Building Management Systems and Operation

Subjects: Automation & Control Systems

Contributor: Panagiotis Michailidis, Iakovos Michailidis, Socratis Gkelios, Elias Kosmatopoulos

Artificial neural networks (ANNs) have become a cornerstone in efficiently managing building energy management systems (BEMSs) as they offer advanced capabilities for prediction, control, and optimization.

Keywords: artificial neural networks ; building energy management ; model-free control ; energy efficiency ; buildings ; predictive energy modeling

1. Motivation

Energy systems are fundamental elements in establishing desirable living standards in modern buildings as they significantly impact the comfort and well-being of occupants. With precise temperature control, optimal lighting, and efficient air circulation, a building transforms into a space that promotes comfort, health, and productivity, elevating the living and working experience within the structures [1][2][3][4][5][6][7][8]. However such systems inevitably render buildings, as significant energy consumers, as devastating sources of impact on the environment degradation that is affecting the quality of life outdoors. Given the growing emphasis on sustainability and the rising cost of energy, the efficient control of such systems has become paramount. Improving their operational efficiency may lead to significant energy savings, lower operational costs, and a reduced impact on the environment [9][10][11][12].

To address such challenging demands, several control approaches have been developed over the years. Traditional methods, such as the ON/OFF control or even rule-based controls (RBCs), have provided a foundational approach to energy management with substantial advantages in energy efficiency and comfort [13][14][15]. However, while these straightforward strategies offered initial benefits in terms of simplicity and ease of implementation, they often fall short in considering optimization and adaptability aspects. Limited by the integrated predefined rules, such frameworks have proven insufficient in adapting toward dynamic building conditions and occupant preferences. Without the capacity to manage the intricate interactions of building systems and external influences like weather changes, these approaches often lead to inefficiencies, heightened energy usage, and compromised comfort for occupants [15][16][17][18][19]. Such a challenge grows even further by integrating demand response approaches, which require quick changes based on grid demands, or RESs in buildings, which hold significant unpredictability [20][21][22][23].

Emerging from these foundational methods, intelligent adaptive and predictive methodologies have begun to gain significant interest in various fields of research [24][25][26][27]. Such control strategies offer a more refined approach for balancing energy efficiency and comfort in BEMSs by adapting to changing conditions and learning from data, ensuring optimal energy use without compromising comfort [28]. By processing real-time information and making predictive adjustments, such intelligent systems have proven adequate in providing a harmonized solution, outpacing traditional control methods in both efficiency and user satisfaction [29][30][31][32][33].

Within the context of intelligent control for systems like BEMSs, two primary segments are often highlighted: model-based and model-free control strategies [34]. Model-based approaches rely on accurate mathematical models of the system being controlled. These models describe how the system behaves under different conditions, allowing for predictive and optimized control [35][36][37][38]. Techniques such as model predictive control (MPC) are classic examples of this approach [39]. Model-free approaches, on the other hand, do not depend on an explicit model of the system. Instead, they learn directly from data or experiences, adapting their control strategies over time. Primary examples of model-free approaches concern reinforcement learning (RL), deep reinforcement learning (DRL), neural networks, fuzzy logic, or the hybrid approaches between them. **Figure 1** portrays the prevalence of each model-free approach for the 2015–2023 period [40][41][42][43].

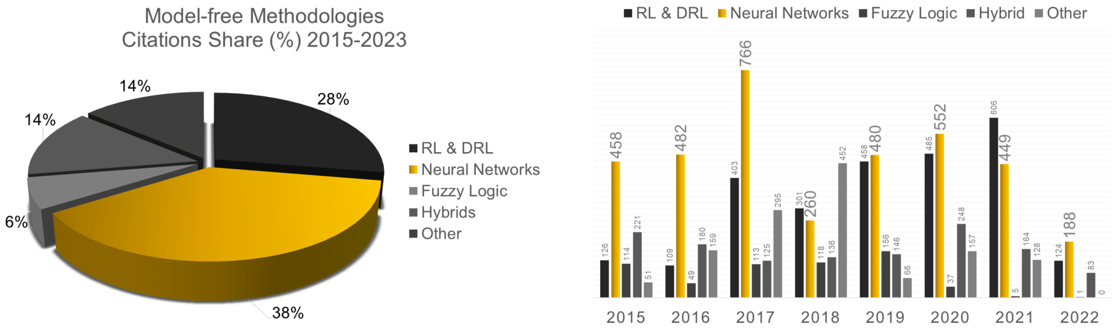

Figure 1. The Model-free HVAC control citations share (%) per methodology (**left**) and the HVAC citations count per methodology (**right**) for the 2015–2023 period.

One particular segment of the model-free control considers the mathematical framework of ANNs. Inspired by the human brain's processing capabilities, it has the potential to be trained, to learn from data, and to adapt over time. Unlike many traditional and intelligent methodologies, ANNs do not require explicit programming or extensive system knowledge [44][45][46]. Leveraging their capability to identify patterns, such mathematical frameworks become exceptionally proficient at predicting energy system behaviors in dynamic environments such as buildings. According to the literature [47], ANNs have shown a remarkable ability in handling non-linearities, uncertainties, and multi-variable systems, often outperforming other techniques in terms of accuracy and adaptability. Their capacity to integrate vast amounts of data, from various sensors and sources, and to derive actionable insights sets them apart [48][49][50]. The potential of ANNs in BEMSs has been further enhanced with the introduction of deeper neural network architectures that consider large-scale mathematical structures that are able to capture complex relationships and patterns in vast amounts of building data [51][52][53]. Such frameworks allow for even more accurate insights into building dynamics, from occupant behavior to equipment inter-dependencies. This evolution in control strategy, driven by deep learning, heralds a new era for BEMSs, where energy savings and comfort are optimized and adapted to both external factors and internal demands [49]. **Figure 1** illustrates the importance of an ANN-based control as a mandatory model-free approach for HVAC systems (2015–2023), which portrays the most common BEMSs in building structures [34]. At this point, it should be noted that deep learning principles may extend beyond traditional artificial neural networks (ANNs), such as through incorporating elements from other machine learning methods such as regression, random forests, and SVMs.

Yet, as with any technology, ANNs are not without their challenges as training them requires a considerable amount of data, and ensuring their robustness and reliability in real-world scenarios remains a pressing concern. Moreover, their black box nature may raise concerns, particularly in critical systems where understanding the rationale behind decisions is crucial [49][51].

Motivated by the extended use of ANNs for predicting and optimizing energy system behavior in buildings in a building environment, the current work evaluates several highly cited ANN-based works from 2015–2023, and it considers the optimization of different BEMSs, such as HVAC, DHW, LS, and RES frameworks, along with their integrated applications. By analyzing different ANN methodologies and concepts, the primary aim of the current work is to gather, categorize, and evaluate their different attributes, as well as to consider the aggregated studies and to provide a thorough evaluation of the different patterns and trends that the ANN control frameworks exhibit toward BEMSs. Identifying such patterns is essential for identifying future directions, to obtain meaningful conclusions regarding the capacity and potential of ANN-driven applications in BEMSs, and to deliver a comprehensive overview of the particular control domain.

2. Primary Building Energy Management Systems Types

BEMSs are crucial for the automation and optimization of energy use within a building's various systems. ANNs play a pivotal role in such devices by enabling the predictive control and optimization of energy usage. They analyze historical and real-time data to forecast energy demand, enhancing the efficiency of heating, cooling, and lighting equipment. ANNs also adapt to changing environmental conditions and user behaviors, ensuring optimal energy consumption while maintaining the comfort levels in buildings. The following attributes break down the operation of the most common BEMSs and illustrate their challenges regarding the relative ANN applications [7][54]:

- **Heating, Ventilation, and Air Conditioning (HVAC):** HVAC systems regulate the indoor climate to maintain comfort. They are complex with fluctuating loads and numerous sub-components, thus making them prime candidates for ANN-based optimization. The challenge lies in creating sufficient ANN models to accurately predict thermal loads and system responses to various conditions. ANNs need extensive training data to capture all possible scenarios, including seasonal changes and occupancy patterns.

- **Domestic Hot Water (DHW):** DHW systems provide hot water for residential or commercial use. ANN-based controls for DHW systems may predict hot water demand and optimize energy use while ensuring availability. The challenge is to model the sporadic usage patterns and integrate them with other systems like solar heating, which can be unpredictable due to weather variations.

- **Lighting Systems (LSs):** Smart lighting controls adjust based on occupancy and ambient light levels. ANN can optimize lighting for energy savings while maintaining comfort. The challenges include the need for real-time responsiveness to sudden environmental changes and accurately modeling human presence and movement patterns.

- **Renewable Energy Systems (RESs):** These include photovoltaic panels, wind turbines, etc., which supply sustainable energy. ANN-based controls are adequate for predicting energy production and managing storage or grid exports. Challenges arise from the inherent unpredictability of renewable sources and the complexity of integrating them with traditional energy systems. (It should be mentioned that, while RESs like wind and solar power are inherently variable, advancements in weather forecasting and predictive analytics have greatly improved their predictability. This technological progress enables more reliable energy production forecasts, thereby mitigating the impact of their natural unpredictability. Thus, the integration and stability of renewable energy in power systems are continuously enhancing).

- **Energy Storage Systems:** Batteries and thermal storage systems are used to balance supply and demand. ANNs may provide predictions of when to store energy and when to release it based on predictions of future energy prices and demand. The main challenge is the dynamic nature of energy markets and consumption patterns.

- **Integrated Building Management Systems (IBEMSs):** IBEMSs concern the integration of multi-device systems, including the abovementioned BEMSs, or any other appliances in the building environment, for holistic building energy management.

The multiverse role of ANNs with respect to the different BEMSs are summarized in the following **Figure 2**.

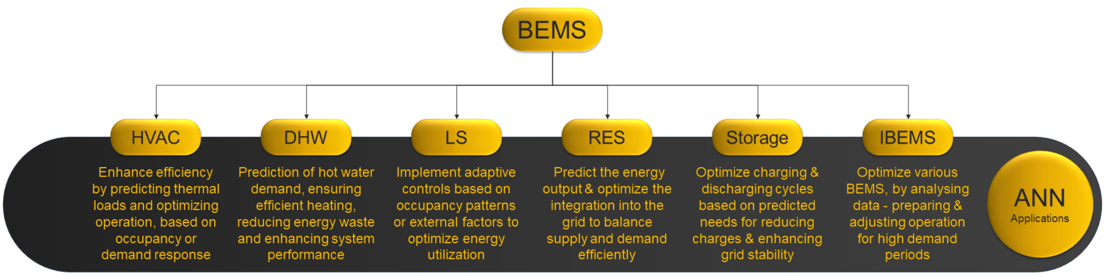

Figure 2. The role of ANN applications for BEMS control and optimization.

3. General Description of Artificial Neural Network-Based Control in Building Energy Management Systems

In order to provide the abovementioned functionalities for the different BEMSs, ANNs may be utilized in a specific manner. To this end, the general operation of ANNs in controlling the different BEMS frameworks typically follows a process of data collection, model training, prediction, and control action. The following **Figure 3** provides a diagrammatic representation of the process:

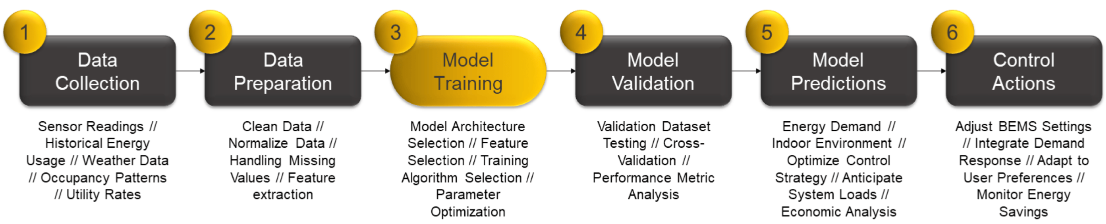

Figure 3. The general scheme of ANN-based control for building management systems (BEMSs).

More specifically, the five-step methodology of **Figure 3** integrates the following aspects:

- **Data Collection:** This involves gathering BEMS-related real-time data from environmental sensors, energy meters, and other IoT devices, along with historical energy usage patterns, current weather conditions, occupancy levels, equipment status, and utility rates. These data form the basis for making informed decisions.
- **Data Preparation:** The raw data undergo rigorous cleaning to rectify inconsistencies and fill gaps, and this is followed by feature engineering to highlight relevant predictive factors. This process is crucial for fostering the ANN's predictive accuracy, thus ensuring it receives quality input for optimal energy management performance.
- **Model Training:** In this step, the ANN is configured and trained using historical data, weather forecasts, and feature selection to recognize patterns and dependencies. The ANN architecture is designed and the parameters are optimized.
- **Model Validation:** In this stage, a dedicated validation dataset is utilized to evaluate the model's predictions, while cross-validation ensures the model's performance is consistent across different subsets of the data. A performance metric analysis is conducted assessing accuracy, precision, and other relevant metrics to gauge the model's predictive power.
- **Model Predictions:** The trained model is then used to forecast future energy demand, predict indoor environmental conditions, and perform optimization with the help of the model predictive control. This includes determining the best start and stop times for equipment, anticipating system loads, and conducting economic analysis for cost-saving measures.
- **Control Actions:** The final step is where the BEMS acts on the ANN and outputs to the control the building's energy systems. This includes adjusting HVAC settings, regulating lighting, operating shades and blinds, managing RES, integrating demand response strategies, adapting to user preferences, and monitoring/reporting on energy savings to stakeholders.

References

1. Badar, A.Q.; Anvari-Moghaddam, A. Smart home energy management system—A review. Adv. Build. Energy Res. 2022, 16, 118–143.
2. Zhou, B.; Li, W.; Chan, K.W.; Cao, Y.; Kuang, Y.; Liu, X.; Wang, X. Smart home energy management systems: Concept, configurations, and scheduling strategies. Renew. Sustain. Energy Rev. 2016, 61, 30–40.
3. Kim, H.; Choi, H.; Kang, H.; An, J.; Yeom, S.; Hong, T. A systematic review of the smart energy conservation system: From smart homes to sustainable smart cities. Renew. Sustain. Energy Rev. 2021, 140, 110755.
4. Beaudin, M.; Zareipour, H. Home energy management systems: A review of modelling and complexity. Renew. Sustain. Energy Rev. 2015, 45, 318–335.
5. Fayyaz, M.; Farhan, A.A.; Javed, A.R. Thermal comfort model for HVAC buildings using machine learning. Arab. J. Sci. Eng. 2022, 47, 2045–2060.
6. Prakash, A.; Shrivastava, A.; Tomar, A. An Introduction to Smart Building Energy Management. In Control of Smart Buildings: An Integration to Grid and Local Energy Communities; Springer: Singapore, 2022; pp. 1–13.
7. Vamvakas, D.; Michailidis, P.; Korkas, C.; Kosmatopoulos, E. Review and Evaluation of Reinforcement Learning Frameworks on Smart Grid Applications. Energies 2023, 16, 5326.
8. Marinakis, V. Big data for energy management and energy-efficient buildings. Energies 2020, 13, 1555.
9. Lee, D.; Cheng, C.C. Energy savings by energy management systems: A review. Renew. Sustain. Energy Rev. 2016, 56, 760–777.
10. Raji, B.; Tenpierik, M.J.; Van Den Dobbelsteen, A. The impact of greening systems on building energy performance: A literature review. Renew. Sustain. Energy Rev. 2015, 45, 610–623.
11. Verbeke, S.; Audenaert, A. Thermal inertia in buildings: A review of impacts across climate and building use. Renew. Sustain. Energy Rev. 2018, 82, 2300–2318.
12. Elaouzy, Y.; El Fadar, A. Energy, economic and environmental benefits of integrating passive design strategies into buildings: A review. Renew. Sustain. Energy Rev. 2022, 167, 112828.
13. Clauß, J.; Stinner, S.; Sartori, I.; Georges, L. Predictive rule-based control to activate the energy flexibility of Norwegian residential buildings: Case of an air-source heat pump and direct electric heating. Appl. Energy 2019, 237, 500–518.

14. Peña, M.; Biscarri, F.; Guerrero, J.I.; Monedero, I.; León, C. Rule-based system to detect energy efficiency anomalies in smart buildings, a data mining approach. Expert Syst. Appl. 2016, 56, 242–255.

15. Salpakari, J.; Lund, P. Optimal and rule-based control strategies for energy flexibility in buildings with PV. Appl. Energy 2016, 161, 425–436.

16. Stoffel, P.; Maier, L.; Kümpel, A.; Schreiber, T.; Müller, D. Evaluation of advanced control strategies for building energy systems. Energy Build. 2023, 280, 112709.

17. Michailidis, P.; Pelitaris, P.; Korkas, C.; Michailidis, I.; Baldi, S.; Kosmatopoulos, E. Enabling optimal energy management with minimal IoT requirements: A legacy A/C case study. Energies 2021, 14, 7910.

18. Michailidis, I.T.; Sangi, R.; Michailidis, P.; Schild, T.; Fuetterer, J.; Mueller, D.; Kosmatopoulos, E.B. Balancing energy efficiency with indoor comfort using smart control agents: A simulative case study. Energies 2020, 13, 6228.

19. Hossain, J.; Kadir, A.F.; Hanafi, A.N.; Shareef, H.; Khatib, T.; Baharin, K.A.; Sulaima, M.F. A Review on Optimal Energy Management in Commercial Buildings. Energies 2023, 16, 1609.

20. Charoen, P.; Kitbutrawat, N.; Kudtongngam, J. A Demand Response Implementation with Building Energy Management System. Energies 2022, 15, 1220.

21. Chen, X.; Li, J.; Yang, A.; Zhang, Q. Artificial neural network-aided energy management scheme for unlocking demand response. In Proceedings of the 2020 Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1901–1905.

22. Meng, Q.; Xi, Y.; Ren, X.; Li, H.; Jiang, L.; Yang, L. Thermal energy storage air-conditioning demand response control using elman neural network prediction model. Sustain. Cities Soc. 2022, 76, 103480.

23. Nicolosi, G.; Volpe, R.; Messineo, A. An innovative adaptive control system to regulate microclimatic conditions in a greenhouse. Energies 2017, 10, 722.

24. Lian, Y.; Shi, J.; Koch, M.; Jones, C.N. Adaptive robust data-driven building control via bilevel reformulation: An experimental result. IEEE Trans. Control. Syst. Technol. 2023.

25. Sun, Y.; Chen, X.; Wu, S.; Wei, W.; Wang, W.; Deng, S. Performance analysis of air source heat pump space heating system with an adaptive control for supply water temperature. Appl. Therm. Eng. 2022, 211, 118401.

26. Michailidis, I.T.; Manolis, D.; Michailidis, P.; Diakaki, C.; Kosmatopoulos, E.B. A decentralized optimization approach employing cooperative cycle-regulation in an intersection-centric manner: A complex urban simulative case study. Transp. Res. Interdiscip. Perspect. 2020, 8, 100232.

27. Yao, R.; Zhang, S.; Du, C.; Schweiker, M.; Hodder, S.; Olesen, B.W.; Toftum, J.; d'Ambrosio, F.R.; Gebhardt, H.; Zhou, S.; et al. Evolution and performance analysis of adaptive thermal comfort models—A comprehensive literature review. Build. Environ. 2022, 217, 109020.

28. Gholamzadehmir, M.; Del Pero, C.; Buffa, S.; Fedrizzi, R. Adaptive-predictive control strategy for HVAC systems in smart buildings—A review. Sustain. Cities Soc. 2020, 63, 102480.

29. Telsang, B.; Djouadi, S.; Olama, M.; Kuruganti, T.; Dong, J.; Xue, Y. Model-free control of building HVAC systems to accommodate solar photovoltaicEnergy. In Proceedings of the 2018 9th IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Charlotte, NC, USA, 25–28 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–7.

30. Biemann, M.; Scheller, F.; Liu, X.; Huang, L. Experimental evaluation of model-free reinforcement learning algorithms for continuous HVAC control. Appl. Energy 2021, 298, 117164.

31. Ahn, K.U.; Park, C.S. Application of deep Q-networks for model-free optimal control balancing between different HVAC systems. Sci. Technol. Built Environ. 2020, 26, 61–74.

32. Haddam, N.; Boulakia, B.C.; Barth, D. A model-free reinforcement learning approach for the energetic control of a building with non-stationary user behaviour. In Proceedings of the 2020 4th International Conference on Smart Grid and Smart Cities (ICSGSC), Osaka, Japan, 18–21 August 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 168–177.

33. Michailidis, I.T.; Schild, T.; Sangi, R.; Michailidis, P.; Korkas, C.; Fütterer, J.; Müller, D.; Kosmatopoulos, E.B. Energy-efficient HVAC management using cooperative, self-trained, control agents: A real-life German building case study. Appl. Energy 2018, 211, 113–125.

34. Michailidis, P.; Michailidis, I.; Vamvakas, D.; Kosmatopoulos, E. Model-Free HVAC Control in Buildings: A Review. Energies 2023, 16, 7124.

35. Gruber, M.; Trüschel, A.; Dalenbäck, J.O. Model-based controllers for indoor climate control in office buildings–complexity and performance evaluation. Energy Build. 2014, 68, 213–222.

36. Váňa, Z.; Cigler, J.; Širokỳ, J.; Žáčeková, E.; Ferkl, L. Model-based energy efficient control applied to an office building. J. Process. Control 2014, 24, 790–797.
37. Li, P.; O'Neill, Z.D.; Braun, J.E. Development of Control-Oriented Models for Model Predictive Control in Buildings. Ashrae Trans. 2013, 119, 1.
38. Lee, K.h.; Braun, J.E. Model-based demand-limiting control of building thermal mass. Build. Environ. 2008, 43, 1633–1646.
39. Fotopoulou, M.C.; Drosatos, P.; Petridis, S.; Rakopoulos, D.; Stergiopoulos, F.; Nikolopoulos, N. Model predictive control for the energy Management in a District of buildings equipped with building integrated photovoltaic systems and batteries. Energies 2021, 14, 3369.
40. Michailidis, I.T.; Kapoutsis, A.C.; Korkas, C.D.; Michailidis, P.T.; Alexandridou, K.A.; Ravanis, C.; Kosmatopoulos, E.B. Embedding autonomy in large-scale IoT ecosystems using CAO and L4G-CAO. Discov. Internet Things 2021, 1, 1–22.
41. Arroyo, J.; Manna, C.; Spiessens, F.; Helsen, L. Reinforced model predictive control (RL-MPC) for building energy management. Appl. Energy 2022, 309, 118346.
42. Ye, Y.; Qiu, D.; Ward, J.; Abram, M. Model-free real-time autonomous energy management for a residential multi-carrier energy system: A deep reinforcement learning approach. In Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence, Yokohama, Japan, 7–15 January 2021; pp. 339–346.
43. Zhang, B.; Hu, W.; Ghias, A.M.; Xu, X.; Chen, Z. Multi-agent deep reinforcement learning-based coordination control for grid-aware multi-buildings. Appl. Energy 2022, 328, 120215.
44. Zhang, H.; Feng, H.; Hewage, K.; Arashpour, M. Artificial neural network for predicting building energy performance: A surrogate energy retrofits decision support framework. Buildings 2022, 12, 829.
45. Rumelhart, D.E.; Widrow, B.; Lehr, M.A. The basic ideas in neural networks. Commun. ACM 1994, 37, 87–93.
46. Bishop, C.M. Neural networks and their applications. Rev. Sci. Instruments 1994, 65, 1803–1832.
47. Moon, J.W.; Kim, J.J. ANN-based thermal control models for residential buildings. Build. Environ. 2010, 45, 1612–1625.
48. Seo, J.; Kim, S.; Lee, S.; Jeong, H.; Kim, T.; Kim, J. Data-driven approach to predicting the energy performance of residential buildings using minimal input data. Build. Environ. 2022, 214, 108911.
49. Michailidis, P.; Michailidis, I.T.; Gkelios, S.; Karatzinis, G.; Kosmatopoulos, E.B. Neuro-distributed cognitive adaptive optimization for training neural networks in a parallel and asynchronous manner. Integr. Comput. Aided Eng. 2023, 31, 19–41.
50. Elbeltagi, E.; Wefki, H. Predicting energy consumption for residential buildings using ANN through parametric modeling. Energy Rep. 2021, 7, 2534–2545.
51. Ferreira, P.; Ruano, A.; Silva, S.; Conceicao, E. Neural networks based predictive control for thermal comfort and energy savings in public buildings. Energy Build. 2012, 55, 238–251.
52. Mahmoud, M.A.; Ben-Nakhi, A.E. Architecture and performance of neural networks for efficient A/C control in buildings. Energy Convers. Manag. 2003, 44, 3207–3226.
53. Amarasinghe, K.; Wijayasekara, D.; Carey, H.; Manic, M.; He, D.; Chen, W.P. Artificial neural networks based thermal energy storage control for buildings. In Proceedings of the IECON 2015-41st Annual Conference of the IEEE Industrial Electronics Society, Yokohama, Japan, 9–12 November 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 5421–5426.
54. Mason, K.; Grijalva, S. A review of reinforcement learning for autonomous building energy management. Comput. Electr. Eng. 2019, 78, 300–312.

Retrieved from https://encyclopedia.pub/entry/history/show/123312