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Review Article

Energy Consumption and Optimisation in Indoor Farming: A Review

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ABSTRACT

This review explores the key components of crop production and energy consumption in indoor farming, where it usually consists of systems such as LED lighting, ventilation (fans), humidity and hydroponics systems to offer controlled environments for crop growth. However, these systems consume large amounts of energy. Thus, it is necessary to reduce this energy consumption in crop production. This review examines three modelling approaches for energy optimisation, namely: white box (physics-based), black box (data-driven), and grey box (a hybrid of the two). Each method's strengths and limitations are discussed in terms of their application to indoor farming. The findings emphasise the importance of selecting the right optimisation model based on specific goals and resources, with the potential to significantly improve energy efficiency in indoor farming. Further research is encouraged to refine these models and support sustainable food production.

Keywords: Controlled environment, crop production, energy efficiency, lighting system, model types

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INTRODUCTION

Malaysia is a developing country where its urbanisation is faster than that of its Southeast Asian neighbours. The urbanisation of the country is expected to reach 88% in 2050. Urbanisation is a process where land is used to build tall buildings. Hence, there will be less space for agricultural activities in the cities. Arising from it, food security

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has become a problem. To ensure a sufficient food supply, food must be transported from rural areas. This will cause a rise in the food price. During the COVID-19 pandemic that affected 186 countries between December 2019 and March 2020, it was observed that there was a significant increase in the risk of severe food insecurity. The number of people facing such insecurity rose from 135 million in January 2020 to 265 million by the end of the year (Food Security Information Network, 2020). The pre-COVID era allowed food to be transported worldwide, and this mode was stopped suddenly during the outbreak of the pandemic. City lockdowns and shop closures have caused limited access to farm inputs such as seeds, fertilisers, and labour. This had resulted in low production of vegetables (Sridhar et al., 2023). According to Gregorio and Ancog (2020), the pandemic had caused the agricultural production volume in Southeast Asia during the first quarter of 2020 to reduce by 3.11% due to labour shortage and 100.77 million individuals were affected by it.

There is a solution proposed by Professor Dickinson Despommier (1999) to grow vegetables and fruits in the empty spaces in the cities, including rooftops, old buildings and factories. This concept is known as vertical farming. By the definition of the Cambridge Dictionary, vertical farming is the activity of growing crops in many layers, one above the other, inside a building or under the ground, often in a specially controlled environment. The statistics of the 2021 Global CEA Census Report showed that the common crops being grown in vertical farming included salad greens (58%), herbs (49%), microgreens (46%) and other leafy greens (40%).

There are several key components in a vertical farm. They are the multi-layer growing shelves, artificial lighting, air conditioning system, irrigation system (soil medium), hydroponic system (soilless medium) and ventilation system. In most vertical farming systems, hydroponic systems are used to replace soil as a growing medium that provides nutrients to the crops. Compared to conventional greenhouses or open fields, hydroponic farming requires a lot less fresh water. Due to the closed system, there is almost no evaporation and no runoff. A larger interest in vertical farming and hydroponic farming will emerge when fresh water becomes a rarer resource, reducing the requirement for water in agriculture.

One of the most concerning issues of the operation of vertical farming in the cities is the energy consumption. The operation of vertical farming consumes a large amount of electricity. Artificial lighting, temperature control, and hydroponics systems are the most energy-consuming components of an indoor farm. According to the 2021 Global CEA Census Report, vertical farms have a significantly higher average energy use at 38.8kWh per kg of produce as opposed to traditional greenhouses, which average 5.4kWh per kg of produce, which is about 7 times higher. In the same report, it was mentioned that the biggest sources of energy consumption in vertical farming are lighting (55%), cooling or ventilation (30%) and heating (11%). Several studies reported that the light-emitting diode (LED) alone accounts for about 55 to 65% of vertical farm operations. Electricity for lighting has been found to be the greatest energy consumer in vertical farms.

This paper has the following objectives: (1) to provide an overview of the energy usage of vertical farms; and (2) to identify the current research in the energy-saving methods of vertical farm operation. The advantages and disadvantages of each type of energy optimisation approach are also discussed in this paper.

REVIEW METHODOLOGY

To ensure a comprehensive understanding of the background and current state of vertical farming technologies, a search was conducted across four databases: Google Scholar, ScienceDirect, ResearchGate and Google Search (as a supplementary). The search was conducted using a few specific keywords, including: "vertical farming", "indoor farming", "hydroponics", "energy consumption", "lighting", "energy optimisation", and "energy saving". Most of the selected papers were published after 2015, except those that explained the most fundamental theory of related topics, such as the history of lighting and indoor vertical farming. After selection, the papers were categorised according to black-box, white-box and grey-box modelling approaches.

Cultivation Methods

Hydroponic System

Plants or crops can be grown without soil in this system. Instead of soil, the roots are immersed in a nutrient-rich water solution that supplies the nutrients. The use of water is effective. Since water resources are also scarce nowadays, the saving of water is also becoming the focus of the agricultural field. By 2050, more than half (57%) of the global population will live in regions where water scarcity occurs for at least one month each year (Boretti and Rosa, 2019). Soil cultivation consumes a large amount of freshwater. Therefore, a method to save water in the agricultural field is important. In indoor farming using hydroponics systems, 70 -95% of water can be saved (Mir et al., 2022). Romeo et al. (2018) also supported this statement by the findings, where hydroponic systems consumed water seven times lower than greenhouse and four times lower than open-field agriculture.

Aeroponics System

This is a type of soilless cultivation method where plant roots are suspended in a closed chamber and sprayed with nutrient solution to provide the essential nutrients for root growth. This method allows root access directly to oxygen and can have a faster growth rate compared to the traditional cultivation method. Aeroponics systems also reduce water consumption compared to soil-based cultivation. Another advantage of it is the minimal space usage that makes it suitable for application in cities where land availability is limited.

Aquaponic System

It is a symbiotic ecosystem where aquaculture and hydroponics are integrated in a recirculating environment. In this system, the waste from the fish provides an organic food source for the plants. The plant acts as a filter to purify the water, and then the water is cycled back to the fish tank. This symbiotic relationship reduces the need for fertilisers and allows for the opportunity of dual harvest of crops and fish.

Components of Vertical Farming

Lighting

By growing crops indoors, artificial lighting is essential to replace natural sunlight that provides energy for the photosynthesis reaction. In the early stages, fluorescent lamps were used as the source of lighting for crop growth (Wheeler, 2008). More than 10% of the total photon emission within the photosynthetically active radiation (PAR) spectrum (400-700 nm) is produced by these fluorescent lights (Bantis et al., 2018). Fluorescent lights, on the other hand, lack the necessary energy to enable the growth of highly productive plants. Throughout use, the photon output gradually decreases. In commercial indoor farms, high-intensity discharge (HID) lighting was also used. The spectrum output source of light can be fixed with an HID lamp to grow crops effectively. The main drawback of HID lamps is that they are extremely difficult to handle thermally in a plant factory and can scorch leafy greens at close separation distances (Mitchell & Sheibani, 2020). McCree (1972) published an article that defined the wavelength range of PAR as 400-700 nm. This has encouraged plant factory researchers to use specific narrow-band lighting within plant factories. LEDs were brought into this as they are waveband selectable. Nowadays, LED has become the most popular artificial lighting being applied in vertical farms.

Temperature and HVAC Control

Initially, it was difficult for vertical farms to effectively control the temperature across multiple growing environments. However, improvements in temperature management have been made because of developments in HVAC (heating, ventilation and air conditioning) systems, including the incorporation of energy-efficient cooling and heating technology. Real-time monitoring and changes are made possible by the development of accurate climate modelling and automation systems, assuring the ideal temperature and humidity levels for varied crops at various growth phases.

Energy Consumption of Vertical Farming

The usage of artificial lighting, heating, and cooling systems, as well as the requirement for irrigation and ventilation, all contribute to the energy demand in indoor farming.

Compared to traditional farming, indoor farming has been found to have higher energy consumption. The structure is established with thermal insulation and is completely isolated from the outdoor environment. The advantage of this design is the protection of the crops from the negative effects of pests and weather. To replace sunlight and control the indoor climate, artificial lighting (LED) and heating, ventilation, and air conditioning (HVAC) systems are used to create optimal conditions for crop growth. Therefore, the main energy consumption of indoor farming is lighting and HVAC (Graamans et al., 2018).

Energy use per kilogram of product varied widely. More than half of the farms used less than 10 kWh per kilogram, and 20% used even less, under 1 kWh per kilogram. But some farms used a lot more energy, which pulled up the average. So, the middle value (median) was 5.4 kWh per kilogram, but the average was much higher at 22.5 kWh per kilogram (Horomia & Gordon-Smith, 2021). The comparison was shown in Figure 1.

Lighting has been concluded to be the biggest energy consumer in vertical farms. According to the 2021 Global CEA Census report, lighting accounted for 55% of the energy consumption. In addition, based on the research of Avgoustaki and Xydis (2020), lighting costs are approximately 80% of the electricity consumed, while the total electricity reaches up to 40% of the total operating expenses. The significant electricity usage for lighting is primarily due to the crops requiring extended periods of artificial light for photosynthesis, especially when natural sunlight is not available.

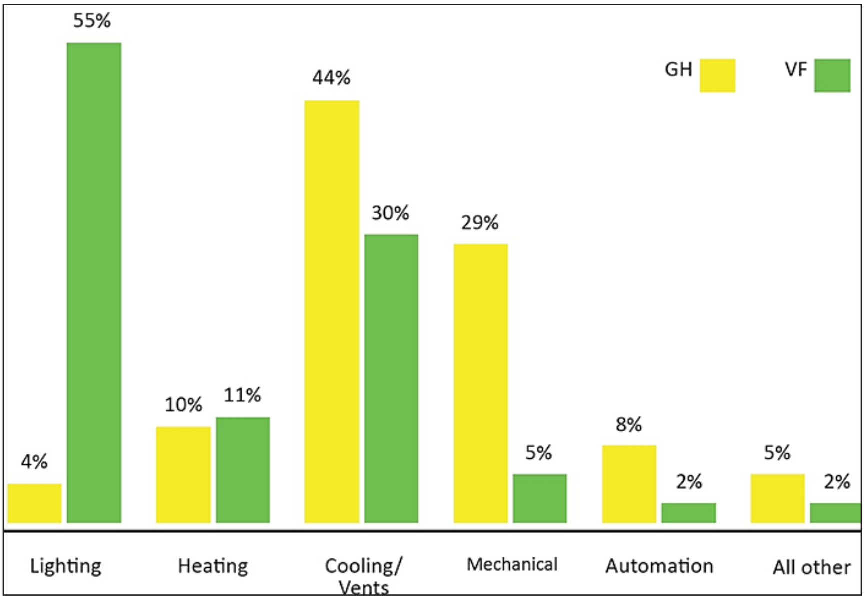

Figure 1. Breakdown of energy consumption in greenhouses (GH) and vertical farms (VF) (Horomia & Gordon-Smith, 2021)
Note. y-axis represents the percentage of energy consumption

The required light levels for office buildings should be between 300 and 600 lux, whereas the value for indoor lettuce growing is between 10000 and 18000 lux (Eaton et al., 2021). In traditional outdoor farming, sunlight acted as the sole source of light energy for photosynthesis. Most of the crops growing indoors require a photoperiod of 12-16 hours for photosynthesis. Thus, electricity expense for lighting is unavoidable in indoor farming. According to Ampim et al. (2022), if developed countries such as the United States adopt vertical farms extensively, the country's energy needs can increase up to eight times from the current amount generated by all the power plants.

In the energy profiling research of a plant factory by Shaari et al. (2021), air conditioning systems or HVAC (heating, ventilation and air conditioning) have higher energy consumption (51%) compared to lighting systems (36%). In their plant factory, the air conditioning system runs longer than the LED lights. This is an exception to the research concluded by other scholars mentioned above. However, in the report of the American Council for an Energy-Efficient Economy, HVAC systems are identified as the second most significant energy consumers. Their energy usage can range from 25% to 50% of the total energy consumption, depending on factors such as location, facility type, and the specific crops being cultivated. Another main reason for the high energy consumption of HVAC is the internal heat loads. According to Graamans et al. (2020), heat loads are caused by the high-density crop production, limited volume and lack of natural ventilation. Heat loads required more energy for the cooling and ventilation system to maintain the optimal temperature inside. They advised the future designer to include a better façade for natural heat dissipation. This suggestion was proven by Sohn et al. (2023), who included more outlets for airflow in their container farm and successfully improved the airflow. Natarajan et al. (2022) also stated that by adding external fans to indoor farms, the temperature can be decreased. This natural temperature control can save energy as well.

In addition, most indoor farming uses a hydroponic system to grow vegetables instead of soil-based methods. The pumping system is working continuously twenty-four hours per day to deliver water that contains essential nutrients throughout the entire system for crop growth (Sihombing et al., 2018). In fact, they proved that continuous watering is not necessary for the hydroponic system, in which they found that intermittent operation of the pumping is a better solution to reduce the energy consumed.

Earlier research by Barbosa et al. (2015) compared the energy consumption between greenhouse and outdoor methods for lettuce planting. They found that the greenhouse produced more yield than conventional methods but consumed 82 times more energy per kilogram produced. The most energy-consuming parts were heating and cooling, lighting and the pumping system. Besides, extensive research by Arcasi et al. (2024) compared the energy consumption of vertical farms in three different cities, i.e., Naples, Riyadh and Stockholm. They represent three climatic conditions: hot-summer Mediterranean climate, hot desert climate and warm summer humid continental climate.

The lighting system consumed 65% to 85% of the energy, followed by HVAC. The circulating fan consumed less than 1% energy. The increase in photosynthetic photon flux density (PPFD) required also increased the total energy consumption of three farms. PPFD measures how many PAR photons are arriving at a specific leaf area (μ mol/ (m^{-2}/s)).

Despite the numerous advantages that vertical farming offers over traditional agricultural practices, high energy consumption emerges as a pivotal challenge. Vertical farming systems can have significant energy needs, which raises expenses and has an adverse effect on the environment. As a result, improving energy efficiency in vertical farming systems has emerged as a crucial factor in the pursuit of sustainable agriculture. Researchers from across the globe have been diligently exploring diverse methods to enhance the energy efficiency of vertical farms. To implement sustainable agriculture, the next section will evaluate the technology and strategies for maximising energy efficiency in vertical farming systems. The challenges and opportunities for optimising energy efficiency in vertical farming systems will be highlighted by examining current practices and energy consumption patterns.

Energy Optimisation Review

There have been some changes in the technologies used in vertical farming over the years to reduce energy usage and increase productivity. In this review, we divided the related studies into three major types, i.e., physical structure, data-driven and hybrid. The categories reflect the most popular approaches in indoor farming energy optimisation. By analysing these three types, we can better understand how each contributes to advancements in the field.

In modelling processes, there are three main categories, i.e., the black-box, white-box and grey-box modelling (Arendt et al., 2018; De Buck et al., 2023; Zaidan et al., 2019). Black-box modelling focuses on data-driven approaches, and white-box modelling is based on physical structure. Grey-box is a mixture of both.

White-box Modelling

With the growing trend of computer technology and artificial intelligence, researchers have begun to employ increasingly advanced methods for optimising energy usage in vertical farming. White-box modelling simulates the energy consumption patterns of a whole building by considering building geometry, internal heat levels, sublevel systems and operation parameters (Kim et al., 2022). Hence, it requires the users to have a thorough understanding of building knowledge for better output results (Amara et al., 2015). The white box model has the benefit of having a strong explanatory ability, but inputting all the specific structural parameters might be time-consuming (Pan et al., 2023). Usually, white-box modelling is used to simulate energy consumption and optimise the HVAC systems, lighting and other energy-consuming systems in indoor farming.

The optimisation of vertical farming energy use can also be increased by including energy software that can model and simulate the energy consumption of indoor buildings. EnergyPlus™ and Transient System Simulation Program (TRNSYS) are the most popular building energy modelling (BEM) software for white-box modelling. EnergyPlus™ is a comprehensive building energy simulation software employed by engineers, architects, and researchers to simulate various aspects of a building's energy usage, including heating, cooling, ventilation, lighting, appliances, and water consumption. EnergyPlus was developed by the US Department of Energy for indoor building energy simulation processes. Figure 2 illustrates the working flowchart of EnergyPlus. TRNSYS is a software that can simulate the behaviour of transient systems. It contains extensive libraries of components that allow the modelling of the performance of different systems such as pumps, turbines, HVAC systems, and weather data processors.

The robustness of EnergyPlus has been proven by several scholars. Hachem-Vermette and MacGregor (2017) designed their indoor growing centre in Canada by simulating the operation of the usage of photovoltaic panels and Solid Oxide Fuel Cells as additional energy sources. They were able to reduce the thermal load by 65% and energy consumption by 30%. Wang and Iddio (2022) simulated the misting systems used for cooling and humidification in the indoor farming facility. The simulation result was compared with the measured data. The model produced by EnergyPlus successfully reduced 4.7% of electricity and 48.1% of natural gas use. EnergyPlus was also applied by Liebman-Pelaez et al. (2021) in the simulation of a container farm.

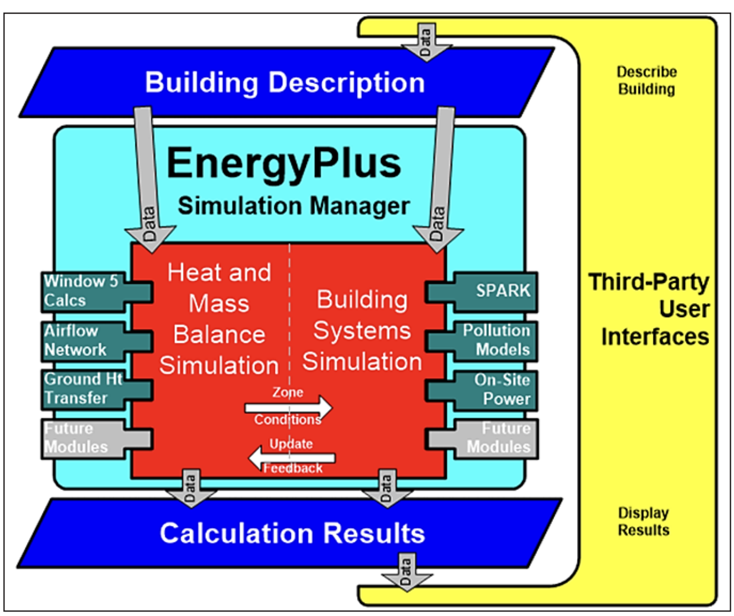

Figure 2. EnergyPlus flowchart (U.S. Department of Energy, 2022)

The information, including outdoor climate, building envelope, lighting load, crop parameters and lighting system and plant evapotranspiration, was entered into the EnergyPlus software. Although the model was found to be underestimating the cooling energy consumption, it overestimated the lighting, equipment and dehumidifier energy consumption. Eaton et al. (2023) modelled energy use of a multi-layer plant factory for lettuce growth in EnergyPlus by entering the specifications of building information, environmental control, crop parameters and lighting system into it. Several models were simulated for selection. Their lighting saving strategy saved 24% energy, the HVAC model saved 40-69% and maintaining the elevated levels of CO2 saved energy by 13-14%. In total, the software model was able to reduce energy consumption by 46%.

One of the advantages of EnergyPus is the ability to predict the energy consumption on an hourly or monthly basis. This allows management teams to accurately manage the operation of their indoor buildings. Shabunko et al. (2018) and Lamagna et al. (2020) had proven the effectiveness of EnergyPlus in the benchmarking of energy consumption. In terms of indoor farming, Dahlan et al. (2018) demonstrated the monthly energy prediction of a tomato greenhouse as shown in Figure 3.

TRNSYS was used by Talbot et al. (2022) to compare the energy performance between a greenhouse and a container farm. In their experiments, the physical spaces of the greenhouse and container were modelled using TRNSYS. The parameters being compared were (1) the energy consumption, (2) the peak electricity demand and (3) the associated greenhouse gas emissions. As a result, analysis of TRNSYS showed the container farm has better performance with lower energy consumption, lower peak electricity demand and less greenhouse gas emissions.

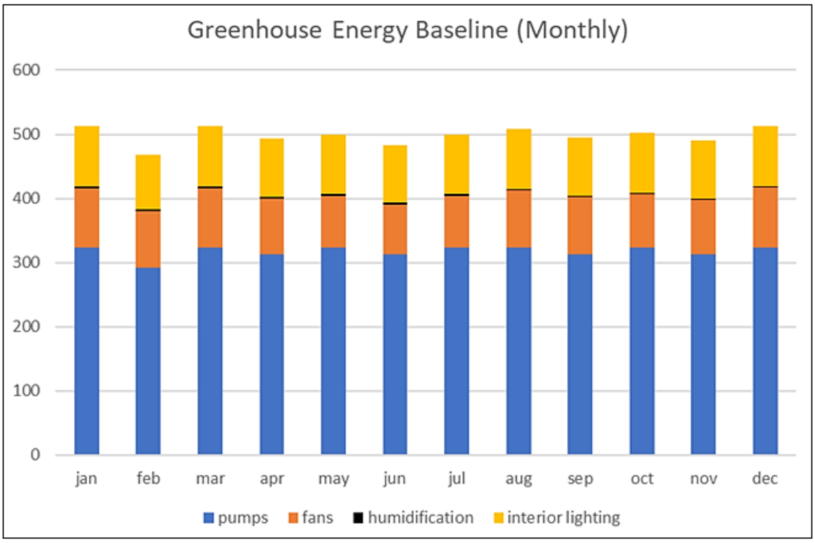

Figure 3. Energy (kWh) profiling of a plant factory by Dahlan et al. (2018)

Wai et al. (2022) investigated the energy consumption of the cultivation of strawberries in controlled environment rooms under a tropical climate using TRNSYS for modelling purposes. The developed model was validated by comparing the computed room air temperature from the model with the experimental room temperature. The statistical analysis revealed that the developed TRNSYS model was accurate in simulating the indoor condition with an RMSE at 9.2%. Besides, Yeo et al. (2022) demonstrated the combination of TRNSYS and CFD models. The physical specification of the rooftop greenhouse was designed using the software. The thermal energy flow was calculated using the BES. Energy exchange inside the greenhouse was also. They were able to reduce the energy load by 5.2% (464, 673 MJ). An alternating air temperature management (ATM) was applied to change the indoor temperature over time, where different temperatures were provided during the day and night. This ATM approach was able to further reduce the energy consumption for 11.8%. TRNSYS's ability to predict the energy use of a strawberry greenhouse was proven by Ogunlowo et al. (2023). In the research of Rasheed et al. (2020), TRNSYS successfully reduced the energy by suggesting different ventilation systems and thermal screens. Thus, TRNSYS is a reliable tool in energy modelling of indoor farming.

Black-box Modelling

One of the black box approaches to optimise indoor energy consumption is called model predictive control (MPC). MPC is a type of advanced control strategy that models inputs to predict future behaviours and make optimal control decisions. During each control interval, the MPC algorithm aims to enhance future plant performance by calculating a series of upcoming adjustments to manipulated variables (Qin & Badgwell, 2003). MPC is used in many different fields of engineering, including process engineering, power electronics, building climate and energy and manufacturing (Schwenzer et al., 2021).

MPC was a popular choice in energy optimisation. Achour et al. (2020) applied an MPC method to optimise the climate variables in a greenhouse. The controlled parameters included temperature, relative humidity, CO_2 rate, lighting levels, natural ventilation and energy consumption. The system was operated via a wireless sensor network (WSN) and a centralised model predictive controller. The proposed model was a supervisory model with real-time control to effectively manage the overall energy and water demand. MATLAB was the software used to mathematically model the system. The proposed model can significantly reduce the energy consumption and CO2 emissions, although the exact amount of energy saved was not mentioned. MPC was also discovered by Bersani et al. (2021) to minimise the total energy use in a greenhouse. The MPC model acted as an optimisation model to determine the optimal control signals related to the hot water flow in the heating plant. In the MPC model testing stage, the heating system was manipulated according to the difference between the current temperature and the proposed optimal temperature. The results showed that 30% of electric power was saved by this MPC approach.

Mathematical models have been proven by several researchers. Pimentel et al. (2023) proposed a model for the purpose of energy efficiency by using a formulation via the P-graph framework. P-graph is a combinational approach to synthesising and optimising process networks. It has demonstrated significant superiority in lowering the associated computational load and is incredibly effective at solving problems with high combinatorial complexity. The case study results point to potential savings of up to 40% in the cost of imported electricity for the given day and up to 31% for the full year. Another mathematical model called Mixed-Integer Linear Programming (MIP) models was presented by Delorme and Santini (2022). A mixed-integer programming (MIP) problem is characterised by having certain decision variables constrained to take integer values (e.g., whole numbers like -1, 0, 1, 2, etc.) at the optimal solution. Delorme and Santini (2022) proposed a polynomial number of variables (M1), a pseudo-polynomial number of variables (M2) and a hybrid MIP, which only used binary variables (M3) to minimise the energy consumption of automatic elevators in their plant factory. M1 was concluded to be the most efficient model.

Artificial intelligence methods are the most popular trend in energy optimisation of indoor farms. Different algorithms such as genetic programming, deep learning and Bayesian networks were applied to simulate and reduce energy consumption. Murakami et al. (2018) developed an addictive Bayesian network for the minimisation of energy cost in plant factories. A Bayesian network is a probabilistic model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). It is an effective technique for simulating complex systems and generating predictions from ambiguous or insufficient data. By considering the effect of weather factors on electric power consumption, an appropriate operation plan of cultivation systems was decided to reduce energy cost while producing plants with the same amount and quality. Simulation results showed that the operation plan of cultivation systems properly reflected the effect of electricity charge and weather factors on electric power consumption to reduce energy cost. A total of 1.13% energy cost was saved.

Two nonlinear models, i.e., genetic programming (GP) and feedforward artificial neural networks (FNNs), were combined by Olvera-Gonzalez et al. (2021) to predict energy consumption in closed indoor farms. GP is an evolutionary computation (EC) technique that automatically solves problems without having to tell the computer explicitly how to do it (Langdon et al., 2008). FNN is a neural network where information moves in only one direction—forward—from the input nodes, through the hidden nodes and to the output nodes. There are no cycles or loops in the network. In this research, inputs included in the models were light intensity, RGB components, white light component, light operation frequency and the duty cycle of the farm. The GP model had a training accuracy of 96.1%, and the FNN model had 98.99% accuracy. In terms of testing accuracy, the GP model achieved 95.35%, and the FNN model achieved 98.21%.

Thus, the FNN model was concluded to have better generalisation than GP. Khudoyberdiev et al. (2020) developed fuzzy logic as a control for energy optimisation in an IoT-based hydroponics environment. Fuzzy logic is an AI technique that describes the linguistic control value in the form of control parameters. It describes human preferences and experiences via fuzzy rules and membership functions. The parameters in this paper included water and humidity levels. These parameters came from the water pump, overflow system, dehumidifier and fogging system. This study used the fuzzy logic control module to define the operating duration limit and working level for the actuators based on IF-THEN rules while considering the optimised data and current sensing data. The outcomes proved the fuzzy logic to be a feasible method to control the operation of the hydroponics system, as 18% of energy consumption was reduced. Hu and You (2024) utilised deep learning techniques to develop an energy model for lettuce production in a plant factory. Deep learning is a machine learning technique that mimics human neural networks to learn and predict future trends from existing datasets. The parameters, including temperature, humidity, and carbon dioxide level, are controlled in the deep learning network to create an optimal growing condition for the crops. As a result, an 8.75% reduction in energy consumption was achieved by this model.

Grey-box Modelling

Talbot and Monfet (2024) constructed a dynamic crop model that can predict the growth of lettuce and integrate it into TRNSYS. The growth model is an algorithm proposed by van Henten (1994) and was adjusted by using the growth requirements of lettuce. The adjusted growth model was modelled in the TRNSYS software for energy analysis. They concluded the predicted energy use of the grey-box model had 3.5% variation compared to the experimental data.

Another grey-box modelling of combining KASPRO (a dynamic model to calculate the climate conditions in greenhouses) and EnergyPlus was carried out by Graamans et al. (2018). The purpose of EnergyPlus was to compensate for the differences between a greenhouse and a plant factory. The simulation showed that the plant factory consumed more energy than greenhouses. This is caused by artificial lighting. However, in terms of energy use efficiency, the plant factory showed better performance than greenhouses (1411 MJ kg^{-1} dry weight vs 1699 MJ kg^{-1} dry weight).

EnergyPlus, as a modelling tool alone, is not accurate as the crop biological processes, such as evapotranspiration, soil's heat conduction, and convective and radiative heat exchanges between the plants' canopy, can contribute to the energy consumption. Therefore, Ledesma et al. (2022) co-simulated the operation of a hydroponics farm by considering the crop growth model in MATLAB. The output of MATLAB became input for EnergyPlus, and the EnergyPlus Co-Simulation Toolbox was used to communicate with MATLAB. The thermal load decreased by 42%.

Unlike white-box modelling and black-box modelling, which are popular in the energy optimisation of indoor farming, grey-box modelling is not a common practice. In the meantime, grey-box modelling is popular in other building thermal and energy optimisation. Kim et al. (2022) reviewed 21 articles published from 2006 to 2022 on this topic. Hence, grey-box modelling is proven to be robust in energy optimisation. Future indoor farm energy optimisation can consider this approach as shown in Table 1.

The graph shows comparisons of energy-saving techniques used in indoor farming across various research studies using different modelling tools. Black-box and white-box models are used to categorise the studies, and each bar shows the stated percentage of energy savings. In the black-box category, Khudoyberdiev et al. (2020) used Bayesian fuzzy logic to reach higher savings of about 20%, whereas Hu and You (2024) utilised a deep learning model and produced moderate energy reductions. Using an unidentified black-box technique, Murakami et al. (2018) showed negligible energy savings. Using TRNSYS software, Yeo et al. (2022) transitioned to white-box models and obtained modest savings that were comparable to those of a deep learning model (Hu & You, 2024). The EnergyPlus-based investigations by Hachem-Vermette and MacGregor (2017) and Eaton et al. (2023), however, demonstrate noticeably greater energy savings, with the study demonstrating about 30% and the study reaching over 50% (Eaton et al., 2023). This implies that compared to black-box methods, white-box models—especially EnergyPlus—generally result in greater energy savings. The comparison was shown in Figure 4.

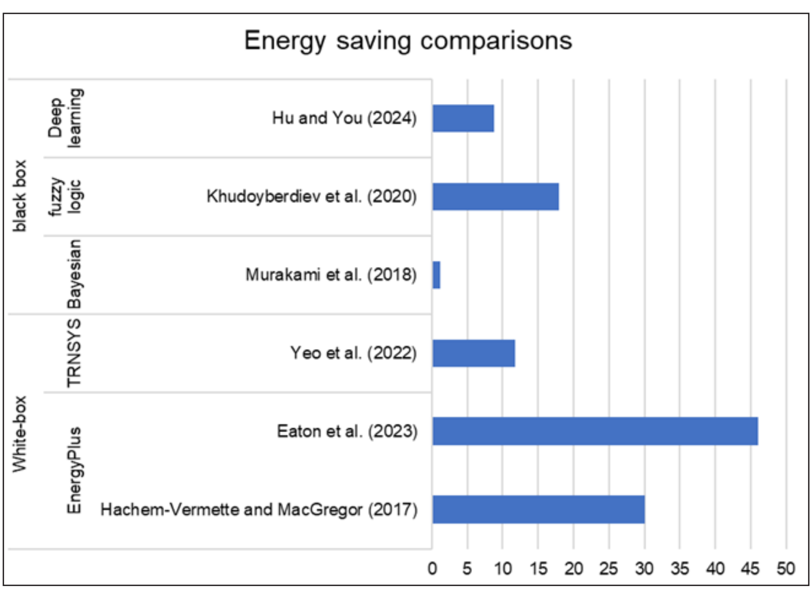

Figure 4. Energy saving comparison

Table 1
Summary of energy optimisation research

Models	Platforms/ Algorithms	Authors	Type of Facility	Outcomes
White box	EnergyPlus	Hachem-Vermette and MacGregor (2017)	Indoor growing centre	able to reduce the thermal load by 65% and energy consumption by 30%
		Liebman-Pelaez et al. (2021)	Container farm	An hourly prediction model of energy consumption was constructed
		Wang and Iddio (2022)	Indoor farm facility	Electricity reduces by 4.7%, and natural gas reduces by 48.1%
		Eaton et al. (2023)	Multi-layer plant factory	Total energy saving by 46%
	TRNSYS	Talbot et al. (2022)	Greenhouse vs container farm	Container farms show better performance in terms of energy usage, electricity and greenhouse gas emissions.
		Wai et al. (2022)	Indoor strawberries cultivation	Simulation with 9.2% RMSE
		Yeo et al. (2022)	Rooftop greenhouse	Energy saving by 11.8%
		Ogunlowo et al. (2023)	Strawberry greenhouse	Accurate energy consumption prediction
		Rasheed et al. (2020)		Design different ventilation and thermal screens
Black box	MPC algorithm	Achour et al. (2020)	Greenhouse	Reduce the energy consumption and CO2 emissions
		Bersani et al. (2021)	Greenhouse	30% of electric power was saved
	Mathematical models: P-graph	Pimentel et al. (2023)	Lettuce vertical farms	Reduce 40% of electricity for the given day and 31% for the full year
	Mathematical models: MIP models	Delorme and Santini (2022)	Plant factory	Minimised the energy consumption of automatic elevators
	Bayesian network	Murakami et al. (2018)	Plant factory	Reduce 1.13% of energy cost
	Genetic programming + Feedforward artificial neural network	Olvera-Gonzalez et al. (2021)	Closed indoor farm	GP: training accuracy 96.1%, testing accuracy 95 35% FNN: training accuracy 98.99%, testing accuracy 98.21%
	Fuzzy logic	Khudoyberdiev et al. (2020)	IoT-based hydroponics environment	18% of energy consumption was reduced
	Deep learning	Hu and You (2024)	Plant factory	Reduce 8.75% energy consumption

Table 1 (*continued*)

Models	Platforms/ Algorithms	Authors	Type of Facility	Outcomes
Grey-box	TRNSYS + dynamic crop model	Talbot and Monfet (2024)	Controlled agriculture environment spaces	3.5% variation in the predicted energy model
	EnergyPlus + KASPRO	Graamans et al. (2018)	Greenhouse vs Plant Factory	The plant factory showed better energy use efficiency
	EnergyPlus + crop growth model in MATLAB	Ledesma et al. (2022)	Rooftop farms	Reduce thermal load by 42%

DISCUSSION

White-box models focus on thoroughly understanding the physical processes that drive energy consumption, whereas black-box models prioritise prediction accuracy, often at the expense of interpretability (Shahcheraghian et al., 2024).

The advantages of EnergyPlus as a white-box model are that it provides and considers all details of the whole building in the modelling process. This enables us to study the relationship between the outputs and building structures. The white-box model required extensive descriptions of the buildings and calibration efforts. Thus, it is suitable for complex building systems optimisation (Kim et al., 2022). The occupant comfort can be taken into consideration. The white-box models can be constructed from the prior information without the need for any observation (Amara et al., 2015) or historical operation data (Shahcheraghian et al., 2024). EnergyPlus is usually applied for preliminary simulation, and MOGA requires the data to be collected first. But a white-box model is more difficult to construct, as they need to include all the data. EnergyPlus has an extensive library of building components. It contains a toolbox that provides integrated and concurrent solutions, heat balance-driven computations, flexible sub-hourly time steps, comprehensive heat and mass transfer calculations, advanced fenestration models, illuminance and glare assessments, component-based HVAC modelling, and a variety of predefined HVAC and lighting control strategies. According to Zhu et al. (2012), EnergyPlus has sub-hourly, user-definable time steps for the interaction between thermal zones and the environment, and variable time steps for interactions between the thermal zones and the HVAC systems. It allows users to design HVAC systems by inserting and connecting components. The whole system can be modified and controlled using the Energy Management System feature without recompiling the program source code.

Black-box modelling uses data in computational, machine learning and statistical analysis to develop models. This method builds the relationship between the energy consumption and influencing variables through the empirical models based on the historical data (Liu et al., 2019).

The process of black-box modelling consists of data collection, data pre-processing, feature selection, model training and model testing. Data pre-processing, including data cleaning, outlier elimination and data integration. In feature selection, the most useful variables are selected by users for the training stage. Data training is the process of training the model to learn patterns in each dataset. Lastly, the model testing stage will validate the performance of the produced model. Some popular black-box models included Support Vector Machine (SVM) and Artificial Neural Network (ANN).

However, there are some limitations and uncertainties in using white-box modelling for energy modelling in indoor farming. The uncertainties in energy modelling of white-box modelling come from three reasons, i.e., occupants, building and climate factors. The existence of occupants such as humans and crops is related to energy consumption and cannot be accurately predicted. The energy consumption of occupants is influenced by factors such as thermal comfort requirements, weather, building area, crop density and economic considerations. The micro-weather factor has a stronger influence on indoor farm energy use. The utilisation of climate data to predict the energy consumption of indoor farms will produce different results accordingly. Besides, the details of the building parameters are difficult to collect for the inputs. It is almost impossible to collect accurate data through field studies. Physical parameters of buildings are not always known or are not available; so, it is not always easy to obtain a building energy prediction by means of a simulation software based on physical parameters (Ferlito et al., 2015). In black-box models, high-quality datasets are required to produce an accurate model. Most importantly, a black-box model cannot explain the principles of heat transfer (conduction, convection and radiation) in the indoor farm (Yu et al., 2022).

In addition, the control of the working period of LED in indoor farming, i.e., the photoperiod, has been discovered in previous studies as well. One early study by Tennessen et al. (1995) discovered the effects of pulse-LED on tomatoes. They found that intermittent light will not affect crop production as the photosynthesis rate remains the same. Filatov et al. (2021) used a vertical farming system and two lighting techniques in their study. The first, which served as the control, included setting the LED lights' daily light and dark cycles to 16/8 hours. On the other hand, the experimental set included an 8/4-hour light/dark schedule that was split into two parts (2300–0700 and 1100-1900). They were able to cut down the electricity consumption by 10% without affecting the crop yield. Carotti et al. (2021) studied the effects of pulsed red and blue LED light on lettuce growth. Two switching frequencies of LED were applied on the crops, i.e., 850kHz (high switching frequency) and 293kHz (low switching frequency). The study discovered that the low frequency of pulsed light can increase the energy use efficiency by 40% and maintain the crops' qualities. Olvera-Gonzalez et al. (2021) also proved that pulsed LED-lighting can save energy consumption by more than 12%. Hence, the control of photoperiod in indoor farming can be included in the energy optimisation approaches as well.

CONCLUSION

Indoor farming provides a promising solution to meet the world's food demand and reach food security. By applying the existing technologies, including LED lighting, fans and humidifiers for climate control, and hydroponic systems, indoor farms can operate efficiently in controlled environments. These systems play an important role in crop growth conditions. However, the energy consumption associated with these technologies is larger than that of traditional agriculture. Thus, a focus on innovative approaches to reduce energy use is needed.

This review highlights three main approaches to energy optimisation in indoor farming, viz., white box, black box, and grey box modelling. Each method has its advantages and disadvantages. Grey models can combine the advantages of both white box and grey box modelling approaches.

Ultimately, optimising energy consumption in indoor farming is essential for enhancing its sustainability and economic viability. The review suggests that while significant progress has been made in understanding and improving energy use through various modelling approaches, there remains a need for further research to develop more integrated and adaptive optimisation strategies. By advancing these methods, indoor farming can achieve higher energy efficiency, reduce operational costs, and contribute more significantly to sustainable food production. Continued innovation in this field will be vital to address the challenges of energy consumption and to unlock the full potential of indoor farming systems.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest in this paper.

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