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Demonstrating a smart controller in a hospital integrated energy system

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ABSTRACT

Integrated energy systems have recently gained primary importance in clean energy transition. The combination of the electricity, heating and gas sectors can improve the overall system efficiency and integration of renewables by exploiting the synergies among the energy vectors. In particular, real-time optimization tools based on Model Predictive Control (MPC) can considerably improve the performance of systems with several conversion units and distribution networks by automatically coordinating all interacting technologies. Despite the relevance of several simulation studies on the topic, however, it is significantly harder to have an experimental demonstration of this improvement. This work presents a methodology for the real-world implementation of a novel smart control strategy for integrated energy systems, based on two coordinated MPC levels, which optimize the operation of all conversion units and all energy vectors in the short- and long-term, respectively, to account also for economic incentives on critical units. The strategy that was previously developed and evaluated in a simulation environment has now been implemented, as a supervisory controller, in the integrated energy system of a hospital in Italy. The optimal control logic is easily actuated by dynamically communicating the optimal set-points to the existing Building Management System, without having to alter the system configuration. Field data collected over a two-year period, firstly when it was business as usual and when the new operation was introduced, show that the MPC increased the economic margin and revenues from yearly incentives and lowered the amount of electricity purchased, reducing dependency on the power grid.

1. Introduction

The clean energy transition is a fundamental pathway required to reduce energy-related carbon emissions and mitigate the effects of climate change. Among the steps that should be taken, there is the efficient coordination of different energy production technologies in integrated energy systems [1]. They involve the integration of electricity, heating, cooling [2] and even the transportation sector [3] within the same energy system concept, with several advantages in terms of flexibility [4] and overall efficiency [5].

In the past, operating individual energy systems was rather straightforward, as it was sufficient to coordinate the available plant with the demand of a given energy vector, providing a linear energy flow from the source to the end-user. However, nowadays a new paradigm of integrated energy systems has emerged, with the contribution of energy distribution networks and interconnected flows of different energy vectors (i.e. energy is subject to several conversion processes from one form to another in order to be stored or transferred more efficiently). This concept has brought about the need for advanced techniques to cope with this higher complexity. In particular, these systems can become “smart” with the addition of a smart control strategy, i.e. automatic and with advanced optimization features.

Several new methods for the design, optimal management and control of integrated energy systems have been proposed in the scientific literature. For instance, the optimal sizing of on-grid and off-grid systems with the integration of renewable energy sources and renewable fuels is carried out in Ref. [6], while the authors in Ref. [7] couple the system design with the optimization of its operation, reducing carbon emissions of a neighborhood with distributed resources by $(30 \div 40)$ %.

Another trend in research on complex energy systems is focusing on their operation optimization, as mentioned in Ref. [8]. This is done through multi-objective optimization methods [9], algorithms that

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schedule an entire operating year with a lower level of detail [10], algorithms that allocate the load [11] and dispatch the short-term production with a day-ahead perspective [12], and even algorithms that combine both approaches [13].

Probably, however, advanced control is the most challenging task according to Ref. [14], as it requires combining the accuracy in the optimization results with a computational speed sufficient to produce a reliable control action. Li et al. [15] propose a hierarchical control strategy for multi-energy systems, divided into different tasks for forecasting and dispatching the load, and finally for the control of the actuators in the system. The strategy is tested in simulation by means of the TRNSYS software and demonstrates an optimal yearly performance. Similarly, Yan et al. [16] develop an energy management control method with a carbon trading scheme and verify it in a simulation example of a low-carbon economy.

Another widely studied strategy is Model Predictive Control (MPC), which carries out optimal control of a given system by exploiting the prediction of a model and external inputs, and updates the control action at every defined time interval [17]. In the energy sector, the most widespread field of application of MPC is for heating and air conditioning systems, while implementation for more complex energy systems (e.g. district heating networks in Ref. [18]) has emerged only recently.

As for integrated energy systems, Hu et al. [19] develop a multi-time scale MPC strategy for the tasks of day-ahead scheduling and intra-day adjustments, at the end of which a 3.8% reduction in cost is achieved. A significant number of these studies presents predictive controllers enhanced with data-driven forecasting methods [20], e.g. multi-agent deep Q networks [21].

Nonetheless, it is paramount to highlight that all the cited works limit the presentation of their solutions to simulation environments [16]. This step is fundamental as it gives the possibility to simultaneously test different control strategies and system configurations through evaluation platforms [22], but it does not allow innovative solutions to reach a high Technology Readiness Level [23] and be exploited in reality.

Some examples of the real-world demonstration of innovative control solutions are presented by Kim et al. [24] regarding the experimental tests of an MPC for a chiller unit, by the TEMPO project consortium [25] regarding a district heating smart substation optimally controlled by an MPC, and by La Bella and Del Corno [26] regarding an Italian heating system. Additionally, researchers from the STORM project successfully tested in two real applications a controller based on machine learning [27] capable of shifting heating and cooling demands in district energy networks [28]. These applications are noteworthy and show the superior performance of such algorithms. However, the literature does not show the actual implementation and testing of an MPC controller in more complex integrated energy systems in order to obtain a demonstrated smart energy system. The main reasons for the lack of real-scale demonstrators of smart energy systems are (i) that it is difficult to setup such large-scale experimental sites (unlike individual conversion units or components) and (ii) there is the risk of compromising the quality of service provided to users or activities during testing. The latter is even more limiting when dealing with critical end-users, e.g. hospitals [29]. Furthermore, most experimental works on smart controllers are based on tests carried out for limited periods (e.g. days/weeks), and a long-term evaluation of these advanced solutions is not possible.

This paper deals with these challenges by defining a methodology for the implementation, testing and demonstration of smart controllers for integrated energy systems. This methodology is applied to the energy system of a hospital where a novel control strategy has been successfully demonstrated. The novel strategy is constituted by a double optimization algorithm (with daily and yearly optimization horizons) for defining the control action while also considering the long-term goals [13]. This algorithm, developed by the authors, is considered relevant when economic incentives for production plants are assigned on a yearly basis, e.g. as in the case of high efficiency cogeneration units in the Italian legislation. While the work in Ref. [13] involved the preliminary phases of algorithm conceptualization and operability verification in a simulated environment, there was no interaction with the physical system. The real implementation, connection and long-term demonstration of the novel strategy is, on the other hand, provided in the present paper. The work, carried out within the DISTRHEAT project [30], thus provides the following contributions to the literature.

- The integrated methodology for developing, implementing and demonstrating a smart control strategy for integrated energy systems (with all conversion units and energy vectors), including the adopted communication protocols.
- The real-world demonstration of the control strategy in an operating hospital, which is generally recognized as a critical environment due to the importance of the service provided and the difficulty in accessing or modifying the management strategy.
- The implementation of security measures for ensuring a safe operation if the new control algorithm encounters any issues, and the demonstration that these measures are successful in such a delicate test site.
- The experimental data of two years of continuous operation, when it was business as usual and when the new strategy was introduced, in order to provide insights on the long-term performance of the latter (which provides significant added value compared to existing experimental studies).

2. Methods

This section describes the whole methodology adopted to conceptualize a novel control algorithm for integrated energy systems and to bring it to the real-world demonstration phase. This is shown in Fig. 1.

It can be noted that the methodology is divided into three main phases.

1. **Development phase.** The integrated energy system of the case study, as well as the interactions between the systems sections and units, are analyzed. All relevant features of the conversion units and distribution networks in the integrated energy system are collected, e.g. from manufacturers' datasheets and system diagrams. In parallel, the requirements and constraints of the new control strategy are determined. The strategy is conceptualized and the corresponding set of algorithms are selected and assembled (Section 3).
2. **Simulation phase.** The new control strategy is evaluated on a digital twin of the case study (Section 3), in order to ensure its feasibility before interacting with the real system. It is also possible to verify the fulfillment of the requirements and to apply necessary changes.
3. **Demonstration phase.** Once the control strategy has shown its potential in a virtual and safe environment, the final phase consists of implementing and demonstrating this with real field tests (Section 4).

All phases of the methodology are subject to feedback loops that, as soon as an issue or error is encountered, return back to a previous activity to make adjustments and improve the robustness of the controller. The lessons learnt from the issues emerged during this methodology are discussed in Section 4.

The requirements of the control algorithm are derived from the specific case study but are considered valid for general integrated energy systems with similar features. The key requirements are identified as follows.

- *R*-IES: *Integrated Energy System.* The new strategy should be designed to optimize the management of all sections of the systems, including all energy conversion units and multiple interacting energy vectors.

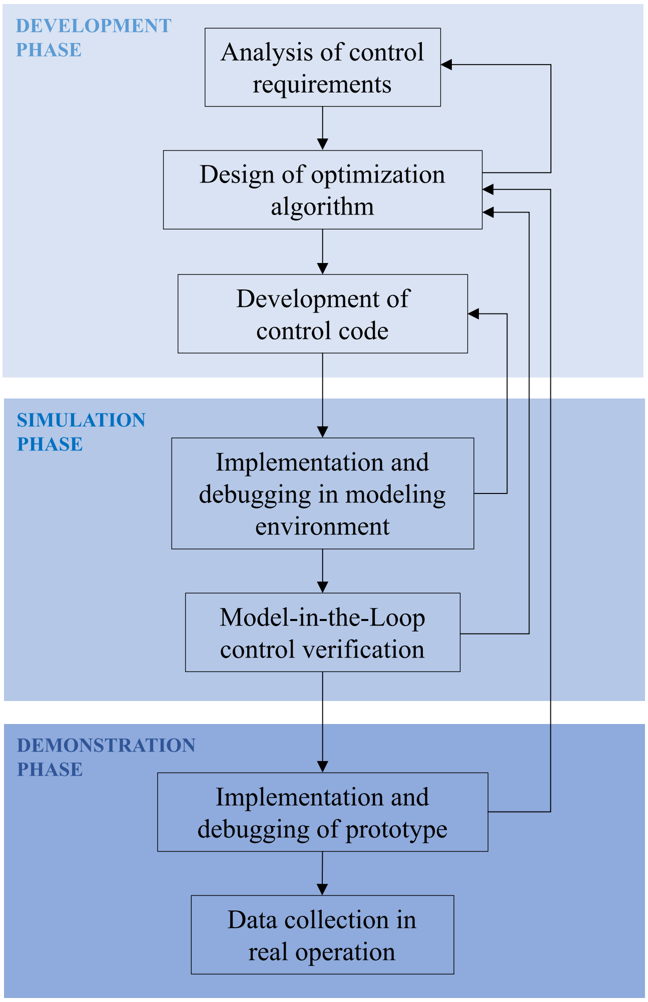

Fig. 1. Methodology for the development and demonstration of a novel control strategy for integrated energy systems.

- *R*-MPC: *a new management strategy based on Model Predictive Control* (MPC). The new strategy should improve the control performance and robustness by continuously updating optimization in real-time, based on the prediction of a model [17]. The superiority of MPC over traditional strategies has been demonstrated in several studies [13,19,31].
- *R*-MTS: *Multiple Time Scales.* The new management strategy should be designed not only to satisfy short-term objectives (e.g. operating cost over a few days), but also long-term goals and constraints. One of the key examples is the credits (i.e. a form of incentive representing a revenue for the utility) awarded to high efficiency cogeneration units based on yearly energy saving criteria [10]. In the Italian regulation, cogeneration units that meet two energy efficiency indices evaluated on yearly data [10,13] obtain incentives which are determined though a procedure based on yearly consumption/production. Hence, system operators are generally interested in carrying out real-time control actions that also consider long-term future effects and, therefore, can bring long-term benefits.
- *R*–CF: *Computational Feasibility.* The proposed algorithm has to be suitable for on-site implementation through standard computing units.

In order to meet these requirements, the control strategy was structured into two interacting MPC optimization levels, to deal with short-term and long-term features simultaneously. The related details as well as the verification of compliance with these requirements are reported in Section 3.

3. Controller development and simulation

This section gives an overview of development and simulation phases (Fig. 1), which consist of conceptualizing the control algorithm and carrying out a preliminary verification in a simulation environment. Here, the basic architecture and main results of the application are summarized, while the full details are reported in Ref. [13].

Energy systems dedicated to complex end-users (e.g. hospitals) are subject to high complexity, not only because they involve several energy vectors, but because production, distribution in heating and cooling loops, and delivery have to be coordinated in the most profitable and safe way. In order to reach the control requirements defined in Section 2, the control problem of the integrated energy system (requirement *R*-IES) was divided into two interacting control modules.

- **LoTS module**: a Long-Term Supervisory controller performs yearly scheduling of the integrated energy system, considering long-term goals and constraints coherently with requirement *R*-MTS. It determines the boundaries of operation for the real-time control actions [13], in order to lead the system to a more profitable overall performance. These problem and boundaries are updated daily.
- **ShoTS module**: a Short-Term Supervisory controller solves a unit commitment problem for the integrated energy system over a few days, and determines the actual control action while meeting the LoTS boundaries. In detail, the energy inputs and outputs to each unit are variables of the optimization problem, and are calculated by solving that optimization problem, i.e. Mixed Integer Linear Programming. Being an MPC, the control is updated every 15 min during operation (meeting requirement *R*-MPC), taking into account information on the actual operation of the system.

The controller models of the energy conversion units included in the modules are based on physical laws set with the parameters from the manufacturers' datasheets (e.g. efficiency curves). The objective function of both MPC modules is the minimization of the operating cost for the related prediction horizon, with all typical unit commitment constraints (energy demand satisfaction and technical constraints [13]).

The heating and cooling energy sent from the integrated energy system to the heating and cooling distribution branches is controlled through dedicated distribution modules, the demonstration of which was carried out in an operating environment in Ref. [31].

The novel prototype to be demonstrated is constituted of the integration of the LoTS and ShoTS modules within an integrated energy system, as shown in Fig. 2.

The controller code, as well as the communication between the modules, was firstly verified in a simulation environment operated in MATLAB®/Simulink®. The real system was, in this case, replaced by its digital twin, a detailed model that emulates its dynamic behavior in any external conditions. The digital twin was created through a library for high-detail simulation of energy systems developed by the authors and validated in previous studies [31]. In detail, the simulation models are based on physical laws (e.g. energy balance equation) set with parameters from the network.

The tests were carried out in a Model-in-the-Loop (MiL) configuration, by using the MPC modules to control the digital twin [13]. As noted in Section 2, this phase is paramount to ensure the effectiveness and feasibility of the controller before involving the real system to some extent. The relevant results that have to be checked are related to the overall yearly economic and energy performance as well as to the following indices.

- Fulfilment of *R*-MTS: global energy results obtained at the end of the year, in order to verify if the long-term objectives are achieved thanks to the MPC controller.

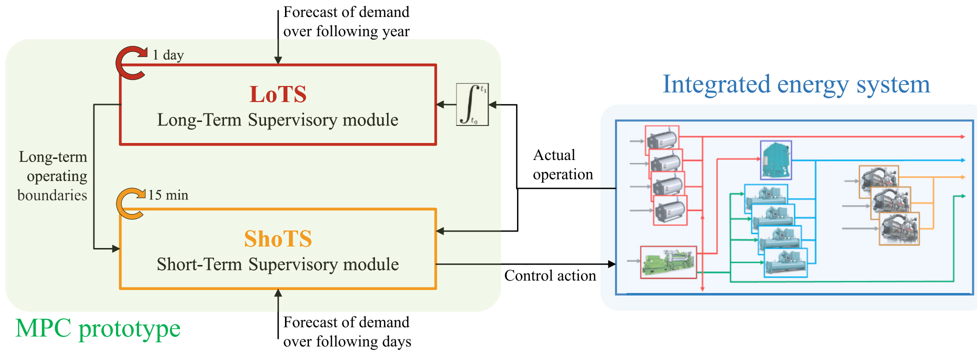

Fig. 2. Architecture of the proposed control prototype for integrated energy systems.

- Fulfilment of *R*–CF: average computational time to compute the solution, in order to understand if each control module is able to produce a solution in a time interval that is compatible with the MPC implementation (i.e. 15 min for ShoTS, 1 day for LoTS).

The MiL tests involved the simulation of the integrated energy system, including all energy conversion units and heating and cooling distribution networks, for a realistic operating year in two situations: the business-as-usual (BaU) management (i.e. standard operating strategy based on scheduled set-points) and the MPC management (i.e. set-points for plant operation established online by the MPC controller). The boundary conditions and disturbances (i.e. the way the environment interacts with the system) were the same for the two situations in order to provide a valid comparison.

The most significant results [13] that emerged from the simulation phase were summarized as follows.

- The overall operating cost was reduced by 10% in the MPC operation, compared to the BaU.
- Despite an increase in fuel consumption by 9.9%, the purchase of electricity in the MPC operation was reduced by 27%, indicating a lower dependency on the power grid.

The overall efficiency and primary energy saving of the cogeneration unit were increased by 5% and 12%, respectively, due to a lower amount of heat dissipated into the environment and to a more profitable operation of all conversion units. This led to higher revenues deriving from a 10% increase in energy efficiency credits for high efficiency cogeneration (*R*-MTS).

- The computational time for all ShoTS solutions (*R*–CF) was always shorter than 20 s with a standard laptop, with the most part of the occurrences shorter than 5 s. Since the ShoTS run times were much shorter than the time-step, and this was the most critical module from the computational point of view (the LoTS module is updated daily), controller feasibility in real implementation was confirmed.
- Finally, the effectiveness of the proposed algorithm was assured by the fact that both control modules achieved convergence in all occurrences, despite the variety of the boundary conditions encountered throughout the year.

It is concluded that the development and simulation phases were successful, as all requirements were achieved, as reported in Table 1. The controller was evaluated as suitable to be implemented in practice through the actual demonstration phase, presented in the following sections.

Table 1
Compliance of the new control strategy with the established control requirements.

Requirement	Description	Compliance of new strategy
R-IES	Control strategy should be designed to manage an integrated energy system	Control algorithm is general and makes it possible to include any kind of energy vector and conversion unit
R-MPC	Control strategy should be optimal and updated in real-time (e.g. MPC)	Control strategy is designed with two MPC optimization levels
R-MTS	Control strategy should be designed for multiple time scales to also account for long-term objectives	Two interacting MPC levels allowed for 10% increase in yearly incentives
R–CF	Control strategy should be computationally feasible for on-site implementation	All algorithm computations take less than 20 s (most occurrences are shorter than 5 s) over whole year

4. Case study and implementation

This section reports the full description of the case study, with a focus on the characteristics and composition of the energy system. Then, the controller installation is described, which was carried out according to the timeline shown in Fig. 3.

After the selection of the test site, the measurement and control equipment were installed to monitor the plant performance and determine the benchmark. Moreover, the Building Management System (BMS) was prepared for its integration with an external supervisor. Successively, the control code of the strategy described in Section 3 was implemented in the case study to operate in the background (i.e. collect the data, perform the calculation but not send any control command), to test its robustness without endangering the energy system or stopping the service. Finally it was linked to the BMS, and the data collection campaign to determine the new controller performance started.

4.1. Case study description

The case study is the Sant'Anna Hospital of Cona, close to the city of Ferrara (Emilia-Romagna region), in northern Italy. It has around 900 beds and manages more than 27,000 hospitalizations per year. The hospital has demands of heating, cooling and electricity, as well as a demand for high-temperature energy for producing steam, which is used for other special utilities (e.g. sterilization department and laundry). The yearly demands of these energy vectors (for the year 2021), normalized with reference to electricity for confidentiality reasons, are reported in Table 2.

The hospital buildings of the site (Fig. 4) are supplied by heating and cooling networks. These are fed by an integrated energy system (Fig. 5), the items of which are listed below.

- Four identical natural gas-fed boilers;
- Three identical natural gas-fed steam generators;

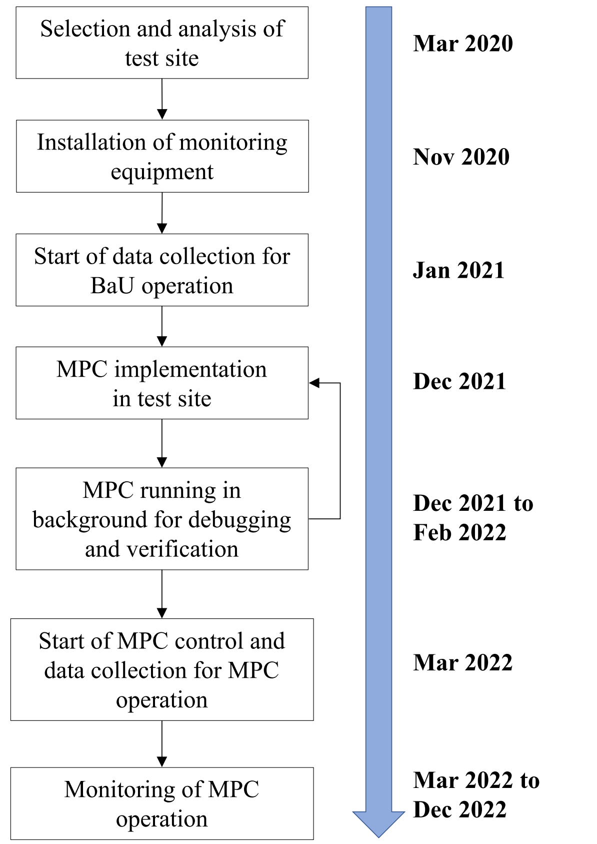

Fig. 3. Timeline of implementation and demonstration of the control prototype in the hospital case study.

Table 2
Yearly energy demands of the hospital (for the year 2021). The values are normalized with reference to electricity, for confidentiality.

	Heat	Cold	Electricity	Steam
Normalized yearly energy demand [–]	0.96	0.31	1	0.12

Fig. 4. View of the Sant'Anna hospital of cona (ferrara, Italy).

- A cogeneration internal combustion engine, namely Combined Heat and Power (CHP), for producing electricity and heat at different temperature levels. Heat is recovered from the intercooler, oil circuit, cooling water circuit and flue gases. It is used to heat a water flow which is sent to the heating circuit;
- An absorption chiller (ABS), fed by a fraction of the heat recovered from the CHP;
- Four identical electricity-fed chillers.

The main technical characteristics from the datasheets of these units are reported in Table 3.

The energy center is connected to the power grid, so that any surplus electricity from the CHP can be injected into the grid, while electricity is purchased when demand (including the power to the electric chillers) exceeds production.

4.2. Monitoring equipment and data collection

The monitoring network and its equipment was designed and installed to collect all the information needed to run the plant efficiently, gathering data about the status of the technical equipment and the energy requirements of the buildings. Regarding the real-time consumption and energy flows through the main distribution hospital networks, several measuring devices have been installed in the site in order to monitor the real-time data. As well as the natural gas consumption, the heating, cooling and electrical loads were monitored through the variables and sensors listed in Tables 4–6.

It is worth mentioning that the steam generators, placed in a dedicated area, have little interaction with the rest of the infrastructure. Indeed, they provide heat for services that cannot be delayed and, therefore, cannot be included in the optimal management. Dedicated sensors and actuators were not installed. The natural gas supplied to the steam generators is accounted for in the total natural gas consumption, but the management of these units is not involved in the optimization.

4.3. Demand forecast

As shown above, the MPC needs to be fed by the forecast of the disturbances (i.e. the external inputs from the environment that cannot be directly controlled) in order to perform the optimization. In this case, typical disturbances are energy demands and costs. The methods adopted for energy demand forecasting are specialized for the timeframe they refer to.

In detail, the first forecast addresses yearly demands (LoTS module) with a daily time resolution, which helps to gain a perspective of the overall energy needs and, consequently, to plan the energy production according to the maintenance schedule. This forecast is performed starting from historical data of consumption (e.g. electricity and natural gas) and production from conversion units.

The second forecast (ShoTS module) defines the energy demand over the following few days with a quarter-hour timestep. This is performed through an Artificial Neural Network.

Moreover, to feed both the modules with the required economic information, a daily evaluation of energy price and their forecast for the rest of the year is performed according to electricity and fuel market price trends, maintenance of critical items and plant loads.

4.3.1. LoTS yearly forecast

The disturbances for the LoTS module consist of the daily energy demand of all vectors for the whole year. As mentioned, the demand forecast was carried out from historical data (e.g. natural gas consumption) and assumptions based on state-of-the-art techniques and legislation.

4.3.1.1. Heating demand. The heating demand has been historically met by the boilers and the CHP unit. Therefore, the total heat production can be considered as equivalent to the sum of their productions which, in turn, can be evaluated starting from the natural gas consumption. Natural gas from the network and the fraction feeding the CHP unit ($m_{ng,tot}$ and $m_{ng,CHP}$, respectively) are available data. In order to find the actual demand, this production has been reduced by the distribution losses $\eta_{distribution}$ and heat exchangers losses $\eta_{th,exchange}$ (assumed as 0.98 and

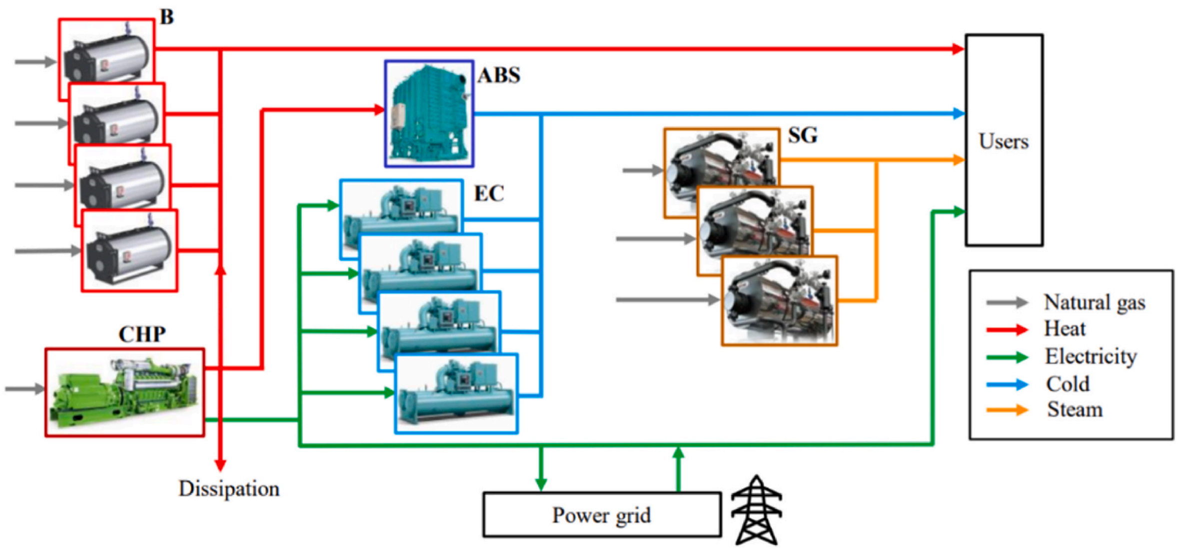

Fig. 5. Schematic representation of the hospital thermal power station with the energy conversion units and energy vectors. Heating and cooling flows are collected and sent to the district heating and cooling loops toward the buildings. B: boilers. CHP: Combined Heat and Power. ABS: absorption chiller. EC: electric chillers. SG: steam generators.

Table 3
Technical parameters of the conversion units in the thermal power station. The nominal output power is normalized with respect to the CHP electrical output for confidentiality reasons.

Parameter	Boiler	CHP plant	Absorption chiller	Electric chiller	Steam generator
Number of units	4	1	1	4	3
Input	Natural gas	Natural gas	Heat	Electricity	Natural Gas
Output	Heat	Electricity | Heat	Cold	Cold	Steam
Nominal output [–]	2.6	1 | 0.93	0.52	1.6	1.3
Nominal efficiency [–]	0.92	0.447 | 0.422	0.77	2	0.87
Supply temperature [°C]	93	93	6	6	–
Return temperature [°C]	73	73	12	12	–
Supply pressure [bar]	–	–	–	–	3

Table 4
Sensors installed for monitoring the heating load.

Unit	Energy flow	Monitored variables	Sensors installed
CHP	Heat output High-temperature dissipated heat Low-temperature dissipated heat	Supply/return temperature and volumetric flow rate	Ultrasonic flow meter (E + H Proline Prosonic Flow 91 W), × 2 Pt100 thermometer (E + H RTD omnigrad TST310)
Boilers 1–4	Heat output	Supply/return temperature and volumetric flow rate	Ultrasonic flow meter (E + H Proline Prosonic Flow 91 W), × 2 Pt100 thermometer (E + H RTD omnigrad TST310)

Table 5
Sensors installed for monitoring the cooling load.

Unit	Energy flow	Monitored variables	Sensors installed
Absorption chiller	Heat input Cooling energy output	Supply/return temperature and volumetric flow rate	Ultrasonic flow meter (E + H Proline Prosonic Flow 91 W), × 2 Pt100 thermometer (E + H RTD omnigrad TST310)
Overall	Overall cooling energy (including electric chillers)	Supply/return temperature and volumetric flow rate	Ultrasonic flow meter (E + H Proline Prosonic Flow 91 W), × 2 Pt100 thermometer (E + H RTD omnigrad TST310)

0.99, respectively, according to Ref. [32]), and by the inlet heat to the absorption chiller $E_{th,ABS}$ and to the steam boilers E_{SG} (assumed according to their activation). These steps are reported in Eqs. (1)–(3):

$$E_{th,B} = \left(m_{ng,tot} - m_{ng,CHP}\right) LHV\ \eta_B\ \eta_{distribution}\ \eta_{th,exchange} \tag{1}$$

$$E_{th,CHP} = m_{ng,CHP}\ LHV\ \eta_{th,CHP}\ \eta_{distribution}\ \eta_{th,exchange} \tag{2}$$

$$E_{th,tot} = E_{th,B} + E_{th,CHP} - E_{th,ABS} - E_{SG} \tag{3}$$

where LHV is the fuel lower heating value, η_B is the boiler nominal efficiency and η_{CHP} is the CHP thermal efficiency.

4.3.1.2. Cooling demand. The cooling demand is met by the electric chillers and the absorption chiller. In order to evaluate the production of the electric chillers, the electrical energy consumption profile (i.e. the sum of the electrical energy bought from the grid and self-consumed from the CHP production) of the whole hospital is analyzed. A base-load for electric appliances is identified by the average load in the period from September to May, when space cooling is not active. The surplus electrical energy in the remainder of the year (June to August) is assumed to be the input to the electric chillers. This input is then converted into cooling energy in order to estimate the electric chiller production $E_{C,EC}$ in Eq. (4). The absorption chiller production $E_{C,ABS}$ is instead evaluated according to its activation as in Eq. (5).

Table 6
Sensors installed for monitoring the electricity load.

Unit	Energy flow	Monitored variables	Sensors installed
Power grid connection	Electrical energy sold to grid Electrical energy purchased from grid	Voltage, current, power factor	Enel Distribuzione Actaris
CHP	Electricity output	Voltage, current, power factor	High Precision Multifunction Electronic meter (Telematica sistemi MT860-MID)

$$E_{c,EC} = EER_{EC} \cdot E_{el,EC} \cdot \eta_{c,distribution} \cdot \eta_{c,exchange} \tag{4}$$

$$E_{c,ABS} = EER_{ABS} \cdot E_{th,ABS} \cdot \eta_{c,distribution} \cdot \eta_{c,exchange} \tag{5}$$

with EER_{EC} and EER_{ABS} being the energy efficiency ratios of the electric and absorption chillers, respectively. They are assumed constant, similarly to the assumptions adopted in the previous paragraph concerning the thermal efficiencies.

The total cooling demand is represented by the sum of electric and absorption chillers cooling production reduced by the distribution and heat exchangers losses, as in Eq. (6):

$$E_{c,tot} = \left(E_{c,EC} + E_{c,ABS}\right) \eta_{c,distribution}\ \eta_{c,exchange} \tag{6}$$

4.3.1.3. Electrical demand. The electrical energy demand E_{el} is evaluated starting from the net energy exchanged with the power grid and that produced by the CHP ($E_{CHP,el}$). In order to evaluate the demand profile, the sum of these terms is then reduced by the electrical energy that feeds the electric chiller previously evaluated and by the losses due to distribution. These steps are represented in Eqs. (7) and (8):

$$E_{el} = \left(E_{grid,bought} + E_{CHP,el} - E_{grid,sold} - E_{el,EC}\right)\eta_{el,distribution} \tag{7}$$

$$E_{CHP,el} = m_{ng,CHP}\ \mathrm{LHV}\ \eta_{el,CHP} \tag{8}$$

4.3.2. ShoTS daily forecast

The disturbances for the ShoTS module consist of the power demand of all energy vectors for a prediction horizon of 48 h, sampled every 15 min. These values are forecasted by means of a multi-output Artificial Neural Network with the following input features.

- Time features (hour, day, week and derivate trigonometric functions of the time instant that represent the elaboration of daily and intraday trends of the considered variables [33]);
- Demand of the previous 48 h sampled every 15 min.

The Artificial Neural Network is trained with the data collected from the plant after the installation of the measurement equipment described in Section 4.2. The full procedure for the development of this method is reported in Refs. [33,34]. According to the MPC concept, the forecast is updated and used by the ShoTS module every new algorithm run, i.e. every 15 min.

4.4. Controller implementation and communication protocol

Nowadays, efficiently running utility plants needs a real-time data analysis, automatic data export processes, state-of-the-art control units and, above all, a large amount of data. All features and attributes were missing in the BaU control system.

For this reason, a new, integrated and centralized SCADA system was installed and tested for managing energy production and dispatchment to the hospital utilities. In detail, all control and data logging units were remoted in the control room. For this, the following tasks were carried out.

- Upgrading of the existing BMS software (from SE TAC Vista to SE EcoStruxure Building Automation);
- Installing new control units (SE EcoStruxure Building SmartX Server AS-P);
- Reviewing and updating the control logics of the CHP and ABS;
- Integrating the new control units in the SCADA system.

As for the MPC implementation, it was decided to run the MPC separately from the BMS, in order to guarantee continuity of service by maintaining a physical separation between the two systems. In this way, the MPC runs in parallel with the BaU control logic of the hospital thermal power station. A dedicated computer (with a resilient power supply unit) to run the MPC was installed in the site and the real-time communication between the BMS and the MPC was set up as in Fig. 6. The algorithm receives the disturbance forecast (Section 4.3) and data regarding the actual operation of the plants from the BMS. The algorithm calculates the optimal set-points of the flow variables and sends them to the BMS, which uses them to control the equipment in the real system. The variables that can be actively controlled through this configuration are.

- Activation and modulation of the CHP;
- Number of active boilers (for maintaining the supply temperature of the district heating);
- Activation of the ABS.

The electric chillers are activated in cascade to maintain the supply temperature of the cooling loop.

Real-time local data are transferred between BMS and MPC through the standard industrial protocol Modbus TCP, considering the technical specifications of the BMS software. In detail, the BMS is configured as a Modbus TCP server, sharing variables with read and write access to external clients. The MPC, running on the dedicated computer in the same network of the BMS, is the only client with authorized access. Additionally, a connection to the utility network was implemented, in order to be able to access the MPC from remote locations (e.g. for maintenance, debugging and supervision purposes).

As stated above, the primary requirement for the exploitation of the MPC strategy is that continuity of service is guaranteed. This is paramount for any integrated energy system, but it is even more important for critical systems such as hospitals. In this respect, apart from the physical separation between the MPC and BaU control logic, an additional backup security logic was installed in the BMS. This watchdog control logic switches back to the BaU operation written within the BMS as soon as any issue of the MPC is detected (e.g. the MPC does not reach convergence). In this way, the energy delivery is guaranteed, even if not optimal. Meanwhile, the detected algorithm error can be solved remotely by the system operator and the MPC control can be restored.

The MPC implementation as well as the reliability of the backup watchdog control logic were verified during the debugging procedure described in Section 4.5.

4.5. Debugging and testing procedure

The hardware implementation of the MPC and the setup of the communication was carried out with the help of the local system integrator, responsible for the implementation of the Modbus TCP server. In parallel, the dedicated computer with the client software for real-time data exchange and optimization was installed (Section 4.4).

The validation of the architecture and data exchange was verified during the commissioning phase by the system operator and system integrator. In this phase, data exchange between BMS and MPC was

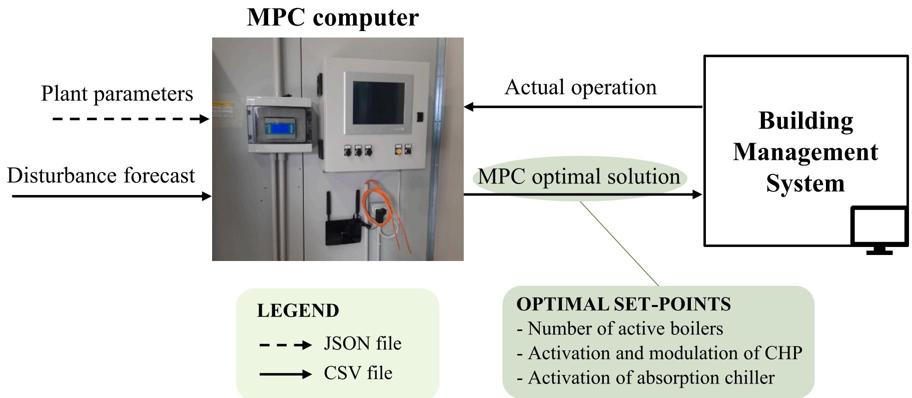

Fig. 6. Communication between the MPC computer for the control algorithm and the existing BMS of the hospital.

verified to ensure that all the variables were correctly configured, and writing access was guaranteed for the set-points identified.

As is well-known, a key aspect was to maintain a high level of reliability and to guarantee continuity of service, due to its critical importance for the hospital. To achieve this, the writing procedure of the new set-points was firstly tested offline (i.e. with the equipment locally disconnected from the BMS control and the algorithm running in the background). More in detail, the MPC controller was set up to carry out the real-time optimization based on the data exchanged with the BMS. After the first implementation, a debugging procedure was implemented in order to monitor the system and, when necessary, tune the parameters related to the physical models adopted during the optimization process. This was implemented through the analysis of the log data produced by the MPC algorithm, which were saved in local files and sent to a centralized database of the system operator for data analysis.

The main issues encountered and solved during the implementation and debugging phase are reported in Table 7. Finally, after solving the derived issues, the robustness of the algorithm and of the communication protocols was verified. Hence, the writing procedure of the new set-points was transferred online: the MPC set-points were written in the BMS and sent to actually control the equipment. The positive results in these final tests concluded the validation procedure.

5. Results and discussion

This section presents the experimental results obtained from the data collection campaigns in the hospital test site. The data collected during BaU operation ranges from January 2021 to February 2022, while data collected with the MPC are related to the period March 2022 to December 2022 (Fig. 3).

Firstly, the benchmark is defined through linear regression, in order to prevent the comparison between different operating modes being affected by external conditions. Then, the BaU and MPC operation are compared. Finally, the overall performance of the new strategy is evaluated after normalizing the BaU and MPC results with respect to the benchmark.

5.1. *Definition of the benchmark*

The process of defining the benchmark of the thermal power station after the first monitoring campaign was carried out considering the test site characteristics and the energy plant architecture. On the one hand, no structural or substantial modifications were made to the energy plant configuration. On the other hand, to achieve accurate comparisons between different periods, it is necessary to isolate the effect external factors have on the energy data, e.g. plant availability and weather conditions, which influence the hospital energy needs.

The procedure generally adopted by the utility consists of determining the benchmark of the integrated energy system independently of the changes in the external environment (outdoor temperature, variation of heated volume, etc.). Regression analysis was introduced on the test site, in order to apply an unbiased comparison between different control strategies (in this case, BaU vs. MPC), since all the external and non-controllable effects have been isolated.

The procedure to obtain this benchmark for comparison consists of the following steps.

1. Identification of the benchmark energy parameters;
2. Determination of the independent external variables to be used for the regression process;
3. Elaboration of the regression mathematical model;
4. Normalization of the benchmark energy parameters with respect to the related independent external variables.

In this work, linear regression on the thermal power station

Table 7
Most frequent operating issues of the MPC controller implemented in the real site and related solving action.

Issue	Cause	Action
Absence of data in remote database	Issues with remote database	Contact IT Support
	Gateway offline	Contact local plant operators to check connection and reset gateway
	PC offline	Contact local plant operators to check PC status and reset it
	No modbus communication	Contact local plant operators to check ethernet cables. Eventually reset PC remotely
No optimization results produced	Error in data exchange	Correction of data exchange format
	MPC scheduler stopped	Identification of bug in MPC code and restart of scheduler
Optimization results not correct	MPC algorithm not correctly tuned	Analysis of results and identification of incorrect parameter to be changed

Table 8
Acceptance criteria of the regression analysis for the definition of the benchmark operation.

Parameter	Description	Acceptance criteria
R^2	Coefficient of Determination of regression	>0.75
CV RMSE	Coefficient of Variation of Root Mean Square Error	<0.2
STAT T	t-statistic of each independent variable	>2
MBE	Mean Bias Error, i.e. average value of residuals between real value and predicted by model	<0.005%

production and hospital energy needs was elaborated, in compliance with the acceptance criteria defined in Table 8.

Considering the type of application and the test-site characteristics, the following assumptions were made.

- static variations on energy consumption are not considered, as no major efficiency/architectural interventions were made on the test site;
- variations in hospital room occupancies and heated volume were neglected due to their limited impact and the insufficient statistical accuracy of the available data;
- the standard operation of the CHP was at a fixed point (fixed electricity output), so its benchmark electricity production is only affected by plant availability (i.e. when the plant is under maintenance or is switched off for technical reasons, the availability is set to zero to eliminate the influence of these particular conditions on regression);
- steam consumption was not considered, as the steam circuit is operated independently from the other energy networks.

The external variables used for regression are the heating degree days HDD (calculated with a reference temperature of 20 °C), the cooling degree days CDD (calculated with a reference temperature of 18 °C), and the availability of the CHP plant. The obtained linear regression models are reported in Eqs. (9)–(13), with a_i, b_i and c_i being the regression coefficients to be determined:

$$E_{CHP} = a_1 \cdot h_{CHP} + b_1 \tag{9}$$

$$H_{CHP} = a_2 \cdot h_{CHP} + b_2 \cdot \mathrm{HDD} + c_2 \tag{10}$$

$$NG_{CHP} = a_3 \cdot h_{CHP} + b_3 \tag{11}$$

$$NG_{th} = a_4 \cdot \mathrm{HDD} + b_4 \tag{12}$$

$$C_{ABS} = a_5 \cdot h_{CHP} + b_5 \cdot CDD + c_5 \tag{13}$$

where.

- E_{CHP} is the CHP electricity production;
- h_{CHP} is the CHP availability;
- H_{CHP} is the CHP useful heat production (including heat sent to the ABS);
- NG_{CHP} is the natural gas consumption of the CHP;
- NG_{th} is the natural gas consumption for heating use;
- C_{ABS} is the cooling production of the ABS;

The results of the benchmark analysis, applied to the monthly data collected from the previous year, are summarized in Table 9.

Considering the results of the regression, the only regression model underperforming with respect to the thresholds identified is the ABS cooling production model, which is based on the CHP operating hours and the cooling degree days as independent variables. This lack of precision could be due to the fact that the ABS was manually controlled over the analyzed period. In other words, its activation was not directly managed only on the basis of the external temperatures but also on other hardly quantifiable factors (e.g. end of thermal season, contractual constraints with the hospital client, etc.). Nevertheless, due to the fact that the ABS will be automatically controlled by the MPC, this regression is assumed as the benchmark for comparison. Moreover, according to the generally accepted procedure for the definition of the benchmark, the energy saving is calculated with reference to the lower boundary of the variance [35]. Since the variance in the ABS regression is higher, the saving for this element is underestimated, providing a worst case scenario for comparison.

Table 9
Regression parameters of the definition of the benchmark operation.

Parameter	R^2 score	CV RSME	Stat t	MBE
CHP electricity production	0.965	0.031	16.690	0.000
CHP heat production for heating use	0.942	0.148	12.720	0.000
CHP gas consumption	0.997	0.010	56.334	0.000
Natural gas consumption for heating use	0.801	0.211[a]	5.366–3.072	0.000
ABS cooling production	0.735[a]	0.718[a]	4.863–1.202[a]	0.000

[a] Values outside threshold (see Table 8).

5.2. Monitoring results

A complete and detailed two-year dataset is available to compare the BaU (2021) and MPC (2022) operation. The data collected are sampled every 15 min and, thus, provide insights on the detailed real-time operation of all plants. While analyzing these data, it is possible to verify the conditions in which the MPC demonstrates the best capabilities or major criticalities, as well as to see the difference in how the two management strategies operate in comparable periods. Some examples of this investigation are described below.

Fig. 7 illustrates the daily high-temperature and low-temperature dissipated heat from the CHP, as well as the heat supplied to the ABS in June. A comparison is reported between the two operating strategies. The data are normalized with respect to the maximum heat value of the selected period. The first few days of the month are excluded because the CHP was shut down, probably due to maintenance or unavailability, at the beginning of June 2021. While in the BaU operation the ABS is subject to more frequent shut-downs, the MPC manages to use the ABS unit to its maximum potential. This comes together with a notable reduction in high-temperature dissipation, most likely because more useful heat is recovered from the engine.

Fig. 8 shows a similar trend in the improved management of the CHP and ABS. While in a few days in October 2021, the chiller was shut down even though the CHP was still operating (and dissipating heat), in 2022 the MPC decided to keep it in operation. The outdoor conditions of the two periods were comparable.

Therefore, it can be seen that the MPC outperforms the a priori control logics generally used by utilities to operate integrated energy systems, and provides a real-time optimal performance based on actual conditions. This is particularly evident in mid-seasons, when weather is extremely variable and difficult to predict, and in summer.

5.3. Comparison between BaU and MPC operation

The most relevant results that can be drawn from this test site regard the overall long-term performance of the MPC, as it can verify if the original control requirements were met.

Table 10 reports the efficiency parameters of the CHP calculated on a yearly basis with the two operating strategies. It can be noted that the MPC is able to drive the CHP to more efficient operating ranges compared to the BaU operation, as both electrical and thermal efficiency increase by more than 1.4%. This means a higher fuel utilization factor and, consequently, leads to primary energy saving and lower carbon emissions. In addition, the requirement for high efficiency cogeneration (fuel utilization factor higher than 75%) is reached to a higher extent. This is expected to lead to higher incentives.

These benefits are achieved thanks to an overall 33.8% reduction in heat dissipation from the CHP engine, as shown in Table 11. The most part of this reduction is realized with reference to the high-temperature heat, which is recovered and used in the ABS or in the district heating. Higher savings could be obtained if low-temperature heat were further recovered e.g. for domestic hot water production (currently not included as a separate feature).

The operation of the ABS, with specific reference to the cooling

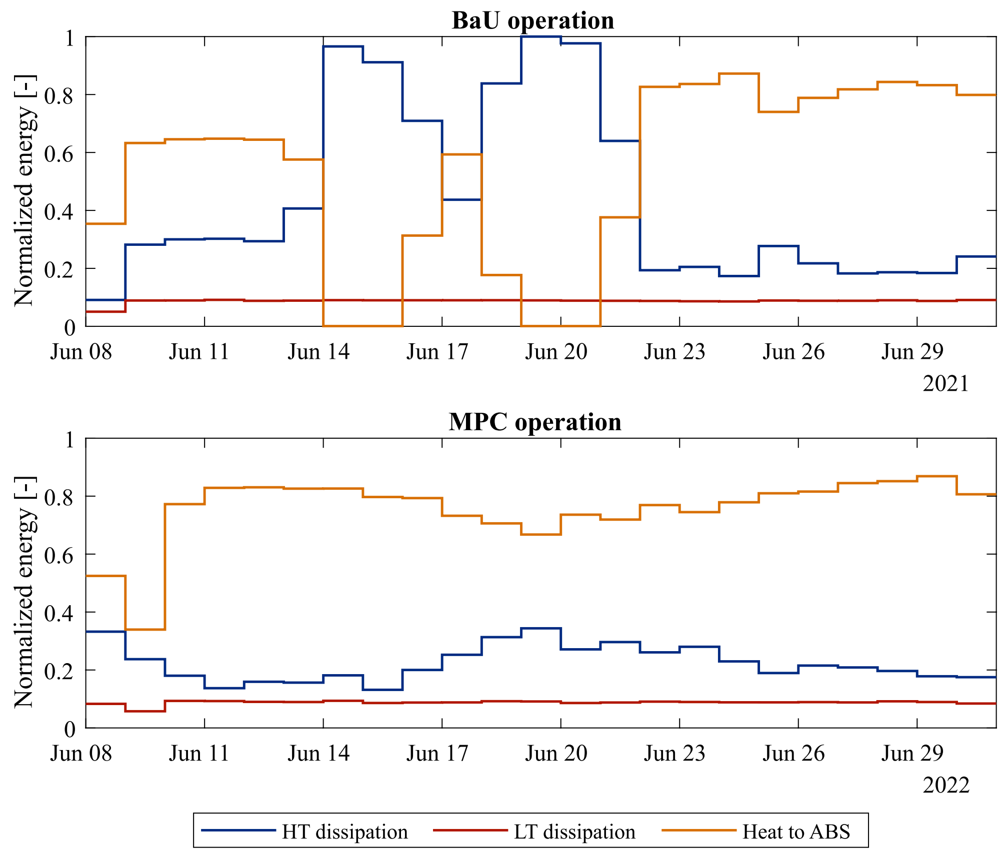

Fig. 7. Comparison of the daily high-temperature (HT) and low-temperature (LT) dissipated heat and heat to the absorption chiller (ABS) in the two operating strategies in June. The data are normalized with respect to the maximum heat value of the selected period, for confidentiality.

degree days, in the two operating modes, is reported in Table 12. It can be noted that the MPC is more efficient in fulfilling the cooling requirement, as the cooling energy produced for a given amount of CDD is lower. In addition, the ratio between the cooling energy provided by the ABS and the running time increased in the new operating strategy, confirming that the unit operates more efficiently. Despite this, the share of cooling energy provided by ABS decreased if compared with the total cooling load. This is because, with the pandemic under control, hospitals are returning to their normal activities, with an increase in outpatient appointments and, consequently, an increase in base load. Moreover, the cooling degree days increased by 45%, as 2022 was on average warmer than 2021. Since the size of the ABS is not sufficient to cover the overall hospital demand, the increased load in 2022 was covered by the ABS to a smaller extent. However, the data demonstrates that a bigger ABS, when operated efficiently by the MPC, would have also increased its cooling share.

Finally, the key economic and energy drivers for the operation of this integrated energy system are compared in Table 13. Three concomitant benefits were achieved: (i) a slightly lower natural gas consumption, (ii) a great reduction in the electricity purchased from the grid and (iii) an increase in the energy efficiency credits awarded to the CHP primary energy saving. These factors led to a lower dependency of this system on the power grid and to higher revenues for the system operators. Furthermore, the injection of electricity into the grid remained fairly stable. It was concentrated mainly during night hours, when the hospital demand was lower. This further demonstrates the capability of the MPC to operate the CHP in the most profitable way.

It is also highly relevant to state that these experimental results, obtained though field tests in an operational (and highly critical) test site, are in accordance with the results obtained in the simulation phase. Indeed, similar trends in terms of (i) reduced withdrawal from the grid, (ii) reduced dissipation from the CHP and (iii) increased energy efficiency credits were obtained in the MiL case study (Section 3). It is therefore demonstrated that the methodology presented in this work is reliable, as it developed and demonstrated an original smart controller for an integrated energy system with a high level of security and efficiency.

6. Conclusions

This work presented a Model Predictive Controller (MPC) developed for the integrated energy system of a hospital test site in Italy. The controller operates with two time scales, controlling the system in real-time while also performing yearly scheduling. The algorithm was designed based on the site requirements and firstly verified in a simulation environment. Then, it was implemented in the real case study according to well-defined tasks: (i) installation of monitoring equipment to collect data on all energy flows (ii) setup of new hardware equipment (i.e. a dedicated computer); and communication protocols (i.e. open protocols to easily exchange data and files with the existing equipment); (iii) setup and debugging of the algorithm on the new hardware; (iv) verification of its reliability and implementation of a watchdog control logic for service security. Finally, data collection was carried out for two operating years: one year with the business-as-usual management and almost one year with the MPC management.

The smart controller, implemented and tested in the operational case study, met all the requirements initially defined. In particular, the key quantitative results of this activity can be summarized as follows.

- The MPC improved the management of the Combined Heat and Power unit by increasing the fuel utilization factor by 1.4% and reducing overall dissipation by 34%;

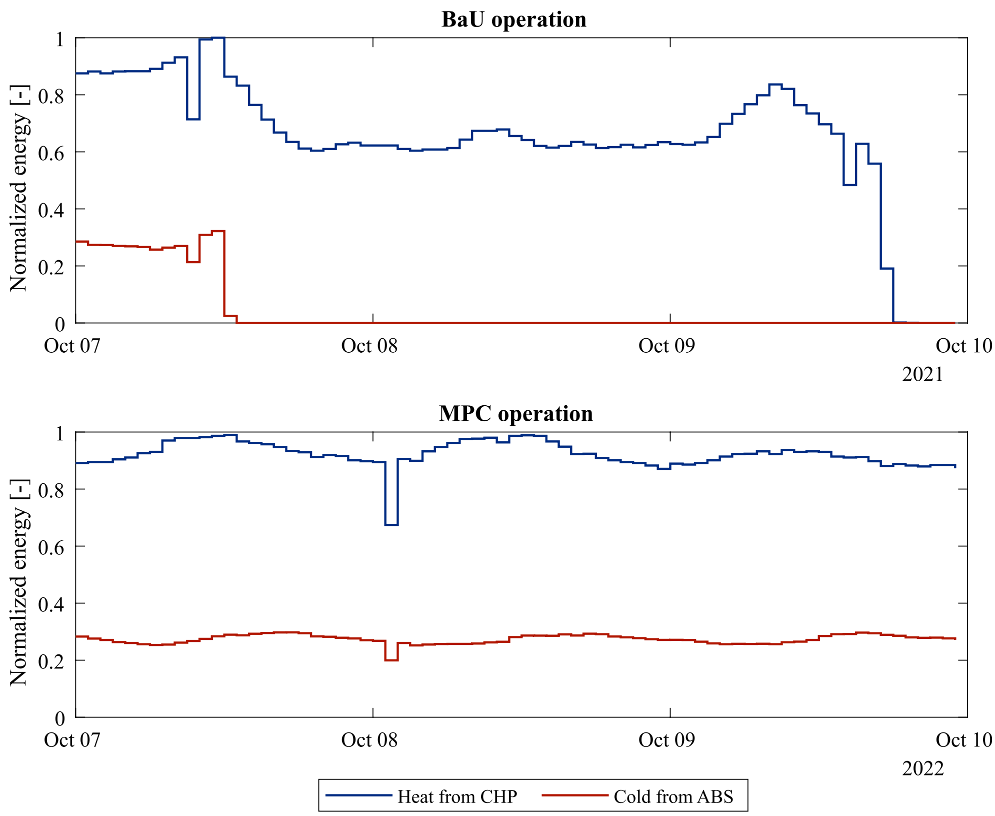

Fig. 8. Comparison of the heat from the CHP and heat to the ABS in the two operating strategies for some days in October. The data are normalized with respect to the maximum heat value of the selected period, for confidentiality.

Table 10
Comparison of efficiency parameters of the CHP in the BaU and MPC operation.

	Electrical efficiency		Thermal efficiency		Fuel utilization factor	
BaU (2021)	0.432		0.347		0.779	
MPC (2022)	0.438	+1.4%	0.353	+1.7%	0.790	+1.4%

Table 11
Comparison of heat dissipation from the CHP in the BaU and MPC operation. The values are normalized with respect to the overall dissipated heat in 2021, for confidentiality.

	High-temperature dissipated heat [−]		Low-temperature dissipated heat [−]		Overall dissipated heat [−]	
BaU (2021)	0.73		0.27		1	
MPC (2022)	0.40	−45.2%	0.26	−3.7%	0.66	−34.0%

Table 12
Comparison of the absorption chiller operation in the BaU and MPC operation.

	% variation MPC vs. BAU
Total cooling production/CDD	−16.6%
ABS cooling production/ABS running time	+25.0%
ABS cooling production/Total cooling production	−13.8%
CDD	+45.6%

- A higher portion of heat was recovered from the engine and fed to the absorption chiller, allowing this unit to be exploited to a greater extent (+25% compared to its running time);
- The three main economic parameters that drive the management of the integrated energy system were improved: natural gas consumption was reduced by 0.15%, electricity purchased was reduced by 21.49%, and the gain from incentives was enhanced by 1.18%.
- Relevant information can be drawn from the investigation of the datasets from two years of field tests.

Table 13
Comparison of the economic drivers in the MPC operation with respect to the BaU operation.

	% variation MPC vs. BAU
Natural gas consumption	−0.15%
Purchase of electricity from grid	−21.49%
Energy efficiency credits	+1.18%

It is also worth noting that the whole methodology, from the conceptualization of the control structure, to its simulation, to its testing in the operating environment, proved to be successful, as comparable results were obtained in the two verification phases. Most importantly, the reliability of the proposed control solution, as well as the backup control logics, were demonstrated in an extremely challenging site. It is well-known that hospitals provide a critical service that must not be subject to interruptions or other issues. Hence, demonstrating a reliable control solution that does not jeopardize the service and simultaneously guarantees optimal management can be considered a significant finding. This methodology and control solution may be safely extended to the integrated energy systems of other sites, regardless of their criticalities, leading to additional energy saving.

Apart from further data collection and investigation in this test site, future studies will be dedicated to enhancing the long-term accuracy and applicability of the proposed MPC controller. For instance, alternative methods to forecast the energy demands over the year will be tested, e.g. through detailed building modeling. In addition, the performance of this solution in case studies with short-term and long-term storage technologies, as well as with other energy vectors, will be evaluated.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Nomenclature

E: energy [MWh]
C: cooling energy [MWh]
EER: Energy Efficiency Ratio [−]
H: heat [MWh]
h: plant availability [h]
LHV: fuel lower heating value [MWh kg^{-1}]
NG: natural gas consumption [kg]
m: mass [kg]
η: efficiency [−]

Subscripts

c: cooling
el: electricity
ng: natural gas
th: heating

tot: total

Acronyms
ABS: Absorption chiller
B: Boiler
CF: Computational Feasibility
CHP: Combined Heat and Power
CSV: Comma Separated Value
EC: Electric chiller
IES: Integrated Energy System
JSON: JavaScript Object Notation
LoTS: Long-Term Supervisory module
MiL: Model-in-the-Loop
MPC: Model Predictive Control
MTS: Multiple Time Scale
ShoTS: Short-Term Supervisory module
SG: Steam generator