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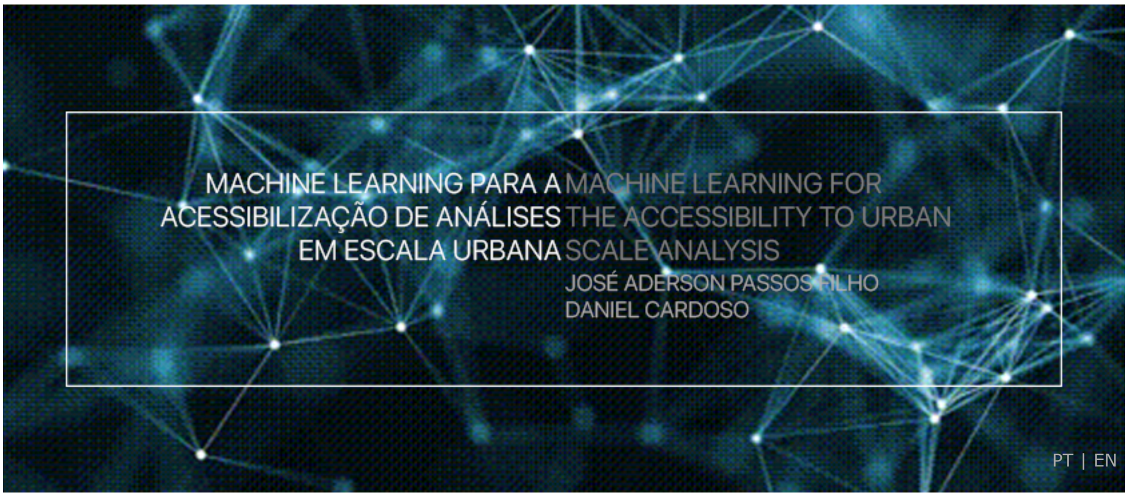

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Abstract

This paper proposes the use of Machine Learning to simplify and make accessible the obtaining of complex analyses' results, particularly in the assessment of thermal comfort on the urban scale. The complex relationship between planning, city shape, and climate requires the use of strategies for analyzing and producing urban space that often exceeds the planner's expertise. Building tools that, besides powerful, make it easier and faster for planners to act quickly and continuously, requires thinking about the trade-off between accuracy and speed of the methods applied. From a technological, political, and environmental point of view, the proposed method aims to improve the understanding of the implications of buildings on the urban environment and to contribute to the production of the contemporary city through the construction of information.

Keywords: Urban planning, Machine learning, Thermal comfort

1 Introduction

Planning, city shape, and climate conditions at the urban scale are all elements of a complex relationship that requires the use of strategies in space analysis and production. Such strategies must be adapted to the high complexity of urban systems as well as to specific climates. In order to improve the city's residents' health, and increase their social life, it is recommended to consider local climatic particularities, to promote their environmental comfort (Zhao et al., 2011). Cities are the principal place of human occupation, including Brazilian ones (IBGE, 2010), and we believe that the complexity of large urban centers should be approached based on a theoretical and technical framework, which includes tools not only powerful but able to facilitate the planners' rapid and constant action.

According to NBR 15220-1 Brazilian technical standard (ABNT, 2003), most of the country's territory is located in the hot and humid Bioclimatic Zone number 8, which includes almost all coastal capital cities. Within this zone, shading and natural ventilation are required as corrective measures for hours of the year in thermal discomfort. Software capable of expressing these corrective measurements through solar geometry calculations and natural ventilation simulations is part of the toolset for climate and environmental comfort analyses in computational design and planning approaches. Simpler and less costly, solar geometry calculations are often able to deliver results fast enough for the planner's task. However, natural ventilation simulations using Computational Fluid Dynamics (CFD) software typically involve long response times that are obstructive to the rapid iterations required in contemporary approaches to analysis and practice of design and planning (Wilkinson, Bradbury and Hanna, 2014, p. 1). Furthermore, the implementation of such simulations demands a high level of technical and theoretical deepening, which is not always part of the architects' and planners' education.

This paper proposes the use of Machine Learning for the simplification and accessibility of methods to obtain complex analyses' results. The proposal is presented as a way to circumvent the need for greater technical proficiency in tasks that require more analytical rigor in the assessment of thermal comfort in urban spaces. According to Mena (2011, p. 300), Machine Learning is a simplifier tool, as it is a technology that allows the compression of large and diverse data sets in just a few variables that are most significant to the problem at hand. Therefore, as a function of simplifying variables, the remodeling of the problem is proposed: predominant building dimensions and azimuth orientations of urban canyons replace configuration parameters of complex computational simulations that involve more than just urban shape geometry. Thus, Machine Learning can act as a device to approximate planning professionals of different areas and levels of technical knowledge sharing the theme of thermal comfort. By extrapolating the proposal to other themes, one can consequently think of this technology as a way to facilitate and increase the reach of professionals to in-depth methods related to planning, in a simplified and more efficient way, closer to the capacity of an expert technician.

Objects of study in the area of Architecture and Urbanism are treated in a multidisciplinary manner. Their varied quality criteria often require in-depth understandings that are not all present in a single professional. It becomes possible to think that a higher level of autonomy is achievable with strategies like the one presented in this paper. For his or her assessments, a single professional or researcher can tackle his or her problem from the in-depth perspective of various technical issues through the use of models simplified through Machine Learning. From a technological, political, and environmental perspective, the proposed method aims to contribute to the production of the contemporary city, improving the understanding of the direct implications of buildings on the urban environment. Ascher (2010) emphasizes the importance of understanding new urban dynamics linked to the way society itself is rapidly changing. Quick responses, not necessarily accurate, become interesting for the convergence in common denominators between so many criteria involved in urban planning's decision-making processes.

This research deals with the construction of information on urban thermal comfort, mapping this variable through the processing of climate files and city shape data, reducing the cost of computational simulation methods, and making the process more accessible. The adopted methodology starts from the definition of descriptive parameters of the urban shape, correlating them to results obtained in natural ventilation and shading simulations. The objective of this work is to elaborate a simplified model of urban thermal comfort through the implementation of Machine Learning algorithms, aiming at a broader application of this type of analysis in decision-making processes, and to emphasize the importance of these computational techniques in the production of the contemporary city.

2 Machine Learning

According to Belém, Santos, and Leitão (2019, p. 274), in recent decades, computational advances have changed the way architects and planners work in design and planning. Computing has revolutionized architecture, and computational approaches are now fully incorporated into design practice. Belém, Santos, and Leitão (2019, p. 274) also say thata new computational revolution is underway, being driven, according to Bishop (2006), by advances in Machine Learning.

Machine Learning is a branch of Artificial Intelligence-based on computational statistics and optimization procedures that explores self-improving learning techniques for problem-solving or performing specific tasks. Unlike other approaches to Artificial Intelligence, branches from which Machine Learning originates try to build systems that do not have to be programmed to get things done. Also, in the specific case of Machine Learning, mathematical models are built from sampled data, called training data, so that the model's parameters are progressively adapted until their performance in specific tasks is improved without any human intervention (Bishop, 2006; Behera and Das, 2017, cited inBelém, Santos and Leitão, 2019, p. 274-275).

Alternatively explained (Figure 1), Machine Learning works differently from classical programming, which has the rules and data of a problem as inputs to obtain the answers (the outputs). In Machine Learning, training data and previously obtained answers are inputs to the rule estimation, this time as an output. The estimated rules are used with a new dataset to obtain predictive answers, connected to a new classic programming iteration.

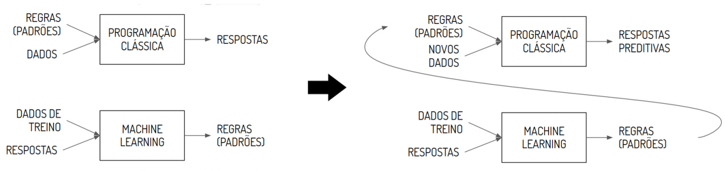

Fig. 1: Classical programming and Machine Learning. Source: the authors, 2019.

An example of the impact of this technology on areas where it has been applied, Machine Learning has refined key computational processes in almost every economic sector. Its early adoption provided a powerful impetus for innovation. It showed the potential to expand awareness of optimization, automation, and estimation problems (McKinsey Global Institute, 2017, cited in Khean, Fabbri and Haeusler, 2018, p. 95). In addition to this, several other areas have also been affected (Magoulas, 2001), such as medicine (Magoulas and Prentza, 2001; Deo, 2015), physics (Ferreira, 2018), and finance (Bolton and Hand, 2015). Also, according to Brynjolfsson and McAfee (2017), recent research suggests that advances made in Machine Learning could be as transformative today as electricity was a hundred years ago.

Historian Mario Carpo (2016, cited by Khean et al., 2018, p. 238) predicts that the next digital shift in architecture and urbanism will come with the convergence of unprecedented computational power and big data to make large-scale computational strategies (such as genetic algorithms, computational metaheuristics, and some Machine Learning) a more viable and widespread approach to design and planning.

3 Facilitation of complex analyses

Khean, Fabbri, and Haeusler (2018, p. 96) argue that architecture has traditionally been a discipline almost entirely devoid of rigorous data analysis. However, data is increasingly becoming a protagonist in interactive design. By comparison, urban planning, which has long been supported by data analysis, can be further refined by the same trend. Khean, Fabbri, and Haeusler (2018, p. 96) further explain:

> [Data] can be collated from the surrounding, analyzed, manipulated, and evaluated in the design process, and in some cases, visualized through the final product. In recent years, research efforts have produced a wealth of computational tools for data-driven design useful for a range of applications. However, developing frameworks for data-driven design has continued to depend on a combination of experience, intuition, and manual knowledge building and retrieving.

Experience and intuition are premises for the development and application of in-depth complex analysis methods, and this work proposes Machine Learning as a means to circumvent these prerequisites. This technology has not yet been widely understood or adopted in architecture and urbanism. However, there are examples of neural networks[1] applied in the development of predictive tools in construction, more specifically for estimating the cost of buildings, depending on variables fewer and more accessible to obtain than in other methods, such as floor area and quantity, year of construction and price of main supplies (Luu and Kim, 2009; Elsawy, Hosny and Razek, 2011). Cudzik and Radziszewski (2018, p. 77) suggest that the adoption of Artificial Intelligence and Machine Learning techniques will result in more intuitive tools in design.

4 Machine Learning and computational fluid dynamics

Tamke, Nicholas and Zwierzycki (2018, p. 3) believe that intersections between Machine Learning and computer simulations can enable the practice of intuition about what is being simulated. The same authors (2018, p. 3) complement:

> The integration of simulation into computational design workflows gave rise to a performance-based design methodology. The use of parametric as well as generative design tools with structural, energetic, or other simulation tools is today state of the art practice. Like any other simulation practice, this approach requires a good understanding of the relations within the underlying structural, mechanical, thermodynamic, or other system, data on the behavior of the elements, and efficient computational tools for the calculation of the underlying complex models. None of these areas is usually well covered in the design process, which is characterized by ill-defined problems, constant changes to fundamental parts of the systems to simulate, lack of time, resources, and as well data on the behavior of the material and system to be simulated. While experienced practitioners rely on these situations on intuition, ML can act similarly and predict out of precedent simulation results, how new systems would behave.

As examples, Wilkinson, Bradbury, and Hanna (2014) introduce Machine Learning in engineering to accelerate complex simulations, such as Computational Fluid Dynamics and predict plausible complex patterns of wind interference using supervised learning Methods[2] and Tamke et al. (2017) use the same technique for form-finding in complex systems.

Computational Fluid Dynamics analysis typically involves response times that are obstructive to the rapid iterations required in contemporary approaches to analysis practice of design and planning. In this paradigm, architects can quickly generate vast numbers of alternative scenarios, but face the lengthy task of evaluation and selection (Wilkinson, Bradbury and Hanna, 2014, p. 1). One solution to this problem by Wilkinson et al. (2013) is in the early stages of tall building design, using precomputed procedural model sets, building shape characteristics, and Machine Learning through artificial neural networks. In this example, it has been shown that significantly faster prediction times can be achieved while approximation errors are minimized to tolerable levels for the task at hand.

5 Accuracy versus speed

Computational Fluid Dynamics, of great importance for safety, comfort, and efficiency, is above all one of the most intense and time-consuming simulations in the performance evaluation of the architectural and urban form. Therefore, it is typically early in the design stage that it is difficult to guide decisions through the use of this tool, due to the slow feedback from conventional Computational Fluid Dynamics methods. In such approaches, this kind of simulation, slow and accurate, is best invested in later stages. It is therefore prudent to consider trade-off compromises between accuracy and speed, sacrificing accuracy in favor of speed during these early stages so that more possibilities can be analyzed (Wilkinson, Bradbury and Hanna, 2014, p. 2).

According to Wilkinson, Bradbury, and Hanna (2014, p. 2), air movement in natural ventilation in architecture and urbanism can be analyzed more error-tolerantly. This approach differs from the high-risk scenarios where the use of Computational Fluid Dynamics is commonly applied, such as in aircraft engineering, spacecraft, automobiles, among others. This scenario is especially true in the early stages of design and planning when refinements to both the simulation method and the simulated object can be done a posteriori.

The concept of accuracy-speed trade-off supports the idea that in these early stages of fast and less accurate feedback there may be more room for design exploration and optimization (Chittka, Skorupsko and Raine, 2009). This concept suggests that, for low-risk issues, it is usually better to make faster, less accurate decisions. This method implies that, in the scope of more complex problems, it is better to have a broader perspective on performance variability rather than an accurate but limited perspective that addresses fewer possibilities.

According to Chittka, Skorupsko, and Raine (2009, p. 400), the trade-off between accuracy and speed is confirmed by biology examples in the efficiency of certain animal species:

> When it takes a long time to solve a difficult task, and the potential costs of errors are low, the best solution from the perspective of an animal might be to 'guess' the solution quickly, a strategy that is likely to result in low decision accuracy.

Accordingly, Burns (2005) states that making more decisions with more errors (quick and inaccurate analysis) results in better overall performance than making decisions with fewer errors in a more demanding stance (slow and accurate analysis). He exemplifies with bees that collect more nectar for the hive when their individual behavior is on average sloppier and more intense, rather than careful and precise. This example provides a good analogy for characterizing thermal comfort on an urban scale.

6 Proposal

Machine Learning can simplify the complexity of an analysis that considers both climatic and thermal comfort aspects on the urban scale. To this approach, it is first necessary to understand how complex and costly a conventional method is, involving solar geometry calculations and computational fluid dynamics simulations.

One way to correlate climate and comfort makes use of Olgyay's chart. Olgyay's bioclimatic chart (1963) describes corrective strategies for the climate of the built environment. The chart shows a central comfort zone, outside which points representing certain moments of thermal discomfort throughout the year in the climate of a specific locality can be adapted from the corrective strategy zone in which it is located. In the example in Figure 2, the city of Fortaleza, in northeastern Brazil, belonging to the Bioclimatic Zone number 8, may have points outside its comfort zone corrected by using natural ventilation. The chart also tells the minimum wind speed needed to correct the temperature and humidity condition expressed by a point on the chart.

The points marked on Olgyay's chart can be obtained by reading weather files by software capable of extracting this information. In the example of Figures 2 and 3, a weather file of Typical Meteorological Year (TMY) format was used for the city of Fortaleza, obtained from the website of the Energy Efficiency in Buildings Laboratory of the Federal University of Santa Catarina, LabEEE-UFSC (Universidade Federal de Santa Catarina, 2019). The software Grasshopper — a parametric modeler for the Rhinoceros 3D computer-aided design platform — imported its data, through the Ladybug Tools weather analysis plugin, and interpreted it in the graphs of Olgyay's chart and the histograms in Figures 2 and 3 by an algorithmic definition implemented in a Visual Programming Language (VPL).

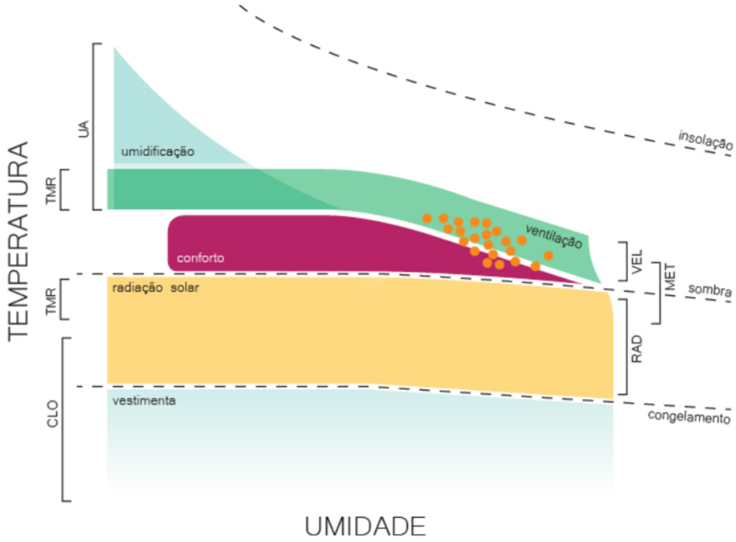

Fig. 2: Olgyay’s chart for the city of Fortaleza. Source: the authors, 2019.

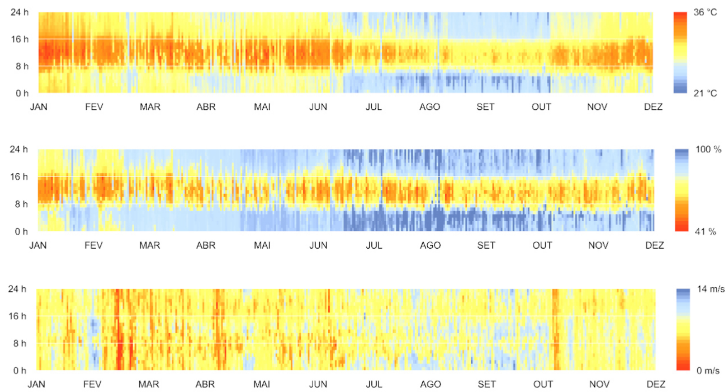

Fig. 3: Annual histograms of dry bulb temperature, relative air humidity, and wind speed for the city of Fortaleza. Source: the authors, 2019.

Olgyay's chart defines which points are outside comfort conditions and what appropriate wind speeds should be able to correct them. The weather file contains the speed value to be compared with those corrective minima (usually measured by instruments located at airports of the referred city). If this basic speed value is greater than or equal to the appropriate speed, thermal comfort may be possible to achieve. It remains to be seen, though, whether urban shape will allow it. This is where Computational Fluid Dynamics simulations are implemented. One of the software indicated for this task is Ansys CFX, commonly used in structural analysis in engineering (Wilkinson et al., 2013, p. 2) but applied here for comfort analysis according to appropriate methodology (Leite, 2015).

Thus, a Reynolds Averaged Navier-Stokes (RANS) simulation is performed following the methodology presented by Leite (2015), using the k-ε turbulence model set at 5%. The simulation is configured isothermally according to the dry-bulb temperature, without taking convective forces into account, with the convergence criterion defined at 10-4, which can be considered reasonably converged. An unstructured mesh is modeled and used in conjunction with a layer of prismatic cells on the floor and on the faces of buildings within a cylindrical domain, observing the appropriate minimum proportions to reduce the blocking effect (Figure 4).

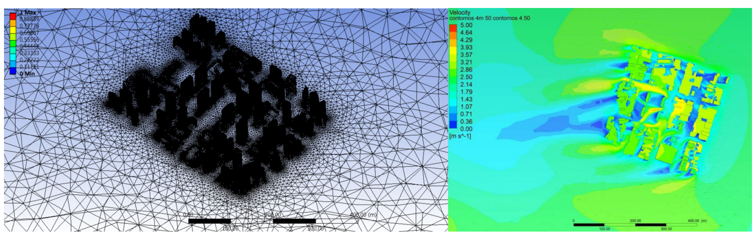

Fig. 4: Mesh and results visualization in Computational Fluid Dynamics. Source: Leite, 2015.

Thus, a percentual value of the analyzed area is obtained that comprises regions of the simulated domain where the wind speed meets the minimum requirement to act as a corrective strategy. Then the part of those regions where no shadows occur throughout the year is subtracted, computed by means of solar geometry calculations and cumulative shadow graphs performed by the same Ladybug tool for Grasshopper (Figure 5). This concludes an analysis with the conventional, slow approach, highly demanding for the specialist who performs it.

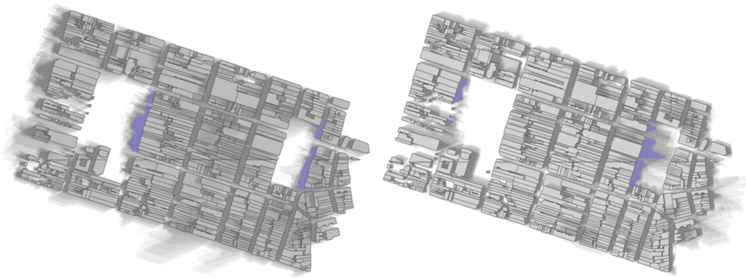

Fig. 5: Examples of cumulative shadows studies. Source: the authors, 2019.

When using Machine Learning, however, it is possible to train the computer to generate a simpler model that describes the phenomenon of thermal comfort. It would refer specifically to the climate conditions of the analyzed urban space. Also, it would use the same markers utilized in the conventional approach already described, that is, through a percentual indicator that shows how significant is the comfortable portion of the studied space. Nevertheless, Machine Learning algorithms would define the new comfort model based on more straightforward variables such as predominant building dimensions and azimuth orientations of street axes.

As Moreira (2018) suggests, by using a Database Management System (DBMS) and applying a Geographic Information System/Computer-Aided Design (GIS/CAD) toolset, it is possible to download the geometries of the urban shape so they can be analyzed on a large scale. Then, following the application of the conventional approach of comfort analysis on sufficient urban spaces for the formation of a training set, a matrix is obtained whose tuples[3] Correlate only the easily obtainable variables (building dimensions and street orientations) with the results of the analyses. Tamke, Nicholas, and Zwierzycki (2018, p. 3) refer to this kind of emergent practice as short-circuiting simulations. Artificial neural networks may finally extrapolate the learned patterns between simple variables, or features, and their results, for new cases, beyond the training set, without applying the conventional approach (Figure 6).

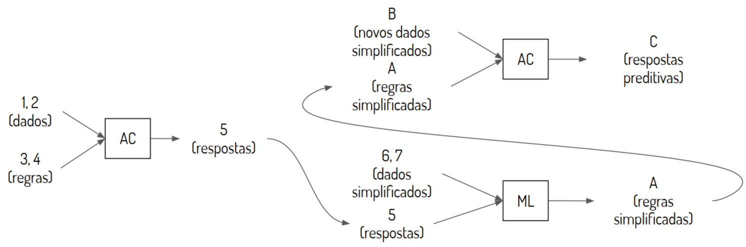

Fig. 6: Conventional approach and Machine Learning, where: 1) Climatic analysis; 2) Urban shape; 3) Computational Simulations; 4) Complex comfort models; 5) Comfort indicators; 6) Surrounding buildings dimensions; 7) Street axes orientation; A) Comfort-shape correlation simplified model; B) Building dimensions and street axes orientation for new cases; C) Estimated comfort indicators. Source: authors, 2019.

7 Verifications

Still, in its developmental stages, this research is in the construction phase of the training set of Machine Learning algorithms. It involves a considerable amount of simulations to be carried out. In a similar work focusing only on natural ventilation simulations with Computational Fluid Dynamics, with no solar geometry calculations and with a strict focus on structural rather than thermal performance, Wilkinson et al. (2013) arrive at results with about 600 simulations. However, the mark of less than 6.1% of error for the pressure coefficient readings along the complex surfaces of the tested buildings is clear evidence of this similar method’s efficiency. By working with simpler geometries with low levels of detail in perpendicular extrusions of building polygons, the present research expects to find results within similar error margins.

8 Conclusions

The Machine Learning, as a method of solving complex problems, has been used in computer science since the 1950s. With its earliest examples, such as the model of Arthur Samuel's 1952 Checkers, proving for the first time that a machine could learn to play better than its maker in a short time (Samuel, 1959). According to Sjoberg et al. (2017, p. 554), it is conceivable that such a moment could also occur in the field of design and planning, where a tool could eclipse the ability of humans to consider and respond to the vast number of variables and relations in a complex system.

However, even before such a moment arrives, the ability to obtain necessary and sufficient results in in-depth analyses involving complex phenomena may already be able to be enhanced through Machine Learning, even if the machine does not have full autonomy.

Reduced time and computational cost contribute to the work of less theoretically and technically in-depth professionals on specific aspects of architecture and urbanism, without the need for a complete understanding of all variables involved. According to Tamke et al.:

> The ability to work [...] [allowing] a systematic exploration of options through the designer, [with the computational approach], […] can build up an intuition about promising design directions and explore them quickly. These explorations can also take place through the automated generation of design options and subsequent evaluation and reiteration of the form-found solutions according to given aims (Tamke et al., 2017, p. 100).

As Tamke et al. (2017, p. 101) put it, Machine Learning was introduced in engineering to accelerate complex simulations, providing fast, reliable, and accurate approximations of results to inform the designer, leaving calculations 200 to 500 times faster than in traditional methods. Aligned with the same thinking is what is said by many authors (Chronis et al., 2012; Lomax, Pulliam, and Zingg, 2001; Lu, Tcheng, and Yerramareddy, 1991; Samarasinghe, 2007) regarding the trade-off between speed and accuracy, which claim that there is a need to adjust the level of precision of simulations to the optimal response time in specific applications.

Therefore, with the remodeling of the problem through Machine Learning, and with the use of simple variables, we seek an approximation of urban planning professionals from various areas and levels of technical knowledge that have in common the theme of thermal comfort. By extrapolating the proposal to other themes, one can think of this technology as a way of facilitating and increasing the professionals' reach to subjects related to planning that depend on a deeper theoretical and technical framework for their comprehension. This contributes to making these professionals more autonomous, able to interact more productively with specialists. Thus, through the construction of information, the increased comprehension of buildings' implications on the urban environment aims to contribute to the production of the contemporary city from a technological, political, and environmental perspective.

Acknowledgments

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1 Artificial Neural Networks are a paradigm in Machine Learning, inspired by biology, capable of solving complex signs processing and pattern recognition problems. Its concept borrows the understanding of how the central nervous system of a human operates through neural ways and connections and translates that in a computational system (Khean et al., 2018, p. 239).

2 Supervised learning is a learning method in Machine Learning that uses a training set containing the input and corresponding output. The outputs are used to guide the learning process (Belém, Santos, and Leitão, 2019, p. 276).

3 In the context of relational database. A line or a tuple is a data structure that corresponds to a record of information of correlated fields or attributes in the theme of a matrix (Oracle, 2019).