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Optimizing Energy Consumption in Smart Buildings Through Web-Integrated AI and Cloud-Driven Control Systems

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Abstract

The rapid development of smart buildings has contributed substantially to the effort of enhancing energy efficiency and reducing greenhouse emissions. Towards this end, the implementation of AI technologies and cloud-driven control programs that analyze and adapt building operations pose a natural next step. Smart buildings should leverage AI for continual energy-consumption-cycle ("ADVISOR") optimization through demand response, in-depth analytics, fault detection, predictive maintenance, and anomaly mitigation.

The extensive information generated by building-process automation and control (PAC) systems, such as supervisory control and data acquisition (SCADA) data, renders everyday operation and maintenance both complicated and time consuming. These information resources can, however, be exploited to systematically optimize the building's real-time energy consumption with the help of computer-based analytical artificial intelligence (AI) programs. The combination of a web-integrated AI system that monitors building processes and a cloud-based control-system platform that can dynamically manage operation responses is proposed to address the challenge of optimizing energy consumption in smart buildings.

Keywords: Smart buildings, energy optimization, integrated circuits, energy consumption optimization, cloud-controlled factory, cloud-controlled industry, cloud control, cloud control policy planning, web-integrated, web-integrated artificial intelligence system, web-integrated AI, web-integrated AI system, web-integrated artificial intelligence.

Introduction

Smart Buildings can be seen as the next step in the evolution of civilization. History has shown that technological advances open new possibilities and that, when those possibilities become feasible at the level of the general public, the entire environment changes. Increased automation reduces physical work. Wheels and roller bearings were already visible in a few civilizations of the ancient world, but the real revolution began in the Industrial Revolution. When industry started using them to reduce labor force, the entire world changed. It would be easy to improve the level of living for the entire population by using the current level of automation, but the distribution of wealth is deficient. The same happened with the introduction of electricity, the telephone, the radio and television, the computer. Time will surely correct it. Intelligence must be applied to the right places, at the right times, with the right criteria, so that it can really make a difference. It is said that smart buildings should provide increased comfort for their inhabitants. In reality, faced with climatic change, the level of energy optimization is much more important than the comfort factor.

The main problem of smart buildings is in the large amounts of expensive equipment used for optimization. An intelligent system should at least provide the possibility of integrating the interventions already made, in order to increase the comfort and optimize the energy consumption of the building. The optimization of energy consumption can be much improved by the use of techniques that operate at the level of artificial intelligence, which are capable of investigating the behaviour of the building over time and to establish the most efficient operation scenarios. Data can be collected using dedicated hardware, or directly on the web, if the energy producer also functions as a large trading platform. Then, only the decision should be made locally, significantly reducing costs.

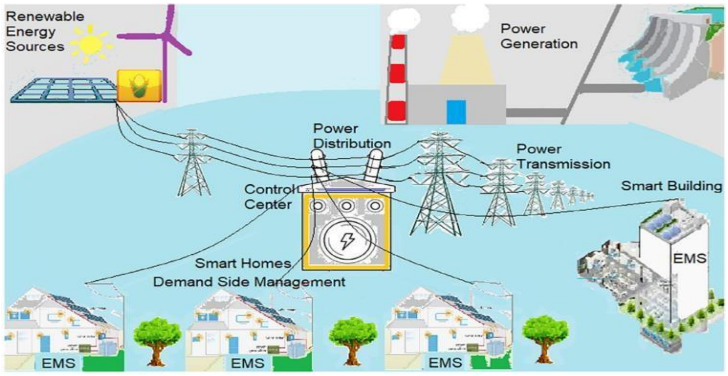

Fig 1: Integrating Smart Energy Management System with Internet

1.1. Background and Significance

Smart buildings optimize energy use through automated controls that draw on external context. For example, demand response adjusts energy consumption to reduce costs and maintain grid stability. Controls for energy-consuming assets can be adapted in response to signals from the electric grid or aversive signals such as demand spikes and price increases.
Automation systems often base asset operation on internal data such as occupancy, space temperature, and ambient lighting levels. Deeper relationships with energy supply systems are also important, however. Scenarios include smart grid signals that provide an indication of power availability, the carbon intensity of energy generation, and the state of home occupant demand or feedback. These signals can be used to shift consumption away from scheduling conflicts or from a low grid-availability period to a low-cost or low-carbon period. AI can be applied in combination with cloud-based control systems to detect and diagnose blocking faults, provide a fault response, and reduce energy consumption during operation.

Equ 1: Multi-Objective Optimization

$$\max_{\mathbf{z}} \sum_{j=1}^{m} w_j f_j(g(\mathbf{z}))$$

Let:

- $f_1, f_2, \ldots, f_m$: Predicted properties
- $w_1, \ldots, w_m$: Weights or preferences

2. Background

Smart buildings incorporate technologies—sensors, data networks, software platforms, and control mechanisms—that transform traditional buildings into dynamic responsive environments. The building environment is monitored at various locations using diverse sensors that track conditions such as temperature, lighting levels, window status, humidity, and occupant presence. The data are transmitted and stored in centralized databases for analysis by software systems that recommend changes to the control architecture or implement changes automatically through the control mechanisms.

The high concentration of electrical energy consumption in cities is evident, with buildings accounting for 65–70% of total electricity demand. Up to 30–50% of the operational cost of commercial buildings can be attributed to energy consumption, emphasizing the potential savings through intelligent energy control systems. Therefore, the smart building concept has received special attention in the context of energy conservation. The building environment variables directly affect occupant comfort, prompting the implementation of building subsystems activation policies designed to maintain comfort levels. However, maintaining occupant comfort can also be achieved by modifying the building subsystems operating characteristics, such as switching on a fan to improve air circulation within the building.sense of risk management is likely to be disastrous for owners and challenging for insurers. A property management company depends heavily on trust from owners. Lack of risk discipline and low dependence on owners are likely leaving property management without owners' trust. Long- standing distrust from owners could put the property in a taxing situation.

2.1. Overview of Smart Buildings

Smart building technology is considered one of the most important drivers of next-generation smart cities. Smart buildings can optimize operations and performance by connecting different systems and devices in the building for both real-time and automated control. With the shrinking of urban infrastructures, intelligent management and resource allocation become more and more important. Unlike traditional buildings, smart buildings support various services and functions that facilitate the efficient use of resources and improve occupant comfort and convenience.Integration with the Internet of Things, Artificial Intelligence, Big Data, Cloud Computing, and Cyber Physical Systems leads to the development of smart buildings. However, smart buildings account for 32% of the total final energy consumption in the world. Therefore, controlling/scaling down the energy consumption is becoming a critical challenge for smart buildings. The proposed system presents a smart building data collection and control system with an optimization model that takes advantage of the different load characteristics of a building and the building operation constraints to reduce the operating costs of the building.

2.2. Importance of Energy Efficiency

Advances in information and communication technologies (ICTs) have given rise to the emergence of smart buildings, provided with sensors, and the capability to react to the external environment. Smart buildings not only react to sensor inputs but also use external data sources to optimize the operations related to energy consumption. Energy efficiency and operation at low cost have become urgent needs in smart buildings. Energy- optimization approaches allow smart buildings to curtail energy consumption during expensive energy hours, while maintaining the comfort level of the occupants. The availability of smart device data in the cloud has opened new possibilities for building-automation systems.

Deep web-integrated artificial-intelligence techniques can extract patterns from the available data in the cloud and provide pre-made control-commands for the smart devices, which can interact with the devices through device APIs. Pattern-identification and control-command generation are expensive and time-consuming tasks and are best performed in deep web-based systems where large CPU and-memory resources are available. These control commands are sent to the smart buildings in real time, based on the anomaly detection or demand-response scenario.

Equ 2: Cloud-Based Model Training & Deployment

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla \mathcal{L}_t$$

Let:

- θ_t: Model parameters at time t
- η: Learning rate
- $\nabla \mathcal{L}_t$: Gradient of loss

3. Web-Integrated AI Systems

Smart buildings must adjust their energy consumption adaptively in response to real-time pricing signals issued by utilities. Advanced AI-based web interaction can provide a workable framework for data gathering, data mining, data deduction and interactive resource control. These functions are essential to smart buildings when mitigating energy consumption and operational cost. A cloud-driven control system needs to be established to adjust the power consumption of electrical appliances within a building, especially plug-in electrical appliances, in real time through response to fluctuations in electricity prices.

In an intelligent building environment, a large number of electric loads—such as air-conditioning systems, fork-lits, lift trucks, vending machines, LCD TVs, printers and photocopiers—are connected to the smart grid, which provides the utility for these electric loads to operate. The power consumed by these electrical appliances can be scheduled according to real-time rates in order to minimize the total electric cost. For example, during busy-periods, demand is generally high and the electricity rates charged by utilities increase accordingly. If the power stored in the appliances during the off-peak periods can be utilized in the busy-periods, a demand-response operation can be achieved and the costs to customers as well as within the operating system of the utilities can be reduced.

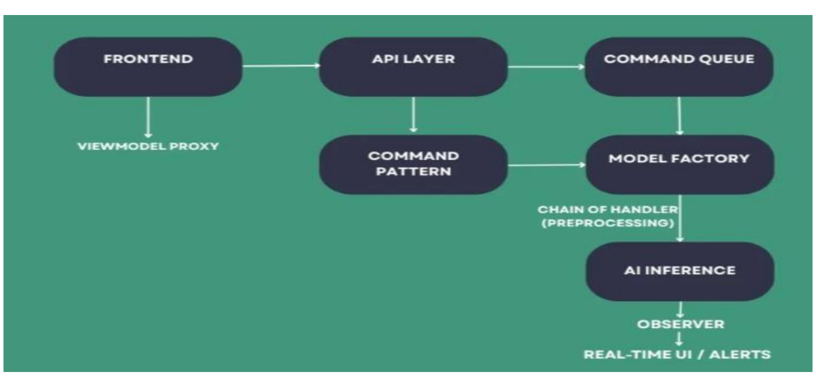

Fig 2: Architecting AI-Integrated Web Applications

3.1. Architecture of Web-Integrated AI

The electricity grid is one of society's most critical infrastructures. Providing electricity 24/7 supports all other major infrastructures, such as water and food. Even short outages can have major public health and economic implications. During extreme weather events, people tend to hunker down in their residence, drastically increasing energy use and the likelihood of brownouts and blackouts. It is therefore imperative to balance demands on the grid during these times. Given that buildings comprise 40% of US energy use and produce the greatest greenhouse gas emissions, more efficient control of building energy consumption through the use of artificial intelligence is key to achieving these goals. Smart buildings of the future must minimize energy consumption and respond to grid events. A growing number of smart buildings collect data from a myriad of Internet of Things (IoT) devices. This data can be mined for patterns and used to predict and forecast events, but without a way to control buildings, the information goes unused. To close this loop, control of buildings is required in near real-time. λPIXIE is an intelligent energy optimization system that incorporates prediction nodes in the cloud to analyze sensor data and send control signals back to buildings for demand response, predictive maintenance, and day-ahead forecasting. This closed loop not only saves occupants money on utility bills but also increases the reliability of the grid by lowering peak load during extreme weather events.

3.2. Data Collection and Analysis

Intelligent buildings generally have a limited number of security breaches per year, so a security focus that would allow breaches for a short time frame in order to optimize energy consumption may be acceptable. This capability provides operations staff with a demand response or demand management capability on the building. Figure 7 illustrates the feeds to the predictive analytics and decision engine; a building may supply several feeds, among which are the occupancy counts, the operating status of HVAC and other mechanical equipment, the operational state of lights, and historical usage or consumption data for all utilities. Integration with other facility systems may generate additional information useful for load or energy optimization, e.g., the security system may provide information on persons who are kept in the building during a curfew. Web-integrated AI systems provide the front-end cadencing and visualization of the state-of-the-building information and analytics, leveraging the data-collection, analytics, and cloud-driven control system described below.
Figure 8 summarizes the cloud-driven control of the smart building. Integration with electrical-system signals from the utility or grid operator may provide price or curtailment requests, and corresponding real-time data-processing services may serve as flex-role or energy-optimization-control engines for the facility. Adaptive forecasting and trending of load within a facility provides input to asset-management services and predictive-maintenance services for building assets. Cloud control provides bidirectional integration with mechanical, lighting, and other building controls as well as electrical-system- measurement devices within a facility. Following the prediction that total smartphones on the planet will exceed the number of people, a smartphone app allows occupants to adjust lighting or HVAC operation within their building locations.

Equ 3: Web-Based Interaction and Feedback

$$\mathcal{D}_{\text{aug}} = \mathcal{D} \cup \{(M_i, A(u, M_i))\}$$

Let:

- U: Set of platform users
- $A(u, M_i)$: User u's annotation or feedback on molecule M_i
- $\mathcal{D}_{\text{aug}}$: Augmented dataset with user feedback

4. Cloud-Driven Control Systems

Smart buildings have become a prime target for energy consumption reduction. A Web-integrated Artificial Intelligence (AI) helps modeling the behavior of a smart building given all the data collected, while a control system executed in the cloud acts on the energy consumption of the building in order to improve its building energy efficiency. The main challenge in the development of an energy optimization system is the way consumed energy is managed. The next step for energy reduction is acting on the parameters which determine that consumption. Smart building control systems must adapt to their occupants while maintaining a balance between low energy consumption and high level of comfort inside the building.

The expected large deployment and penetration of sensors in buildings will enable efficient information flow about building occupancy. It will be used as a basis for building control systems that, by reacting dynamically to changing conditions, will lead to a more effective use of energy. The Comprehensive Inspirational Energy Management System Using Building Energy Optimization (CIMES-BEO) demonstrates the integration of flexible demand response of buildings through the cloud by applying data collected in other CIMES components. Adding energy consumed by a piece of equipment and related data to the existing database enables the use of data mining algorithms to extract useful information that will contribute to the improvement of energy consumption as well as equipment maintenance in facilities. Among the most important key performance indicators for the Building Automation (BA) devices and equipment are the Energy Consumption Index and the Number of Activities per day.

4.1. Cloud Infrastructure Overview

A cloud infrastructure provides the fundamental virtualized resources of processing power, memory, networking, and storage. These resources can be either elastic or nonelastic. Elastic services can be dynamically added or removed to allow the client to scale its services up or down. The cloud infrastructure allows a service provider to build large data centers that can offer services that either use the built-in elasticity of the infrastructure to respond to variable workloads or serve a fixed number of users with the stable internal workloads. A demand response framework can offer several benefits to inhabitants of a smart building. Some of these benefits can be realized by the inhabitants during the demand response event hours by actively participating in demand response events. Others can be realized by participating in type 2 demand responses, which aim to reduce energy usage by determining the necessary device maintenance needs before they happen. Development of a web- integrated artificial-intelligence-based buildings energy-consumption-optimization system with a cloud-driven control framework enables these benefits.

4.2. Real-Time Data Processing

Two key elements of a web-integrated AI system provide the capabilities necessary to achieve higher levels of energy consumption optimization. First, the complete set of AI algorithms encapsulates the knowledge for analyzing, quantifying, predicting, classifying, and preparing the large amount of data.
Second, a cloud infrastructure supports the collection of a wide range of data as real-time information from the agent network, as well as the detailed control of the agent network based on the information processed by the AI algorithms. The data provided to the client is processed through the entire framework—from data collection and algorithm processing to key mathematical computations. A responsive and interactive system can be implemented via the networked device in every room.

The building supervisor and lower-level controllers run on specialized server hardware. The building supervisor can be located in the cloud, with the lower-level controllers resident in a dedicated server room in the building. The building supervisor receives data from the lower-level controllers and analyses the pattern of energy consumption. When it detects inefficient energy use, it sends a request to the lower-level controllers for a change of operation. Alternatively, the building supervisor can run locally, identifying shifting patterns of energy use. The building supervisor is also responsible for querying and aggregating information from other buildings, presenting each building manager with a ranking of its own energy consumption pattern during the last time window.

Equ 4: Sensor Data Acquisition

$$\mathbf{s}(t) = \mathrm{SensorReadings}(t)$$

Let:

- t: Time index
- $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_n(t)]$

5. Energy Consumption Optimization Strategies

A variety of strategies can be implemented to reduce smart building energy consumption, approaching the problem from different directions. Demand response is a popular method for alleviating the electrical grid during spikes, and energy utilities reward the consumer financially for willingness to reduce demand. Demand response is challenging, however: it requires extreme caution regarding energy used by the building and with all equipment controls.
Because the situation is dynamic and volatile, an aggregator must ensure that building demands meet the requirements for stability of the grid at all times.

5.1. A second approach is the implementation of predictive maintenance.

Efficient operation can be maintained via regular equipment maintenance. Even when all equipment operates well, conditions may suggest a need for acceleration in replacement and maintenance. Unlike demand response, which focuses on generating savings during those peak demand spikes, predictive maintenance avoids spikes and sudden surges of electrical consumption simply by ensuring that all equipment works in perfect condition. Surveys and equipment diagnostic evaluations offer leaks and defective parts detection, allowing regular maintenance scheduling following a priority based on the loads and electricity consumption level of the building.

Demand Response Techniques

Demand response techniques enable buildings to actively adjust their energy consumption in response to fluctuating electricity prices, thereby alleviating stress on the power grid during peak demand periods. Real-time price signals serve as triggers for modifying the operation of non-critical energy loads— such as air conditioning and heating, ventilation and air conditioning (HVAC) systems, electric lighting, and battery storage—resulting in cost savings for facility operators and mitigation of the grid's peaks.

Web-integrated AI systems monitor both electricity consumption and corresponding prices, identify periods warranting load reduction, evaluate the importance of ongoing load usage, control non-critical devices to minimize consumption during peak periods, and assess the effectiveness of these interventions. Simultaneously, cloud-driven control systems leverage up-to-the-minute grid conditions and real-time price data, corroborate warnings from AI analyses, execute demand-response commands, and determine the relative importance of connected loads before dispatching control directives to the load management controllers for execution.

5.2. Predictive Maintenance

Numerous innovative maintenance strategies have emerged since the Industrial Revolution, encompassing predictive maintenance, condition-based maintenance, remote maintenance, and reliability-centered maintenance. These methodologies rely heavily on the advent of technological intelligence and associated infrastructures, which facilitate the implementation of such activities. Predictive maintenance aims to schedule maintenance actions based on the actual condition of the assets, thereby optimizing their availability. These methods have gained traction not only in the realm of smart manufacturing but also, albeit to a lesser extent, in smart buildings.

Smart building systems are highly susceptible to various shades of faults and operational failures, periodically impacting tenant comfort and engendering substantial nonessential power consumption. A considerable fraction of such incidents can be averted or substantially mitigated through lethal assessment and strategic implementation of predictive maintenance operations. The proposed web-integrated artificial intelligence system in conjunction with a cloud- driven control framework effectively addresses such malfunctions either by timely alerting the concerned central building administration or by automatic isolation of the faulty loads, thereby averting discomfort and unwarranted expenses.

Equ 5: Feature Engineering for AI Modeling

$$\mathbf{x}(t) = \begin{bmatrix} s_1(t) \\ \frac{1}{\tau}\sum_{k=0}^{\tau-1} s_2(t-k) \\ \mathrm{Hour}(t) \\ \cdots \end{bmatrix}$$

Let:

- $\mathbf{x}(t) = f(\mathbf{s}(t))$: Feature vector derived

This could include:

- Moving averages
- Time-of-day encodings
- Lagged variables

6. Case Studies

Smart Building Services with Web-Integrated AI Systems for Energy Consumption Optimization in Smart Buildings are sources of valuable, highly detailed data about the operation of the buildings and the consumption systems—such as heating, ventilation, and air conditioning (HVAC)—located inside of them. At the same time, Cloud-Driven Control Systems for Energy Consumption Optimization in Smart Buildings can consume the data of these services and provide control directives that optimize power consumption. When demand response is applied, many smart buildings equipped with these technologies can adjust their collective energy consumption so as to keep the grid in balance. Other optimization strategies, such as predictive maintenance or innovative lifecycle management, become possible as well.

The described approach relies on the services provided by the aforementioned Smart Building Services with Web-Integrated AI Systems for Energy Consumption Optimization in Smart Buildings and the directives generated by the Cloud-Driven Control Systems for Energy Consumption Optimization in Smart Buildings. Two representative examples of such systems are presented here, offering a practical perspective on the use of integrated artificial intelligence for the optimization of energy consumption in smart buildings

6.1. Successful Implementations

Web-integrated Artificial-Intelligence and Cloud-Driven Control Systems are commonly implemented in several contexts. Modern commercial and public buildings can reduce peak consumption and control demand response by adjusting the power consumption of their central plant equipment to match internal demand. The control of lighting, heating, ventilation, and air conditioning (HVAC) can also be adjusted in real time to take advantage of off-peak prices and maximize the use of on-site power generation—and it can respond automatically to demand-response events. In residential buildings, such demand-response measures help deliver reliable power to buildings without adding costly new resources. Industrial applications include predictive maintenance, forecasting utility system demand and monitoring, and the evaluation of the energy use of new systems in the design and commissioning of buildings. Energy-optimization technologies that analyze consumption, detect anomalies, predict consumption, and influence-building consumption can find and eliminate wasted energy in both residential and commercial settings. Ideally, these approaches also provide a positive user experience by offering insights about how an occupant's behavior affects their energy consumption.

6.2. Comparative Analysis of Energy Savings

A recent survey studied the effectiveness of eleven smart building optimization and demand response methodologies compared in terms of energy saving percentages. The obtained results indicated that unsupervised energy optimization methods for smart buildings can contribute to savings of up to 72%, and that demand response can achieve up to approximately 64% savings. Demand response therefore demonstrated notable energy-saving potential in these studies. Furthermore, it is worth highlighting a regression model that predicted a potential 40% reduction in energy consumption for both residential and office buildings.
Various techniques for optimizing smart building energy consumption closely relate to energy efficiency and demand response. Important considerations when developing energy models include the impacts of factors such as humidity, temperature, sunlight, and occupant presence. Evidence of the efficacy of web-integrated AI systems in optimizing smart building energy use is also apparent in the literature.

Equ 6: AI-Based Energy Consumption Prediction

$$\mathcal{L}(\theta) = \frac{1}{T}\sum_{t=1}^{T}\left(E(t) - \hat{E}(t)\right)^2$$

Let:

- $E(t)$: Actual energy consumption at time t
- $\hat{E}(t)$: Predicted energy consumption
- $\hat{E}(t) = f_\theta(\mathbf{x}(t))$: AI prediction function with parameters θ

7. Conclusion

Energy consumption optimization—particularly demand-response (DR) management—is identified as one of the most promising strategies for smart buildings contributing to energy savings and emission reductions. Enabling smart buildings with flexible power trading and smart demand management requires a smart energy consumption optimization system that monitors, analyzes, and controls energy usage. Real-time building and environment status information and context awareness combined with AI-powered optimization can optimize energy use within a building.

The integration of web-based AI data analytics and cloud-driven control mechanisms layer on top of building Wi-Fi infrastructure—providing a low- deployment-cost, low-maintenance-cost solution—is described. This integrated web-and-cloud approach shows advantages over a local network architecture and control scheme.

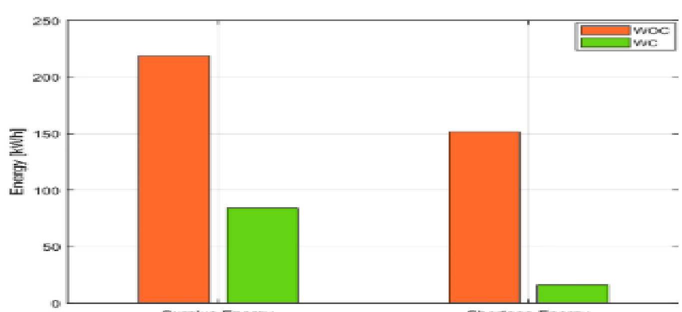

Fig: Energy management system in smart buildings based coalition game theory

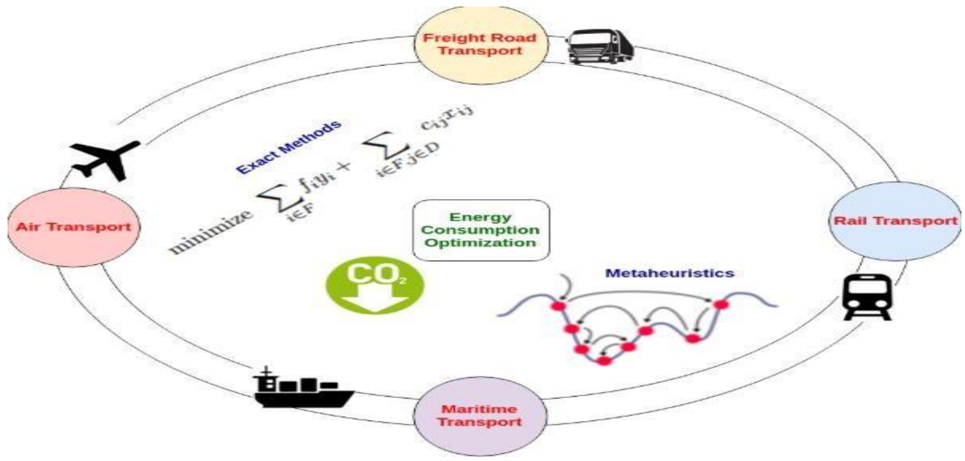

Fig 3: Optimizing Energy Consumption in Transportation

7.1. Future Trends

Buildings represent a significant fraction of the energy consumed in many locations. The continual growth of energy consumption, driven by a steady increase in the population and the affluence of the population, is expected to result in a 57% increase in world energy consumption between 2004 and 2030. The challenge of limiting this increase is the key driver towards the integration of intelligence into the operation of building systems.

Web-integrated AI mechanisms for optimizing energy consumption are expected to modify the comfortable environment of buildings with external conditions at a scale and grain finer than those previously used, acting to minimize the amount of energy supplied, and at the same time optimizing the demand scheduling in response to variable utility prices. Architecture for the application of AI incorporates the collection and analysis of external and internal data that determine a strategy for energy reduction. Control systems that operate the variable grid loads provide the capability to turn on, turn off, or shift the time of operation of load devices. Cloud-driven control allows the intelligence of these mechanisms to be located at the cloud level with only simple operational instructions distributed to load points, enabling dynamic interactions with changing conditions inside the building, as well as in the wider environment and the utility market conditions.

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