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Sustainable Energy Management Using Machine Learning

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Abstract

The global energy sector is encountering escalating difficulties, including rising demands for efficiency, shifts in supply and demand patterns, and a lack of optimal management analysis. Utilizing machine learning (ML) to process energy sector data can gradually address these issues. ML algorithms have the capability to analyze equipment data, construct predictive models, and address sustainability-related problems. In smart cities, the integration of machine learning algorithms enables automatic responses to fluctuations in electricity prices, facilitating effective control of energy consumption. Systems employing machine learning can assist energy suppliers in adapting to variable renewable energy supplies. Worldwide, there is a growing emphasis on low-emission energy sources, leading to increased installed capacities of solar photovoltaic, wind farms, and marine energy systems. Consequently, artificial intelligence and machine learning are poised to play a vital role in effectively managing the challenges of the energy sector. The implementation of micro-grids presents significant challenges that necessitate advanced control techniques like model predictive control (MPC). This paper focuses on employing MPC for energy management in micro-grids and aims to provide an up-to-date overview of the development of MPC methods for sustainable energy management.

Keywords: machine learning, predictive modelling, sustainable management

1. Introduction

In the last few decades, the world's energy sector is facing growing challenges, such as a demand and efficiency increase, supply and demand pattern change, and the absence of a best management analysis. In developing countries, this challenge is even more intense. Debnath K. B. (2018) claims that a large number of greenhouse gases is contributing a vital role to the global warming due to the burning of coal, oil and gas are creating a harmful greenhouse effect that is causing global warming and climate change. To combat this climate change, it is necessary to reduce produced greenhouse gases like CO2 emission from fossil fuel and to use alternate renewable energy sources (RES) like solar photovoltaic (PV) panels, wind turbines and water dams to generate electricity with very little cost of operation and green energy environment. Cities implementing green energy need smart grids to integrate both the sources of energy to get uninterrupted power supply and to optimize resource management by the data driven control system. On the other hand, As solar and wind power generation depends on sunshine and wind speed, there can be a shortfall or excess energy generation by RES. Thus, for continuous power supply to load and to avoid voltage and frequency fluctuation, the local onsite micro-grid is integrated into the main power grid called the macro-grid. When RES generates less power, the macro-grid will supply the remaining power and when RES generates excess power, it can sell it to the macro-grid. Excess energy by RES can also be stored in lithium-ion battery, but it is relatively expensive. For this reason, Erdinc, O. and Uzunoglu, M. (2012) from energy sector argue that there is a huge need to sustain our natural resources like coal, oil and gas for further energy production. Moreover, Cajot S, et al. (2017) states that the mentioned global energy and environmental challenges have led city governments to gradually modify their policies, decisions, and strategies towards greener and energy efficient approaches. The efficient use of energy could reduce energy demand, thus increasing monetary savings, reducing greenhouse gas, and improved energy security. Qiao, R. and Liu, T. (2020) developed a method to quantitatively predict the effect of greening on building energy consumption to support decision makers for implementing urban greening policy. From the economic and technical challenge point of view, the smooth running of the power system by switching between macro-grid to micro-grid is challenging. Weather data must accurately predict renewable energy production. Production of energy must foresee the demand of individual households and aggregated power consumption of a larger region. Overall power production, transmission, distribution and delivery to the consumer have to be more tractable, viable and cost-efficient for all parties like a stakeholder, government regulators, clients and consumers.

ML is prevalent in almost every renewable energy research (e.g., solar, wind, hydrogen, and hybrid) for optimization, design, management, estimation and distribution. The proposed AI algorithms for renewable energy research are complex and expensive. These models need to be simplified and cost-effective. Energy use information improvement with worker banks and other gadgets running constantly should be planned without cooling the energy and cost reserve funds. Energy forecasting and planning are important for different kinds of stakeholders for making the decisions of sustainable future energy development globally. The accuracy of energy demand forecasting models allows a great interest in different applications to avoid unexpected power blackouts as well as reduces the operating costs. ML models like support vector machines, artificial neural network, Gaussian processes, K-nearest neighbor and others overcome the problems of irregularity and complexity in modern energy. Below, we briefly introduce commonly used ML algorithms in energy related industrial applications.

2. Methodology

Machine learning is a set of techniques that can automatically distinguish patterns in data, and then to predict future data, or to perform other kinds of decision making under uncertainty. There are three main types of ML methods namely supervised learning (predictive), unsupervised learning (descriptive), and reinforcement learning. In these paper, we mainly focus on the first two types of ML algorithms. In the supervised learning methods, the purpose is to discover a mapping from inputs to outputs, given a labeled set of input-output pairs. In the unsupervised learning methods, while only the inputs are given, the purpose is to recognize interesting patterns in the data. Unlike supervised learning, this is a much less distinct problem, as there is no confidence of what patterns to look for, and there is no specific measure of error to use.

Decision tree algorithms

Kotsiantis S. B. et al. (2006) proposes a decision tree method to construct a model of decisions made based on actual values of attributes in the data. Decisions fork in tree structures until a prediction decision is made for a given record. Decision trees are trained on data for classification and regression problems. Decision trees are often fast and accurate and a big favorite in machine learning. The most popular decision tree algorithms are Classification and Regression Tree (CART), Chi-squared Automatic Interaction Detection (CHAID), Decision Stump, Conditional Decision Trees.

Bayesian Algorithms

Lowd D. and Domingos P. (2005) investigates Bayesian methods that explicitly apply Bayes' Theorem for problems such as classification and regression. The most popular Bayesian algorithms are Naive Bayes, Gaussian Naive Bayes, Multinomial Naive Bayes, Bayesian Belief Network (BBN) and Bayesian Network (BN).

Clustering algorithms

Clustering, like regression, describes the class of problem and the class of methods. Clustering methods are typically organized by the modeling approaches such as centroid-based and hierarchal. All methods are concerned with using the inherent structures in the data to best organize the data into groups of maximum commonality. The most popular clustering algorithms are: k-Means, k-Medians, Expectation Maximisation (EM) and Hierarchical Clustering

Artificial neural network algorithms

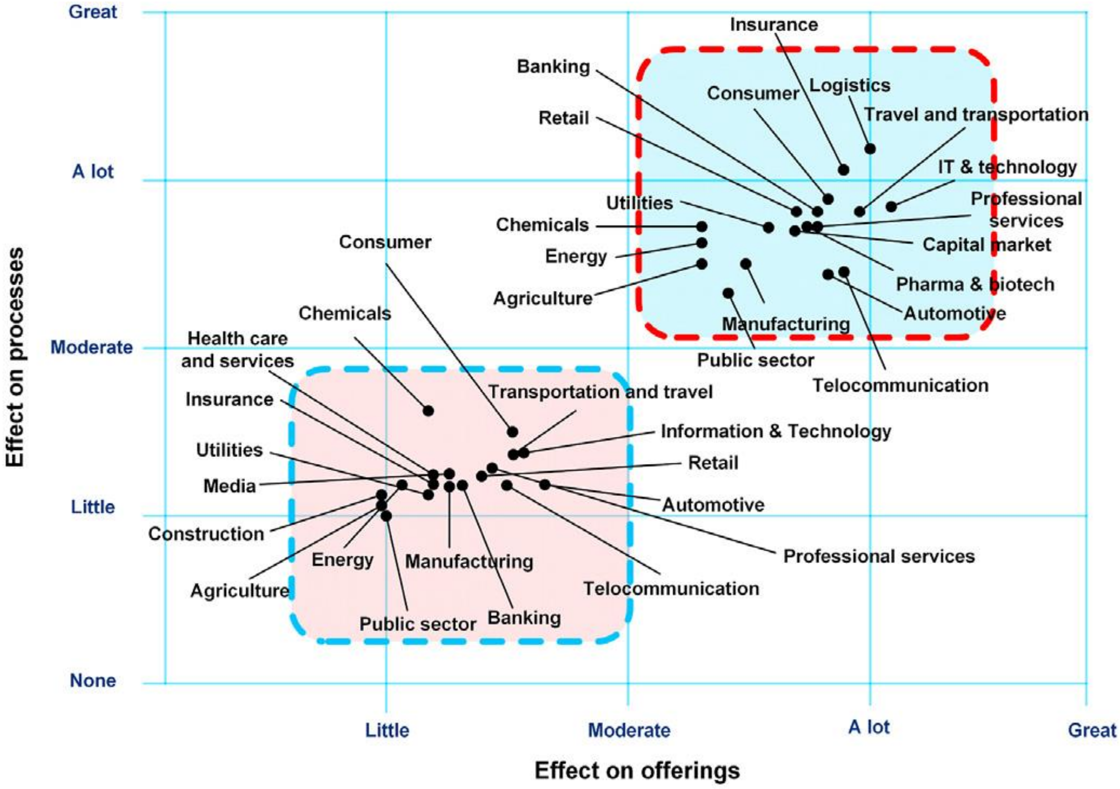
Artificial Neural Networks are models that are inspired by the structure and/or function of biological neural networks as implemented by Abdufattokhov S. et al. (2022). They are a class of pattern matching that are commonly used for regression and classification problems but are really an enormous subfield comprised of hundreds of algorithms and variations for all manner of problem types. The most popular artificial neural network algorithms are Single Layer Perceptron, Multilayer Perceptrons, Back-Propagation, Stochastic Gradient Descent, Hopfield Network and Radial Basis Function Network (RBFN).

The importance of predictive modeling in different energy source sectors

Renewable energy generation consists of dispatchable (synchronous) power such as hydropower and biomass, and variable (or asynchronous) generation such as wind and solar. While synchronous generation may be added seamlessly to the generation mix, the inclusion of asynchronous generation requires more care. The variable nature of such renewable sources makes the total output of the grid supply unpredictable, and their integration into the system leads to system instabilities. These two issues necessitate, amongst other things, the predictive modeling of variable renewable energy resources as well the use of new methodologies for enhancing system strength.

ML advancement has been building experimental machines to perform different kinds of intelligent behavior in the energy industry. The ML will be the heart of almost each major technological system such as power system cybersecurity, financial markets, payments, nuclear power plants, electrical grids, logistics, manufacturing, building construction and so on. Figure 1 shows the impact of AI on the energy and business sectors according to Abdufattokhov S. et al. (2022). We can see that energy is a very important parameter and that it will play a key role in the world economy in the near future. Expectations are higher for the impact of ML on energy businesses across different industries. The part of the red line in Figure 1 covers the impact of ML technology on different types of business over the next five years. The horizontal axis explicates the "Effect of offerings," and the vertical axis shows the "Effect of processes." The "Effect of Offerings" provides increased opportunities and impact of ML in different sectors (accept or reject as desired), and the "Effect of Processes" is a series of actions or steps taken to achieve a specific goal. Most organizations predict higher impacts on energy information technology (IT), manufacturing and operations, customer oriented activities, and supply chain management. Leaders of industrial companies expect to have a higher impact on the energy, manufacturing, and operation sectors. Besides, the leaders of different industrial companies expect the most significant impact on manufacturing and operations.

Figure 1: The influence of Machine Learning on both the energy and business domains.



3. Results and Discussions

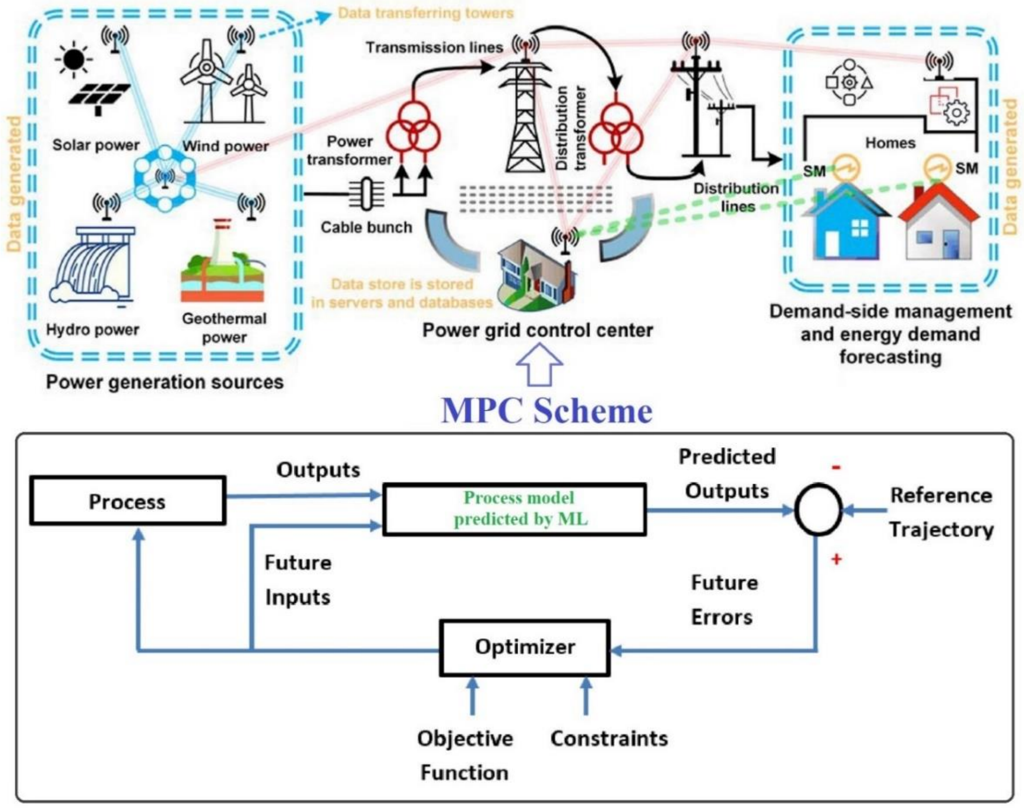
Modern power system automation is primarily concerned with three key technical aspects: maintenance, control, and technical management. The objective of power system control is to achieve optimal efficiency and network quality, while maintenance aims for high availability and reliability. Technical management, on the other hand, seeks to deliver a performance that encompasses both social and economic benefits. To fulfill the overarching goals of reliability, performance, and benefits, a comprehensive approach is required. This involves the development of an intelligent maintenance-control-management system that integrates these components seamlessly. Industry reports highlight that maintenance costs constitute a significant portion, ranging from 15% to 40% of total production costs. Moreover, a substantial portion of these costs, approximately one-third, is attributed to incorrect and unnecessary maintenance practices. Given the time and resources involved, there is a pressing need for the implementation of advanced predictive maintenance control to optimize the maintenance processes.

The Energy Management System (EMS) offers a diverse range of control solutions, ranging from straightforward heuristic strategies employing hysteresis operation mode by Zhonghai Ch. et al.(2023), approaches utilizing artificial intelligence through fuzzy logic by Naderi, E. et al. (2017), to intricate control algorithms designed for optimizing multi-objective functions by Abdufattokhov S. et al. (2021).

Among these methodologies, Model Predictive Control (MPC) stands out, proving effective in addressing complex control issues in the industry and gaining widespread attention and adoption within the research community. MPC is a multivariable control method grounded in optimization functions. With a suitable model of the plant in place, MPC theory strives to bring the predicted plant output as close as possible to the desired reference, considering the constraints supported by the plant. Over the past decade, control engineers have been actively working on integrating MPC with Machine Learning (ML) to overcome challenges in modeling system dynamics. For applications of MPC-based ML algorithms aimed at enhancing efficient energy management, readers can refer to sources proposed by Neto A. (2008) and Abdufattokhov S. et al. (2020).

ML tools play a crucial role in extracting valuable insights from new data, facilitating the control of intricate energy systems. The symbiotic relationship between big data and ML has become a daily necessity, as intelligent tools efficiently optimize and analyze the vast datasets generated by power systems. The integration of big data and ML tools significantly enhances various aspects, including planning and decision-making, inspections, condition monitoring, supply chain optimization, and accreditation. This, in turn, contributes to improving the efficiency and accuracy of modern energy systems. In Figure 2, the interconnected nature of large data and ML is visually represented, showcasing real-time applications in energy systems. The synergy between big data and ML proves instrumental in bolstering the reliability of energy systems. This includes ensuring the efficient utilization of renewable resources and storage, refining operations management, and optimizing asset maintenance. Moreover, the combination facilitates improved forecasting efficiency for equipment, such as predicting renewable energy generation by aggregating data from sources like wind, solar, hydro, geothermal, and tidal, and integrating it with environmental data.

Figure 2: Big data and ML based MPC applications.



The collaborative use of big data and AI further benefits safety and demand management. For instance, it aids in outage response and forecasting, predicts the consumption and generation patterns of small customers and producers, and contributes to ensuring a positive consumer experience. This encompasses meeting consumer load demands while enhancing overall satisfaction.

4. Conclusion

This research primarily centers on the application of machine learning methods in various sectors of renewable energy sources to promote sustainable development. The mentioned studies highlight diverse fields where machine learning technology has been employed to exemplify green engineering practices. The common thread in most of these studies is the overarching goal of enhancing effectiveness without causing harm to the environment. The core focus lies in the integration and optimization of renewable sources through machine learning technologies within the power grid. This integration aims to enhance the resilience, reliability, stability, efficiency, and overall management of the power system, including load planning. The utilization of machine learning in these contexts holds the potential to drive advancements in green energy practices.

Moving forward, future research will delve deeper into exploring additional machine learning methods to ascertain the most suitable approach for specific fields, be it electricity, water, crop analysis, and beyond. This ongoing exploration seeks to further refine and tailor machine learning applications to the unique requirements of each sector, contributing to a more comprehensive and effective utilization of renewable energy sources for sustainable development.

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