J. Electrical Systems 20-11s (2024): 2336-2340

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Application of Artificial Neural Networks for Urban Daylight Assessments: A State of the Art Survey

Journal of Electrical Systems

Abstract: - Artificial neural networks (ANNs), a subset of machine learning, have emerged as transformative tools for building performance simulation, enabling efficient processing of large and complex databases. One such area is evaluating daylight performance in urban environments, where ANNs can predict solar radiation and daylight availability while accommodating the complexities of urban morphology and dynamic sky conditions. The integration of ANNs into urban daylight simulation holds the potential for improving efficiency and accuracy, while reducing computation time based on learned patterns between input and output parameters. Once trained on simulation data, ANNs enable instantaneous predictions of daylight measures based on inputs, including annual climate dataset and the design parameters of the buildings under evaluation. This paper surveys the current state of the art in Artificial neural networks (ANNs) and their applications in urban daylight simulation. The survey aims to (a) explore the potential of ANNs in the light of current approaches to daylight simulation; (b) provide an overview of research on the primary tasks involved in ANN-based daylight prediction models and the architectures adopted to organize these tasks; (c) present a taxonomy of ANN approaches. The impact of this work on future studies of ANNs and what factors researchers should consider when combining machine learning techniques with daylight performance simulation are also discussed, along with future research directions.

Keywords: Daylighting, Urban Daylight Simulation, Machine Learning, Artificial Neural Networks, Climate-Based Daylight Modelling.

I. Introduction

Population growth coupled with rapid urbanization poses challenges for urban planners and architects, one of which is ensuring adequate daylight access. Given that the sky is often obstructed by the adjacent buildings and that the access to direct sunlight and skylight is restricted, it is imperative for designers to be aware of the impact of the urban context on daylight performance in the early stages of the design process. Dense urban developments require careful consideration of how to balance access to daylight while minimizing glare and overheating. The efficient use of daylight relies on how well it is controlled and delivered to interior spaces, not only in terms of occupant comfort and well-being, but also in terms of energy efficiency. With buildings contributing over a third of global energy-related carbon emissions, it is critical to adopt efficient daylighting strategies for energy efficiency [1,2]. The importance of daylight in urban settings is not only because of the visual improvement it gives to the spaces, but also because of the environmental issues which are in debate today, since it means less energy consumption for buildings.

A variety of methods have been developed for daylight performance prediction, ranging in their scope, complexity and precision of prediction [3]. These methods can be classified into three major categories, namely analytical methods, physical modeling and computer simulations. Conventional daylight prediction methods rely on mathematical expressions or graphical tools such as Waldram diagrams and the BRE protractors [4,5]. Physical modelling is an alternative method in which a scale model is used to investigate the distribution of daylight within the test space. The process typically includes taking a series of measurements inside the scale model under real or artificial skies. A detailed physical model is capable of producing reliable predictions, but it becomes impractical when evaluating multiple design parameters [6]. Through the last decades there has been a growing interest in daylight simulations in line with the technical and practical development of advanced computational tools. This has resulted in design decisions related to daylight being verified through daylight performance simulations rather than relying on rules of thumb. A wide range of daylight metrics have been developed to support the design process regarding daylight performance. They can be classified as either static or dynamic. Static metrics are those that quantify daylight illumination under one sky condition and at one point in time. Among static metrics, the daylight factor is the oldest and is still the most widely used method for evaluating daylight performance. Under the assumptions of CIE overcast sky distributions, daylight factor is expressed as the ratio between external and internal illuminance, and the contribution from direct sunlight is not taken into account [7,8]. Static metrics possess some potential limitations – not least of which is the inability to cater for the effects of varying sky conditions. Recent advances in alternative methods, such as the climate-based daylight modeling, have been shown to perform better in evaluating dynamics of daylight variability. Dynamic daylight analysis involves predicting a cumulative measure based on long-term record of weather conditions. Unlike the conventional daylight factor, dynamic metrics enable predictions of illuminance for a full year, taking into account changing sun positions and sky conditions [9]. Each metric reveals certain characteristics of the annual daylighting profiles. Daylight Autonomy, for instance, describes how often the illuminance at an individual sensor point is above a threshold (i.e. 300 lux), whereas for Useful Daylight Illuminance, it is how often the illuminance is between two thresholds (i.e. 300 and 3000 lux) [10]. It is

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important to note that these are abstract quantities, meaning that they represent aggregated values derived from the illuminance time-series data across space and over the observation period.

While computer simulations provide a means to test various design scenarios, detailed models are required to ensure accurate representation of the real-world. Urban daylight simulation allows designers to evaluate the daylight potential in relation to the surrounding environment, extending the scope from individual buildings to the entire neighborhood. However, significant complexity arises when numerous variables are involved, such as the urban context, spatial orientation, configuration of openings, surface properties, and the ways in which these factors interact with one another. Another challenge is that computer simulations often require specialized technical expertise, which makes them less practical for designers in the early stages of design. Given the increased complexity of simulation models, recent efforts are directed by designers towards the use of machine learning algorithms, such as artificial neural networks (ANNs). Using models that have been trained on simulation data, these algorithms can automate decision-making processes regarding daylight design and improve the overall building performance. ANNs can be trained based on learning algorithms, thereby enabling predictions in real-time. The method is capable of capturing the underlying non-linear relationships between variables, modifying the weights of connections in response to changing conditions and optimizing parameters to improve daylight performance [11]. This study aims to analyze and describe current approaches to the implementation of ANNs in urban daylight simulations, with the objective of identifying key research directions. In this context, an examination of the components of an ANN model is given with respect to daylighting performance, as well as a taxonomy of ANN approaches within the framework of purpose of prediction, level of application and output parameters. The paper concludes with a discussion of the limitations of the ANN methodology and suggestions for future research.

II. An Overview Of Artificial Neural Networks

A. Components of Artificial Networks

Machine learning (ML), deep learning (DL) and artificial neural networks (ANNs) are related but distinct concepts within the field of artificial intelligence. ML is a broad term encompassing the ability of machines to automatically learn patterns from data, while DL and ANNs are subsets of ML that rely on a layered structure of algorithms corresponding to different aspects of information processing. Both DL and ANNs are composed of a set of interconnected nodes, namely neurons, organized in layers to form a network. The network typically includes an input layer, one or more hidden layers, and an output layer, each of which plays a distinct role in processing information. The main difference between DL and ANNs lies in their complexity and the depth of the networks (the number of layers) employed. An ANN is typically considered a DL when it has a neural network of three or more layers [12].

The structure of the artificial neural network is somewhat similar to that of the human brain [13,14]. An ANN consists of interconnected neurons in layers that form a network and has the advantage of training itself to adapt to changes in input data. The neuron is the basic unit of the network whose function it is to receive inputs from the neurons in the previous layer, process them through activation functions, and transmit output to the neurons in the subsequent layer based on the connection weight and a predefined threshold value. The architecture of a neural network is characterized by interconnected neurons in layers processing inputs through weighted combinations, which is also known as a multi-layer perceptron (MLP). MLPs offer the advantage of capturing nonlinear relationships in data, thereby enabling efficient pattern recognition. A schematic representation of a multilayer perceptron with two hidden layers is depicted in Fig 1.

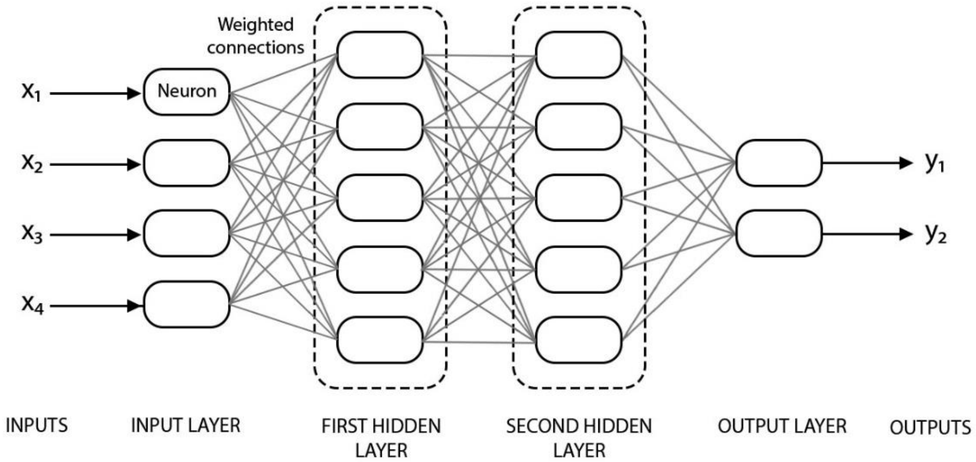

Fig. 1. A multilayer perceptron with two hidden layers

As shown in Fig 1, the network is fully connected and each neuron receives connections from the neurons in the previous layer. The weight and bias are considered to be key components of the network [15]. The former represents the strength of the connection between the neurons in two consecutive layers, and the latter refers to the error that results in an incorrect estimate of the association between input variable and the output (target) variable. As new data is incorporated into the model, the network iteratively adjusts its weights and biases to reduce errors and improve the accuracy of predicitons. The process of updating the model parameters is known as training and repeats itself until the error is below a certain threshold. The training process can occur in forward direction (feed-forward neural networks) or in both forward and backward directions (recurrent neural networks). While feed-forward neural networks process information in a single direction from input to output, recurrent neural networks contain feedback loops where information is fed back into the network [12].

There are two fundamental approaches to training artificial neural networks, namely supervised and unsupervised learning. Supervised learning involves the use of labeled data for training, meaning that the input data is explicitly paired with the desired output. This approach is considered to be more in line with most applications, where the goal is to predict a target value for a given input data. The second approach, unsupervised learning, is exploratory in nature and there is no predefined labels. This approach can be applied in cases in which the aim is to discover hidden patterns and relationships within unlabelled data [12].

The training process involves hyperparameter tuning, which essentially refers to the process of selecting the optimal hyperparameters for use in training the ANN model. Hyperparameters in an ANN significantly influence the efficiency of training and typically includes parameters such as the number of hidden layers and neurons, the learning rate, the number of epochs, the batch size and the activation function [16].

B. Implementation of Artificial Neural Networks for Daylight Prediction

As technology advances, artificial intelligence methods are increasingly being integrated into daylight research and design practice, complementing traditional daylight simulation models to some extent. Artificial Neural Networks (ANNs) have recently drawn large attention in the daylight design community, mainly due to its capabilities in parallel processing, learning and pattern recognition [17]. Existing methods for daylight simulation often require comprehensive model description including both design and operational variables, such as geometry, surface materials, weather conditions and blinds state. These methods tend to be costly and relatively time-consuming when processing large and complex datasets. Unlike conventional simulation methods, ANNs are capable of learning highly complex patterns between variables and offering predictions derived from patterns learned from the data. Through the use of sophisticated learning algorithms, ANNs can provide a quick and rough estimation of the model's response to a new set of inputs, enabling interactive decision-making processes. Yet, the application of ANNs in daylight-related studies is still in its early stages. In order to predict the performance of complex systems, ANNs employ a diverse range of algorithms, few of which appear to have been implemented and studied so far. The performance of ANN models largely depends on the type of learning algorithm used, along with the characteristics of data. One of the potential challenges that designers may face when implementing ANNs is selecting the correct learning algorithm for a given dataset. This is crucial as incorrect algorithms can lead to fluctuations in the training accuracy. To overcome this challenge, it is essential to understand the principles of various learning algorithms and their applicability in a particular context. Hence the analysis and interpretation of data can be challenging and less straightforward than that obtained by the conventional simulation method [18,19].

The process of integrating ANNs into daylight assessment typically involves evaluating daylight performance through simulation, preprocessing the data for the ANN, building the ANN model, and ultimately selecting the best model and corresponding hyperparameters for daylight prediction through validation. The entire model development process, as illustrated in Fig 2, implies a series of stages.

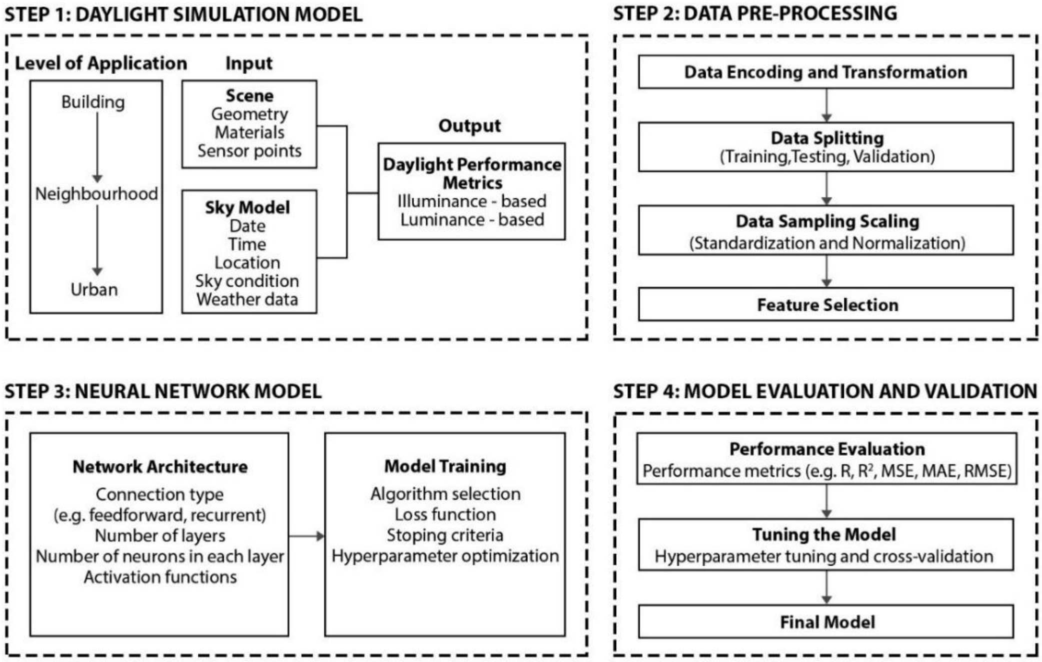

Fig. 2. A typical workflow for a daylight prediction model using an artificial neural network

As shown in Fig 2, the application of ANNs for predicting daylight performance involves making decisions regarding the selection of relevant variables, the optimal design of neural network architecture, the strategy for the training process, and the system that accurately represents the daylight performance of the buildings under evaluation. Given the various approaches available to researchers for accomplishing these tasks, it is essential to establish a systematic procedure that effectively develops an ANN capable of capturing the variability in daylight as influenced by the input parameters such as location, sky conditions and architectural features. By implementing appropriate algorithms, the ANN can provide valuable insights into how different factors influence daylight performance, ultimately leading to more informed design decisions.

III. Method

Existing approaches were categorized through a review of the literature, with the aim of understanding the implementation of ANNs in the prediction of daylight performance. A Boolean keyword search was conducted in three literature databases, Web of Science, ScienceDirect, and Google Scholar, using relevant keywords and the operators "AND" and "OR" to target the results. The search strategy included the following three groups of terms: (1) Artificial Neural Network (ANN); (2) Urban daylight assessment; and (3) Multi-objective optimization. The terms were used as keyword filters across all database searches.

The classification approach was structured around specific themes, serving as a framework for reviewing relevant research. These themes are outlined below.

1) Purpose of Prediction
Optimization, accuracy testing, calculation
2) Level of Application
Building level, neighbourhood level, urban level
3) Output Parameters
Daylight performance, thermal comfort, energy consumption

The purpose of prediction involves evaluating architectural parameters through optimization, assessing the predictive performance of the model through accuracy testing and performing computations to derive specific values. The level of application is categorized into three scales of analysis: building level, neighborhood level, and urban level. Building level analysis refers to the prediction of daylight performance for individual rooms or entire buildings, exploring how ANNs can be applied to optimize various architectural components including façade design, window placement, interior layout, shading devices and material properties. Neighbourhood level refers to the immediate surroundings, focusing on groups of buildings and their interactions within a localized area, while urban level refers to a larger scale of analysis, focusing on broad spatial planning frameworks to ensure optimal daylight access in urban districts. Finally, output parameters describe the final performance indicators produced by the model based on its learned patterns. The review included a total of 210 papers, focused on various aspects of daylight performance including its impact on energy consumption and thermal comfort.

IV. Results And Discussion

The findings about the main approaches of ANNs are illustrated in Fig 3, which visually represents their categorization across the three dimensions of purpose of prediction, level of application and output parameters. While the categories in each dimension are inherently interrelated and often partially overlap, for example optimization and accuracy testing often involves calculation, examining them as distict motivations offers valuable insights into how ANNs are applied in daylight research and practice. Regarding the purpose of prediction, the review suggests that ANNs have predominantly been utilized by researchers for the optimization of building performance, enabling for a more comprehensive assessment of daylight performance, energy consumption and thermal comfort at the building level. Among the studies reviewed, 53% utilized ANN algorithms for optimization and decision-making, 34% focused on calculation, and the remaining 13% applied ANNs for accuracy testing.

The most frequently studied output parameter was related to energy consumption, which accounted for 56% of the studies. The studies in this category incorporated an ANN model within a multi-objective optimization framework, addressing the interaction between energy consumption and daylighting. Following this, the next most studied output parameter was daylight performance metrics, which represented 30% of the studies. The least studied output parameter was thermal comfort, which was included in only 14% of the studies.

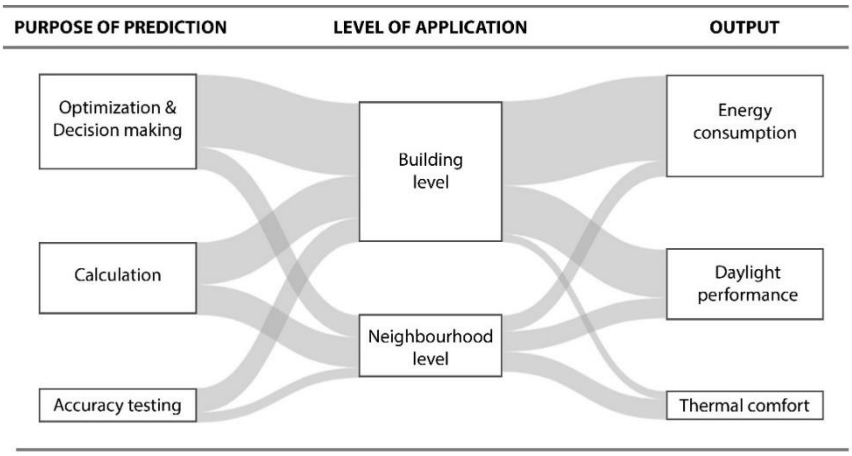

Fig. 3. Main themes for daylight studies utilizing artificial neural networks (The width of the paths reflects the relative count of papers)

While the interactions between buildings and their surrounding environment present additional challenges, only a limited number of studies (28%) have attempted to extend the application of ANN models to the neighborhood context and no studies were found that applied these models to urban contexts. Most studies have focused on analyzing individual rooms or buildings, often excluding the impact of external factors such as light reflection from the surrounding surfaces. Studies focusing solely on solar energy, without considering any aspect of daylight availability, were excluded from this research as they fell outside its scope.

V. Conclusion

This paper examined the role of artificial neural networks (ANNs) in daylight research, focusing on three dimensions of their implementation, these being purpose of prediction, the type of output data integrated into the model, and the scale at which the models have been applied, ranging from individual building analysis to neighborhood-level studies. By structuring research around these themes, the classification approach enabled identifying trends and gaps within ANN-based daylight studies. It is evident that through optimization frameworks, ANNs identify optimal architectural configurations to balance daylight performance, energy efficiency, and thermal comfort. Yet, an aspect that remains relatively unexplored is the impact of physical obstructions in the surroundings on daylight performance. While ANNs have demonstrated significant promise in predicting daylight performance and supporting architectural design decisions, there remains a need for a more comprehensive exploration of their advantages and limitations, specifically when applied at the urban scale. Future research could investigate the potential for implementing ANNs at larger scales to capture the dynamic interactions present in real-world urban and neighborhood contexts.

Acknowledgment

I am grateful to Dogus University for providing the facilities and resources for this project.

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