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An Overview Mechatronics Systems Design of Modelica-Based Model Predictive Control Strategies for CO_2 Heat Pump Systems

Nagendra Singh[1,*], Sanjeev Kumar Verma[2]

Abstract

The growing adoption of renewable energy technologies poses challenges to energy supply stability, necessitating increased flexibility in energy demand. This paper introduces a Modelica-based Model Predictive Control (MPC) strategy aimed at keeping the supply water temperature within the range of 55°C to 75°C while minimizing energy consumption and electricity expenses throughout a year. A comprehensive, high-fidelity model representing a school building in Oslo, Norway, was developed using Modelica and exported as a Functional Mock-up Unit (FMU) to facilitate smooth integration with MATLAB/Simulink for real-time simulation and control implementation. The findings indicated that the Model Predictive Control (MPC) strategy resulted in annual electricity savings of 8.0 MWh (3.2%) and financial savings of 11,479 NOK (6.7%) compared to a Proportional-Integral (PI) controller. Additionally, it provided savings of 85.07 MWh (25.9%) and 46,967 NOK (22.8%) in comparison to a fixed rule-based baseline controller. With the increasing adoption of renewable energy technologies, the reliability of energy supply faces challenges, highlighting the need for enhanced flexibility in energy demand management. The results underscore the effectiveness of MPC as a dependable and cost-effective solution for managing thermal energy systems.

Keywords: DHW systems, functional mock-up unit, heat pump system, model predictive control, thermal tank

INTRODUCTION

This study examined the economic feasibility of electricity price-based control strategies for the CO_2 heat pumps in Oslo, Norway, with a focus on improving the flexibility of a CO_2 heat pump system in school buildings and removing current obstacles. This research explains in details with application of mechatronics.

***Author for Correspondence**
Nagendra Singh
E-mail: Singh.mech2008@gmail.com

[1]Assistant Professor Department of Mechanical Engineering, Institute of Engineering and Technology, Dr. Bhimrao Ambedkar University, Swami Vivekanada Campus, Khandari, Agra, Uttar Pradesh, India
[2]Assistant Professor Department of Mechanical Engineering, Central Instrumentation Facility Research and Development Cell, Lovely Professional University, Phagwara, Punjab India

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Role of Heat Pumps in Enhancing System Flexibility

Over the past ten years, there has been a notable increase in the use of renewable energy. Reports state that the rate of renewable capacity additions in 2023 was the fastest in 20 years, increasing by about 50% to nearly 510 GW. Renewable energy sources are predicted to generate 42% of the world's electricity by 2028, with wind and solar PV accounting for 25% of this total. In Norway, which has one of the highest percentages of electricity produced from renewable sources, hydropower produces about 136.49 TWh of electricity annually, or roughly 88% of the nation's total power generation [1]. Furthermore, with a total capacity of

5372 MW at the beginning of 2023, wind, and solar power produced 15,051 GWh, or around 10% of Norway's electrical generation. Due to the extreme weather dependence of solar and wind power, integrating a large percentage of renewable energy sources can lead to unreliable electricity output. Flexible energy systems are often proposed as a solution to this problem [2]. Flexibility can be measured in several ways because it can have multiple meanings and implications depending on the situation. System flexibility, for example, might be defined as the capacity to transition energy consumption from high-cost to low-cost times. Furthermore, a flexible system can assist in reducing peak electricity consumption as well as peak grid loads. Additionally, flexibility refers to the capacity to modify its operational tactics to achieve a specific goal. Generally speaking, a flexible system enables substantial load control.

Heat pumps are an effective electro-thermal technology that can be used in energy systems to boost system flexibility. Heat pumps' dynamic operation provides some flexibility and allows for thermal management. Because heat pump systems can be combined with thermal energy storage, they enable the separation of energy supply and demand. The function of heat pumps in energy systems, especially in heating systems, has been the subject of numerous research. In the German intraday market, for example, it has been demonstrated that heating systems with heat pumps and thermal storage are more profitable. Additionally, because heat pump systems are inherently flexible, homes that employ them can lower expenses by accessing local energy markets [3]. However, introducing bigger storage into the system may result in delayed response times when altering the heating system, which limits the capacity to fully leverage the flexibility of heat pumps at the control level. MPC has been universally acknowledged as an efficient solution to this problem. The effects of MPC on heat pump and storage systems have been compared with conventional heat pump controllers in both short-term and long-term tests. The results show that MPC lowers total expenses in both cases and increases the heat pump's coefficient of performance (COP). Furthermore, regardless of prediction accuracy, MPC has demonstrated considerable promise in domestic hot water (DHW) systems, where energy consumption falls and COP rises while user comfort is maintained [4]. These studies demonstrate how MPC may efficiently shift loads, lower costs, and improve efficiency in systems that include energy storage and heat pumps.

Concepts of Heat Pumps and Energy Storage

For energy systems to function effectively, flexibility is essential, especially in the face of obstacles like changing weather patterns and electricity costs. Heat pumps and energy storage frequently play a key role in improving the flexibility of energy systems, according to numerous studies that have examined how to assess and achieve flexibility in energy systems. Walden et al. investigated heat pump flexibility and discovered that as the heat pump's working load range increases, so do the financial advantages. They did, however, also discover a flexibility barrier, above which further load flexibility offers diminishing benefits [5]. In one instance study, the net value of a heat pump with a minimum load of 55% was 19.3% higher than that of a heat pump without flexibility. Furthermore, rather than depending on just one signal, flexibility in energy systems can be examined in terms of time, power, and energy. Under various energy supply scenarios, the adaptability of a home energy system with a heat pump and thermal storage was examined. Three scenarios with different wind energy shares—7%, 25%, and 60%—as well as real-time electricity pricing were used to simulate the system. The flexibility potential was measured and the heat pump power and storage capacity were adjusted to optimize the operation cost. The findings showed that between 33% and 100% of electric demands could be moved to other periods, and that system design had a significant impact on both flexibility potential and operating costs. To address the fluctuations in power costs and renewable energy production, a thermal energy supply system with a high-temperature heat pump and thermal energy storage was created. Li et al. concentrated on optimizing the size and operation of an energy system consisting of a heat pump, thermal energy storage, and photovoltaic (PV) panels to achieve energy and cost savings [6]. The system demonstrated flexible heat pump operation, using thermal storage to buffer the fluctuations in renewable energy and electricity costs. After the optimization to minimize the operational costs or emissions, the system achieved a 6% cost reduction compared to a rule-based control strategy. According to their research, annual expenses and self-consumption decreased by 6.61% and 2.39%, respectively. In a similar vein, to optimize energy savings, Gaucher-Loksts et al. investigated three setups based on Building Integrated Photovoltaic and an air source heat pump for powering a household.

MPC has become a potent technique for handling the intricacy of building energy systems, which have to deal with quick climatic changes and thermal inertia. It is ideal for increasing operational flexibility and energy efficiency because of its capacity to predict and optimize system behavior [7]. The benefits of MPC over rule-based or conventional control have been shown in several research. For example, MPC for a seasonal storage system supplied 80% of the district heating network's heating needs while reducing annual heat losses to just 4%. When MPC was used in a multi-heat pump HVAC system, occupant discomfort was greatly decreased and energy savings of up to 37.3% were attained. When compared to feedback and fuzzy control techniques, MPC has also demonstrated superiority in lowering peak loads and enhancing control stability [8]. This paper expands on the potential of MPC by combining robust forecasting, adaptive scheduling, and economic optimization to improve energy system performance. When taken as a whole, these studies demonstrate that MPC is a crucial facilitator of more intelligent and effective energy management. The actual use of MPC, especially with real-time interaction, is still in its early stages, despite the fact that many research have investigated its use in building energy systems. Creating a building model that is realistic, control-oriented, user-friendly, and computationally efficient is one of the biggest problems. Open-source Modelica modules like Buildings and IDEAS provide useful model creation templates to handle this. While some earlier research employed MPC in real-time settings, others used Modelica for control-oriented or real-time applications. Nevertheless, these efforts usually rely on simplified models and do not incorporate high-fidelity, physically detailed systems. For example, Modelica was used to construct MPC, but it was restricted to simple thermal models; hydraulics and thermodynamic cycles were not included [9]. On the other hand, by combining MPC with a real-time, high-fidelity Modelica model, the current study marks a substantial advancement. To provide more realistic system responses and control choices, this includes thorough modeling of hydraulic networks and thermodynamic behavior. The resulting framework provides a unique and useful method for real-time building energy optimization by bridging the gap between simulation and control.

Research Gap: Complex Thermodynamic Models and MPC

Particularly in complicated heating systems, integrating MPC with high-fidelity Modelica-based system models in real-time applications is extremely difficult. Prior studies have investigated the application of MPC in real-time simulation systems, as well as the usage of Modelica for control-oriented modeling and real-time simulation. Nevertheless, there is still little integration of high-fidelity, complex thermodynamic models with MPC frameworks. For example, MPC is frequently applied to simplified thermal models without taking into account complex hydraulic or thermodynamic processes [10]. This gap indicates that there is still much to learn about the smooth integration of high-fidelity, detailed system models with MPC. Recent research has begun using Functional Mock-up Units (FMUs) as an interface for co-simulation between external MPC frameworks and high-fidelity Modelica models in response to this gap. For instance, Erfani et al. created an FMU-based co-simulation that combined MATLAB/Simulink MPC with a model of a residential construction. Although these contributions demonstrate the potential of FMU-based MPC integration, most applications have concentrated on situations driven by home comfort [11]. In contrast, by focusing on system-level actuation and integrating intricate thermodynamic processes in a CO_2 heat pump with thermal storage, the current study expands on this line of work.

This study's real-time data exchange and dynamic control updates were made possible by the FMU technology, which enables smooth interaction between a full Modelica-based system model and MATLAB/Simulink. Few research have reported such implementations for complicated heating systems to the best of our knowledge, which emphasizes the uniqueness and usefulness of the suggested framework [12]. The specific goal of this work was to bridge the gap between theoretical control strategies and actual system deployment by optimizing the functioning of a school building energy system in Oslo, Norway, which consists of a CO_2 heat pump and a thermal storage tank.

INTEGRATING MPC WITH DYMOLA SIMULATION

The Norwegian demo case at the Voldsløkka School and Cultural area, which is situated in the mid/northern region of Oslo, serves as the basis for the study [13]. To accommodate specifically new 810 students, a newly built secondary school building (the S-building) and an existing cement factory (the Heidenreich building, or H-building) were retrofitted. A bridge on the second level connects the S-building to the H-building. A sports hall, a cultural center, and a cultural hall are also included in the demo. The new construction's 11,100 m² and the H-building's 2900 m² are used for school and cultural events. The school has a cutting-edge heating technology that provides space heating by combining geothermal energy with a CO_2 heat pump. About 80–90% of the S-building's space heating needs were intended to be met by the CO_2 heat pump, with district heating acting as a backup and for peak loads and residential hot water warming. Heat from two gas coolers—a high temperature gas cooler and a low temperature gas cooler—is extracted from the boreholes and upgraded for use in the building by the CO_2 heat pump. The high temperature gas cooler generates heat, which is stored in a 400L water tank. A separate connection that is attached to the water storage tank is used to distribute domestic hot water on demand. To provide the appropriate temperature control, sensors, and valves are incorporated throughout the system [14]. The supply temperature of the heat pump's high temperature gas cooler and the tank temperature were chosen as control variables in the MPC design for this investigation. To maximize the performance of the CO_2 heat pump system in the building under observation, this study's methodology integrated an MPC system with a simulation environment based on Dymola. An optimization algorithm and a grey-box heat pump model make up the MPC controller.

The tank temperature was added as a system restriction, and the power price estimate was utilized as an economic signal for the target function. The grey-box model and the optimization algorithm evaluated these inputs to determine the ideal compressor power. The Dymola environment's white-box heat pump model, which replicated the system's intricate thermodynamic behavior, received this control signal. To represent the building's total thermal response, the white-box model interacted with a building model [15]. Real-time optimization under realistic system dynamics driven by fluctuating electricity prices and thermal constraints is made possible in the co-simulation setup by the MPC (implemented in MATLAB/Simulink) exchanging inputs and outputs with the Modelica-based plant through the FMU interface at each control step. It is crucial to remember that the RC building model representation was only used in the Modelica model. The CO_2 heat pump and water storage subsystem are the main subjects of the predictive grey-box model utilized for MPC. The energy balance, temperature evolution, and heat pump performance of the tank were described by this system-level model, which was developed while the FMU interface recorded the thermal dynamics of the building.

Building Model Validation: Space Heating Return Water Temperature

The ground source CO_2 heat pump served as the central component of the heating and cooling system for the Voldsløkka School and Cultural area's thermal energy system. The main energy source is boreholes, which store extra heat and provide free cooling. District heating is used to meet peak heating loads as needed. District Heating Model: This provides more heat when demand is at its highest. Building Model: Describes the building's thermal properties as well as its heating and cooling requirements. Thermal Tank Model: This model stores thermal energy and enables the system to effectively balance heating loads [16]. Model of CO_2 Heat Pump: the system's central component, which uses energy extracted from the boreholes to meet both heating and cooling demands. Borehole Model: A model of the ground wells used to store extra heat and extract heat for the heat pump; district heating and boreholes are connected to the thermal tank and CO_2 heat pump, which subsequently distribute the building's heating and cooling. Heat and cooling are transmitted according to real-time demand and energy availability, with component interaction following the system layout. the streamlined system model, emphasizing just the essential elements utilized in the MPC architecture. The building, the CO_2 heat pump, and the thermal tank were among them. The system was streamlined for MPC optimization by excluding the boreholes and district heating from the simplified version utilized for control [17]. By concentrating on the most important components of the system using electricity, this streamlined structure enabled effective operation of the heat pump without unduly complicating the MPC algorithm. Only these essential components were utilized for the MPC creation because the electricity price served as the optimization's aim function. The CO_2 heat pump system has two gas coolers and one evaporator, each of which provides a distinct temperature for heating and cooling.

The system was simulated using the Modelica IDEAS library. IDEAS was used to simulate the heat pump's primary component. The high temperature gas cooler and the low temperature gas cooler were simulated by connecting two heat exchanger components from the standard Modelica library to the heat pump model. By combining these elements, the model successfully depicts the CO_2 heat pump system's effectiveness and performance across a range of operating circumstances. Following the model's construction, the actual measured inlet temperatures of the evaporator and the two gas coolers during a seven-day period were entered to validate the model. the contrast between the simulated value and the high-temperature gas cooler's actual measured outlet temperature [18]. The actual measured values are represented by the orange line, while the Modelica simulation results are represented by the blue line. The model validation was completed because of the strong agreement between these outcomes, which proved the model's accuracy. According to ASHRAE Guideline 14–2014, the validation was quantified with an R^2 value of 96%, a normalized mean bias error (NMBE) of 0.009%, and a coefficient of variation of the root mean square error (CV-RMSE) of 3.3%.

The CO_2 heat pump model was deemed reliable for future usage since all of the model calibration parameters were within the advised range. The five main modules—the building envelope, internal heat gain, space heating system, ventilation system, and weather conditions—were used to create the building model [19]. The TwoElements component from the IDEAS library was used to create the building envelope module, which simulated heat transfer processes using an RC thermal network. Based on the national standard for energy demand computation in buildings, Ns3031, a constant internal heat gain of 130 kW (11.8 W/m² for the 11,000 m² floor area) was applied to reflect the heat produced by lights, equipment, and building inhabitants. The three internal gains were added up, and the coincidence of these loads was taken into account when calculating the internal gain item in the model. The model only considered the high-temperature gas cooler from the CO_2 heat pump, which was in charge of space heating, to improve computational efficiency for MPC reasons [20]. Domestic hot water was not included because it was provided by the district heating system, and the ventilation system was modeled as a mechanical air supply supplying 25 kg/s to maintain basic interior air quality criteria. the comparison of the measured data for the building space heating system's return water temperature.

There was a brief transient period at the start of the simulation since the Modelica model was initialized with a return water temperature of 20 °C. Once the system achieved steady operation, validation measures were computed over the 60-day dataset [21]. The following calibration values were found for the return water temperature: R^2 of 87.54%, NMBE of -0.12%, and CV-RMSE of 8.53%. The building model was deemed reliable for subsequent use because every model calibration parameter fell within the suggested range.

Importing FMU Into MATLAB/Simulink for MPC Implementation

The FMU was used to make it possible to integrate the Modelica model with MATLAB/Simulink for the MPC implementation. Dynamic models created in Modelica or other simulation tools can be exported and utilized in a variety of simulation environments, including MATLAB/Simulink, thanks to FMUs, which are package models that adhere to the FMI standard. The Modelica modeling environment, which contains the model equations, parameters, and solver settings, is used to export the Modelica model as an FMU file [22]. The FMI Toolbox is then used to import this FMU into MATLAB/Simulink, enabling it to operate as a Simulink block that communicates with control logic, MATLAB scripts, and other system elements. In this study, an FMU file was created from the Modelica model of the heating system, which contained the CO_2 heat pump, building model, and thermal tank.

The water storage tank temperature at the previous time step, the CO_2 heat pump high temperature gas cooler's outlet water temperature, and the heating demand for the space heating were all calculated by the FMU. These FMU outputs were sent into the MATLAB-implemented MPC model, which optimized system performance using historical system states and electricity price signals [23]. To update the heating load for the subsequent time step, the MPC model computed the necessary heat pump compressor power for the current time step, which was passed back into the FMU. For the best control, this iterative procedure guaranteed real-time coordination between the MPC and the real-time simulation. Using MATLAB's sophisticated optimization capabilities for the MPC algorithm while utilizing Modelica's intricate physics-based modeling of the heating system is one of this approach's main advantages. The FMU made it possible for the system to operate in a co-simulation environment where the Modelica model was subjected to real-time control operations from the MPC [24]. This combination architecture supported a modular approach to system development while improving accuracy and flexibility.

Analytical Derivation for Physical Consistency

To maximize the performance of a hydronic heating system that included a CO_2 heat pump, an MPC strategy was created in this study. The MPC's goals were to increase the heating system's flexibility, lower operating costs, and improve system efficiency. Several crucial processes were involved in the creation and execution of the MPC, which are described here. The process started with building a simulation model of the whole heating system, including the water storage tank, CO_2 heat pump, and related heating system parts. Modelica's IDEAS library was used to construct the model [25]. Dynamic phenomena including changes in mass flow rates and temperature differentials throughout the course of the cycle are captured by the CO_2 heat pump model. For the state space function of MPC, a simplified CO_2 heat pump cycle model was also developed. The following basic energy and mass balance equations served as the foundation for the CO_2 heat pump system's mathematical depiction.

Since the goal of this work was to demonstrate the FMU–MPC integration and system level control framework, dynamic fluctuations in COP were not explicitly modeled. The energy and mass balance was used to create a reduced-order state-space model of the CO_2 heat pump and water storage tank for the MPC implementation. The nominal operating point, which corresponds to the rated heat pump capacity and the steady-state tank temperature, was used to linearize the nonlinear equations [26]. Since the governing equations had already been verified, a data-driven identification strategy utilizing input-output data from the Modelica model was not used. For FMU-based MPC applications in particular, the analytical derivation guarantees complete physical consistency and transparency between the simulation and predictive models.

Control Approach: Considering Heating Demand, Tank Temperature, and Electricity Pricing

The CO_2 heat pump system's MPC strategy was to reduce operating expenses while preserving tank temperature and system effectiveness. The control approach considers the effects of heating demand, tank temperature, and time-varying power pricing to do this. The MPC controller calculates the best control actions to promote economical and energy-efficient operation by forecasting system behavior over a future horizon. The electricity cost in this study was determined by multiplying the heat pump compressor's electricity consumption by the time-varying electricity price [27]. The maximum compressor power from the CO_2 heat pump serves as the prediction horizon, or the entire time during which the optimization is carried out. The space heating system's instantaneous tank temperature in degrees Celsius. For the MPC implementation, this continuous formulation was actually discretized with a 1-hour sample interval.

The weighting factor that strikes a compromise between keeping the tank temperature within a specific range and reducing electricity expenditures is called λ. To highlight the economic goal and clearly assess the controller's reaction to the time-varying electricity price, the value of λ in this study was set to a tiny value of 0.01. Rather than the quadratic penalty term, the strict limits in the MPC formulation guaranteed the tank temperature. The ultimate decision guaranteed a balanced and understandable formulation because tests with higher λ values decreased the controller's price-responsiveness without appreciably improving thermal stability. Weather conditions were considered as measured inputs and modeled as system disturbances [28]. The Modelica model was used to calculate the heating demand, which is influenced by these inputs. The MPC algorithm took into account the ensuing heating demand, which in turn influences the dynamics of the water tank and the heat pump. When determining the best control inputs for the subsequent time step, the controller took these measured disturbances into consideration.

Dynamic Optimization and Cost Minimization

Two other control strategies were used for comparative analysis to assess the MPC controller's performance. The following three control scenarios were investigated in total. Controller for PI: In accordance with the design supply temperature mentioned in the HVAC specification, the PI controller kept the tank temperature at a steady set point of 60 °C. Each controller was expected to keep the outlet tank temperature as close to this level as feasible. This temperature level was also known as the baseline supply. Baseline controller: Using a fixed compressor power schedule, the baseline controller applied full power from 8:00 a.m. to 10:00 p.m. and reduced power to 80% from 10:00 p.m. to 8:00 a.m. MPC controller: The MPC controller sought to strike a compromise between the need to keep the tank temperature within a predetermined range and changes in electricity prices. Based on the ideal control trajectory calculated at each time step, it dynamically modified the compressor power. To minimize energy costs while maintaining the tank temperature limitations, the MPC strategy specifically increased compressor power during times of low electricity prices to store thermal energy in the tank and decreased power usage during times of high prices.

RESULTS

The study's findings are shown in this section to show how well the suggested MPC-based control technique works to maximize the performance of the heat pump and thermal tank system. The examination starts with the MPC operating point and prediction horizon tuning procedure, emphasizing the trade-offs between cost effectiveness and temperature management. After that, the MPC's performance is contrasted with that of a traditional PI controller, with an emphasis on important metrics like temperature control, energy consumption, and operational cost reductions [29]. The MPC's adaptability to fluctuating heat demand and electricity prices is also examined. These findings offer a thorough assessment of the viability and benefits of the suggested strategy for handling intricate energy systems.

Impact of Flow Rate on Compressor Power and Temperature Lift

The impact of changing mass flow on the MPC control signal's performance. The resilience of MPC in reaching the target water temperature in the tank is demonstrated by the upper subplot, which displays tank temperature profiles for various flow rates. All of the scenarios preserve the desired temperature range. The compressor power is shown in the lower subplot, where higher mass flow rates lead to lower compressor power requirements because of increased heat transfer efficiency. The necessary temperature lift over the heat pump cycle was decreased by a larger flow rate, which enhanced the thermal exchange between the gas cooler and the water tank. Because of this, the compressor used less electricity to produce the same heating effect. Nevertheless, the incremental gain becomes minimal over 2 kg/s, suggesting declining returns in terms of energy savings [30]. Furthermore, this operating point exhibits the best capacity to sustain temperatures above 55 °C, which is the lower limit of the tank temperature range, after the initial transient period.

The effects of various prediction horizons on the simulated signals in the MPC-controlled system, with particular attention to the compressor power and water tank temperature. Because the MPC was able to predict future changes in electricity prices earlier thanks to the extended prediction horizons, the controller was able to optimize compressor power utilization and reduce expenses. However, as the upper subplot illustrates, prediction horizons of 30 hours resulted in a discernible drop in the tank temperature, frequently falling below the necessary 55 °C threshold. This raised the possibility of breaking the system's functioning requirements. Maintaining the temperature objectives was crucial, even though the MPC prioritized price optimization [31]. The 24-hour horizon was selected because it demonstrated a balance between price minimization and temperature tracking parameters, guaranteeing the supply temperature above 55 °C for most of the time while efficiently reacting to price fluctuations. Furthermore, the CO_2 heat pump and storage tank system's step-response analysis revealed a dominant time constant of roughly 4–5 hours. Thus, the chosen 24-hour prediction horizon covers almost five times the system's primary dynamic time scale, guaranteeing that the MPC retains computational efficiency while capturing the crucial thermal dynamics. The CO_2 heat pump system's performance comparison between the MPC, baseline, and PI controllers. A control example for January, which is the coldest month of the year, is displayed in the results. The top subplot shows the heat pump outlet temperature from the MPC results as well as the tank temperature dynamics under the PI, baseline, and MPC controllers.

Compressor Power and Electricity Price Dynamics

As previously stated, state variables in the MPC algorithm were given for reference. The compressor power to the heat pump under MPC, PI, and baseline control techniques is compared in the middle subplot. The hourly power price profile in Oslo (the black line) and normalized heat demand for 2024 (the red line) are two examples of the external disturbances shown in the bottom subplot. A short-term market imbalance recorded in the Nord Pool dataset during a cold winter is represented by the noticeable peak in electricity prices around the 400th hour. To facilitate comparison with the cost of power, the normalized heat demand was computed using the Modelica model and scaled. To guarantee that the tank temperature reached and remained at this predetermined point, the compressor power was continuously regulated. Nevertheless, changes in the price of electricity did not affect the PI controller. The heat demand was mostly followed by the compressor power trend. The compressor power rose in tandem with the rise in heat demand. The baseline results (the green line) demonstrate that the tank temperature trend was in opposition to the heat demand trend since the compressor power follows a set schedule as previously presented. The fixed compressor power was insufficient and the tank temperature decreased when heat demand was high, which meant that more heat was extracted from the tank. The fixed compressor input raised the tank temperature when heat demand was minimal. Although both the PI and the baseline controllers demonstrated some degree of dynamic thermal response, neither takes the cost of electricity into account when operating. This was especially noticeable during the notable price peak that occurred between the 400th and 450th hour. The need for heat rose throughout this time, peaking at the 420th hour, and electricity rates likewise skyrocketed. As a result, the PI controller's compressor power input stayed high, just like the baseline controller's, which could lead to expensive electricity. On the other hand, the MPC controller considers both the cost of electricity and the tank temperature. During the period of high prices, the MPC controller decreased the compressor power input. As a result, the MPC algorithm found the best balance between decreasing electricity expenditures and preserving the necessary tank temperature. The main functional advantage of MPC over traditional control strategies is that it balances cost minimization and temperature constraint satisfaction by anticipating future changes in electricity prices and proactively adjusting compressor power, whereas baseline controllers control tank temperature reactively. For a whole year, the same control techniques were used [32]. The observed patterns align with the January case. To keep the tank temperature at the setpoint of 60 °C, the PI controller continuously modified the compressor power. As previously mentioned, the baseline controller ran on a fixed compressor power schedule. The MPC controller, on the other hand, dynamically managed the trade-off between reducing electricity costs and keeping tank temperature within acceptable bounds. The total electricity bills for the MPC, PI, and baseline controllers were 159,440 NOK, 170,919 NOK, and 206,407 NOK, respectively, when only the base cost of electricity (without including grid tariffs and taxes) was taken into account. This shows that the MPC controller lowered power expenses by 22.8% when compared to the baseline controller and by 6.7% when compared to the PI controller.

Balancing Energy Efficiency and Cost Savings with MPC

The main variations in performance between the baseline, PI, and MPC techniques. The MPC achieves the lowest annual electricity use at about 243 MWh, followed by the PI controller at 251 MWh and the baseline at 328 MWh, according to the blue bars. The electricity cost is represented by the orange bars, where the MPC likewise produced the lowest cost (159.4 kNOK) when compared to the baseline (206.4 kNOK) and PI (170.9 kNOK). The cost savings are more substantial at 6.7%, even though MPC's energy use was only roughly 3.2% lower than PI's. The PI controller, on the other hand, only reduced costs by 17.2% while reducing energy use by 23.5% when compared to the baseline. These results imply that although MPC saves somewhat more energy than PI, it has a bigger cost-cutting benefit due to its flexibility in responding to fluctuating electricity costs [33]. The MPC showed significant cost and energy savings when compared to the baseline, with a marginally larger gain in energy reduction because it took tank temperature into account. In general, temperature tracking-focused management tactics tend to increase energy efficiency, although cost-cutting strategies that react to electricity prices are more successful. These goals were balanced by the MPC strategy, which led to concurrent cost and energy savings.

DISCUSSION

The case study school building's heating system is an example of a somewhat complicated heating system. It took great thought to simplify this system to create a Modelica model for the study. The accuracy of the heat pump model—in this example, the CO_2 heat pump—was given particular care because the study's main focus was on applying the MPC for heat pump flexibility. Modelica CO_2 heat pump models are typically constructed with commercial libraries, such as TIL. However, the conventional heat pump model found in the open Modelica library IDEAS was selected, taking into account computational resources and the model's practical usability. To replicate the two gas coolers found in the actual system of the case study building, this model was connected to two heat exchangers. Its calibration was verified to guarantee dependability [34]. Adjusting the MPC to the physical model in Modelica was another difficult part of the research.

Converting the Modelica model to an FMU file and doing co-simulation in MATLAB/Simulink was chosen as the strategy after several approaches were investigated. In addition to addressing the integration issues, this approach provides a helpful resource for upcoming research. The state-space model of the heat pump and thermal tank was employed for the MPC design, which is a conventional method. Tuning the Modelica model and MPC algorithms together needed a lot of work, including choosing the right restrictions and parameters to guarantee effective execution. Electricity and operating costs were significantly reduced by using the MPC, with savings of 8.0 MWh (3.2%) and 11,479 NOK (6.7%) when compared to the PI controller and 85.07 MWh (25.9%) and 46,969 NOK (22.8%) when compared to the baseline controller. These results demonstrate how MPC can improve energy and economic efficiency by adapting dynamically to changes in power prices and system conditions. Deeper understanding of the useful advantages and implementation techniques for MPC in comparable systems may be obtained by more examination of the particular operational scenarios that contribute to these savings. The MPC's ability to improve building flexibility was further proved by its implementation. MPC made it possible for the building to function as a flexible demand resource by actively controlling the heating system in response to signals about power prices and changes in heat demand. This flexibility was essential for incorporating renewable energy sources and resolving the growing supply-side volatility. During times of very high electricity prices, the MPC controller occasionally permitted the tank temperature to drop below the minimum threshold, which could result in an inadequate heat supply to maintain indoor temperature set points.

Challenges in Implementing MPC for Real-World Systems

The mass flow rate from the gas cooler to the thermal tank was fixed at 2 kg/s in this study to simplify the MPC algorithm, but varying it could enhance heat transfer efficiency. Future research should include mass flow rate as an additional manipulated variable in the MPC framework. The study also did not consider the building envelope's thermal flexibility, an area for prospects [35]. The MPC did not consider how inside temperatures dynamically respond to low supply temperatures. Future research aims to incorporate building envelope dynamics to boost MPC effectiveness. Implementing MPC in real-world systems faces hurdles like computational demands, precise modeling, and handling disruptions. Future studies should tackle these challenges, enhance MPC reliability, and explore widespread adoption methods. Key areas include model simplification, FMU integration, and MPC tuning.

This review focuses on model-based ventilation control in nearly zero energy buildings (nZEBs), which have slower responses to disturbances due to high insulation and air tightness.Internal heat gains have a greater impact, and variable occupancy patterns (, e.g., offices, schools) make HVAC control more complex. All-air ventilation systems can also mismatch heating and ventilation demands. These factors make controlling internal environmental quality (IEQ) in nZEBs challenging. Model predictive control (MPC) is a potential solution, as it considers current conditions and future disturbances/demand. MPC uses state estimation to predict future system/building states, enabling the controller to optimize outputs by solving an optimization problem. The objective is typically to minimize energy use while maintaining thermal comfort, with constraints and future disturbances factored in. The optimal control problem uses the identified model to verify the solution and optimize outputs.

In total 14 studies are evaluated where MPC was implemented to control the ventilation system. Out of these studies, 6 use an all-air ventilation system of climatization while in the other studies hydronic systems (, e.g., a heat pump with a TABS system) are used for space heating. In 10 out of the 14 evaluated studies the developed MPC framework is implemented in a real operating building or a small experimental test building, the remaining studies are simulation studies. In these four remaining studies typically measurement data is obtained from the building to develop a virtual test model that is used inside the MPC framework to perform a co-simulation.

Modeling Approaches for MPC in Buildings

Most buildings studied are office buildings (8 out of 10), with one residential and one academic building also included. The MPC framework relies on a model that represents the actual building and system. Various modeling approaches are used, ranging from simple regression models (black box) and RC models (grey box) to detailed white box models (, e.g., Modelica). Recently, machine learning techniques like random forest and neural networks have also been applied to model identification. The model identification process is a key focus in literature, as it dominates the development of an MPC framework. The goal is to create a simple yet accurate dynamic model of the building and HVAC system for MPC predictions. A reduced-order model simplifies the computation process, significantly cutting the time needed to solve the optimal control problem. Typically, MPC for ventilation systems controls supply air temperature, with only 4 out of 14 studies also controlling room CO_2 levels. The MPC regulates VAV boxes in the ventilation system, determining airflow rate and supply air temperature at each time step.

The ventilation MPC's cost function aims to minimize energy use while prioritizing thermal comfort. Soft constraints are applied to comfort constraints, penalizing temperature (and CO_2) setpoint violations. The comfort cost is weighted significantly higher than energy cost, prioritizing occupant comfort over energy efficiency. Ventilation control is often nonlinear, making the MPC problem complex to solve due to nonlinear constraints. In all-air systems, airflow rate and supply air temperature vary over time, requiring either nonlinear optimization for a more accurate representation or simplification to handle the nonlinear constraints. MPC for ventilation control yields energy savings of 17–55% versus rule-based control (RBC), though baseline definitions vary. Input data variability and uncertainty are often overlooked in savings calculations. Future implementation should focus on transferring MPC methods to other buildings. A key bottleneck is the expertise required for MPC implementation, as it demands extensive data and fine-tuning in model identification, typically specific to a building or system type.

CONCLUSION

This study employed an FMU-based co-simulation platform to demonstrate the effectiveness and efficiency of a Modelica-based Model Predictive Control (MPC) framework for a CO_2 heat pump system paired with a water tank in a school building located in Oslo. The main innovation lies in the integration of a detailed Modelica model with MPC through the FMU interface, facilitating real-time interaction between the predictive control algorithm and intricate thermodynamic and hydraulic dynamics. The case study reveals significant energy and cost savings: 8.0 MWh (3.2%) and 11,479 NOK (6.7%) relative to the PI controller, and 85.07 MWh (25.9%) and 46,967 NOK (22.8%) compared to the baseline controller, all while maintaining operational constraints, such as ensuring tank temperatures remain above 55 °C for most of the operational period. The MPC's advantages over traditional control methods such like PI were underscored by its ability to leverage dynamic electricity pricing and effectively respond to system disturbances. The MPC demonstrated enhanced adaptability not only by responding to changing electricity costs but also by addressing thermal demand variations, offering significant economic advantages. This adaptability illustrates its potential to meet the increasing need for flexibility within the energy sector, where risks on the supply side are prevalent. The results emphasized the vital role of predictive control in utilizing demand-side flexibility to tackle challenges such like peak load management and fluctuations in renewable energy generation. Despite the promising results, there are challenges to implementing MPC in real-world applications, such as computational demands, the need for accurate system modeling, and tuning the MPC for optimal performance. Future research should focus on addressing these challenges by exploring real-time optimization techniques, improving system models, and scaling the control strategy to larger systems or different building types. Ensuring the long-term reliability and maintenance of MPC systems will also be crucial for widespread adoption in practical applications. This study highlights the potential of MPC to transform heating system control, offering significant cost savings, increased system flexibility, and improved adaptability.

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