Neural Network-based Model Predictive Control System for Optimizing Building Automation and Management Systems of Sports Facilities

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Abstract

Sports facilities are considered complex buildings due to their high energy demand and occupancy profiles. Therefore, their management and optimization are crucial for reducing their energy consumption and carbon footprint while maintaining an appropriate indoor environmental quality. This work is part of the SportE3.Q project, which aims to manage and optimize the operation of sports facilities. A neural network (NN)-based model predictive control (MPC) management and optimization system is proposed for the heating, ventilation, and air conditioning (HVAC) system of a sports hall in the sports and events complex of Qatar University (QU). The proposed approach provides an integrated dynamic optimization method that accounts for future system behaviour in the decision-making process, consisting of a prediction element and an optimizer. A NN is used to implement the dynamic prediction element of the MPC system and is compared with other machine learning (ML)-based models, which are support vector regression (SVR), *k*-nearest neighbor (*k*NN), and decision trees (DT). The NN-based model outperforms the other ML models with an average root mean squared error (RMSE) of around 0.06 between the actual and the predicted values, and an average R of 0.99 as NNs are popular for their high accuracy and reliability. Two schemes of the proposed NN-based MPC system are investigated for managing and optimizing the operation of the hall's HVAC system for an enhanced energy use and indoor environment quality as well as for providing occupancy profile recommendations to aid the facilities' managers in handling their operation. In alignment with the objective of the SportE3.Q project, up to 46% energy reduction was achieved while jointly optimizing the thermal comfort and indoor air quality. In addition, Scheme 2 of the proposed system provided productive occupancy recommendations for a healthier indoor environment.

Keywords: Model predictive control, neural networks, energy management and optimization, sports facilities

Nomenclature

Abbreviations

AHU Air Handling Unit

AV Audiovisual

BAMS Building Management and Automation System

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BEM Building Energy Modeling

BESS Building Energy Storage System

BIM Building Information Modeling

BIPV Building Integrated Photovoltaic

CFD Computational Fluid Dynamics

CO2 Carbon Dioxide

CUSP Computational Urban Sustainability Platform

DAE Deep Autoencoders

DT Decision Trees

EIA Energy Information Administration

ERU Energy Recovery Unit

FCU Fan Coil Unit

FPGA Field Programmable Gate Array

HVAC Heating, Ventilation, and Air Conditioning

IoT Internet of Things

LSTM Long Short Term Memory

ML Machine Learning

MOGO Multi-Objective Genetic Optimization

MPC Model Predictive Control

MSE Mean Squared Error

PMV Predicted Mean Vote

PSO Particle Swarm Optimization

QU Qatar University

RES Renewable Energy System

RMSE Root Mean Squared Error

SVM – BP Support Vector Machine-based Backpropagation

SVR Support Vector Regression

WDCP Weighted Difference Change-Point

WMA Weighted Mean Average

*k*NN *k*-Nearest Neighbor

Symbols

Act Activity Level or Metabolic Rate [W/m^2]

c	System's Parameter
e	Error Value
J	Cost Function
k	Sample of Time
m	Number of Data Samples
n	Number of Data Features
n_c	Control Horizon
n_p	Prediction Horizon
$NumPpl$	Number of People
OW	Output Weight
Q	Flow Rate [kg/s]
r	Reference Value of System's Output
RH	Relative Humidity [%]
s	Scale Parameter
T	Temperature [°C]
u	System's Input
w	Weight Parameter
x	System's State
y	System's Output

Subscripts

amb	Ambient
FA	Fresh Air
max	Maximum
min	Minimum
SA	Supply Air
sp	Setpoint

1. Introduction

Due to the growing world population, economy, and technological development, the global energy demand and consequently the emission of greenhouse gases are increasing. In 2017, fossil fuels plants, which have a high carbon footprint, were used to generate 64.5% of the electricity in the world [1], since they are cheaper to establish and operate. The buildings sector accounts for more than one-third of the total energy consumption worldwide and nearly 40% of the direct and indirect CO2 emissions [2]. In 2019, the highest level of CO2 emissions due to the use of electricity and air conditioning systems in buildings was recorded [2]. The heating, ventilation, and air conditioning (HVAC) systems are the most extensively operated components of buildings, which consume about 40% of the total building energy [3]. The US Energy Information Administration (EIA) reported that the electricity use in buildings is expected to rise to nearly double between 2018 and 2050 [4] due to the increased world population and technological development, among other reasons.

Sports facilities, in particular, are known for their exceptionally high energy demand profile as they encompass open and enclosed areas of large space and involve different types of activities such as offices, arenas, stadiums, swimming pools, etc. They require extensive lighting, air ventilation and conditioning, and broadcasting requirements, and they operate at high-occupancy seasonal rates [5]. Hence, unlike other types of buildings (e.g., commercial, residential, etc.), it can be challenging to efficiently manage their operation to maintain the minimum energy use and the well-being of the users while fulfilling the requirements of the involved activity (i.e., lighting, air ventilation and conditioning, and others provided services). That is, unlike other buildings in which the installed devices and equipment are the same, sports facilities include different areas with different use scenarios, distinct architecture, and dissimilar occupancy patterns. Additionally, modeling their energy consumption and indoor thermal quality is associated with several aspects as the sports facilities' functions, and operations vary from one region to another following the climate conditions (e.g., temperature, humidity, etc.) and other environmental factors.

Although the challenging management aspects of sports facilities, a moderate number of studies have been investigated to optimize their operation. Two main categories of techniques are being used, which are based on (i) conventional physics-based models and (ii) data-driven models. The former depends on the physics-based mathematical representation of the system under study, while the latter uses previously recorded data to perform a current task. Moreover, data-driven-based solutions are becoming increasingly popular as they are based on artificial intelligence (AI) and machine learning (ML). For example, in [6], physics-based models were used to manage the thermal comfort in a football stadium designed for hot and humid climates using a computational fluid dynamics (CFD)-based approach. While a data-driven model was proposed in [7], in which a multi-objective genetic optimization (MOGO) algorithm was used to minimize the electricity consumption of the HVAC system in a swimming pool employing the building information modeling (BIM) for historical data generation.

Approaches using physics-based models require the availability/formation of reliable mathematical models which might be difficult and/or time consuming for complex buildings. In addition, thorough and case-specific building information (e.g., material, geometry, windows size, etc.) is required for creating reliable models. On the other hand, data-driven models require a significant amount of training data and might have larger computational overhead. However, intelligent data-driven based techniques for optimizing the management of sports facilities are attracting growing interest from both academia and the industry due to their performance superiority versus approaches employing physics-based models [8].

In this context, optimizing the operation of sports facilities using data-driven models is still raising different challenges with the significant advancements made in building management and automation systems (BAMSs) via the integration of AI and ML, internet of things (IoT), edge/cloud computing and other cutting-edge technologies [9, 10]. Specifically, besides the issues raised by: (i) the management of such heterogeneous digital data since data in sports facilities are diverse in terms of sources and nature [11, 12]; and (ii) data scarcity due to the lack of benchmarking repositories to train data-driven models, one can recognize the need for inter-disciplinary thinking when implementing such a BIM optimization method on sports facilities [13]. Accordingly, recorded data in sports facilities represent indoor human activities, the energy consumption of different installations, operation states of various devices and equipment (electronic, electrical and mechanical equipment, etc.), and other building information [14]. Therefore, engineering knowledge and methods should be combined with human-science-based techniques to devise data collection and interpretation in a clever approach for each building considered [5, 15].

Minimizing the energy consumption and maximizing the quality of the indoor environment in sports facilities is of utmost importance because of their high energy demand profile due to their operational requirements, and on the other side, since the quality of the indoor environment significantly impacts the players' performance and the comfort of the spectators. For instance, enabling high indoor humidity levels cannot support the evaporation process of sweat, which is required when exercising [16]. To that end, an ensemble of studies has been proposed during the last years to design data-driven models for managing energy usage and the indoor environmental quality of sports facilities. For instance, in [17], a load monitoring and estimation framework was proposed for energy consumption prediction in swimming pools using a weighted difference change-point (WDCP) regression model. While in [18], an intelligent energy management system was developed for complete monitoring and management of the electrical system of a stadium.

Neural networks (NNs) have been applied in several works towards managing and optimizing energy usage and thermal comfort in sports facilities. A static NN model was used in [19] to optimize the BAMS's operation of an aquatic center to achieve energy savings and to maintain users' thermal comfort. In [20], a NN-based model was developed for component sizing optimization using multi-objective genetic optimization for a heating system of outdoor swimming pools. NNs were utilized in [21] to predict the water evaporation rate in indoor swimming pools. In contrast, in [22], a hybrid swimming pool's thermal model was developed combining thermodynamic laws and NNs. Additionally, a NN-based prediction model for the thermal environment of a stadium was developed in [23] utilizing the details of the indoor conditions and the users. In [14], an intelligent sports facility management system was developed employing a hybrid model using support vector machine-based backpropagation (SVM-BP) algorithm and a NN for predicting the passenger flow for an improved facility operation management. NNs were used to capture a static behaviour for prediction, optimization, or modeling applications in most of the existing studies.

Moreover, deep learning has recently attracted the attention of the sports facilities research community since it can significantly help predict energy usage or thermal comfort while avoiding over-fitting issues. Typically, in [13], a predictive maintenance approach using an unsupervised anomaly detection was proposed based on deep autoencoders (DAE). It aimed to detect faults of the HVAC system in a sports facility by analyzing the residuals of the measured and predicted energy consumption. Typically, after recording data using IoT devices and BAMS, data was processed before being fed into the DAE for predicting the failures. Although this scheme was quite simple to be implemented as it used unsupervised learning, the overall study had the limitation of not assessing the anomaly detection accuracy and false alarm rates.

The capability of NNs can be leveraged when combined with other principles, such as the NN-based model predictive control (MPC) system introduced in [24], which combines the theory of MPC and NNs. MPC is advantageous because it systematically considers the future system behaviour during the control design stage while fulfilling the system operating constraints [25]. In [26], a review was presented to promote the applications of MPC-based systems in buildings for their great potential in improving their energy use and performance. For example, it was applied in [27] for HVAC systems control in university buildings in which an error model was used to improve the performance of the MPC system under weather forecast uncertainty. While in [28], a stochastic MPC formulation was applied utilizing control theory and Chance-constraint method for building climate control. Additionally, in [29], an MPC strategy was developed for radiant floor systems in office buildings. In [30], an MPC-based framework was proposed for the optimal energy management of a district with five buildings equipped with vertically-placed building integrated photovoltaic (BIPV) systems and battery energy storage systems (BESS), where a weighted mean average-based (WMA) forecasting model was employed.

Unlike the conventional MPC system, the NN-based MPC system does not require prior knowledge of the dynamics of the building's BAMS nor defined system operating conditions. Instead, it utilizes an NN-based black-box model developed utilizing the system's historical data. The black-box model, which captures the system dynamics to predict the future system behaviour, can be developed using other AI and ML algorithms. It is commonly used to model nonlinear systems in the context of forecasting and estimating their behaviours as in [31, 32] using support vector regression (SVR), in [33] using *k*-nearest neighbor (*k*NN), and in [34] using decision trees (DT).

In [35], an AI-based MPC framework was proposed to reduce the natural gas consumption of heating systems in commercial and institutional buildings. It was employed to optimize the transition between night set-back and daytime indoor air temperature setpoints as a function of the expected weather conditions. In [36], an ML-based MPC framework was investigated to control the building's HVAC system in terms of the temperature of the indoor environment, and a comparison was presented for different control scenarios.

NNs are popular for accurately modeling complex functions and representing them in an interpreted model form.

The NN-based MPC system was used in [37] for regulating the operation of the HVAC system in a public building to achieve minimized energy consumption and adequate thermal comfort levels, and in [38] for regulating the operation of air-conditioning systems to determine the control decision that achieves energy savings while maintaining the desired indoor conditions. Additionally, in [39], an MPC-based approach was used to manage the operation of HVAC systems in terms of energy use and thermal comfort in multi-zone buildings in which the forecasting model was implemented using a long short term memory (LSTM) network. In this paper, an NN-based MPC system is proposed for the management and optimization of sports facilities in terms of energy use and the indoor environment quality employing a dynamic NN model.

That is, sports facilities are equipped with sophisticated BAMSs with continuous data logging of sensors measurements, actuator signals, and other system's properties resulting in large amount of BAMSs' data recorded. Hence, using a data-based model, namely a dynamic NN-based model is ideal as it provides an AI-based practical and disposable solution capable of addressing the challenges associated with physics-based models and static data-driven models in terms of model's accuracy and reliability. High fidelity and comprehensive physics-based models of complex systems might not be procurable [40, 41]. While static data-based models - such as the one used in [19] - are used to perform basic assessments as they do not account for time-varying phenomena unlike dynamic models which can simulate time-dependent systems' behaviours [42].

Table 1 summarizes the pertinent works described in this framework that were proposed for optimizing BAMSs of sports facilities. Specifically, each framework has been described in terms of the appearance year, adopted approach, sports environment, limitation, and best performance. Assessing the state-of-the-art in sports facilities management and optimization is quite challenging due to the difficulty of comparing existing works. This is mainly due to the lack of open-access datasets and platforms for reproducing research results. Additionally, different evaluation metrics have been deployed to assess the performance of the sports facilities management algorithms in the previous studies as depicted in Table 1. This complicates further the comparison of reported results. Generally, most of the previous studies only focused on one aspect of the sports facilities' operation, e.g., energy management (e.g., [7, 18]), thermal comfort monitoring (e.g., [23]), peak load reduction (e.g., [17]), or fault detection (e.g., [13]). While for studies investigating MPC-based systems in the same context (e.g., [43]), they aim to develop standalone control systems to determine the best control commands of actuating devices such as fans, dampers, etc. This requires substituting the existing control program in the BAMS and potentially installing additional hardware.

This work develops a data-driven management and optimization system covering the three aspects: energy efficiency, users' thermal comfort, and health and safety using an NN-based MPC system that focuses on minimizing energy consumption and maximizing indoor environment quality. The MPC system is employed distinctively to design a framework that complements the existing control system without making significant changes, to provide the optimized control setpoints, and possibly recommendations regarding the best occupancy schedules that managers can utilize to improve the management of their facilities. Hence, the proposed approach makes a flexible and practical solution that can be deployed to enhance the performance of the existing BAMS of the sports facilities.

1.1. Aim and contribution

The contribution of this work is the development of an integrated management and optimization framework using an NN-based MPC system for the BAMSs of sports facilities that actively accounts for the current and future system transitions in the decision-making process. Additionally, it considers the three aspects of the facility's operation demonstrated in Figure 1: energy efficiency, users' thermal comfort, and health and safety. It presents a successful deployment of the NN-based MPC system for sports facilities management in terms of energy use and indoor environment quality and an exceptional adaptation of MPC systems that hold promising potential for developing intelligent and autonomous management systems for buildings in general and sports facilities in particular.

The proposed framework is demonstrated on a sports hall for optimizing the BAMS's functions in terms of the HVAC system's operation. It aims to establish the foundation for applying NN-based MPC systems for managing sports facilities' operation in general, and in terms of their HVAC systems in particular given that HVAC systems are one of the most energy consumers in buildings [44] and their operation affects the indoor environment quality. This is a follow-up of the preliminary work presented in [45] regarding deploying an NN-based MPC system for indoor temperature setpoint selection towards achieving energy savings and adequate thermal comfort levels in sports facilities. The proposed NN-based system in this paper functionally extends to include optimizing additional settings of the HVAC system and the occupancy profile. The optimization objective function of the proposed system is improved

Table 1 Summary of studies for BAMSs' management and optimization of sports facilities.

Work	Year	Approach	Sports environment	Limitation	Best performance
[13]	2021	HVAC fault detection using autoencoders	Sports complex	No information about the accuracy of the fault detection and false alarms.	Distribution of the prediction error
[14]	2020	Passenger flow prediction using SVM-BP-based NN	Sports cultural centers	Not suitable for the sports cultural center with less passenger flow.	MSE curves
[20]	2020	NN-based MOGO	Swimming pool	The impact of various heats obtained from the sun on the temperature variation of the pool water was not considered.	R = 0.999
[23]	2018	NN-based prediction of thermal comfort	Stadium	Data of only three days were used in the performance evaluation, which were not representative of the most thermal fluctuation occurred during the different periods of the month/year.	RMSE = 0.1081, MAE = 0.079
[17]	2018	Peak load reduction using WDCP regression	Swimming pool	Focus only on small swimming pools dedicated to the residential buildings.	Peak load reduction = 3.15%.
[7]	2017	MOGO-based electricity optimization	Swimming pool	Required in addition to the accurate BIM and building energy modeling (BEM) models, a combined collection of human-centric identification of perceived comfort levels and buildings' operation patterns via automated sensing of physical parameters.	Electricity saving percentage = 39%
[18]	2016	Energy optimization using ANN	Stadium	Utilized only the analysis of easily measured current and voltage waveforms.	N/A
[19]	2014	NN-based energy usage and thermal comfort optimization	Aquatic center	High complexity and validated only on simulated data.	MSE = 0.0015

to account for indoor air quality as one of the primary goals. The main advantage of this work compared to [45] is the active consideration of the quality of the indoor environment that relates to the health and safety of the users. The improved NN-based MPC framework in this work targets the optimization of (i) the cooling temperature setpoint, (i) the supply air temperature setpoint, and (iii) the fresh air flow rate to jointly minimize energy consumption and maximize thermal comfort while maintaining a healthy and safe indoor environment. Additionally, it can be configured to provide guidance on the appropriate occupancy schedules. This piece of information can be utilized by managers to improve the management of their facilities.

The objective of this work is the following:

- Developing a NN-based MPC management and optimization framework for the HVAC system of a sports hall in the sports and events complex of Qatar University (QU) employing the BIM model of the facility,
- Providing an integrated dynamic optimization approach that accounts for the current and future system behaviour in regulating the operation of the facility's BAMS as it includes a prediction element and an optimizer,
- Jointly managing and optimizing the operation of the HVAC system of the sports hall in terms of energy usage, thermal comfort, and indoor air quality towards achieving the best trade-off utilizing a rule-based model,
- Investigating different sports events scenarios using two schemes of the proposed system, which are without and with occupancy profile recommendations aimed for the facilities' managers to handle the facility's operation better,
- Presenting a comparative analysis between the proposed NN-based prediction model and other ML-based models.

The remainder of the paper is organized as follows. The description of the case study used to develop and validate the work is presented in Section 2. Moving forward, in Section 3, the work's methodology is presented in terms of the

Fig. 1. The three aspects of the operation of sports facilities.

theory of MPC and the details of the proposed NN-based MPC management and optimization framework. The results and discussion are presented in Section 4. Next, conclusions and future works are discussed in Section 5. Lastly, the details of evaluation scenarios are provided in the Appendix.

2. The Multi-Purpose Hall of the QU Sports and Events Complex

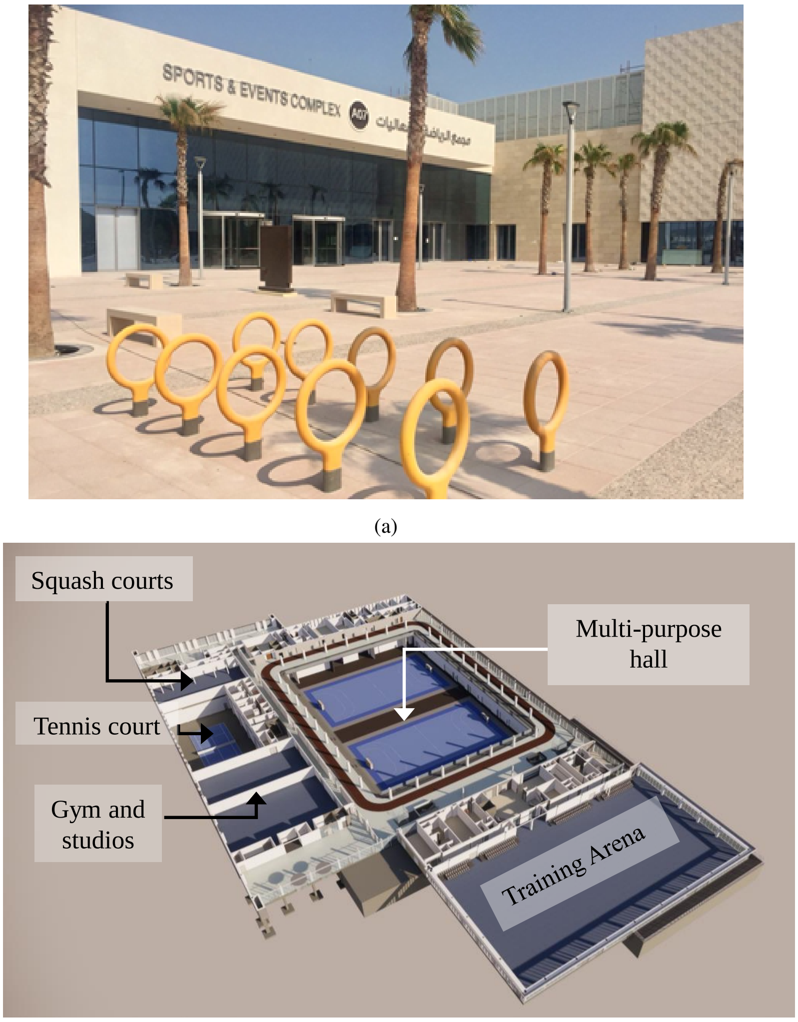
The sports and events complex of QU, demonstrated in Figure 2, is one of the pilots of the SportE3.Q project [1]. It occupies a total area of 25,500 m^2 of the university campus, located on the northern outskirts of Doha city, the capital of Qatar. It has the following sports-related spaces: a multi-purpose hall, a training arena, a gymnasium, a martial arts area, an exercise area, an indoor tennis court, and squash courts. It has three levels: (i) the semi-basement level, (i) the ground floor level. and (iii) the mezzanine level. The ground floor level has the main entrance, gymnasium, exercise area, squash courts, training arena, cafeteria, and the upper part of the multi-purpose hall that has the running pitch and other supporting functions. The semi-basement level has the multi-purpose hall, tennis court, VIP entrance, kitchen, players changing rooms, and other supporting functions. The mezzanine floor has the VIP lounge, offices, and audiovisual (AV) rooms. The building has a concrete structure with cavity exterior walls of multiple layers expect at the main entrance where curtain glass walls are used. The internal walls have commonality except for areas with soundproofing materials. The building relies on mechanical ventilation as it does not have operatable windows. The building envelope is shown in Figure 3, and the details of the characteristics of envelope surfaces, floors, and windows are summarized in Table 2.

[1] www.sporte3q.com/

Table 2 The characteristics of the envelope of the QU sports and events complex.

Component	Description	Details
Structure	concrete structure on the lower level and a steel support system that holds up the upper floor and the roof	-
Roof	flat roof holds up the mechanical ventilation system of the building.	constructed from a concrete structure, multiple insulation layers, topped with concrete paving
	pitched roof with a slope of 1.5°	constructed from trapezoidal steel, insulation layer, standing seam sheet, supported by a steel frame system
Walls	exterior walls as cavity walls of multiple layers	blockworks with insulation layer
	external walls made of curtain glass	double glaze with fixed frames
	internal walls with commonality except for areas with soundproofing materials	a blockwork with reinforcement, insulation, glass fiber reinforced concrete panel bolted by steel structure
Window	unoperatable windows	double glaze with fixed frames
Floor	cast reinforced concrete structure and floor finishing material	concrete structure, floor finishing material in the sports-related areas is rubber and hardwood

Mainly, the QU sports and events complex is equipped with (i) a chilled water distribution system that is linked to an in-campus district cooling plant, (ii) water-cooled energy recovery units (ERUs) serving toilets, (iii) water-cooled air handling units (AHUs) serving large spaces, (iv) water-cooled fan coil units (FCUs) serving small spaces, (v) gym tools and equipment, (vi) office equipment (i.e., computers, screens, etc.), and many others. The case study in this work is the multi-purpose hall, the largest conditioned space in the complex that extends from the ground floor to the roof, that has a total floor area of about 7,500 m^2. It is served by four AHUs typically regulated at an indoor cooling temperature of 20 °C, a rated fresh air flow rate setting, an AHU supply air temperature of 16 °C, and it is designed to accommodate up to 1200 people when operated in the sports mode. Figure 4 illustrates the diagram of the AHUs of the multi-purpose hall.



(a)

(b)

Fig. 2. The QU sports and events complex (A courtesy of the Capital Projects – QU and Astad (2021)).

Fig. 3. The envelope of the QU sports and events complex (A courtesy of the Capital Projects – QU and Astad (2021)).

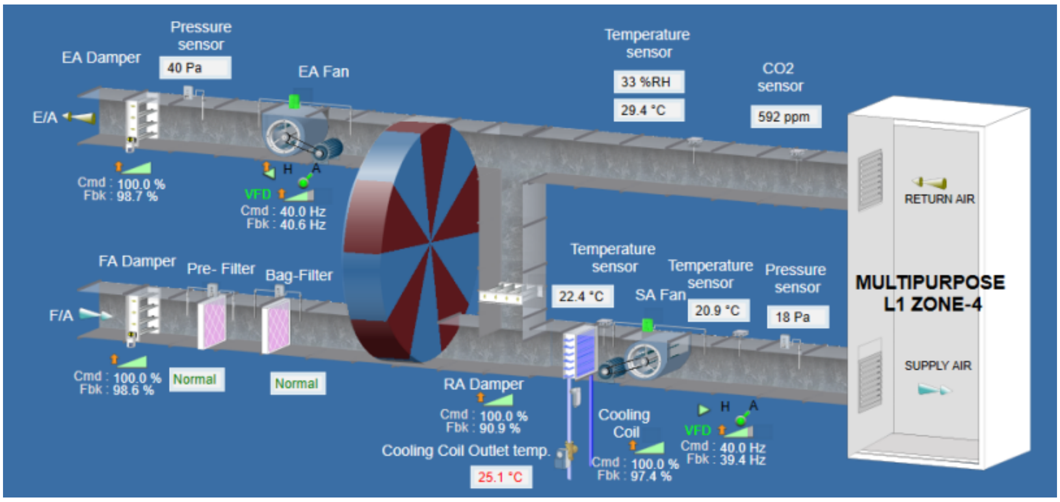


Fig. 4. The diagram of the AHUs serving the multi-purpose hall of the QU sports and events complex (A courtesy of the Capital Projects – QU and Astad (2021)).

2.1. *The development of the Energy Plus simulation model*

The BIM model of the QU sports and events complex containing its architecture, construction, and mechanical details is used to develop the Energy Plus simulation model using Design Builder software. Figure 5 presents the block diagram of the process of developing the building thermal and energy model. The BIM model is first reduced to only include the relevant details to the thermal and energy model mainly in terms of the building envelope in general and the multi-purpose hall in particular. Table 3 presents the materials properties of the surfaces.

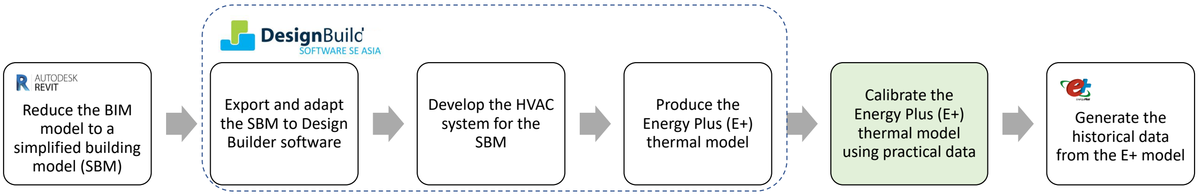


Fig. 5. The process of the development of the building thermal and energy model.

The simplified BIM model is exported from Revit to Design Builder software. Then, a simplified HVAC system is developed. It consists of a district cooling plant and a water distribution system that supplies chilled water to the cooling coils of the AHUs and FCUs of the facility. For the AHUs serving the multi-purpose hall, their specifications are set in accordance with the technical details obtained from the manufacturer's datasheets. Given that the other facility spaces are not precisely the focus of this work, their air conditioning and ventilation are realized using FCUs to account for the heat transfer dynamics between the multi-prose hall and its supporting spaces. The Energy Plus simulation model, of the main details presented in Table 4, is produced using Design Builder software.

Utilizing the actual building historical data of the sensing and actuating devices, the Energy Plus model, essentially in terms of the AHUs serving the multi-purpose hall, is calibrated using GenOpt algorithm [46]. The AHUs' temperature setpoints and actuators' commands are set following the information deduced from the experimental data. Additionally, the occupancy is assumed to be zero by using data of Fridays for the calibration and then the validation, which is the official weekend in Qatar because the historical occupancy information is not available. Given that the consumers in the AHUs are the fans, the particle swarm optimization (PSO) algorithm is used to optimize the fan power coefficients, which are used to calculate the fan's consumption that, is a function of the supply flow rate. The optimization objective is to minimize the difference between the actual and the simulation model-produced AHUs' energy consumption after having the actual settings of the temperature setpoints and actuators' commands and the outside weather conditions applied in the simulation model as per the empirical historical data.

The calibrated model reliably mimics the actual operation as demonstrated in Figure 6 in which a comparison is illustrated between the actual and simulation data for three different days of the year of one of the multi-purpose hall's AHUs in terms of the following measurements : (i) supply air temperature (first row), (ii) return air temperature (second row), (iii) return air humidity ratio (third row), and (iv) power consumption (fourth row). The simulation model is then used for historical data generation to develop the proposed system and to test and validate the presented work.

Table 3 The properties of the surfaces' material used in the Energy Plus model.

Material	Properties			
	Thickness [m]	Conductivity [W/m-K]	Density [kg/m3]	Specific Heat [J/kg-K]
Brickwork outer	0.1	0.84	1700	800
Concrete block	0.1	0.51	1400	1000
Concrete cast-in-place gray	0.3	1.046	2300	657
Concrete masonry unit wall	0.2	0.54	1550	840
External wall	0.4	0.02	100	1000
Glass Wool	0.1445	0.04	12	840
Gypsum board	0.0159	0.16	800	1090
Gypsum Plasterboard	0.025	0.25	900	1000
Gypsum Plastering	0.013	0.4	1000	1000
Gypsum Wall board	0.0125	0.65	1100	840
Lightweight concrete	0.2032	0.53	1280	840
Metal steel top	0.01	230	2700	897
Metal surface	0.0008	45.28	7824	500
Plasterboard	0.013	0.25	2800	896
Polyurethane insulation	0.18	0.032	32	1674
Shock absorber rubber	0.1	0.138	930	2092
Stone board finish	0.03	2.9	2750	840
Stone Wool	0.1025	0.04	30	840
Timber flooring	0.005	0.14	650	1200
Wood	0.0376	0.15	608	1630

Table 4 The main details of the Energy Plus model.

Class		Description	Value
District cooling plant		Nominal Capacity	4711.31 kW
Pump		Maximum supply flow rate	0.306096 m^3/s
		Motor efficiency	90%
Air loop	AHU type 1	Fan efficiency	83.4%
		Maximum supply flow rate	18.79 m^3/s
		Maximum outdoor flow rate	3.62 m^3/s
	AHU type 2	Fan efficiency	83.2%
		Maximum supply flow rate	16.77 m^3/s
		Maximum outdoor flow rate	3.62 m^3/s
Schedule	Cooling setpoint schedule	Temperature setpoint of the indoor cooling	Range of 18 - 25 °C
	Chilled water flow setpoint temperature	Temperature setpoint of the cooling coils' inlet water	6 °C
	Air loop cooling setpoint temperature	Temperature setpoint of the AHU supply air	Range of 14 - 16 °C
	Light Schedule	The on/off status of the lights	"ON" during facility's operation timing
	Activity Schedule	The amount of heat gain per person in the zone under design conditions [47].	Range of 100 - 1159 m^3/s-W
	Clothing Schedule	The amount of clothing being worn by a typical zone occupant [47].	1.1 Col
	Work efficiency	The efficiency of energy usage within the human body that will be used for thermal comfort calculations [47].	0
	Outdoor CO2 levels	The CO2 concentration of the outdoor air	415 ppm

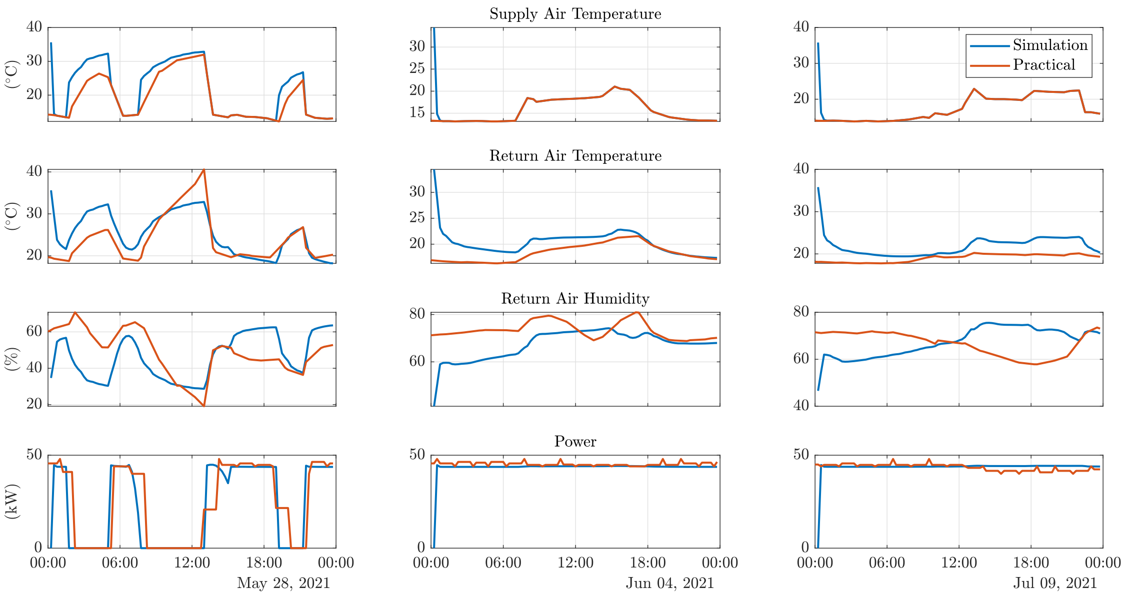


Fig. 6. Validation results of the calibrated AHU of the multi-purpose hall.

3. Methodology

3.1. The theory of MPC

The MPC system consists of an optimizer and a prediction model of the system under study [25]. It attempts to optimize the inputs $u(k)$ according to a known objective function while considering the system's future behaviour. Let the system states be $x(k) \in \mathbb{R}^{n_x}$, where n_x is the number of states, representing the variables that describe the system state/condition at an arbitrary time k, and they are dependent on the inputs $u(k)$. Additionally, the system parameters $c(k)$ represent the attributes that influence the system states which are not among the system inputs $u(k)$. Essentially, applying the inputs $u(k)$ given the system parameters $c(k)$, the system transitions to new states $x(k+1)$ and so on for the consequent time samples. In addition, the system has the outputs $y(k) \in \mathbb{R}^{n_y}$, which are a subset of the system's states that have tracking requirement. That is, they are desired to reach certain reference values $r(k) \in \mathbb{R}^{n_y}$, where n_y is the number of outputs. Based on the system outputs $y(k)$ and their reference values $r(k)$, the MPC system attempts to determine the optimal inputs $u(k)$ using numerical optimization by solving for the inputs that achieve the best-predicted performance in accordance with the desired objective. This is possible due to the MPC-integrated prediction model conveying the inputs-states and hence the inputs-outputs relationship.

The MPC system has two main parameters, which are the prediction horizon, n_p, determining the extent to which the system investigates the future when solving for the control actions, i.e., the inputs $u(k)$, and the control horizon, $n_c \in [1, n_p]$, representing the number of control actions to be optimized at every step [48]. That is, the MPC system's optimization solver attempts to determine the best inputs $u(k)$ by solving for solutions that minimize the value of the cost function, J. The cost function is formulated based on the application requirement in which the significant variables/parameters to the optimization problem will be taken into consideration. Hence, it does not have a single expression. In this work, the cost function has two elements, which are the error signal, $e(k) = y(k) - r(k)$, between the outputs and the reference values, and the rate of change in the control actions, $\Delta u(k)$. It is formulated as:

$$J = \sum_{j=1}^{n_y} \sum_{i=1}^{n_p} \frac{w_j}{s_j} e_j^2 (k+i|k) + \sum_{i=0}^{n_{p-1}} w_{\Delta u} \Delta u^2 (k+i|k) , \tag{1}$$

where w_j and s_j are the weight and the scale parameters of the error signal of the jth output variable, respectively, $e_j(k+i|k)$ is the error value of the jth output at the ith prediction horizon step, $\Delta u_j(k+i|k)$ is the input difference value of the jth output at the ith prediction horizon step, and $w_{\Delta u}$ is the weight parameter of the change in the control action that can be set empirically to tune the MPC system to achieve the desired objective. The weight parameters w_j are used to tune the MPC system when multiple outputs are involved as they determine the relative importance of the variables to the optimization objective. In contrast, the scale parameters are used to normalize the error signals to avoid optimization failure or sub-optimality due to output variables' diverse magnitudes.

3.2. The proposed NN-based MPC system

This work aims to optimize the HVAC system's control settings to achieve an acceptable energy use and indoor environment quality using the proposed NN-based MPC system. The system under study, which is the multi-purpose hall of the QU sports and events complex, has five states, three parameters, and three inputs as described in Table 5. Figure 7 presents the block diagram of the proposed NN-based MPC framework. A NN-based model is used as the MPC system's prediction model that is trained using Bayesian optimization algorithm in the offline stage as explained in Section 3.2.2. The system outputs are the power usage, the thermal comfort level indicated by the predicted mean vote (PMV) index, and the indoor CO2 level. They explain the building status in terms of efficiency and indoor environment quality. The reference values are set as the minimum possible AHUs' power usage r_1, the average thermal comfort levels ($r_2 = 0$) [49], and the typical indoor CO2 level in occupied spaces ($r_3 = 600$ ppm) [50]. The output scale parameters s_1, s_2, and s_3 are set to the reference values r_1, r_2, and r_3.

A rule-based outputs' weights model is used to determine the appropriate choice for the outputs' weights as described by Algorithm 1. When the hall is not occupied, the objective is to minimize the power usage, making it the dominant output. Suppose the hall is occupied and the indoor CO2 level exceeds 800 ppm. In that case, the objective is regulating the indoor air quality at healthy and safe conditions meaning that the indoor CO2 level is the dominant output given that levels exceeding 1000 ppm can be dangerous and life-threatening to users [50]. Otherwise, all three outputs are equally important. The selection of the weights values OW_1, OW_3, and OW_{all} is made empirically as 15, 15, and 0.3, respectively.

Algorithm 1 Rule-based outputs' weights model($Power$, $CO2_{\text{indoor}}$, $NumPpl$, OW_1, OW_3, OW_{all})

Input: $CO2_{\text{indoor}}$ - indoor CO2 level, $NumPpl$ - Number of people present, OW_1 - weight setting for dominant output of power usage, OW_3 - weight setting for dominant output of indoor CO2 level, OW_{all} - weight setting for equally important outputs
Output: The outputs' weights w_1, w_2, w_3
if $NumPpl = 0$ **then**
  $w_1 = OW_1$, $w_2 = 0$, $w_3 = 0$
else if $CO2_{\text{indoor}} > 800$ ppm **then**
  $w_1 = 0$, $w_2 = 0$, $w_3 = OW_3$
else
  $w_1 = w_2 = w_3 = OW_{\text{all}}$
end=0

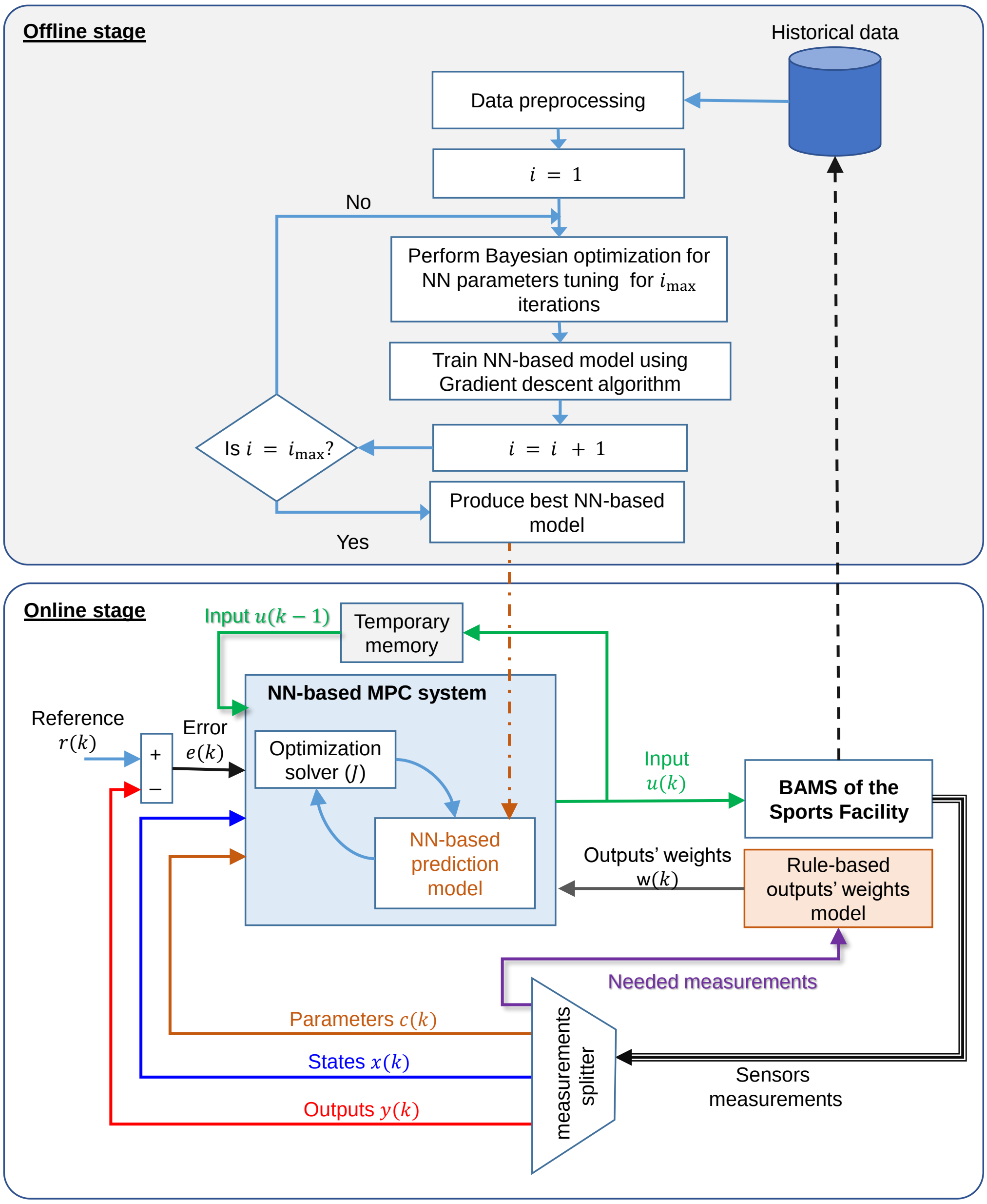


Fig. 7. Block diagram of the NN-based MPC framework for sports facilities operation management and optimization.

Table 5 The details of the system's states, inputs, and parameters of the multi-purpose hall of QU sports and events complex.

Variable type		Description
States		AHUs' power usage ($Power$ [W])
		Thermal comfort level (PMV)
		Indoor CO2 level ($CO2_{\text{indoor}}$ [ppm])
		Indoor temperature (T_{indoor} [°C])
		Indoor relative humidity (RH_{indoor} [%])
Inputs		Indoor temperature setpoint ($T^{\text{sp}}_{\text{indoor}}$ [°C])
		AHU supply air temperature setpoint ($T^{\text{sp}}_{\text{AHUSA}}$ [°C])
		AHU fresh air flow rate setpoint ($Q^{\text{sp}}_{\text{AHUFA}}$ [kg/s])
Parameters	Surrounding environment	Outside temperature (T_{amb} [°C])
	Surrounding environment	Outdoor CO2 level ($CO2_{\text{outdoor}}$ [ppm])
	Uncontrolled input	Number of people present ($NumPpl$)

3.2.1. The proposed schemes of the NN-based MPC system

Figure 8 demonstrates the two schemes of the proposed NN-based MPC system that are investigated. In Scheme 1, the system is configured to deduce the appropriate management actions in terms of the temperature setpoints for the indoor environment and the AHU's supply air, and the fresh air flow rate into the multi-purpose hall. In Scheme 2, an additional feature is enabled to extrapolate the ideal number of people that should be present in the hall given the current conditions of the indoor and outdoor environments according to the optimization objective. The optimal number of people who can occupy the space without altering the indoor environment quality depends on the type of activity the users are performing and the outside and inside weather conditions. For instance, the air quality in terms of the CO2 level can no longer be maintained at safe and healthy levels if the number of users involved in a particular activity exceeds a particular value. The CO2 generation rate per person is proportional to the intensity of the activity undertaken. Additionally, the outdoor CO2 levels are not controllable, and hence the CO2 concentration of the fresh air introduced to the conditioned space limits the BAMS's air quality management capacity. These are all taken into consideration in Scheme 2 such that a recommendation, aimed for the facilities' managers regarding the appropriate occupancy detailing, is provided. In addition, as presented in Table 6, a set of constraints are defined for the inputs in terms of minimum u_{min} and maximum u_{max} values, which are based on the actual operation of the HVAC system of the multi-purpose hall such that they are deduced from the practical data of the AHUs' settings. Additionally, they confirm with the ASHRAE standards for the thermal comfort of users involved in moderate levels of activities [51]. Note that the setting related to input $NumPpl$ is only relevant for Scheme 2.

Table 6 The details of the inputs of the proposed NN-based MPC system.

Input	u_{min}	u_{max}
Indoor temperature setpoint ($T^{\text{sp}}_{\text{indoor}}$ [°C])	18	25
AHU supply air temperature setpoint ($T^{\text{sp}}_{\text{AHUSA}}$ [°C])	14	16
AHU fresh air flow rate setpoint ($Q^{\text{sp}}_{\text{AHUFA}}$ [kg/s])	0.1	4.4
Number of people present ($NumPpl$)	0	2000

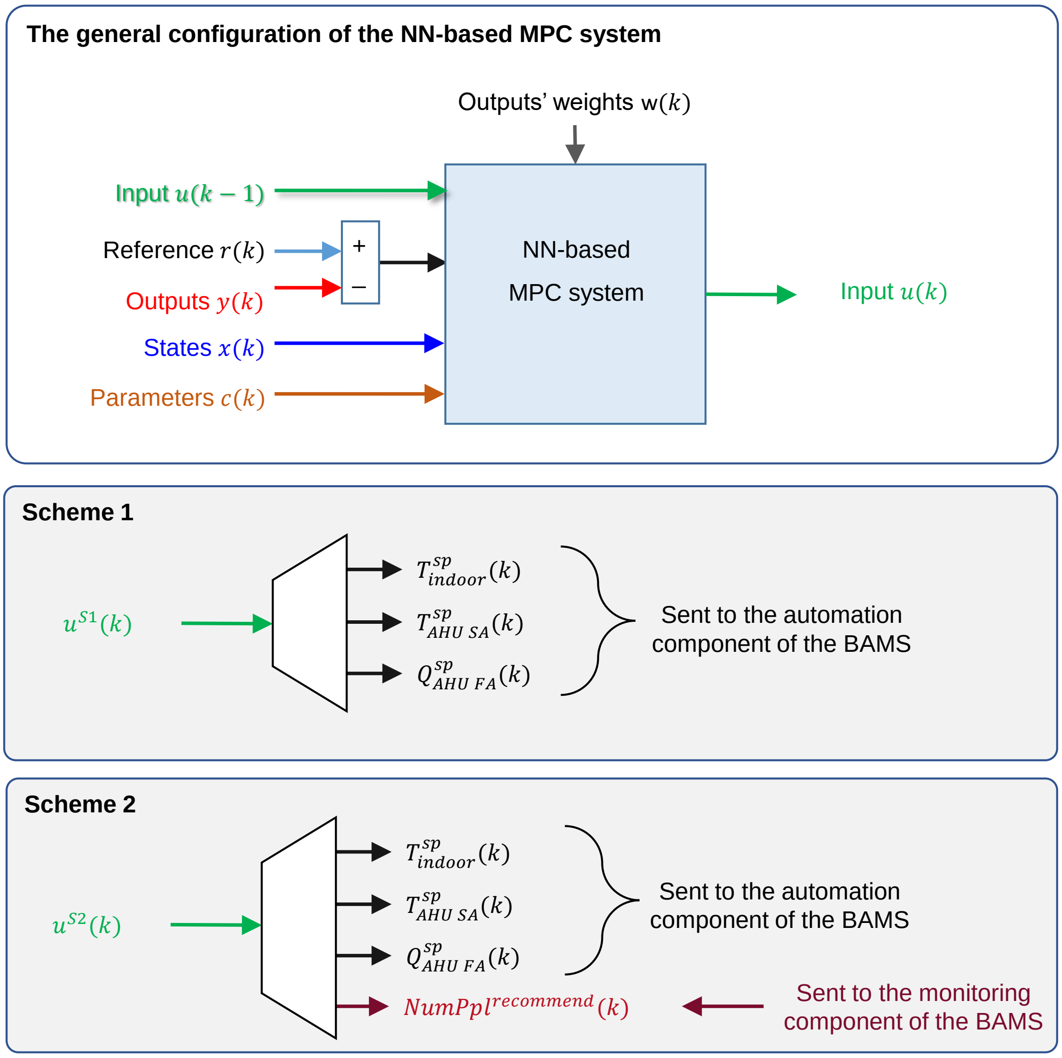


Fig. 8. Block diagram of the two schemes of the NN-based MPC framework.

3.2.2. The NN-based prediction model

The NN-based dynamic prediction model shown in Figure 9 aims to express and capture the behaviour of the hall's operation over time given its states $x(k) \in \mathbb{R}^5$, parameters $c(k) \in \mathbb{R}^3$, and inputs $u(k) \in \mathbb{R}^3$. The NN-based prediction model can be expressed by:

$$F = \text{Train\_NN}\left(x(k+1), [x(k), c(k), u(k)]\right), \tag{2}$$

where $x(k) = [\,Power(k), PMV(k), CO2_{\text{indoor}}(k), T_{\text{indoor}}(k), RH_{\text{indoor}}(k)]$, $c(k) = [T_{\text{amb}}(k), CO2_{\text{outdoor}}(k), NumPpl(k)]$, $u(k) = [T^{\text{sp}}_{\text{indoor}}(k), T^{\text{sp}}_{\text{AHUSA}}(k), Q^{\text{sp}}_{\text{AHUFA}}(k)]$, and the prediction is computed by:

$$\hat{x}(k+1) = F\left([x(k), c(k), u(k)]\right). \tag{3}$$

It is a modified version of a first-order multivariate autoregressive model in which the value is regressed on the previous value of the time series along with other influencing signals (i.e., inputs and parameters). The system under study exhibits overly steady and slow dynamics. Hence, this implementation is sufficient for reliable performance at the minimum computational complexity. That is, for the system under study, the implementation of a higher-order

NN-based autoregressive-like model where multiple previous time steps are taken into account is superfluous, which will result in an unnecessary increase in the computational overhead of the proposed framework.

A single layer feed-forward NN-based prediction model was developed, in which the information propagates in the forward direction from the network's input nodes, through the hidden layer, and to the output nodes. The NN has 11 inputs: the five system's states, the three system's parameters, and the three system's inputs. It has five outputs that are the system's states at the next time sample. The Energy Plus model was used to generate the training dataset, consisting of the building operation data at various conditions in terms of occupancy information, HVAC system settings, and outside weather conditions.

The training dataset was collected for 20 days in May at a rate of 4 samples/hour with a total of 1920 samples. The training was performed in MATLAB 2021b on a virtual machine with 64 GB RAM, a 10-cores Intel(R) Xeon(R) CPU with 2.39 GHz speed running on a 64-bit Windows 10 OS. Data pre-processing was performed to normalize the raw data. The training of the NN model was carried out using a 10-fold cross-validation and Bayesian optimization algorithm for the ranges presented in Table [52]. The k-fold cross-validation is a well-known approach used for ML-based models validation [52]. It is used to assess how well the developed model generalizes to independent datasets such that the training and validation sets crossover in successive rounds such that each data point has a chance of being validated against. That is, the dataset was first partitioned into 10 equally (or nearly equally) sized segments (also called folds). Subsequently, 10 iterations of training and validation of the NN model were performed such that within each iteration, a different fold of the data was for validation (comprising of 10% of the dataset) while the remaining 9 folds, which make 90% of the dataset, were used for training. Finally, the results of the multiple training iterations were averaged. While for the Bayesian optimization algorithm, a posterior distribution of functions that best describes the objective function is constructed. The optimization algorithm keeps track of past iterations to find better choices for the next set of hyper-parameters to evaluate. As the number of evaluations increases, the posterior distribution is improved, and the algorithm becomes more confident of the choice of the hyper-parameters set that is worth exploring [53].

Table 7 The ranges of hyper-parameters of the NN-based prediction model's tuning process using Bayesian optimization.

Parameter	Number of neurons	Activation function	Learning rate
Range	10 - 15	Sigmoid, Tanh	1e-5 - 1e-1

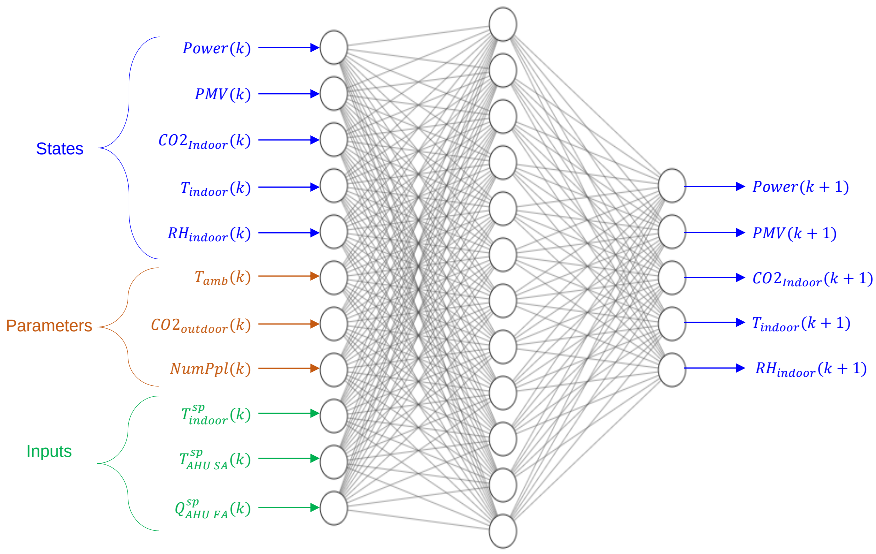


Fig. 9. Block diagram of the NN-based dynamic prediction model.

Figures 10 - 13 present the training results of the NN-based prediction model. In Figure 10, the blue graph represents the actual objective function. The green graph represents the estimated objective function, approximating the objective function using a probabilistic model for the hyper-parameters mapping to a probability of a score on the actual objective function. The x-axis represents the evaluation iteration. The y-axis represents the optimization objective function, which is the 10-fold cross-validation mean squared error (MSE) between the true and the predicted values. The optimal model had 12 hidden neurons and used Tanh activation function, achieving a conforming training and validation MSE of 0.00421 as shown in Figure 11 and a narrow error distribution as shown in Figure 12. Additionally, the regression plots are shown in Figure 13 present verification of the performance of the NN-based model by displaying the model's outputs concerning the true targets for training and validation, which is very fair with R = 0.99. Hence, the NN-based prediction model demonstrated a decent generalization and satisfactory prediction performance.

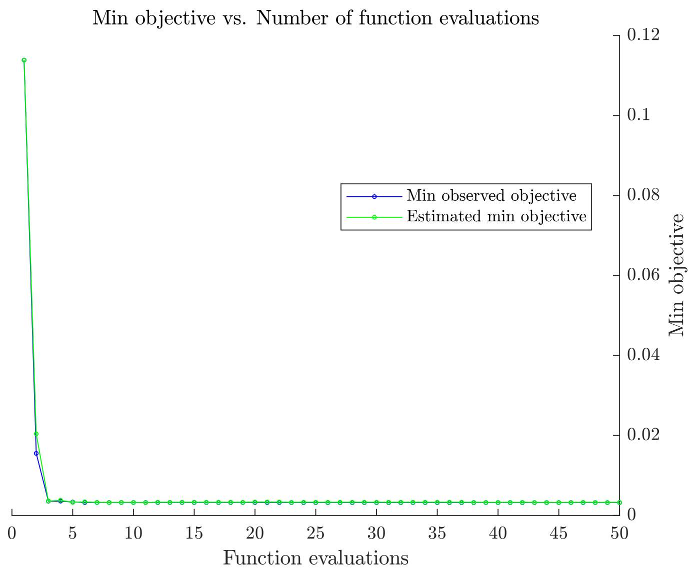


Fig. 10. The plot of the Bayesian optimization process for the NN-based prediction model's hyper-parameters tuning.

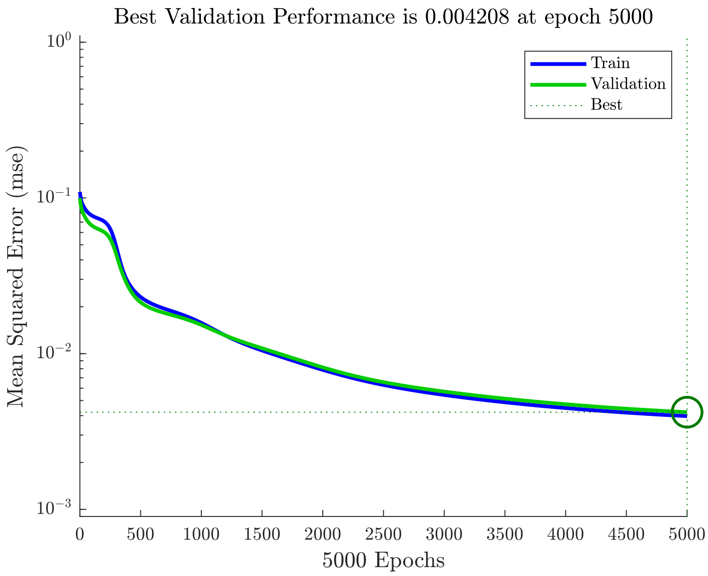


Fig. 11. The NN-based prediction model training performance plot.

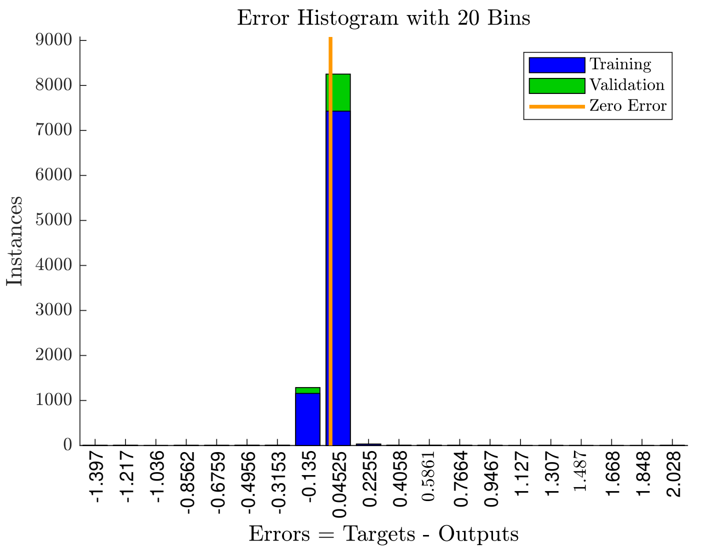


Fig. 12. The error histogram of the optimal NN-based prediction model.

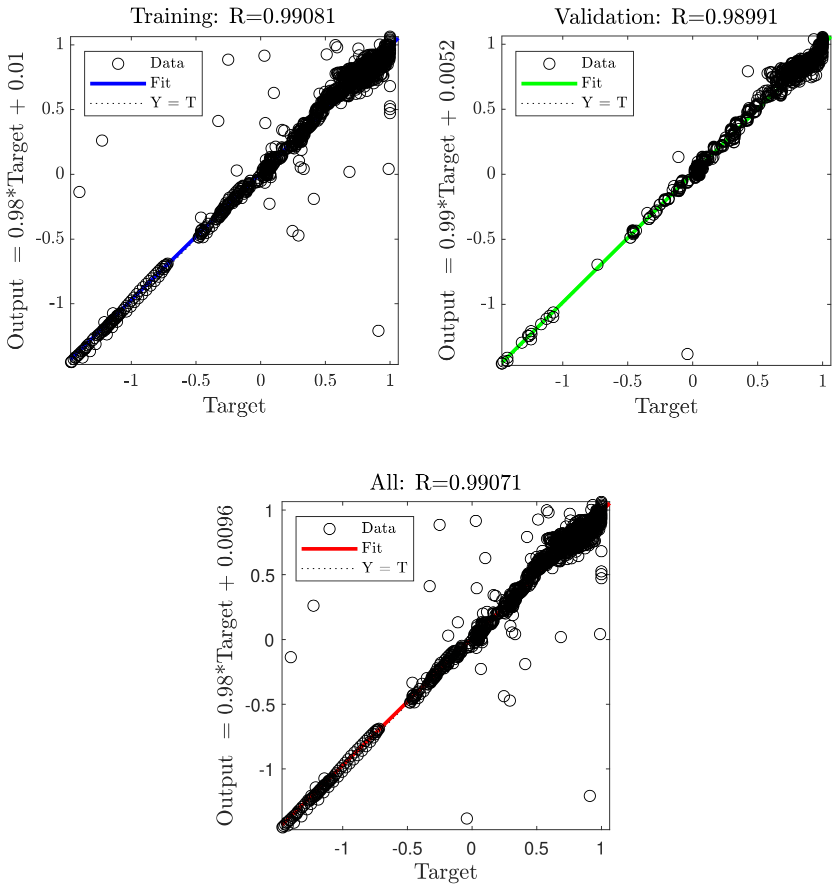


Fig. 13. The regression plot of the optimal NN-based prediction model.

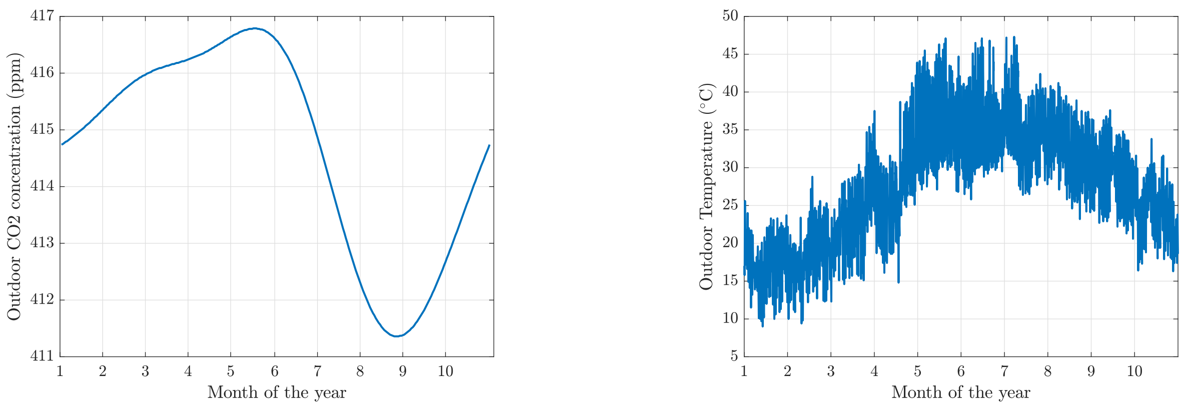
4. Results and Discussion

4.1. *Evaluation scenarios*

The Energy Plus simulation model of the multi-purpose hall of QU sports and events complex was used to simulate and generate the evaluation data for the eight scenarios described in Table 8. Each scenario was run for 24 hours, and the data sampling was every 15 min. Further details of the evaluation scenarios are provided in Appendix A. The scenarios investigation was made as to (i) the occupancy and use profile in terms of the number and gender of people present, the type of activity they are engaged in, and (i) the month of the year that determines the outdoor CO2 concentrations and the ambient weather conditions. The activity level determines the amount of heat released into the conditioned environment due to the occupancy as per Table A.11. The indoor CO2 concentration rate depends on gender, age, and the metabolic rate (i.e., activity level) as presented in Table A.12. Figure 14 shows a sample of the properties of the outside weather conditions where the global average outdoor CO2 concentration for the year 2021 is demonstrated in Figure 14a, and the ambient temperature of Doha city is shown in Figure 14b. In Appendix A, Table A.13 presents the details of the scenarios used for evaluating the proposed framework.

Table 8 The list of considered scenarios for evaluation.

Scenario	Event	Date (Day-Month)	Number of people
1	Basketball game	15-5	600
2	Basketball game	30-5	1100
3	Football match	20-6	1200
4	Crossfit competition	28-6	300
5	Football match	1-8	1700
6	Basketball game	15-7	120
7	Football match	5-8	2500
8	Crossfit competition	17-8	1600



(a) The average daily global outdoor CO2 concentration for 2021 [54].

(b) The ambient temperature of Doha city form the simulation model.

Fig. 14. The outside weather conditions used in the evaluation of this work.

The scenarios were devised to cover diverse occupancy cases and use profiles of the sports hall to promote evaluating and validating the performance of the proposed framework for various and wide-ranging operating conditions/levels. They consist of various potential events that could take place in the sports hall (e.g., football, basketball, crossfit) with a range of HVAC system operation levels (i.e., different cases of occupancy and involved activities). The cooling load and air ventilation requirements are expected to be lower for events with fewer people present and/or lower activity levels performed, such as the case with Scenarios 1 and 6 when basketball games are held with a limited number of fans. However, football games are more popular and involve many people attending the event. Scenarios

3, 5, and 7 represent different examples of football matches with various cases of fans' attendance. On the other hand, crossfit competitions of evolving popularity and recognition [55], presented in Scenarios 4 and 8, involve exercises of high intensity performed by athletes with limited audience numbers. Additionally, the gender of users/occupants is factored in the scenarios designed to account for their effects on the HVAC system's load. That is, the indoor CO2 generation rates are higher for males than for females [56]. Even though the potential scenarios that could take place are unlimited, we believe that the selected ones are representative and sufficient to demonstrate the performance of the proposed approach.

It is worth noting that only the summer season is considered when devising the scenarios during which the HVAC system has the peak cooling load. That is, for buildings located in regions characterized by hot and humid weather conditions - as is the case under study - extensive space cooling is required for most of the year. On the other hand, standard air conditioning is applied for the rest of the year, i.e., winter, to maintain the air quality and ventilation requirements [5]. HVAC systems are the most extensively operated equipment and the most significant energy consumer in buildings. Hence, it is practical to focus the analysis on this operation mode (i.e., operation during summer season), where achieving energy savings is crucial while maintaining an adequate indoor environment quality. To determine the overall activity level $Act^{overall}_{\text{met}}$ and the normalized CO2 generation rate $CO2^{overall}_{\text{IndoorRate}}$ of the people in the conditioned space, the following linear approximation was used:

$$\begin{aligned} Act^{overall}_{\text{met}} &= \frac{1}{\sum_j N_j} \sum_i N_i Act^i_{\text{met}}, \\ CO2^{overall}_{\text{IndoorRate}} &= \frac{N_{\text{male}} CO2^{male}_{\text{IndoorRate}} + N_{\text{female}} CO2^{female}_{\text{IndoorRate}}}{N_{\text{male}} + N_{\text{female}}}, \end{aligned} \tag{4}$$

where N_j is the number of people performing activity Act^i_{met}, N_{male} and N_{female} are the number of adult males and females present, respectively, and $CO2^{male}_{\text{IndoorRate}}$ and $CO2^{female}_{\text{IndoorRate}}$ are the normalized CO2 generation rates for adult males and females, respectively.

4.2. Prediction models using ML algorithms: A comparison

The prediction model used in the MPC system is not limited to the NN-based model. However, a reliable prediction model is essential as the performance of the MPC system is highly dependent on the accuracy of the prediction model. That is, the MPC system uses the prediction model to look into the future towards finding the best control action. In this section, a comparison is presented among other data-driven prediction models using common ML regression algorithms, which are DT [57], SVR [57], and *k*NN [58]. The performance of those models on the problem at hand is compared with the NN-based prediction model presented previously in Section 3.2.2. The models' training was conducted using Scikit-Learn library, which is an open-source ML library for Python programming language [59], using Bayesian optimization algorithm. It was carried out on the virtual machine with 64 GB RAM, a 10-cores Intel(R) Xeon(R) CPU with 2.39 GHz speed running on a 64-bit Windows 10 OS. Similar to the NN-based model training, data normalization was performed, and the optimization of the hyper-parameters was performed using 10-fold cross-validation for the hyper-parameters ranges presented in Table 9. In Appendix B, the information of the optimized models is presented.

A summary of the prediction performance of all of the data-driven models is demonstrated in Figure 15 evaluated on the training dataset and the eight scenarios, while Figure 16 and Figure 17 present the regression plots of the four models on the training dataset and the scenarios dataset, respectively. The under-fitting issue was observed with the DT-based and SVR-based models as shown in Figure 16a and Figure 16b, respectively. It was found that the SVR-based model performed poorly with over a RMSE of 0.25, and R of around 0.79 on the training and the scenarios datasets. For SVR, this multivariate modeling problem was difficult to realize by decision boundaries reliably. The DT-based model was able to model the system dynamics with R of around 0.82 and 0.95 on the training and the scenarios datasets, respectively. However, better performance was achieved by the *k*NN-based NN-based models with an average R of over 0.95 and a RMSE of less than 0.1 on the training and the scenarios datasets.

Generally, *k*NN-based models are prone to over-fitting issues, and they are computationally expensive, inefficient, and sensitive to outliers in the data. For the problem at hand, the most accurate and reliable performance was achieved by the NN-based model with an average RMSE of around 0.06 and an average R of 0.99. It had the best generalization on the diverse data. The NN-based models can realize and represent multivariate problems with high accuracy.

Table 9 The ranges of hyper-parameters of the other ML algorithms for models' tuning using Bayesian optimization.

Algorithm	Parameter	Range
DT	The maximum depth of the tree	1 - $m/2$
	The minimum number of samples required to split a node	2 - m
	The number of features to consider when performing the split	1 - n
SVR	The kernel type	Polynomial, Gaussian
	The kernel coefficient	1e-4 - 1e-3
	The polynomial kernel degree	2 - 3
	The penalty parameter	1 - 10000
	The Epsilon in the epsilon-SVR model	1 - 50
*k*NN	Number of neighbors	1 - $m/2$

m is the number of data samples, n is the number of data features.

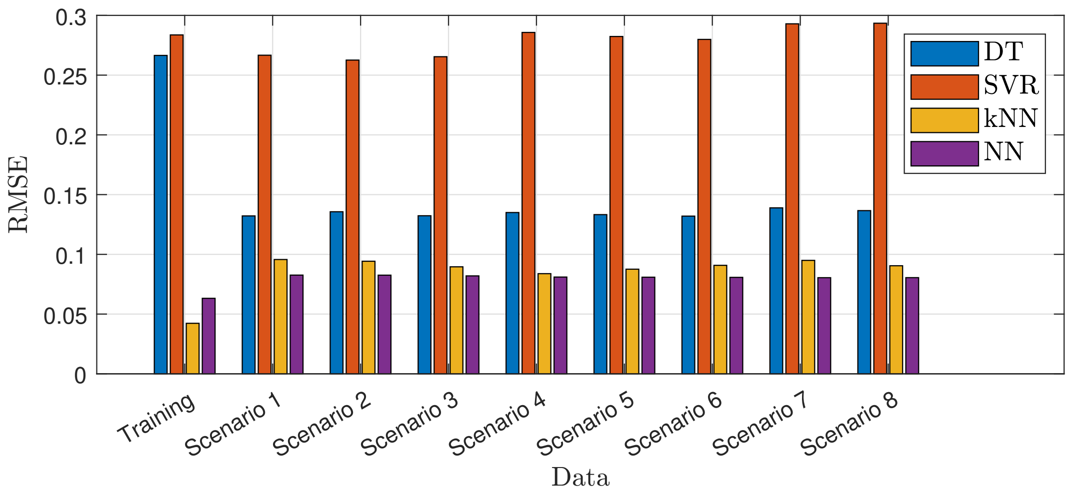


Fig. 15. The RMSE of the ML prediction models on the training and the scenarios data.

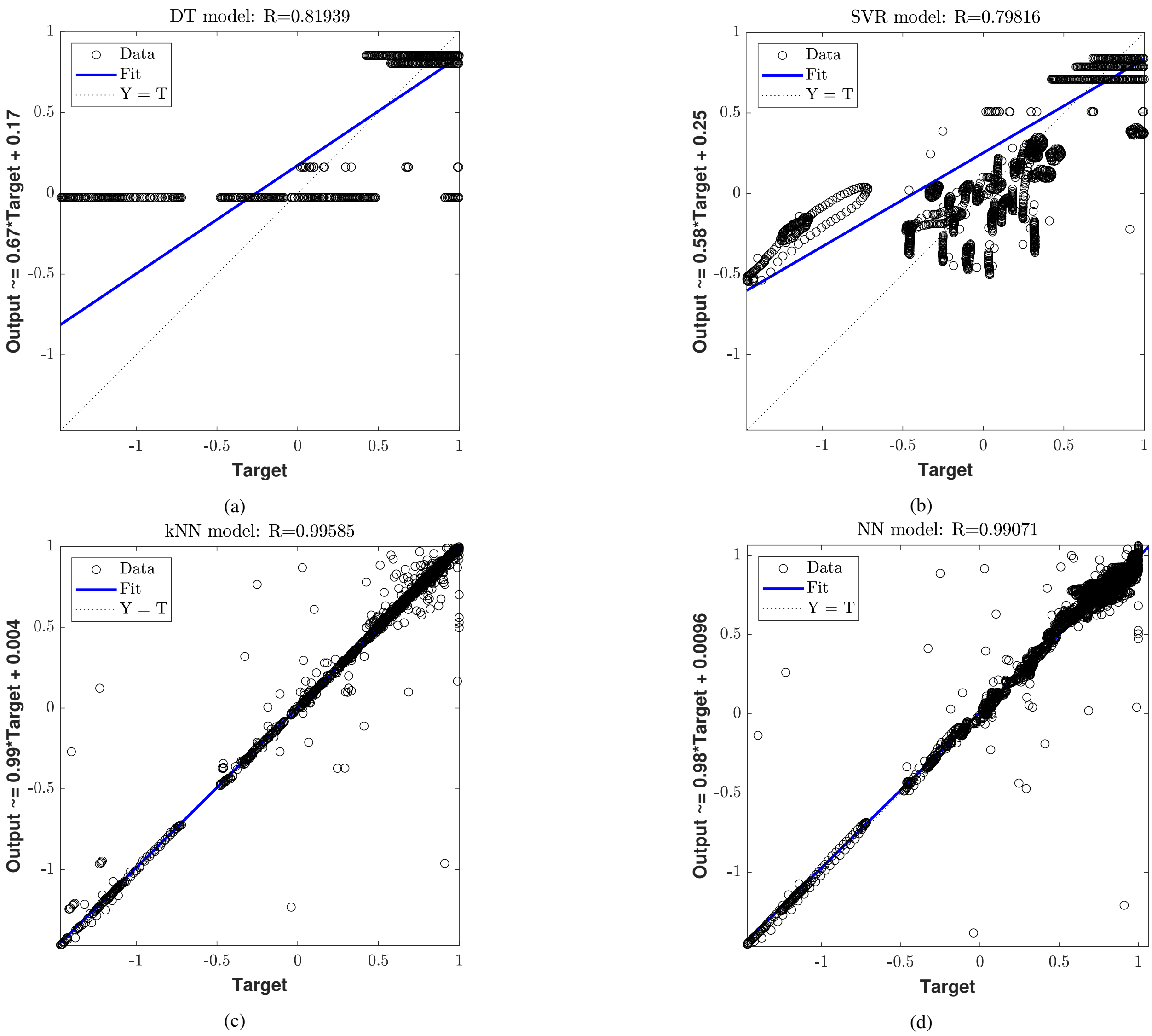


Fig. 16. The regression plots of all of the ML prediction models using the training data.

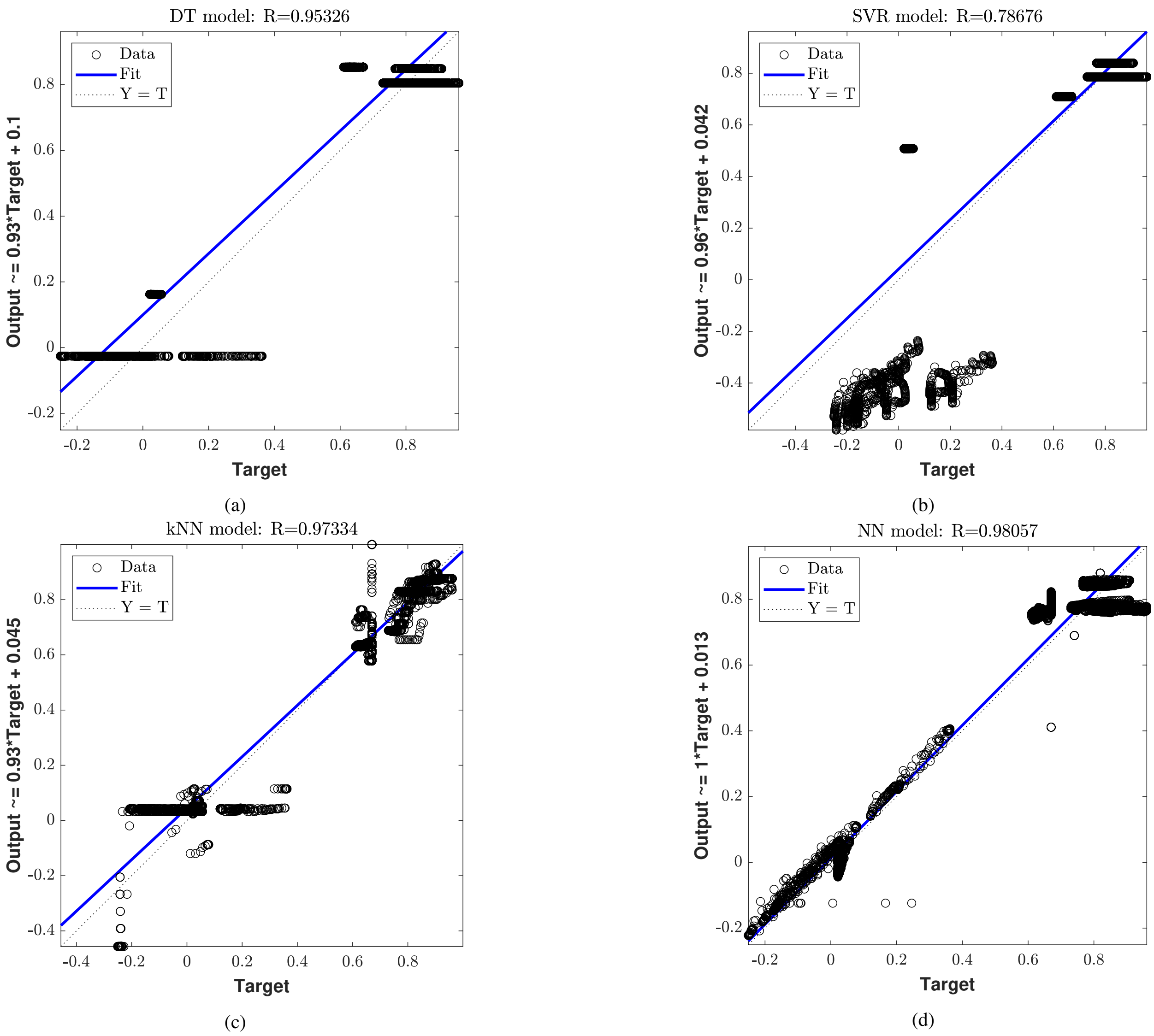


Fig. 17. The regression plots of all of the ML prediction models using the scenarios data.

4.3. *Evaluation of the proposed NN-based MPC management and optimization system*

The evaluation of the proposed framework was carried out in MATLAB/Simulink using the Energy Plus co-simulation toolbox [60]. Two benchmarks were used for the evaluation of the NN-based MPC system for the management and optimization of the HVAC system of the multi-purpose hall of QU sports and events complex, which are:

1. **Benchmark 1**: The typical operation conditions with an indoor cooling temperature setpoint of 20°C, a rated fresh air flow rate setting, and an AHU supply air temperature of 16°C.
2. **Benchmark 2**: A simple control strategy as follows:

$$
\begin{aligned}
T^{\text{sp}}_{\text{indoor}} &= \begin{cases} 20^{\circ}\text{C} & \text{during occupancy period} \\ 25^{\circ}\text{C} & \text{during non} - \text{occupancy period} \end{cases} \\
Q^{\text{sp}}_{\text{AHUFA}} &= NumPpl \times \text{Minimum fresh air per person}
\end{aligned} \tag{5}
$$

where Minimum fresh air per person is 0.0094 m^3/s for sports arenas [61]. In terms of the MPC system's parameters settings, a prediction horizon (n_p) of 3 steps (i.e., 45 min) and a control horizon (n_c) of 2 (i.e., 30 min) were used as per the work conducted in [45]. The occupancy schedule used was 8 am to 6 pm.

Table 10 The evaluation results of the proposed NN-based MPC system on the eight scenarios.

	Scenario	Number of people	Overall activity level (W/m^2)	Average PMV	Average indoor CO2 level (ppm)	Energy reduction (%) Benchmark 1	Energy reduction (%) Benchmark 2
1	Basketball game	600	122.242	-0.006	451.244	46.881	20.871
2	Basketball game	1100	114.557	-0.031	476.491	46.679	20.523
3	Football game	1200	130.008	-0.082	489.636	44.832	17.756
4	Crossfit competition	300	251.417	0.531	450.015	39.145	9.370
5	Football game	1700	128.518	0.102	515.766	43.972	16.426
6	Basketball game	120	162.625	0.184	422.732	44.491	17.366
7	Football game	2500	130.472	0.192	568.388	43.841	16.164
8	Crossfit competition	1600	301.094	0.883	642.604	39.210	9.245

Figures 18 - 27 and Table 10 present the evaluation results of the NN-based MPC system for the management and optimization of the HVAC system of the multi-purpose hall operated in sports mode on the eight scenarios. The proposed NN-based MPC system is aimed to optimize the BAMS's operation of the sports hall's AHUs to manage the energy use, thermal comfort, and indoor air quality. This is a complex trade-off. That is, less cooling energy is required when the space temperature is set at a higher value. However, based on the number of people present and the type of activity they perform, their thermal satisfaction can be altered. On the other hand, the increased fresh air flow rates may increase or reduce energy consumption based on the temperature of the outside air and the other HVAC system settings.

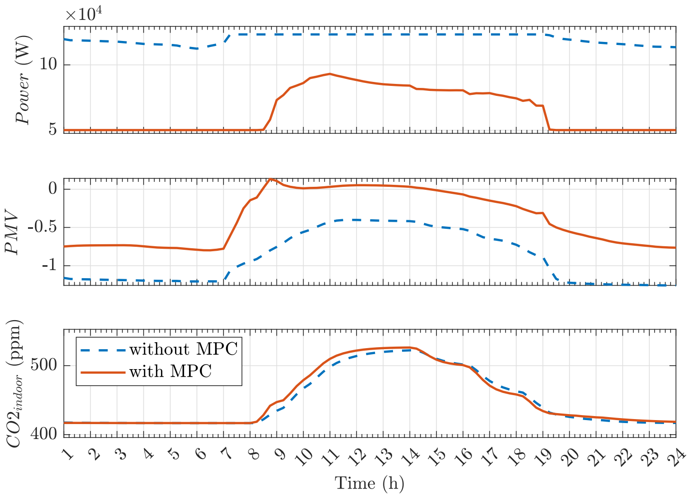
Compared with Benchmark 1, i.e., the typical operation conditions, the proposed NN-based MPC system helped consistently reduce consumption by 39% to 47% while maintaining adequate indoor environment quality in terms of thermal comfort and indoor CO2 levels. In Scenarios 1 - 3 shown in Figures 18 - 20, the percentage of athletes involved in moderate to heavy activities is less than 3% of the hall's users, and around 96% of the people present are spectators with low levels of activity. For those scenarios, where football and basketball games were held with an average overall activity level of 122 W/m^2, the indoor temperature setpoint was moderately regulated by the proposed NN-based MPC system to 25°C during the non-occupancy period, and between 23 and 24°C during the hall's operating times. During the occupancy period, the thermal comfort levels were convenient with a PMV in the range of -0.2 to 0.2. However, in Scenario 4 (Figure 21), where a crossfit competition was held, elevated PMV was observed, ranging from 1 to 1.5 with a maximum absolute difference of 0.4 compared to Benchmark 1. This is because about 20% of the hall's users performed intense exercises, so they were likely to experience thermal discomfort.

In comparison with Benchmark 1, a significant portion of the achieved energy saving is attributed to the fact that the indoor temperature setpoint was set by the proposed framework to 25°C during non-operating hours and the reduced supply air temperature setpoint of 14°C. Additionally, it was 2°C to 4°C higher than Benchmark 1 during the occupancy period, which was primarily insignificant as the thermal comfort levels indicated by the PMV values were within the acceptable range. Similar performance was achieved in terms of the indoor air quality indicated by the indoor CO2 levels below 650 ppm for the aforementioned scenarios, which are within the healthy range [50]. They were higher for scenarios with high occupancy and/or involving high-intensity activities.

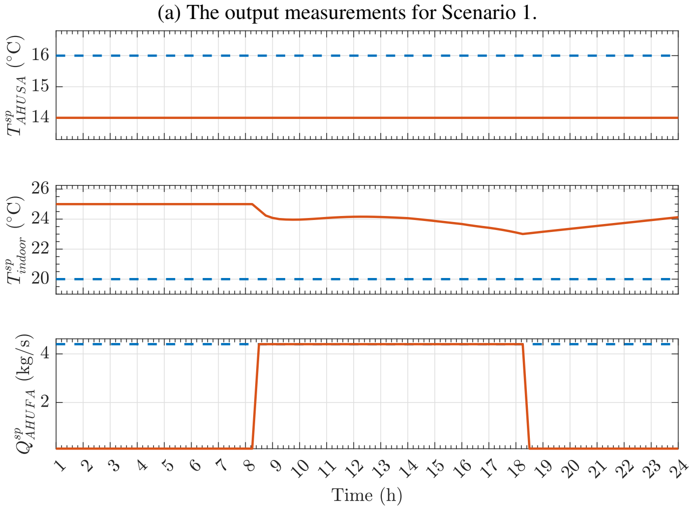
Compared to the simple control strategy (i.e., Benchmark 2), the proposed NN-based MPC system achieved varied yet passable performance for the eight scenarios based on the type of activity involved and the number of people present with up to 21% energy reduction. In Scenarios 5 - 7, in which the overall level of the performed physical activities was moderate, the proposed MPC system managed the hall's indoor environment achieving an average PMV of around 0.2 and 16% consumption reduction. As shown in Figures 22 - 24, this was achieved by regulating the indoor temperature setpoint between 22°C and 25°C during the hall's operating times, unlike the simple control strategy with a constant indoor cooling temperature setpoint of 20°C. They had a relatively similar performance during the non-occupancy period in which the indoor temperature is set to 25°C, while the supply air temperature was set to 14°C using the proposed framework and 16°C using the simple control strategy. Additionally, at the end of the operation period (i.e., at hour 18), the indoor cooling temperature setpoint determined by the NN-based MPC system was gradually increased at a rate of 1°C/hour, unlike the simple control strategy in which it was abruptly switched to 25°C. Additionally, a 9.3% energy reduction was achieved for scenarios of the crossfit competitions (i.e., Scenarios 4 and 8). The cooling load of the HVAC system serving the sports hall increased due to the high activity levels performed, and the thermal comfort levels were elevated with an average PMV of about 0.9.

Nevertheless, Scenarios 7 and 8 capture incidents where the hall was over-occupied. The evaluation of Scenario 24 is illustrated in Figure 24, which represents a football match held with over 2400 fans attending, and Scenario 8, shown in Figure 25, simulated an intense crossfit competition with 1600 attendees. Between 10 am and 11 am, the weight parameter w_3 was set to 15, given that the indoor CO2 level exceeded the predefined threshold of 800 ppm. However, the HVAC system could not regulate the indoor air quality given that it has been operating at the maximum capacity already. In these cases, Scheme 2 of the proposed approach is useful, in which a recommendation regarding the appropriate occupancy is provided. That is, Scheme 2 can factor the conditions of the outdoor and indoor environments and the criteria on the indoor environment to determine the appropriate number of people present in the hall. For instance, the expected indoor CO2 levels, if the $NumPpl$ recommendation is followed, are demonstrated in Figures 26 and 27, which are well below 1000 ppm. This piece of information can be utilized by managers to improve the management of their facilities. Limitations on the real-time application of scheme 2 might arise. However, Scheme 2 of the proposed framework can be employed to enhance the planning of the sports event or improve the attendance registration management and coordination whenever applicable.

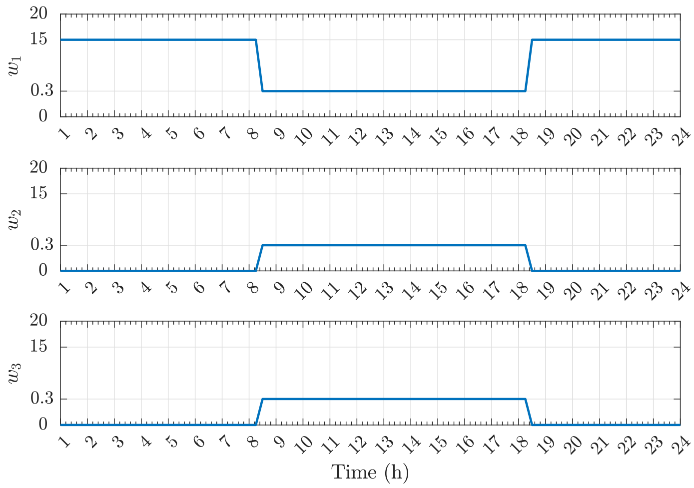
Overly, elevated indoor CO2 levels and PMVs have been observed for the corssfit competition events such as Scenarios 4 and 8 as a considerable number of people who attended the event are expected to perform intense physical activities. Additionally, those events experience increased cooling load, and hence more energy is required to condition the sports hall. Consequently, there might be less opportunity for energy reduction. Football and basketball games are popular with higher fans to players ratio than crossfit sport. The majority of attendees are fans who are generally seated or involved in minimal physical activity levels. The required energy for air conditioning and maintaining the indoor environment quality vary depending on the number of attendees and the outside weather conditions. For the scenarios of football and basketball games presented in this study, energy reduction was the highest of 44% - 46% compared to Benchmark 1 and 16% - 20% when compared to Benchmark 2. Finally, it was observed that the performance of the proposed NN-based MPC framework in terms of thermal comfort and indoor air quality was adequate and comparable to both benchmarks while achieving considerable energy savings.



(a) The output measurements for Scenario 1.

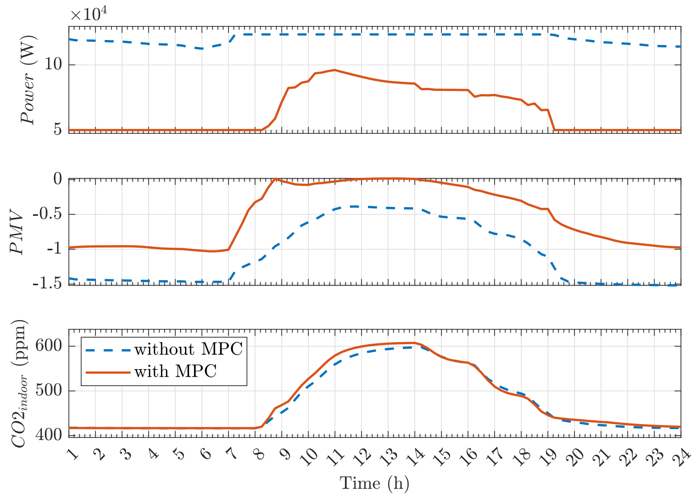


(b) The HVAC system's settings for Scenario 1.

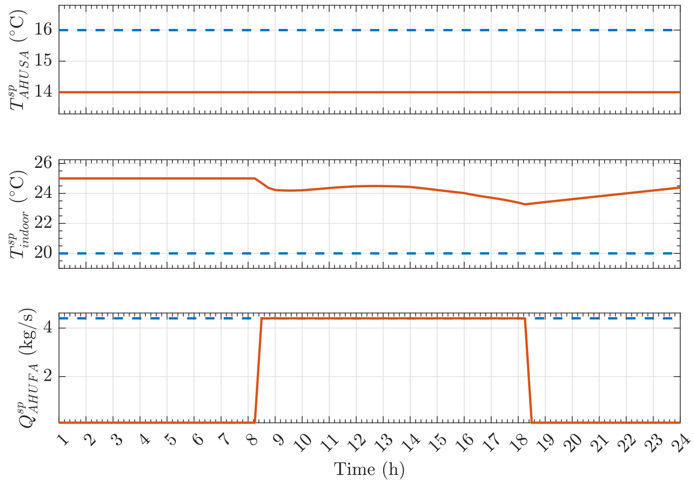


(c) The output weight parameters for Scenario 1.

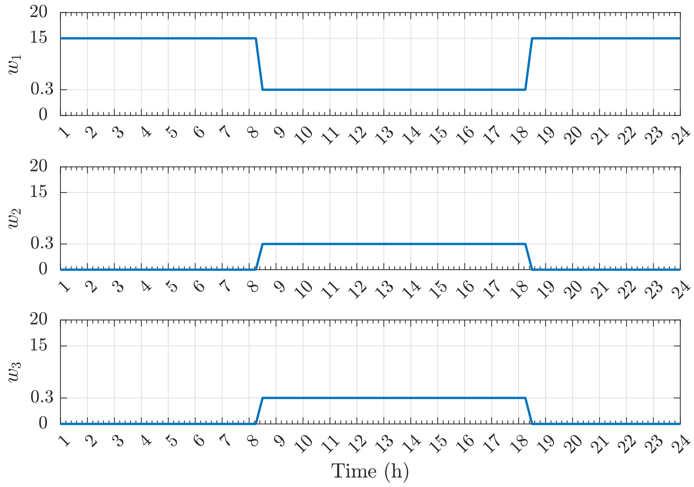
Fig. 18. The results of using Scheme 1 of the NN-based MPC system for Scenario 1 in comparison with the typical operation conditions (Benchmark 1).



(a) The output measurements for Scenario 2.

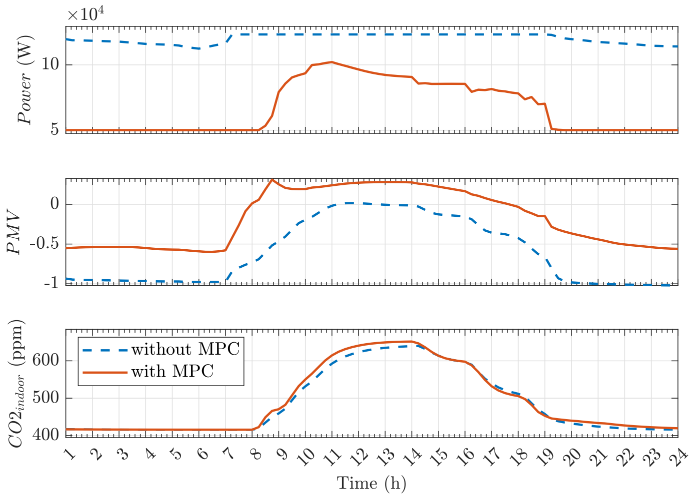


(b) The HVAC system's settings for Scenario 2.

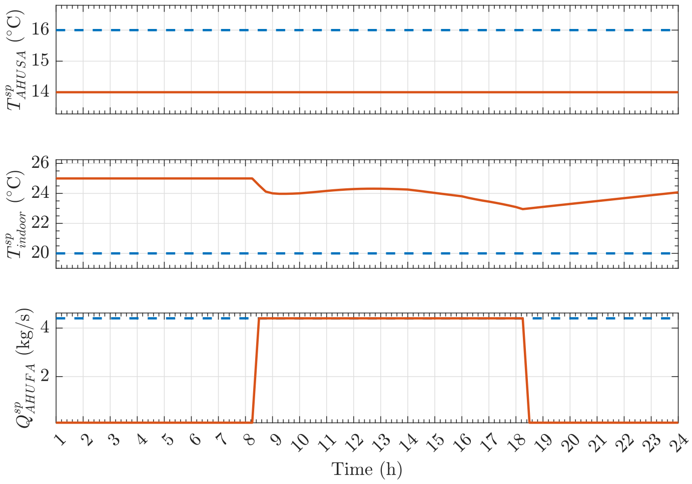


(c) The output weight parameters for Scenario 2.

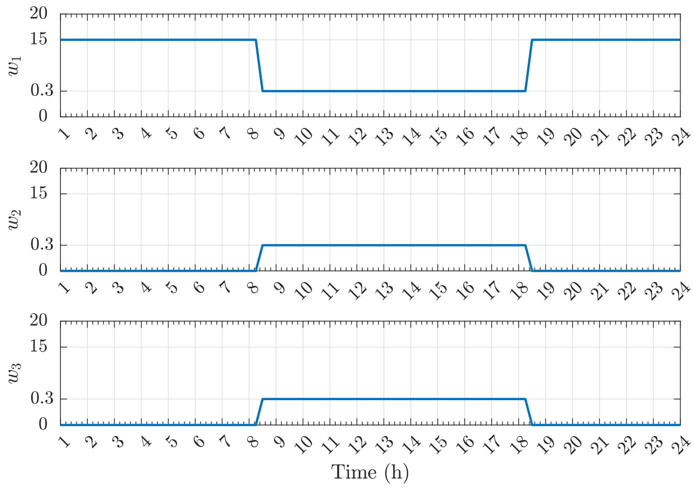
Fig. 19. The results of using Scheme 1 of the NN-based MPC system for Scenario 2 in comparison with the typical operation conditions (Benchmark 1).



(a) The output measurements for Scenario 3.

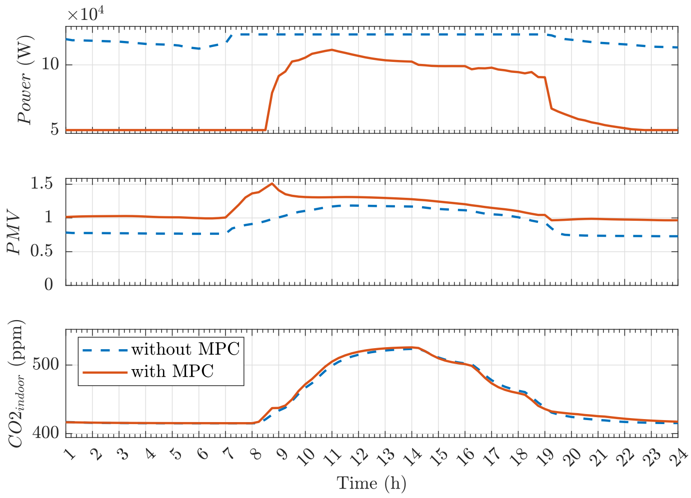


(b) The HVAC system's settings for Scenario 3.

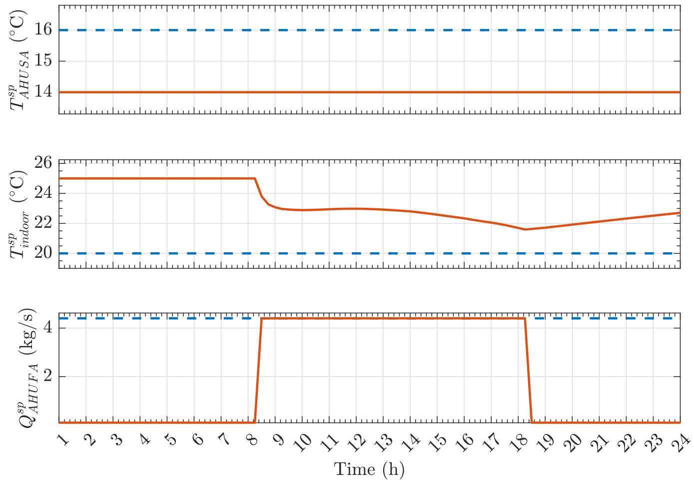


(c) The output weight parameters for Scenario 3.

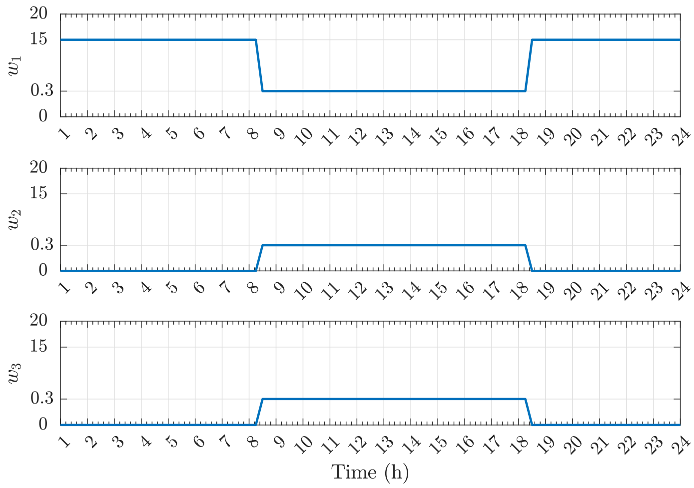
Fig. 20. The results of using Scheme 1 of the NN-based MPC system for Scenario 3 in comparison with the typical operation conditions (Benchmark 1).



(a) The output measurements for Scenario 4.

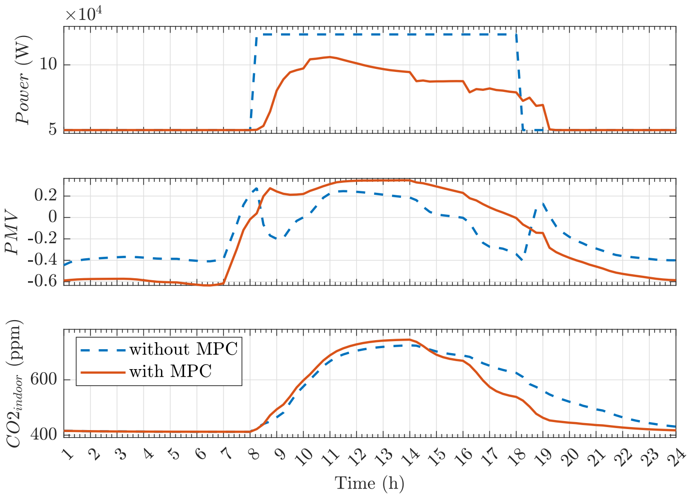


(b) The HVAC system's settings for Scenario 4.

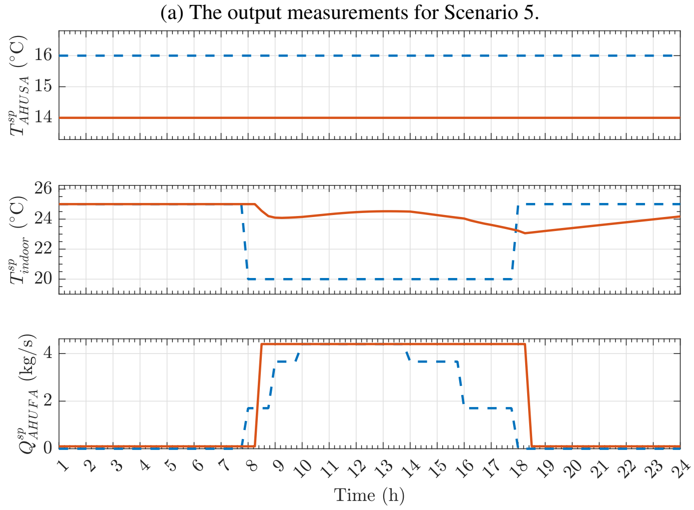


(c) The output weight parameters for Scenario 4.

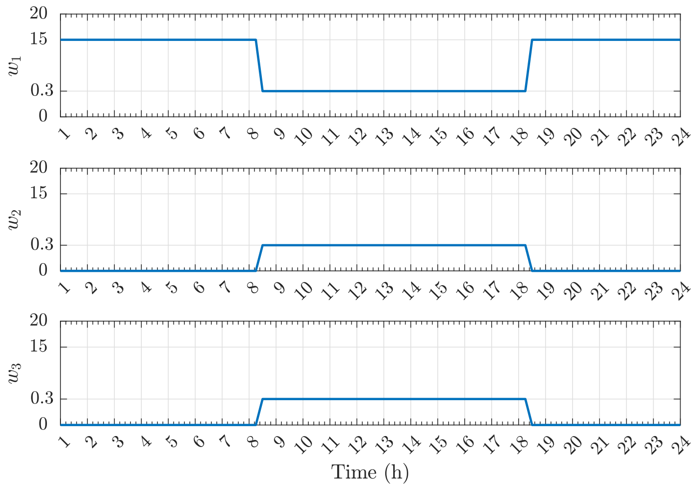
Fig. 21. The results of using Scheme 1 of the NN-based MPC system for Scenario 4 in comparison with the typical operation conditions (Benchmark 1).



(a) The output measurements for Scenario 5.

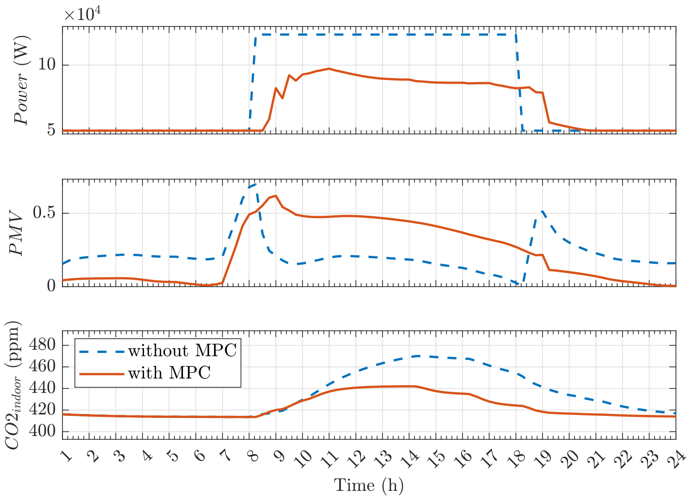


(b) The HVAC system's settings for Scenario 5.

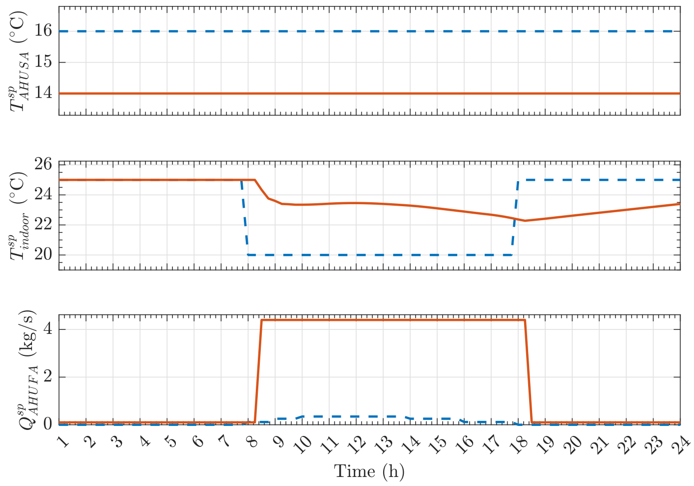


(c) The output weight parameters for Scenario 5.

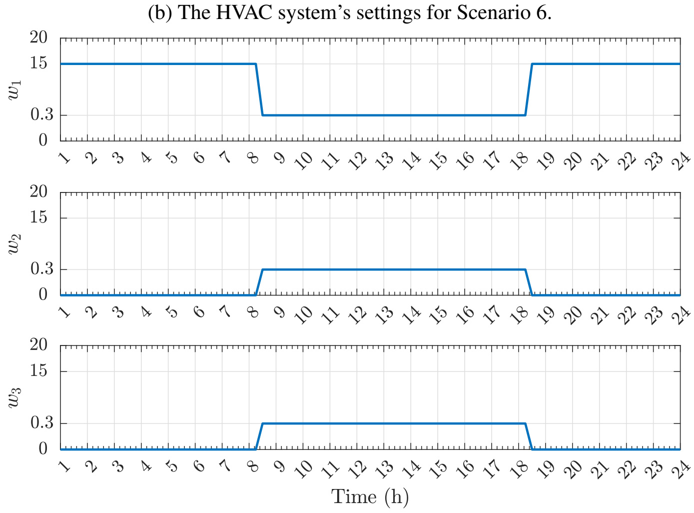
Fig. 22. The results of using Scheme 1 of the NN-based MPC system for Scenario 5 in comparison with the simple control strategy (Benchmark 2).



(a) The output measurements for Scenario 6.

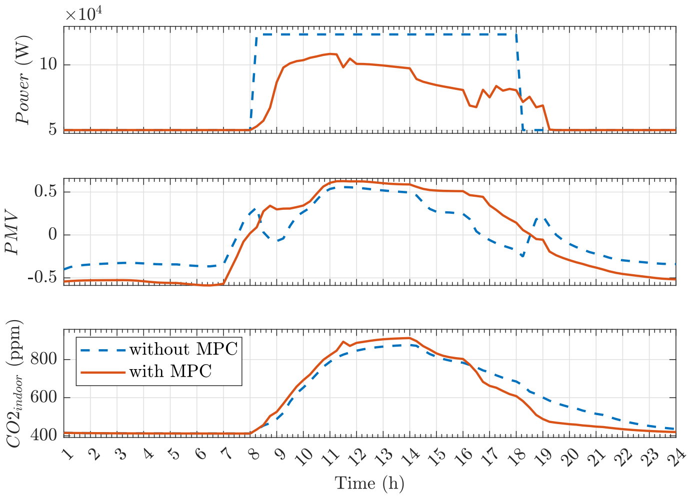


(b) The HVAC system's settings for Scenario 6.

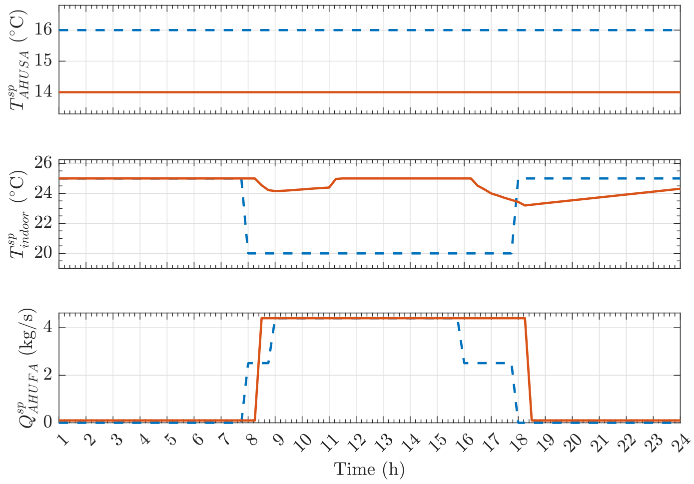


(c) The output weight parameters for Scenario 6.

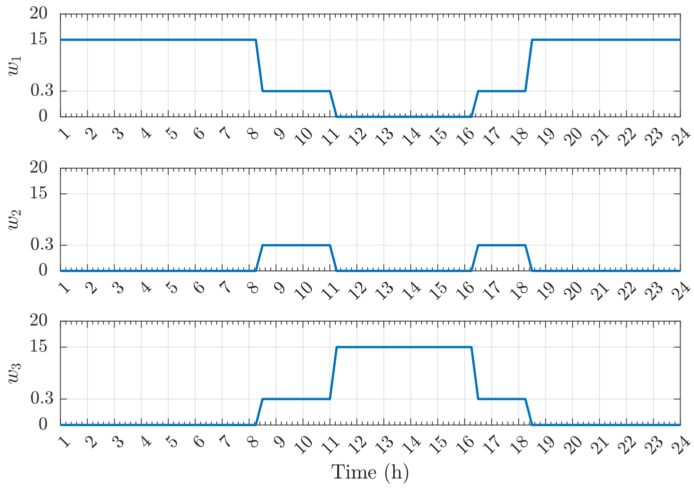
Fig. 23. The results of using Scheme 1 of the NN-based MPC system for Scenario 6 in comparison with the simple control strategy (Benchmark 2).



(a) The output measurements for Scenario 7.

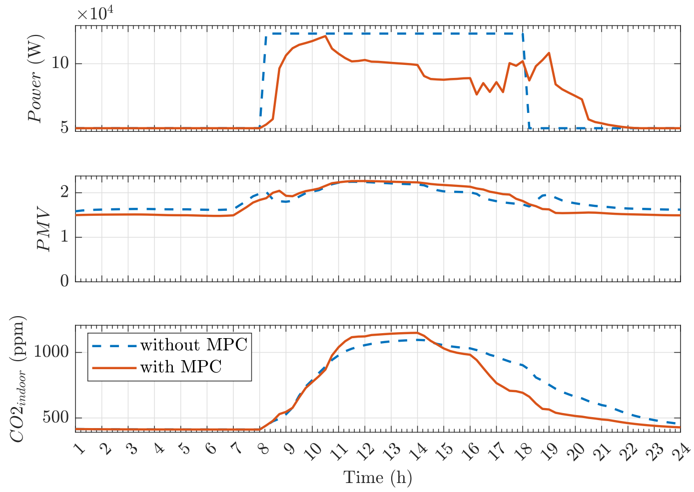


(b) The HVAC system's settings for Scenario 7.

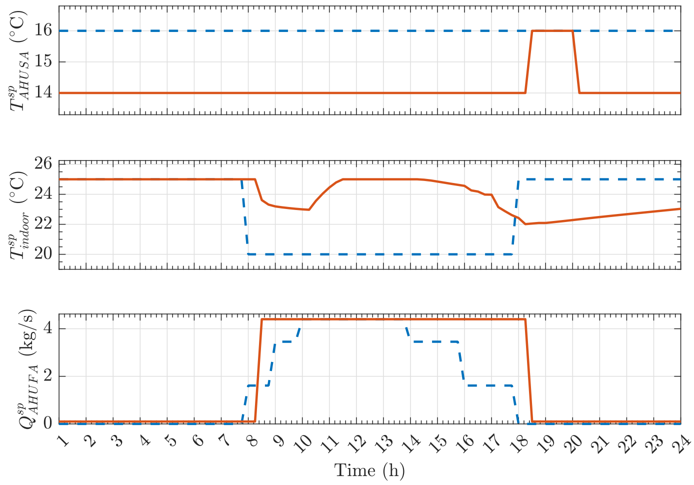


(c) The output weight parameters for Scenario 7.

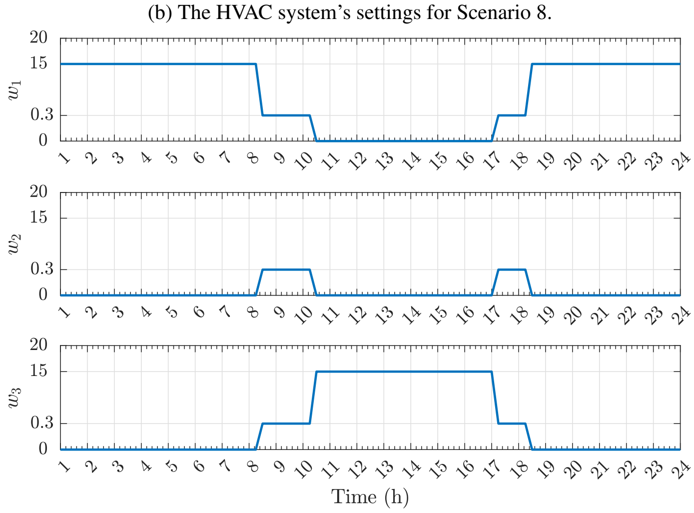
Fig. 24. The results of using Scheme 1 of the NN-based MPC system for Scenario 7 in comparison with the simple control strategy (Benchmark 2).



(a) The output measurements for Scenario 8.



(b) The HVAC system's settings for Scenario 8.



(c) The output weight parameters for Scenario 8.

Fig. 25. The results of using Scheme 1 of the NN-based MPC system for Scenario 8 in comparison with the simple control strategy (Benchmark 2).

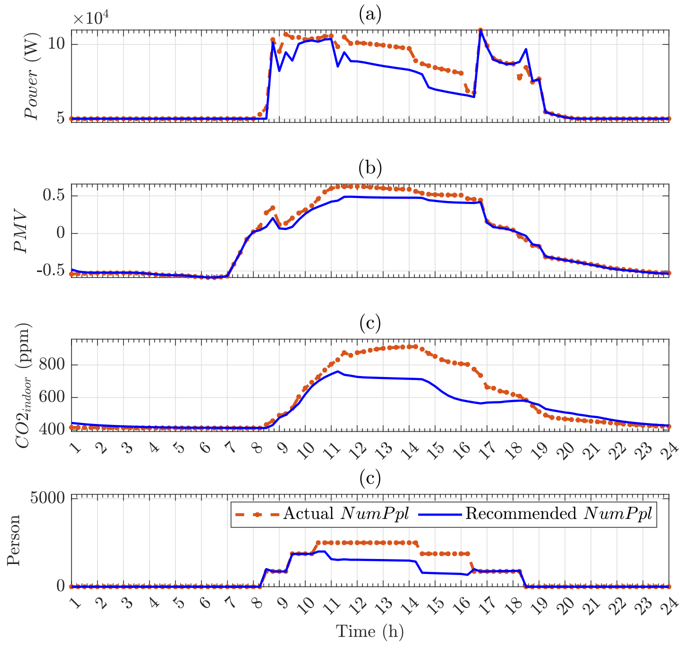


Fig. 26. The evaluation of Scheme 2 of the proposed MPC system for Scenario 7 with and without the *NumPpl* recommendation.

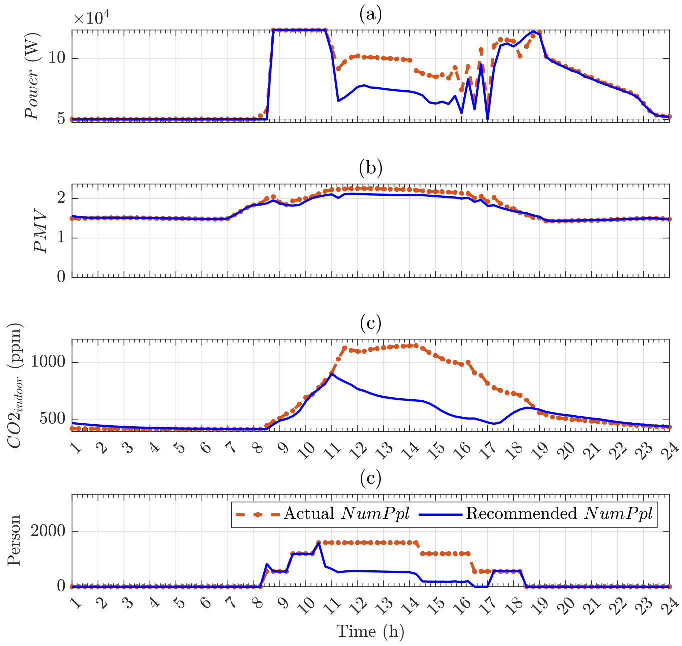


Fig. 27. The evaluation of Scheme 2 of the proposed MPC system for Scenario 8 with and without the *NumPpl* recommendation.

4.4. Important remarks and consideration

The proposed framework was demonstrated successfully on a sports hall in a sports complex that is, unlike other types of spaces, considerably large and can involve several kinds of sports events such as indoor football, basketball, crossfit, etc., with a considerable number of users. It established the foundation for applying the NN-based MPC system for the management of sports facilities' operation in general and in terms of their HVAC systems in particular. That is, HVAC systems are one of the most energy consumers in buildings [44], and their operation affects the indoor environment quality and the thermal satisfaction and comfort of the users. Given the nature of the involved sports activities and hence the air conditioning and ventilation requirements for a healthy and thermally comfort indoor environment for users, the integrated management and operation optimization offered by the proposed NN-based MPC system has indisputable advantages even when considered for a distinctive and somehow isolated area of the sports facility, such as the one considered in this study. Furthermore, the NN-based MPC system supports multi-objective optimization, and hence it can be expanded to include other aspects of the system operation that can be in terms of the management of other services such as lighting, water distribution, etc., or as a distributed control framework for the whole sports facility [62].

If the NN-based MPC system is desired to include the management of other aspects of the facility's operation or the systems of the facility that have a direct or indirect association with the proposed framework's functionality are modified, the following may be required:

- updating the NN-based prediction model used based on the new BAMS's data collected after the made changes,
- updating the list of controlled variables that are to be optimized,
- updating the cost function's elements and consequently the rule-based outputs' weights model to accommodate the adjustments,
- re-tuning the MPC system in terms of the weights and scale factors to achieve the desired performance of the NN-based MPC system.

This includes but is not limited to replacing damaged units with others of different properties, upgrading existing systems, adding new services or features, and installing supplementary clean energy systems. Additionally, in terms of the data-driven prediction element of the MPC system, other types of NNs can be used, such as deep NN, LSTM, etc., for more complex applications on sports facilities. In this paper, a single-layer NN was sufficient to obtain a reliable performance at the minimum computational complexity because the HVAC system of the sports hall exhibits overly steady and slow dynamics. Thus, the deployment of a more sophisticated NN-based prediction model (e.g., where multiple previous time steps are taken into account, etc.) is superfluous, resulting in an unnecessary increase in the computational overhead of the proposed framework.

Considering an analogous application of this study, the limitations and/or the considerations of the proposed framework are mainly related to (i) the integration of the framework into the BAMS of the sports facility and (ii) the degree of freedom of the existing technology in the facility in terms of the type of provided services (i.e., mechanical ventilation, automated natural ventilation, etc.) and the number of controlled variables (i.e., setpoints, flow rate, etc.). The proposed framework's ability to optimize the facility's operation is bounded by the available systems, provided services, and capacity. Hence, for the practical application of the proposed framework, it is assumed that the facility is equipped with a sufficiently sophisticated BAMS and the required hardware of the IoT components (i.e., sensors, actuator, etc.) for achieving the desired optimization objective. Then, the following is required:

- Developing/configuring a host for the NN-based MPC framework on hardware or a web-server or a hybrid solution for providing the essential IoT functions: connectivity, data processing, and potentially a user interface. Python or C libraries for data processing, communication, and AI and MPC[2] implementations can be used. Examples of useful hardware for these kinds of applications are Raspberry Pi [63], FPGA [64], and other microcontrollers [65].
- Establishing and synchronizing a two-way communication link between the host and the BAMS of the sports facility such that the required measurements for the framework are sent from the BAMS to the host, and the controlled variables are transferred from the host to the BAMS (e.g., setpoint, etc.). This link can be via wired or wireless communication,
- computing unmeasured outputs required to solve the optimization problem (e.g., PMV).

[2]https://github.com/forgi86/pyMPC, Accessed on 5th of March, 2022.

5. Conclusion

In this work, a NN-based MPC management and optimization system for the BAMSs of sports facilities was developed. It was applied for optimizing the HVAC system's operation of a sports hall in QU sports and events complex, and was validated using a calibrated Energy Plus simulation model. The proposed system provided an integrated dynamic optimization approach that accounts for the current and future system behaviour in the decision-making process. It includes a prediction element and an optimizer. It aimed to manage and optimize the BAMS of the HVAC system of the sports hall in terms of energy usage, thermal comfort, and indoor air quality.

The quality and accuracy of the prediction model of the MPC system are crucial to the overall performance of the proposed MPC system. Since it is impractical to obtain explicit mathematical models for complex buildings such as sports facilities, a NN was used to implement a dynamic prediction element of the MPC system. The prediction performance of the NN-based model was compared to other ML-based models using DT, SVR, and *k*NN algorithms. The best and most reliable prediction performance was observed for the NN-based model with an average RMSE of around 0.06 between the actual and predicted values, and an average R of 0.99 as NNs are famous for their ability to represent complex interdependencies with high accuracy.

Two schemes of the proposed NN-based MPC system were investigated under eight various sports events scenarios, with/without occupancy recommendation aimed for the facilities' managers to handle the facility operation better. As a result, the proposed approach achieved up to 46% energy reduction while jointly optimizing the indoor environment's thermal comfort and indoor air quality. Additionally, the second Scheme of the proposed system provided efficacious recommendations for an improved, safe, and healthy indoor environment. It is worth noting that the eight scenarios were chosen as representative examples of the different possible sports events considering the variation in the activities involved and the occupancy details.

We plan to implement and integrate the proposed NN-based MPC approach in the computational urban sustainability platform (CUSP) developed at Cardiff University; it is a decision-support tool built to deliver urban analytics and enable interactive monitoring and inform decision-making a web interface. In addition, it can promote co-simulation across disciplines and predict future scenarios towards a sustainable future operation, and architectural-urban intelligence [66]. Additionally, we plan to expand the proposed framework to include optimizing the management of the water distribution system and the lighting system of the sports hall. .

6. Acknowledgment

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Appendix A. The Details of the Evaluation Scenarios

Table A.11 Metabolic rates for typical activities in sports-related spaces [49, 67].

Activity	Metabolic rate (Act_{met})	
	W/m^2	W/person
Seated, quiet	60	108
Standing, relaxed	70	126
Standing, light activity	93	167
Walking (on level surface), 0.9 m/s	115	207
Walking (on level surface), 1.2 m/s	150	270
Walking (on level surface), 1.8 m/s	220	396
Calisthenics/exercise	175 - 235	315 - 423
Crossfit [68]	458 - 644	825 - 1159
Volleyball	232	418
Basketball, competitive	290 - 440	522 - 792
Football	464	835
Sports - Running in 15 km/h	550	990

1 met = 58 W/m^2 and the standard adult body surface area = 1.8 m^2 [69].

Table A.12 The normalized CO2 generation rates at 273 K and 101 kPa for ranges of ages (based on mean body mass in each age group) [56].

	CO2 generation per person	
	L/(s.met)	m^2/(s.W)
Average adult male (Age between 21 and 60)	3.800E-3	3.640E-8
Average adult female (Age between 21 and 60)	2.975E-3	2.850E-8

1 met = 58 W/m^2 and the standard adult body surface area = 1.8 m^2 [69].

Appendix B. The Final ML-based Prediction Models from The Bayesian Optimization Procedure.

Table B.14 The optimized hyper-parameters of the ML-based prediction models from the Bayesian optimization tuning procedure.

Algorithm	Parameter	Optimized value
DT	The maximum depth of the tree	946
	The minimum number of samples required to split an internal node	1060
	The minimum number of samples required to split an external node	1036
	The number of features to consider when performing the split	8
SVR	The kernel type	2nd order polynomial
	The penalty parameter	3678.59
	The Epsilon in the epsilon-SVR model	1
*k*NN	Number of neighbors	8

m is the number of data samples, *n* is the number of data features.

Table A.13 The details of the considered scenarios taking place in the multi-purpose hall of QU sports and events complex for evaluation and testing.

Scenario	Event	Date(Day-Month)	Total number of people	Description			
				Number of group	Group description	Gender	Activity
1	Basketball game	15-5	600	5	main players	male	heavy
				5	main players	male	moderate
				10	substitute players	male	Seated quiet
				100	female -fans	female	Seated quiet
				5	males - organizers and staff	male	Seated quiet
				5	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				5	males - organizers and staff	male	Standing, light activity
				380	males - fans	male	Seated quiet
				55	males - fans	male	Standing, relaxed
				30	males - fans	male	Standing, light activity
2	Basketball game	30-5	1100	5	main players	male	heavy
				2	main players	male	moderate
				10	substitute players	male	Seated quiet
				100	female -fans	female	Seated quiet
				5	males - organizers and staff)	male	Seated quiet
				5	males - organizers and staff)	male	Walking (on level surface), 0.9 m/s
				5	males - organizers and staff)	male	Standing, light activity
				888	males - fans	male	Seated quiet
				50	males - fans	male	Standing, relaxed
				30	males - fans	male	Standing, light activity
3	football match	20-6	1200	8	main players	male	heavy
				2	main players	male	moderate
				10	substitute players	male	Sports - Running
				200	female -fans	female	Seated quiet
				5	males - organizers and staff	male	Seated quiet
				5	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				5	males - organizers and staff	male	Standing, light activity
				450	males - fans	male	Seated quiet
				390	males - fans	male	Standing, relaxed
				125	males - fans	male	Standing, light activity
4	crossfit competition	28-6	300	25	main players	male	heavy
				15	main players	male	heavy
				15	main players	male	Calisthenics
				25	female -fans	female	Seated quiet
				25	female -fans	male	Standing, relaxed
				10	males - organizers and staff	male	Seated quiet
				25	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				15	males - organizers and staff	male	Standing, light activity
				20	males - fans	male	Seated quiet
				70	males - fans	male	Standing, relaxed
				55	males - fans	male	Standing, light activity
5	football match	1-8	1700	8	main players	male	heavy
				2	main players	male	moderate
				10	substitute players	male	Sports - Running
				300	female -fans	female	Seated quiet
				20	males - organizers and staff	male	Seated quiet
				20	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				20	males - organizers and staff	male	Standing, light activity
				600	males - fans	male	Seated quiet
				500	males - fans	male	Standing, relaxed
				220	males - fans	male	Standing, light activity
6	Basketball game	15-7	120	5	main players	male	heavy
				5	main players	male	moderate
				10	substitute players	male	Seated quiet
				20	female -fans	female	Seated quiet
				5	males - organizers and staff	male	Seated quiet
				5	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				5	males - organizers and staff	male	Standing, light activity
				45	males - fans	male	Seated quiet
				10	males - fans	male	Standing, relaxed
				10	males - fans	male	Standing, light activity
7	football match	5-8	2500	8	main players	male	heavy
				2	main players	male	moderate
				10	substitute players	male	Sports - Running
				500	female -fans	female	Seated quiet
				20	males - organizers and staff	male	Seated quiet
				20	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				20	males - organizers and staff	male	Standing, light activity
				700	males - fans	male	Seated quiet
				700	males - fans	male	Standing, relaxed
				520	males - fans	male	Standing, light activity
8	crossfit competition	17-8	1600	150	main players	male	heavy
				150	main players	male	heavy
				100	main players	male	Calisthenics
				50	female -fans	female	Seated quiet
				50	female -fans	female	Standing, relaxed
				100	males - organizers and staff	male	Seated quiet
				100	males - organizers and staff	male	Walking (on level surface), 0.9 m/s
				100	males - organizers and staff	male	Standing, light activity
				100	males - fans	male	Seated quiet
				200	males - fans	male	Standing, relaxed
				500	males - fans	male	Standing, light activity

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