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KI4HVACs - Energy efficiency optimization of HVAC systems through predictive algorithms and modeling using machine learning

Energieeffizienzoptimierung von HLK-Systemen durch prädiktiver Algorithmen und Modellbildung mittels maschinellem Lernen

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2 Introduction

HVAC systems are usually responsible for more than 40% of the energy consumption of residential and commercial buildings, making optimizing system efficiency a priority, both economically and ecologically. It is expected that as the impacts of climate change increase, the need for HVAC systems will increase too. In particular, in commercial and industrial environments the need for direct cooling and ventilation will rise strongly. Comprehensive optimization of HVAC systems can typically reduce energy consumption and costs by 20 to 40%, improve system reliability through more efficient operation, and significantly reduce a building's carbon footprint. In contrast, in real life HVAC systems in existing buildings but also in new buildings are usually only parameterized during the planning and commissioning. Thereafter, ongoing monitoring, combined with a reconfiguration or optimization of the system, is usually neglected.

The aim of KI4HVACs (Figure 1) is to use machine learning, without explicit modeling, to evaluate and optimize system and operating states, as well as to plan predictive maintenance not only according to wear and associated costs but also in respect to their effects on building energy consumption. The focus of the optimization strategy is on the configuration of HVAC settings and the efficiency of maintenance planning. The novelty of this approach is that there is no need to intervene in the control of the HVAC system. The developed AI can therefore also be used as a retrofit for existing systems across all manufacturers. In addition, the optimization can also take place on data from multiple systems and the learning phase of the AI algorithms used is massively shortened through pre-trained models.

The core of the technical innovation is an approach consisting of a combination of reinforcement learning, supervised learning and an iterative control strategy based on a Model Predictive Control (MPC) architecture, which compensates the deviations between the actual and expected values, e.g. minimization of model inaccuracies. The evaluation of the system and the expected savings of 30% energy and 40% costs compared to existing systems is carried out in a dynamic system-in-the-loop simulation, which enables the developed technology to be tested in a wide range of use cases. Ultimately, however, the developed approach will be tested in a real system in a test building of the project partners over the long term to obtain experimental confirmation of the simulation results. The results and the proposed AI approach are of great relevance for building owners and facility managers, planners and system integrators, manufacturers and suppliers of HVAC systems and building management systems, building operators and tenants, all of whom are required to improve the energy efficiency of HVAC systems.

3 Content Description

3.1 System Architecture

A common approach for optimizing short-term energy costs is to fully replace the HVAC control unit with model predictive control based on machine learning. It should be noted that HVAC systems are increasingly using complex control logics, which significantly increases the demand for machine learning systems. By using the latest AI methods, such as reinforcement learning, current research achieves significant energy savings. The biggest drawback is that the control unit must be completely replaced, resulting in significant limitations and additional costs such as system shutdown during installation, significant limitations during retrofitting (machine learning control unit must be expanded), and experts in AI knowledge for control engineers, opaque control commands generated by neural networks, and so on.

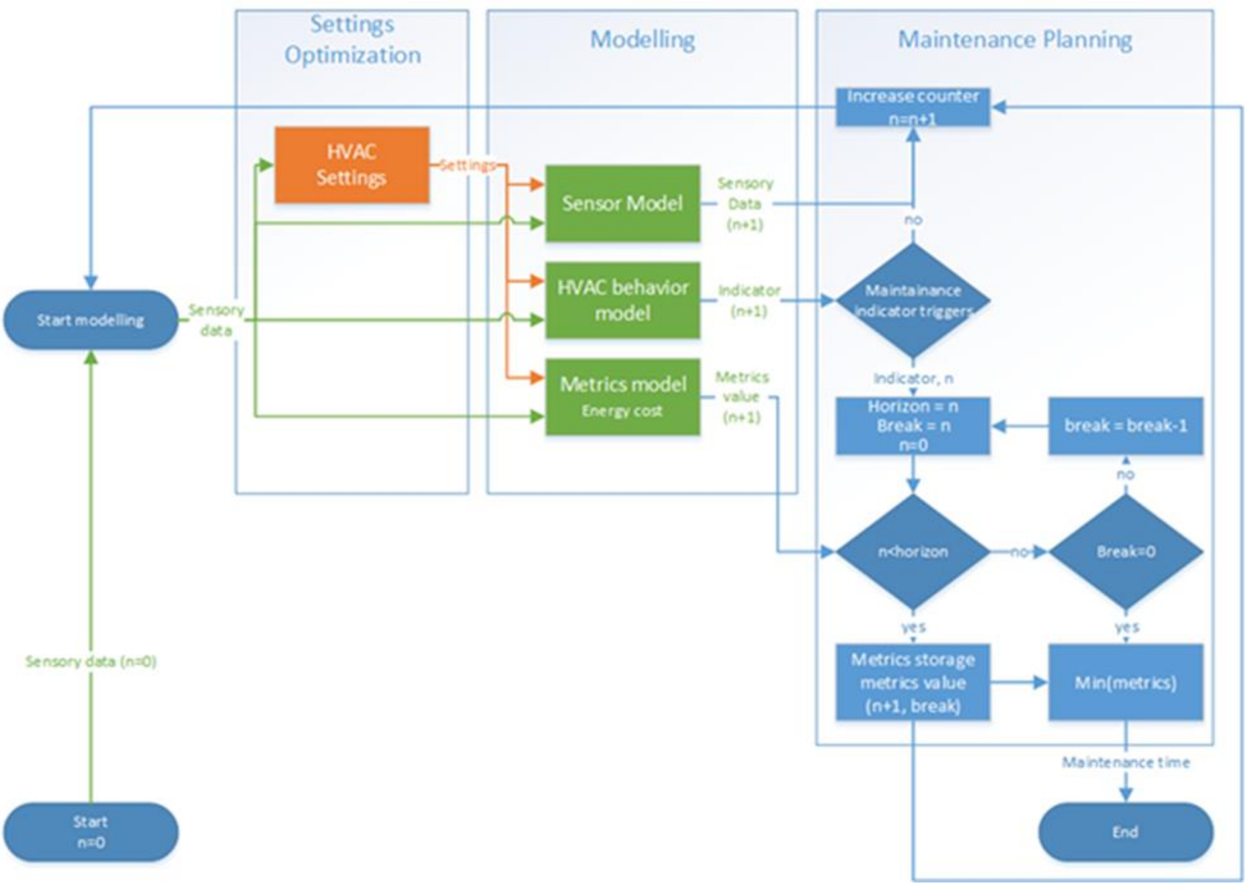

Figure 1 KI4HVACs system architecture

To avoid this, KI4HVACs proposes an innovative new approach based on optimizing the settings of an existing HVAC control unit. As a result, existing control units can be used, with independent AI optimizing the settings. Our approach can therefore be interpreted as an add-on, which only indirectly intervenes in the control. This allows for significant flexibility in retrofitting existing systems as well as in new construction. The control engineer retains full competence with respect to the control and receives a tool that allows for optimal configuration of the system for energy consumption.

Furthermore, current approaches to HVAC maintenance can be divided into the following three high-level categories: a) proactive, performance-monitored maintenance; b) preventive, scheduled maintenance; and c) reactive, unscheduled or no maintenance. There is extensive research on the identification of possible failures of HVAC systems. However, these are limited to identifying possible errors. Other key elements, such as energy cost optimization of HVAC operation or possible extension of device lifecycle, are not considered. Current approaches use for example a combination of acoustic sensor networks combined with unsupervised learning to detect potential failures. Some approaches go a step further and try to determine the optimal maintenance time based on the condition of the system. However, the energy costs of HVAC operation are never the optimization criterion. Maintenance predictions based on possible failures generally provide higher stability than optimizations based on fluctuating energy costs, especially for renewable energy sources.

Therefore, the central core elements of our approach are a combination of 1) reinforcement learning and 2) supervised learning, both of which represent the optimization criterion "energy costs/consumption," and thus in combination represent a high potential for innovation in reducing total energy consumption and costs. The reinforcement learning part is used to optimize HVAC settings, achieving short-term energy optimization. The supervised learning part handles the prediction of predictive maintenance optimizations (optimized for energy costs) and the long-term selection of HVAC settings, which are predicted iteratively based on HVAC metrics and sensor prediction models. The biggest challenge is the accuracy of the models, which can be partially improved by potentially expanding additional sensors. One project goal is to achieve an optimal balance between the desired accuracy and the minimum number of sensors. The second possibility for minimizing deviations between actual and expected values is an iterative control strategy that minimizes the effects of deviations. Additionally, there is the possibility of indirectly deriving and learning potentially relevant system information from sensor values through the

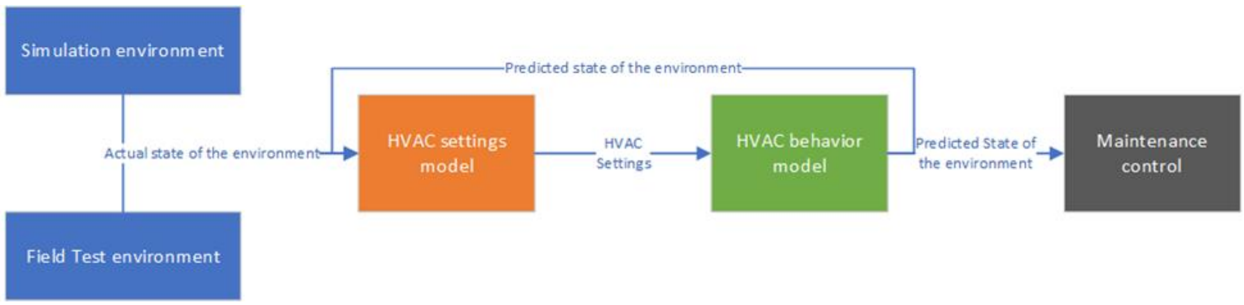

Figure 2 KI4HVACs information flow

application of neural networks."
Figure 2 visualizes our system approach and outlines the four main system components:

1. Sensor and Actuator network: This component monitors and controls the building's environment, including the HVAC system. In this system approach, the sensor and actuator network is combined/substituted by the simulation environment, which enables virtual monitoring and control of the HVAC system.

2. HVAC setting model: This model uses reinforcement learning to optimize the HVAC system's settings based on the current state of the environment. By analyzing data from the sensor and actuator network, the model can adjust the HVAC system's settings to achieve optimal energy efficiency.
3. HVAC behavior model: This model uses supervised learning to predict the future state of the environment based on the current sensory data and the HVAC settings. The HVAC behavior model uses supervised learning to predict the future state of the environment based on the current settings and sensory data. The supervised learning model is trained on historical data to identify patterns and trends in the environment, allowing it to predict future environmental conditions accurately.
4. Maintenance control logic: This component uses a decision tree to determine when maintenance is required. By monitoring the HVAC system's performance, the maintenance control logic can detect potential issues and schedule maintenance to prevent downtime and minimize energy waste.

The general information flow of the system:

1. The actual state of the HVAC system is sent to the HVAC settings model that decides the optimal settings of the system based on the current state of the environment.
2. HVAC settings as well as the actual sensory data sent to the HVAC behavior model that predict the next state of the environment.
3. The future state of the environment is sent to the maintenance control logic that checks whether the maintenance is required.
4. If not, the future state is looped back to the HVAC settings model to determine the optimal settings of the HVAC system based on the potential predicted future state of the environment.
5. This loop continues until the maintenance time is determined by the Maintenance control logic.

All these activities are performed at time = 0. At the next time step (time =1) the new actual state of the environment is used to repeat the loops and determine the maintenance time and set up the HVAC till time =2.

3.2 Simulation Environment

For the implementation of the real environment and the training of the RL-Algorithm, before the field tests a simulation model mimicking the real system was built. This model was built using TRNSYS, which offers a flexible and customizable platform for HVAC Systems as well as the possibility on integrating Reinforcement Learning into the energy system analysis and optimization. Overall, TRNSYS is a powerful and versatile simulation tool and has been widely used and validated, making it a valuable tool for researchers, engineers, and designers in the field of energy analysis and renewable energy systems design. In this project TRNSYS is used to simulate a test-bed and its HVAC components as well as connecting it to RL by modeling a generic ventilation system and the connection to the surroundings as building typology and environmental impact.

3.2.1 Generic Ventilation System

In the course of the feature selection, schemes of different ventilation systems were examined and based on this, a generic model was developed to cover all possible combinations of individual components in a ventilation system. This model was used to identify all possible sensors and actuators of a ventilation system and based on this, find the metrics for system optimization. The generic model was prepared in such a way that all measured and influencing variables could be assigned to the individual components of the ventilation system and thus individual sensor data could be used to directly interfere with the operating states or faults of the individual components. The generic simulation was based upon five different ventilation systems for office buildings including the EnergyBase in Vienna, which offers a intelligent system with a dessicant cooling process in which humidity and temperature are regenerated in order to increase the efficiency and is shown in Figure 3 on the left. The other four systems were based on more state of the art systems with heat regeneration as well as humidification of the air. A example is the ventilation system of the project partner Radel & Hahn which is seen in Figure 3 on the right.

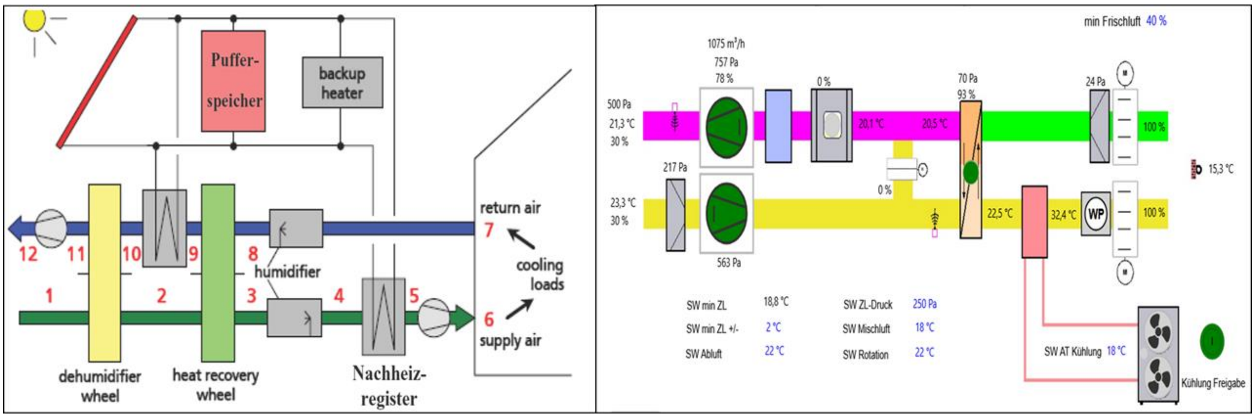

Figure 3 : Examples of existing ventilation units considered: EnergyBase (left), Radel&Hahn (right)

By considering these systems and comparing the function as well as the components a generic ventilation system was developed and possible sensory data according to maintenance and efficiency indicators added as seen in Figure 4.

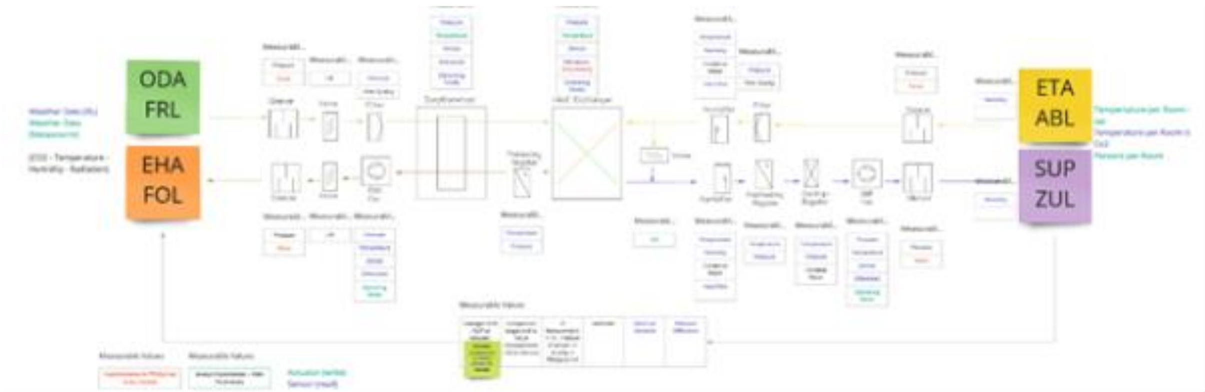

Figure 4 Generic Ventilation System with maximum sensory data

In order to test the system also in combination with an AI maintenance and efficiency model, for the simulation a simplified version was developed as the RL-Model is not able to deal with missing data points or components that are redundant in the usage for efficiency reasons such as pre- and postheating register. As the RL-Model also should not deal with the internal logic of the system but mainly control the comfort and environmental boundaries of the system, these redundant components could be reduced to a bare minimum resulting in a simplified model for the simulation, as shown in Figure 5, without a reduction of the simulation's precision as the gains and losses could be divided in active and passive ones to simulate for example a heating register or a dehumidifier with the right combination of a mixing valve and heating register.

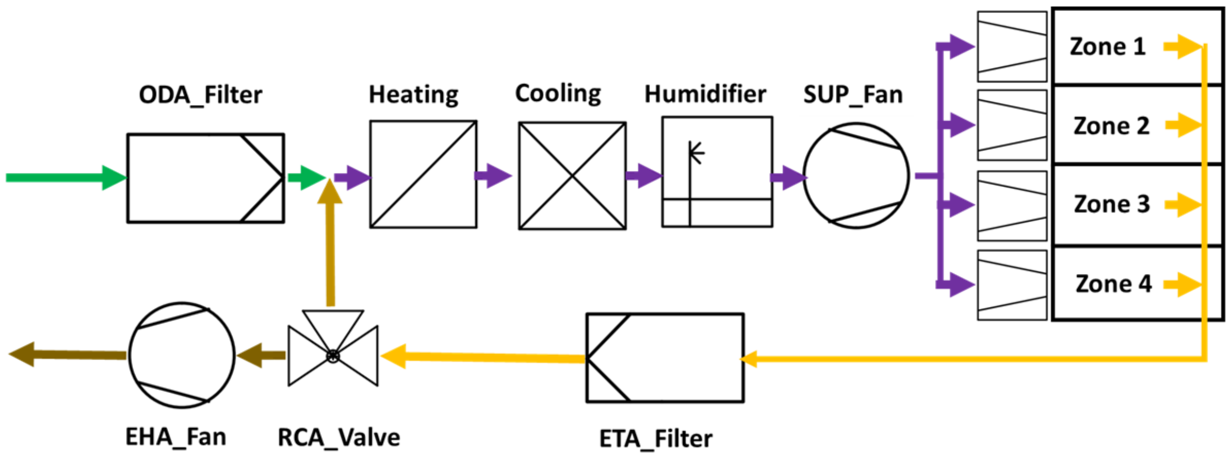

Figure 5 Generic Ventilation System with simplified function for RL optimization

To not only fit the components but also the behaviour of the reals system to the simulation, different control logics were built in the simulation which were also based on the five units examined as well as based on literature research. A sixth logic was implemented in order to also include a logic in which the AI can freely decide on all actions set. The six logics used are as follow:

0 AI-Based
1 Time-Based
2 Temperature-Based
3 CO2-Based
4 Temperature- and CO2-Based
5 Time- and Temperature-Based

As mentioned, in the AI-Based logic there is no real logic implemented, but the RL decides on all actions to be set.

In the Time-Based logic, it is assumed, that the persons are present from 08:00 to 17:00 whereas the ventilation unit also switches on 2 hours before and off 2 hours after the presence in order to condition the room.
For the temperature-based logic, the ventilation system tries to keep the room at a certain temperature level in order to make it more comfortable, not limited to any occupancy time.
In the CO2-Based logic the ventilation unit switches on at 50% of the capacity over 600 ppm, 80% of the capacity over 800 ppm CO2-level and increases to full power at over 1000 ppm CO2-level. This shall keep the air quality at comfortable limits.
The other two implemented logics then are couplings between the ones mentioned above.

This implementation made a more realistic run of the simulation possible as it could be fitted to more buildings resulting in a generic ventilation system and control logic by choosing the right settings.

3.2.2 Environment

The simulation environment was created in TRNSYS 18 according to the generic model from Figure 5. For this purpose, a parameter list was designed that regulates the inputs and outputs between simulation and artificial intelligence. This parameter list serves to simplify the interface and to use the same nomenclature in order to keep the parameters recognizable afterwards and also makes it comparable to the real system.

For the system-in-the-loop simulation environment, a four-level simulation was built and shown in Figure 6. This consists of:

- Coupling
- Weather data
- Building simulation
- Ventilation components
- Energy calculation

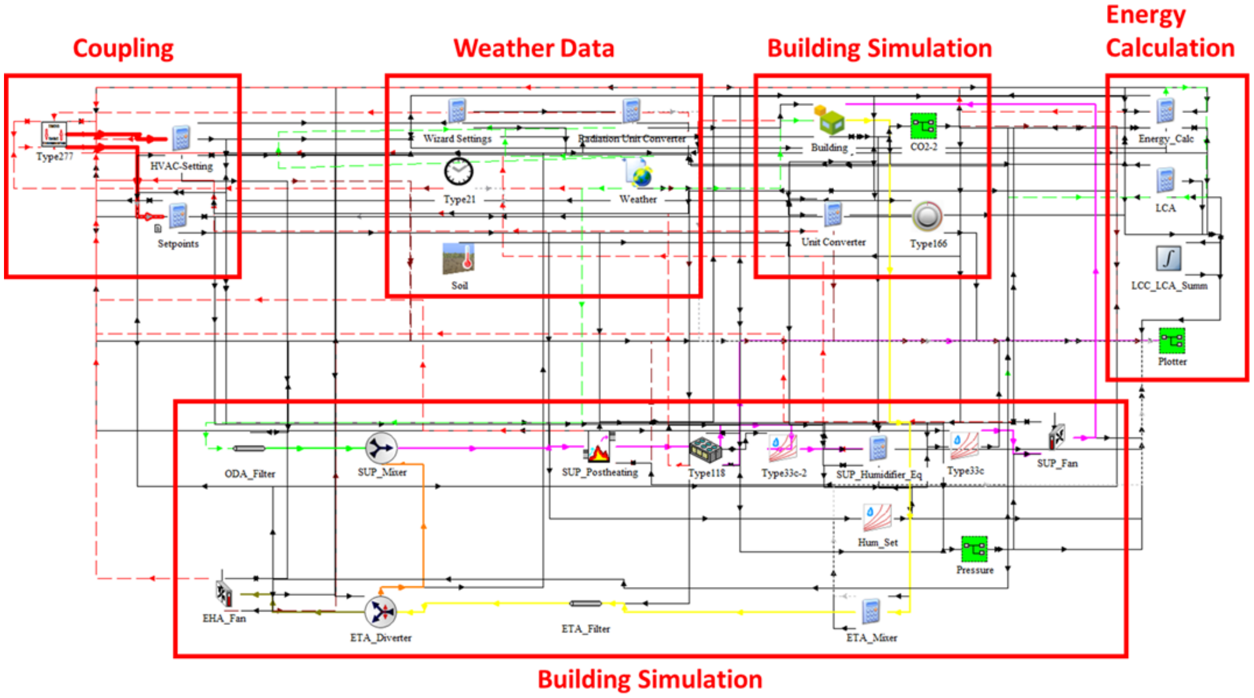

Figure 6 : Simulation setup in TRNSYS18

For the system-in-the-loop environment the parameters were checked with the hardware sensory data of the testbed and implemented in the simulation. The simulation was then verified in order to test it in different conditions and with different input criteria and is described in the section Verification. After the tests for the running simulations the coupling with TRNSYS-Type277 was implemented.

The coupling is used for communication between artificial intelligence and TRNSYS. This coupling is defined by the parameter list, which regulates the inputs and outputs between the two components. The Parameter list includes each in- and output that is needed for the decision-making-process of the AI. The inputs define the simulation model e.g. which temperatures of the zones shall be reached, which components are included in the system and which control logic should be used in order to reach plausible results. The outputs are given by the simulation calculation by each timestep. They include room temperatures, operation states of the individual components and error-indicating parameters of the decision tree. The outputs are used to teach and test the AI.

In the first step, the weather data of weather stations is used to set up the simulation and to create data sets for training the AI. After successful creation of the simulation and recorded monitoring data, the weather data will be replaced by the measured weather data at the specific location to compare and validate the simulation with the real application. The coupling between real measured values and the simulation is also performed by the Type277 coupling interface.

The building simulation consists of a four-zone model. Each zone forms a separate room which is supplied with the required climate conditions by the external ventilation system. Each zone has an area of 5x5 m and can be controlled separately. This implementation was chosen to simulate a real building and to adjust the decisions of the ventilation system based on different comfort parameters. The room dimensions serve as a reference for the calculation. As the ventilation unit can vary from case to case, the losses of the room are scaled when using higher volume flows. This means that, the higher the maximum volume flow of the ventilation unit, the higher the infiltration and transmission losses of the building in order to keep the input / output balance of the system stable. The implemented building model is depicted in Figure 6.

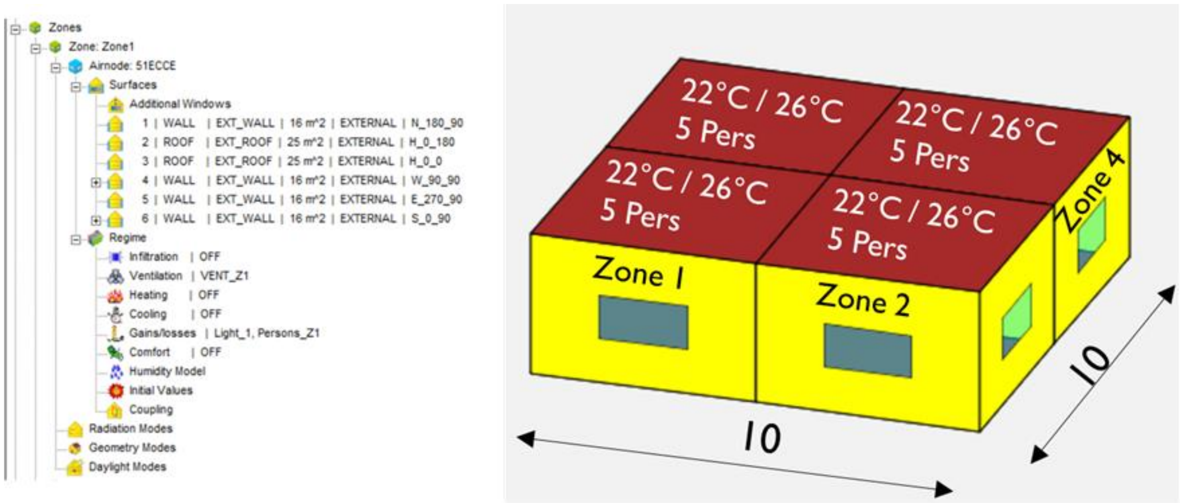

Figure 7 Implemented Building in TRNSYS18

The ventilation components are located outside the building-zones and are composed of the generic ventilation model. The ventilation system was created outside the zones, as ventilation systems are usually designed for an entire building and not for individual zones. Furthermore, by creating the ventilation system outside the building simulation, the components can be controlled and read out separately. Through the generic simulation model of the ventilation system, all common ventilation systems in execution can be covered and thus one simulation model for as many systems as possible can be implemented.

By creating the decision tree in and tests of the AI, it was determined that due to the black box of the AI and the measured parameters, the AI could not directly respond to the function of individual components and also could not deal with the elimination of measurement parameters. Therefore, in the following step, all redundant components such as preheating and postheating registers are to be reduced to the essential functions of a ventilation system. This simplifies the control logic, but nevertheless gives about the same accuracy of the simulation, since the basic functions are given and the outcome for the building-zones remains the same. For artificial intelligence, the simulation will be started with a minimum number of sensors and more sensors and parameters will be added depending on the use of the system. A detail of the ventilation unit model with reduced sensory data and simplified control logic can be seen in Figure 7.

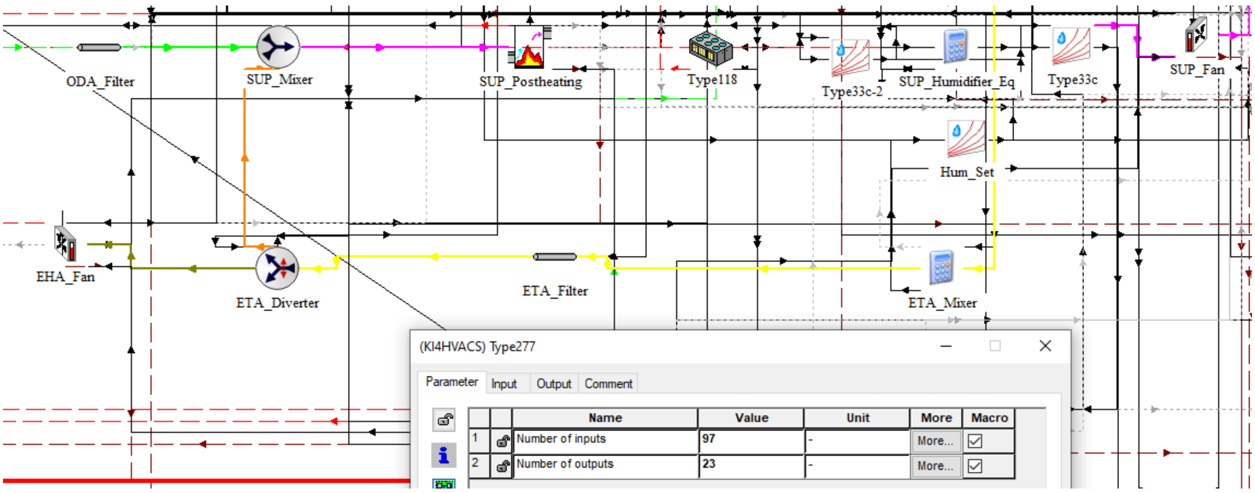

Figure 8 Simplified ventilation unit in TRNSYS18

With this model each for the predictive maintenance relevant component only is provided once and therefore decisions can be made based on output values and not direct sensory data. This increases the flexibility of the system and also reduces the amount of sensors needed.

The Main difference regarding the outputs of the simplified model are the efficiency parameters. As state of the art ventilation units use heat recovery and postheating registers to keep the energy demand low, the simplified model does not include these components. However by giving reduction factors the components can be also simulated in the simplified environment. For example by heating the building up to 18 °C with “free” energy when the ventilation system is running, a heating recovery is simulated without being integrated in the simulation. The energy is not always free but the reduction factor depends on the volume flow rate, indoor temperature and CO2 -Value of the Zone. Also the ETA_Diverter simulates a mixing valve and simplifies to a function of the heat recovery.

3.2.3 Validation

The most relevant inputs for the validation of the system such as indoor temperatures, humidity ,pressure difference and energy consumption have been compared in the simulation in order to validate the right settings for the simulations as the RL algorithm then uses the same inputs for the real environment and shall be able to predict correct values.

Due to the generic model generation and missing data of the real weather data, the curves of these values are not perfectly overlapping but more importantly follow the same pattern which results in a good baseline for the RL model to train the algorithm and choose actions for efficiency measures. In case of the real life testing, the values then are scaled to fit the real system and thus can be used in order to set the actions.For the weather data compared weather from Meteonorm according to the climate at the Location of the Radel & Hahn building is used, resulting in deviations of the forecast.

To validate the results a one-year simulation is performed and as shown in Figure 8 the temperature- and time-based control (B5) is fitting better than the temperature-based control (B2) as also in the real system (RH) a temperature- and time-based control logic is implemented. The weekly pattern of the temperature is fitting well for B5, only the negative spikes at the end of the day is shorter than in the real environment, as in the simulation all persons leave at the same time, resulting in fewer gains at the end of the day. In the real environment the persons leave at different times resulting in wider spread temperature decrease. In B2 the temperature is kept stable during the whole day as the control logic is not depending on the occupation of the building but resulting in a higher deviation from the real system. By looking on the yearly data, the graph also shows the same pattern only deviating strongly in the summer-pikes of the real system due to the deviating thermal mass of the building and the Zeros in the winter which are caused by errors of the monitoring system. Overall for the prediction of the efficiency of the system the simulation produces reasonable results for the training of the RL-Model. For the implementation in real systems the right control logic has to be chosen as the system is trained on that behavior which, for the reviewed system this would be Control Logic 5.

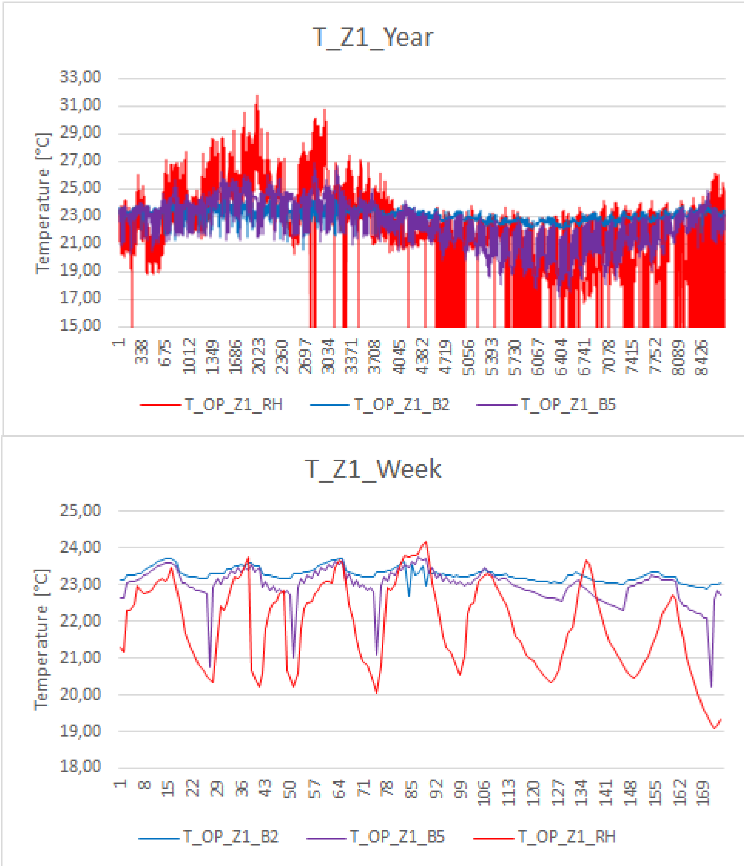

Figure 9: Monitoring comparison of the temperature

Regarding the humidity, as shown in Figure 9, also control logic 5 is fitting better to the real system as the unit switches off during the night resulting in pressure drop and as humidity decrease. Due to a malfunction of the humidifier in the real system the humidity during winter is lower than in the simulation and can not be compared. But due to the results during summer the simulation can be seen as validated.

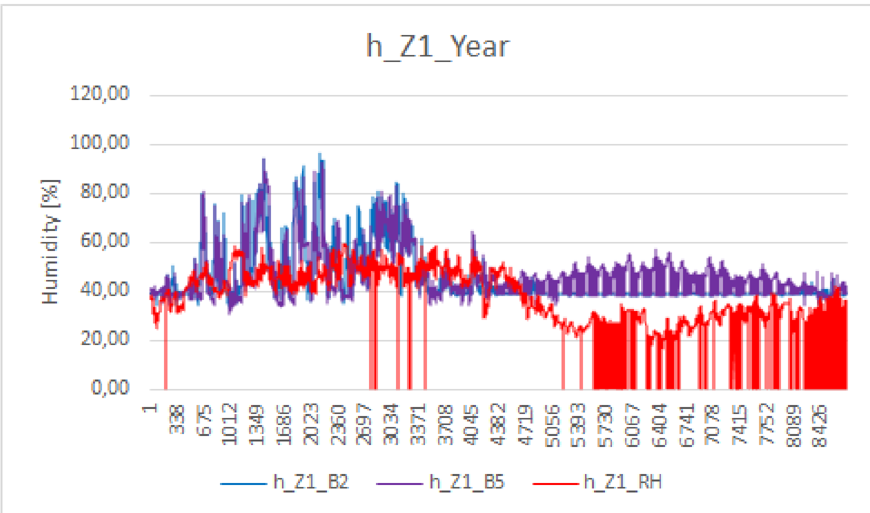

Figure 10: Monitoring comparison of the humidity

In the pressure difference, in Figure 10, in the beginning of the year a maintenance has been done resulting in a pressure drop and misfit of the simulation and real environment. During the rest of the year the simulation is fitting well with the real environment and can be used for training the prediction model and RL-Model as also night-switches and pressure increase over the year is shown and corresponding to the real unit.

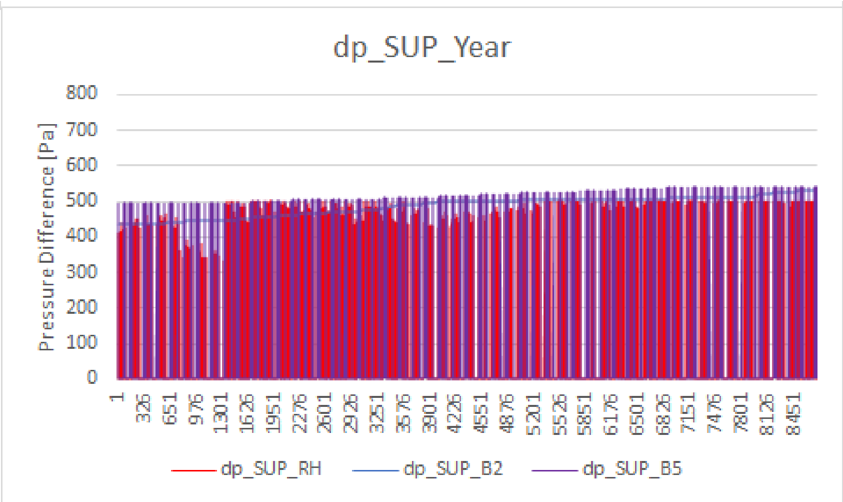

Figure 11: Monitoring comparison of the pressure difference

As no Energy Data of the real System is Monitored only the temperature, humidity and pressure difference of the simulation could be matched to the real system. In order to validate the energy Performance of the Simulation, the electricity demand of the fan has been compared to the simulation and the simulated power has been scaled accordingly shown in Figure 11. Here also the deviation between wintertime and summertime can be seen at timestep 1400. As the monitoring data fails at Timestep 4900, the switch again to winter-consuption is only seen in the control B5.

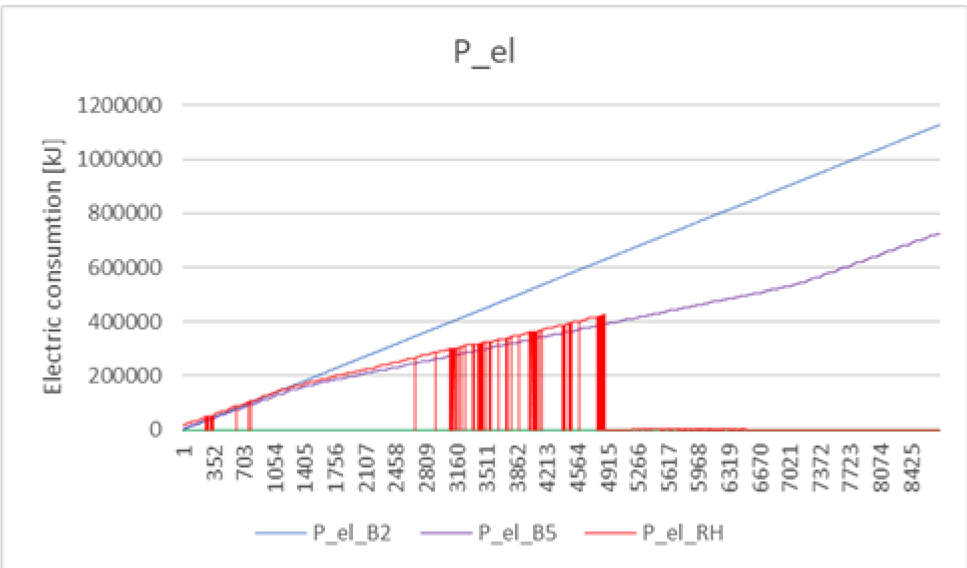

Figure 12: Monitoring comparison of the electric consumption

For the thermal energy a calculation has been performed given the volume flow rate of the valves and the temperature difference performed by the ventilation unit in order to scale the thermal energy used which was based on the temperature shown in Figure 8.

These results align to the behavior of the real system and thus can be used in order to train the RL. As mentioned, for the implementation in a different system the one shown, the control logic and scaling factors for the chosen unit have to be adapted in the simulation.

3.3 Modelling Approach

The modelling approach consists of two models: Energy efficiency via reinforcement learning for short-term optimization, and predictive maintenance for long-term optimization.

3.3.1 Energy Efficiency via Reinforcement Learning

Optimizing energy efficiency in building systems requires both short-term responsiveness and long-term planning. Reinforcement learning (RL) enables immediate adjustments to reduce energy consumption while ensuring comfort for residents. In addition, predictive maintenance detects problems with devices at an early stage, allowing repairs to be planned more effectively. This extends the service life of the systems and prevents energy losses. Together, these methods form a comprehensive framework for sustainable energy management.

3.3.1.1 Deep Reinforcement Learning

In reinforcement learning (RL), an agent interacts with its environment in discrete time step t to maximize the cumulative rewards. In each step, the agent observes a state s_t, selects an action ata_tat based on a strategy π, and applies it. It then receives a reward r_t. The environment transitions to a new state s_{t+1} and delivers the next reward r_{t+1}.

We selected a well established algorithm for continuous action spaces, Deep Deterministic Policy Gradient (DDPG). It is a model-free, off-policy actor-critic method [Lil2016]. DDPG uses two neural networks: an actor that proposes actions and a critic that estimates their Q-values. To improve training stability and efficiency for complex tasks, DDPG features target networks and experience replay.

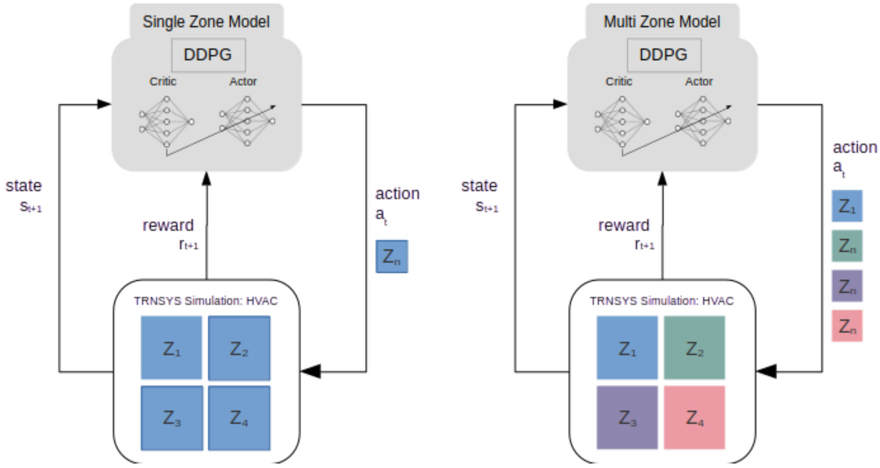

Figure 13: Overview of the single zone and multi zone RL Models.

The design of the efficiency model is based on the simplified HVAC-Model (see 3.1). The defined subset of parameters used for the models abstracts sufficient information from the HVAC system so that the RL model can determine sufficiently effective optimisation strategies. Reducing the number of parameters also ensures that the model can be applied to a wide range of HVAC systems and can thus operate without a high degree of system-specific knowledge.

Two different AI control strategies were developed during the project. One is a single-zone AI model (Figure 13, left side), which sets all other zones to the same values based on the prediction for one zone. And the other is a multi-zone model (Figure 13, right side), which provides separate predictions for each zone.

In the single zone, the input parameters used for the energy efficiency model are the ambient temperature measured outside the building (T_Amb) and the respective operating temperature in zone 1 (T_OP_Z1). The action parameters used by the AI to control the behavior of the HVAC system are the setpoint temperature of zone 1 (T_Set_Z1), the ventilation volume flow for the respective zone (VFR_Set_Z1), and the recirculated air (f_Mix_RCA), which is the fresh air supply for the entire system.

Single Zone Model	
Input	T_Amb, T_OP_Z1
Output	f_Mix_RC, T_Set_Z1, VFR_Set_Z1

Multi Zone Model	
Input	T_Amb, T_OP_Z1, T_OP_Z2, T_OP_Z3, T_OP_Z4
Output	f_Mix_RCA, T_Set_Z1, FR_Set_Z1, T_Set_Z2, VFR_Set_Z2, T_Set_Z3, VFR_Set_Z3, T_Set_Z4,VFR_Set_Z4

The multizone features the same parameters as the single zone but scaled up to control all zones separately.

Reward

For training and optimization, the reward function is crucial in guiding the agent toward decisions that prioritize energy efficiency and comfort for the building's occupants. The reward includes three factors:

- *Power consumption*,
- *Air quality*,
- *Thermal comfort*,

and implemented as following:

$$\text{reward} = -\left(\text{reward}_{t_{\text{comfort}}} + \text{reward}_{\text{power}} + \text{reward}_{\text{CO}_2}\right)^2$$

Power consumption

This term quantifies the energy used by the ventilation units. The capping at 100,000 units prevents rare extreme power values from destabilizing learning.

$$\text{reward}_{\text{power}} = \frac{\min\left(100{,}000,\ Q_{Z_1} + Q_{Z_2} + Q_{Z_3} + Q_{Z_4}\right)}{7000}$$

Air quality

This term ensures that air quality remains within acceptable limits. It is only activated when the average CO_2 level in all zones exceeds 450 ppm and results in a penalty that increases proportionally to the CO_2 concentration.

$$CO_2 = \frac{CO_{2,Z_1} + CO_{2,Z_2} + CO_{2,Z_3} + CO_{2,Z_4}}{4}$$

$$\text{reward}_{CO_2} = \begin{cases} \frac{CO_2 - 450}{80}, & \text{if } CO_2 > 450 \\ 0, & \text{otherwise} \end{cases}$$

Thermal comfort

This term rates how much the temperature in each zone differs from an optimal comfort temperature (comfort_temp). The optimal temperature is calculated based on the ASHRAE Standard 55-2010 [Ash2017]. The average absolute deviation from this range is calculated to indicate the overall thermal discomfort.

$$\text{reward}_{t_{\text{comfort}}} = \left| T_{\text{optimal}} - \frac{T_{\text{OP},Z_1} + T_{\text{OP},Z_2} + T_{\text{OP},Z_3} + T_{\text{OP},Z_4}}{4} \right|$$

3.3.1.2 Baselines

To evaluate the performance of the proposed energy efficiency models, we compare them with conventional HVAC control systems, which serve as a baseline.

Baseline Temp

A straightforward approach to temperature control maintains a constant setpoint, specified as "Baseline Temp" in this simulation. The control algorithm adjusts the HVAC system accordingly, without considering individual zone valves or flow adjustments. Such strategies are common and usually lack optimization measures. It has following settings:

Baseline Window

A slightly more advanced logic is to maintain the temperature within a defined temperature window. To do this, the current average temperature of all zones is compared with a minimum and maximum value that define the window and sets the temperature accordingly to following:

$$T_{\text{set}} = \begin{cases} 25, & \text{if } 5 \leq \text{Month} \leq 7 \\ T_{\text{OP\_Mean}}, & \text{if } 22 < T_{\text{OP\_Mean}} < 23 \\ 22, & \text{otherwise} \end{cases}$$

3.3.1.3 Metrics

To evaluate the performance of the control strategies, two important key metrics are tracked and analyzed:

- Cumulative Power Consumption
- Cumulative Thermal Discomfort

Cumulative Power Consumption

The total electrical energy consumed by all four zones during the evaluation period, which spans several years. At each time step, the system calculates the current power consumption for each zone and adds it incrementally to the cumulative total power, as following:

$$P_{\text{cumulative}} \leftarrow P_{\text{cumulative}} + \sum_{i=1}^{4} Q_{Z_i}$$

Cumulative Thermal Discomfort

The accumulated temperature deviation from the dynamically calculated optimal comfort temperature over time.

$$C_{\text{cumulative}} \leftarrow C_{\text{cumulative}} + \left| T_{\text{optimal}} - \frac{1}{4} \sum_{i=1}^{4} T_{\text{OP},Z_i} \right|$$

The optimal comfort temperature is not a fixed value but varies depending on the outside temperature (T_Amb) according to a linear model that results in a dynamic setpoint. It adjusts upward in warm weather and downward in cold. This approach reflects real adaptive comfort models, such as ASHRAE 55 [ASH2017].

3.3.1.4 Experiment Setup

The weather data used for the simulation comes from historical measurements recorded at the Sopron site between 2011 and 2016. To allow for a fair comparison of the algorithms, separate training and validation datasets were created. Each dataset comprises weather data from three years, with all algorithms, including the baselines, being evaluated using data from 2014 to 2016.

Simulation						
Type	**Training**			**Validation**		
Weather [year]	2011	2012	2013	2014	2015	2016
Time [h]	0 - 8760	8761 - 17520	17521 - 26280	0 - 8760	8761 - 17520	17521 - 26280

3.3.1.5 Results

Key Evaluation Metrics

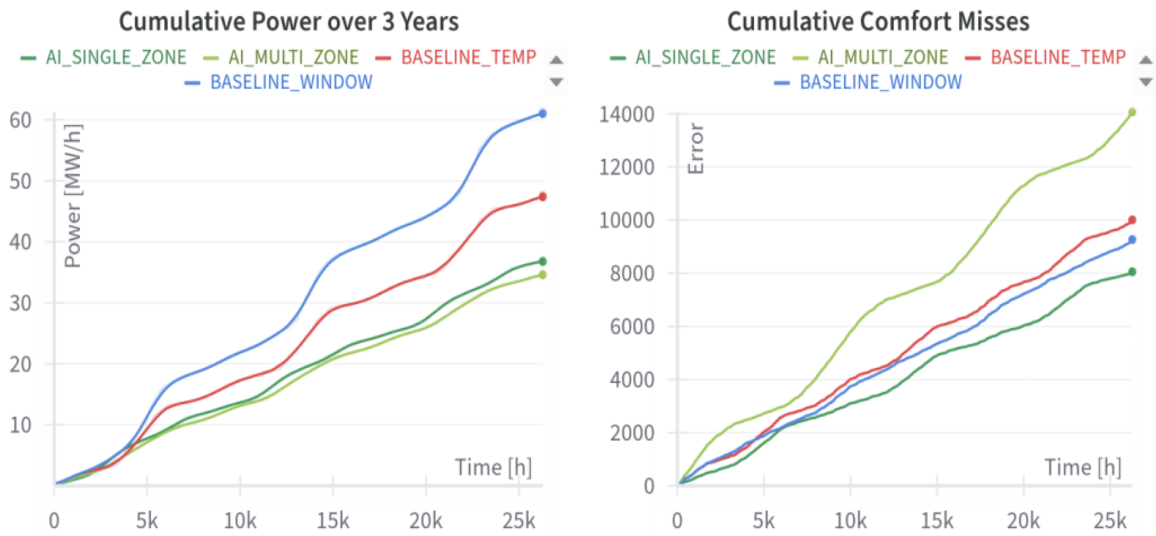

Figure 14: The key evaluation metrics over 3 years for all control strategies, on the left the cumulative performance and on the right the cumulative comfort losses.

Figure 14 illustrates the key findings, with AI_MULTI_ZONE system (light green) beeing the most energy-efficient, using about 44% less energy than the BASELINE_WINDOW, calculated as (61 MWh - 34 MWh) / 61 MWh ≈ 44%. The AI_SINGLE_ZONE closely follows, demonstrating good generalization without specific zone adaptations. The BASELINE_TEMP (red) consumes significantly more energy, and the BASELINE_WINDOW (blue) has the highest consumption at around 61 MWh.
Both AI models reduce energy use and effectively adapt to seasonal patterns, allowing HVAC systems to optimize performance throughout the year.

Temperature

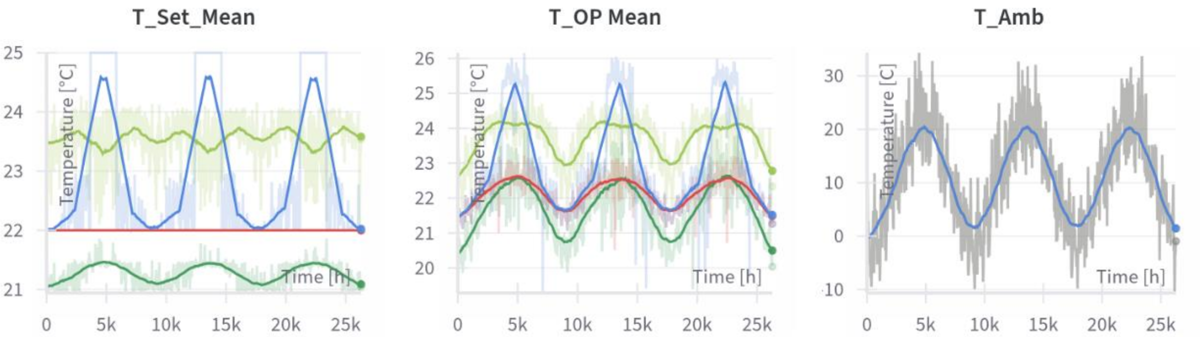

Figure 15: Temperature dynamics over three years shows distinct behavioral patterns among the various HVAC control strategies.

The left graph in Figure 15 shows the average target temperature at which both AI models, AI_MULTI_ZONE and AI_SINGLE_ZONE, smoothly adapt to seasonal fluctuations, thereby optimizing heating and cooling requirements. The middle graph shows the operational room temperature differences. AI_SINGLE_ZONE adapts closely to comfort temperatures and shows low deviations, while AI_MULTI_ZONE is responsive but exhibits greater fluctuations and tends to fall below the setpoints in the warmer months, with energy efficiency taking priority over thermal comfort. In comparison, the stepwise setpoints of BASELINE_WINDOW lead to abrupt temperature changes, and BASELINE_TEMP has difficulty meeting comfort requirements, especially in summer and winter. In summary, the AI_SINGLE_ZONE model effectively balances comfort and energy efficiency and ensures stable conditions throughout the year. AI_MULTI_ZONE offers energy savings but compromises thermal comfort, as shown by the temperature fluctuations. Overall, the single-zone approach shows clear advantages in terms of responsiveness and consistency with adaptive comfort theory.

Energy

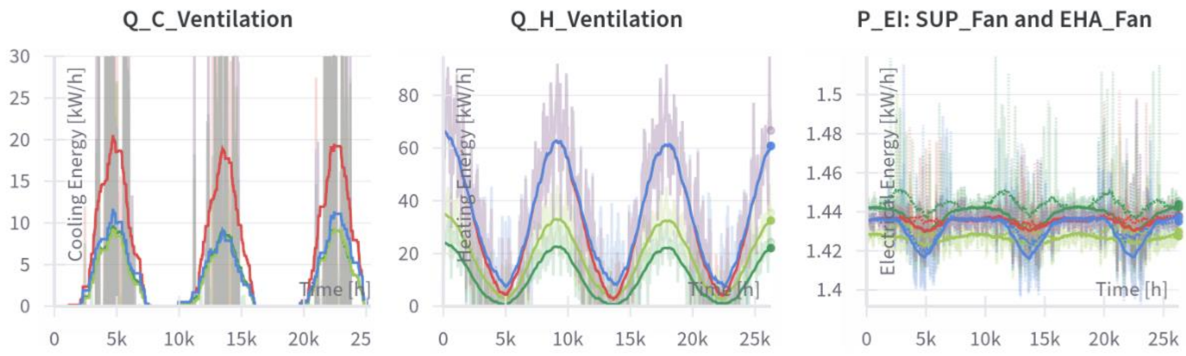

Figure 16: The energy consumption of the HVAC system over three years split in energy for cooling (left), heating (centre) and electrical power (right) for operating the fans.

The center graph of Figure 16 illustrates heating energy consumption, showing high demand in winter and near-zero usage in summer.

BASELINE_WINDOW and BASELINE_TEMP show significantly higher energy usage than AI-based strategies, reacting inefficiently to changing conditions and often overshooting heating needs. In contrast, AI_SINGLE_ZONE and AI_MULTI_ZONE maintain lower heating energy usage across all seasons, with AI_MULTI_ZONE achieving the greatest reductions. This demonstrates the effectiveness of AI controllers in minimizing unnecessary heating by adapting to real-time thermal demand, although it does come with a slight trade-off in comfort.

The left panel shows a reversed seasonal pattern in cooling energy, peaking in summer and showing minimal use in winter. BASELINE_TEMP uses the most energy, with both baselines demonstrating inflexible behavior. AI_SINGLE_ZONE and AI_MULTI_ZONE, however, consume significantly less energy during peak times and maintain a more balanced response to thermal loads. AI_SINGLE_ZONE outperforms AI_MULTI_ZONE slightly in cooling efficiency while keeping indoor comfort.

The right panel shows stable fan energy consumption throughout the year, with minor reductions during low thermal load periods for both AI strategies.

In summary, the analysis confirms that AI-based control strategies, particularly AI_MULTI_ZONE, enhance energy efficiency across heating, cooling, and electrical domains, while AI_SINGLE_ZONE effectively balances energy savings and thermal comfort.

CO2 and Recirculated Air

The CO2 concentration graph in Figure 18 on the right, shows that both AI_SINGLE_ZONE and AI_MULTI_ZONE maintain CO2 levels just below the 450 ppm threshold, indicating a trade-off between air quality and energy efficiency. These strategies reduce the need for conditioned outdoor air by achieving recirculation rates (graph on the left side of Figure 18) of 58% to 62%.

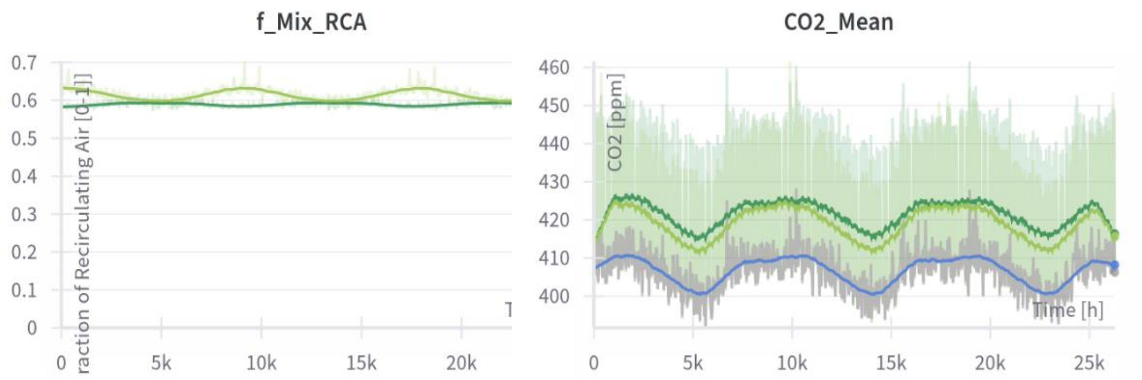

Figure 18: The left graph shows the average indoor CO2 levels across all zones, the right graph illustrates the proportion of recirculated air used by each control strategy.

<u>Volume Flow Rate</u>

Figure 19 displays the volume flow rates for zones Z1 through Z4. AI-based controllers operate at much lower average flow rates compared to baseline strategies that use a fixed flow. They show rhythmic fluctuations that align with seasonal thermal load cycles, allowing them to adapt to local demands without unnecessary airflow, thereby enhancing energy efficiency.

Overall, the AI strategies effectively balance acceptable air quality with system efficiency while maximizing the use of recirculated air.

Figure .19: The volume flow rate over time for zones Z1 through Z4

Overall, the volume flow rate patterns clearly differentiate adaptive and non-adaptive strategies. The AI models respond dynamically to real-time demands and optimization goals, minimizing airflow during periods of low demand and increasing it only when justified by comfort or air quality objectives.

3.3.2 Predictive Maintenance Models

The original concept for predictive maintenance was to determine the optimal time for a component change those accounts for degradation of system performance near the end of components life cycle. However, according to the experts, the potential savings for changing components of the HVAC system before its breakdown provides minor cost savings compared to the cost of components. Therefore, the approach was adapted to determine the time of the components breakdown that would allow preparations and scheduling of the maintenance to be made ahead of time.

Figure 20 Maintenance indicators behavior, 7 years

The maintenance indicators pattern of behavior is extremely long-term making it difficult to predict using the above mentioned methods, because of the rare occurrence of the changes. The pattern of behavior is characterized by the slow rate of change with a threshold value that resets the indicator.

Therefore, a simple linear regression was used to predict the behavior of the maintenance indicators. The simulation environment has provided the threshold values for all indicators. The threshold value was set as 0.99 of the maximum value of the simulated data. The model uses past values(input) to predict future values(output) and re-evaluates its predictions at the regular intervals (timestep) (Figure 21). Input, output and timestep parameters are optimized to minimize the error in breakdown prediction as well to extend the planning horizon. The further the prediction is, the bigger the error but allows more time for planning. The actual choice depends on the complexity of the maintenance planning as well as how critical the component.

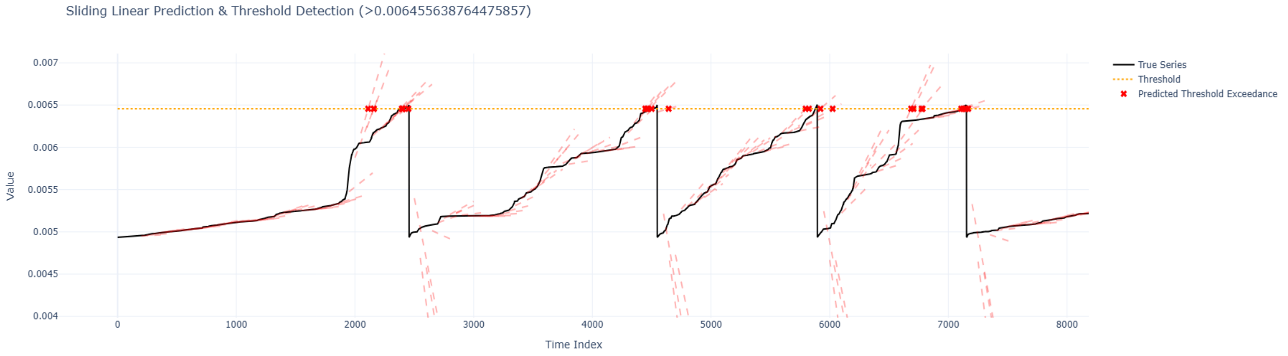

Figure 21 Sample of threshold determination prediction

4 Economic and Ecological assessment

To check the efficiency of the RL-models as well as the maintenance models whether predictive maintenance is sufficient or if an inefficient operation state until failure of the components is more sustainable, a decision tree as well as a life cycle assessment including operation, maintenance and change of components was included in the simulation. As the simulation was based on the same ventilation unit, no assessment for the production and destruction of the unit itself but only the maintained components were included in the simulation.

Therefore, a decision tree was implemented in the simulation in order to decide which indicators predict a certain failure of components and decide on a time-interval in which these components need to be changed. The maintenance always impacts the cost and ecological impact of the system and thus results in either predictive maintenance or inefficient run of the components due to degradation.

4.1 Decision Tree algorithm

Due to the high complexity of the HVAC-Model, the simplified model has been used for designing the decision tree as all similar components like pre- and postheating register have the same indicators for maintenance. On the right side all components of the ventilation System have been listed and on the other side the parameters group for each component was defined. As there is only one Ventilation unit for all four Zones the parameter groups were used for the decision making and not parameters on their own. As the temperature of zone 1 has the same impact as temperature in zone 2 and so on, all temperatures have been combined to “Temperature”. Same logic goes for pressure difference, electric demand and thermal demand

The defined components and parameter groups then have been simulated in numerous ways and different settings in order to define a standard behaviour of the system. In the following step, settings have been implemented in the simulation in order to simulate system failures and depict how each component behave, and which parameter influences other components until the state of failure. The paths for the components and parameters to failure are depicted in the Figure 22.

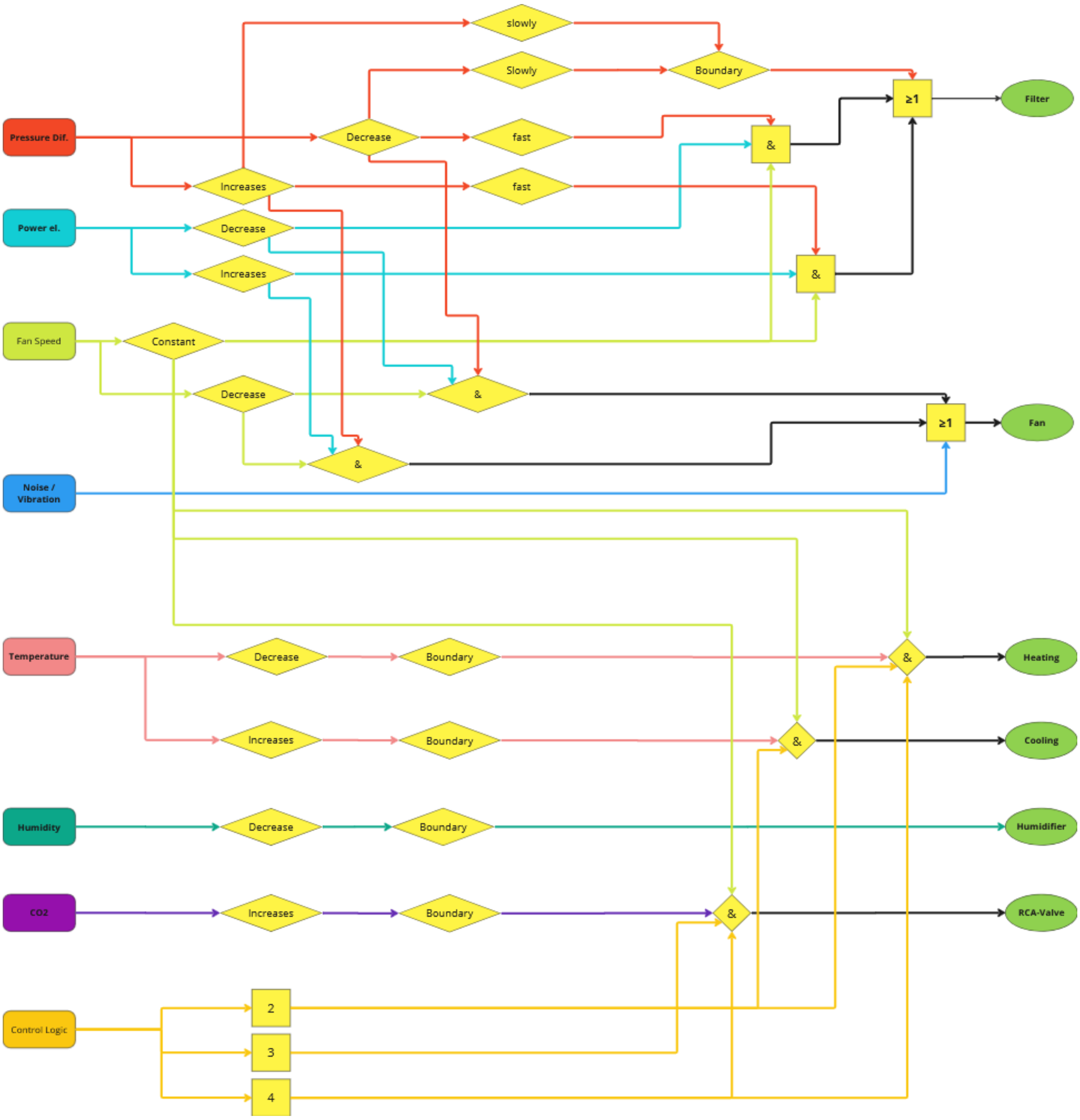

Figure 22: Decision tree

Green ellipse depicts the components of the ventilation system whereas the colored rectangles with rounded shapes are the parameter groups. Marked in yellow are the states of change for each parameter. For example in the pressure difference it is important, that when it changes slowly over time it is a normal

state. But if there is a sudden drop or increase of the pressure difference it is most probably due to an error of a component.
Also logic connections are implemented as often an error can only be depicted if two parameters change. For example if the temperature decreases under the boundary, it could be that the fan is just switched off. But if the temperature decreases by a constant fan speed, it is most probably a fault in the heating register. By considering the Control Logic parameter, only the states 2 to 4 are shown in the logic even if 0 to 5 is implemented. This is due to the logics behind the numbers of the generic ventilation system

0. AI-Based
1. Time-Based
2. Temperature-Based
3. CO2-Based
4. Temperature- and CO2-Based
5. Time- and Temperature-Based

Logic 0 is not implemented, as the AI decides on the set parameters an they do not refer to an Error. Logic 1 is not implemented as no borders concerning CO2 or Temperature are implemented and therefore cannot be checked. Logic 5 is not implemented as it is the same decision path as logic 2.

With this Decision Tree of the ventilation unit, tests for the prediction model could be done in order to find the most critical parameters for the metrics.

According to the Decision tree, the most critical parameters are the pressure difference, electrical power and fan speed, as these parameters can directly connect to two components and also change the most in the course of the simulation.

4.2 Analysis of results

To determine the ecological and economic influence of the AI-Model compared to standard control logics, ecological and economical parameters were implemented in the simulation.
The simulation was fitted to the real System of the Industrial Partner of Radel & Hahn in order to check the impact on the costs and environmental influences.
To do so all relevant parameters of the energy efficiency model and the prediction model were adapted with factors according to their influence on the costs and environmental impact due to production, energy demand during operation and destruction phase. The factors were evaluated by literature review and conducting the industrial partners for their expertise with these parameters. The following table shows the factors for the costs in € and the environmental impact in kg_{CO2eq}

Parameter	**Economical Impact**	**Ecological Impact**	**Note**
Electric Energy	0,238 €/kWh**	156 g/kWh*	

Thermal Energy	0,105 €/kWh**	201 g/kWh*	
Maintenance	123 €/h**	7 kg/h***	Estimated travel time 1 hour per Maintenance
ODA_Filter	50 €	10 kg	0,5 hours Maintenance Time
SUP_Hum	200 €	100 kg	0,5 hours Maintenance Time
SUP_Postheating	500 €	200 kg	3 hours Maintenance Time
SUP_Cooling	500 €	250 kg	3 hours Maintenance Time
SUP_Fan	800 €	300 kg	3 hours Maintenance Time
ETA_Filter	50 €	10 kg	0,5 hours Maintenance Time
EHA_Fan	800 €	300 kg	3 hours Maintenance Time

*According to OIB Guideline 6 2023
**Data from Industrial Partners
***Traveling with a Car powered by fossil fuels (140 g/km) for one hour (50km)

The electrical and thermal energy demand occur during standard operation and increase over the time. The maintenance only is required when a component fails. Everytime a component fails it has to be changed which concludes in one hour of travel time and additionally the maintenance time for each component. Travel time also has an impact on the ecological side as a fossil powered car is considered in the calculation. During the maintenance time only the economic impact is included.
All other components increase the demand according to their error in both, the ecological and the economic impact as the components have to be bought or at least repaired and also new components have to be produced which needs a lot of material and energy during the process

Due to the high difference between the energy prices and the costs of changing a component according to the simulation, the ventilation system can run up to 1250 hours (52 days) at an inefficient level and still be cheaper and more sustainable than changing the cheapest components in advance. Therefore, not predictive maintenance but rather delayed maintenance should be focused in order to keep the operation of the system more economically and ecologically feasible.

In order to still save energy due to inefficient behaviour of the components and to check the efficiency of the AI Model, different Simulations have been performed.The control logics compared are the following:

- Baseline by keeping the Temperature at 22°C following Control logic 5
- Single Zone model by keeping the comfort in the boundaries
- Multi Zone model by keeping the comfort in the boundaries during training phase

During the first three years of the simulation, the AI-Model is still in the training phase, learning from the Simulation's behaviour and previous settings of the preset control logic 5. After the training phase in years 4-6, the model goes to the experimental phase, testing new settings and thus resulting in a difference of the energy performance.

In Figure 23 the different logics and their life-cycle costs (LCC) are shown over a 6 year-simulation. As the Simulations always rely on the same ventilation unit only the costs during the operation are counted as "life cycle costs". Only component changes, maintenance costs and energy prices are included to make the logics more comparable in their performance.

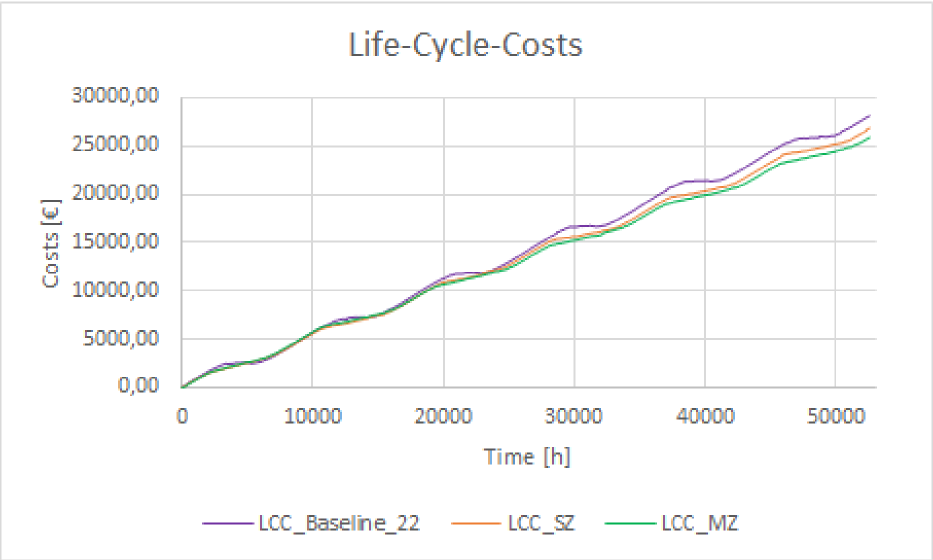

Figure 23: Life Cycle Costs in 6 years

In Figure 23 the same logics are compared due to their life cycle analysis (LCA) resulting in CO2 equivalent for the used energy in operation and grey energy of the component changes. Again the same simulation is used resulting in a comparison of only the operational emissions and emissions during maintenance.

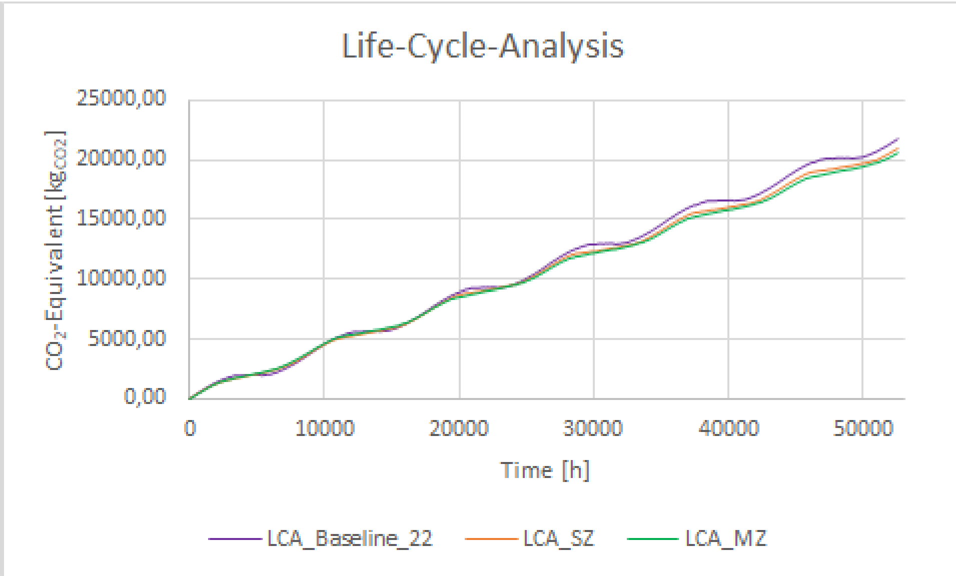

Figure 24: Life Cycle Analysis in 6 years

As seen in Figure 23 and Figure 23, during the first three years of the simulation, the different models behave quite at the same cost- and CO2-Performance. This results due to the training phase of the AI-Model. In year 4-6 the Model switch to the testing phase and results in a better performance.
A Detail of the fist year for the LCC as well as the LCA is shown in Figure 15. In both cases the Baseline results in almost the same values as the two AI-Control logics due to the consistent performance of the AI-Models. Only during the winter months, the Baseline is performing worse then the AI-Model resulting in better comfort during this season.

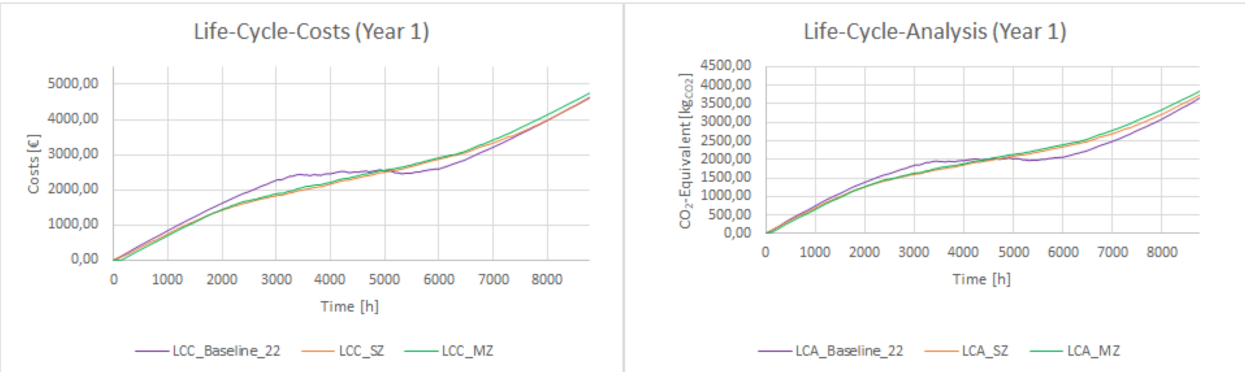

Figure 25: LCC (left) and LCA (right) in year 1

In Figure 25 the fourth year of the simulation is shown. In this case it is shown, that after the training hase, the AI-Modes are already performing better than the Baseline.Also the Multi-Zone Model performs better then the single-zone model due to the higher flexibility of the settings.

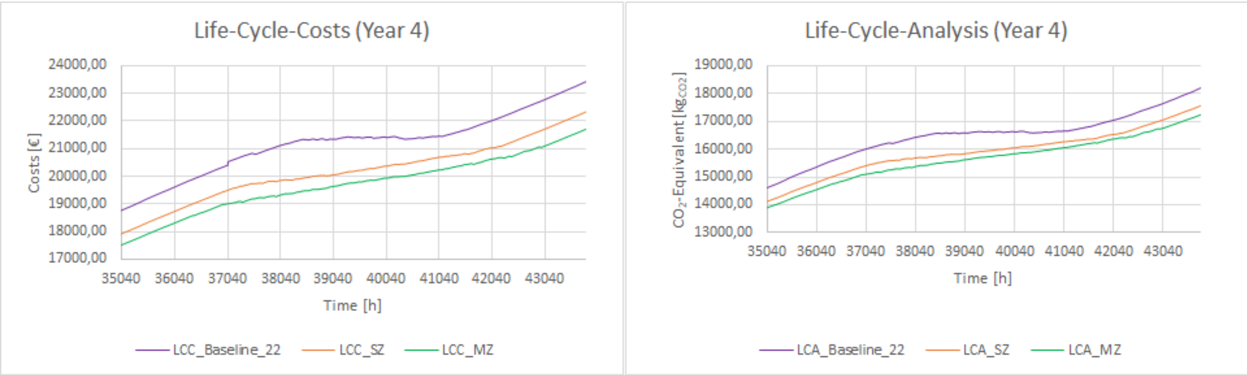

Figure 26: LCC (left) and LCA (right) in year 4

Comparing the years in for each performance, it can be seen in Figure 26, that the Baseline is performing almost the same during each year. The Singlezone-Model performs better in year 4 but then slowly decreases the efficiency most probably due to the comfort standards that have to be kept and limited action values as all zones are controlled in the same way. For the multizone-mode the energy demand is reduced right after year one and kept quite stable afterwards.

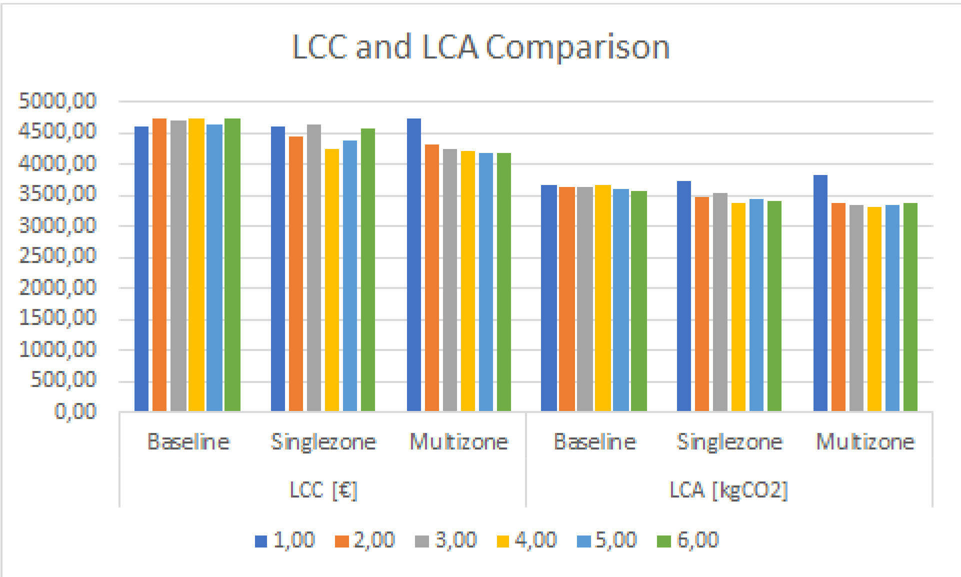

Figure 27: LCC and LCA yearly comparison

In the Single-zone model, after three years there is a drop of the costs as well as the CO2-Equivalent resulting in an decrease of almost 10% of the yearly costs as well as 8% of the yearly CO2-Emissions.Due to the comfort boundaries the RL corrects the settings and in year six only a decrease of 3% of the costs and 4.5% of the CO2-Demand are reduced.

In the multizone model, after three years of the simulation the costs and CO2-Emissions both drop about 10% comparing the baseline. After six years of the simulation, the values compared to the baseline both drop about 12% for the costs and 6% for the CO2-Emissions.

5 References

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[Lil2016] Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., ... & Wierstra, D. (2016). *Continuous control with deep reinforcement learning*. arXiv preprint arXiv:1509.02971.

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