launch a Level 3 “eyes-off” system in 2028, starting with the Cadillac Escalade IQ. The company is merging technology from Cruise subsidiary with existing Super Cruise platform to enhance AI assistance, utilizing a new centralized computing platform for improved performance. The new system applies advanced LiDAR, sensors, and gaze-tracking technology to ensure safety. All GM EVs are equipped with a sophisticated RB system that leverages ML to optimize energy recovery across the full EV line-up. This approach is based on the DL model that processes data from the vehicle DC bus, GPS, and external sensors to predict optimal braking scenarios. The system adapts in real-time to different driving conditions, including weather and road surface changes. GM’s algorithm also incorporates predictive maintenance features, using the braking data to estimate component wear and schedule servicing. The AI model is continuously updated over the air, allowing for fleet-wide improvements based on aggregated driving data [193].

Automotive industry supplier companies like Brembo, ABB, Bosch, Continental, and others are developing AI-powered braking systems for improved four-wheel braking efficiency and stability [194]. For example, an all-electric motorsport series Formula E (GENBETA) utilizes AI and cloud technology to generate enough energy on a mountain descent to power a full lap [195]. An AI-fed, camera-based rear braking system of Tesla, a leading American clean energy automotive company, has demonstrated superior performance over traditional Ultrasonic Sensor Setups (USSs) in recent independent safety evaluations. By integrating high-resolution vision data with ANNs, Tesla’s “Vision” system achieves faster obstacle detection and more precise modulation of RB during reverse maneuvers. Thanks to detection times of less than 0.5 s, this technology allows Tesla’s EVs to slow down 15% faster than competitors from BMW, Mercedes, and Volkswagen, which still rely on sound-wave-based sensors that respond in 0.8 s [196]. The system seamlessly integrates RB with friction brakes, using AI to adjust stopping force dynamically based on the size and trajectory of obstacles. Additionally, ML models analyze braking data to monitor system health and predict maintenance needs, reducing long-term costs.

The study [17] announces an ANN-based control strategy ensuring the high regenerative power along with passengers’ comfort. Here, once the braking command is received from the sensors, the corresponding deceleration rate is assigned by the backpropagation ANN. To manage braking, the required speed and time needed to reach the target are estimated by the hyperbolic tangent function. To set the range of the regenerative force, acceleration, velocity, and jerk signals are assessed, providing a predefined rather than random velocity. An ANN is used here to set the acceleration and deceleration limits. During the research, CarSim simulation software [197] was applied, considering the vehicle dynamics when applying the brake on a vehicle. During the simulation, the speed control

commands were received from MATLAB/Simulink, and the output data were obtained by dynamic modeling in CarSim. The voltage, speed, current, battery efficiency, and battery state data were forwarded to the ANN, which generated the corresponding deceleration rate. By varying the weight and initial speed of the EV and the road surface type, the learning data for the multilayer perceptron were obtained. Various deceleration rates were tried to estimate the comfort range of passengers from the corresponding jerk values.

The introduction of external communication and energy flows, such as Vehicle-to-Everything (V2X) and Vehicle-to-Road (V2R), to autonomous driving enables predictive energy management strategies. Self-driving EVs utilize V2X, high-definition maps, and GPS to anticipate deceleration conditions, planning ahead for long-distance coasting. According to [59], this leads to an increase in regenerative energy recovery by 15% to 40% in urban environments with potential boosting of up to 50% [198].

In [199], an intelligent RB control strategy is developed, which accounts for the coupling effects of driving conditions and AI behavior. This technology is suitable to dynamically adjust energy recovery while improving both driving stability and vehicle efficiency.

The authors of [59] recommend multi-objective optimization to jointly harmonize energy efficiency, braking safety, and smoothness. Advanced hierarchical frameworks show the ability to increase overall energy recovery by 10–15% along with maintaining braking comfort and reduction in battery degradation by 5–8% over the vehicle lifespan [200]. These systems successfully collaborate with Electronic Stability Programs (ESPs), Autonomous Emergency Braking (AEB), and other longitudinal and lateral control systems to enable customized, scenario-based EER strategies.

So, with the continuous evolution of self-driving EVs and hybrids, AI-based management approaches are emerging as a pivotal technology for maximizing energy recovery. Such methods further leverage ML and RL algorithms to adaptively adjust control strategies at unstable driving environments, thereby enhancing energy utilization in mobile robotics.

7. Conclusions

AI delivers new advantages for manufacturing, transportation, logistics, healthcare, and other fields where robots are used, such as real-time adaptability, intelligent predictive management, reduced operational errors, deployment time and costs, increased sustainability and processing speed, enhanced HRI, extended equipment life, and many others. Meanwhile, AI also causes alarming issues, undermining many of its benefits. The need to search for compromises between efficiency and other quality factors against the backdrop of additional energy consumption of AI-equipped robotic “brains” is one of the most painful points of all modern industries. The presence of such an energy utilization problem is compounded by the fact that developers and consumers often overlook it.

Considering two features of AI—the ability to reduce energy consumption of robots and the increased need for energy due to real-time computing, cloud computing, edge computing, and learning models, the authors nevertheless regret to state that they are unable to assess whether AI actually improves net energy efficiency. Unfortunately, despite the thoroughness and versatility of their analysis, this research does not present a balance model showing how much energy AI saves in mechanics, motion, routing, or energy recovery and how much energy is consumed by the computational layer.

Among the reasons for this situation may be the limitations of the proposed review, including data heterogeneity, the multiplicity of sources, and the difficulty of comparing results across various types of robots and technologies. In this regard, the review might be more rigorous if the publications on AI-supported EER were classified according to certain criteria, for example, in a synthetic comparative table. However, in modern robotics,

machines, technologies, and their management are so intertwined that the authors failed to separate them when assessing the energy balance resulting from their synergy.

Meanwhile, such a balance model was not found even in highly specialized studies included in this research, though many of them contain data about energy savings, energy recovery, shortened programming time, or system performance improvement coming from scientific studies or from company materials.

Obviously, the challenge lies in the fact that efficiency evaluation is produced for isolated mechanical systems based on their energy capacity to perform the required useful work (1)–(3), whereas AI requires additional energy to supply cloud servers beyond the robotic cell.

It is encouraging that the review uncovers solutions for stationary and mobile robotics, the competent use of which can have the greatest impact on energy savings. The most important of these are AI-assistive process planning and programming, technological improvements for eliminating unnecessary movements using proper joint configurations and force allocation, time-saving management of vehicle pathing and routing, selection of advanced electronics and low-loss PECs, cost-effective motors, gears and sensing systems, as well as organization of efficient power distribution and energy recovery.

This leads to a future research agenda, which should include the development of tools to measure the net energy balance of AI by going beyond isolated mechanical systems. Additionally, new design benchmarks for different classes of robots and robotic cells, as well as comparable energy consumption metrics, are awaiting their appearance along with conduction of experimental studies beyond simulations.

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Abbreviations

The following abbreviations are used in this manuscript:

ABS	Antilock Braking System
AC	Alternating Current
ACO	Ant Colony Optimization
ACU	Autonomous Control Unit
AEB	Autonomous Emergency Braking
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AR	Augmented Reality
BOA	Butterfly Optimization Algorithm
CSA	Cuckoo Search Algorithm
DC	Direct Current
DL	Deep Learning
DOF	Degrees Of Freedom
EER	Energy-Efficient Robotics
ES	Energy Source
ESP	Electronic Stability Program
EV	Electric Vehicle

FLC	Fuzzy Logic Control
GaN	Gallium Nitride
GA	Genetic Algorithm
GM	General Motors
GPS	Global Positioning System
GWO	Gray Wolf Optimization
HRI	Human–Robot Interaction
IFR	International Federation of Robotics
IPP	Intelligent Path Planning
JC	Joint Configuration
LiDAR	Light Detection and Ranging
LLM	Large Language Model
ML	Machine Learning
MPC	Model Predictive Control
NLP	Natural Language Processing
OECD	Organization for Economic Cooperation and Development
PEC	Power Electronic Converter
PnP	Pick-n-Place
PS	Power Source
PSO	Particle Swarm Optimization
PV	Photovoltaic
RAG	Retrieval-Augmented Generation
RB	Regenerative Braking
RL	Reinforcement Learning
RRT	Rapidly-exploring Random Tree
SiC	Silicon Carbide
SLAM	Simultaneous Localization and Mapping
SMC	Sliding-Mode Control
TEB	Timed Elastic Band
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
UR	Universal Robot
USS	Ultrasonic Sensor Setup
USV	Unmanned Surface Vessel
UUV	Unmanned Underwater Vehicle
V2R	Vehicle-to-Road
V2X	Vehicle-to-Everything
WBG	Wide Bandgap
WOA	Whale Optimization Algorithm
WPT	Wireless Power Transfer

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