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Multi-objective optimization of thermochromic glazing properties to enhance building energy performance☆

G.R. Araújo [a,b,*], Henriqueta Teixeira [b], M. Glória Gomes [b], A. Moret Rodrigues [b]

[a] IN+, Department of Mechanical Engineering (DEM), Instituto Superior Técnico, Universidade de Lisboa, Av Rovisco Pais, Lisbon, 1049-001, Portugal
[b] CERIS, Department of Civil Engineering, Architecture and Georresources (DECivil), Instituto Superior Técnico, Universidade de Lisboa, Av Rovisco Pais, Lisbon, 1049-001, Portugal

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ABSTRACT

Glazings systems are responsible for significant building gains and losses regarding energy and thermal loads. Thus, current research has converged on finding glazing solutions that minimize heating, cooling, and lighting needs. One example of innovative glazing systems is thermochromic glazings. These glazings change their optical and thermal properties according to their surface temperatures by darkening at higher temperatures and consequently decreasing visible and solar transmittance. These property transitions have an impact not only on the heating and cooling needs of a building but also on the electric lighting needs. This research aims to study the impact that different switching temperature ranges and thermochromic coating transmittance values have on the energy use of an office room in different climates. This is accomplished with the annual energy simulation for heating, cooling, and electric lighting energy use of an office with a thermochromic glazing system in two different climates. A multi-objective optimization process is integrated to minimize the office's thermal, lighting, and total energy use according to the thermochromic glazing transition temperatures and transmittances. Optimization results show highly conflicting values between the office room's electric lighting and climatization energy use, showing that electric lighting energy use can increase up to 200% with low transition temperatures. Additionally, optimum solutions show improvements of 15% in total energy use against one off-the-market thermochromic glazing.

1. Introduction

Buildings account for 40% of energy consumption in Europe (European Commission, 2021), and urban population is estimated to grow at an alarming rate from 55.3%, in 2018, to 60% by 2030 (United Nations, 2018). To reduce energy consumption, research has been converging towards the reduction of building energy consumption and achieving Net-Zero buildings (Nations, 2020). Window glazing allows the transmission of natural light into the building interior, which has a positive effect on energy consumption by lowering the electric lighting needs. However, glazing is responsible for significant heat exchanges that can harm the building's thermal performance (Ye et al., 2012). Thus, it is no surprise that researchers have been studying methods to improve the performance and adaptation of the building glazing systems. Smart glazing technologies have been showing promising results in increasing thermal comfort and reducing building energy consumption (Cuce and Riffat, 2015; Rezaei et al., 2017). Particularly, Thermochromic Glazing (TCG) is a smart passive glazing solution that incorporates a coating of a thermochromic material in the glazing system that changes its thermal and optical properties according to its surface temperature. This is achieved through a thin-layered coating placed between two glass panes (Rezaei et al., 2017).

Vanadium Oxide (VO2) is generally the chosen material to produce TCG coatings because when it reaches a critical transition temperature (T_c), the material transitions from semi-conductor to metal according to a hysteresis process (Lee, 2002). Alas, VO2 has a high T_c of 68 °C, which is significantly higher than typical room temperatures. To solve this issue, manufacturers can dope the thermochromic coating with other constituents to alter the coating's T_c and glass solar and visible transmittance (τ_{sol} and τ_{vis}) values to obtain suitable TCG properties that provide energy consumption benefits (Cuce and Riffat, 2015; Lee, 2002; Rezaei et al., 2017; Saeli et al., 2010). However, cold climates still struggle to provide the TCG chromic coating with the required

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* Corresponding author.
E-mail address: goncalo.r.araujo@tecnico.ulisboa.pt (G.R. Araújo).
URL: https://goncalo-araujo.github.io (G.R. Araújo).

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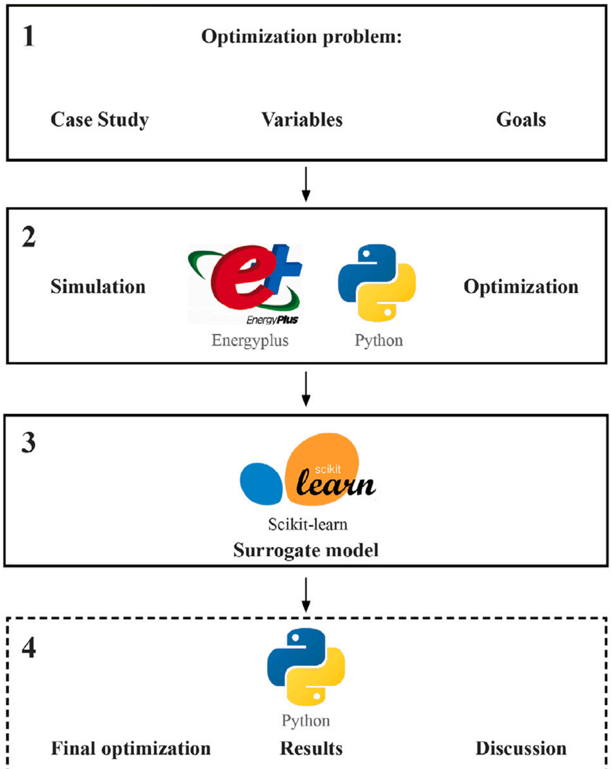

Fig. 1. Proposed research workflow.

temperature to transition. Therefore, TCG systems are reported to present smaller improvements against traditional glazing systems in a cold climate than a TCG system in warmer climates (Aburas et al., 2019; Liang et al., 2015; Saeli et al., 2010; Tällberg et al., 2019; Teixeira et al., 2022). Because of this climatic amplitude, TCG systems require different properties to yield the best performances. Other studies have focused on the effect that TCG T_c, τ_{sol} and τ_{vis}, and hysteresis loops have on building energy needs (Giovannini et al., 2019; Lee, 2002; Saeli et al., 2010; Warwick et al., 2014, 2015; Ye et al., 2012). Results show that a quick transition, meaning narrow and steep switching temperature ranges, and lower T_c generally represent bigger energy savings.

Most studies pointing out energy savings with TCG account for climatization and electric lighting energy needs but report a decrease in the former with an increase in the latter. This means that despite the thermal benefits provided by the TCG, its use harms daylighting performance (Liang et al., 2015; Teixeira et al., 2022). Thus, lower transition temperatures that allow the glass to switch to darker states, can eventually offset the improvements obtained in climatization energy needs with increasing electric lighting energy needs. This trade-off means that when manufacturing and applying TCG, one must consider ideal T_c, τ_{sol}, and τ_{vis} values that improve thermal performance, without critically harming lighting performance for a specific climate. However, to our knowledge, not much has been done to understand these implicit trade-offs in different climates and in a building's energy consumption. Finding the best TCG properties that provide the least energy consumption for both electric lighting energy needs and climatization needs can be treated as a Multi-Objective Optimization (MOO) problem.

MOO is an optimization process typically employed in the Architecture, Engineering, and Construction (AEC) industry due to the inherent conflicting objectives of buildings' performance (Araújo et al., 2021; Nguyen et al., 2014; Pereira et al., 2020, 2019; Waibel et al., 2019; Wortmann et al., 2015). Additionally, most objectives in building performance optimizations are outputs from simulation tool functions that perform extensive mathematical calculations (Nguyen et al., 2014; Wortmann et al., 2015). Thus, these time-consuming functions are usually approached as derivative-free optimization problems with a class of algorithms known as metaheuristics (Nguyen et al., 2014; Pereira et al., 2020; Waibel et al., 2019). According to the "No-Free-Lunch" theorem for optimization, there is not a single algorithm that outperforms all others in all problems (Wolpert and Macready, 1997). Thus, one must try multiple algorithms to explore a wider solution space (Wortmann et al., 2015; Nguyen et al., 2014).

Pereira et al. (2019) apply a MOO approach to optimize the cost and Useful Daylight Illuminance (UDI) of an exhibition space by performing three optimization runs of 200 iterations each. Araújo et al. (2021) performs a three-objective MOO process to minimize an urban area's rehabilitation cost, and maximize its thermal, and daylighting performance. Both studies obtain significant improvements with the MOO process but highlight the need to perform more iterations to explore a wider solution space and guarantee optimal solutions. However, doing so would require more computational power and time. Pereira and Leitão (2020) later addresses this issue by applying computational parallelization techniques and manage to optimize a building's structural element 6 times faster. Alas, results and computation time are still considered below expectations by the authors. Another approach to speed up simulation results is the integration of surrogate models that approximate simulation results (Thrampoulidis et al., 2021). With this approach, Araujo et al. (2022) couple Machine Learning surrogate models that approximate the objective functions to optimize a building block rehabilitation that minimizes its cost, total annual energy needs of the building block, and standard deviation among buildings. Results document a significant decrease in the optimization time from ≈ 68000 to ≈ 800 s.

This research integrates a surrogate model with a MOO process of a TCG in an office room and compares it with an off-the-market TCG system in two different climates. The objectives of this MOO process are to minimize the office's heating, cooling, and electric lighting energy needs. This process will help quantifying the existing conflicts between different end-uses (electric lighting and climatization) of an office's energy needs regarding different TCG properties such as T_c, the switching temperature range of τ_{sol} and τ_{vis}, as well as their range of values. The first step is to create a surrogate model of the objectives (to reduce the computational cost of simulations) by integrating an automated baseline optimization process with multiple metaheuristics and low number of iterations. This is done with the validated simulation software EnergyPlus (Drury et al., 2000) and a Python environment (Araujo et al., 2022). Finally, the surrogate model is integrated with the best performing metaheuristic for 5000 iterations to obtain the TCG optimum values.

The innovation of this study lies in the optimization of theoretical properties of a TCG for multiple-objectives and in the integration of a surrogate model that speeds up the whole process. Consequently, this work can guide TCG manufacturers into achieving the best performance for local climates, by altering the TCG's properties. Which in turn, contributes to the achievement of the United Nations Sustainable Development Goals (SDG) 11 "Sustainable Cities and Communities" and 13 "Climate Action", since it can help mitigate energy poverty and decarbonize the building sector, contributing to more sustainable cities and the mitigation of climate change.

2. Methodology

This research can be sub-divided into 4 sub-sections: (1) Case-Study, (2) baseline optimization, (3) surrogate model creation, and (4) final optimization (Fig. 1).

1. The case study section presents the studied office room and the different climates considered for this study. An initial analysis of a standard TCG with EnergyPlus is performed. In this sub-section, the TCG properties, simulation inputs, and outputs for our case study are also presented.

Table 1
Thermochromic glazing properties simulated for each temperature state (Teixeira et al., 2022).

T [°C]	5	15	25	45	65	85
U [W/(m^{2}K)]			1.6			
τ_{vis}	0.72	0.69	0.63	0.36	0.11	0.02
ρ_{visF}	0.07	0.07	0.06	0.05	0.04	0.04
ρ_{visB}	0.07	0.07	0.06	0.05	0.04	0.04
τ_{sol}	0.69	0.67	0.64	0.50	0.34	0.26
ρ_{solF}	0.06	0.06	0.06	0.05	0.05	0.05
ρ_{solB}	0.06	0.06	0.06	0.05	0.05	0.05

2. The baseline optimization section describes the optimization problem objectives and decision variables. Afterward, this optimization problem is integrated with multiple metaheuristics to perform simulation-based iterations which are then used to build the surrogate model.
3. The surrogate model section describes the training dataset, machine learning model used, and accuracy scores.
4. In the final optimization section, the results obtained with the final optimization with the surrogate model are presented and discussed.

2.1. Case study description and simulation settings

This work is based on previous research (Teixeira et al., 2022) and considers a pre-calibrated building energy simulation model of an office room facing southeast in Copenhagen, Denmark, and the same room in Lisbon, Portugal. Denmark is characterized by a cold climate, and Portugal by a warm Mediterranean climate (Fig. 2) (Peel et al., 2007). The office has roughly 20 m^2 of floor area and 10 m^2 of window area. The window is composed of a TCG assembly (12 mm), air gap (12 mm), and a Low-E coated glass (6 mm) (Fig. 3). Table 1 describes the TCG solar-optical and thermal properties at different stages of surface temperatures. It is visible that significant changes occur mostly in the τ_{sol} and τ_{vis} values, ranging from 0.69 to 0.26 and 0.72 to 0.02 at 5 °C and 85 °C, respectively. It is visible that τ_{vis} shows a higher decrease than τ_{sol} with the thermochromic transition.

For the simulation and analysis process, EnergyPlus (Drury et al., 2000) was coupled with Eppy (Philip, 2019), a scripting language for IDF files in Python. Eppy allows the automation of specific changes in IDF fields and objects, runs IDF files, and processes results. An initial simulation was performed with the standard TCG system to obtain the office's total cooling, heating, and lighting electricity rate (W). The office room was modeled with an occupation of one person during work hours and weekdays. Additionally, the electric equipment considered comprises laptop and desktop units. The zone sensors for Energyplus were located at a desk position for the period of one year, both for thermal and lighting outputs. The electric lighting control, HVAC parameters, and remaining simulation inputs are described accordingly in Table 2.

2.2. Baseline optimization

The goal of the present research is to understand and report how different TCG coating properties impact an office room's climatization and electric lighting energy needs. Thus, the main aim to find the theoretical TCG properties that provide the case study's yearly minimum heating, cooling, and electric lighting energy use (f_1 in Eq. (1) and f_2 in Eq. (2)).

For the decision variables, a function that approximates τ_{sol} and τ_{vis} values for different TCG surface temperatures is modeled (Eq. (3)). This is described according to the initial (T_{min}) and final (T_{max}) temperatures of transition, and the respective minimum and maximum τ_{sol} that the TCG system can reach. This describes a linear transmittance

Table 2
Simulation inputs and outputs.

	Values
Occupation	1 person weekdays from 9 to 6
Air changes/hour	1.0 h^{-1}
Electric equipment	Desktop (155 W): from 9 to 6 Laptop (30 W): from 9 to 6
Artificial lighting	Available during occupation (110 W)
Lighting control	Set-point of 500 lux
HVAC set-points	During occupation: 20–24 °C
SCOP/SEER	4.43/7.98
Simulation period	30 timesteps per hour, 1 year period
Outputs	Total Cooling Rate [W], Total Heating Rate [W], Electric Lighting Rate [W]

variation during the thermochromic phasing (Warwick et al., 2014). Additionally, it comprises a static behavior when the glazing surface is below or over the temperature thresholds for each state. With this function (Eq. (3)), it is possible to approximate multiple variations of TCG systems with different properties.

For the simulation process, the temperatures 5, 15, 25, 45, 65, and 85 °C were considered for the TCG optical data establishment. Thus, for the optimization process, Eq. (3) was applied to calculate the approximated τ_{sol} and τ_{vis} at the given temperatures. To accomplish this, the decision variables are T_{min}, T_{max}, τ_{solmax}, and τ_{solmin}, and they can vary from 0 to 95 °C for T_{min} and T_{max}, and 0.1 to 0.9 for τ_{solmin} and τ_{solmax}. For the τ_{vis} values, the same equation (Eq. (3)) was used by replacing τ_{solmin} and τ_{solmax} for τ_{vismin} and τ_{vismax}, but with $\tau_{vismin} = 0$ at all conditions.

Finally, the considered optimization constraints assure that T_{min} is not larger than T_{max}, and τ_{solmin} than τ_{solmax}. Fig. 4 illustrates Eq. (3) variables and compares the previously simulated TCG transmittance values in Table 1 and approximated TCG transmittance values. Moreover, it describes the transition temperature (T_c) and transmittance variation ($\Delta\tau_{sol}$) in a TCG system. Results for this approximated TCG show errors of ≈ 0.05 kWh/m^2 and ≈ 0 kWh/m^2, for heating and cooling and electric lighting energy use in Copenhagen's office room; and ≈ 0.05 kWh/m^2 and ≈ 0.1 kWh/m^2 for Lisbon's, which shows minimum errors with the approximated values.

$$f_1\ \left(T_{min},\ T_{max},\ \tau_{solmax}, \tau_{solmin}\right) = HVAC\ \mathrm{kWh/m^2} \tag{1}$$

$$f_2\ \left(T_{min},\ T_{max},\ \tau_{solmax}, \tau_{solmin}\right) = Lighting\ \mathrm{kWh/m^2} \tag{2}$$

$$\tau_{sol}\ \left(T,\ T_{min},\ T_{max},\ \tau_{solmax}, \tau_{solmin}\right) = \\ = \begin{cases} \tau_{solmax} & \text{if } T \leq\ T_{min} \\ \tau_{solmax} - \frac{\tau_{solmax}-\tau_{solmin}}{(T_{max}-T_{min})} \times \left(T - T_{min}\right) & \text{if } T_{min} < T < T_{max} \\ \tau_{solmin} & \text{if } T \geq\ T_{max} \end{cases} \tag{3}$$

$T\ \in\ \{5, 15, 25, 45, 65, 85\}$, $T_{min}\ \in\ [0, 95]$, $T_{max}\ \in\ [0, 95]$, $\tau_{max}\ \in\ [0.1,\ 0.9]$, $\tau_{min} \in [0.1,\ 0.9]$

Since each EnergyPlus TCG simulation takes roughly 20 s, to explore a vast solution space within these variables and constraints thousands of simulations would have to be ran, which would render the process highly time-consuming, or even unfeasible. As such, a baseline optimization of 500 iterations was performed with 4 metaheuristics algorithms, two from the evolutionary class of algorithms (Bäck and Schwefel, 1993), and two from the particle swarm class (Kennedy and Eberhart, 1995). Particularly, the NSGAII, NSGAIII, OMOPSO, and SMPSO (Deb and Jain, 2014; Godínez et al., 2010; Nebro et al., 2009) algorithms were applied to the studied optimization problem. To evaluate the optimization performance the algorithms' non-dominated solutions are calculated, which are solutions that cannot improve more in one objective, without harming the other (Censor, 1977).

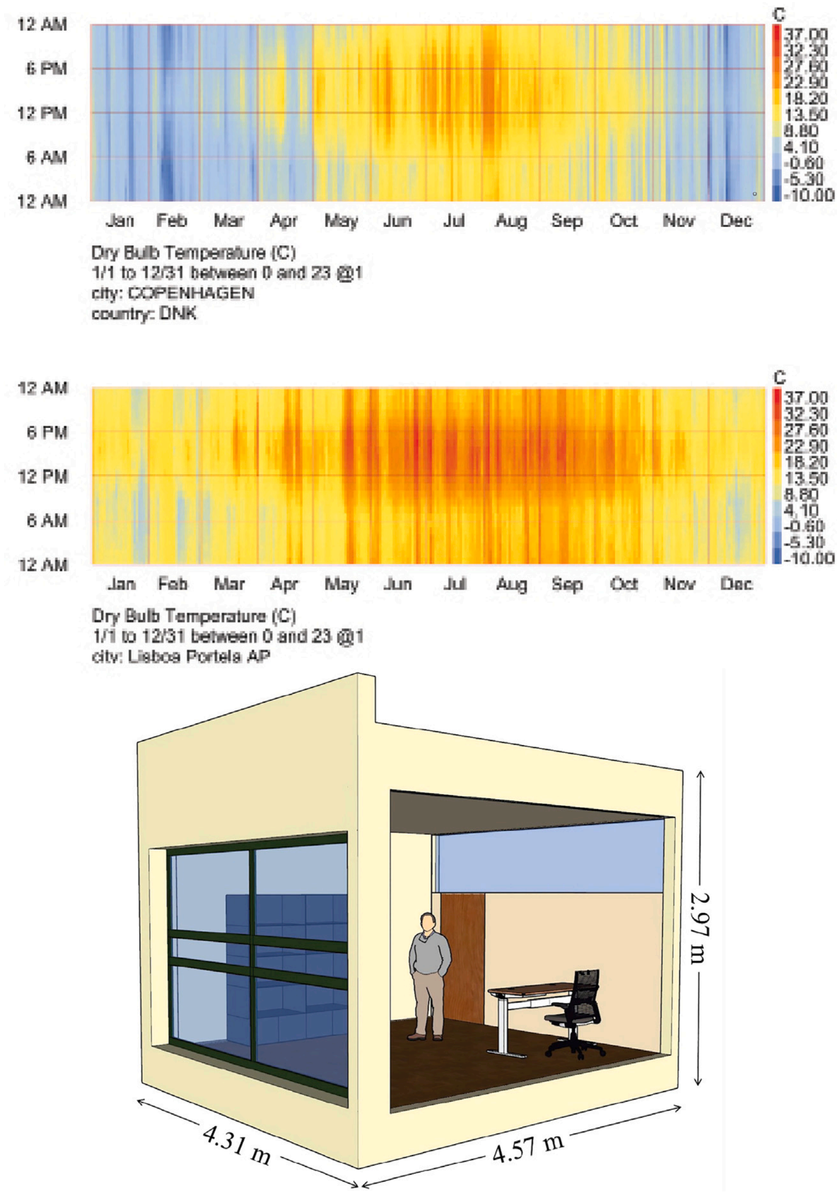

Fig. 2. Top — Denmark (top) and Lisbon (bottom) yearly dry bulb temperature. Bottom — 3D model of the office room used as a case study.

After a total of 2000 iterations, the results and variables were compiled into a database to train a Supervised Learning algorithm (Caruana and Niculescu-Mizil, 2006) capable of building an accurate surrogate model (Araujo et al., 2022; Bamdad et al., 2020; Thrampoulidis et al., 2021; Wortmann et al., 2015) to predict the results for the given variables significantly faster than a simulation. Thus, with the surrogate model, thousands of iterations can be performed, and optimal results obtained at an incomparably lower computational cost than with Energyplus.

2.3. Surrogate model

For the surrogate model of the objective functions, machine learning techniques were adopted to approximate f_1 and f_2 values (Eqs. (1) and (2)), which are described as regression problems. Particularly, the supervised learning algorithm Extra Trees Regressor (Caruana and Niculescu-Mizil, 2006; Mendes-Moreira et al., 2012) was used with the SciKit-Learn package for python (Pedregosa et al., 2019) with an off-the-shelf computer desktop unit. A total of 2000 iterations were performed with the different metaheuristics, each with 500 iterations in which the tested solution variables are described in Section 2.2, Eq. (3). The results are merged into a database, and split into a training and test set respectively with 70% and 30% of the 2000 total samples. To evaluate the surrogate model accuracy the test set's coefficient of determination (R^2 score), Root Mean Squared Error (RMSE), and the elapsed time to predict the test set were documented. Finally, the error distribution between predicted and simulated results of the test sample is plotted to understand the confidence of predictions for both climates.

Table 3 shows similar results for both climates regarding the surrogate model accuracy. However, RMSE results show slight deviance for both climates. It can be observed that heating and cooling energy use has a RMSE of 0.19 and 0.05 kWh/m^2 for Lisbon and Copenhagen respectively, while electric lighting energy use has a RMSE of 0.28 and 0.16 kWh/m^2. This can be explained by the poorest performance of TCG systems in cold climates mentioned in Sections 1 and 2.1. Since TCG systems have less impact in cold climates, the values of f_1 and f_2 have smaller amplitudes. Thus, with similar performance levels, RMSE values will be smaller for the cold climate. Finally, it is possible to state that the regression accuracy is outstanding and the accuracy loss with

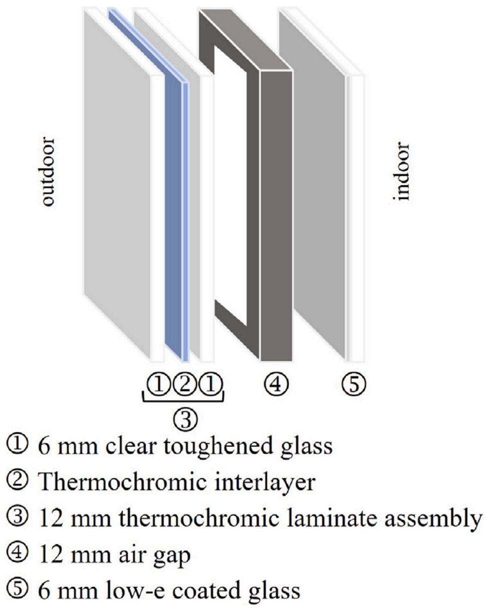

Fig. 3. Thermochromic glazing layers.

Table 3
Regression model scores for both climates.

	Lisbon		Copenhagen	
Objective	f1	f2	f1	f2
r^2 score	0.99	0.98	0.98	0.99
RMSE [kWh/m^2]	0.19	0.28	0.05	0.16
Elapsed time	0.2	0.2	0.2	0.2

the surrogate model predictions combined with the recorded regression times significantly outperforms the simulation approach.

From the error distribution plot illustrated in Fig. 5, it is visible that the regression model for Copenhagen's climate had significantly smaller errors than Lisbon's climate, where errors were between −1 and 1 kWh/m^2. However, all models have shown acceptable accuracy with at least more than 150 instances predicted with an error of ≈ 0. We can now perform thousands of iterations without the need to perform any simulation, with minimum errors.

3. Results

Simulation results for the original TCG show hourly heating and cooling rates, and the different climatization (heating and cooling) energy use for these different climates are illustrated in Fig. 6. This energy use is calculated by considering the office's equipment energy needs affected by the SCOP/SEER of 4.43/7.98 respectively, as described in Teixeira et al. (2022). The Copenhagen's office hourly rates of heating and cooling hit maximums of 500 W, particularly during winter. Whereas in Lisbon hourly rates for heating and cooling reach maximums of 300 W during summer. Additionally, electric lighting rates for Copenhagen are superior than for Lisbon. Finally, the office room in Copenhagen requires a yearly total of 14.45 kWh/m^2 for heating and cooling, 3.90 kWh/m^2 for electric lighting, and a total of 18.40 kWh/m^2. Whereas Lisbon respectively requires 9.70 kWh/m^2, 3 kWh/m^2, and a total of 12.7 kWh/m^2.

For the final optimization, the proposed surrogate model was integrated with the optimization problem defined in Section 2.2. The optimization objectives were to minimize both electric lighting energy use and heating and cooling energy use. To do that, 10000 iterations of different TCG properties were performed with the NSGAII algorithm for each climate.

Fig. 7 shows the plot with all the tested solutions according to the results of each objective on the x-axis (electric lighting energy use) and y-axis (heating and cooling energy use), and the sum of the two objectives (total energy use) on the z-axis. By looking at the graphs of both climates, a clear conflict among objectives for different TCG properties is visible. It is noticed that minimum heating and cooling energy use both in Lisbon and Copenhagen's climate correspond to maximum electric lighting energy use values. Therefore, it is possible to conclude that modeling TCG production for a single objective, such as heating and cooling energy use, does not necessarily represent the optimal TCG solution that will save the most energy. Furthermore, it is visible that the absolute minimum value for the total energy use of the office room is represented by a balanced performance regarding thermal and lighting energy use. When comparing both climates' results, it was noticeable that there is a higher amplitude of total energy use values for the Lisbon climate than for Copenhagen's ranging between from 11 to 16 kWh/m^2 and 17 to 18 kWh/m^2 respectively.

From these results, the TCG solutions that yielded the minimum values for f_1, f_2, and their sum were selected and compared with the original TCG system (Fig. 8). It is visible that Copenhagen's climate TCG optimization yielded almost no significant results when compared to the original TCG system, with improvements of ≈ 7% of the total energy use for the TCG with minimum $f_1 + f_2$, f_1, and f_2. Results are noticeably different for the Lisbon climate, since the TCG optimization shows more sensitivity to the optimization goals. For the minimum $f_1 + f_2$, the optimum TCG solution obtained improvements of ≈ 15% against the original system with 10 kWh/m^2. Moreover, the highest total energy use is represented by the TCG optimized for f_1 which causes a significant increase of 200% (from 3 to 9 kWh/m^2) in the electric lighting energy use of the office. Finally, the optimum TCG for minimum f_2 yields a total energy use of 13.9 kWh/m^2 from which ≈ 90% was for heating and cooling.

To better understand the TCG properties variation for these objectives results, the Pareto front with non-dominated solutions was illustrated according to their T_c in a heatmap from 0 to 80 °C, and according to their $\Delta\tau_{sol}$ illustrated in the size of the plot markers (Fig. 9). This figure shows that for the cold climate of Copenhagen, lower T_c values provide smaller thermal energy use, while higher T_c values represent minimum lighting energy use since the TCG is switching to a darker reflective state at higher temperatures. Additionally, minimum total energy consumption occurs for TCG systems with small T_c values but not the smallest. Finally, it can be noticed that all optimal TCG systems for Copenhagen have high $\Delta\tau_{sol}$.

For the climate of Lisbon, more results are worth emphasizing. Not only do the total energy consumption values have higher amplitude, but also the inherent trade-offs between thermal and lighting energy use according to different TCG glazing systems are significantly more visible. Particularly, it is visible that higher T_c and $\Delta\tau_{sol}$ values for TCG solutions provide minimum lighting energy use but maximum thermal energy use, while lower T_c and $\Delta\tau_{sol}$ values provide minimum thermal energy use but maximum lighting energy use. As seen, both these heuristics do not represent minimum total energy consumption. For Lisbon's case, it is observed that minimum total energy use is represented by TCG solutions with balanced values for both T_c and $\Delta\tau_{sol}$.

To take an individual look at some TCG optimal solutions, a TCG solution with the minimum heating and cooling energy use, electric lighting energy use, and total energy consumption for both climates were selected and plotted for their respective τ_{sol} and τ_{vis} according to their surface temperature (Fig. 10). Fig. 10A, B, and C illustrate the three optimal TCG solutions for the climate of Copenhagen, and D, E, and F for the climate of Lisbon. Fig. 10D shows the TCG solution that provides the office room in Lisbon's climate with the minimum heating and cooling energy use. It is visible that both the TCG τ_{sol} and τ_{vis} have extremely low values at all temperatures. This indicates that the TCG would provide the minimum thermal energy use, but electric

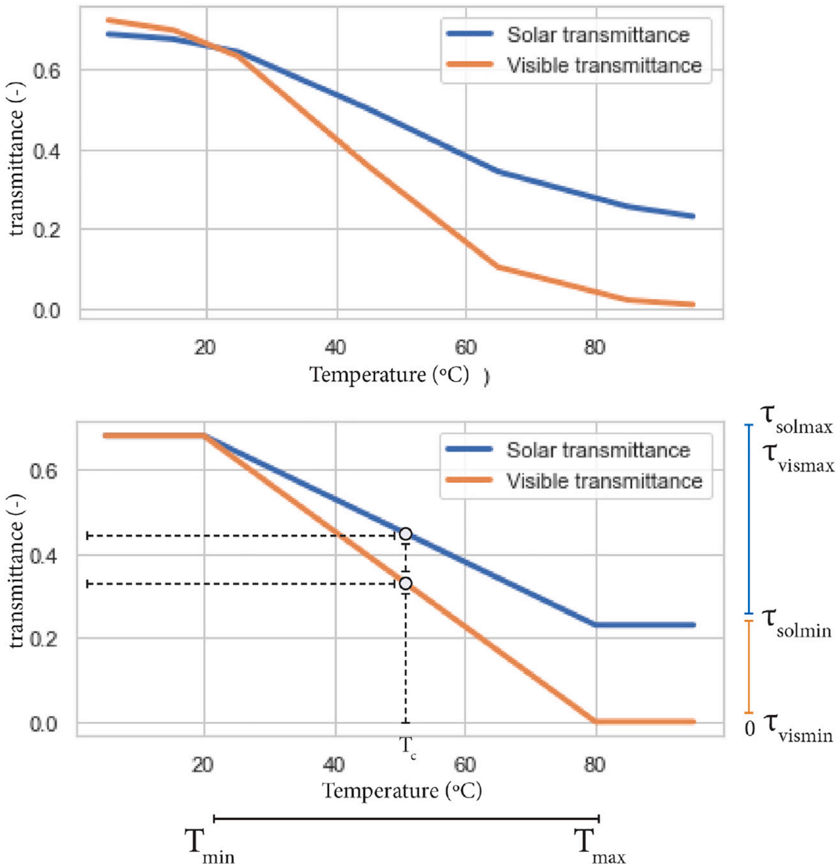

Fig. 4. τ_{sol} and τ_{vis} values of Thermochromic glazing at different temperatures for one simulation (Top). Approximated τ_{sol} and τ_{vis} values for simulations for the optimization problem (Bottom).

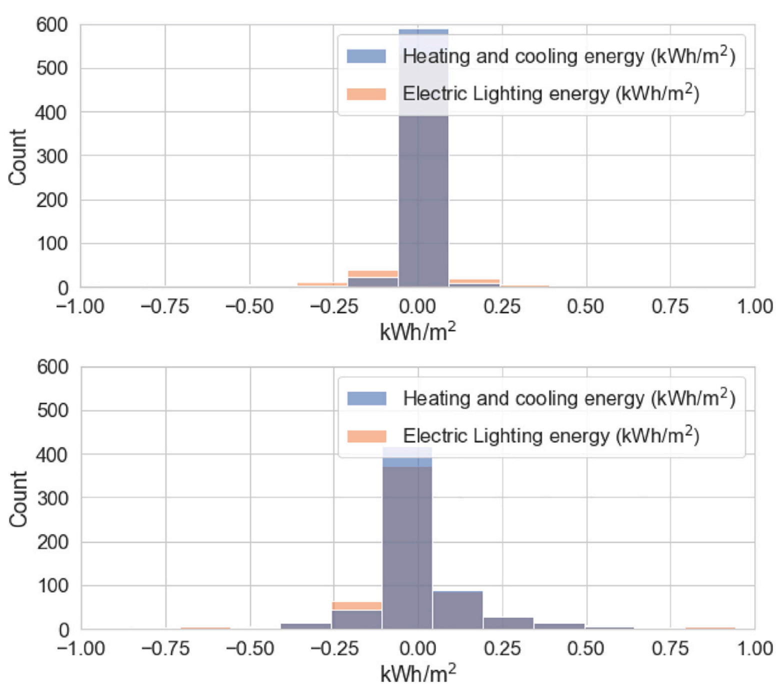

Fig. 5. Error value distribution plot for the test sample in Copenhagen's climate (Top), and Lisbon (Bottom).

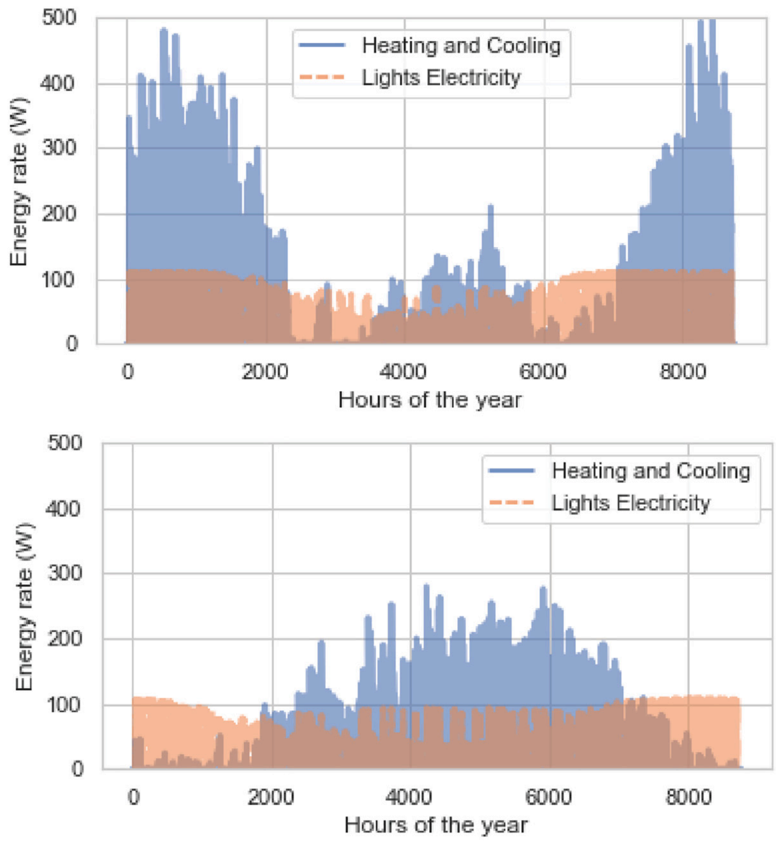

Fig. 6. Hourly heating and cooling, and Electric lighting Rate for Copenhagen (Top) and Lisbon (Bottom).

lighting dependence would increase for the office users to have the required 500 lux for their activities. Fig. 10E shows the TCG solution that provides the minimum total energy consumption. It is visible that the minimum energy use is provided by a TCG τ_{solmax} and τ_{vismax} of ≈ 0.6 that transition to ≈ 0.3, and 0 from ≈ 25 to ≈ 65 °C. These values grant the optimal balance between thermal and lighting energy use that provides the minimum total energy consumption. Fig. 10F shows the TCG solution that yields minimum lighting energy use. In this plot, it is noticed that the TCG initial temperature of transition is ≈ 45 °C, which is significantly higher than Fig. 10D or Fig. 10E. The final transition temperature of ≈ 90 °C, and τ_{solmax} and τ_{vismax} are higher than D or E since higher τ_{sol} and τ_{vis} values increase daylighting.

These trade-offs are marginally less perceptible in cold climates, but they are still present. Fig. 10A shows the optimal TCG solution that yields minimum heating and cooling energy use for Copenhagen's climate. This TCG solution shows initial and final transition temperatures of ≈ 15 °C and ≈ 45 °C respectively. Additionally, τ_{sol} and τ_{vis} values range from ≈ 0.9 to ≈ 0.2, and from ≈ 0.9 to 0, respectively. Fig. 10B shows the TCG solution that returns the minimum total energy consumption. It is visible that it has the same temperature ranges as Fig. 10A, but its τ_{sol} and τ_{vis} values range from ≈ 0.9 to ≈ 0.3, and from ≈ 0.9 to ≈0 respectively. Finally, Fig. 10C represents the optimal TCG solution that returns the minimum lighting energy use. It is visible that Fig. 10C has a slope similar to Fig. 10F but a lower initial transition temperature of ≈ 15 °C (same as A and B), and a final transition temperature of ≈ 82 °C. τ_{sol} and τ_{vis} ranges are similar to plots D and E except for the final τ_{sol} value of ≈ 0.35.

As seen, T_c values and steeper τ_{sol} variations do not represent a smaller energy consumption for both climates. Particularly for cold climates, a T_{min}, T_{max}, τ_{solmin}, and τ_{solmax} values of 15 °C, 45 °C, 0.9, and 0.2 respectively, yield the minimum total energy use. Whereas for warm climates, the minimum total energy use is obtained with a T_{min}, T_{max}, τ_{solmin}, and τ_{solmax} values of 25 °C, 65 °C, 0.6, and 0.23 respectively.

3.1. Critical discussion and limitations

The added value of this work lies in (1) the MOO approach of the TCG and (2) the use of surrogate models to speed up the simulation.

For (1), to the authors best knowledge, there are no similar studies that perform optimization of theoretical TCG properties. Saeli et al. (2010) test 4 TCG solutions with different sizes and properties for 8 climates. Results show a better energy performance in warmer climates with lower T_c (38.5 °C). Warwick et al. (2015) performed a parametric sensitivity analysis with the aim to find the best TCG properties. The authors perform a parametric study of 4 different T_c values, and 4 different hysteresis widths in 3 different climates. Results show the best energy performance in warmer climates for a TCG with low T_c (35 °C) and a narrow switching temperature range.

The present study goes one step further since it explores thousands of possible properties for theoretical TCG with the MOO approach. In agreement with the previous findings, results show a better energy performance for warmer climates. However, not also the optimum T_c (45 °C) value was slightly higher, but also the switching temperature range was wider than previous findings. This could be explained by the vast theoretical TCG explored with the MOO approach, which identified TCG solutions with slightly lower τ that gradually switched to darker states. Thus, it did not activate the 500 lux lighting set-point as fast.

For (2), the use of the surrogate models to predict theoretical TCG solutions energy performance made it possible to considerably speed-up the TCG simulation time. Therefore, the optimization algorithms were able to converge in optimum solutions requiring significantly less computational time.

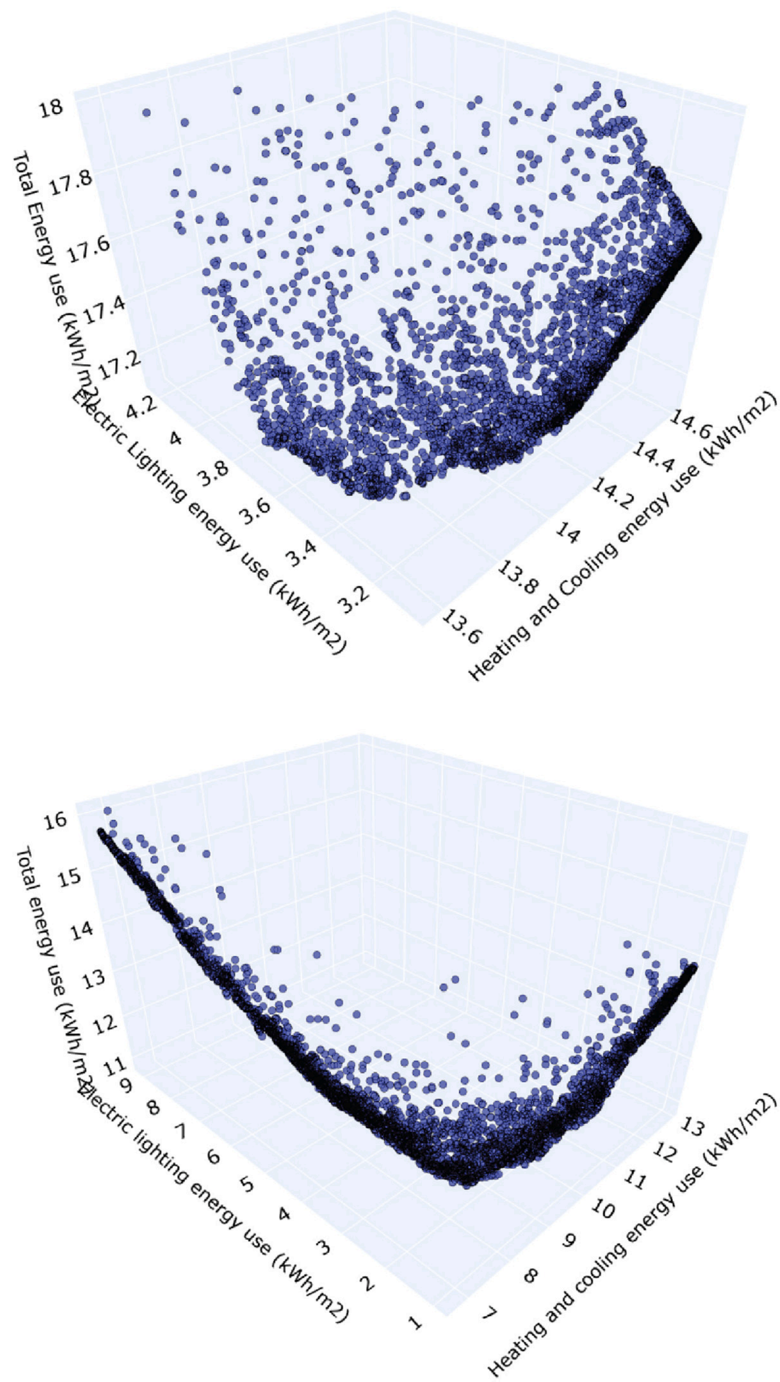

Fig. 7. Tested solutions with NSGAII for Copenhagen (Top) and Lisbon (bottom). Results for each objective (x- and y-axis) and the sum of both objectives (z-axis).

Overall, these results show that TCG optimal solutions have different properties for different climates and could benefit from benchmarking these different performances to help manufacturers tailor TCG properties for local climates. The observed increase of 200% in the electric lighting energy needs could be explained by the optimum theoretical TCG for f_1 consisting of a significantly low τ_{sol} and τ_{vis} that is constantly darkened, thus contributing to higher electrical lighting energy needs.

The following limitations could have influenced the obtained results in Section 3 as well as constrain the drawn conclusions: climates studied; geometry and location of the case study; and all the simulation inputs included in Table 2. Additionally, the indoor daylighting illuminance was calculated with Energyplus (USDOE, 2021) that uses the split-flux method (Hopkinson et al., 1954), which is suitable to assess rooms with a cubical shape and no internal partitions such as the case of the office room in this study. This method is used during the simulation to control the electric lighting by estimating the illuminance levels at a single reference point. Other advanced simulation methods (e.g., Radiance) should be used to perform a more detailed spatial daylighting analysis.

4. Conclusions

After performing a multi-objective optimization with the goal of finding the best combination of theoretical thermochromic glazing (TCG) properties, results show different optimal solutions that minimize both the electric lighting energy needs and heating and cooling

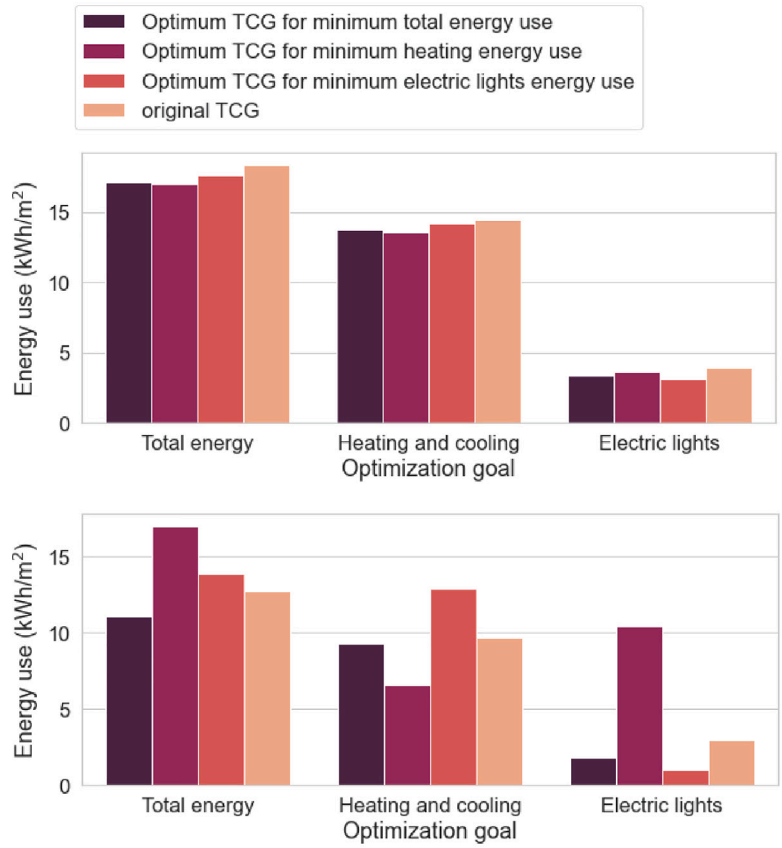

Fig. 8. Office energy use for the Optimum thermochromic glazing of the proposed goals. Comparison with the original in Copenhagen (Top) and Lisbon climate (Bottom).

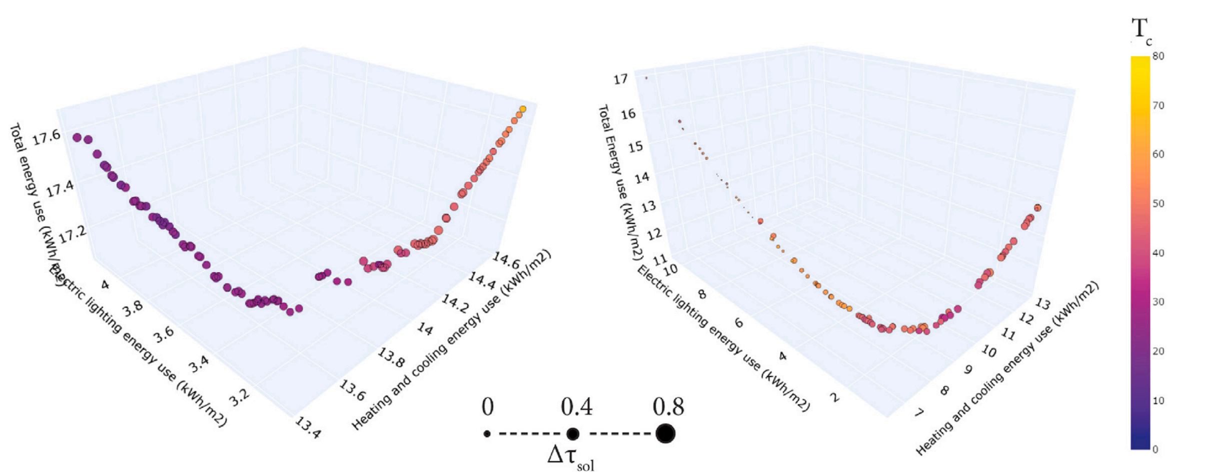

Fig. 9. Pareto front plot of non-dominated solutions of the optimization problem for Copenhagen (left) and Lisbon climate (right). Results are mapped according to their T_c and $\Delta\tau_{sol}$ values in color and size, respectively.

energy needs of an office room for Lisbon and Copenhagen climates. Additionally, the presented study shows how minimum transition temperatures and transmittance values minimize heating and cooling energy use while being capable of increasing the electric lighting energy needs by 200%. The opposite is obtained for the lighting energy use with high transition temperatures and transmittance values. When compared with an off-the-market TCG, optimal solutions managed to improve the office total energy use by 7% and 15% for Copenhagen and Lisbon climate respectively. These results demonstrate: (1) that the minimum total energy consumption requires a TCG with balanced and specific properties for each climate, and (2) how the properties of a TCG inversely impact both the zone's electric lighting, and heating and cooling energy needs. This process can help guide TCG manufacturing according to these optimum properties.

Since there are optimal TCG properties for different climate zones, future developments in the TCG field must be focused on benchmarking different optimal TCGs for different climate zones, and in production processes that allow the manipulation of transition temperatures and hysteresis loops. Further research is planned to investigate the economic impact of different TCG systems at the building and urban

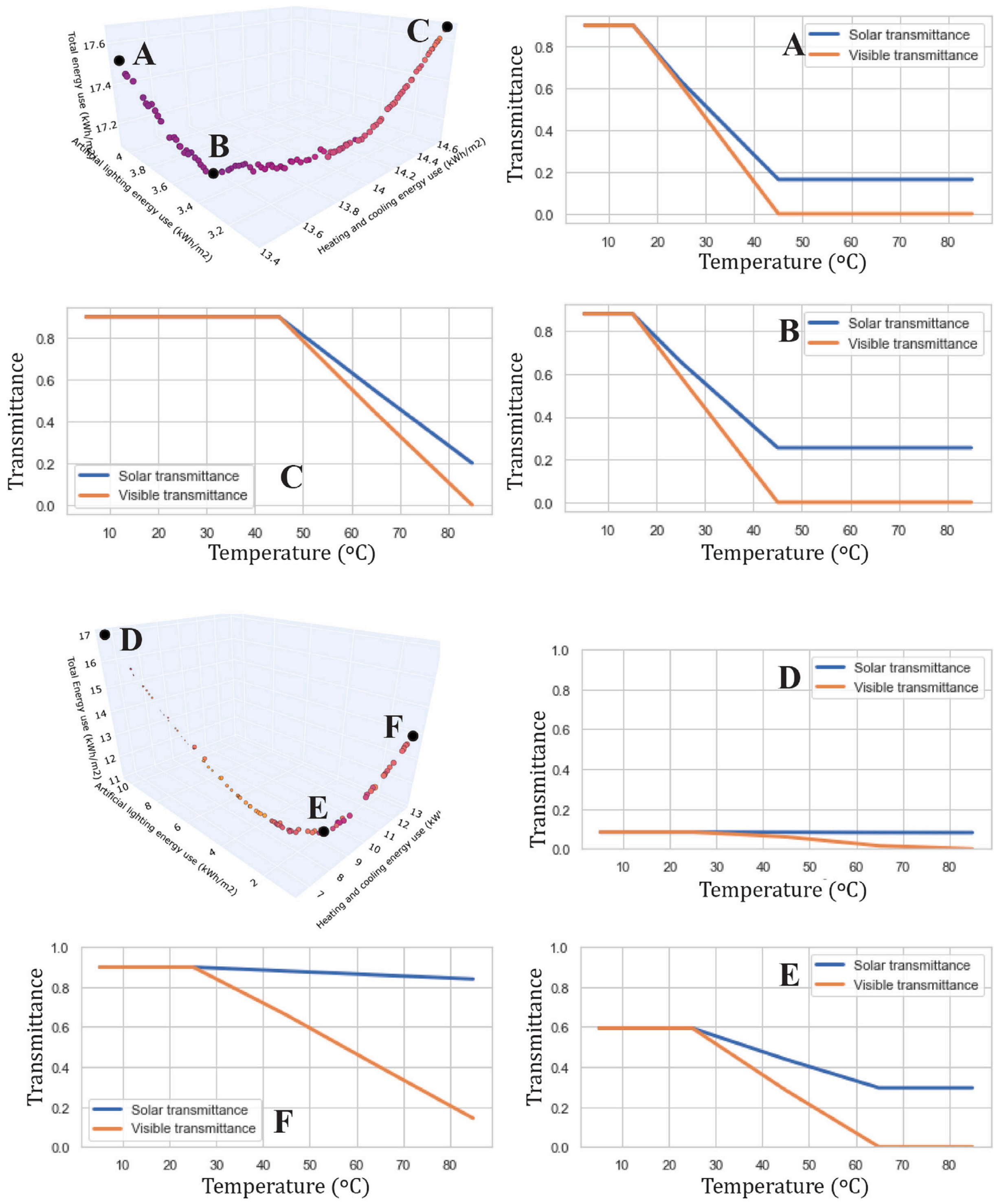

Fig. 10. Thermochromic glazing properties for each optimal solution in both climates. Copenhagen: (A) minimum heating and cooling needs, (B) Minimum total energy needs, (C) Minimum lighting needs; Lisbon: D, E, F, respectively.

levels and compare them with other smart glazing technologies for the AEC industry.

CRediT authorship contribution statement

G.R. Araújo: Writing – original draft, Methodology, Investigation, Conceptualization, Software. **Henriqueta Teixeira:** Writing – review & editing, Methodology, Investigation, Conceptualization. **M. Glória Gomes:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **A. Moret Rodrigues:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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