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A Review on Virtual Testbed Frameworks for Implementation of Various HVAC Control Strategies

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Abstract: *This literature survey provides a review of virtual testbed frameworks for the implementation of various Heating, Ventilation, and Air Conditioning (HVAC) control strategies. With the advancement of technology and the increasing demand for energy-efficient HVAC systems, virtual testbeds have emerged as powerful tools for evaluating and optimizing control strategies. This survey examines the existing literature on virtual testbed frameworks, highlighting their key features, advantages, and limitations and specifically with the frameworks that supports implementation of reinforcement-based control methods and allow implementation of baseline methods for testing various control strategies. It also presents an overview of different HVAC control strategies that have been implemented and evaluated using these frameworks. The survey aims to provide researchers in the field of HVAC control with a valuable resource for understanding the state-of-the-art virtual testbed frameworks and their applications.*

Keywords: Virtual testbed, HVAC optimization, building simulator, RL implementation.

I. INTRODUCTION

Heating, Ventilation, and Air Conditioning (HVAC) systems play a crucial role in providing indoor comfort, maintaining energy efficiency in buildings and improving living standards of the peoples. The development and implementation of effective control strategies are essential to optimize the performance of HVAC systems. However, evaluating and optimizing these strategies in real-world environments can be time-consuming, expensive, and challenging due to the complexity of building systems and the potential impact on occupants.

Virtual testbed frameworks have emerged as an alternative approach to overcome the limitations of physical testing by providing a simulated environment for testing and evaluating HVAC control strategies. These frameworks enable researchers and practitioners to assess the performance of different control algorithms, evaluate energy-saving potential, and optimize system operation without the need for costly and time-consuming physical prototypes.

Traditional testing methods often involve physical prototypes or full-scale implementations, which can be expensive and time-consuming. Virtual test beds eliminate the need for costly hardware, infrastructure, and physical installations, significantly reducing expenses associated with testing and experimentation. This cost-effectiveness allows for more extensive testing and iteration, leading to better-optimized control strategies.

A virtual test bed provides the flexibility to simulate different building scenarios, HVAC system configurations, and control strategies. It allows researchers and engineers to test a wide range of parameters, algorithms, and operational conditions without the constraints imposed by physical limitations. Virtual test beds can also be easily scaled up to simulate complex multi-zone buildings or even entire building complexes, enabling the evaluation of control strategies for large-scale applications.

These simulators accelerate the development and optimization of HVAC control strategies. They provide a platform for rapid testing and evaluation, allowing for quick iterations and adjustments. Researchers can assess the impact of various control parameters and algorithms on system performance in a shorter timeframe, leading to faster optimization and fine-tuning of control strategies.

These virtual test beds enable comprehensive evaluation of HVAC control strategies in a controlled and repeatable environment. Researchers can simulate different weather conditions, occupancy patterns, and load profiles to evaluate the performance of control strategies under various scenarios. This comprehensive evaluation allows for a deeper understanding of the strengths and limitations of different control strategies and facilitates the identification of optimal solutions.

The data-driven insights from the testbeds provide valuable information for assessing and comparing different control strategies. The availability of comprehensive data allows researchers to make informed decisions, identify areas for improvement, and guide the development of more effective control strategies.

II. LITERATURE REVIEW

Belmans, B., Aerts, D., Verbeke, S., Audenaert, A., & Descamps, F. (2019)

The Ventilation Controls Virtual Test Bed was used to simulate the performance of a typical office building under a variety of conditions, including different weather patterns, occupancy levels, and ventilation strategies. In this paper, a virtual test bed for simulating and comparing single- and mixed-mode ventilation strategies in office buildings. It is based on the EnergyPlus simulation software and includes a detailed representation of the building's envelope, HVAC system, and occupants.

Mixed-mode ventilation is a ventilation strategy that combines natural ventilation with mechanical ventilation. Natural ventilation is the process of cooling and ventilating a building using outdoor air that is drawn into the building through open windows and doors. Mechanical ventilation is the process of cooling and ventilating a building using fans and air conditioning units.

The results showed that mixed-mode ventilation can reduce the energy consumption of office buildings by up to 30% compared to single-mode ventilation. The energy savings are achieved by using natural ventilation whenever possible and by using mechanical ventilation only when necessary.

The test bed developed in this study is a valuable tool for studying the performance of different ventilation strategies in office buildings. It can be used to evaluate the energy efficiency and comfort of different ventilation strategies and to design new ventilation systems that are more efficient and comfortable. [1]

Huang, S., Wang, J., Fu, Y., Zuo, W., Hinkelman, K., Kaiser, R. M., He, D., & Vrabie, D. (2021)

In this paper an open-source virtual testbed for a real Net-Zero Energy Community was proposed. The testbed uses EnergyPlus simulation software and uses high-resolution data for the community's buildings, HVAC systems, and energy generation and storage systems. This allows for more accurate simulations of the community's performance.

The testbed includes a simulation framework that consists of four modules: pre-processing, modeling, optimization, and post-processing. The pre-processing module fills data gaps through interpolation, the modeling module simulates the developed models, the optimization module performs model-based optimizations using input data and objective functions, and the post-processing module processes simulation and optimization results based on predefined metrics.

The simulator includes details like buildings, infrastructure, and energy systems. The model is calibrated to real-world data, which allows researchers to generate realistic energy consumption and emissions profiles. The testbed is designed in a modular way. This allows researchers to easily add new features and functionality to the testbed and can simulate the performance of the community under a variety of conditions, including different weather patterns, occupancy levels, and energy use patterns.[2]

Storek, T., Wüllhorst, F., Koßler, S., Baranski, M., Kümpel, A., & Müller, D. (2021)

The primary objective of the study is to evaluate the performance of various advanced building automation algorithms, including Model Predictive Control, RL, and Swarm Intelligence. These algorithms are known for their potential to improve energy efficiency in buildings when compared to traditional control algorithms.

The paper talks about the cloud-based architecture needed to develop a virtual test bed. The paper then describes the architecture of the virtual test bed. It is a three-tier architecture, consisting of a data layer, a simulation layer, and a user interface layer. The data layer stores weather data, building information, and occupancy data. The simulation layer uses

EnergyPlus to simulate the operation of the building under different conditions. The user interface layer allows users to create virtual buildings, set up experiments, and run simulations.
The paper then presents a case study in which the virtual test bed was used to evaluate an advanced building automation algorithm. The paper also proposes the building model in the cloud as a digital twin to building energy system and looks on the opportunity to integrate BOPTEST framework to the simulation.[3]

Blum, D., Arroyo, J., Huang, S., Drgoňa, J., Jorissen, F., Walnum, H. T., Chen, Y., Benne, K., Vrabie, D., Wetter, M., & Helsen, L. (2021)
BOPTEST, for benchmarking building HVAC control algorithms using high-fidelity building emulators. The framework is designed to be easy to use and to provide a common platform for comparing different control strategies.
BOPTEST consists of three main components: a building emulator, a control algorithm interface, and a benchmarking tool. The building emulator is a high-fidelity model of a building that can be used to simulate the performance of different control strategies. The control algorithm interface provides a way to connect different control algorithms to the building emulator. The benchmarking tool allows users to compare the performance of different control strategies under different operating conditions.
It is used to benchmark a few different control strategies for a variety of building types. The results of these studies have shown that BOPTEST can be used to effectively compare different control strategies and to identifythe most effective strategy for a particular building.
The building emulator is based on the EnergyPlus building energy simulation software.The control algorithm interface is based on the OpenAI Gym reinforcement learning environment.[4]

Arroyo, J., Manna, C., Spiessens, F., & Helsen, L. (2021)
The article proposes a novel approach to building optimization testing using the OpenAI Gym environment. The BOPTEST framework is a software tool that allows users to test the performance of building optimization algorithms under a variety of conditions. The OpenAI Gym environment provides a standardized platform for developing and testing reinforcement learning agents.
The authors of the article argue that the combination of BOPTEST and OpenAI Gym provides a powerful tool for building optimization. The BOPTEST framework allows users to define a variety of building models and optimization objectives. The OpenAI Gym environment allows users to train reinforcement learning agents that can automatically find optimal solutions to the building optimization problem.
The authors of the article demonstrate the effectiveness of their approach by using it to optimize the performance of a building heating and cooling system.The framework allows users to define a variety of building models and optimization objectives, and it provides a variety of KPIs like energy consumption, cost, comfort, occupancy, CO2 emissions, etc. that can be used to evaluate the performance of the optimization algorithm.[5]

Wang, Z., Chen, B., Li, H., & Hong, T. (2021)
The literature describes an open-source simulation environment called AlphaBuilding for training and validating algorithms to control residential loads. The environment is based on the OpenAI Gym interface and uses reduced-order models to simulate the thermodynamics of thermostatically controlled loads (TCLs). The parameter values for the models are determined from the connected smart thermostat data of real households. Reduced-order models are typically much faster than full-order models, which makes them suitable for large-scale simulations.
The environment is compatible with the OpenAI Gym interface, which makes it easy to use with existing reinforcement learning libraries. The environment includes a variety of built-in functions, such as retrieving the parameters and weather forecasts, that can be used to facilitate control strategies that require predictive information.It has the capability to produce community level simulation.[6]

Jia, M., & Srinivasan, R. (2020)
The article presents a novel approach to evaluating the performance of buildings. The authors propose a coupled simulation approach that couples the EnergyPlus™ building energy simulation software with an occupant behavior

model. This approach allows for the simulation of the interaction between building systems and occupant behavior, which can lead to more accurate predictions of building energy use.

The proposed approach allows for the simulation of the interaction between building systems and occupant behavior, which can lead to more accurate predictions of building energy use. Second, it can be used to identify the key factors that influence building energy use, which can help building owners and operators to improve the energy efficiency of their buildings. Third, it is a relatively easy and cost-effective approach to implement.

The authors also found that the coupled simulation can be used to identify the key factors that influence building energy use, such as occupant behavior, lighting levels, and HVAC settings. It also gave more accurate predictions.[7]

Chervonyi, Y., Dutta, P., Trochim, P., Voicu, O., Paduraru, C., Qian, C., Karagozler, E., Davis, J. Q., Chippendale, R., Bajaj, G., Witherspoon, S., & Luo, J. (2022)

The paper proposes a semi-analytical industrial cooling system model for reinforcement learning. The model is based on a simplified version of the Navier-Stokes equations, and it is able to predict the temperature distribution in an industrial cooling system with high accuracy. The model is then used to train a reinforcement learning agent to control the cooling system in order to minimize energy consumption.

The proposed method is evaluated on a simulated industrial cooling system. The results show that the reinforcement learning agent is able to learn to control the cooling system in order to minimize the energy consumption, while still maintaining the desired temperature distribution. The proposed method is a promising approach for the control of industrial cooling systems.

The challenge in the cooling system is that it's often subject to disturbances, such as changes in the ambient temperature or the load on the heat source. This makes it difficult for the RL agent to learn a control policy that can maintain the performance of the cooling system in the face of disturbances.[8]

Findeis, A., Kazhamiaka, F., Jeen, S., & Keshav, S. (2022)

Beobench is a toolkit that provides a unified interface for accessing building simulations for reinforcement learning. It supports a variety of building simulation engines, including EnergyPlus, OpenStudio, and Dymola. Beobench also provides a number of features that make it well-suited for RL, such as the ability to generate training data, evaluate RL agents, and visualize the results of RL experiments.

Beobench can be used to accelerate the development of RL agents for building control. They demonstrate this by using Beobench to train an RL agent to control the heating and cooling of a building.Beobench can be used to train RL agents to optimize the ventilation of buildings. This can be done by controlling the air flow, the temperature of the air, and the humidity of the air.

The authors of Beobench believe that it has the potential to make RL more accessible to researchers and practitioners in the building energy domain. They hope that Beobench will help to accelerate the development of new and innovative building control strategies.

Beobench can be used to train RL agents to participate in demand response programs. This can be done by controlling the load on a building's electrical system in response to changes in the price of electricity.Beobench can be computationally demanding this is a potential limitation.[9]

Vazquez-Canteli, J. R., Dey, S., Henze, G., & Nagy, Z. (2020)

City learn is a python-based gym environment it consists ofa two-stage process. First a city is modeled as a network of nodes, each of which represents a building or group of buildings. The nodes are connected by links, which represent the physical infrastructure that transports energy between the nodes. The model also includes a weather forecast, which is used to determine the demand for energy.

In the second stage, a reinforcement learning algorithm is used to train a set of agents to manage the energy consumption of the buildings in the city. The agents are trained to minimize the cost of energy while meeting the demand for energy. The agents interact with each other in a decentralized manner, and they do not have access to the full state of the system.

The performance of the reinforcement learning agents is evaluated using a simulation of the city. The simulation is run for a predetermined number of days, and the total cost of energy is recorded. The results of the simulation are used to compare the performance of different reinforcement learning algorithms.
The environment is non-stationary, meaning that the state of the environment is constantly changing. This can make it difficult for reinforcement learning agents to learn an optimal policy. Another challenge is that the environment is partially observable, meaning that the agents do not have access to all the information needed in decision making. This can also make it difficult for reinforcement learning agents to learn an optimal policy.
Despite the challenges, reinforcement learning is a promising approach for demand response and urban energy management.[10]

Jiménez-Raboso, J., Campoy-Nieves, A., Manjavacas-Lucas, A., Gómez-Romero, J., & Molina-Solana, M. (2021):
Sinergym is a physics-based model to simulate various aspects of building behavior, such as temperature, airflow, and lighting. This allows for accurate representation of real-world conditions and enables the RL agents to learn and adapt to different scenarios.
The framework's control component provides a set of tools and interfaces for designing and implementing RL algorithms. It includes customizable reward functions, action spaces, and observation mechanisms to facilitate the training process. Sinergym also incorporates a feedback loop that continuously evaluates the RL agent's performance, allowing for iterative improvements and optimizing the building's energy consumption.
One of the key strengths of Sinergym is its scalability and versatility. It supports both single-building simulations and large-scale simulations of interconnected buildings or building clusters. This enables researchers and practitioners to evaluate the performance of RL agents in diverse contexts, from individual structures to complex urban environments.
It has customizable building models and reward functions. It also has inbuilt visualization and debugging tools. Pretrained RL models can be easily implemented in this environment.[11]

Scharnhorst, P., Schubnel, B., Fernández Bandera, C., Salom, J., Taddeo, P., Boegli, M., Gorecki, T., Stauffer, Y., Peppas, A., & Politi, C. (2021):
The modelling used in Energym is based on the EnergyPlus simulation engine. These models can be used to simulate the performance of different control strategies. The library includes a number of pre-configured control strategies for benchmarking, as well as having the ability to create custom control strategies.
Energym provides a user-friendly interface for configuring and running simulations with different control strategies. It may support the integration of different control algorithms and offer a range of performance metrics for evaluating and comparing their effectiveness. The library might also provide visualization tools but not as sophisticated as sinergym to analyze the energy performance and behavior of buildings under different control scenarios.
The Energym library also includesother features that can be used to create and use building energy models, such as A graphical user interface that can be used to create and edit EnergyPlus input files. A number of tools that can be used to analyze the results of EnergyPlus simulations.[12]

Moriyama, T., De Magistris, G., Tatsubori, M., Pham, T.-H., Munawar, A., & Tachibana, R. (2018):
The RL test bed is a software platform that allows researchers to develop and test RL controllers for data center cooling systems. The test bed is based on the open-source simulation platform EnergyPlus.
The test bed has been used by researchers to develop and test a number of RL controllers for data center cooling systems. These controllers have been shown to be able to reduce power consumption by up to 22% while maintaining a similar temperature range. It provides a realistic simulation of a data center cooling system and a variety of RL algorithms that can be used to control the cooling system.
The test bed provides a user-friendly interface that makes it easy to develop and test RL controllers. The interface allows users to specify the parameters of the RL algorithm, the reward function, and the initial state of the system. The interface also allows users to visualize the performance of the RL controller.[13]

Zhang, Z., & Lam, K. P. (2018):

The GYM-Eplus simulation framework is a software tool that allows users to train and evaluate deep reinforcement learning (DRL) agents for controlling HVAC systems. The framework is based on the OpenAI Gym environment. The GYM-Eplus framework includes a number of features that make it well-suited for training DRL agents for HVAC systems.

The GYM-Eplus framework uses the EnergyPlus building energy simulation software to create a realistic simulation of HVAC systems. This allows users to train DRL agents that can learn to control HVAC systems in a way that is both energy-efficient and comfortable for occupants.A variety of sensors and actuators: The GYM-Eplus framework supports a variety of sensors and actuators that can be used to control HVAC systems. This allows users to train DRL agents to control a wide range of HVAC systems.

The GYM-Eplus framework allows users to define a flexible reward function that can be used to train DRL agents. This allows users to train DRL agents to optimize for different objectives. The GYM-Eplus framework has been used to train DRL agents for a variety of HVAC systems, including radiant heating systems, variable refrigerant flow (VRF) systems, and heat pumps.[14]

Touzani, Samir, Granderson, Jessica, Pritoni, Marco, Kiran, Mariam, Krishnan Prakash, Anand, Wang, Zhe, & Agarwal, Shreya. (2021)

FlexDRL is built on top of OpenAI Gym, a popular open-source platform for reinforcement learning research. OpenAI Gym provides a standardized environment for DRL agents to interact with, which makes it easy to compare different algorithms and settings.

FlexDRL extends OpenAI Gym by adding support for building energy management. It does this by providing a co-simulation environment that couples the EnergyPlus building energy simulation software with the Modelica battery and photovoltaic (PV) models.

This co-simulation environment allows FlexDRL agents to learn how to control building energy systems in order to minimize energy costs while meeting occupant comfort and other requirements.

It supports a variety of DRL algorithms, including Q-learning, policy gradients, actor-critic and a co-simulation environment that couples EnergyPlus with Modelica. FlexDRL has been used to evaluate the performance of DRL algorithms for a variety of building energy management tasks, including Demand-side management, Peak shaving, Energy arbitrage, Building retrofit optimization.[15]

Zhang, C., Shi, Y., & Chen, Y. (2022)

This paper proposes a framework called BEAR which is based on the physical principles of the building environment. This framework does require modelling engines like Modellica. This works on self-designed simulator with approximation of the environment. Thus, it does not require any external engines whiles testing different control methods on the buildings.

This open-source implementation gives a wide range of predefined building models, weather types and geographic locations to choose from. The user can also define their own building models and customize the predefined rewards for maximum thermal comfort or power consumption. Due to the absence of any external dependencies this gym environment needs only python for testing or various RL and other baseline control strategies like model prediction control and rule-based controls. The proposed Open-AI gym environment performed equally well when compared to the EnergyPlus simulator. Though it lacks methods and functions to monitor KPIs of the tests.[16]

III. CONCLUSION

Through this literature survey, we have reviewed the existing research on virtual testbed frameworks for HVAC control. The survey highlights the diverse features and capabilities of these frameworks, ranging from the simulation of building dynamics to the integration of different control algorithms. It also emphasizes the benefits of virtual testing, including reduced time and cost requirements, improved system performance, and the potential for energy savings.

Some frameworks do not need any modelling engines that need to run in parallel like BEAR framework, but they provide coarse view of the building environment. Some provide various testing; complex reward generation and sophisticated report generation features like sinergym and energym. While others provide simple easy to use simulation framework. Testbeds like beobechprovide a close approximation of the building environment at cost of higher computation demand. This framework can help accelerate the testing of new control strategies and also allow people with limited domain knowledge in the building sector to get involved in the discovery of new control strategies.

REFERENCES

[1]. Belmans, B., Aerts, D., Verbeke, S., Audenaert, A., & Descamps, F. (2019). Set-up and evaluation of a virtual test bed for simulating and comparing single- and mixed-mode ventilation strategies. Building and Environment, 151, 97–111. https://doi.org/10.1016/J.BUILDENV.2019.01.027

[2]. Huang, S., Wang, J., Fu, Y., Zuo, W., Hinkelman, K., Kaiser, R. M., He, D., & Vrabie, D. (2021). An open-source virtual testbed for a real Net-Zero Energy Community. Sustainable Cities and Society, 75, 103255. https://doi.org/10.1016/j.scs.2021.103255

[3]. Storek, T., Wüllhorst, F., Koßler, S., Baranski, M., Kümpel, A., & Müller, D. (2021, September 1). A virtual test bed for evaluating advanced building automation algorithms. https://doi.org/10.26868/25222708.2021.30637

[4]. Blum, D., Arroyo, J., Huang, S., Drgoňa, J., Jorissen, F., Walnum, H. T., Chen, Y., Benne, K., Vrabie, D., Wetter, M., & Helsen, L. (2021). Building optimization testing framework (BOPTEST) for simulation-based benchmarking of control strategies in buildings. Journal of Building Performance Simulation, 14(5), 586–610. https://doi.org/10.1080/19401493.2021.1986574

[5]. Arroyo, J., Manna, C., Spiessens, F., & Helsen, L. (2021, September 1). An Open-AI gym environment for the Building Optimization Testing (BOPTEST) framework. https://doi.org/10.26868/25222708.2021.30380

[6]. Wang, Z., Chen, B., Li, H., & Hong, T. (2021). AlphaBuilding ResCommunity: A multi-agent virtual testbed for community-level load coordination. Advances in Applied Energy, 4, 100061. https://doi.org/10.1016/j.adapen.2021.100061

[7]. Jia, M., & Srinivasan, R. (2020). Building Performance Evaluation Using Coupled Simulation of EnergyPlusTM and an Occupant Behavior Model. Sustainability, 12(10), 4086. https://doi.org/10.3390/su12104086

[8]. Chervonyi, Y., Dutta, P., Trochim, P., Voicu, O., Paduraru, C., Qian, C., Karagozler, E., Davis, J. Q., Chippendale, R., Bajaj, G., Witherspoon, S., & Luo, J. (2022). Semi-analytical Industrial Cooling System Model for Reinforcement Learning.

[9]. Findeis, A., Kazhamiaka, F., Jeen, S., & Keshav, S. (2022). Beobench. Proceedings of the Thirteenth ACM International Conference on Future Energy Systems, 374–382. https://doi.org/10.1145/3538637.3538866

[10]. Vazquez-Canteli, J. R., Dey, S., Henze, G., & Nagy, Z. (2020). CityLearn: Standardizing Research in Multi-Agent Reinforcement Learning for Demand Response and Urban Energy Management.

[11]. Jiménez-Raboso, J., Campoy-Nieves, A., Manjavacas-Lucas, A., Gómez-Romero, J., & Molina-Solana, M. (2021). Sinergym. Proceedings of the 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 319–323. https://doi.org/10.1145/3486611.3488729

[12]. Scharnhorst, P., Schubnel, B., Fernández Bandera, C., Salom, J., Taddeo, P., Boegli, M., Gorecki, T., Stauffer, Y., Peppas, A., & Politi, C. (2021). Energym: A Building Model Library for Controller Benchmarking. Applied Sciences, 11(8), 3518. https://doi.org/10.3390/app11083518

[13]. Moriyama, T., De Magistris, G., Tatsubori, M., Pham, T.-H., Munawar, A., & Tachibana, R. (2018). Reinforcement Learning Testbed for Power-Consumption Optimization (pp. 45–59). https://doi.org/10.1007/978-981-13-2853-4_4

[14]. Zhang, Z., & Lam, K. P. (2018). Practical implementation and evaluation of deep reinforcement learning control for a radiant heating system. Proceedings of the 5th Conference on Systems for Built Environments, 148–157. https://doi.org/10.1145/3276774.3276775

[15]. Touzani, Samir, Granderson, Jessica, Pritoni, Marco, Kiran, Mariam, Krishnan Prakash, Anand, Wang, Zhe, & Agarwal, Shreya. (2021, February 08). FlexDRL v1.0. [Computer software]. https://github.com/LBNL-ETA/FlexDRL. https://doi.org/10.11578/dc.20210311.8.

[16]. Zhang, C., Shi, Y., & Chen, Y. (2022). BEAR: Physics-Principled Building Environment for Control and Reinforcement Learning.