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Real-time rolling-horizon energy management of public laundries: A case study in HSB living lab

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A R T I C L E I N F O

Keywords:
CO2 emission reduction
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Rolling horizon
User's preferences

A B S T R A C T

Energy Management Systems (EMSs) play a vital role in managing energy consumption for both utilities and consumers. By using EMSs, utilities can influence on energy usage and ensure a more reliable and efficient grid operation, while consumers can make informed decisions about their energy consumption, leading to significant cost savings and reduced environmental impact. In this paper, a real-time rolling-horizon model is developed for managing energy consumption in public laundries aiming at minimizing energy costs, peak demand, and CO2 emission under the traditional Energy-Based Tariff (EBT) and the Power-Based Tariff (PBT). The developed model can not only reduce energy costs, peak demand, and CO2 emission by optimal task scheduling for washing machines and tumble dryers but also ensure users' preferences for a comfortable lifestyle. To demonstrate the effectiveness of the proposed EMS, several simulations were performed under different scenarios using real data and by a realistic case study in HSB living lab demonstration site. The simulation results reveal that implementing the proposed EMS can significantly decrease energy costs and peak demand in public laundries by 13.59% and 39.40%, respectively, when using the PBT tariff. However, the reduction in energy costs and peak demand is negligible when using the EBT tariff. Likewise, the results indicate that using the EMS and changing tariffs have a minimal impact on CO2 emissions reduction.

Introduction

Nowadays, electrical distribution grids are being upgraded to smart grids, which provide financial and technical benefits to both operators and consumers. In smart grids, time-variable electricity prices and economic incentives can be communicated to consumers by digital communication systems, with the goal of reshaping their load profiles [1]. However, it can be particularly challenging for end-consumers to schedule their electricity consumption under time-variable electricity prices without an energy management system (EMS) [2]. An EMS is an intelligent automation system that schedules the devices of the user to reduce energy costs and peak demand while adhering to the user's preferences for a comfortable lifestyle [3]. In literature, the development of EMS has been widely studied and is briefly outlined in the following.

The developed EMSs have mainly focused on solving day-ahead scheduling problems. For instance, in [4], a multi-objective optimization model has been proposed to schedule and manage various household devices and energy supply options in smart homes. In [5], an EMS for residential buildings has been developed to minimize energy costs and CO_2 emissions under different user preferences. In [6], an EMS has been developed that models different controllable household appliances including power-shiftable and time-shiftable devices to reduce electricity bills and generation costs without causing discomfort for users. The authors of [7] presented an EMS for smart buildings based on *meta*-heuristic optimization algorithms to alleviate peak demands and reduce electricity costs while minimizing user waiting time. In [8], an EMS has been implemented for microgrids including smart homes to minimize operating costs, emissions, and peak-to-average ratio under different pricing programs. In [9], distributionally robust hierarchical coordination for energy management of smart homes has been developed to minimize daily operation costs in a community of smart homes. In the developed EMS, thermal loads are locally triggered to be on/off by temperature conditions. Furthermore, a stochastic multi-objective EMS for smart homes has been proposed in [10] to minimize energy costs as the primary objective and maximize the thermal comfort of users as the second objective.

In addition to day-ahead EMS, some research has also focused on real-time EMS that uses feedback to modify and improve control signals

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Nomenclature

Indices and Sets

t	Index of time
i	Index of objective function
s	Index of scenarios
w	Index of washing machines
d	Index of tumble dryers
p	Index of programs.
S_W	Set of consumption scenarios for washing machine
S_D	Set of consumption scenarios for tumble dryer
N_W	Set of washing machines
N_D	Set of tumble dryers
N_T	Set of intervals within the rolling time window

Variables

PL_t	Load demand/ peak load of the public laundry
$PL^{peak}, \overline{PL_h}$	Daily/ hourly peak load of the public laundry
$PW^p_{w,t,s}, pw^p_{w,t}$	Consumption matrix/ consumption value of washing machine
$PD^p_{d,t,s}, pd^p_{d,t}$	Consumption matrix/ consumption value of tumble dryer
$BW^p_{w,s}, BD^p_{d,s}$	Binary value indicating whether the washing machine/ tumble dryer is turned on (1) or turned off (0)
PPW^p_w, PPD^p_d	Power profile of washing machine/ tumble dryer
$F_{cost}, F_{emission}$	Value of cost/ emission objective function
$F_i(X)$	Objective function i
δ	A positive value less than 1
ε	A very small positive number in the augmented ε-constraint method
α	Slack variables in the augmented ε-constraint method

Parameters

T_f, T_s	Preferred finish time/ start time
Δt	Length of intervals within the rolling time window
n^p, m^p	Total number of intervals within *LOP*
$\pi^{spot}_t, \pi^{Fixed}$	Spot market price/ daily fixed cost
π^{EBT}, π^{PBT}	EBT/ PBT price tariff
E^{CO2}_t	Average CO_2 emission rate of electricity production
Δ	Maximum permitted time gap between the scheduling
L	Right-hand side parameters in the augmented ε-constraint method

Abbreviations

EMS	Energy management system
DSO	Distribution system operator
MILP	Mixed integer linear programming
EBT	Energy-based tariff
PBT	Power-base tariff
HSB LL	HSB living lab
PUT	Preferred use time
LOP	Length of operation
EC	Energy consumption
MOOP	Multi-objective optimization problem

iteratively over a scheduling horizon. For instance, in [11], a real-time demand response algorithm based on deep reinforcement learning has been designed for the optimal scheduling of home appliances. The authors of [12] developed a model predictive control for energy management of smart buildings to minimize electricity bills under variable energy price tariffs. In [13], a real-time EMS for building microgrids has been developed in which the degradation of batteries is accurately modelled. In [14], a model predictive control based EMS has been proposed to minimize total energy consumption and cost of smart homes by shifting heat pump loads to off-peak hours. In [15], a hierarchical model predictive control for energy management of multiple buildings has been implemented to minimize energy costs while considering comfort criteria. The authors of [16] proposed a real-time rolling horizon-based algorithm for residential home energy management to minimize the cost payment by optimally scheduling smart appliances and improving the utilization of renewable energy. In [17], a multi-objective and real-time smart residential energy management system has been developed to minimize energy costs and thermal discomfort by controlling indoor illuminance and temperature levels. The authors of [18] proposed a multi-objective optimization problem for real-time energy management in smart homes that concurrently minimize monetary energy costs and the total dissatisfaction experienced by home occupants.

To fully leverage the benefits of flexible demand and prevent local increases in peak demand, a new tariff structure has been designed by distribution system operators (DSOs) where the network tariff is calculated based on the peak demand of each individual customer. For instance, in Sweden, Netherlands, and Germany, customers can opt for an hourly electricity pricing scheme that is based on the hourly prices of the Nordic day-ahead electricity market, Nord Pool Spot. In addition, customers are charged based on the maximum power consumed during the entire calendar month [19]. By reducing peak demand, the significant investments in reinforcing and expanding of distribution networks decreases and grid reliability, cost efficiency, and environmental sustainability are enhanced. Some studies have examined this type of tariff structure to develop the EMS. The authors of [20] presented a two-stage energy and flexibility-based EMS for residential buildings to minimize energy costs under monthly power-based tariffs. In [21], an operational model for a home EMS has been developed with two objective functions: minimizing both the maximum peak demand and the total cost. It should be noted that to reduce peak power costs, the common approach is to minimize short-term peak demand under the assumption that consumers will be charged based on daily peak demand. However, this approach could be suboptimal since households are billed for their monthly peak consumption.

This paper aims to develop an EMS to minimize energy costs, peak demand, and CO_2 emissions of public laundries. Public laundries are communal facilities where people can wash and dry their clothes using coin-operated or card-operated washing machines and tumble dryers. The energy management of public laundries with respect to residential buildings can be particularly challenging. Since in residential buildings, the number of controllable appliances such as washing machines and tumble dryers is typically limited. In contrast, public laundries, designed to serve a more extensive user base, house a significant number of washing machines and tumble dryers to accommodate a larger volume of laundry needs. This disparity in scale requires distinct management and scheduling strategies to ensure efficient operation and user satisfaction in public laundry facilities. Note that the overall peak demand of the public laundry depends on the coincidence of the consumption of washing machines and tumble dryers. On the other hand, high-quality service should be delivered to customers of public laundries. In [22], a heuristic real-time EMS for public laundries was proposed that considers demand charge tariffs to reduce the financial risk associated with these tariffs, while ensuring the quality of services delivered to laundry users. Although the results demonstrate that the electricity cost and peak-load of public laundries can be reduced by the proposed EMS, however, there is no assurance that it will be the best or most optimal scheduling. To address these issues, the developed EMS has been formulated as a mixed

Table 1
Comparison between the proposed model and other existing methodologies.

Ref	Electricity tariff		Objective			Scheduling horizon		Demonstration		Model type
	EBT	PBT	Cost	Peak load	Emission	Real-time	Day-ahead	Simulation study	Realistic study	
[4]	✓	×	✓	×	×	×	✓	✓	×	Nonlinear
[5]	✓	✓	✓	✓	✓	×	✓	✓	×	MILP: weighted sum
[6]	✓	×	✓	✓	×	×	✓	✓	×	PSO
[7]	✓	×	✓	×	×	×	✓	✓	×	GA
[8]	✓	✓	✓	✓	✓	×	✓	✓	×	MIQCP: multi-objective
[9]	✓	×	✓	×	×	×	✓	✓	×	MILP
[10]	✓	×	✓	✓	×	×	✓	✓	×	MILP: multi-objective
[11]	✓	×	✓	×	×	✓	×	✓	×	MPC
[12]	✓	×	✓	×	×	✓	×	×	✓	MPC
[13]	✓	✓	✓	✓	×	×	✓	✓	✓	MILP
[14]	✓	×	✓	×	×	✓	×	✓	✓	MPC
[15]	✓	×	✓	×	×	×	✓	✓	×	MPC
[16]	✓	×	✓	×	×	✓	×	✓	×	MCMIP
[17]	✓	×	✓	×	×	✓	×	✓	×	MILP
[18]	✓	×	✓	✓	×	✓	×	✓	×	MILP: multi-objective
[20]	✓	✓	✓	✓	×	✓	×	✓	✓	MILP
[21]	✓	×	✓	✓	×	✓	×	✓	×	MILP
[22]	✓	×	✓	✓	×	✓	×	✓	×	Heuristic algorithm
This paper	✓	✓	✓	✓	✓	✓	✓	✓	✓	MILP: multi-objective

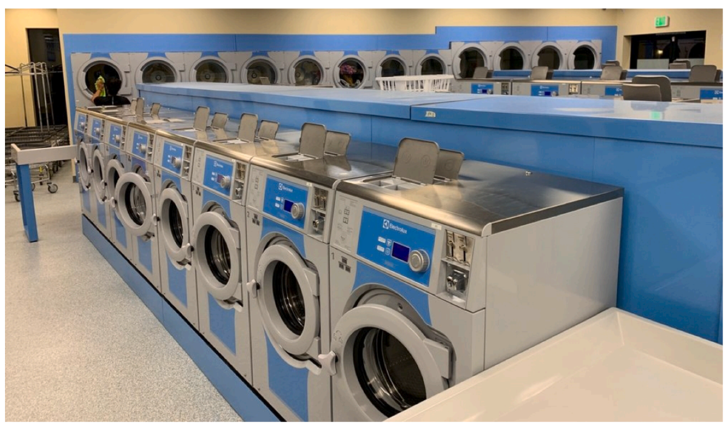

Fig. 1. A snapshot of a public laundry facility [23].

integer linear programming (MILP) problem and implemented using a real-time rolling horizon-based algorithm. Accordingly, the EMS solves an optimization problem iteratively and determines the optimal time of washing machines and tumble dryers for the next control intervals under different grid tariffs. Table 1 summarizes the comparison between the proposed model and other existing methodologies.

The specific contributions of this paper are summarized as follows:

- Formulating a real-time rolling horizon-based optimization model managing energy consumption in public laundries while considering users' preferences for a comfortable lifestyle. The model ensures optimality of solutions, enabling effective management of energy consumption in public laundries.
- Reducing the daily and monthly peak demand of public laundries to minimize energy costs. This can lead to significant economic benefits and improve technical performance of the power grid.
- Validation of the performance of the developed EMS using real data of the end-user behaviour in HSB Living Lab (HSB LL) demonstration site, Sweden.

The rest of the paper is organized as follows. Section 2 presents the power demand modelling of public laundries and Section 3 describes the model formulation of the developed EMS. The augmented ε-constraint based solution algorithm is presented in Section 4. The real demonstration site at HSB Living Lab is described in Section 5. Section 6 discusses simulation results and presents test results from a real demonstration site. Finally, Section 7 presents the main conclusions from the paper.

Power demand modelling of public laundries

A snapshot of a public laundry facility is shown in Fig. 1. As can be seen, the facility has several washing machines and tumble dryers that are available for registered users. To wash/dry clothes, a user selects a free washing machine/tumble dryer and sets parameters such as program and preferred use time ($PUT = [T_s, T_f]$). Once parameters are set, the EMS determines the best time to start the washing machine/tumble dryer within the PUT. The washing machine/tumble dryer is in a waiting state until the determined start time is reached. Accordingly, the power demand of the public laundry can be calculated based on the coincidence of the consumption of washing machines and tumble dryers:

$$PL_t = \sum_{s=1}^{S_W} \sum_{w=1}^{N_W} PW^p_{w,t,s} \times BW^p_{w,s} + \sum_{s=1}^{S_D} \sum_{d=1}^{N_D} PD^p_{d,t,s} \times BD^p_{d,s} \quad (1)$$

where, S_W and S_D represent the possible consumption scenarios of the washing machine and tumble dryer, respectively, within the PUT. Similarly, N_W and N_D represent the number of washing machines and tumble dryers. Likewise, PW and PD are the consumption matrices of the washing machine and the tumble dryer, while BW and BD are binary

$$PW^{p}_{w,t,s} = \begin{array}{c} \hspace{2.5cm}\overbrace{\hspace{6.5cm}}^{\text{Preferred Use Time of washing machine}}\hspace{2cm} \\ \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pw^{p}_{w,1} & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pw^{p}_{w,2} & pw^{p}_{w,1} & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \vdots & pw^{p}_{w,2} & pw^{p}_{w,1} & \cdots & \vdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pw^{p}_{w,n^{p}} & \vdots & pw^{p}_{w,2} & \cdots & pw^{p}_{w,1} & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & pw^{p}_{w,n^{p}} & \vdots & \cdots & pw^{p}_{w,2} & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & 0 & 0 & pw^{p}_{w,n^{p}} & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 0 & \vdots & 0 & 0 & \cdots & pw^{p}_{w,n^{p}} & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \vdots & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \vdots & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \vdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \end{bmatrix} \end{array} \tag{2}$$

$$PD^{p}_{d,t,s} = \begin{array}{c} \hspace{2.5cm}\overbrace{\hspace{6.5cm}}^{\text{Preferred Use Time of tumble dryer}}\hspace{2cm} \\ \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pd^{p}_{d,1} & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pd^{p}_{d,2} & pd^{p}_{d,1} & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \vdots & pd^{p}_{d,2} & pd^{p}_{d,1} & \cdots & \vdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & pd^{p}_{d,n^{p}} & \vdots & pd^{p}_{d,2} & \cdots & pd^{p}_{d,1} & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & pd^{p}_{d,n^{p}} & \vdots & \cdots & pd^{p}_{d,2} & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & 0 & 0 & pd^{p}_{d,n^{p}} & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 0 & \vdots & 0 & 0 & \cdots & pd^{p}_{d,n^{p}} & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \vdots & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \vdots & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \vdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \end{bmatrix} \end{array} \tag{3}$$

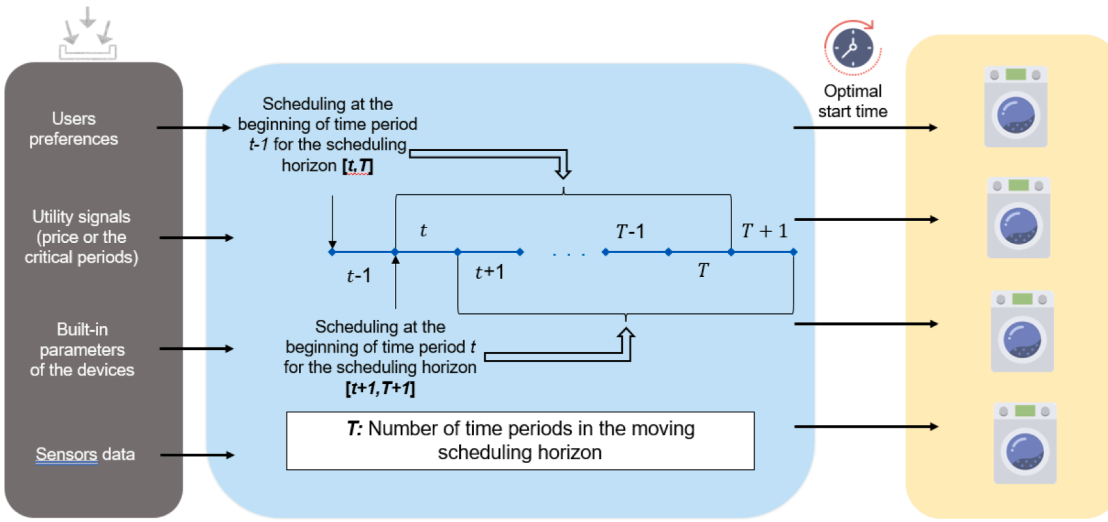

Fig. 2. Schematic diagram of real-time rolling horizon energy management system.

variables that take a value of "1″ when the washing machine or tumble dryer is in use, and ″0″ otherwise. The consumption matrices for the washing machine and the tumble dryer are given in (2) and (3), respectively.

The size of these matrices is $N_T \times N_T$, where $N_T = T/\Delta t$ is total intervals within the rolling time window. Likewise, Δt is the length of the time interval. The possible consumption scenarios of the washing machine and tumble dryer can be seen in the preferred use time. To ensure that the clothes are ready before T_f, the length of operation (*LOP*) of washing machine and tumble dryer in the respective program *p* should

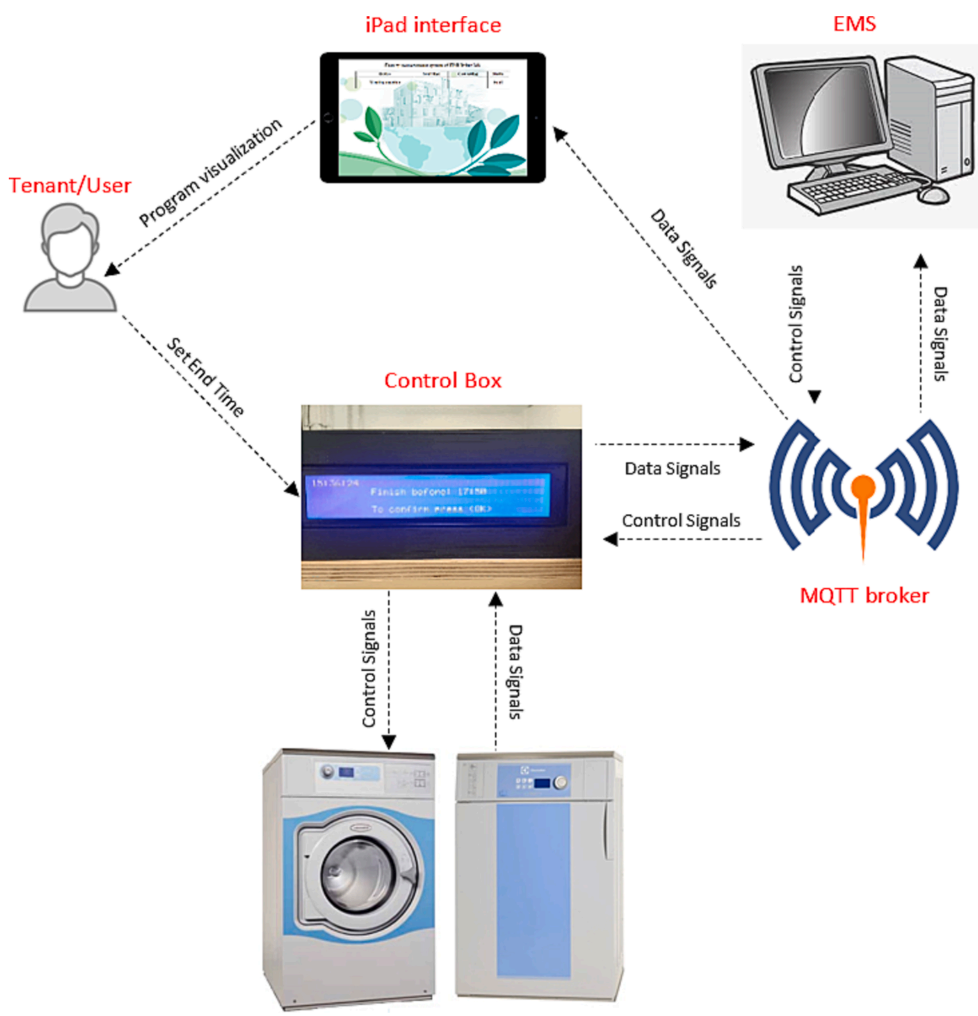

Fig. 3. Schematic diagram of the developed energy management system.

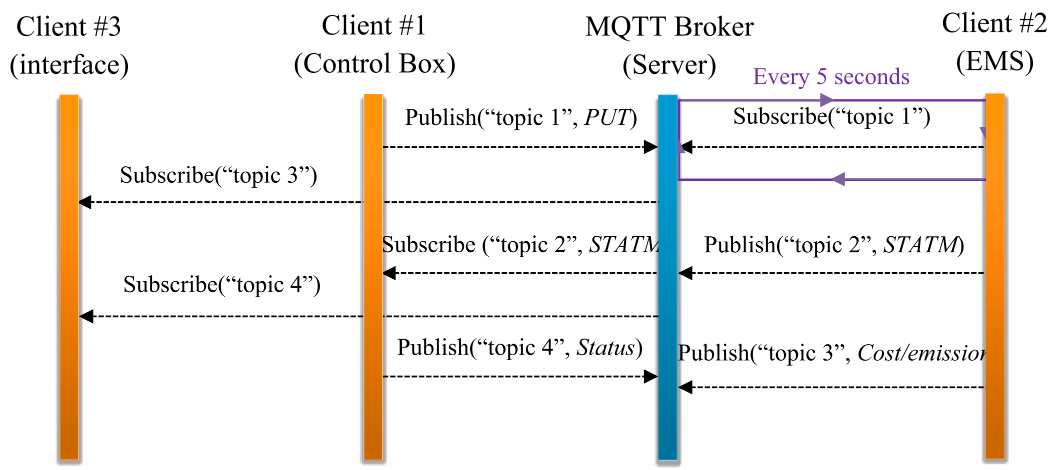

Fig. 4. MQTT messaging sequence diagram.

be considered while generating possible consumption scenarios. In other words, any scenario that violates this condition should be disregarded. Accordingly, the calculation of consumption matrices for the washing machine and the tumble dryer is outlined in Algorithm 1.

Algorithm 1: Calculation of consumption matrices

1. Enter the power profile of the washing machine/tumble dryer for each program p as:
   PPWwp=pww,1p, pww,2p,…,pww,nppPPDdp=pdd,1p, pdd,2p,…,pdd, mppwhere, n^p and m^p are total number of intervals within LOP of the washing machine and the tumble dryer, respectively.
2. Calculate the total consumption scenarios of the washing machine and tumble dryer as:
   Sw=Tf,w-Ts,w-LOPwpΔtSd=Tf,d-Ts,d-LOPdpΔt

Initialize $PW^p_{w,t,s}$ and $PD^p_{d,t,s}$ with a zero matrix of size $N_T \times N_T$.
For $s = (1+T_{s,w}/\Delta t)$ **to** S_W:
For $t = 1$ **to** n^p:
$PW^p_{w,s,s} = pw^p_{w,t}$.
END.
END.
For $s = (1+T_{s,w}/\Delta t)$ **to** S_D:
For $t = 1$ **to** m^p:
$PD^p_{d,s,s} = pd^p_{d,t}$.
END.
END.

It should be mentioned that the power profile of the washing machine or tumble dryer in the program p can be experimentally determined or estimated based on the corresponding LOP and its energy consumption (EC) as follows:

$$pw^p_{w,t} = \frac{EC^p_w}{LOP^p_w} \tag{4}$$

$$pd^p_{d,t} = \frac{EC^p_d}{LOP^p_d} \tag{5}$$

Model formulation of the developed EMS

The rolling horizon method is a widely used approach in various fields, including energy management systems, and it can be applied to public laundries to optimize energy consumption in real time. The method is based on the concept of model predictive control, which involves using real-time data at discrete intervals to optimize energy consumption over a specific control horizon while considering future time periods.

The rolling horizon method is illustrated in Fig. 2, where the preference data of washing machines and tumble dryers are updated for upcoming intervals $[t, T]$ at the beginning of time period $t-1$. This ensures that the most up-to-date information is used to optimize energy consumption. The method then uses the updated preference data to obtain the optimized results, which are then used to generate control commands for the washing machines and tumble dryers for the upcoming time period. The decision variables of the upcoming time period are only sent to the washing machines and tumble dryers as control commands, and the process is repeated for each time period within the control horizon. By continuously updating the preference data and optimizing energy consumption over the control horizon, the rolling horizon method can effectively manage energy consumption in public laundries in real-time [24].

In the following of this section, the objective function and constraints of the proposed real-time rolling horizon energy management system are presented.

Objective function

The proposed EMS for public laundries aims to minimize two objective functions, i.e., cost (F_{cost}) and emission ($F_{emission}$):

$$Minimize\{F_{cost}, F_{emission}\} \tag{6}$$

The optimization is performed iteratively within a rolling time window. The cost function for each iteration i consists of the spot market price and the network fee including a fixed part, energy-based part, and power-based part according to (7) for energy-based tariff (EBT) and (8) for power-based tariff (PBT). Indeed, power-based network tariffs serve as a penalty for peak consumption.

$$F^{EBT}_{cost} = \sum_{t=i}^{i-1+N_T} \left[\left(\pi^{spot}_t + \pi^{EBT}\right) \times PL_t \right] \times \Delta t + \pi^{Fixed} \tag{7}$$

$$F^{PBT}_{cost} = \sum_{t=i}^{i-1+N_T} \left[\left(\pi^{spot}_t + \pi^{EBT}\right) \times PL_t + \pi^{PBT} \times PL^{peak} \right] \times \Delta t + \pi^{Fixed} \tag{8}$$

In (7) and (8), π^{spot}_t is the hourly spot price, π^{Fixed} is the fixed daily cost for the electricity contract, π^{EBT} is the EBT, π^{PBT} is the PBT, and PL^{peak} is the daily peak demand of the public laundry. It should be mentioned that the π^{PBT} is scaled to the daily time period since the scheduling

Table 2
Data and grid tariff [29].

	EBT	PBT
Fixed fee	99.50 €/year	53.51 €/year
Energy based fee	0.018 €/kWh	0.010 €/kWh
Power based fee	–	0.1453 €/kW/day

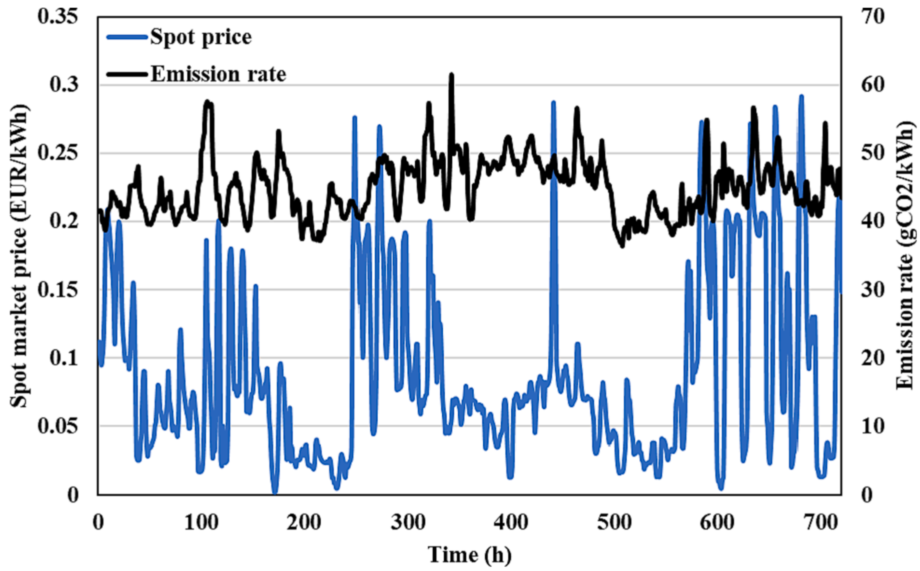

Fig. 5. Spot market price and CO_2 emission rate for the month of April 2022.

horizon is 24 h.

The objective function related to the total emissions within the rolling time window is calculated as follows:

$$F_{emission} = \sum_{t=i}^{i-1+N_T} \left[\mathrm{E}_t^{CO2} \times PL_t \right] \times \Delta t \tag{9}$$

where, E_t^{CO2} represents the hourly average CO_2 emission rate of electricity production.

Constraints

To make the proposed energy management system feasible, the following technical and economic constraints must be met.

Scheduling constraints

The washing machine or tumble dryer should only start once before T_f and cannot be turned off before completion of their tasks. To account for these requirements, the following constraints are defined:

$$\sum_{s=\left(1+T_{s,w}/\Delta t\right)}^{S_W} BW_{w,s}^{p} = 1 \tag{10}$$

$$\sum_{s=\left(1+T_{s,w}/\Delta t\right)}^{S_D} BD_{d,s}^{p} = 1 \tag{11}$$

The starting time of the tumble dryer depends on the completion of the washing machine task as the clothes need to be dried for some time after being washed. Therefore, the following constraint should be considered:

$$\sum_{s=\left(1+T_{s,w}/\Delta t\right)}^{S_W} BD_{w,s}^{p} \times ord(s) + LOP_w^p \le \sum_{s=\left(1+T_{s,w}/\Delta t\right)}^{S_D} BD_{d,s}^{p} \times ord(s) \tag{12}$$

where, $Ord(s)$ is the position of a member in a respective set. Due to hygiene precautions, it is not desirable to have a large time gap between the starting time of the washing machine and tumble dryer. Therefore, the following constraint should also be considered:

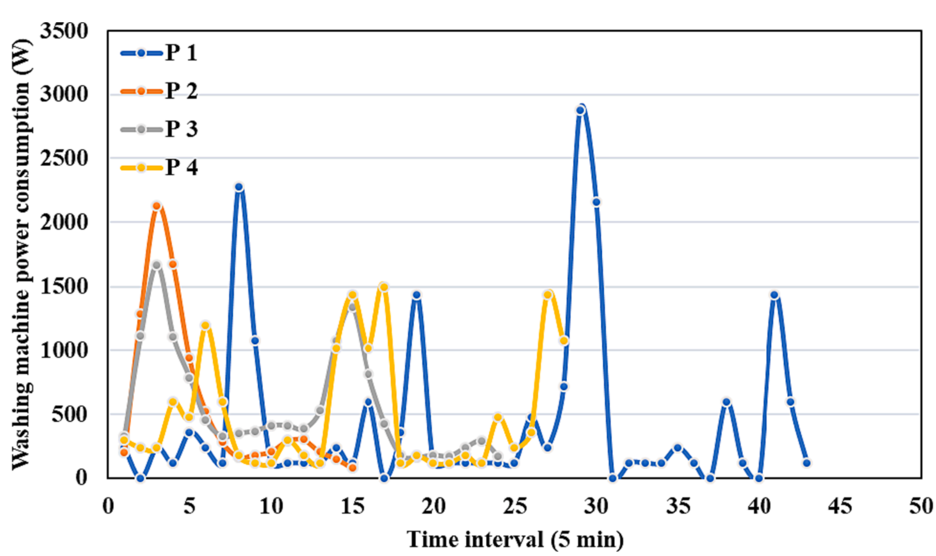

Fig. 6. Load profile of washing machine in different programs.

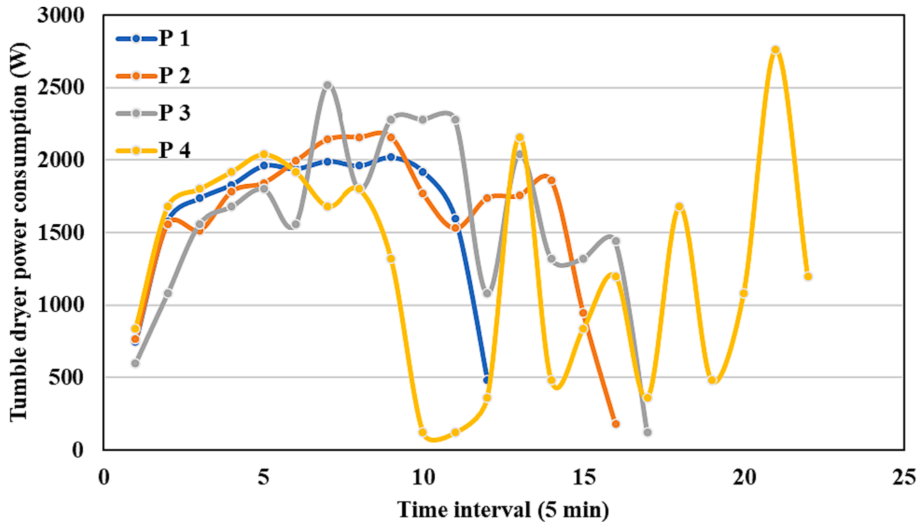

Fig. 7. Load profile of tumble dryer in different programs.

$$Ord(s^{'}) \times U\left(BD^{p}_{d,s^{'}} - BD^{p}_{d,s^{'}-1} - \delta\right) \leq (Ord(s) - 1) \times U$$

$$\left(BW^{p}_{w,s-1} - BW^{p}_{w,s} - \delta\right) + \Delta_{d,w}; \forall s^{'} \in PUT_d, s \in PUT_w \tag{13}$$

where, $U()$ represents a unit step function, δ is a positive value less than 1 and Δ is the maximum permitted time gap between the scheduling of the washing machine and tumble dryer.

Peak demand constraint

The daily peak demand drawing from the grid can be determined by the following equation:

$$PL^{peak} \geq \overline{PL_h} \tag{14}$$

where, $\overline{PL_h}$ represent the hourly load demand for the public laundry. To calculate the hourly load demand, the average value of PL_t of the corresponding hour h is obtained.

To model the user's comfort preferences, as outlined in Algorithm 1, possible consumption scenarios for the washing machine and tumble dryer are generated within the preferred use time ($PUT = [T_s, T_f]$). One of generated scenarios is selected as the best solution, therefore, it is guaranteed that the clothes are ready after T_s and before T_f. Likewise, constraint (13) has been considered to prevent a large time gap between the starting time of the washing machine and tumble dryer.

Multi-objective augmented ε-constraint solution of the developed EMS

The Multi-objective optimization problem (MOOP) does not have a unique solution that optimizes all objective functions simultaneously. Instead, the concept of efficiency or Pareto optimality is introduced in MOOP. The Pareto optimal solutions are those that cannot improve any objective function without compromising the performance of at least one other objective function [25]. Then, the decision maker should choose the most suitable compromise solution among the available Pareto optimal solutions. In this section, the augmented ε-constraint method is presented to solve the developed EMS.

Augmented ε-constraint method

The augmented ε-constraint is a proficient optimization method. In

Table 3
Monthly task profile of the washing machine and tumble dryer in the HSB LL.

Task	Washer 1	Dryer 1	Task	Washer 1	Dryer 1	Task	Washer 1	Dryer 1
D1 #1	8–12, P2	12–14, P1	**D12 #1**	9–12, P3	12–14, P2	**D23 #1**	8–12, P1	12–14, P3
D1 #2	13–17, P3	18–20, P1	**D12 #2**	14–17, P4	17–20, P1	**D23 #2**	15–18, P3	18–20, P1
D2 #1	9–12, P2	12–14, P2	**D13 #1**	8–11, P2	11–13, P3	**D24 #1**	12–15, P3	15–18, P1
D2 #2	13–16, P2	16–18, P1	**D13 #2**	12–14, P2	14–16, P2	**D24 #2**	15–18, P2	18–20, P4
D3 #1	8–10, P2	10–12, P1	**D14 #1**	8–10, P2	1r0-12, P3	**D25 #1**	13–16, P3	16–19, P4
D3 #2	12–15, P3	15–18, P4	**D14 #2**	11–14, P3	15–18, P1	**D25 #2**	9–12, P2	12–15, P3
D4 #1	8–12, P1	12–14, P1	**D15 #1**	8–10, P2	10–12, P1	**D26 #1**	8–11, P2	11–13, P1
D4 #2	15–18, P2	18–20, P2	**D15 #2**	10–13, P4	13–18, P4	**D26 #2**	11–14, P3	14–16, P3
D5 #1	8–10, P2	10–12, P3	**D16 #1**	9–11, P2	11–14, P1	**D27 #1**	9–12, P3	12–14, P2
D5 #2	14–18, P4	18–20, P2	**D16 #2**	13–16, P2	16–19, P3	**D27 #2**	9–12, P3	12–14, P2
D6 #1	9–12, P2	12–14, P1	**D17 #1**	8–10, P2	10–12, P3	**D28 #1**	15–18, P2	18–20, P3
D6 #2	13–16, P3	16–19, P4	**D17 #2**	12–15, P3	15–18, P4	**D28 #2**	13–17, P1	17–19, P2
D7 #1	8–11, P2	11–13, P1	**D18 #1**	9–12, P2	12–14, P2	**D29 #1**	10–12, P2	12–14, P1
D7 #2	12–15, P3	15–19, P4	**D18 #2**	14–18, P1	18–20, P1	**D29 #2**	14–17, P1	17–20, P1
D8 #1	8–10, P2	10–12, P2	**D19 #1**	12–14, P2	14–16, P2	**D30 #1**	9–12, P2	12–15, P2
D8 #2	10–12, P2	12–14, P1	**D19 #2**	15–18, P2	18–20, P2	**D30 #2**	12–14, P2	15–19, P2
D9 #1	8–10, P2	10–12, P2	**D20 #1**	8–11, P2	11–13, P2	**D31 #1**	9–13, P1	14–17, P2
D9 #2	10–13, P3	13–18, P3	**D20 #2**	13–16, P4	16–20, P3	**D31 #2**	15–18, P2	18–20, P2
D10 #1	8–12, P2	12–14, P1	**D21 #1**	8–12, P1	12–14, P2			
D10 #2	12–17, P2	17–19, P2	**D21 #1**	12–16, P4	16–19, P1			
D11 #1	8–10, P2	10–12, P3	**D22 #1**	14–17, P3	17–20, P1			
D11 #2	12–15, P3	15–18, P4	**D22 #1**	8–11, P2	11–14, P4			

Table 4
Operation results of the public laundry in the HSB LL.

	W/O EMS		With EMS	
	EBT	PBT	EBT	PBT
Energy cost (€)	27.962	22.775	26.834	22.176
Power cost (€)	–	8.226	–	5.115
Total cost (€)	27.962	31.001	26.834	27.291
Emission (kgCO2)	7.575	7.575	7.596	7.580
Monthly peak demand (kWh)	2.429	2.429	2.428	1.472

this method, a main objective function is selected among all objective functions, for instance, $F_1(X)$, and other $(n-1)$ objective functions are incorporated into the problem using equality constraints that retain slack variables (i.e., $\alpha_2, \alpha_3, \dots, \alpha_n$), while the right-hand side parameters, (i.e., $L_2, L_3, \dots, L_n$) are varied to obtain Pareto optimal solutions:

$$\min_{X\in\Omega,\ \alpha\in R^+} F_1(X) - \varepsilon(\alpha_2 + \alpha_3 + \cdots + \alpha_n) \tag{15}$$

Subjected to:

$$F_i(X) + \alpha_i \le L_{i,r}, i = 2, \cdots, n; r = 0, \cdots, N \tag{16}$$

In (15), ε is a very small value, e.g., $\varepsilon = 10^{-3}$.

A commonly used approach to determining $L_2, L_3, \dots, L_n$ is by employing a payoff matrix, which can be described in the following steps [26]:

Algorithm 2: Payoff matrix calculation

The optimal value for each objective function, denoted as $F_i^*(X^*)$, is calculated by solving the minimization problem $\min_{X\in\Omega} F_i(X)$ separately for each $i = 1, \cdots, n$.

1. Regarding the optimal value and solution of each objective function, i.e., $[F_i^*(X_i^*), X_i^*], i = 1, \cdots, n$, obtained from the step 1, the following vectors are constructed:
   For $i = 1$ to n:
   F1Xi*,…, FiXi*,…,FnXi***END.**
   Then, the payoff matrix can be formed as following:

$$\begin{bmatrix} F_1^*(X_1^*) & \cdots & F_i(X_1^*) & \cdots & F_n(X_1^*) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ F_1(X_i^*) & \cdots & F_i^*(X_i^*) & \cdots & F_n(X_i^*) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ F_1(X_n^*) & \cdots & F_i(X_n^*) & \cdots & F_n^*(X_n^*) \end{bmatrix}$$

2. If the maximum and minimum values of each objective function in the i th column of the payoff matrix are denoted as $F_i^{max}(X)$ and $F_i^{min}(X)$, respectively, then, the right-hand side parameters can be calculated as:
   Li,r=Fimax-Fimax-FiminN×rwhere, N is the number of equal distance intervals in the range between 0 and $F_i^{max} - F_i^{min}$.

Best compromise solution

The EMS needs to select the best compromise solution among the Pareto optimal solutions, which can then be applied to the washing machines and tumble dryers. Indeed, different approaches like Fuzzy theory, AHP, and VIKOR can all be used to determine the best solution based on specific considerations. Fuzzy theory's strength lies in its ability to handle real-world data characterized by imprecision and uncertainty. Meanwhile, AHP and VIKOR are established methods for addressing multi-criteria decision-making challenges, especially when the objective is to assess both the best and worst solutions across multiple criteria. In this paper, the best solution is discerned through the construction of a trade-off curve, a technique achieved using fuzzy set theory. To this end, the i th The Pareto optimal solution of the j th objective function is transformed into a fuzzy number using the following membership function [27]:

$$\mu_{ij} = \begin{cases} 1 & g_{ij} \le g_j^{min} \\ \dfrac{g_j^{max} - g_{ij}}{g_j^{max} - g_j^{min}} & g_j^{min} \le g_{ij} \le g_j^{max} \\ 0 & g_{ij} \ge g_j^{max} \end{cases} \tag{17}$$

In (17), g_j^{max} and g_j^{min} are the maximum and minimum Pareto optimal solution of j th objective function. Accordingly, the normalized membership function for each nondominated solution can be calculated as:

$$\mu_i = \frac{\sum_{j=1}^{n}\mu_{ij}}{\sum_{j=1}^{n}\sum_{i=1}^{m}\mu_{ij}} \tag{18}$$

A higher membership function indicates that a solution achieves a higher degree of satisfaction compared to other solutions. Therefore, the best compromise solution can be identified as the one with the highest value of normalized membership function.

Description of the real demonstration site at HSB living lab

The proposed EMS has been effectively implemented for a public laundry facility located in HSB LL, a multi-family residential building comprising 29 apartments within the Chalmers University campus area [28]. Fig. 3 illustrates the schematic diagram of the implemented EMS within the HSB LL. As can be seen, there is a dedicated control box for each washing machine and tumble dryer, allowing users to configure the *PUT*. The control box initiates the washing machine or tumble dryer at the optimal start time which is determined by the EMS. The results are then displayed to the user through the iPad interface. Within this setup, all data transmission is carried out using the MQTT protocol. Fig. 4 shows the MQTT messaging sequence diagram. As can be seen, the control box of the washing machine or tumble dryer publishes the *PUT* data under the topic "topic1″ to the broker. The EMS subscribes continuously to this topic every 5 s to access this data. After the EMS has read, decoded, and processed the data, it can then determine the optimal start time (*STATM*) and publishes it under the topic "topic2″ to the broker. The control box subscribes the broker under the topic "topic2″ to access the *STATM*. Subsequently, the control box determines whether to activate the washing machine or tumble dryer based on the *STATM*. The optimal cost and emission are sent to the broker under the topic "topic3″. Likewise, the status of washing machine and tumble dryer are sent to the broker under the topic "topic4″. The interface client subscribes to these topics to display the information on the iPad. It should be noted that during hours when most machines are occupied, users can initiate the washing machine or tumble dryer without waiting for the EMS by simply pressing the start button on the control box. This allows for immediate activation and usage without relying on the EMS.

Accordingly, the step-by-step workflow of the proposed EMS is summarized as follows:

Algorithm 3: Real-time rolling-horizon energy management of public laundries

Initialize $\overline{PL}$ with a zero vector of size $1 \times T$ and enter the load profile of washing machines and dryer in each program.
For $i = 1$ to $T/\Delta t$:
Connect to the MQTT broker.
Subscribe to related topics and read *PUT* data of available washing machine and tumble dryer, then, decoded and process the data.
Wait until beginning of optimization interval of i.

1. Run algorithm 2 to calculate the payoff matrix.
   Solve the following optimization problem using augmented ε-constraint method in (15) and (16) to obtain Pareto optimal solutions:
   Minimize Fcost,FemissionSubjected to: 7-
   14Determine the best compromise solution among the Pareto optimal solutions using (17) and (18), which can then be applied to the washing machines and tumble dryers.

Connect to the MQTT broker.
The optimal start time of available washing machine and tumble dryer, encoded in JSON format, and published to the topics associated with the control.

(*continued on next page*)

(*continued*)

Algorithm 3: Real-time rolling-horizon energy management of public laundries
Update $\overline{PL}$ according to the power consumption of scheduled washing machines and tumble dryers.
END

Case studies, results, and discussions

To demonstrate the effectiveness of the developed EMS, several simulations are performed under different scenarios using real data and by a realistic case study. The cost and emission are calculated under different tariffs and are compared with a reference case when the EMS is not used. That is, for the reference case, washing machines and tumble dryers begin operating when their assigned tasks are submitted and continue to run until the tasks are finished. Also, the impact of the EMS on the peak-demand reduction of the public laundry is studied. The energy management horizon is set between 8 a.m. and 8p.m. A control time interval of 5 min is established, resulting in a total of 144 intervals over the entire energy management horizon.

Data

The data and grid tariffs are given in Table 2 [29]. As can be seen, all electricity tariffs include a fixed annual fee for utilizing the grid, as well as a fee for energy consumption. However, the PBT tariffs include an additional fee for daily peak demand. The hourly spot price is based on the Nordic electricity market which can be obtained from [30]. The spot

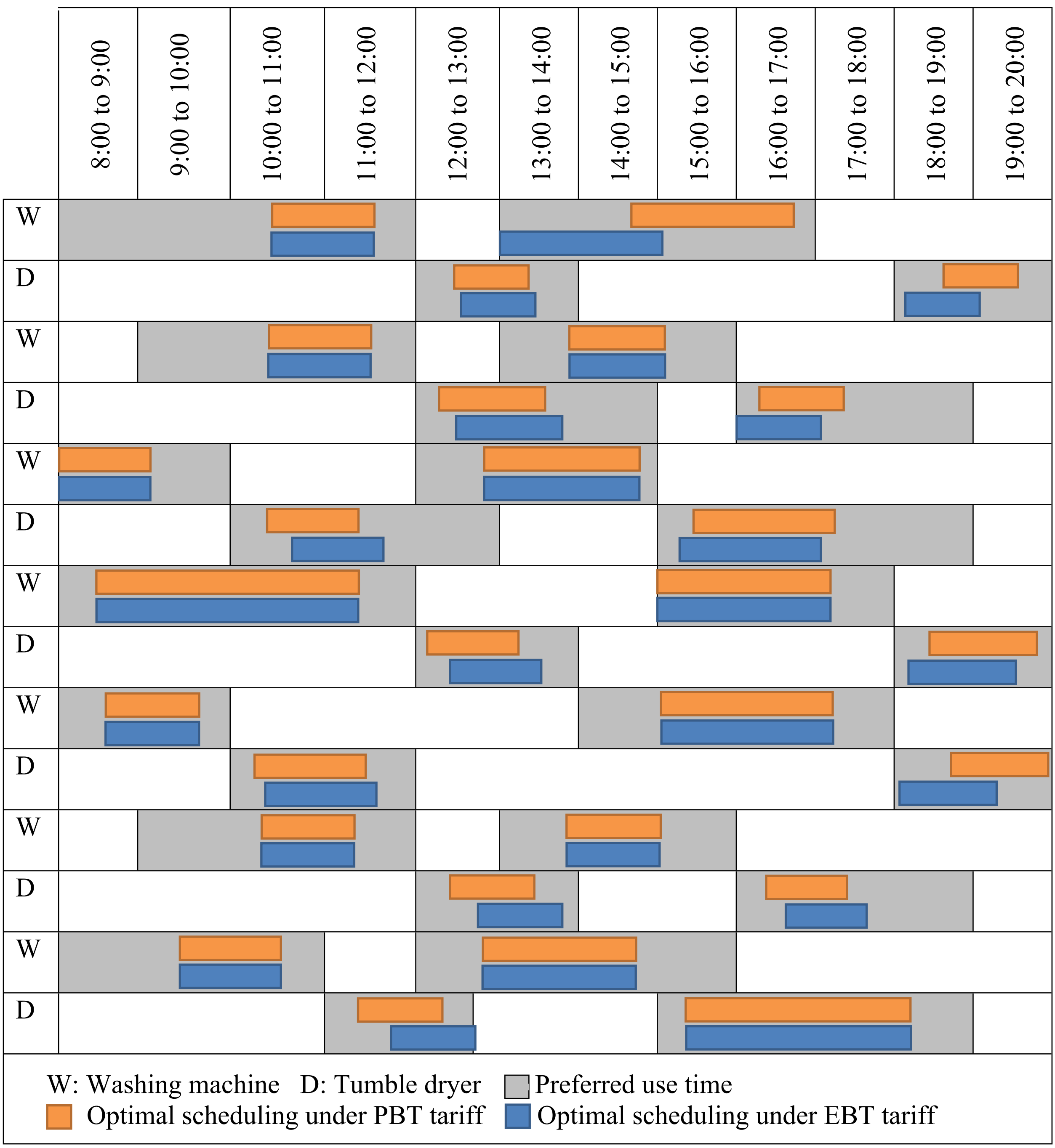

Fig. 8. The task profile and optimal service time during the study period.

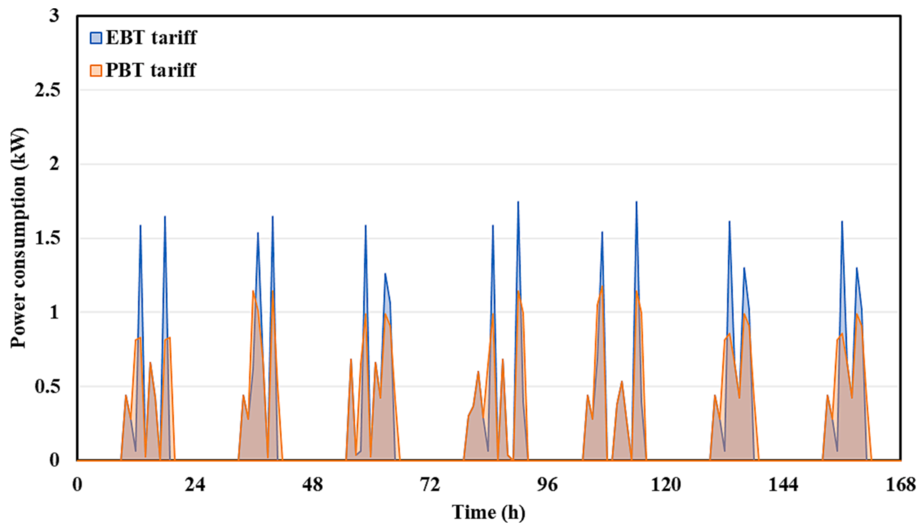

Fig. 9. Power consumption profile of the public laundry in EBT and PBT tariffs.

prices for the month of April 2022 are shown in Fig. 5. It should be mentioned that an energy tax of 0.034 €/kWh should also be paid by customers in addition to the electricity cost and grid tariff. The hourly average CO_2 emission rate of electricity production for the same month is obtained from [31] and shown in Fig. 5. As mentioned, there are one washing machine and one tumble dryer in the HSB LL. The consumption data corresponding to each program of the washing machine and tumble dryer are obtained from experiments and presented in Figs. 6 and 7, respectively. It should be mentioned that programs 1 to 4 are the most used programs by HSB LL users for washing and drying their clothes. In order to evaluate the effects of cost and emission objectives in the energy management of public laundries, the proposed EMS is investigated in 3 different cases:

- Case 1: only the cost objective function minimization is considered.
- Case 2: only the emission objective function is considered.
- Case 3: the two objective functions are considered in a multi-objective optimization using augmented ε-constraint multi-objective optimization.

The proposed EMS was developed using Python programming language, and the optimization process is performed by the *glpk* solver on a computer running Windows 10 operating system. The computer has an Intel Core i7 processor with a speed of 2.30 GHz and 16 GB of RAM.

Test results from the real demonstration site at HSB living lab

The maximum permitted time gap between the starting of the washing machine and tumble dryer is assumed 4 h, i.e., $\Delta_{d,w} = 4$. The monthly task profile of the washing machine and the tumble dryer in the HSB LL is shown in Table 3. As can be seen, total number of tasks is 62 which 31 tasks are for the washing machine and 31 tasks are for the tumble dryer.

The aim of this case is to minimize energy cost of the public laundry. The electricity costs, CO2 emissions, and monthly peak demand of the public laundry during the study period for different scenarios are summarized in Table 4. The results show that under the PBT tariff the total cost and the monthly peak demand of the public laundry are reduced by 13.59 % and 39.40 %, respectively, when the EMS is utilized compared to when it is not used. However, the effectiveness of the EMS under the EBT tariff is found to be insignificant for the public laundry, namely, using the EMS results in a reduction of the total cost and the monthly peak demand by 0.41 % and 0.04 %, respectively. This highlights the importance of the EMS in improving energy management in public

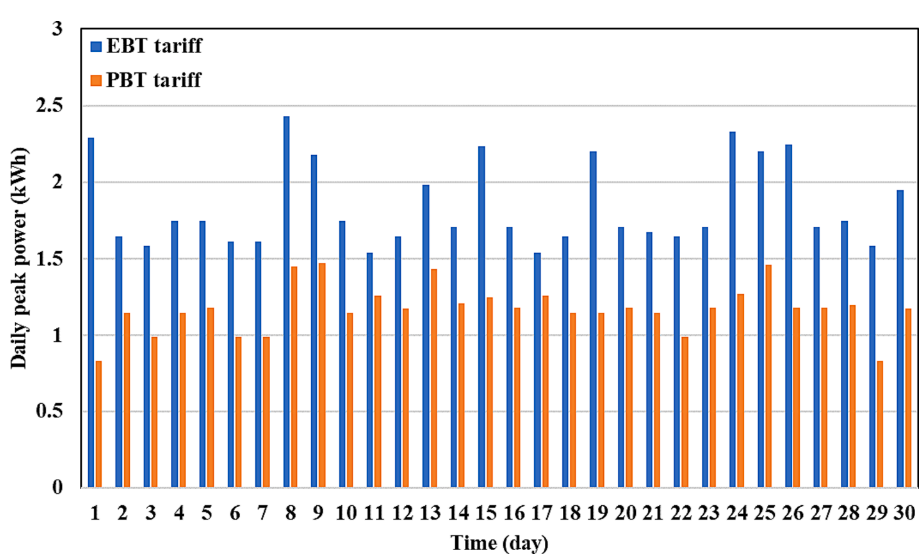

Fig. 10. Daily peak demand of the public laundry.

Table 5
Operation results of the public laundry in the HSB LL.

	W/O EMS		With EMS	
	EBT	PBT	EBT	PBT
Energy cost (€)	27.962	22.775	28.635	23.448
Power cost (€)	–	8.226	–	7.627
Total cost (€)	27.962	31.001	28.635	31.075
Emission (kgCO2)	7.574	7.574	7.532	7.532
Monthly peak demand (kWh)	2.429	2.429	2.429	2.429

laundries under the PBT tariff. The results indicate that using the EMS and changing tariffs have a minimal impact on CO_2 emissions reduction. The reason is that the primary objective of the EMS is to reduce costs.

The task profile and optimal service time for the washing machine and the tumble dryer during the first week of the study period are illustrated in Fig. 8. As depicted, all tasks are completed within the *PUT* to ensure the user's preference. Likewise, under the PBT tariff, the EMS aims to decrease the daily peak demand by reducing the concurrent usage hours of washing machines and tumble dryers. For example, in the first task, the starting time of the washing machine has been changed from 13:00 to 14:40 to avoid simultaneous usage with the tumble dryer. While under the EBT tariff, the washing machine and tumble dryer are used simultaneously.

In Fig. 9, the hourly power consumption profile of the public laundry under EBT and PBT tariffs is compared during the corresponding week. As can be seen, the PBT tariff results in a much smoother power consumption profile compared to the EBT tariff. The reason is that in this case, the EMS aims to reduce concurrent usage hours of washing machines and tumble dryers under the PBT tariff. The daily peak demand of the public laundry under the EBT and the PBT tariffs are compared in Fig. 10. As can be seen, the utilization of the PBT tariff results in a significant decrease in the daily peak demand of 39.3 %. Although it also led to a slight cost increase of 1.67 % compared to the EBT tariff. These results confirm the effectiveness of the proposed EMS in terms of energy cost and peak demand reduction for public laundries.

This case aims to minimize CO_2 emissions. Table 5 presents the operation results of the public laundry for different scenarios during the study period. The results indicate that the CO_2 emissions are lower compared to Case 1. This is because the primary objective of the EMS is to minimize the CO_2 emissions resulting from the electricity consumption of the public laundry. However, these reductions are neglectable since as illustrated in Fig. 5, the CO_2 emission rate has low variation, and therefore, changing the starting time of the washing machine and tumble dryer has not had a considerable effect on reducing CO_2 emissions. On the other hand, the total cost and monthly peak demand are increased in this case compared to Case 1. Based on these results, it can be concluded that selecting CO_2 emissions as the primary objective function in the EMS of the public laundry is not an effective approach.

In this case, the two objective functions are considered in a multi-objective optimization using augmented ε-constraint multi-objective optimization. According to the results of Case 2, the energy cost is selected as the primary objective function and the CO_2 emission

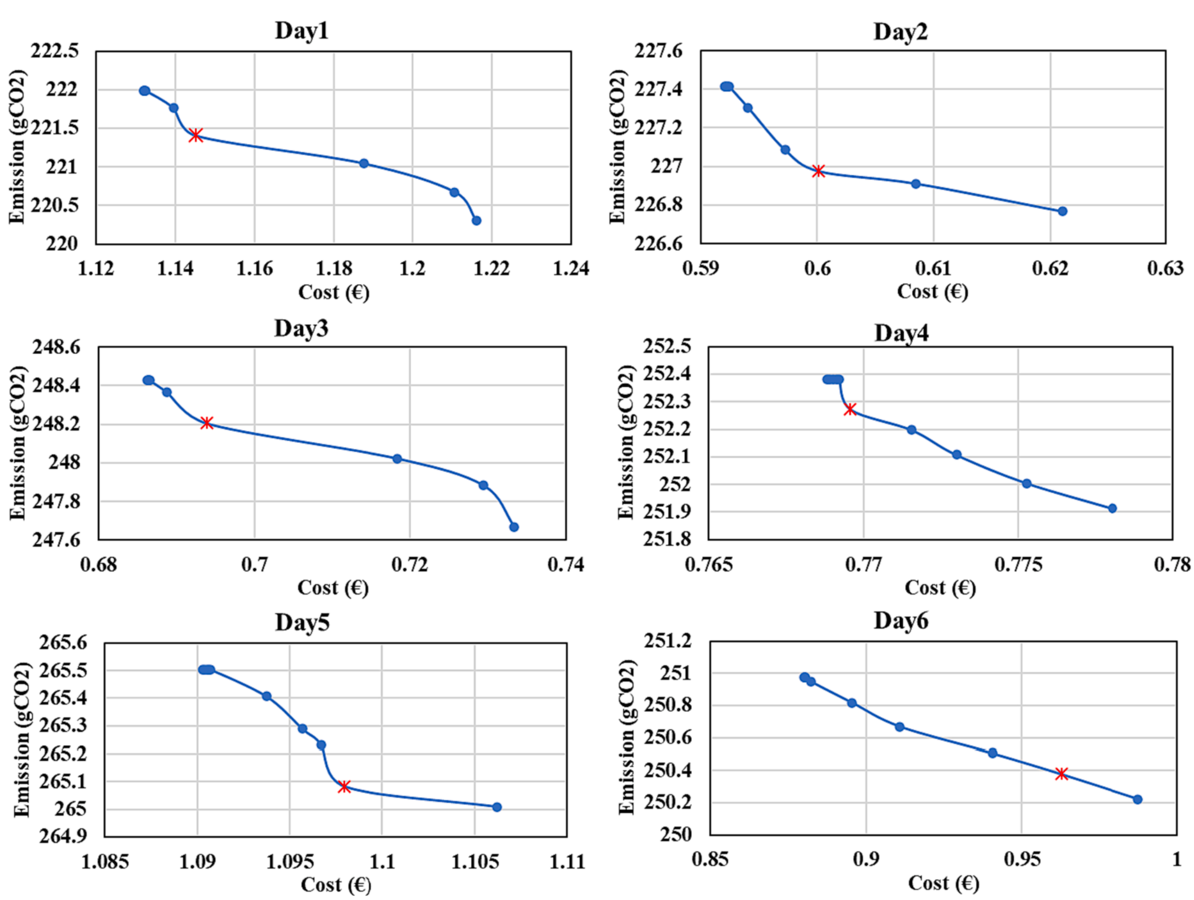

Fig. 11. Pareto optimal and best compromise solutions.

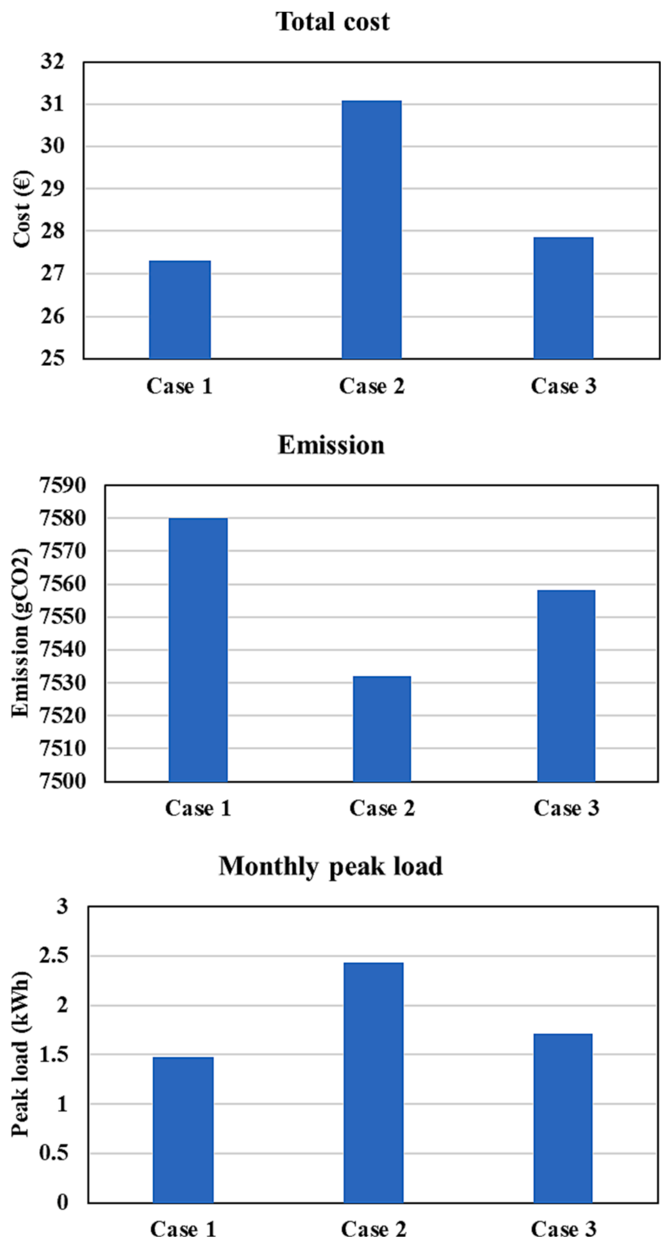

Fig. 12. A comparison between the best compromise solutions in Case 1, Case 2, and Case 3 in terms of total cost, emission, and monthly peak load.

objective is incorporated into the optimization problem using equality constraints. Fig. 11 illustrates the Pareto optimal and best compromise solutions of the EMS under the PBT tariff. As can be seen, the cost and emissions conflict with each other, meaning that as the cost decreases, emissions tend to increase and vice versa. The best compromise solution which is shown by red stars in Fig. 11 is the most balanced trade-off between conflicting objectives.

Fig. 12 compares the best compromise solutions obtained from the EMS under the PBT tariff with the results of Case 1, where cost is minimized, and Case 2, where emission is minimized. As depicted, the total cost and monthly peak demand in Case 3 are both lower than in Case 2, but slightly higher than in Case 1, by 2 % and 1.8 %, respectively. Likewise, the CO_2 emission in Case 3 is lower than in Case 1 and higher than in Case 2. It should be noted that as Pareto optimal solutions exist in Case 3, the EMS can select the best compromise solution by considering the sensitivity of the two objective functions for the single objective optimization problems, namely Case 1 and Case 2.

Table 6
Public laundries located in Göteborg student houses.

Student house address	Number of apartments	Number of machines combo	Peak hours
Rännan	63	2	16:00–20:00
Chabo	479	19	16:00–22:00
Gibraltar guesthouse	100	3	16:00–20:00
Sångsvanen	119	3	08:00–22:00
Kapellgången	77	4	16:00–20:00
Gibraltargatan 78	208	9	14:00–22:00
Gibraltargatan 80	128	4	14:00–22:00
Gibraltargatan 82&94	368	5	10:00–00:00
Gibraltargatan 84–92	418	11	07:30–00:00
Dr Forselius Backe	118	3	09:00–00:00
Dr Wigardhs gata	84	3	12:00–00:00
Total:	2162	66	–

Test results from public laundries located in Göteborg student houses

As shown in Table 6, there are 11 student houses in Göteborg that have their own public laundry facilities, which include a total of 66 washing machines and tumble dryers, the same as those used by HSB LL. The total number of tasks in the public laundries is 1980. The monthly task profile of washing machines and tumble dryers in student houses was extracted using the booking system to investigate the effectiveness of the proposed EMS to minimize cost objective and CO_2 emission, simultaneously.

The electricity costs, CO_2 emissions, and monthly peak demand of the public laundry during the study period for different scenarios are summarized in Table 7. The results indicate that implementing the PBT tariff leads to a significant decrease in total cost and peak demand, with reductions of 10.95 % and 45.18 %, respectively. In comparison, while total cost reduces by 5.35 % under the EBT tariff, the reduction in peak demand is only 1.16 %. Likewise, the CO_2 emission reduction under both tariffs is neglectable.

The daily peak demand of the public laundry is shown in Fig. 13. It is evident that implementing the EMS in combination with the public PBT tariff results in a much smoother power consumption pattern compared to the EBT tariff. More in detail, the monthly peak demand reduces by 44.54 % while the cost increases by 7.75 %. It should be mentioned that the daily peak load and its cost have only been calculated based on consumption of washing machines and tumble dryer and other consumptions are not considered since they are not controlled.

Conclusion

This paper presents a real-time rolling-horizon energy management model for public laundries that aims to minimize energy usage, peak demand, and CO_2 emissions. The proposed model optimizes the optimal operation of washing machines and tumble dryers while considering users' preferences. The effectiveness of the energy management system is evaluated under both traditional energy-based and power-based network tariffs. The results indicate that the EMS can effectively

Table 7
Operation results of the public laundry in the Göteborg student houses.

	W/O EMS		With EMS	
	EBT	PBT	EBT	PBT
Energy cost (€)	682	631	645	606
Power cost (€)	–	154	–	93
Total cost (€)	682	785	645	699
Emission ($kgCO_2$)	253	253	253	253
Monthly peak demand (kWh)	44.59	44.59	44.07	24.44

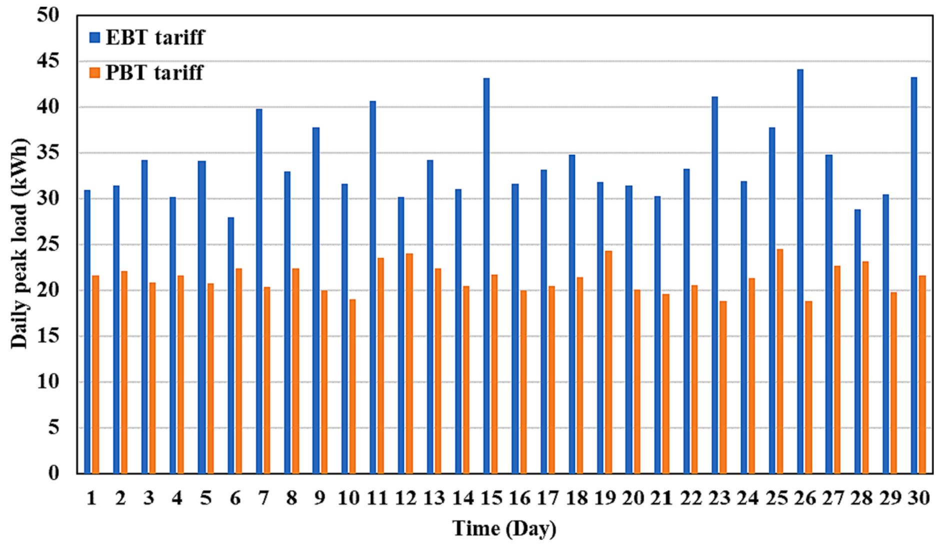

Fig. 13. Daily peak demand of the public laundry.

reduce energy costs and peak demand of public laundries under the PBT tariff, and energy costs under the EBT tariff. Likewise, the results indicate that the use of the EMS and the change of tariffs have a minimal impact on the reduction of CO_2 emissions. In future work, it is desirable to focus on the provision of flexibility by public laundries to the operator of the distribution grid, in order to increase the economic benefits of public laundries and improve technical performance of grids.

CRediT authorship contribution statement

Mohammadreza Mazidi: Methodology, Software, Visualization, Writing – original draft. **Elena Malakhatka:** Investigation, Data curation, Software. **David Steen:** Conceptualization, Investigation, Validation. **Holger Wallbaum:** Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mohammadreza Mazidi reports financial support was provided by Chalmers University of Technology.

Data availability

Data will be made available on request.

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