Artificial Intelligence Against Climate Change

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***Abstract*—The industrial, transportation, and residential sectors draw the most energy in the United States. With most energy created by burning fossil fuels, a highly inefficient method of energy creation, global greenhouse gas levels are rising, raising the temperature of the earth, causing natural processes to become unbalanced. The health of the earth is declining. The rise of technology and persisting growth of computing devices known as the Internet of Things (IoT) and increasing automation of systems through Artificial Intelligence (AI) and Machine Learning (ML) is a factor of energy expenditure as more humans desire devices and more systems are built. The ethical implications of utilizing new technology should be evaluated before creating more. This paper explores modern computing systems in the sectors that draw the most energy, and, more specifically, the role AI and IoT play in them. Each sector may become more energy efficient, productive, and safer by introducing edge computing through IoT devices and coupling it with AI computing abilities that already automate most processes. Multiple studies show energy consumption and costs are lowered when edge computing is paired with the IoT and AI. There is less human involvement, more regularity in execution and performance, and more widespread use because of the accessibility. This creates safer, cheaper, energy-efficient systems that utilize existing technology. The ethical implications of these systems are much more positive than what already exists. Coupling the power of AI with the IoT will reduce energy expenditure in modern systems and create a more sustainable world.**

***Index Terms*—Artificial Intelligence, Internet of Things, Machine Learning, Ethics, Sustainability, Energy Efficiency, Edge Computing, Fog Computing**

I. Introduction

In the United States, certain sectors – industrial, transportation, and residential – draw the most energy. These sectors are having actuators and sensors increasingly integrated into their increasingly automated management systems. Global warming has also been increasing due to a rapid burning of fossil fuels in the last century, releasing atmospheric CO_2. The increase in energy consumption was closely linked with the inception of the Industrial Revolution, which did revolutionize the tools humans have access to. It is unrealistic to ask humans to give up the tools and technology we rely on for daily activities, so we should utilize the technology to stem the rise of climate change. By effectively using Artificial Intelligence (AI) and the Internet of Things (IoT) we can use energy as efficiently as possible, allowing us to keep our technology and create a sustainable future.

The detriments of climate change are perilous and imminent. The average global temperature has risen 1°C since the Industrial Revolution and it has been estimated that if it increases by one more degree, we will reach a tipping point – a point of climate change of which there is no return or reversing of the damage on the earth. It will lead to higher temperatures across the globe. The equator will continue to warm, causing the land that is normally arable to be pushed northward, where unfortunately soil is either lacking nutrients or soil is rocky. The occurrence of natural disasters, such as forest fires and hurricanes, will increase. As temperatures rise, glaciers will melt, the rainy season will be shorter, and drinkable water will decrease. Without arable land and water, we will not be able to produce enough food to feed the inhabitants of the earth. This change is set to happen by 2035 if we continue at our current rate of energy consumption and fossil fuel burning. It is our responsibility as humans to stop the damage we have imposed on this shared habitat. We do not have a second earth.

Current solutions to mitigate climate change are either very niche or very small, therefore ineffective in altering global infrastructure in the ways we need to truly stop global warming. Individuals have the ability to make choices about recycling, or using reusable napkins and other small changes, but changes on an individual level will not make a huge difference. In addition, some government subsidies are offered for employing more sustainable practices, such as using certain fuel sources. Unfortunately the cost of continuing practices that increase global warming are usually cheaper than finding an alternative. There have been individual efforts by large tech companies to employ practices that utilize technology, but these are fairly niche. Google DeepMind has been used to reduce the energy that cools it's data centers and Microsoft SilviaTerra which tracks the health of forests [16]. While these solutions are effective, they do not influence the infrastructure of modern economies and households in ways that will stop global warming. In addition, developed countries have the luxury of affording alternative solutions, whereas developing nations are relying on cheap methods of achieving success, which usually incorporate the use of fossil fuels in ways that are rapidly increasing greenhouse gas emissions. By changing the way devices in the IoT are used by their AI counterparts, we can positively alter all modern systems and infrastructures to reduce their energy consumption.

In our modern era of technology, there are sensors everywhere tracking the status of our environment and helping us make decisions. This abundance of computing devices with the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction is known as the Internet of Things. Artificial Intelligence replicates human intelligence by interpreting data to achieve a human-programmable goal. Coupled with modern hardware technology, it can process thousands of data points rapidly.

AI technology is currently used to automate systems around the world, such as thermostats in homes or assembly lines in factories, by processing mass amounts of data collected from sensors from a selected area using human-programmed algorithms, detecting patterns that may go unnoticed by humans. The IoT is rapidly growing as we create more sensors, automators, and devices that can track more system parameters than ever before. The trends in automation and device creation will continue. Technology pervades everything in the modern world. Rather than oppose technological development that has driven human innovation for the last few decades to reduce energy expended creating new products, we should capitalize on existing technology to reduce energy waste and improve efficiency of modern systems. In this paper, we will explore how AI's processing capabilities coupled with the growing IoT can be utilized to identify areas and patterns of wasted energy and autonomously correct wasteful practices while adhering to human standards of comfort, in turn mitigating climate change to an extent humans are not capable of doing on their own.

Despite IoT, AI, cloud computing and edge computing all generating CO_2, we can leverage these technologies to not only reduce their own energy consumption, but the systems they are embedded in as a whole. It is unrealistic to reverse our reliance on these technologies, so we should instead use them effectively. In the rest of this paper I will outline energy consumption the United States, systems that control the industrial, transportation, and residential sectors, and how they may be improved upon to stem our global greenhouse gas production, as well as the ethical implications of using technology in this way.

II. Background

In this section, I describe where the most energy is consumed in the United States and how AI and the IoT function.

A. Energy Consumption in the United States

The residential, transportation, and industrial sectors draw the most energy in the United States [11]. Their distributions can be observed in Table I. Additionally, two-thirds "of anthropogenic greenhouse gases (GHGs) emission originates from fossil fuel combustion in the transportation and industrial sector" [7]. The transportation sector alone has become the second largest contributor of CO_2 emissions, which have currently posed the most serious problem to the environment as the biggest contributor to climate change. [7]. Meanwhile, industries consume the most power in any country and "buildings in use or under construction are the greatest single indirect source of carbon emissions accounting for 50% of total emissions" [8], [10].

Currently, electricity is used to power industrial settings, transportation networks, and residential communities (as well as commercial enterprises). Due to current methods of production and the makeup of the fuel mix, electricity is highly energy inefficient. It is delivered at about 30% efficiency since the primary energy contained in the fuel is only partially exploited [10]. Automated systems that work with the IoT to manage energy distribution and use in buildings, transportation networks, and industrial settings will reduce energy consumption.

TABLE I
Energy Drawn in the United States by Sector [11]

Sector	AI Managing System	Energy Drawn in U.S.
Industrial	32%	Industrial IoT (IIoT)
Transportation	29%	Energy Management System (EMS)
Residential	20%	Building Management System (BMS)
Commercial	18%	Management System (MS)
Other	1%	–

B. AI and the IoT

The sectors mentioned require dynamic power management and contain ample sensors and actuators – IoT – that can be utilized by AI [8]. AI can collect the vast range of data from these settings, can determine energy patterns, and can then implement human-specified goals based on energy use trends.

AI that is hardware-accelerated is capable of efficiently processing a multitude of data while the IoT is capable of providing an abundance of data. Artificial Intelligence is generally understood to be able to mimic aspects of human intelligence in its computations. This includes planning, learning, problem solving, decision making, pattern recognition and more. Generally, through the use of training data and specific algorithms, AI is able to be applied to varying scenarios to carry out useful computations. Together, AI and the IoT, may identify patterns humans cannot discover easily or possibly at all often due to the large quantity of data to sort through or the complexity of the patterns created by interacting factors in a system. Machine Learning (ML) is a subset of AI that is able to learn relationships from large datasets it is trained on [2]. It enhances AI in that it allows AI to "learn" without specific programming or algorithms. Essentially, ML allows a system to gauge the accuracy of its results to recycle the useful data, parameters, and computations back into its own algorithm to refine its computations to become more accurate in its intended purpose. ML can find linkages between locations, times, and quantities in datasets and AI can build on ML connections to provide automated warning and advice [2]. AI and ML use different modelings based on the human-programmable goal to be reached, as can be observed in Table II.

C. Importance of Mathematical Modeling

As mentioned, Machine Learning enhances Artificial Intelligence by providing a way to mutate algorithms to become more responsive to their systems and more accurate in their computations. There are several ways to achieve this depending on what the system is intended to be used for. Depending on system use, there are best practices for identifying relevant data, collecting relevant data, feeding the data back into the system, and revising the algorithm. In this section, we will describe how this is achieved in some detail.

Because algorithms are originally written by humans in some capacity, they are therefore based on mathematical theories and principles. We devise mathematical models to model system behavior and data flow. ML algorithms take initial mathematical models and revise them for better functioning within the system. In Table II, several Mathematical Models and their use are explained.

To begin, differential equations are often utilized in making predictions about how climate systems will behave, allowing us to predict what response our system should make to preserve a comfortable space for humans while remaining energy efficient. This is because differential equations allows for coupling any source and sink terms, remaining robust through dimension reductions and changes in the system, giving insight to interconnections within a complex system – the climate network – that humans would not be able to track or model themselves. As best stated by Huntingford, “knowledge of controlling processes points to model parameters that most strongly influence projections, guiding measurement campaigns to aid uncertainty reduction” [2].

Nonlinear equations and regressions serve a similar purpose in terms of understanding the system, similarly allowing for the encapsulation and tracking of many parameters in a complex system – something linear models would be unable to do. [2], [4] This aids us in understand complex and variable climate systems.

Non-linear, Non-Gaussian Models are useful for ML prediction and inferences when we are dealing with spatio-temporal processes, since climate systems contain many state-space problems where mechanisms are latent, or hidden, so only resulting data is observable and available.

TABLE II
TYPES OF MATHEMATICAL MODELING AND THEIR CORRELATING USE

Types of Mathematical Modeling	**Purpose**	**Example of ML Applications**
Differential Equations	Continuous and coupled to account for parameters in a system that may be intertwined	Climate System [2]
Nonlinear Equations/ Regressions	Allows encapsulation and tracking of many parameters	Climate System [2,4]
Nonlinear, Non-Gaussian Inferences	Models randomly changing systems based only on current state	Climate System [2]
Kalman Filtering-Based Gray Box	Predict and determine statistical process control limits for fault detection	HVAC Systems [3]
Q-learning	Identifies best action given current state	Lighting Control System [3]
Directed Graphs	Allows parameters to be given varying importance to uncover relationships in nonlinear data	ESM [2]
Gaussian Models	Models systems with many parameters that may be unknown	Tracking headcount in rooms [3]
Linear Regressions	Used for resource prediction, response time, throughput and CPU utilization	Choose Best Edge Node [9]

The Kalman Filtering system is a subset of Non-linear, Non-Gaussian Models that is slightly simpler than other models, which can help in subset systems within the climate network.

Q-learning differs from previous mentioned mathematical models in that it is a model-free learning algorithm. It is useful in systems that are non deterministic and irregular, telling agents what actions to take in certain situations without an environment model. For that reason, it can be used to control lighting control systems, often turned on and off randomly. It can be used to manage light intensity, identify daylight trends, and used in conjunction with occupancy-detection [3].

Directed graphs are often used in conjunction with other methods, but are useful alone as well. Directed graphs model system parameters as nodes with connecting edges that have associated weights, or ’biases’. The larger the bias, the stronger the connection, showing how certain parameters interact with one another, showing trends within the ESM. These are often used with neural networks, where each node makes up a neuron. Using deep learning or neural net approaches avoid specifying a process and instead work with data to improve understanding or multivariate relationships in nonlinear systems. Upon each iteration of data through the system, weights are updated to better reflect system interaction [2].

Gaussian models are similarly to neural networks in that it works on data and observable functions rather that input state. A Gaussian process is a collection of random variables such that a subset of them has a multivariate normal distribution. The process ”is specified by a mean function and a covariance matrix” [2]. Since it is a non-parametric approach, it allows for direct representation of uncertainty and prior beliefs, powerful in nonlinear regression analyses. Predicting capability past sample inputs is necessary for predicting future states of systems.

Lastly, linear regressions are some of the most simple mappings between variables. It models the relationship between a response and at least one related variable. It is often used to track resource prediction, response time, throughput, and CPU utilization. These are easy to track since they are physical node performance variables based on data flow. Tracking node with best performance allows us to choose the best node for computation purposes in Industrial Systems.

We have not included many mathematical models in this short discussion, however, we aim to emphasize the diversity of models available and their varied purposes and applications to the sectors that could utilize AI and ML to increase energy efficiency. Mathematical models help process data most efficiently in any system. The existence of many show that despite the variation in systems and circumstances, there is an existing model that can be utilized to perform energy efficiency computations effectively.

D. Summary

Different systems warrant different tracking mechanisms. There are multiple models and equations that may be used for a system, varying in use based on the parameters to be tracked and outcome AI is expected to produce, often selected by humans running the system. Humans are beginning to use AI and the IoT in effective ways to achieve goals with more speed and precision than ever before.

III. Existing Technology

A. Buildings

BMSs consist of low-cost personal and hyper-local sensors that track user habits and utilize green energy and storage resources for environmental sustainability while implementing smart systems with autonomous decision making [3]. They are cost-effective, energy-efficient and maintain user comfort. This is becoming increasingly important as demand for energy increases while dominant energy supplies continue to dwindle.

The IoT allows cost-effective integration of sensors to monitor and identify different energy and environment-related parameters to determine building's health, energy requirements, and electricity usage behavior of subsystems [1], [3]. Energy consumption data can be obtained from modules monitoring and controlling a variety of physical conditions [1]. Data can consist of humidity, temperature, user preference, weather predictions, human activity in certain locations, etc. The data and correlating parameters are transmitted over a wireless local area network (WLAN) or a wireless personal area network (WPAN), often to a central control station where the energy management logic can instruct specific calculations to provide the users with an energy management solution.

AI suggests changes that can be implemented autonomously if given user permission to correct energy-inefficient trends [1]. Current Building Management Systems (BMSs) logic can be seen in Fig. 1. For example, if the system notices fans are left on when humans are not in the room, it may turn them off. Current technology ranges from AI-based Energy Auditing, Monitoring and Control for Utilities, to Multi-model Climate System Networks, to complete BMSs. Despite varying levels of hierarchy, all residential systems need large volumes of data to identify user trends to function effectively.

Processor availability, speed, connectivity and cheap data storage has increased ML and AI use, and improved hardware has helped with memory and computation, increasing speed and efficiency more than ever before [2]. Because climate change analytics are data-intensive, ML algorithms could not be implemented until recently due to computation architecture and power restraints. However given recent technological developments, BMSs provide an inexpensive, user-friendly system capable of easy installation that will conserve energy in a variety of settings while utilities are used to monitor the efficacy of energy efficiency [1].

B. Transportation

Transportation systems are littered with sensors, actuators, and communication devices to allow for mitigating problems, traffic, congestion, and CO_2 [7]. Every transportation network is filled with sensors, lights, cameras, speed monitors, etc., each able to monitor and report data. AI, blockchain, and cloud computing has made transportation networks grow rapidly. The launch of several IoT applications and frameworks has improved transportation methods while reducing short and long term negative impacts. These improvements in technology include navigation applications, fuel monitoring software, more efficient intersections, calculation of better city planning, etc. By planning for the future, less time is wasted in traffic, on inefficient routes, or by inefficient vehicles.

By integrating data collected from the IoT into Energy Management Systems (EMSs), vehicles can optimally utilize energy while interacting with driver behavior and accounting for the condition of environmental impacts, also making data visible to users [6], [7]. How transportation networks function can be observed in Fig. 2. Increasing the efficiency of real-time data flow and information quality allows us to establish intelligent transportation systems and traffic networks that increase safety and energy efficiency [7].

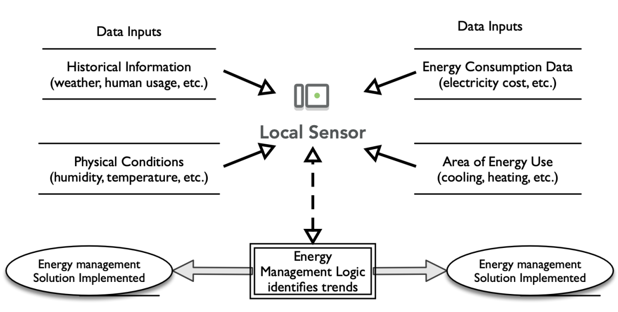

Fig. 1. How Current BMS Technology Executes

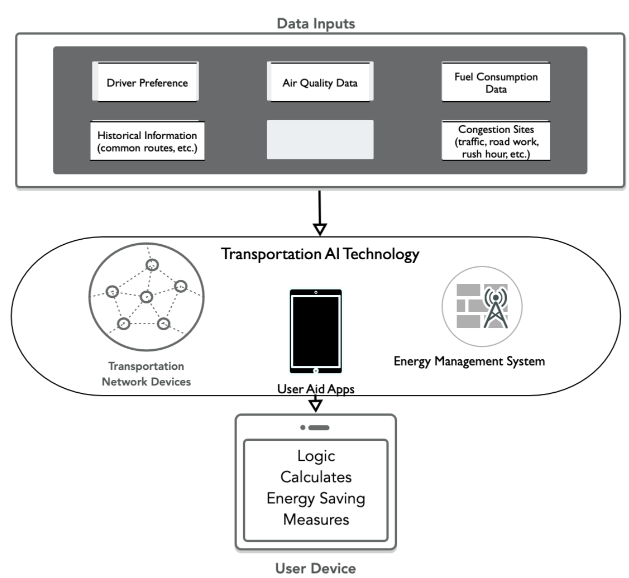

Fig. 2. How Transportation Networks Functions

C. Industry

The industrial sector is beginning to utilize the IoT and AI to full potential, known as the industrial IoT (IIoT) – see Fig. 3 [8], [9]. This sector requires energy efficiency and real-time data to create safe, productive, reliable systems. Industrial systems are often very large and therefore have many data points to collect and, often, machines to run. This influx of data is most commonly sent to the cloud, where calculations are run and directions to continue system performance are sent back to actuators. The magnitude of data sent to the cloud is creating unacceptable forms of latency (time taken for information to travel from one node to the next), packet drops (information that does not send), and failed throughput (amount of packets sent in a given time period), decreasing scalability, reliability, and functionality.

AI and ML can make industrial systems more intelligent, dynamic, flexible, and scalable by creating a networked and remotely accessible system of the industrial machinery [8]. Energy consumption of sensors and adaptations in frequency of data generation can be monitored and implemented with improving Wireless Sensor Networks (WSNs) to facilitate fault and resource prediction, quality management and product development and arrangement [9]. AI can effectively process and control the magnitude of data generated by the growing IIoT.

An emerging form of computing known as edge computing consists of data being sent to nodes close to sensors, rather than the cloud, to reduce traffic, packet drops, and latency. In some of the most successful examples of edge computing, AI algorithms choose the best edge node by predicting cloud processing resource usage, predicting requests, and identifying the best processing module for incoming requests [8]. Optimization algorithms often aid this process. Algorithms also help with time synchronization while linear IoT models enhance prediction accuracy with iterative processing to reduce energy consumption compared to cloud computing, making the IIoT more effective and scalable [9].

The linear IoT model saves energy through edge node reconfiguration and specific edge node selection [9]. Edge node reconfiguration allows nodes to reconfigure in certain time intervals to be able to process the varying types of services that occur in an industrial environment, making them more likely to process incoming requests [9]. Next, edge node selection conducted using the Shortest Estimated Latency First (SELF) algorithm reduces packet drops and latency in non-critical event systems [9]. Efficient edge nodes reconfiguration and selection for IoT nodes reduces energy consumption, uneven packet loss, and increases hit ratios at edge nodes.

IV. Blockades in Technological Progression

The two main challenges slowing technological progression are a lack of cohesion within the engineering community in terms of sharing information and a lack of policy dictating what technology may or may not be implemented and where, outlined in Table III.

A. Lack of Cohesion

Standard benchmarks are needed to evaluate and compare algorithms. By comparing the efficacy and efficiency of algorithms, better decisions can be made about how to implement the algorithms, and more collaboration can occur to improve them. In particular, standard benchmarks will improve and lower the cost of AI use in continuous control tasks, such as self-driving control, urban transportation, and industrial robots [4].

AI-based control creates uniform processes, reducing minor variations in workflow and wasted energy, optimizing the process based on collected data points that can be fed back into the algorithm as the process executes to further reduce energy waste in a process known as reinforcement learning. However, without many AI benchmarks available and standard industry models, it is difficult to standardized typical agent actions and record best methods. In addition, without public standard benchmarks, AI testing environments are often kept secret or vary widely between testing platforms.

Given the cost and difficulty of AI research and the difficulty of comparing independent projects, further complicated by the fact that AI evaluates dynamic systems, progress is slow, uncollaborative, and may take varying paths of development by different groups [4]. As a result there is a lot of unpredictability of typical agent actions and reaching a useful model is often time-consuming and costly [4]. Additionally, there is a noticeable lack of formal proofs for closed-loop systems [4]. In this state of unpredictability, AI cannot function optimally.

Only wealthy companies can afford to develop AI algorithms in these conditions. A suggested solution is an Open Physical Environment Benchmark (OPEB) framework to share different physical environments, either through computer models or 3D printing designs, and lists of cheap materials to replicate testing scenarios. The development of a unified interface to share ideas and progress would allow for collaboration on and integration of different designs that

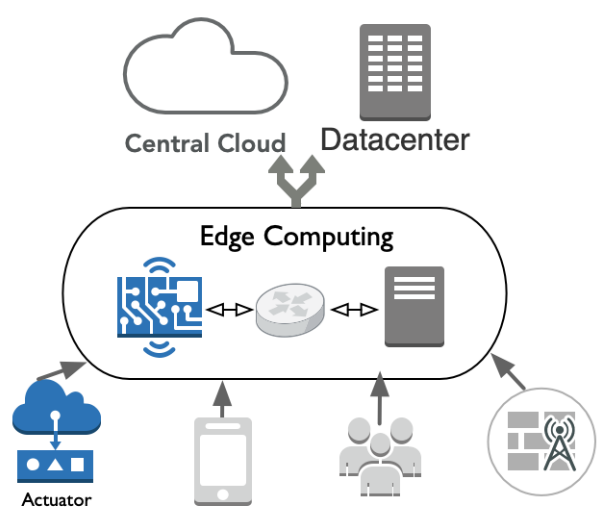

Fig. 3. How the IIoT Functions

address similar problems regardless of hardware, software, and implementation design. This collaboration would accelerate AI development and address challenges seen in real-world physical systems [4].

B. Lack of Policy

Policy-making is a complex process that occurs in adjusting environments and affects the three main pillars of sustainable development: economy, society, and the environment [6]. Currently, policies are created by setting objectives, which are constrained by budget and geophysical restraints. If problems are noticed after implementation of policies, only corrective measures can be applied. This is highly ineffective and less than optimal.

AI can aid with agent-based simulation, opinion mining, visual scenario evaluation, and optimization to support specific cases. By using equations from Game Theory Constraint-Based Models that define variables (activities), constraints (relating variables), and objectives, we can reach strategic equilibrium based on predicted user behavior [6]. Creating well-rounded policies faster by comparing scenarios and weighing pros and cons would lead to the most sustainable development. The sustainable and beneficial policies that AI creates would not only effectively guide and streamline AI technology development and use, but also benefit our economy, society, and environment, making technology development as a whole more efficient and purposeful.

V. Developing Innovations

The potential of the IoT has been realized; therefore, technology is actively being developed that will use data collected from the IoT to improve AI and ML performance. Below are emerging designs in each sector that will improve systems and reduce energy consumption.

A. Buildings

Currently AI allows us to control specific devices within buildings, such as temperature, lights, humidity, shading, etc. This use of existing technology can be improved by connecting more devices from the IoT into BMSs, Multimodal Climate Sensor Networks (MCSNs), – similar to a BMS but often regulating fewer building systems – or even displayed on web interfaces to create more dynamic, efficient, useful systems.

TABLE III
Outline of Obstacles in AI and IoT Development

Issue	Solution	Why We Need It	Implemented By	What It Provides
Lack of Cohesion	Standard Benchmarks for Algorithms	Evaluating and Comparing Algorithms	OPEB framework	Thorough collaboration on AI algorithms to fix global issues
Lack of Policy	Tool for Comparing Scenarios	Sustainable Development	Game Theory Constraint-Based Model	Comparision of Alternate Scenarios

As buildings get used, thermal characteristics deteriorate, usage patterns change, microclimates change, etc., and eventually performance of the building's system falls short of expectations. The IoT can allow cost-effective integration of sensors to monitor and identify different energy and environment-related parameters, as well as determine building health, energy requirements, electricity usage behavior of subsystems, and more [3]. Sensors can monitor ambient air pollutants, environmental parameters, historic trends, human preferences, cost of electricity, etc. Multiple parameters can be tracked at one time and relayed to a central processor. This information can also be broadcast to a platform that displays trends in a form akin to online social networks [5].

MCSNs can provide a networked way to monitor air quality and control building parameters. Similarly, BMSs can be thought of as cloud-based ecosystems that use social interaction to develop global patterns to achieve goals, use green energy and storage resources for environmental sustainability, and affirm establishment of smart systems with autonomous decision making [3]. Reference Fig. 4 for designs.

MCSNs and BMSs need a large influx of data to work effectively. They take data from sensors, relay it over a wireless network to a central processor, and determine energy-saving methods based on collected parameters. The decision is autonomously implemented into building systems. These decisions may range from turning off unused lights, actively regulating temperature as more bodies enter/exit rooms, storing energy unused energy, etc. By utilizing data that is already being constantly monitored and processed from IoT devices, building systems will become smarter, work more efficiently, and save energy and money. For example, one study concluded that implementing a MCSN that regulates the HVAC machinery by set-point temperature based on human activity and room occupancy reduced the building's energy consumption by 33% [3].

As mentioned, information about parameter trends and energy usage can be put on a web interface. Here, communities may evaluate historic trends and recognize patterns between activity and pollution. Driven by social interaction, users increase awareness of air quality, share knowledge about the observation and management of personal air pollution, and build clean air reputations [5].

Systems can be further improved by storing energy to be used later, pushing energy onto community grids, or drawing energy from the grid at different rates depending on the time of day to become even more efficient and less wasteful. These computations will not only be sped up, but will take less energy to execute if offloaded to edge nodes, rather than processed in a large central processor or cloud. Computing at a local level reduces congestion, latency, and packet dropping. Energy is saved by avoiding re-sending packets, having to execute large computations in one location, and having to expend energy when sending packets over multiple nodes. In turn, implementations of solutions will be more effective, quicker, and energy-efficient.

In conclusion, a zero-energy building may be achieved through high-performance design, integrated physical systems, a symbiotic building within its context, an interactive power grid with the building's energy generation system, and web interfaces [10].

B. Transportation

In the transportation industry, sensors are already integrated in vehicles and traffic networks, relaying data to centers that use AI to calculate and autonomously implement changes, saving energy. Every modern vehicle has a GPS system, speed sensors, and often energy efficiency gauges. Many intersections have cameras, traffic lights, and weight sensors. Depending on the type of networks, accompanying sensors vary. These sensors are a part of the IoT, all collecting information.

Dynamic EMSs could be developed to reduce traffic, pollutant emissions, and cost of transportation, while increasing transportation safety, comfort, and energy efficiency if this data was processed in a larger, interconnected network. User aid devices can be developed that both educate users and regulate transportation. AI can improve fuel efficiency by calculating best performance practices based on processed parameters of speed, energy consumption, and congestion. Efficient routes can be calculated for users. By increasing the monitoring of transportation networks, safety is improved, user comfort is maintained, and energy efficient trends directed by AI and IoT calculations.

Due to the rapid growth of the IoT, AI, blockchain, sensor technologies, cloud computing, and other technologies, data may be offloaded from vehicles into edge nodes for efficient and easy computation. Most transportation data is already offloaded to a remote location to store as history to save user preference, collect trends, and monitor safety. In addition, edge nodes could compute ways to improve the efficiency of transportation networks. Little, if any, additional energy would need to be used to modify existing systems.

Such an existing system of Iot and AI integration is the Intelligent Transportation System (ITS), the subset of IoT currently dealing with transportation. Road-side units can be equipped with edge technology to enable ITS. ITS could

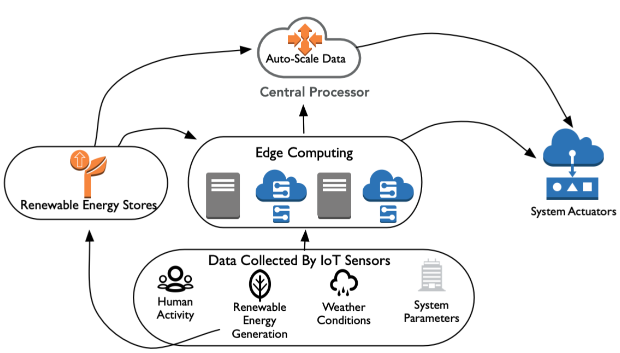

Fig. 4. Architecture for Developing BMS that may potentially achieve net-zero-energy expenditure

support in-vehicle entertainment, context-aware and location-aware services, smart parking, and smart traffic lights [8]. Despite challenges posed, coupling edge computing with the IoT and AI is expected to reduce CO_2 emission on a global scale by developing smart cities, dynamic transportation systems and electrical grids, implementing energy-saving gains [7].

Edge computing, combined with the IoT and AI, can address modern transportation issues due to the increasing number of sensors, actuators and communication devices that can reduce CO_2 emissions on a global scale by developing smart cities, transportation while mitigating traffic issues [7].

C. Industry

As mentioned, the rapidly growing amount of industrial data is beginning to be processed on edge nodes to allow for monitoring, processing, and controlling of critical and event triggering devices with ultra-low latency and necessary data storage. Wireless Sensor Networking (WSN) technology has evolved in such a way that it allows for "better quality management, energy efficiency, fault prediction, product planning, and resource prediction" by connecting sensors in industrial settings [8]. This creates cyber physical systems (CPS), extreme automation, smart factories, industrial robots, actuators and more. This "minimizes human error, lowers risk to human health, improves operational efficiency, reduces costs, improves productivity, and allows higher quality maintenance/customer satisfaction" [8].

In industry, edge computing is responsible for…

- Real-time industrial big data mining for high performance
- Concurrent data collection from multiple types of sensors, robots, and machines
- Fast processing of the sensed data to generate instructions for the actuators and robots within some acceptable latency
- Interfacing incompatible sensors and machines through necessary protocol translation and mapping
- Managing system power management

AI and ML have the power to make manufacturing more intelligent, dynamic, flexible and scalable by creating a networked and remotely accessible system of the industrial machinery – see Fig. 5 [8]. Because many physical sensors are costly and cannot keep abreast with the changing requirements of a factory, incorporating WSN and virtual sensing allows for flexibility and customization while keeping costs low. These networks monitor energy consumption of sensors and adapt the frequency of data generation, while also exploring and managing other energy sources (solar, thermal, etc.) [8].

By sending data that controls industrial processes and machinery to edge nodes to compute energy-saving strategies and most efficient practices, there has been a proven reduction in energy consumption, less use of machinery, and fewer human errors produced due to lack of human involvement [9]. Algorithms exist to help with time synchronization of machines and node computation to reduce energy consumption further, making the IIoT more effective and scalable. Reducing the use of huge machinery commonly found in industrial systems saves a lot of energy [8]. There is an overall increase in economic efficiency and, if other energy sources are managed as well, an increase in renewable energy use [8].

As with any system, new technology brings a lot of challenges, which can be converted to opportunities if better planning and standardization are done [8]. Systems that choose the best edge node exist, working in tandem with models that predict cloud processing resource usage, an AI algorithm to predict requests, and another AI algorithm to allocate incoming requests to the best processing module [9]. A linear IoT model enhances prediction accuracy with iterative processing. An ML algorithm calculates resource prediction in the cloud using linear regression and neural networking based on gathered data from the database of the industrial process, the algorithm products response time, and CPU utilization. These algorithms predict the most likely incoming request, ready near-by nodes, process incoming requests, execute commands, and offload work to the cloud if the edge node cannot handle the size of the computation.

A study that monitored energy consumption and system efficiency showed a reduction in energy consumption and an increase in system efficiency when using the combined edge and cloud computing system, compared to the cloud computing model, which in itself reduces energy consumption compared to regular system processes. Combining AI, the IoT, and edge computing saves energy, reduces costs, and improves existing systems.

VI. Ethical Implications of Emerging Technology

New technology brings an amalgam of new challenges, but these may be harnessed to create opportunities with proper planning. Technological advancement marks human life, so it would be unreasonable to expect humans to abandon the technology that makes our lives easier. Rather, we should harness it to create a more sustainable future.

In order to review the ethical implications of harnessing AI and the IoT in modern systems, I will first define some prominent ethical schools of thought, then consider how modern systems affect our planet and communities, then evaluate them from an ethical point of view. Prominent ethical theories include virtue ethics, consequentialist ethics, and deontological ethics. Virtue ethics asserts that humans should act in ways that cultivate good virtues [17]. Consequentialist ethics asserts the right path of action is the one that produces the most "good", which can be evaluated in terms of pleasure, satisfaction, welfare, etc [18]. Lastly, deontological ethics states that one must do what is "right", which may not always produce the most "good" [19]. In short, the proposed system must maintain human autonomy to make decisions and produce positive effects. [15].

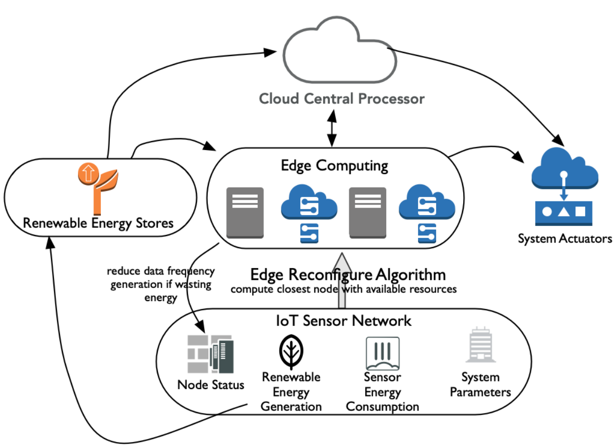

Fig. 5. Model for Energy-Saving IIoT System

Multiple case studies have shown that by utilizing AI and IoT technology, energy consumption of a system is reduced. The evidence is in BMSs, MCSNs, transportation networks, and the IIoT. While many of these are in early stages of development, a poignant example of the effect of AI and the IoT is by Google's DeepMind's ML which has been used to manage the energy consumption of Google Data Centers [11]. Despite energy usage growing 90% from 2000-2005, 24% from 2005-2010, and still slowly increasing, energy usage within the center has been kept flat and energy used to cool data centers has been reduced 40% [12, 13]. This system implemented was able to keep track of the parameters of this system that behave nonlinearly. Traditional formula-based engineering and human intuition could not capture it, nor adapt quickly enough [12]. AI could operate without rules or heuristics of every operating scenario.

Energy consumption is rising and so is global warming. Global warming is ruining viable farmland, melting glaciers and the polar ice caps, and causing more natural disasters than ever before to name a few catastrophic issues. These issues are directly correlated to the rising rate humans are using natural resources. Systems created by joining AI and the IoT not only mitigate, but reduce energy consumption, and therefore resource usage. As explained in sections above, we have already implemented the technology necessary to reduce energy consumption globally into modern infrastructure. The only change we need to make is ensuring these systems auto-regulate energy consumption while performing their jobs and maintaining human comfort. Algorithms to do so already exist. Implementing this solution takes very little human effort and produces the benefit of slowing, if not stopping, wasting of energy.

Evaluated in terms of normative ethical theories, this suggested solution is ethical. In terms of virtue ethics, utilizing IoT and AI in this manner will allow humans to create altruistic systems, therefore acting altruistically themselves. It also allows humans to develop themselves intellectually and socially as they collaborate with others to build these complex systems. By creating systems that reduce the production of greenhouse gases worldwide, we create a sustainable future. In terms of consequentialist ethics, this maximizing the overall "good" in the world, whether that is pleasure, satisfaction, welfare, etc. Longer, healthier, worry-free lives are positive on all accounts. Lastly, for the same reason this proposed solution is virtually and consequentially ethical, it satisfies the requirements of being deontologically ethical. Modifying modern systems to ensure we do not ruin our planet is the ”right” thing to do, even if the change may initially be difficult. Combining the IoT and AI to mitigate global warming is ethical.

It allows humans to achieve more technological progression, reduce global warming, and create a sustainable future. This technology gives humans more options to choose the lifestyle and sustainability options that function best with their respective lifestyle. It also undoubtedly improves energy efficiency. Lastly, this technology allows humans to achieve more autonomy as more devote less time to managing systems, while, simultaneously, more jobs are created through rising productivity and developing systems [14]. It is an ethical improvement from any point of view. Harnessing this emerging technology will provide a better future for humans.

While some concerns may be brought up regarding security, privacy, and work created, this solution does not present any new concerns. In any computing system that processes data, there is a concern that data may be shared by malicious attackers or systems may be hacked to malfunction in ways that may harm society. The systems we are proposing are to process data to make them more energy efficient. If a hacker was to access data, they could do that as the system stands. If a hacker was to make the energy waste energy or resources, they could also make that change now. Wasting resources or causing a system to malfunction is extremely easy and can happen in a variety of ways. Implementing a solution that reduces energy consumption or produces energy reserves can only happen one way. If a malicious attacker was to stop these positive solutions, we would end up where we are today. Therefore, this proposed solution does not present any new ethical concerns or detriment society in any way that is is not currently under threat of. Our proposed solution is an ethical measure.

VII. Future Research

Edge computing is still in its early stages of exploration and more development needs to be done. Comparing the number of packets dropped, latency, and throughput compared to cloud computing still needs a lot of research. More research on what type of edge nodes are most effective in reducing latency and packet dropping and how edge computing affects energy efficiency in different systems compared to what is currently used could further propel technology. We may explore how effective edge computing would affect energy efficiency in other sectors that do not need real-time data as often [9].

In addition, it is important to note that while there have been solutions proposed to specific sectors, solutions may be applied in many scenarios unmentioned. For example, while Google DeepMind is able to effectively cool data centers, this same technique may be used to control cooling in the commercial sector. Microsoft SilviaTerra may be modified to examine coral reefs and monitor their health, as they are one of the largest producers of oxygen on the planet [16]. IIoT solutions to may be modified to run machinery in commercial factories more efficiently. MCSN’s may be modified to function in vehicles to make them even more energy efficient. Solutions proposed in this paper are robust enough to be applicable to any modern technical system.

TABLE IV
Abbreviated List of Parameters Kept Track of in Each Sector

Residential	Transportation	Industrial
• Air Temperature • Light • Humidity • Water	• Gas Mileage • CO_2 Output • Avoiding Traffic • Brake Wear	• Assembly Lines • Lighting • Equipment • Loading

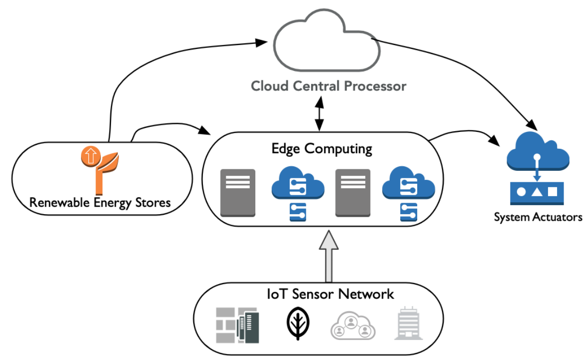

Fig. 6. Future Systems that Utilize AI and IoT

VIII. Conclusion

Buildings, transportation networks, and industrial systems are large and difficult to manage. AI can keep track of the many different system parameters, as outlined in Table IV, better than humans can. Currently, AI helps automate tasks, but no system has properly integrated the IoT, although future systems, shown in Fig. 6 are promising.

Using IoT sensors that relay information about status to humans to processing nodes where AI and ML algorithms function, AI can more accurately allocate energy within a system and run systems more efficiently based on human goals. The result has proven to be reduced energy consumption, minimized human error, lower risk to human health, improved operational efficiency, reduced costs, improved productivity, and higher quality maintenance and customer satisfaction [8].

AI coupled with improved hardware technology can rapidly process the data of any system, which can easily be acquired by the IoT to make effective use of AI technology. By collecting specific information about the environment and presenting the results to users, humans can make decisions about their wasteful habits, can identify trends of energy mismanagement, and can correct practices damaging to the Earth.

References

[1] Bradley D. Bogolea, Patrick J. Boyle, Andrei V. Shindyapin, “Artificial Intelligence-based Energy Auditing, Monitoring and Control,” WO Patent, 118,128, 18 Oct., 2007.

[2] C. Huntingford *et al.*, “Machine Learning and Artificial Intelligence to Aid Climate Change Research and Preparedness’,’ in *Environmental Research Letters*, vol. 14, no. 12, pp. 1-15, 2019.
[3] W. Tushar *et al.*, ”Internet of Things for Green Building Management: Disruptive Innovations Through Low-Cost Sensor Technology and Artificial Intelligence,” in *IEEE Signal Processing Magazine*, vol. 35, no. 5, pp. 100-110, Sept. 2018, doi: 10.1109/MSP.2018.2842096.
[4] H. Mirzaei, M. Fathollahi, and T. Givargis, ”OPEB: Open Physical Environment Benchmark for Artificial Intelligence”, in *Computing Research Repository*, vol. 1707.00790, Jul. 2017.
[5] Greg Niemeyer, Reza Naima, Antero Garcia, Eric Hugh Kaltman, ”Multimodal Climate Sensor Network”, U.S. Patent, 9,332,322, 3 May, 2016.
[6] M. Milano, B. O’Sullivan, and M. Gavanelli, “Sustainable Policy Making: A Strategic Challenge for Artificial Intelligence”, *AIMag*, vol. 35, no. 3, pp. 22-35, Sep. 2014.
[7] H. Kasim, R. Omar, M. H. B. M. Hilme, and A. M. Al-Ghaili, ”Future Fuels for Environmental Sustainability: Roles of Computing”, in *International Journal of Advanced Science and Technology*, vol. 28, no. 10,, pp. 87-95, Oct. 2019.
[8] M. Aazam, S. Zeadally and K. A. Harras, ”Deploying Fog Computing in Industrial Internet of Things and Industry 4.0,” in *IEEE Transactions on Industrial Informatics*, vol. 14, no. 10, pp. 4674-4682, Oct. 2018, doi: 10.1109/TII.2018.2855198.
[9] T. Rahman, X. Yao, G. Tao, H. Ning and Z. Zhou, ”Efficient Edge Nodes Reconfiguration and Selection for the Internet of Things,” in *IEEE Sensors Journal*, vol. 19, no. 12, pp. 4672-4679, 15 June, 2019, doi: 10.1109/JSEN.2019.2895119.
[10] M. M. Ali, ”Energy Efficient Architecture and Building Systems to Address Global Warming” in *Leadership and Management in Engineering*, vol. 8, no. 3, pp. 113-123, Jul. 2008, doi: 10.1061/(ASCE)1532-6748(2008)8:3(113).
[11] American Geosciences Institute, ”What are the major sources and users of energy in the United States?”, *American Geosciences Institute*. [Online]. Available: https://www.americangeosciences.org/critical-issues/faq/what-are-major-sources-and-users-energy-united-states [Accessed: June 24, 2020].
[12] Richard Evans and Jim Gao, ”DeepMind AI Reduces Google Data Centre Cooling Bill by 40%”, *DeepMind*, Jul. 2016. [Online]. Available: https://deepmind.com/blog/article/deepmind-ai-reduces-google-data-centre-cooling-bill-40. [Accessed: Jan. 18, 2020].
[13] Urs Hölzle, ”Data Centers Get Fit on Efficiency”, *Ethical Corp.*, June 2019. [Online]. Available: https://www.ethicalcorp.com/can-ai-light-way-smarter-energy-use. [Accessed: Dec. 13, 2019].
[14] Angeli Mehta, ”Can AI light the way to smarter energy use?”, *Reuters Events: Ethical Corp.*, June 2016. [Online]. Available: https://blog.google/outreach-initiatives/environment/data-centers-get-fit-on-efficiency/. [Accessed: Jan. 18, 2020].
[15] A. Dobrin, ”3 Approaches to Ethics: Principles, Outcomes and Integrity,” *Psychology Today*, 18 May, 2012.
[16] Nicholas Farmen, ”How AI Is Helping Solve Climate Change”, *Smashing Magazine*, Sept 2019. [Online]. Available: https://www.smashingmagazine.com/2019/09/ai-climate-change/. [Accessed: Sept. 21, 2020].
[17] Rosalind Hursthouse and Glen Pettigrove, ”Virtue Ethics”, *Stanford Encyclopedia of Philosophy*, Dec 2016. [Online]. Available: https://plato.stanford.edu/entries/ethics-virtue/. [Accessed: Sept. 21, 2020].
[18] Walter Sinnott-Armstrong , ”Consequentialism”, *Stanford Encyclopedia of Philosophy*, June 2019. [Online]. Available: https://plato.stanford.edu/entries/consequentialism/. [Accessed: Sept. 21, 2020].
[19] Larry Alexander and Michael Moore, ”Deontological Ethics”, *Stanford Encyclopedia of Philosophy*, Oct 2016. [Online]. Available: https://plato.stanford.edu/entries/ethics-deontological/. [Accessed: Sept. 21, 2020].