Integration of Weather and Emission Predictive Control (WEPC) into Building Energy Simulation

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Abstract

Buildings contribute significantly to global carbon emissions, highlighting the urgent need for improved sustainable operational practices. Enhanced efficiency promises cost savings amid climate concerns and digitalization and electrification trends. Intelligent controls are vital for integrating buildings into energy grids, crucial for achieving the EU's target of carbon neutrality by 2050 effectively managing the expanding availability of renewable energy sources. This paper aims to present a simulation-based framework for integrating Weather and Emission Predictive Control (WEPC) into building energy simulations, detailing how weather and emission forecast are simply incorporated to optimize control strategies.

Keywords: weather-and-emission predictive control; dynamic emission; thermal storage; electrical storage; thermal inertia; intelligent control strategy

1. Introduction

At the Paris Climate Agreement in December 2015, nearly 190 parties committed to limiting global warming to 1.5°C, attributing manmade greenhouse gas emissions as the primary drivers of global warming (United Nations Environment Programme and Global Alliance for Buildings and Construction, 2024). The United Nations Environment Programme (UNEP) identifies the building sector as responsible for 38% of carbon emissions, encompassing emissions from both building operations (28%) and the production of building materials, notably concrete and steel. This underscores the urgency for action to mitigate emissions. Additionally, factors such as climate change, the increase of renewable energy sources like photovoltaic (PV) and wind energy, and the electrification of building technology, as noted by the Fraunhofer Institute for Solar Energy Systems, introduce fluctuations in both energy supply and demand. Consequently, power grids experiences daily and seasonal variability in emissions (Fraunhofer Institute for Solar Energy Systems, 2020). Within the current existing building norms and codes, a constant annual static emission factor serves as a parameter for assessing emission balances.

Various concepts and data-driven control strategies, based on model predictive control, deep learning, weather forecast, or artificial intelligence, have been developed in the last decade, outlining energy- and CO_2-saving potentials (Drgoňa et al., 2020; Halhoul Merabet et al., 2021; Hepf et al., 2022; Jia et al., 2019; Thieblemont et al., 2017). Thereby, a few hurdles make it difficult to transform the concept into practice: data-intense algorithms, the creation of digital twins, or the necessity of highly educated employees to manage building technology. Standard building users or building operation managers are not data science experts and cannot apply these concepts to the built world.

Hence these dynamics, particularly concerning emission balance boundaries in building operations, the conventional concept of a static emission factor warrants scrutiny. This underscores the imperative to incorporate dynamic control factors to better address fluctuating emissions associated with building operations. Thus, this paper presents an integration of weather and emission forecasts in building energy simulations aiming to optimize energy consumption.

This paper integrates weather and emission forecasts into building energy simulations to optimize energy consumption and emissions , with Figure 1 summarizing how these predictions influence shading, ventilation,

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heating, cooling, and energy evaluation parameters within an integrated feedback loop.

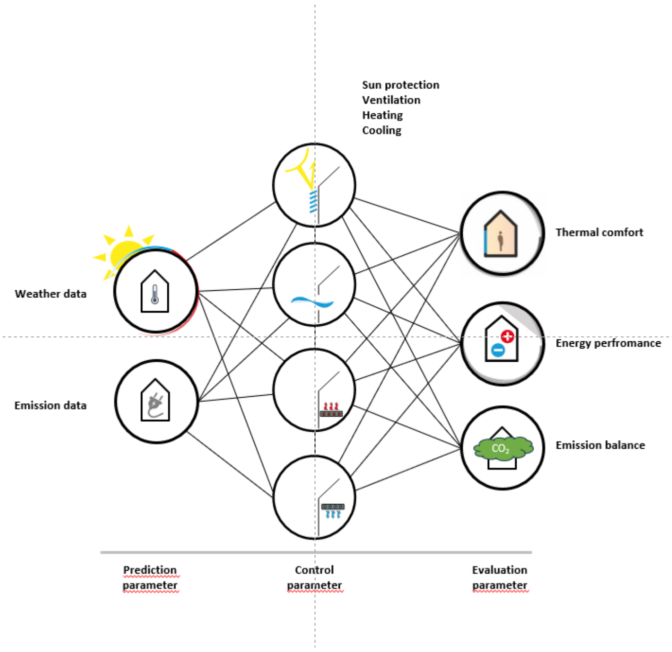

Fig. 1: General Overview

2. Review

As the focus of this paper is the workflow of the weather and emission predictive control, this review outlines the current state of literature in the fields of intelligent building control strategies and the concept of dynamic emissions.

2.1 Intelligent Building Control

Various control methodologies have been proposed, ranging from traditional to advanced systems, aiming to enhance energy efficiency and maintain thermal comfort in buildings. The widely adopted On/Off control method regulates building technology systems primarily based on room temperature thresholds, employing a straightforward three-position controller. Its simplicity and minimal data requirement facilitate practical implementation, especially with thermal building mass. However, other studies suggest that reliance on building thermal mass alone may lead to thermal discomfort, particularly without considering room heat gains or feedback from thermal zones (Gwerder et al., 2009). In contrast to On/Off control, proportional–integral–derivative controllers (PID) provide continuous regulation, utilizing feedback loops to adjust system outputs based on past and present conditions (Deutsches Institut für Normung e.V, 2018). Although PID controllers generally outperform On/Off systems in terms of energy efficiency, they can still result in thermal discomfort due to their inability to handle simultaneous heating and cooling demands and dynamic disturbances like solar radiation changes and internal heat gains (Schmelas, 2017).

Weather-dependent control strategies adjust supply temperatures according to ambient conditions, using heating and cooling curves to define operational thresholds (Bollin et al. 2021). This method optimizes energy consumption by deactivating systems within specified temperature ranges. However, this approach lacks direct feedback on room conditions, necessitating additional systems to ensure thermal comfort. Model predictive controllers (MPC) anticipate future disturbances and system behaviors to optimize responses, aiming to minimize energy consumption and costs while enhancing thermal comfort (Thieblemont et al. 2017). A reasonable number of projects show significant energy savings and improved efficiency when employing MPC strategies (Halhoul Merabet et al., 2021). Despite its effectiveness, MPC requires substantial computational resources and complex modeling, limiting its potential application in the built world. Researchers explore intelligent control strategies based on reinforcement learning (RL) to address the limitations of MPC and other conventional methods. These adaptive systems offer flexibility in adapting to diverse building conditions and optimizing operational parameters, while promising, implementing RL-based strategies requires advanced technical expertise and significant initial investments, restricting their widespread adoption in conventional building settings (Zoltan 2023). It is highlighted that various control strategies for optimizing building performance, emphasizing the trade-offs between complexity, efficiency, and practical implementation (Lee, 2002). Future research should focus on developing simplified yet effective intelligent control approaches that mitigate the challenges posed by current methodologies.

2.2 Dynamic Emissions

The concept of the dynamic emission factor is not new. In Germany, the Agora Enegiewende provides hourly data to the public (Dambeck, 2021) on a national level. On a global scale, the "Electricity Maps" tool provides hourly electricity and emissions data for over 230 regions, covering past, present, and future periods. This platform includes information on CO_2 emissions factors, electricity production, and consumption. (Electricity Maps, 2024). In their research "*Dynamic CO_2 Emission Factors for the German Electricity Mix*," authors P. Wörner, A. Müller, and D. Sauerwein emphasize the need for hourly emission factors as a more realistic evaluation method compared to static emission factors. They argue that static emission factors cannot accurately reflect the future state of an electrified and volatile energy system. Motivated by this, they developed a methodology to calculate a quarter-hourly emission dataset for the electricity mix, which can be incorporated into dynamic simulations. In 2019, authors A. Müller and P. Wörner expanded upon their previous research by calculating future emission factors for the years 2030 and 2050 (Wörner et al., 2019). The article "*Dynamic Prospective Average and Marginal GHG Emission Factors—Scenario-Based Method for the German Power System until 2050*", N. Seckinger and P. Radgen outline a methodology for calculating and evaluating future greenhouse gas (GHG) emission factor. The GHG emissions from electricity generation are based on combustion emissions, excluding upstream emissions. The model also accounts for electricity trade (import and export), storage, and grid losses, making electricity consumption the reference for hourly emission factors (Seckinger, 2021).

In their research "*Plus minus zero: carbon dioxide emissions of plus energy buildings in operation under consideration of hourly German carbon dioxide emission factors for past, present, and future*", A. Studniorz et al. discuss using hourly CO_2 emission factors for evaluating building operations in Germany. They find that grid electricity is primarily used when emission factors are high (winter) and fed back into the grid when emission factors are low (summer). (Studniorz et. al., 2022) In their research "*Impact of a Weather Predictive Control Strategy for Inert Building Technology on Thermal Comfort and Energy Demand*" C. Hepf et al. aim to develop an intelligent, improved, yet simple weather predictive control strategy for thermally inert buildings. They find increased comfort in buildings of heavy and medium construction, although the energy balance improves only marginally. The authors suggest extending the research internationally to various climate zones and including CO_2 emissions as an evaluation criterion. (Hepf et al. 2022). The research potential for calculating future dynamic emission factors is further highlighted in the work of C. Hepf, B. Gottkehaskamp, C. Miller, and T. Auer titled "*International Comparison of Weather and Emission Predictive Building Control*". At five international locations, the authors compare weather and emission predictive control strategies to standard control methods for the years 2020 and 2050. They test the hypothesis that a simple control approach can harness potential energy and emission savings. The authors emphasize the need for intelligent control strategies due to future changes in the power grid from the increase in renewable energy and the need to meet European climate neutrality goals. (Hepf et. al., 2024) This work connects to the previous study and describes the weather and emission predictive control strategy methodology in detail.

3. Methodology

3.1 WEPC Integration

This paper describes a framework to integrate WEPC into thermal dynamic simulations, which is designed to optimize building thermal performance by integrating dynamic simulations utilizing weather data and emission calculations. This approach considers emissions, factoring in the availability of renewable energy sources, and the buildings storage capacities and powers output of the supply systems. This framework is designed to be adaptable to various building technology configurations, though specific adjustments required for different setups are not detailed in this paper. The approach presented was tested and used using TrnSys18. A detailed overview of the process is depicted in Figure 3, showing the multistep process. The process can be broken down into:

- Conduct Initial Thermal Dynamic Simulation: Perform the initial simulation using current weather data to compute the Solar Heat Gains (SHG) and other relevant thermal metrics for each thermal zone.
- Transpose Simulation Results: Calculate future weather conditions by transposing the initial simulation results, incorporating forecast data for ambient temperature and solar radiation.
- Adjust Control Strategies: Modify shading, ventilation, heating, and cooling control strategies based on the transposed future data to optimize energy use and maintain comfort.
- Run Second Thermal Dynamic Simulation: Perform a second simulation that includes the effects of the future data and the adjusted control strategies to predict the system's performance.
- Incorporate Emission Control: Integrate hourly emission data and energy performance metrics into the simulation to evaluate and manage the environmental impact of the building's energy use.

Detailed thermodynamic simulations typically utilize hourly timesteps to numerically verify thermal comfort and calculate energy consumption. This approach is in alignment with ASHRAE 90.1 (Halverson et al., 2014), a widely recognized standard, which often employs hourly simulations. Commonly used simulation engines like EnergyPlus and TRNSYS also default to hourly timesteps. Crawley and Barnaby (2019) indicated that hourly resolution weather data is sufficient for design and code compliance, offering adequate granularity for accurate simulations. While higher resolutions can yield more detailed results, they are often not readily available.

In the context of electricity consumption and carbon intensity, hourly data becomes is necessary as exemplary data is depicted in Figure 3 from Agora. The carbon intensity of consumed electricity can differ significantly from that of produced electricity, especially when imports constitute a substantial share of the consumed electricity. Therefore, it is essential to adopt a consumption-based perspective to accurately capture the carbon footprint of electricity use within a specific zone and time. This can be achieved through flow tracing methodologies that trace the origin of electricity and calculate its carbon intensity (Soimakallio & Saikku, 2012, Bialek, J. (1996). To determine the source of electricity and calculate its carbon intensity, Agora employs a flow tracing methodology. (Trnberg et al., 2019) Figure 2 exemplarily depicts such hourly emission values.

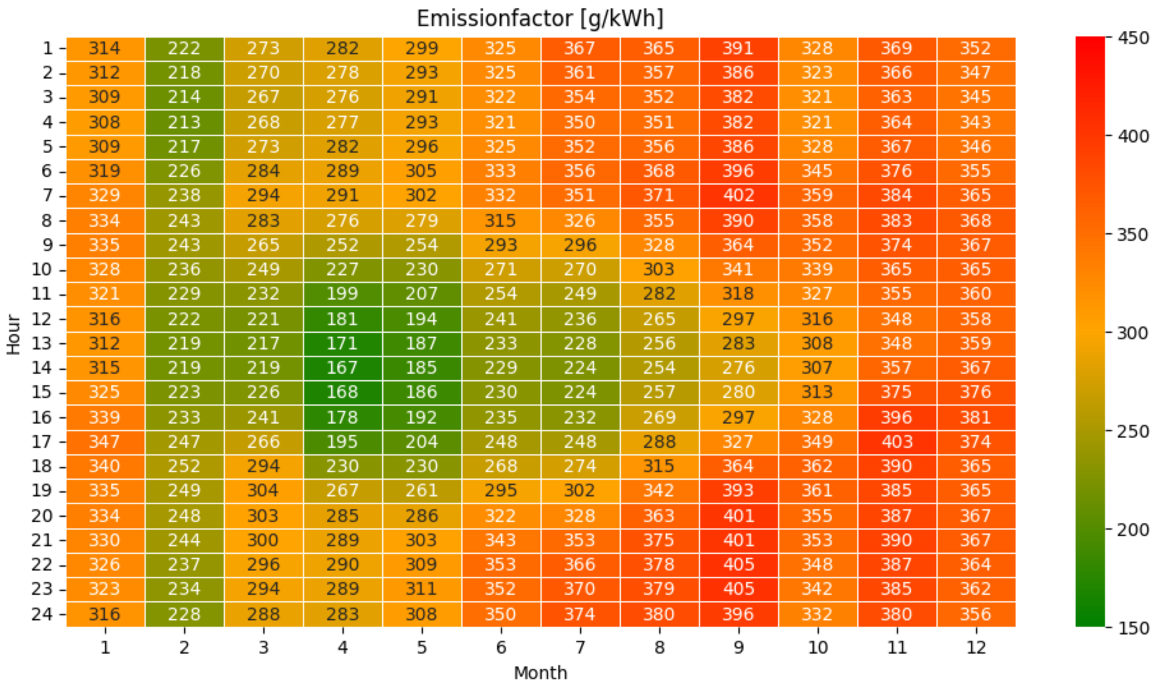

Fig. 2: Exemplary hourly Emissions data from Agora for Munich, Germany for the TRY 2020

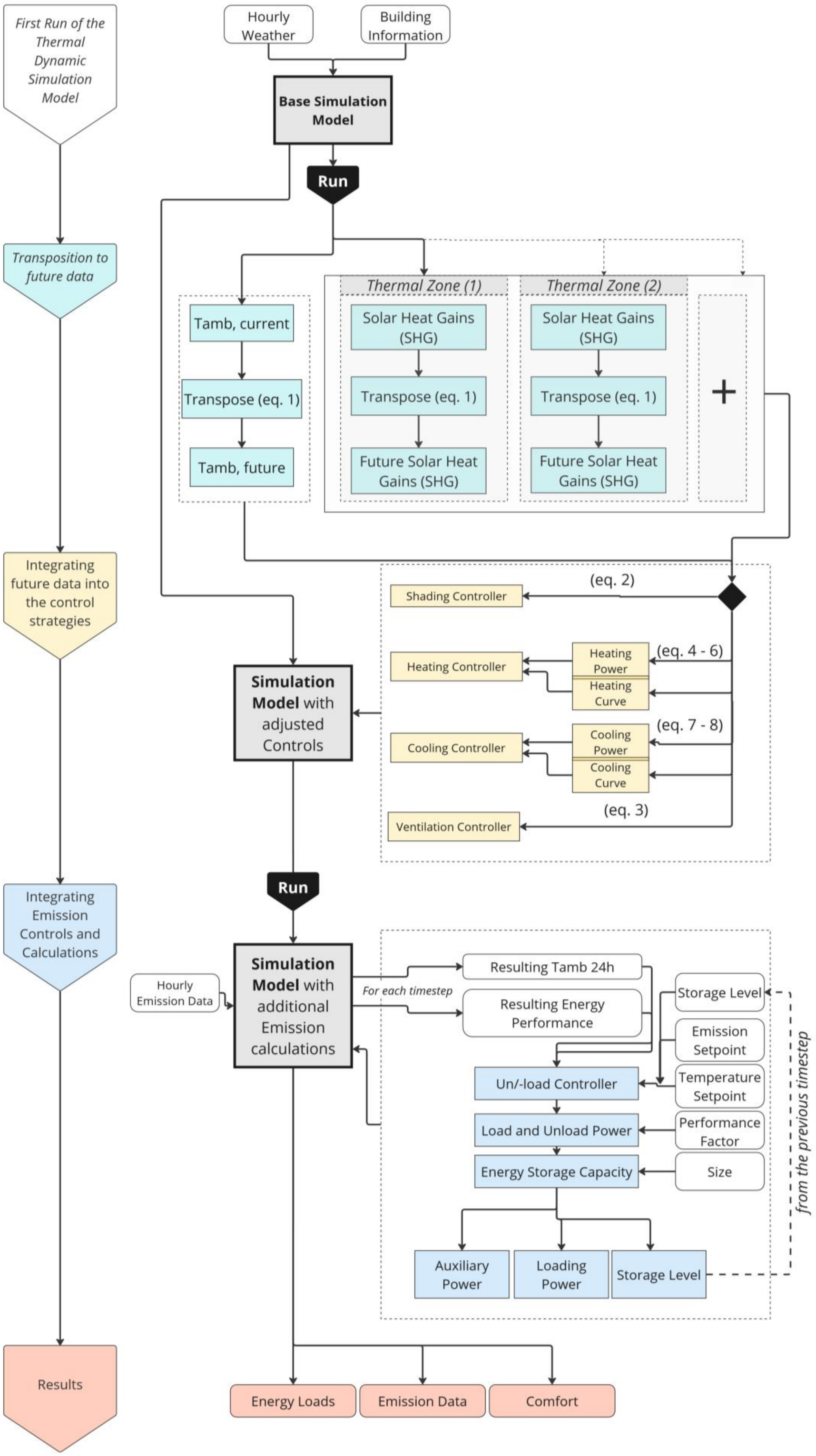

Fig. 3: Detailed Framework Flowchart for Weather and Emission predictive control (WEPC)

3.2 Computation of future data

The initial thermal dynamic simulation utilizes weather data to compute the Solar Heat Gains (SHG), which describe the total solar radiation transmitted through external windows for each thermal zone at each time step. It is recommended to use hourly time steps, though more detailed intervals can be adopted depending on the resolution of the weather data and emissions. Lower resolution data can reduce the accuracy of predictions.

The ambient air temperature from the provided weather file, along with the SHG, is then transposed to describe future conditions. This transposition process involves using data from the current simulation step and incorporating forecast values for future steps. The forecast horizon can vary, typically they have been set between 12 or 24 hours. Weather forecasts tend to lose accuracy the further ahead they predict environmental variables, hence this framework recommends adhering close to this range for good accuracies, but it has not been further investigated. For each future step, the influence of the prediction is reduced by a factor, alpha, to account for the decreasing accuracy of weather forecasts over longer time periods.

Equation 1 describes the transposition of the future data, hence computes an exponentially weighted sum of input variables over a specified number of future timesteps t. In this functi1on, a is a parameter that controls the rate of exponential decay, ensuring that more recent inputs have a greater influence. Each input z_k is weighted by a_k, and the overall sum is scaled. This formulation allows the function to adapt to different numbers of input terms, making it useful for scenarios that require weighted sums over multiple future timesteps.

$$f(a, z_0, z_1 \dots z_t) = (1 - a) \sum_{k=0}^{t} (a^k * z_k) \qquad \text{(eq. 1)}$$

with

- $f(a, z_0, z_1 \dots z_t)$: Exponentially weighted sum of input variables over *t* future timesteps.
- *a*: Decay parameter controlling the rate of exponential decay, with $0 \le a < 10$
- z_k: Input variables at each timestep *k* (where *k* ranges from 0 to *t*).
- *t*: Total number of future timesteps considered.

3.3 Controller Adjustments

The future data for SHG and ambient temperature is than utilized to adjust the heating, cooling, shading and ventilation controls for the initial thermal dynamic simulation to perform a second run, to calculate the hourly energy performance for each zone.

Shading greatly influences the solar heat gains transmitted into the thermal zone, hence adjusting the shading controller, for better temperature control and its impacts on the heating and cooling system to maintain indoor comfort and lower energy consumptions. Shading controllers are often activated based on an ambient temperature setpoint or time based, which could be, with the setpoint sometimes being controlled by a schedule, allowing to adapt to seasonal changes. The adapted equation (eq. 2) also utilizes a setpoint for the ambient temperature, the current solar heat gains and future solar heat gains to print out an active signal.

$$ShadController = \begin{Bmatrix} 1 & if\ T_{amb,current} > 14 \\ 1 & if\ SHG_{current} > 200 \\ 1 & if\ SHG_{future} > 150 \\ 0 & otherwise \end{Bmatrix} \quad \text{(eq. 2)}$$

with

- *ShadController*: Control signal for the shading device, equal to 1 if the shading should be activated, and 0 otherwise.
- $T_{amb,\ current}$: Current Ambient temperature [∘C]
- $SHG_{current}$: Current solar radiation [W/m2].
- SHG_{future}: Forecasted solar radiation for t timesteps ahead [W/m2].

To maintain thermal comfort, temperature control must minimize energy losses or maximize energy gains. This requires controlling air exchange based on transposed future data. Air exchange can be managed using various strategies, such as day and night cooling, different setpoints for varying intensities, and schedules. However, the general concept of integrating future data remains consistent. By incorporating an additional statement that utilizes the Ambient Future Temperature, we can further enhance a Simple Controller.

Equation 3 demonstrates a controller designed to output a specific airflow rate at a certain temperature range. This formular is then used in a greater formular with combined other Airflow formular to control the specific airflow rate for other temperature ranges to a final specific airflow rate.

Temperature is chosen as the primary parameter because temperature control systems are already widely established and integrated into most building HVAC systems (Rehrl and Horn, 2011), making it cost-effective and practical to leverage existing infrastructure. Additionally, temperature is easily measurable and can be accurately predicted using ambient temperature forecasts, allowing the controller to anticipate changes and adjust airflow rates proactively, thus enhancing both comfort and energy efficiency.

$$ACH\_gt23 = \begin{Bmatrix} 3 & Schedule\ if\ T_{air} > T_{amb,\ current}\ and\ T_{amb,\ future} > 23 \\ 0 & otherwise \end{Bmatrix} \quad \text{(eq. 3)}$$

with

- ACH_gt23: Is a specific airflow rate [m s-1]
- Schedule: An optional schedule, equal to 1 if activated, and 0 otherwise.
- T_{air}: Current Zone Air temperature [∘C]
- $T_{amb,\ current}$: Current Ambient temperature [∘C]
- $T_{amb,\ future}$: Futurue transposed Ambiant Temperature [∘C]

After managing passive strategies for shading and ventilation, heating and cooling methods are also adjusted to maintain comfort with low energy consumptions. Both heating and cooling controllers are typically defined by specific curves, which include a supply temperature and a power output. To enhance these controllers, future data is integrated into their formulas. Instead of using the current ambient temperature, the heating or cooling curve incorporates the future ambient temperature (eq. 4). Additionally, future solar radiation is factored into the supply temperature adjustments to reduce energy consumption (eq. 4, 5).

Future solar radiation impacts the power output of the heating and cooling systems: it reduces the heating power output and increases the cooling power output (eq. 6). This adjustment ensures that the systems respond appropriately to anticipated solar gains. The influence of future solar radiation and ambient temperature on these adjustments depends on the specific location, as different regions experience varying solar intensities and weather patterns.

$$T_{sup,\ HT} = \max\left(25.4 - 0.27 * T_{amb,\ future}, 22\right) \quad \text{(eq. 4)}$$

$$\delta T_{soltr,\ future} = \frac{Q_{soltr,future}}{\frac{m_{spec} * c_W}{3.6}} \quad \text{(eq. 5)}$$

$$P_{HT,\ future} = \max\left(P_{HT,\ max} - Q_{soltr,\ future}, 0\right) \quad \text{(eq. 6)}$$

with

- $T_{sup,\ HT}$: Representing the Supply Temperature for the Heating Curve [∘C]
- $T_{amb,\ future}$: Transposed Future Ambient Temperature [∘C]
- $T_{soltr,\ future}$: Transposed incoming solar radiation referring at the area [$\frac{W}{m^2}$]
- m_{spec}: specific mass flow [$\frac{kg}{hm^2}$]
- c_W: specific heat capacity of water [$\frac{KJ}{hm^2}$]
- $P_{HT,\ future}$: Resulting Power Heating Output considering the future data [W]
- $P_{HT,\ max}$: Maximum Power Heating Output [W]

$$T_{sup,\ CL} = \min(25.4 - 0.27 * T_{amb,\ future}, 18) \quad \text{(eq. 7)}$$

$$P_{CL,\ future} = \max\left(P_{HT,\ max} - Q_{soltr,\ future}, 90\right) \quad \text{(eq. 8)}$$

with

- $T_{sup,\ CL}$: Representing the Supply Temperature for the Cooling Curve [∘C]
- $T_{amb,\ future}$: Transposed Future Ambient Temperature [∘C]
- $T_{soltr,\ future}$: Transposed incoming solar radiation referring at the area [$\frac{W}{m^2}$]
- $P_{CL,\ future}$: Resulting Power Cooling Output considering the future data [W]
- $P_{CL,\ max}$: Maximum Power Cooling Output [W]

Using the adjusted Zone Model, which incorporates controls for shading, ventilation, heating, and cooling, the second simulation run results can describe thermal comfort and provides the energy balance. The Energy balance is then used as an input for the pseudo-predictive post-simulation processing, which incapsulates the CO_2 calculation based on some given parameters named the System Model calculations.

3.4 System Model for Emission calculations

The System Model utilizes the hourly energy balance output from the second run of the thermal dynamic simulation, including 24-hour average ambient temperature and an hourly emissions dataset. This model incorporates various building technologies for heating, cooling, and auxiliary consumptions (equipment, electrical, etc.), as well as electrical storage capacities, loading and unloading powers, efficiencies, and the overall dimensions of the system as depicted in Figure 2. This results compute into CO_2 emission with loading and unloading times as well as storage capacity levels.

Complex control strategies are modeled using a pseudo-predictive approach. Instead of developing an algorithm for real-time data prediction, the model assumes that the future data is already known, since the thermal dynamic simulation has already provided all necessary results. Hence, it is possible to identify minimal values within specific periods (typically 1-2 days) and schedules the charging period around these minimal values. Thus, the model:

- Specifies the periods during which storage systems are charged based on the minimum energy requirements identified.
- Determines the timeframe for loading and unloading operations is determined based on the 24-hour average ambient temperature, energy performance loads and low CO_2 emissions. This helps ensure that the system operates efficiently and maintains optimal thermal comfort.

Also, both thermal storage (heating and hot water) and battery storage are modeled using a simple input-output approach. The discharge power required by the storage (e.g., for heating demand) must be available within the storage capacity. If the storage is "empty," the required energy is supplied externally during defined charging periods.

The following equations to define how storage loading capacity and supplementary power are processed, determining the energy purchased from the grid (eq. 9). This energy is subsequently used, along with emission data and the Annual Performance Factor, to compute the system's resulting dynamic CO_2 emissions (eq. 10).

$$\rho_{grid}(t) = \sum_{t=1}^{8760} \left(\frac{\rho_{ld}(t) + p_{xlr}(t)}{JAZ} \right) \qquad \text{(eq. 9)}$$

$$E_{dyn} = \sum_{t=1}^{8760} \left(\rho_{grid}(t) \, * \, \frac{ef(t)}{1000} \right) \qquad \text{(eq. 10)}$$

with

- $\rho_{grid}(t)$: Grid volume of purchased energy [kWh]
- $\rho_{ld}(t)$: Storage loading capacity [kWh]
- $p_{xlr}(t)$: Supplementary Power [kWh]
- JAZ: Annual Performance Factor
- E_{dyn}: Resulting dynamic CO_2-Emissions [kg CO_2]
- $ef(t)$: Emission factor [g CO_2/kWh]

This System Model framework offers a streamlined approach to integrating thermal and electrical storage, enabling efficient emission calculations and providing a foundation for future enhancements. The model does not simulate complex physical processes such as temperature stratification in thermal storage. With a pseudo-predictive the solar radiation data could be precomputed in the first simulations runs of the thermal dynamic simulations, or in a separate solar radiation study, to additionally incorporate the effects of Photovoltaics into the loading and unloading methods.

4. Discussion

The workflow developed in this study demonstrates both potential and limitations when considering its applicability in thermal models and its transferability to real-world building systems. While the workflow's simplicity in utilizing basic mathematical equations and widely available weather data allows for easy implementation in thermal simulations, it faces challenges in direct application to the built environment.

Firstly, the workflow, though simplified, still requires some level of computational power and understanding of HVAC systems. This makes it unsuitable for a straightforward application in real-world scenarios without the support of a computational unit such as a computer or smart controller. Additionally, basic knowledge in HVAC engineering is necessary to comprehend and apply the process, creating a barrier for non-specialists. These factors highlight the complexity that remains despite attempts to simplify, making the direct transfer of the workflow into built environments challenging.

On the other hand, the low technological requirements and the simplicity of the equations used suggest that the workflow could be implemented using basic devices, such as smartphones or low-cost controllers. This broadens the potential for integration into building systems, offering a path for easier connectivity and application in various settings. Moreover, the availability of weather data for any location further supports the feasibility of using this workflow in real-world applications. However, the lack of granular emissions data, available only at a national level, could potentially limit the precision of the workflow when applied to specific local contexts.

In terms of its relevance to ongoing climate change and adaptation strategies, the workflow presents a mixed case. The need for optimization remains significant, especially as the integration of renewable energies and the stability of the grid become increasingly important. The workflow effectively delivers energy savings, emissions reductions while sustaining thermal comfort, aligning with objectives to enhance energy efficiency and support grid stability. This paper focuses on presenting the framework, while prior studies by Hepf et al. (2022, 2024) have implemented this approach. The 2022 study evaluated four configurations, showing energy savings between 3.5% and 11%, impacted by variations in thermal and battery storage. In 2024, the analysis expanded internationally, covering diverse climate zones and reporting emissions reductions of 5% to 25% across various building types. However, the current framework does not consider humidity, which is one of the driving factors in energy consumption, particularly in humid climates where dehumidification significantly impacts energy usage. This limits the workflow's effectiveness in tropical climates.

Additionally, the long-term effectiveness of this approach is debatable. As emission factors decrease in line with European and governmental targets, the impact of further optimization may diminish, reducing the necessity for such workflows. Furthermore, focusing on sufficiency improvements might offer more substantial benefits than efficiency improvements alone. Despite these considerations, in large building energy systems where HVAC management is crucial, the simplicity of this workflow could offer significant benefits by streamlining complex optimization processes.

In conclusion, while the workflow offers promising advantages in certain scenarios, its broader application in the built environment and its alignment with long-term climate strategies require careful consideration. Its success will depend on the specific context, particularly in terms of technological capability, data availability, and the evolving priorities of energy and emission management.

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