Neural Network-based Predictive Control System for Energy Optimization in Sports Facilities: A Case Study

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Abstract

Given the increased global energy demand and its associated environmental impacts, the management and optimization of sports facilities is becoming imperative as they are characterized by high energy demand and occupancy profiles. In this work, the theory of model predictive control (MPC) is combined with neural networks for temperature setpoint selection to achieve energy and performance optimization of sports facilities. It is demonstrated using the building information model (BIM) of a sports hall in the sports complex of Qatar University. MPC systems are powerful as they allow integrated dynamic optimization that accounts for the future system behavior in the decision-making process, while neural networks are advantageous for their ability to represent complex interdependencies with high accuracy. The proposed approach was able to achieve a total energy savings of around 33%. Considerations about the network performance, MPC settings tuning, and optimization sub-optimality or failure are essential during the design and implementation phases of the proposed system.

Keywords: Energy optimization, energy saving, sports facility, neural networks, predictive control

1 Introduction

The global energy consumption is rising significantly due to the increased world population, economic growth, and technological development. Fossil fuels plants were used to generated more than half of the electricity worldwide in 2017 comprising 64.5% of the global electricity generation among other cleaner sources (World nuclear association n.d.). This is because they are cheaper and economical to establish and operate, and they provide electricity over long periods of time. However, the increased global use and dependency on fossil fuels aggravated the global warming dilemma as large amounts of carbon dioxide are released as biproducts. According to the International Energy Agency (IEA), the buildings sector accounts for more than one-third of the total energy consumption worldwide, and nearly 40% of the total direct and indirect CO2 emissions. In 2019, the highest level of CO2 emissions due to the use of electricity and air conditioning systems in buildings was recorded (International Energy Agency n.d.). The heating, ventilation, and air conditioning (HVAC) system is the most extensively operated component of buildings with about 40% of total building energy (Energy.gov 2015). A recent report by IEA indicated that the electricity use in buildings will rise to nearly double the amount between 2018 and 2050 (Hojjati 2019) due to the increased world population and technological development among other reasons.

Among other types of buildings, sports facilities are known for their exceptionally high energy demand profile as they encompass spaces involving different types of activities (i.e., offices, indoor/outdoor arenas, football stadiums, swimming pools, etc.), require extensive lighting and broadcasting requirements, and operate at high-occupancy seasonal rates. Managers are pressed to reduce their facilities incurred operating expenses and running costs due to the increased electricity prices. There have been several studies for the management and optimization of energy use in sports facilities as in (Petri et al 2017) in which a multi-objective genetic optimization algorithm was used to optimize the electricity consumption of the HVAC equipment in a swimming pool employing the building information model (BIM) for historical data generation. In (Song et al 2018), a load monitoring and estimation framework was proposed for energy consumption prediction in swimming pools using a weighted difference change-point regression model. In (Refaat et al 2016), a smart energy management system was developed for full monitoring and management of the electrical system of a stadium. Using data-driven approaches for energy management and optimization employing artificial intelligence algorithms became more attractive given the development in the technologies used in building management systems, which made access to historical data easier.

In this paper, a combination of the model predictive control (MPC) theory and neural networks is used for operation optimization of a sports facility in terms of energy consumption while maintaining acceptable thermal comfort levels of users. The motivation of this work is the development of an integrated temperature setpoint optimization system that accounts for the current and future system transitions in the decision-making process. Neural network-based MPC was introduced in (Åkesson & Toivonen 2006) and used in (Ferreira et al 2012) to regulate the operation of the HVAC system in a public building to achieve optimized energy consumption and adequate thermal comfort levels. Unlike the conventional model-predictive controller, it does not require prior knowledge of the dynamics of the building's HVAC system nor defined operating conditions of the system, but rather, it is developed utilizing the operation data of the system.

The rest of the paper is organized as follows. In Section 2, a review of the related work about applications of neural networks for sports facilities management is presented. The description of the case study used to demonstrate the work is presented in Section 3. In Section 4, the details of the proposed methodology are provided, while the results and discussion are presented in Section 5. Finally, conclusions and future works are discussed in Section 6.

2 Applications of neural networks for sports facilities management

Neural networks have been used previously in applications towards the management and optimization of sports facilities in terms of energy usage and thermal comfort. In (Yuce et al 2014), a static neural network model was used to facilitate operation optimization of the management system of an aquatic center in terms of energy-saving and thermal comfort of the users. In (Li et al 2020), a black-box model was developed using a neural network for component sizing optimization using multi-objective genetic optimization for a heating system of outdoor swimming pools. Neural networks were utilized in (Lu et al 2014) for the prediction of water evaporation rate in indoor swimming pools, while in (Santos et al 2013), a hybrid model of a swimming pool thermal behavior was proposed using thermodynamic laws and neural networks. In (Yoon et al 2018), a neural network-based prediction model for the thermal environment of a sport stadium was developed utilizing details about the indoor conditions and the users. In (Xiao-wei 2020), a smart sports facility management system was proposed employing a hybrid model of a support vector machine-back propagation neural network for predicting the passenger flow in the facility towards improved management of its operation. In most of the research works, neural networks were used in a static framework to achieve prediction, optimization, or modeling.

The capability of neural networks can be leveraged when combined with other principles, as they are known for their ability to model complex functions and represent them in an interpreted model form. For example, the utilization of neural network-based MPC was proposed in (Privara et al 2011) for regulating the operation of air-conditioning systems in which the weather forecast and the thermal model of a building were taken into account to determine the control decision that achieves energy savings while maintaining the desired indoor conditions. Model-predictive control is advantageous because it systematically considers the future predictions of the system behavior during the control design stage while fulfilling the system operating constraints (Camacho & Alba 2013).

3 Description of the case study

The sports and events complex of Qatar University is one of the pilots of the SportE3.Q project. It occupies a total area of 25,500 m^2 of the university campus, which is located on the northern outskirts of Doha city, the capital of Qatar. The complex operates from 8 am to 3 pm, and it includes the following sports facilities: a multi-purpose hall, a training arena, a gymnasium, a martial arts studio, an exercise studio, an indoor tennis court, and squash courts as demonstrated in Figure 1. The case study in this work is demonstrated on the multi-purpose hall, which is the largest conditioned space in the complex that extends from the ground floor all the way to the roof with a total floor area of about 7,500 m^2. It is controlled at a temperature of 22°C during occupancy period, and the sports mode of the multi-purpose hall allows for a maximum occupancy of 1200 people.

The detailed building information model (BIM) of the sports and events complex which contained the architecture, engineering, and construction information of the complex was used to develop the EnergyPlus simulation model using the Design Builder software (Design Builder n.d.). The relevant details were included in the energy model, which are the construction structures and materials, heat transfer coefficients of surfaces, etc. For the purpose of this study, Energyplus HVAC system template of a HVAC ideal loads air system was used. It allows calculating loads without modeling a full HVAC system. It simulates the process of mixing zone air with the specified amount of outdoor air and removing heat and moisture at 100% efficiency to meet the specified controls. It only requires zone control details in terms of temperature setpoint, zone equipment and activity details, and the type of the loads system.

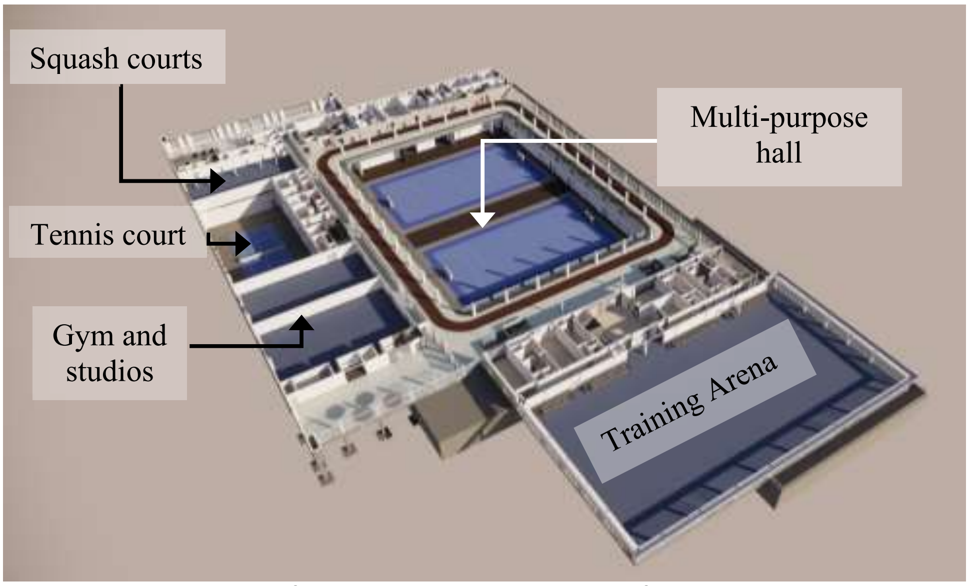

Figure 1. Sketch of the sports and events complex of Qatar University.

4 Neural network-based MPC system for sports facilities energy optimization

This work presents a neural network-based MPC system for temperature setpoint selection towards energy use optimization in a sports facility. The MPC system consists of an optimizer and a prediction model of the building operation to decide the temperature setpoint given a cost function. Let $x(k) \in \mathbb{R}^{n_x}$ be the state of the system at time k, where n_x is the number of states, and $y(k) \in \mathbb{R}^{n_y}$ be the output that is desired to reach a certain reference value $r(k) \in \mathbb{R}^{n_y}$, where n_y is the number of outputs. As demonstrated in Figure 2, based on the system output $y(k)$ and its reference value $r(k)$, the MPC attempts to determine the control input $u(k)$ using numerical optimization by finding the control inputs over a prediction horizon of n_p time steps that provides the best predicted performance according to a given objective function. By applying the control input $u(k)$, the system transitions to a new state $x(k+1)$, after which the same procedure is repeated.

The MPC has two main parameters, which are the prediction horizon, n_p which determines the extent to which the controller investigates the future when solving for the optimized control action, and the control horizon, $n_c \in [1, n_p]$, which represents the number of control actions to be optimized at every step. The cost function J has two elements, which are the error signal, $e(k) = y(k) - r(k)$, between the actual measurement and the reference value, and the rate of change in the setpoint $\Delta u(k)$. The cost function is formulated as:

$$J = \sum_{j=1}^{n_y} \sum_{i=1}^{n_p} \frac{w_j}{s_j} e_j^2(k+i|k) + \sum_{i=1}^{n_{p-1}} w_{\Delta u} \Delta u^2(k+i|k) \qquad (1)$$

where w_j and s_j are the weight and the scale parameters of the error signal of the jth output variable, respectively, and $w_{\Delta u}$ is the weight parameter of the change in the control action. The weight parameters are used to tune the MPC system when multiple outputs are involved, while the scale parameters are used to normalize the error signals to avoid optimization failure or sub-optimality due to output variables diverse magnitudes. It is a common practice that the scale parameter is set to the span of the variable, which is the difference between its maximum and minimum value.

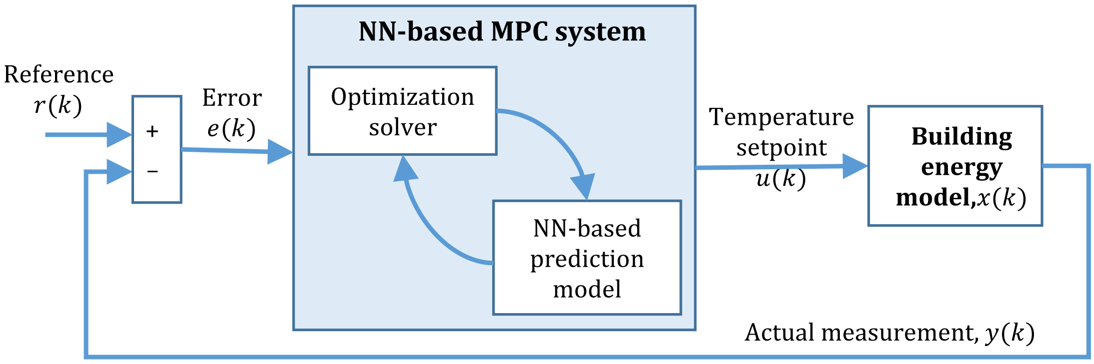

Figure 2 Diagram of the NN-based MPC setpoint optimization framework.

The proposed framework was implemented using MATLAB/Simulink 2018b with EnergyPlus 9.2 for building energy model simulation using the toolbox developed by (Dostal & Baumelt 2019). The sampling time of the building model is 15 min. The model has three states, which are the average predicted mean vote (PMV) of the multi-purpose hall, the cooling energy, (Q_{cool} [Joule]) required to condition the hall, and the ambient temperature (T_{amb}[$^\circ$C]), while it has two outputs, which are the PMV value and the cooling energy, Q_{cool}. The ambient temperature, T_{amb}, was included as a state because it affects the cooling process, which in turn influences the cooling energy requirement and thermal comfort in the conditioned space. The control action (u) is the temperature setpoint (T_{sp}) that is bounded between 18 to 24°C. Sequential quadratic programming was used as the MPC optimization solver with maximum number of iterations allowed of 200.

4.1 Neural network-based prediction model

A dynamic model of the multi-purpose hall of the complex was developed using a neural network. The dynamic model aims to express and capture the behavior of the system over time. As shown in Figure 3, the inputs of the network are the system states $x(k)$ in addition to the temperature setpoint, $T_{sp}(k)$, at time instant k, while the outputs are the states at the consecutive time instant, $k+1$.

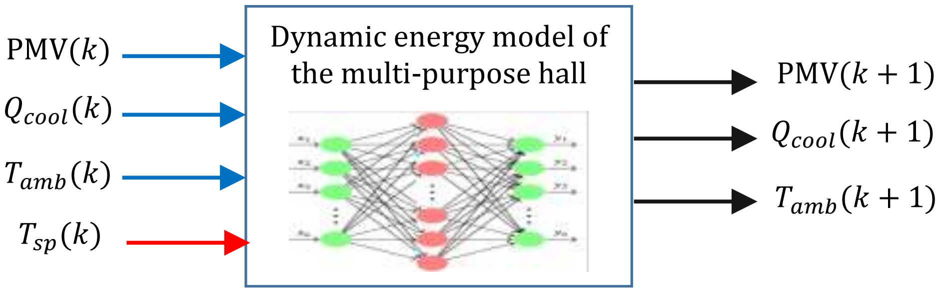

Figure 3. The NN-based dynamic energy model of the multi-purpose hall.

The training of the network was carried out in MATLAB using a dataset generated from the EnergyPlus model. The dataset consists of about 2000 samples collected at different setpoints. The date split procedure was used for evaluating the performance of the neural network, which is a common practice that allows testing the prediction performance of machine learning models in which 85%, 10%, and 5% of the dataset selected at random were used for training, validation, and testing, respectively. A simple single layer network with 15 neurons was trained using the Levenbreg-Marquardt algorithm (Levenberg 1944). Figure 4 shows the performance of the neural network in terms of the mean squared error (MSE) between the network outputs and targets versus iterations on the training, validation, and testing sets. The network demonstrated adequate generalization ability and reasonable performance with a MSE of less than 0.0015 overly, and a coefficient of determination (R^2) of 0.99 for all the sets as shown in the regression plots in Figure 5. The plots demonstrate a verification of the network performance by displaying the network outputs with respect to true targets for training, validation, and testing sets.

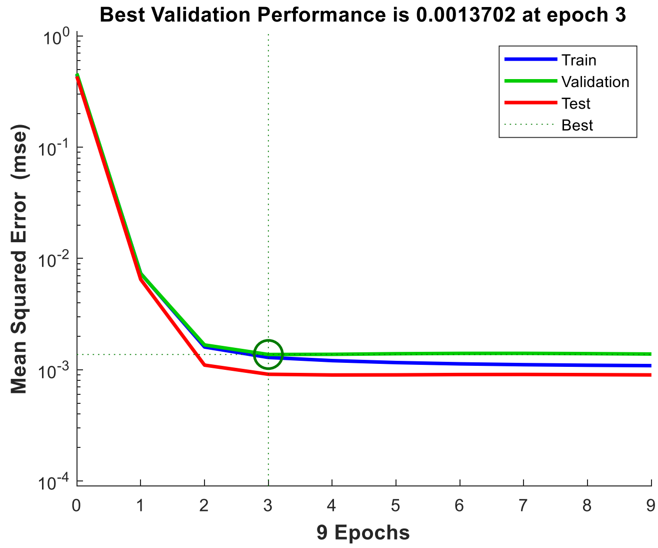

Figure 4. Plot of the neural network-based prediction model performance on the training, validation, and testing sets. The best NN model was recorded at the 3rd epoch at which its performance using the training and validation sets was minimum and matching, and after which the NN started to overfit demonstrated by the diverging train and validation plots.

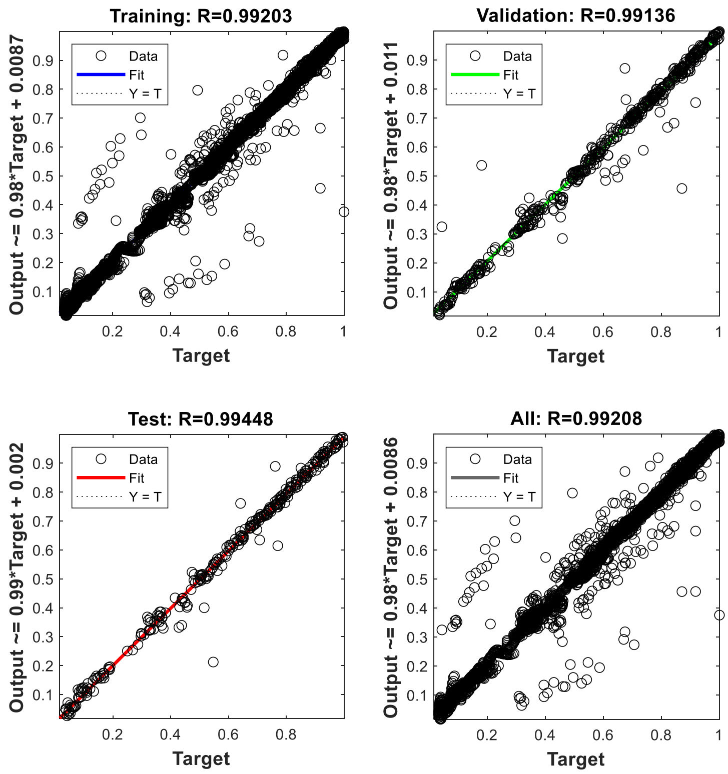

Figure 5. Regression plots of the neural network model on the training, validation, and testing sets. The neural network data fit is rarely perfect in practice, and the off-diagonal data points represent the ones with poor fit.

5 Results and discussion

Multiple experiments were conducted by varying the main parameters of the MPC system using 1 day as the simulation period as presented in Table 1 and demonstrated in Figures 6 – 8. The input signal weight factor used was $w_{\Delta u} = 0.1$, and the reference signal used for the PMV variable was $r_1 = 0$ indicating average thermal comfort levels. Since the cooling energy varies during the day, a dynamic reference signal, $r_2(k) = E_{per} Q_{nominal}(k)$, was used, which represented a proportion of the nominal energy usage ($Q_{nominal}$) based on the parameter E_{per}. Consequently, the maximum achievable amount of energy reduction is 1 - E_{per}. A sinusoidal signal was used to model the nominal energy usage $Q_{nominal}$ of the multi-purpose hall, which its ratings were determined knowing that the space is typically controlled at a temperature of 22°C.

An optimization problem is formulated and solved at every time step, thus the selections of the parameters n_p and n_c contribute to the computational overhead of the MPC system. Careful tuning of the MPC parameters was required to avoid suboptimality issues or encountering infeasible optimization problems, which would result in solver failure. That is, it was found that some selections of MPC settings yielded feasible but non-optimal solutions that poorly satisfied the objective function. In addition, when the optimization solver was unable to find a feasible solution at any time step, the action decided from the previous time step was used.

This optimization problem deals with a complex tradeoff between energy consumption and thermal comfort levels, with one controlling variable being the temperature setpoint. The goal is to achieve reduced energy consumption and adequate thermal comfort levels. Improved thermal comfort levels are fulfilled with lower temperature settings, at the expense of energy which is inversely proportional to the temperature setpoint. If the space temperature is set at a higher value, less cooling energy is required, and it is more likely that the thermal satisfaction of users is altered. Hence, it was observed that ideal reference tracking was not achieved. The energy proportion factor, E_{per} influences the total energy consumption because it determines the energy reference value $r_2(k)$. Greater energy reduction is achieved when the energy reference is reduced as demonstrated in Figure 6. The weight parameters determine the relative importance of the variables to the optimization objective. Thus, in Figure 7, increasing the weight parameter of the PMV value brings it closer to its reference while it has an inverse effect on the total cooling energy indicated by the decreasing energy reduction percentages. Similarly, in Figure 8, larger energy weight parameter settings contributed towards the desired objective in terms of energy reduction unlike the case for the thermal comfort levels indicated by the PMV value. Since multiple variables are involved in the optimization problem, making compromises is inevitable towards achieving the best possible solution.

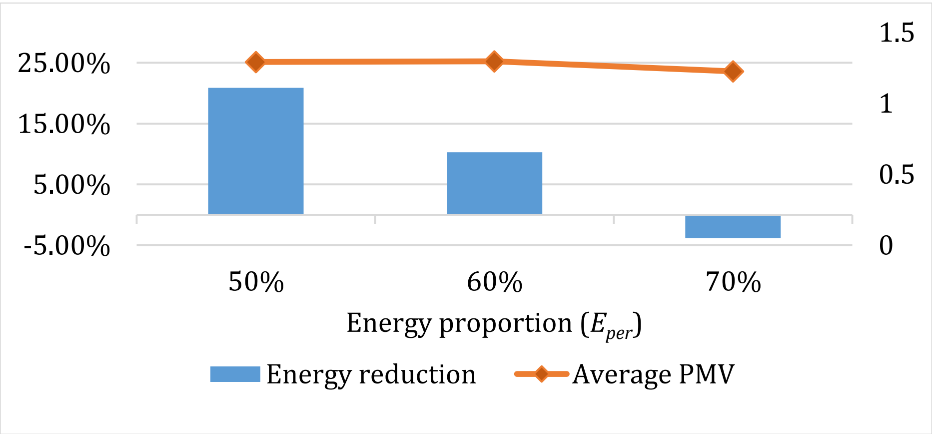

Figure 6. The effect of the desired energy reference on the energy reduction and the thermal comfort levels for $\boldsymbol{n_p = 2}$, $\boldsymbol{n_c = 1}$, $\boldsymbol{w_1 = 6.05}$, and $\boldsymbol{w_2 = 14.05}$.

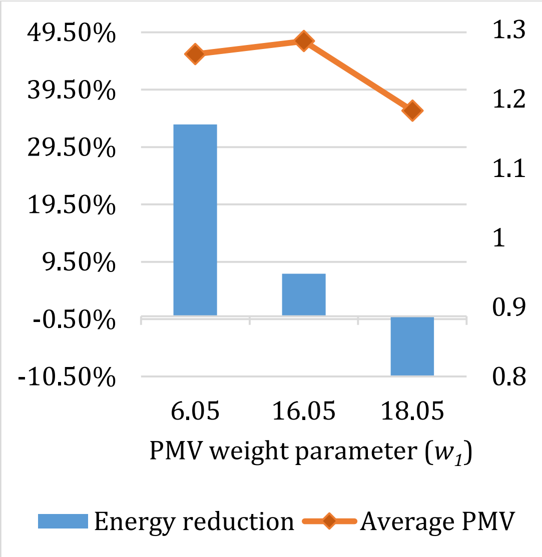

Figure 7. The effect of the PMV weight factor on the energy reduction and the thermal comfort for $\boldsymbol{n_p = 2, n_c = 1}$, and $\boldsymbol{w_2 = 12.05}$.

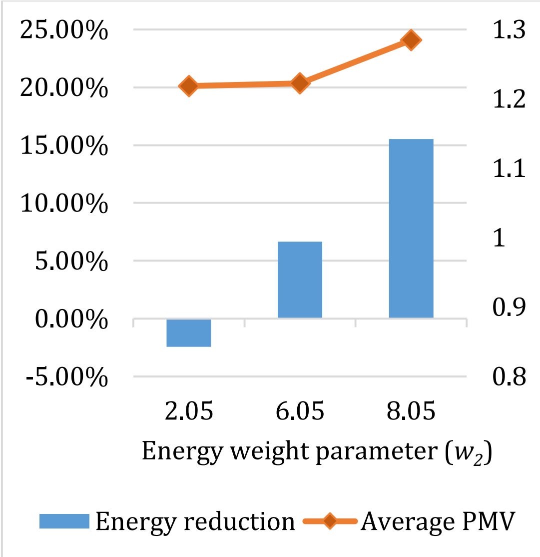

Figure 8. The effect of the energy weight factor on the energy reduction and the thermal comfort for $\boldsymbol{n_p = 2, n_c = 1}$, and $\boldsymbol{w_1 = 2.05}$.

In terms of the prediction and control horizons, as presented in Table 1, the computational time is relatively higher for larger horizons since additional prediction and control steps are performed. The energy was reduced by about 20% when the MPC setpoint optimization system looks 1 hour into the future ($n_p = 4$) since the sampling time is 15 min. The best performance was achieved with the settings of $n_p = 2$ and $n_c = 1$, with energy reduction of 33.45%. In this case, the temperature setpoints are decided based on a 30-minute forecast scope of the system behavior. The performance of the MPC setpoint optimization system is demonstrated in Figure 9 in comparison with the typical case without it. Reference tracking was not fully achieved especially for the PMV value, which was settled at about 1.5 due to this tricky tradeoff, while the average value of the cost function was around 200.

Table 1. The best achieved performance for the different settings of the MPC system in terms of the prediction and control horizons for 40% desired overall energy reduction.

Energy reduction	**Average PMV**	n_p	n_c	w_1	w_2	**Computation time per simulation step (sec)**
33.45%	1.26	2	1	6.05	12.05	0.19
9.94%	1.20	3	2	6.05	0.05	0.22
19.08%	1.24	4	3	6.05	8.05	0.28

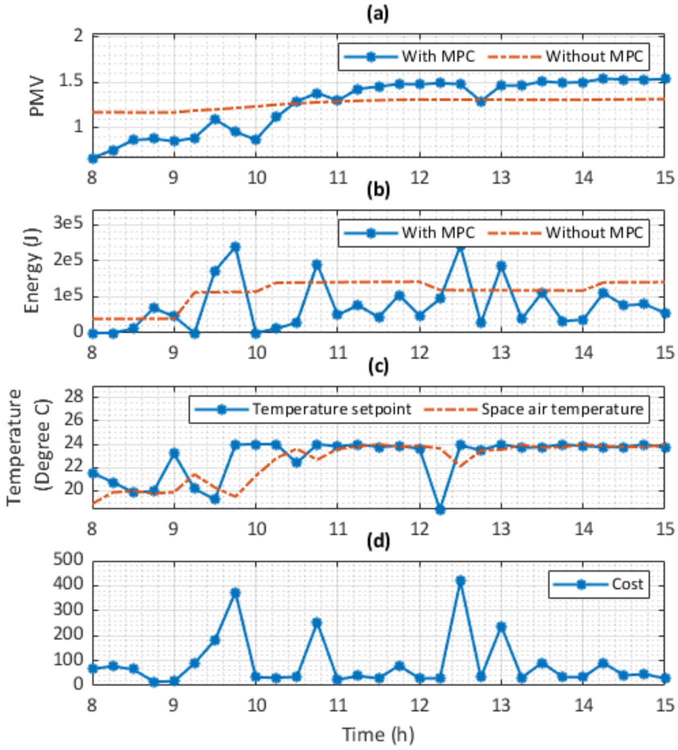

Figure 9. The performance of the MPC setpoint optimization system compared to the typical scenario. (a) The thermal comfort level of users in the multi-purpose hall. (b) The energy consumption of the air-conditioning system of the hall. (c) The temperature of the multi-purpose hall. (d) The value of the MPC optimization cost function.

6 Conclusion

In this work, we demonstrated the effective utilization of a neural network-based MPC system for setpoint selection to achieve energy and performance optimization of sports facilities as a proof-of-concept that was validated using simulation tools on a sports hall in the sports and events complex of Qatar University. MPC systems are powerful as they allow integrated dynamic optimization that accounts for the future system behavior in the decision-making process. A neural network was used for the system prediction element of the MPC system since it is unpractical and difficult to obtain explicit models for complex buildings such as sports facilities. Neural networks are advantageous for their ability to represent complex interdependencies with high accuracy. However, other data-driven regression algorithms can be used such as support vector machine, decision tees, k-nearest neighbors, etc. Nevertheless, the performance of the MPC system is highly dependent on the accuracy of the prediction model, which is used by the MPC to look into the future towards finding the best control action. The proposed approach was able to achieve a total energy savings of around 33%. Considerations about the prediction model performance, tuning of the MPC settings, and optimization sub-optimality or failure are essential during both design and implementation phases. The MPC system for setpoint optimization complements the existing management and automation system of the facility, thus can be easily integrated.

We plan to work on improvements of the proposed system by deploying other advanced optimization algorithms to achieve better tradeoff between the energy use and thermal comfort, and including additional controlling variables such as occupancy rate, lighting system schedules, air ventilation rate, etc. Additionally, the objective function of the optimization problem can be expanded to include factors related to the safety and health of users. Ultimately, we plan to apply the proposed framework for the sports and events complex using both simulation and practical experiments as well as presenting a comparative analysis of the performance of the proposed framework using other machine learning algorithms for the MPC prediction model development.

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