RESPONSIVE BUILDING PERFORMANCE: A CASE STUDY OF ELECTROCHROMIC BUILDING ENVELOPES

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Building envelopes play an important role in the building performance of energy efficiency, thermal insulation, and visual comfort. Controlling solar radiation and daylight through responsive building envelope systems is an emerging sustainable strategy to improve building performance. The effectiveness of responsive building envelopes depends on the dynamic properties of building envelope materials and control algorithms. Architects and researchers are exploring possible ways to integrate responsive electrochromic (EC) glazing materials in building envelopes and testing the dynamic impacts on building performance (DeForest et al. 2013; Hamidpour and Blouin 2018; Eleanor S. Lee et al. 2013). Up to now, the research has tended to focus on control logic, rather than on the responsiveness of the building envelope itself. The modeling of responsive behaviors of an electrochromic building envelope system is challenging due to the dynamic properties of the electrochromic materials and unpredictable behaviors. In this paper, we proposed a case study using four different electrochromic glazing materials to test the impacts of responsiveness on building performance in terms of visual comfort and energy saving for the climate conditions in Tampa, FL. We developed a novel approach, Dynamic Sequence Modeling (DSM), by which these responsive EC building envelope behaviors can be simulated. The simulation results are then used to feed our Supervised Machine Learning (SML) algorithms to enable prediction under changing weather conditions. The SML algorithms are promising avenues to solve this type of predictive learning problem (Murphy 2012). Our SML algorithms seek to optimize performance with altered responsiveness of our EC building envelopes, as a generally capable agent to predict effective responses given similar weather conditions to the learned representation of the climate model. We find that all three responsive building envelope variants demonstrate large improvements in both energy and visual comfort performance compared to the static building envelope. In three EC alternatives, where each has different tint responsiveness, the cooling and heating energy loads were reduced by 54.36% on average, and the illuminance measures had almost the same mean values close to the visual comfort threshold. The most responsive 4-mode EC had the least absolute deviations. On the other hand, the prediction accuracy of supervised machine learning models decreases as the complexity of tint responsiveness (tint mode) increases in electrochromic building envelopes. Our study demonstrates the impacts of responsive electrochromic materials on building performance. Moreover, we show that the complexity of responsiveness decreases the prediction accuracy for SML-based building control of dynamic materials.

Keywords: Building envelope, electrochromic glass, supervised machine learning, building simulation.

INTRODUCTION

From time to time, people tend to overlook the importance of decisions we make in designing, integrating, and operating our building envelope systems. Glazing-materials-based building envelopes have accumulated and amplified impacts on the overall user visual comfort experiences and building energy efficiency. The electrochromic (EC) glazing materials, which we are interested in here, are a type of smart glazing material that has dynamic optical properties and a switchable interface. Electrochromic materials are able to change their color or their optical characteristics in response to an applied voltage(Granqvist 1995). The original study of electrochromic materials can be traced back to S.K. Deb with the early research of electrochromism in 1969 (Deb 1969). Thirty years later, Carl M. Lampert published a paper in which he wrote about the characteristics of chromogenic materials, considering possible applications for improving a building's energy efficiency (Lampert 1984). Since then, more and more evidence has been found in the application of EC in buildings as a promising material for optimizing lighting and energy efficiency of glazing-based building envelope systems (E.S. Lee and Tavil 2007; Aste, Compostella, and Mazzon 2012; Aldawoud 2013; DeForest et al. 2017). With the development of Building Information Modeling (BIM) and simulation approaches to the study of dynamic building performance (Negendahl 2015). With these validated deterministic models and pre-defined activities control functions to represent and visualize building performances, we gain deeper understanding of the relationship between natural and built environmental systems. However, dynamic materials (DM) and phase-changing materials (PCM) provide new possibilities for the optimization of building design and operations (Rauh 1999). There are clear difficulties in adopting the new building materials and technologies, which lie in the incompatibilities of the modeling, design, integration, and evaluation of dynamic materials to the conventional static building models (Casini 2018).

The review of precedent studies regarding the application of EC application as dynamic building envelopes in various locations suggests that using EC could be beneficial to the energy saving of the building, as well as the visual comfort of the occupant. On the other hand, in most cases, the performances differentiate due to variance of EC properties and selection of control strategy in the face of given or unknown climate conditions. There is a trade-off problem between energy efficiency and natural daylighting regarding dynamic glazing. Considering both dimensions, a number of control strategies have been developed in the literature for controlling the EC building envelope. The findings of these studies for evaluating the performance of the EC were mostly based on experiments or simulations. For energy performance investigation, the evaluations of EC glazing depended on several cross-sectional case studies focused on energy load measurements or estimation. For the studies assessing the performance of EC according to its daylighting or visual comfort, some temporal and spatial visual comfort metrics are created and used in both quantitative and qualitative research designs. However, few quantitative types of research have been done to decipher the dynamic patterns of EC with the association of environmental variables from a statistical perspective. Most current studies do not include a time series analysis of environmental variables, nor do they discuss how the simulation performance of EC building envelope with historical weather data could be translated to real solutions under random climate conditions. These research works of control strategy for building glazing systems have several limitations concerning the modeling and learning of EC behaviors, while supervised machine learning allows us to effectively structure the systematic logic between EC and key environmental variables to gain capacities of pattern recognition and eventually control the dynamic building performance. For the supervised machine learning methodology, there are minimum adjustments to the model setup and features required for learning tasks regardless of when and where the EC buildings are situated. The total number of simulation data for performance optimization will be correlated to the accuracy of EC pattern recognition. This SML methodology is based on the statistical analysis of training data to minimize the effort required in solving the EC pattern recognition problem. The identified patterns for EC dynamic behaviors are derived from the optimized overhead simulation. The spatial and time elements are interconnected through this theoretical framework, which is crucial for high-level references on the dynamic EC building performance during the design and modeling process, and in the integration, analysis, and evaluation of post-occupancy experiences.

1. MATERIALS AND METHODS

In our project, we proposed a case study comparing four EC building envelope variants in terms of energy and daylighting performance and decipherability of operation patterns. The following two sections have been designed to prepare two key steps for evaluating of dynamic building performance (energy and daylighting) and supervised machine learning of EC behaviors.

1. 1. A CASE STUDY OF EC INTEGRATED BUILDING ENVELOPES IN TAMPA, FL

1.1.1. VARIANTS OF ELECTROCHROMIC BUILDING ENVELOPES

A parametric designed generic office building model with a net floor area of 153.06 square feet was created with Rhino® and Grasshopper®. Three representative EC building envelope variants were integrated with the building model: 2-Mode EC, 3-Mode EC, and 4-Mode EC of which properties are demonstrated in Table 1. The optical and insulation properties of the building envelopes were modeled in accordance with the manufacturer's specifications. EC optical properties, which are highly relevant in buildings' energy and visual comfort performance were discussed in detail under seven categories: visible light transmission (Tvis), radio frequency (Rf Ext.), solar radiation transmittance (Tsol), Light Reflectance interior range (%Rb Int.), solar heat gain coefficient (SHGC), rate of non-solar heat loss(U-factor), sensitivity (Tdw-K).

EC Glazing	%Tvis	%Rf Ext.	%Rb Int	%Tsol	SHGC	U-factor	Tdw-K
Static Mode	60	16	14	33	0.41	0.28	15
2nd Mode EC	18	10	9	7	0.15	0.28	5
3nd Mode EC	6	11	9	2	0.1	0.28	2
4nd Mode EC	1	11	9	0.4	0.09	0.28	0.6

Table 1: Electrochromic Glazing Material Specifications. Source: SageGlass®.

Given the fact that our simulation study does not intend to investigate any architectural design or system factors other than the EC glazing, we keep other simulation setting identical with each comparative model for focusing on the impacts of EC dynamics on building energy and daylighting performances.

To quantitatively evaluate the impact of EC building envelopes, extraneous environmental variables and geographical context were controlled in the simulation iterations of comparative models. To demonstrate EC potentials in the extremely hot conditions found within the U.S., Tampa was selected as the sample city for our case study. Electrochromic building envelopes are particularly desirable for cooling-dominant climate areas with high solar radiation. As our selected site, Tampa, FL represents the typical hot climate on the eastern sides of the North American continent, characterized by subtropical high temperatures in long summers (avg: 4.9 months) and mild temperatures in short winters (avg: 2.7 months). The annual temperatures in Tampa typically range from 52°F to 90°F as shown in Figure 1.

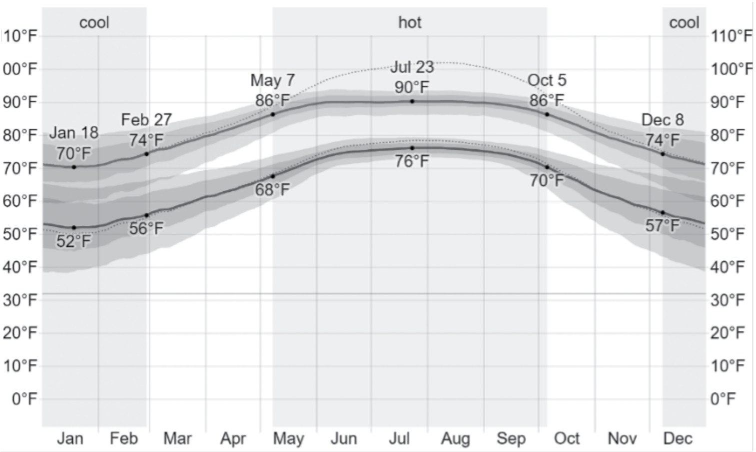

Figure 1: Hourly temperature visualization in Tampa, FL. Source: NASA 2022.

1.1.2. SIMULATION MODELING OF DYNAMIC BUILDING ENVELOPES

The simulation research framework was used and validated in previous research projects (Tällberg et al. 2019). The procedural logic can be summarized as EC building envelopes are first constructed to run the simulation with extended static modes of EC. A post-processing script was developed to examine the hourly simulation data and populate it as new time series sequences, matching the dynamic behaviors of EC. The process ensures that our models approximate closely with the dynamic nature of EC building envelopes. In this study, the simulation workflow consists of three parts in the context of Tampa, FL:

1. Create hypothetical building models with EC variants' discrete phase material properties.
2. Run ClimateStudio® to perform energy and daylighting simulations with the Tampa weather file by connecting to EnergyPlus® and Radiance®.
3. Sequence hourly simulation results to generate dynamic building envelope behavior.

Our comparative simulation research design with four building models is to demonstrate how much improvement we can achieve by each optimized EC building envelope compared to the static glazing scenario. A precedent study provided an overview of the control optimization of EC glazing materials with different optical properties data (Oh et al. 2018).

1.1.3. SUPERVISED MACHINE LEARNING FOR PATTERN RECOGNITION OF EC BUILDING ENVELOPES

The normal tasks for using supervised learning are establishing a model from a set of existing instances and utilizing the model to effectively predict certain label features (here is EC mode) for some unknown instances. After we successfully generate the simulation data set of each EC building envelope, we randomly split the data into two parts: a training set (90%) and a test set (10%). The training instances are sparse simulation data points at random working hours across the year. Three-time series environmental variables are identified as training features. The testing instances are used to evaluate the deciphering performance of the SML model for EC pattern recognition.

Conventional building simulations require accurate knowledge of the state of the model and environment conditions and become ineffective with dynamic models in changing environments. Therefore, we developed a post-processing script to integrate dynamic models in simulation and then used supervised machine learning to deal with uncertain outdoor environmental conditions. We analyzed all relevant environmental variables in the weather file and conducted dimensionality

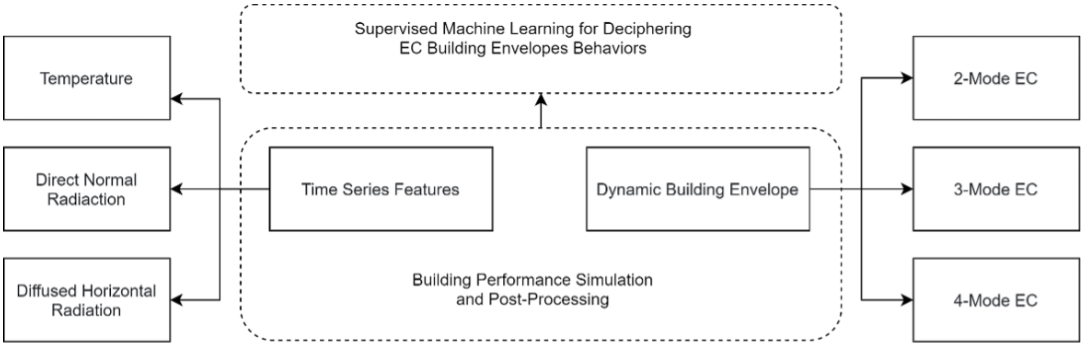

Figure 2: A schematic outline of our simulation modeling process and SML architecture. Source: Author 2022.

reduction to improve the computation efficiency of SML. Seasonal and daily cycles embedded with the time series features are categorical information that needs to be engineered for SML to understand the temporal patterns. The parametric modeling process makes our supervised simple machine learning algorithm applicable to various pattern recognition tasks. An adaptive machine learning approach is preferred for linking the building simulation knowledge with SML to solve the dynamic building performance problems, since the state of the model and natural environmental conditions are more uncertain. Figure 2 illustrates this integration process, we have established a methodology towards a hybrid approach to the electrochromic building envelope systems, blending the benefits of simulation with machine learning. Our framework concurrently engages the development of parametric modeling, simulation of the dynamic building envelope, and analysis of building energy and daylighting performance comprehensively.

2. RESULTS

2.1. SIMULATION COMBINED WITH TIME SERIES ENVIRONMENTAL CONDITIONS

All the simulated energy performance results generated in this study confirm the energy-saving potential of electrochromic building envelopes in Tampa, FL. As mentioned earlier, simulations were run in parallel to understand how EC properties effect affects energy consumption. In this section, these annual performances were resampled as the smoothed weekly scale to compare with each other. Figure 3 shows the buildings' annual total operational energy demands without the EC (Static Glazing) and with EC variants considered. Results showed that the energy demand was significantly higher when the EC dynamics were not taken into account. While the difference in 3 EC building envelope alternatives was relatively small (8.47 %), this difference was around 54.36 % in static glazing building envelope and the average of all EC variants.

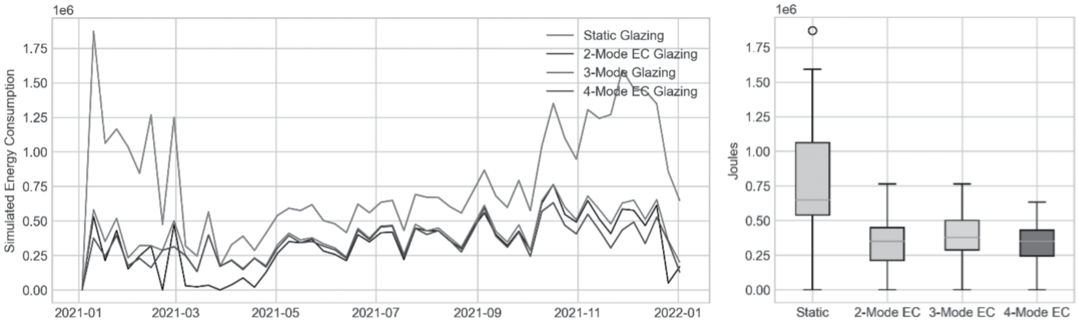

Figure 3: Annual energy performance for each EC building envelope. Simulation of the dynamic building envelopes effectively reduced energy consumption across all settings with the least median under 2-Mode EC. Source: Author 2022.

In the case of the static glazing considered, when 2-Mode EC was compared, a decrease of up to 57.73 percent was observed in annual energy consumption. When the same comparisons were made for 3-Mode and 4-Mode EC, a decrease of up to 48.89 and 56.44 percent in energy consumption values were measured respectively.

The daylighting performance in terms of indoor illuminance was also simulated separately. Figures 4 on the following page show these daylighting simulation results. When EC dynamics were not considered, the results indicated that the indoor illuminance could easily cause visual discomfort with its high daily and seasonal volatility compared to the situation in which EC was used. In annual comparisons, the effect of EC dynamics in winter (solar altitude at its minimum) became more evident. However, these simulated energy and daylighting performance comparisons may not be a convincing method to assess the actual benefit of EC building envelopes because the weather conditions will not be given as the pre-knowledge in real-world scenarios. The randomness of natural environmental variables, an important point that should never be overlooked with dynamic materials, needs to be factored into the equation for optimizing the performance of dynamic building envelopes.

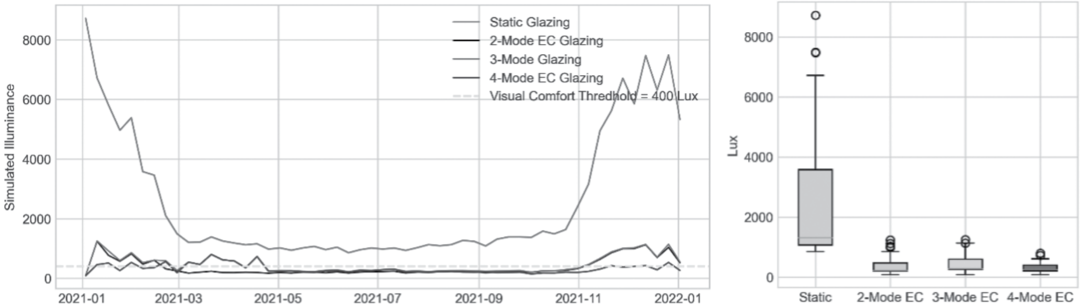

Figure 4: Annual daylighting performance for each EC building envelope. Simulation of the dynamic building envelopes effectively reduced excessive lighting across all settings with the most consistent performance under 4-Mode EC. Source: Author 2022.

2.2. SML CLASSIFICATION OF EC PATTERNS

We conducted randomized testing on the SML for classifying dynamic patterns of all EC building envelope variants. The results show that the precision of classification is inversely related to the complexity of EC behaviors. The SML we tuned achieves a competitive 98.32% classification precision in the 2-mode EC dataset.

EC Glazing	Precision	Recall	F1-score	Support
Static Mode	-	-	-	-
2nd Mode EC	0.9832	0.9829	0.9821	234
3nd Mode EC	0.8732	0.8760	0.8741	234
4nd Mode EC	0.7762	0.7735	0.7733	234

Table 2: Classification precisions on EC dynamic behaviors. Source: Author.

By visualizing the temporal pattern of simulated EC behavior and summarizing the classification performance in Figure 5 on the following page, we found that (a) training an SML model using dynamic simulation data is generally well suited for the pattern recognition of all EC building envelops (b) the learning scheme for less dynamic material shows better results (c) for learning from high dimensional data points, 2D visualization of temporal

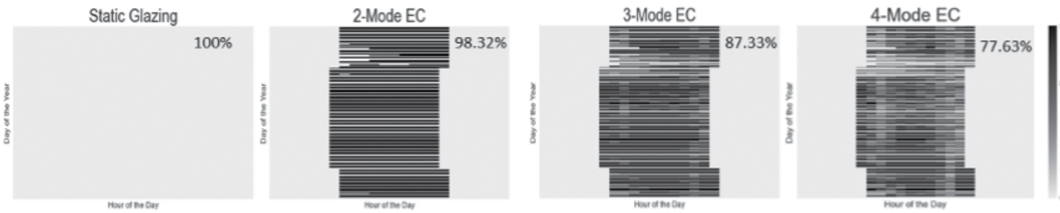

Figure 5: SML weighted precision of classification of EC dynamic behaviors. Source: Author 2022.

or spatial distribution would not be sufficient to show the hidden patterns of EC dynamic (d) as the development of EC materials, the operational decision boundary (Mode of EC) will continue to expand from discrete to linear. There would be a possibility that the training datasets from the simulation can only be sparsely annotated. Then pre-processing methods will be needed for machine learning from these missing or partial EC mode labeling to continue to improve the classification performance.

CONCLUSION

In this article, we have demonstrated the responsiveness of a spectrum of EC building envelopes in Tampa, FL, and how well we can predict the responsiveness. As discussed in the previous sections, dynamic glazing materials, especially electrochromic glazing, have become the material driving factor for the next generations of high-performance building envelopes. The responsiveness of dynamic glazing material is of great significance for improving building performance. This study focused on understanding the impact of responsiveness on the energy and daylighting performance of the building models. The simulation results show that all EC building envelopes with different responsive levels improve visual comfort and energy efficiency, and the performance variance decreases as the responsiveness increases. However, the predictability and controllability decrease as the responsive operation patterns of electrochromic glazing materials get more complicated. The accuracy is still low to using the machine learning approach to decipher responsive EC operations based on simulation data. Further explorations of environmental data are warranted to enhance the predictable responsiveness of electrochromic glazing integrated building envelopes to develop robust modeling and learning techniques for responsive building envelopes.

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