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A cost-optimal predictive operation scheme for sector-coupled energy plants with start-up delays and start-up costs ⋆

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Abstract: In this work we present a cost-optimal energy management scheme for sector-coupled energy plants, focusing on systems that enable gas-to-electricity, gas-to-heat, and power-to-heat conversions. To capture realistic operational challenges, the considered system model incorporates dynamic constraints, including start-up delays and off-time-dependent start-up costs. By accounting for the impact of these factors, we demonstrate on a case study that they can significantly reduce overall operational costs. The energy management problem is cast as a mixed-integer nonlinear programming (MINLP) problem, which is then solved within a model predictive control (MPC) framework. The proposed approach provides a structured methodology for real-time energy management, enhancing energy efficiency while minimizing costs.

Keywords: sector-coupling, energy management, mixed integer nonlinear programming, model predictive control.

NOMENCLATURE

Abbreviations

CHP	Combined heat and power.
ESU	Electricity storage unit.
GB	Gas Boiler.
HP	Heat pump.
TSU	Thermal storage unit.

Parameters

α_{chp}	Coefficient for the correlation between electrical and thermal output of the CHP.
η^{el}_{chp}, η^{he}_{chp}	Electrical/thermal efficiency of the CHP.
η_c, η_d	Charging/discharging efficiency of the ESU.
η_{ch}, η_{dch}	Charging/discharging efficiency of the TSU.
η_{gb}	Thermal efficiency of the GB.
μ^{el}, μ^{he}	Self-discharging rate of the ESU/TSU.
COP	Coefficient of performance of the HP.

Variables

$P_{dem}(t)$	Electrical demand.
$Q_{dem}(t)$	Thermal demand.
$c_{el/gas}(t)$	Electricity/gas prices.
$CS_h(t)$	Boolean variable for cold start-up status of the unit $h = \{chp,\ gb,\ hp\}$.
$D^{SU}_h(t)$	Boolean variable for start-up delay of the unit $h = \{chp,\ gb\}$.
$g^{in}_{chp/gb}(t)$	Gas input to the CHP/GB.
$HS_h(t)$	Boolean variable for hot start-up status of the unit $h = \{chp,\ gb,\ hp\}$.
$P_{buy}(t)$	Purchased electricity.
$P_{c/d}(t)$	Charge/discharge rate of the ESU.
$P_{chp}(t)$	Electrical output of the CHP.
$P^{in}_{hp}(t)$	Electrical power input to the HP.
$Q_{ch/dch}(t)$	Charge/discharge rate of the TSU.
$Q_{chp}(t)$	Thermal output of the CHP.
$Q_{gb}(t)$	Thermal output of the GB.
$Q_{hp}(t)$	Thermal output of the HP.
$SD_h(t)$	Boolean variable for shut-down status of the unit $h = \{chp,\ gb,\ hp\}$.
$SU_h(t)$	Boolean variable for start-up status of the unit $h = \{chp,\ gb,\ hp\}$.
$T^{on/off}_h(t)$	Integer variable for on/off-time duration of the unit $h = \{chp,\ gb\}$.
$U_h(t)$	Boolean variable for on/off status of the unit $h = \{chp,\ gb,\ hp\}$.
$W_{esu}(t)$	Electrical energy stored in the ESU.
$W_{tsu}(t)$	Thermal energy stored in the TSU.
$WS_h(t)$	Boolean variable for warm start-up status of the unit $h = \{chp,\ gb,\ hp\}$.

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1. INTRODUCTION

The urgent need for decarbonization has accelerated the integration of renewable energy sources and the adoption of sector coupling strategies (e.g., Khargonekar et al. (2024); Kroposki et al. (2020); Dall'Anese et al. (2017)). Sector-coupled energy plants enable efficient use of interconnected energy sources and sinks, reducing losses and supporting the transition to sustainable systems. However, their operation is challenging due to complex component dynamics, requiring robust energy management strategies.

Significant research has focused on optimizing the real-time operation of such plants. For instance, Alipour

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et al. (2014) proposed a mixed-integer linear programming (MILP)-based hourly scheduling of combined heat and power (CHP) units, while Sarlak et al. (2022) introduced a nonlinear optimization approach for energy hubs. Capacity planning has also been studied: Cao et al. (2018) applied data-driven stochastic programming, and Geng et al. (2020) combined capacity design with model predictive control (MPC) for scheduling.

MPC has seen increasing application in energy system operations (e.g., Schwenzer et al. (2021)), including electro-thermal microgrids (Rose et al. (2023)), hydrogen networks (Herrmann et al. (2024)), and district heating grids with terminal constraints (Rose et al. (2024)). Data-driven MPC approaches have also been investigated, including applications of Willems' Fundamental Lemma (Bilgic et al. (2022)) and its stochastic extension (Özmeteler et al. (2024)), as well as reinforcement learning-based strategies for real-time energy management (Yadollahi et al. (2024)).

While linear models are common in real-time scheduling, recent work explores nonlinear formulations for improved accuracy. For example, Akulker and Aydin (2023) developed a mixed-integer nonlinear programming (MINLP) model for multi-energy microgrids.

A key challenge in real-time scheduling is the inclusion of detailed operational constraints, such as start-up delays and time-dependent start-up costs. Though they increase complexity, omitting them leads to inaccurate cost estimates. Arroyo and Conejo (2004) and Morales-España et al. (2012) addressed these using MILP formulations including ramping limits and time-dependent start-up costs.

In this paper, we investigate the impact of start-up delays and time-dependent start-up costs on overall cost estimation and system operation. These factors are integrated into an optimization framework formulated as an MINLP problem by extending the formulations in Alipour et al. (2014). To enable computational efficiency in real-time scheduling, we employ an MPC scheme, which approximates a long time-horizon problem within a short prediction horizon. The optimization problem is solved using the global optimal MINLP solver *Couenne* (Belotti (2009)).

The main contribution of this paper is the proposal of a cost-optimal operation scheme for sector-coupled energy plants that explicitly takes into consideration start-up delays and time-dependent start-up costs of energy conversion units, which goes beyond existing formulations for representing start-up and shut-down procedures. A notable feature of our contribution is that the energy management problem is structured as an MINLP problem, which allows it to be solved within a receding horizon framework using MPC and thus enabling real-time energy management capabilities.

The remainder of this paper is organized as follows. Section 2 introduces the system setup and considered mathematical model. Section 3 presents an optimization problem encoding the energy management problem. Section 4 contains simulation results based on a realistic case study and, finally, in Section 5 we provide concluding remarks and outline potential future work.

2. MATHEMATICAL MODEL

We consider a sector-coupled energy plants comprising three types of energy conversion units, namely, a combined heat and power unit (CHP), a gas boiler (GB), a heat pump (HP) as well as two separate storage units, namely, an electricity storage unit (ESU) and a thermal

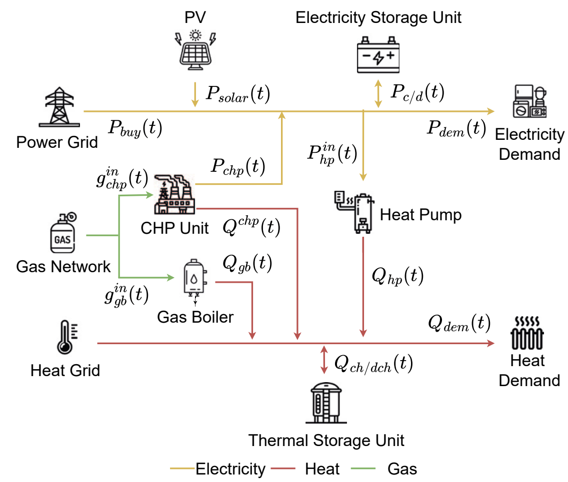

Fig. 1. Example of the type of considered sector-coupled energy plants.

storage unit (TSU). A schematic diagram illustrating an examplary interconnection among the system components is shown in Fig. 1. Detailed descriptions of each component and the associated operating constraints are as follows.

2.1 Energy conversion units

The Combined Heat and Power Unit (CHP). The CHP unit is modeled through an algebraic input-output relation that illustrates the correlation between the gas input $g^{in}_{chp}(t)$ and the resulting electrical output $P_{chp}(t)$ and thermal output $Q_{chp}(t)$, incorporating constant efficiency parameters η^{el}_{chp} and η^{he}_{chp}, i.e.,

$$g^{in}_{chp}(t) = P_{chp}(t)/\eta^{el}_{chp} + Q_{chp}(t)/\eta^{he}_{chp}. \tag{1}$$

Following Wang et al. (2019), we consider that there is a correlation between electrical and thermal outputs of the CHP unit, i.e.,

$$Q_{chp}(t) = \alpha_{chp} P_{chp}(t), \tag{2}$$

where α_{chp} denotes the power-to-heat ratio of the CHP.

Gas Boiler (GB). The GB is modeled using an algebraic input-output relation, illustrating the correlation between the gas input $g^{in}_{gb}(t)$ and the resulting thermal output $Q_{gb}(t)$, incorporating the efficiency parameter η_{gb}, i.e.,

$$g^{in}_{gb}(t) = Q_{gb}(t)/\eta_{gb}, \tag{3}$$

Heat Pump (HP). The HP is defined through an interrelation between the electricity input $P^{in}_{hp}(t)$ and the thermal output $Q_{hp}(t)$, quantified by the coefficient of performance (COP), i.e.,

$$Q_{hp}(t) = \mathrm{COP} P^{in}_{hp}(t). \tag{4}$$

2.2 Energy storage units

Electricity Storage Unit (ESU). The ESU is characterized by a differential equation, where the electrical energy undergoes charging at a rate $P_c(t)$ and discharging at a rate $P_d(t)$, governed by the efficiency parameters η_c and η_d, i.e.,

$$\begin{aligned} W_{esu}(t+1) =& W_{esu}(t)(1-\mu^{el}) \\ &+ (\eta_c P_c(t) - P_d(t)/\eta_d)\Delta t, \end{aligned} \tag{5}$$

where $W_{esu}(t)$ is the stored electrical energy and μ^{el} is the self discharging rate.

Thermal Storage Unit (TSU). Similar to the ESU, the TSU is defined by a differential equation, where thermal energy undergoes charging at a rate $Q_{ch}(t)$ and discharging at a rate $Q_{dch}(t)$, regulated by the efficiency parameters η_{ch} and η_{dch}, i.e.,

$$\begin{aligned} W_{tsu}(t+1) =& W_{tsu}(t)(1-\mu^{he}) \\ &+ \big(\eta_{ch} Q_{ch}(t) - Q_{dch}(t)/\eta_{dch}\big)\Delta t, \end{aligned} \tag{6}$$

where $W_{tsu}(t)$ is the stored thermal energy and μ^{he} is the self discharging rate.

We assume that the input-output efficiencies of the CHP, the GB, as well as the COP of the HP are constant. Analogously, the charging and discharging efficiencies of both the ESU and the TSU are constant.

2.3 Power balance equations

The power balance equations are introduced, ensuring that the difference between purchased or generated power and consumed power always matches the demand, i.e.,

$$\begin{aligned} P_{dem}(t) = & P_{buy}(t) + P_{solar}(t) + P_{chp}(t) \\ &+ P_d(t) - P_c(t) - P_{hp}^{in}(t), \end{aligned} \tag{7a}$$

$$Q_{dem}(t) = Q_{chp}(t) + Q_{hp}(t) + Q_{gb}(t) + Q_{dch}(t) - Q_{ch}(t), \tag{7b}$$

where $P_{dem}(t)$ and $Q_{dem}(t)$ denote electricity and heat demands, respectively. The signal $P_{solar}(t)$ is the photovoltaic generation and $P_{buy}(t)$ is the purchased electricity.

2.4 Start-up / shut-down variables

To define start-up / shut-down, and the operational status of the unit, the following constraints are introduced:

$$SU_h(t) = U_h(t)\big(1-U_h(t-1)\big), \tag{8a}$$

$$SD_h(t) = \big(1-U_h(t)\big)U_h(t-1), \tag{8b}$$

where $SU_h(t)$, $SD_h(t)$ and $U_h(t)$ denote the Boolean variables representing start-up, shut-down, and unit status, respectively and $h \in \{chp, gb, hp\}$ denotes the corresponding energy conversion unit. The variable $U_h(t)$ is 1, if the unit is online and 0 if the unit is offline. Similarly, the Boolean variables $SU_h(t)$ and $SD_h(t)$ take the value of 1 only when the unit starts up or shuts down, respectively; otherwise, they are 0 (see e.g., Alipour et al. (2014)).

2.5 On/off time constraints

Some of the energy conversion units, i.e. CHP, GB, are subject to on/off time limits (Alipour et al. (2014)). For example, some unit may not be able to come back online after a shut-down unless certain minimum time has passed. To quantify the on/off time durations of the units, the following variables are introduced:

$$\begin{aligned} T_h^{on}(t) =& \big(T_h^{on}(t-1)+1\big)U_h(t-1)U_h(t) \\ &+ \big(1-U_h(t-1)\big)U_h(t), \end{aligned} \tag{9a}$$

$$\begin{aligned} T_h^{off}(t) =& \big(T_h^{off}(t-1)+1\big)\big(1-U_h(t-1)\big)\big(1-U_h(t)\big) \\ &+ U_h(t-1)\big(1-U_h(t)\big), \end{aligned} \tag{9b}$$

where $T_h^{on}(t)$ and $T_h^{off}(t)$ are integer variables representing on and off time durations of the corresponding units, respectively, and $h \in \{chp,\ gb\}$.

To enforce the minimum on/off time limits of the units the following constraints are introduced:

$$\big(T_h^{on}(t-1) - X_h^{on} + \epsilon\big)\big(U_h(t-1) - U_h(t)\big) \geq 0, \tag{10a}$$

$$\big(T_h^{off}(t-1) - X_h^{off} + \epsilon\big)\big(U_h(t) - U_h(t-1)\big) \geq 0. \tag{10b}$$

where X_h^{on} and X_h^{off} denote the minimum on and off time limits of the corresponding unit $h \in \{chp,\ gb\}$. Specifically, in (10a), if the on-time duration is less than the on-time limit X_h^{on}, the unit cannot shut down. A similar restriction applies in (10b) for the off-time duration. The slack variable ϵ is chosen within the range $(0,1)$ to prevent the first terms in (10a) and (10b) from being zero, thereby mitigating numerical issues. The constraint (10b) accounts for the shut-down delay time of the h-th unit. However, an additional variable is required to represent start-up delays, which will be introduced in the next subsection.

2.6 Start-up delays

Certain units, such as the CHP or the GB, require a waiting period before producing power output after start-up, known as the start-up delay (Kim and Edgar (2014)). To incorporate these events into the problem, the following additional variables and constraints are introduced:

$$\big(X_h^D - T_h^{on}(t-1) - \epsilon\big)\big(U_h(t) - D_h^{SU}(t)\big) \geq 0, \tag{11a}$$

$$\big(T_h^{on}(t-1) - X_h^D + \epsilon\big)D_h^{SU}(t) \geq 0, \tag{11b}$$

$$D_h^{SU}(t) \leq U_h(t), \tag{11c}$$

where $D_h^{SU}(t)$ is a Boolean variable indicating the presence of a start-up delay and X_h^D represents the duration of the delay for the corresponding unit $h \in \{chp,\ gb\}$. According to these constraints the variable $D_h^{SU}(t)$ can be 1 only if the unit is online, i.e., $U_h(t) = 1$, and it has remained online for a duration of at least X_h^D, otherwise it is 0. As introduced in the previous subsection, the slack variable $\epsilon \in (0,1)$ is selected to prevent numerical issues.

2.7 Variables for different start-up costs

The start-up costs of the units vary based on their off-time duration (Kim and Edgar (2014)). To incorporate this dependency, the following constraints are introduced:

$$\big(X_h^{WS} - T_h^{off}(t-1) - \epsilon\big)HS_h(t) \geq 0, \tag{12a}$$

$$\begin{aligned} \big(T_h^{off}(t-1) - X_h^{WS} + \epsilon\big)&\big(X_h^{CS} - T_h^{off}(t-1) - \epsilon\big) \\ &WS_h(t) \geq 0, \end{aligned} \tag{12b}$$

$$\big(T_h^{off}(t-1) - X_h^{CS} + \epsilon\big)CS_h(t) \geq 0, \tag{12c}$$

$$HS_h(t) + WS_h(t) + CS_h(t) = SU_h(t), \tag{12d}$$

where $HS_h(t)$, $WS_h(t)$ and $CS_h(t)$ represent Boolean variables for hot start, warm start and cold start, respectively, for $h \in \{chp,\ gb,\ hp\}$. X_h^{WS} and X_h^{CS} denote the thresholds for the warm-start and cold-start costs, respectively. Similarly to the delay constraints, one of the variables $HS_h(t)$, $WS_h(t)$, $CS_h(t)$ can be 1 only if the unit is started up, i.e., $SU_h(t) = 1$, and the off-time duration of the unit has exceeded the corresponding threshold. Similarly, as in the previous subsections, the slack variable $\epsilon \in (0,1)$ is introduced to prevent numerical problems.

2.8 Capacity constraints

Each unit's power output is bounded by its minimum and maximum limits. Due to start-up delays of the CHP and GB, the corresponding constraints are given as follows:

$$D_{chp}^{SU}(t)P_{chp}^{min} \leq P_{chp}(t) \leq D_{chp}^{SU}(t)P_{chp}^{max}, \tag{13a}$$

$$D_{gb}^{SU}(t)Q_{gb}^{min} \leq Q_{gb}(t) \leq D_{gb}^{SU}(t)Q_{gb}^{max}. \tag{13b}$$

For the HP, these constraints are given by

$$U_{hp}(t)Q_{hp}^{min} \leq Q_{hp}(t) \leq U_{hp}(t)Q_{hp}^{max}. \tag{14}$$

The energy storage units are constrained by charging/discharging power limits and storage capacity. For the ESU, these constraints are defined as follows:

$$0 \leq P_c(t) \leq P_c^{max}, \tag{15a}$$
$$0 \leq P_d(t) \leq P_d^{max}, \tag{15b}$$
$$W_{esu}^{min} \leq W_{esu}(t) \leq W_{esu}^{max}. \tag{15c}$$

For the TSU, these constraints are given by

$$0 \leq Q_{ch}(t) \leq Q_{ch}^{max}, \tag{16a}$$
$$0 \leq Q_{dch}(t) \leq Q_{dch}^{max}, \tag{16b}$$
$$W_{tsu}^{min} \leq W_{tsu}(t) \leq W_{tsu}^{max}. \tag{16c}$$

To prevent simultaneous charging and discharging, the following constraints are imposed on the storage units:

$$P_c(t)P_d(t) \leq 0, \tag{17a}$$
$$Q_{ch}(t)Q_{dch}(t) \leq 0. \tag{17b}$$

The electricity purchase is constrained as follows:

$$0 \leq P_{buy}(t) \leq P_{buy}^{max}. \tag{18}$$

2.9 Ramp up/down constraints

To prevent rapid fluctuations, ramp constraints are incorporated for the CHP unit and GB as follows:

$$-R_{chp}^{down} \leq P_{chp}(t) - P_{chp}(t-1) \leq R_{chp}^{up}, \tag{19a}$$
$$-R_{gb}^{down} \leq Q_{gb}(t) - Q_{gb}(t-1) \leq R_{gb}^{up}. \tag{19b}$$

3. OPTIMIZATION PROBLEM

To minimize the operational costs of sector-coupled energy plants—including gas and electricity purchases, as well as start-up and shut-down costs—we propose to solve the following optimization problem:

$$\min_{g_{chp}^{in}, g_{gb}^{in}, P_{buy}, U_h} J(g_{chp}^{in}, g_{gb}^{in}, P_{buy}, U_h) :=$$
$$\sum_{t=0}^{T-1} \Bigg(\Big(\underbrace{c_{gas}(t)\big(g_{chp}^{in}(t) + g_{gb}^{in}(t)\big) + c_{el}(t)P_{buy}(t)}_{\text{gas and electricity purchase}} \Big)\Delta t$$
$$+ \underbrace{\big(c_h^{HS}HS_h(t) + c_h^{WS}WS_h(t) + c_h^{CS}CS_h(t)\big)}_{\text{off-time dependent start-up costs}}$$
$$+ \underbrace{c_h^{SD} \times SD_h(t)}_{\text{shut-down costs}} \Bigg), \tag{20a}$$

subject to

$$\left.\begin{array}{r} \text{Operating constraints (1)–(6),} \\ \text{Power balance constraints (7),} \\ \text{On/off time and delay constraints (8)–(11),} \\ \text{Off-time dependent start-up costs (12),} \\ \text{Capacity constraints (13)–(18),} \\ \text{Ramp up/down constraints (19),} \end{array}\right\} \tag{20b}$$

$$W_{esu}(T) = W_{esu}^{max}, \; W_{tsu}(T) = W_{tsu}^{max}, \tag{20c}$$

where T is the time horizon, $c_{gas}(t)$ and $c_{el}(t)$ are gas and electricity prices, c_h^{HS}, c_h^{WS} and c_h^{CS} denote off-time dependent start-up costs and c_h^{SD} denotes shut-down costs for the corresponding unit $h = \{chp, \; gb, \; hp\}$. The constraint (20c) is introduced to facilitate the recursive feasibility of the problem, imposing the storage units to be fully charged at the end of the time horizon. Note that both the cost function and constraints involve Boolean variables and nonlinearities, making this problem a mixed-integer nonlinear programming (MINLP) problem.

The optimization problem (20) is solved by using an MPC approach. That is, it is solved in a predefined time (or prediction) horizon and, by predicting the system's future behavior, it computes a sequence of control inputs that minimize the considered cost function. However, only the first control input from this sequence is applied. After implementation, the system's state is measured or estimated, and the optimization is repeated for the next shifted prediction horizon. This receding horizon strategy enables MPC to continuously adapt to changing conditions and correct prediction errors, enhancing its robustness against model inaccuracies and external disturbances (see e.g., Schwenzer et al. (2021)). Additionally, MPC can approximate the solution of an optimization problem with a longer time horizon by solving it over shorter prediction horizons, thereby reducing computational complexity for highly complex problems such as MINLPs.

4. CASE STUDY

We evaluated the proposed cost-optimal predictive operation scheme on a case study for which we considered 48 hours of energy demand data and a time-discretization with a time step of 1 hour. The optimization problem is formulated and solved using JuMP in Julia, with the *Couenne* solver employed to handle the MINLP formulation. *Couenne* is a global MINLP solver designed to avoid convergence to local minima and ensure global optimality, provided sufficient computational resources and problem tractability (see e.g., Belotti et al. (2009), Kronqvist et al. (2019)). To address the optimization problem in (20), we implement an MPC scheme with a 12-hour prediction horizon and a 1-hour sampling step. This horizon length accounts for on/off time limits, start-up delays, and time-dependent start-up costs. Terminal constraints are imposed on the energy storage units to support recursive feasibility. In our case study, these constraints helped maintain feasibility across time steps without the need for slack variables, provided the initial problem was feasible.

The parameters of the units are summarized in Table 1. Start-up costs depend on off-time duration: a hot start applies if it's under 3 hours, warm if between 3 and 8 hours, and cold if over 8 hours. The electricity and gas prices are illustrated in Fig. 2. Electricity prices are modeled as time-varying due to daily fluctuations, while gas prices are assumed constant for easier interpretation. The electricity and heat demands are depicted in Fig. 3, capturing their variations throughout the day. The data and code for this case study are available in Şen (2025).

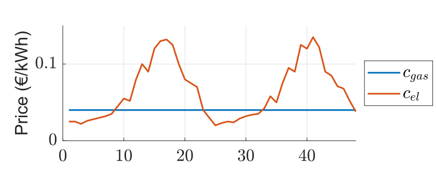

Fig. 2. Electricity and gas prices c_{el} and c_{gas}, respectively.

Simulations were conducted for two distinct scenarios to evaluate the impact of the proposed modeling assumptions. Scenario 1 includes start-up delay constraints, time-dependent start-up costs, energy purchase costs, and shut-down costs. The results for this scenario are illustrated

	Parameter	Value
CHP Unit	η_{chp}^{el}, η_{chp}^{he}	0.9
	α_{chp}	1.7
	P_{chp}	[50, 150] kW
	X_{chp}^{D} / X_{chp}^{on} / X_{chp}^{off}	$2h$ / $3h$ / $1h$
	$R_{chp}^{up/down}$	50 kW
	c_{chp}^{HS} / c_{chp}^{WS} / c_{chp}^{CS}	€ 30/50/100
	c_{chp}^{SD}	€ 20
Gas Boiler	η_{gb}	0.9
	Q_{gb}	[50, 250] kW
	X_{gb}^{D} / X_{gb}^{on} / X_{gb}^{off}	$3h$ / $4h$ / $2h$
	$R_{gb}^{up/down}$	100 kW
	c_{gb}^{HS} / c_{gb}^{WS} / c_{gb}^{CS}	€ 15/25/50
	c_{gb}^{SD}	€ 10
Heat Pump	COP	3
	Q_{hp}	[50, 250] kW
	c_{hp}^{HS} / c_{hp}^{WS} / c_{hp}^{CS}	€ 5/10/20
	c_{hp}^{SD}	€ 5
ESU	η_c, η_d	0.95
	μ^{el}	10^{-2}
	W_{esu}	[40, 400] kWh
	$W_{esu}(0)$	60 kWh
	P_c, P_d	200 kW
TSU	η_{ch}, η_{dch}	0.95
	μ^{he}	10^{-2}
	W_{tsu}	[60, 600] kWh
	$W_{tsu}(0)$	80 kWh
	Q_{ch}, Q_{dch}	200 kW
Power Grid	P_{buy}	[0, 400] kW

Table 1. Units and parameters used in the case study.

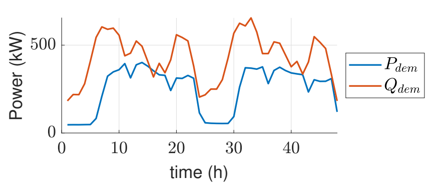

Fig. 3. Electrical and thermal power demands P_{dem} and Q_{dem}, respectively.

in Fig. 4, where positive bars represent power production and negative bars represent consumption. Total demand is obtained by summing both, ensuring power balance.

In Scenario 2, the start-up delay constraints were eliminated, and the cost function was simplified by replacing off-time-dependent start-up costs with time-independent start-up costs. This adjustment allows for evaluating the impact of reduced model complexity on overall costs and unit operation. The simulation results for this scenario are shown in Fig. 5. It is observed that in both scenarios the selection of energy production units is influenced by energy purchase prices to minimize purchase costs. In Scenario 1, the inclusion of time-dependent start-up costs incentivizes earlier unit start-ups. while in Scenario 2, units start later due to time-independent costs. Nevertheless, in both scenarios, units operate at minimum capacity rather than shutting down to reduce start-up and shut-down costs.

The total costs obtained for each scenario are summarized in Table 2. The results reveal that there is a 5.8% difference between the costs of Scenario 1 and Scenario 2, indicating that excluding start-up delay constraints and replacing time-dependent start-up costs with time-independent ones in the cost function lead to higher expenses. Since these

	Total cost value (48h)	Relative difference (%)
Scenario 1	€1292.9	-
Scenario 2	€1368.2	5.8 %

Table 2. Total cost values and relative difference for Scenarios 1 and 2.

costs are evaluated over a 48-hour period, the accumulated impact over an entire year could result in significant cost differences, highlighting the importance of accurately modeling start-up dynamics.

5. CONCLUSION

We have presented a cost-optimal operation scheme for sector-coupled energy plants which explicitly considers start-up delays as well as time-dependent start-up costs of energy conversion units. The operation scheme is cast as the solution of the receding horizon, mixed-integer nonlinear optimization problem (20), which enables real-time energy management. The performance of the proposed scheme was tested on a realistic case study which incorporates time-varying energy costs and demand patterns. The results demonstrate that incorporating start-up delay constraints and time-dependent start-up costs into the optimization process can lead to a significant reduction of the operational expenses.

Future work will extend the analysis to include uncertainties in demand and renewable generation and explore the scalability of the proposed approach for larger and more complex energy networks with state-dependent efficiencies.

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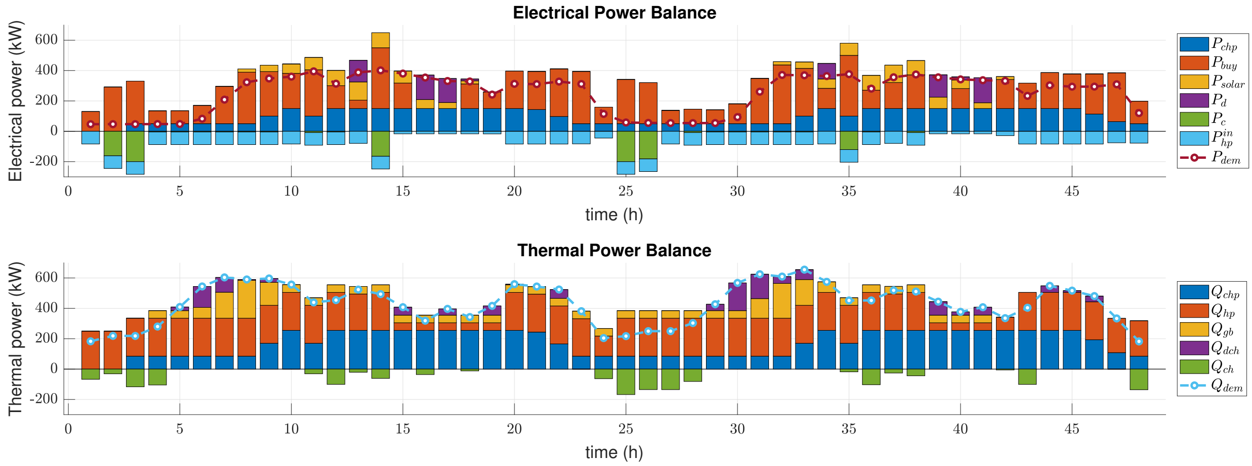

Fig. 4. Evolution of power balances for Scenario 1.

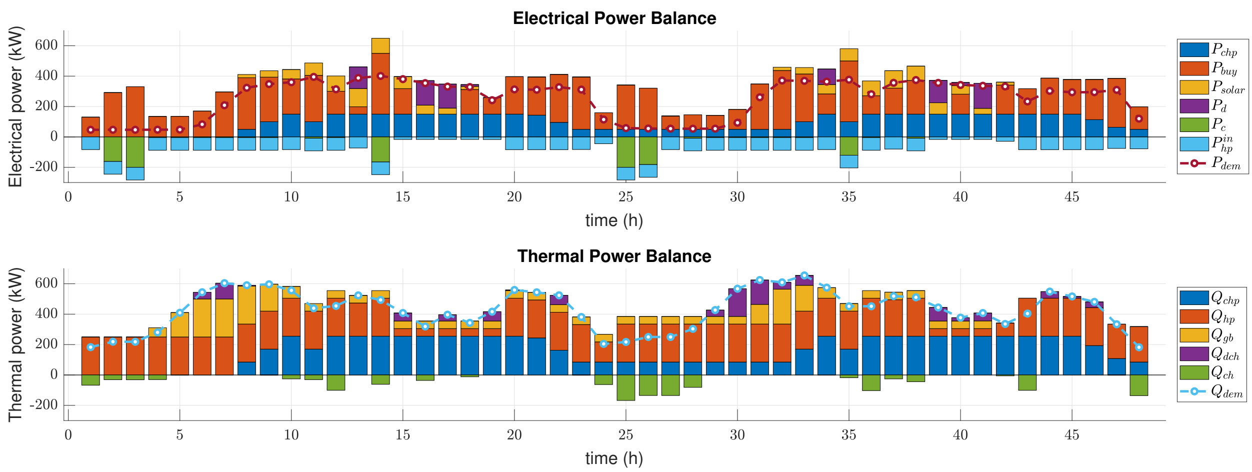

Fig. 5. Evolution of power balances for Scenario 2.

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