AN EVOLUTIONARY ALGORITHM-BASED MODEL PREDICTIVE CONTROL FOR COMBINED ELECTRICAL AND THERMAL ENERGY SYSTEMS

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Abstract

Energy storage is crucial to increase renewable energy adoption in construction. By optimizing their control strategies, operational costs decrease and return on investment improves. Model Predictive Controls (MPC) have been used to optimize the use of energy storage but are costly to implement. This paper presents an MPC with a generalized mathematical model for electrical and thermal storage. A methodology is introduced to account for physical restrictions. Three evolutionary algorithms were compared for the optimization and a Genetic Algorithm was found to best reduce the energy bill with average daily savings of 38.7 %.

Introduction

Driven by decarbonization targets, there is a strong push for increased electrification of building thermal demand coupled with the drive for increased use of renewable energy produced on site. One of the main constraints of Photovoltaic (PV) self-consumption in residential buildings is that a significant amount of the consumption takes place when there is no PV generation. A potential solution to overcome this is energy storage, electrical or thermal, allowing to use the PV excess generated during the central hours of daylight to cover the demand at night and other instants without PV generation. To date, electrical storage has been favoured, but thermal storage can be an additional source for storing surplus PV electricity in buildings with considerably less costs than electrochemical batteries, increasing the self-consumption rate and ultimately, usability of the local resource which yields better economics for the PV system (Psimopoulos et al., 2016).

To shorten the payback time of energy storage systems, it is important to have a sound control strategy. Most building systems use rule-based controls, which have the advantage to be easy to implement and to transfer between buildings (Noye et al., 2022). However, in the case of energy storage, the efficiency of a control strategy depends on the relation between future production and consumption. The advances in data-driven predictive models (Zhang et al., 2021) mean that it is possible to move towards predictive control. Optimal economic dispatch strategies for prosumers with energy storage have been widely investigated and reported in the literature (Liu et al., 2023). Model Predictive Controls (MPC) have shown to be effective at optimizing control prediction (Sultana et al., 2017). They consist in finding the optimal control action based on the constraints defined by a model over a finite receding horizon. MPC formulations over a short period of time, typically a day, to make battery charging/discharging decisions at each time step have been widely used to address different operational scheduling challenges, like the dispatch of energy storage in microgrids (Shang et al., 2020), operation control of multiple battery energy storage systems (Kim et al., 2018), market participation of smart home aggregators (Correa-Florez et al., 2018), or demand response for heat pump assisted solar water heater (Zhao et al., 2023).

Most of the studies address either battery or thermal storage. Combining both technologies lead to increased control complexity, as the storage charge and discharge efficiency, and self-discharge rate differ between technologies, and are time depended in the case of the thermal storage. A single study has been found to address the joint optimization of electrical and thermal storage (Iwafune et al., 2017), where the additional savings from combining both storage technologies are clearly stated. However, results are conditioned by the selected use case, where PV generation stands for around 5 times the averaged consumption, leading to a huge PV surplus that limits the margin for optimization of MPC management strategies.

The main challenge of MPCs in obtaining a model formulation, including physical constraints, that is compatible with optimization techniques, which often means reducing the order of the model and thus its accuracy (Noye et al., 2022). Evolutionary algorithms have been gaining interest for MPC, as they are able to solve non-linear optimization problems with non-differentiable cost functions (see for example Rodríguez del Nozal et al. (2019)).

The present paper builds on top of previous work from this research group, where a scalable and flexible optimization system based on production and load forecasting as a MPC for electrical storage scheduling (Lloréns et al., 2021). In the present work, the main contribution is that both, electrical and thermal storage, are simultaneously considered to optimize their jointly use. A mathematical formulation for an MPC to optimally control a system with renewable electricity production, electrical and thermal storage, and thermal and electrical consumption is presented, together with its optimization via evolutionary algorithms. The reparation method has been improved compared to previous work (Lloréns et al., 2021), so that it provides an interval of possible value, instead of truncating the values to their limits, reducing the exploration capability of the algorithm.

In the following section, the optimization problem is presented before describing the methodology used for the optimization. The methodology is divided between the mathematical formulation of the optimization problem and the methodology to solve it. The test case and how it was implemented is then described before presenting and discussing the results of the study.

Optimization problem definition

The considered system is composed of the following elements: electrical production, electrical and thermal storage, electrical and thermal consumption. A Heat Pump (HP) is used to charge and discharge the thermal storage. Figure 1 illustrates the energy flux between the different elements of the system. The aim of the MPC is to exploit the flexibility potential provided by the thermal storage and the electrical battery to maximize the use of local energy sources.

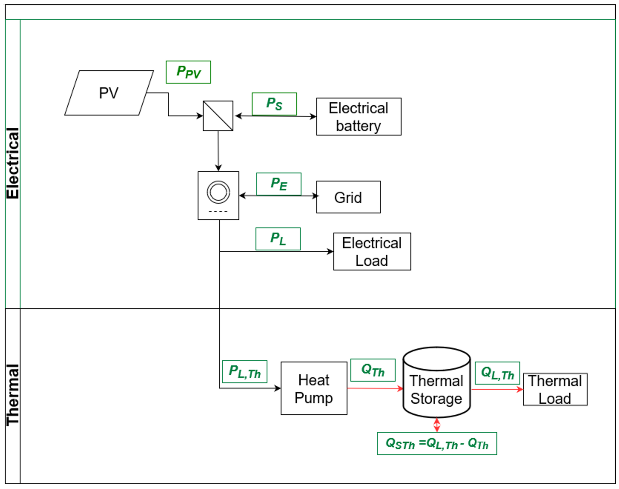

Figure 1: Main energy fluxes of the conceptual energy system to control

Methodology

Figure 2 illustrates the general schema of the MPC presented in this paper. First a general mathematical formulation of the problem is developed based on physical equations. It is divided in three sets of equations: 1) A cost function that represents the objective function to minimize; 2) A set of constraints to ensure the solutions of the optimization are viable; 3) A set of equations that link the different variables necessary for the calculation of the cost and the restrictions between time steps.
Evolutionary algorithms, a category of meta-heuristic optimizations, are then explored to find the optimal solution of the mathematical optimization problem. Three algorithms were compared: Estimation of Distribution Algorithm, Differential Evolution and Genetic Algorithm. The inputs of the optimization process are, on one hand, forecasting data (P_L the electrical load, P_{PV} the photovoltaic production, $Q_{L,Th}$ the thermal load and T_{amb} the outdoor ambient temperature) and, on the other hand, the current

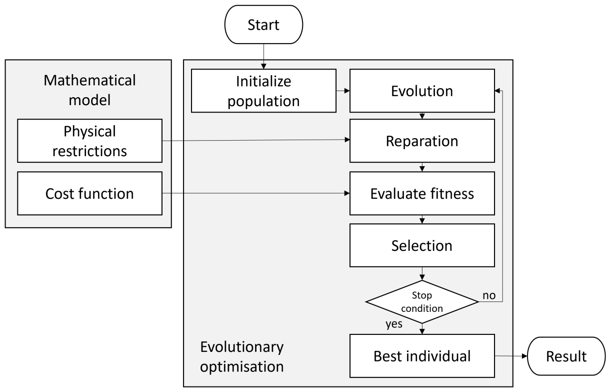

Figure 2: Overview of the MPC architecture

state of the system (charge of the battery SoC_{ini} and of the thermal accumulator $SoC_{ini,Th}$).
The optimization variables are the optimized values for charge and discharge of both the electrical battery (P_S) and the thermal storage (Q_S) for the N next time steps.
A baseline calculation, based on a rule-base reactive control sequence, is done in parallel to evaluate the performance of the evolutionary optimization process.

Mathematical model formulation

This section describes the mathematical formulation of the MPC control. It results in a cost function and a set of constraints used by the optimization algorithm.

Cost function

The mathematical definition of the optimization problem is based on the balance of electrical and thermal energies in the system. The convention used in this paper is that the positive numbers correspond to discharge actions and negative numbers to changer actions. For the electrical part, the energy balance can be expressed as follows:

$$P_{PV}^n - P_L^n - P_{L,Th}^n + P_S^n + P_E^n = 0 \qquad \forall n \in \{1,\dots,N\} \quad (1)$$

Where P_{PV}^n is the PV production, $P_{L,Th}^n$ the electrical load of the heat pump, P_L^n the remaining electrical load, P_S^n the electricity charged (<0) or discharged (>0) from the battery, and P_E^n the electricity drawn from (>0) or injected to (<0) the electricity grid. n represents the time steps of the control system and N the optimization period.
The thermal energy balance is expressed as follows:

$$-Q_{Th}^n - Q_{L,Th}^n + Q_S^n = 0 \qquad \forall n \in \{1,\dots,N\} \qquad (2)$$

Where Q_{Th}^n is the thermal load of the system, $Q_{L,Th}^n$ the thermal energy produced by the heat pump (always <0), and Q_S^n the energy extracted (>0) or injected (<0) from the thermal storage.
The thermal and electrical equations are coupled by the heat pump performance, which is:

$$P_{L,Th}^n \cdot COP = -\,Q_{Th}^n \qquad (3)$$

Where COP is the heat pump's Coefficient of Performance (COP), which is a function of both the storage temperature and the ambient temperature.
Combing Equations 1, 2 and 3, the equation of the conservation of energy is formulated as follows:

$$P_{PV}^{n} - P_{L}^{n} - \frac{1}{COP}(Q_{L,Th}^{n} - Q_{S}^{n}) + P_{S}^{n} + P_{E}^{n} = 0 \quad (4)$$

The objective of the MPC is to maximize the rate of self-consumption of the whole building, which is equivalent to minimizing the energy imported from the grid P_E. To maximize self-consumption, importing electricity need to be avoided, which corresponds to ($P_E > 0$). Thus the objective function to minimize becomes:

$$\sum_{n=1}^{N} \max\left\{0, (P_{L}^{n} + \frac{1}{COP}(Q_{L,Th}^{n} - Q_{S}^{n}) - P_{S}^{n} - P_{PV}^{n})\Delta t\right\} \quad (5)$$

The use of the maximum condition between 0 and P_E avoids the exported electricity to be considered in the cost function and results in minimizing the imported electricity. One limitation of this cost function is that it does not account for the energy stored in the system within the optimization period, and would thus tend to discharge the battery. In addition, the cost function of Equation 5 does not differentiate between a solution with more energy stored in the system at the end of the period and one with an empty storage. To include this effect, the energy stored at the end of the period, weighted by a factor, is added to the cost function. The function to minimize becomes:

$$\sum_{n=1}^{N} \max\left\{0, (P_{L}^{n} + \frac{1}{COP}(Q_{L,Th}^{n} - Q_{S}^{n}) - P_{S}^{n} - P_{PV}^{n})\Delta t\right\} - \alpha_1 \cdot Cap_{\max} \cdot \left[SoC^{N}\right] - \alpha_2 \cdot Cap_{\max,Th} \cdot \left[SoC_{Th}^{N}\right] \quad (6)$$

Where Cap_{max} is the net capacity of the electrical battery, SoC^N the State of Charge (SoC) of the battery at the end of the optimization period, $Cap_{\max,Th}$ the net capacity of the thermal storage, SoC_{Th}^{N} the SoC of the thermal storage at the end of the optimization period, α_1 a positive weighting factor for the electricity stored at the end of the period, and α_2 a positive weighting factor for the thermal energy stored at the end of the period. The drawback of this addition is the loss of physical meaning of the cost function.

Constraints

To ensure that the cost function leads to solutions that make physical sense, six constrains are introduced. The first two equations ensure that the charging and discharging of the battery meet the available battery capacity, one for the maximum capacity and the second for the minimum. The restriction on the discharge of the battery is expressed analytically as:

$$P_{S}^{n} \leq \psi_S \frac{cap_{max}(SoC_{ini} - SoC_{\min})}{\Delta t} - \psi_S \sum_{k=1}^{n-1} (min(0, P_{S}^{k}\psi_S) + max(0, P_{S}^{k}\frac{1}{\psi_S})) \quad (7)$$

And for the charge of the battery the restriction is:

$$-\frac{1}{\psi_S}(\frac{cap_{max}\Delta SoC}{\Delta t} - \frac{cap_{max}(SoC_{ini} - SoC_{min})}{\Delta t} + \sum_{k=1}^{n-1}(min(0, P_{S}^{k}\psi_S) + max(0, P_{S}^{k}\frac{1}{\psi_S}))) \leq P_{S}^{n} \quad (8)$$

Where ψ_S is the battery efficiency, SoC_{ini} the battery SoC at t=0, $SoC_{\min}$ the minimum allowable value for the battery SoC, and ΔSoC the allowed range for the battery SoC.
Similarly, two restrictions ensure that the charging and discharging of the thermal storage keep the tank operation in the allowed range. For charging, the equation is:

$$Cap_{max,Th} - Cap_{max,Th}SoC_{ini,Th} + \Delta t \sum_{k=1}^{n-1}(Q_{S}^{k} + G(T_{Tank}^{k})) \geq \Delta t \cdot Q_{S}^{n} \quad (9)$$

And for discharging:

$$Cap_{\max,Th}SoC_{ini,Th} - \Delta t \cdot \sum_{k=1}^{n-1}(Q_{S}^{k} + G(T_{Tank}^{k})) \geq \Delta t \cdot Q_{S,Th}^{n} \quad (10)$$

Where $SoC_{ini,Th}$ is the thermal storage's SoC at t=0, and $G^k(T_{Tank})$ a function of the tank temperature T_{Tank} that accounts for the thermal losses of the storage.
The fifth restriction limits the power available to charge and discharge the storage to the heat pump maximum capacity ($Q_{Th,max}$):

$$0 \leq Q_{L,Th}^{n} - Q_{S}^{n} \leq Q_{Th\_\max}^{n} \quad (11)$$

Finally, the sixth restriction limits the power requested from the grid to the maximum power (by contract), constraining the flow in or out of the battery by:

$$-P_{L}^{n} - P_{L,Th} + P_{PV}^{n} + P_{S}^{n} \geq -pow_{\max} \quad (12)$$

Where $pow_{\max}$ is the contracted electrical capacity.

Relations between time steps

The additional equations presented in this section are used to calculate how the two SoCs and thermal storage temperature are affected by charge and discharge of the energy system between time steps. For the SoC of the thermal storage, the temporal relationship is:

$$SoC_{Th}^{n+1} = SoC_{Th}^{n} - \left(\frac{Q_{S}^{n} - G\left(T_{Tank}^{n}\right) \cdot \Delta t}{Cap_{max,Th}}\right) \quad (13)$$

The tank temperature in the next time step is:

$$T_{Tank}^{n+1} = T_{Tank,min} + SoC_{Th}^{n+1} \cdot (T_{Tank,max} - T_{Tank,min}) \quad (14)$$

Where $T_{Tank,max}$ and $T_{Tank,min}$ are the maximum and minimum temperature allowed in the tank respectively. For the battery, the update of the SoC between time steps is:

$$SoC^{n+1} = SoC^{n} - \frac{\psi_s \cdot \min\left(0, P_S^n\right) + \left(\frac{1}{\psi_s}\right) \cdot \max\left(0, P_S^n\right)}{Cap_{max}} \tag{15}$$

Control optimization

Evolutionary algorithms

Evolutionary Algorithms are heuristic algorithms based on the Darwin evolution theory known to be efficient at solving complex optimization problems. They are easy to implement since the fitness function does not need to be differentiable. They are based on a population that is evolved stochastically to look for better solutions. Because they are good at keeping diversity, they perform well when it comes to escaping local optimum. Three evolutionary algorithms were tested for the MPC: Estimation of Distribution Algorithm (EDA), Differential Evolution (DE) and Genetic Algorithm (GA).

EDA it is an evolutionary algorithm that focuses on building and updating probabilistic models of promising solutions to guide the search for optimal solutions in optimization problems. DE is an algorithm that optimizes a population of candidate solutions by iteratively combining the differences between their parameter values to progressively converge toward the optimal solution. GA mimics the process of natural selection by iteratively evolving a population of candidate solutions by selecting, recombining, and mutating individuals to find optimal solutions in optimization problems.

Individuals definition

Common to all the algorithm implementation is the definition of the individuals. A solution is represented by a 2N array, where the N first values represent the battery control P_S^n and the N following values, the tank control Q_S^n:

$$\{P_s^0, P_s^1, \ldots, P_s^{N-1}, Q_{s,Th}^0, \ldots, Q_{s,Th}^{N-1}\} \tag{16}$$

Population initialization

An evolutionary algorithm starts by generating an initial population of individuals. Because of the restrictions, a random individual is likely not to be valid. Indeed, the possible values for P_S^n y Q_S^n are constrained by the previous values and how they have affected the SoC of the electrical and thermal storage respectively. A sequential sampling initialization process that incorporates the restrictions was implemented starting from the initial state $x_0 = x(t_0) = (SoC^0, SoC^0_{Th})$ and where P_S^n y Q_S^n depend on P_S^{n-1} and Q_S^{n-1} respectively.

According to the restrictions on charge and discharge of the electrical and thermal storage (Eq. 7-10) the valid range for P_s^n y Q_s^n (the values at the next time step) is as follows:

$$P_s^n \in [-Cap_{max}(1 - SoC^{n-1}), Cap_{max}(SoC^{n-1} - SoC_{min})] \tag{17}$$

$$Q_s^n \in [-Cap_{max,Th}(1 - SoC_{Th}^{n-1}), Q_{L,Th}^n] \tag{18}$$

In physical terms, this means that for discharge, the valid values are those smaller than the energy available at the accumulator and battery, and for charging the valid values are limited by the capacity available in the storage. Besides, for the thermal accumulator the discharge cannot be larger than the thermal load.

Substituting the equation of restriction of maximum load of the thermal storage (11) in (18) gives:

$$Q_s^n \in [max(-Cap_{max,Th}(1 - SoC_{Th}^{n-1}), Q_{L,Th}^n - Q_{Th,max}), Q_{L,Th}^n] \tag{19}$$

And finally, substituting Equation 12 that restricts the maximum load of the electric battery in (17), gives:

$$P_s^n \in [max(-Cap_{max}(1 - SoC^{n-1}), P_L^n + P_{L,Th}^n - P_{PV}^n - pow_{max}), Capmax(SoC^{n-1} - SoC_{min})] \tag{20}$$

Equations 19 and 20 define the range of valid values. Because they are coupled by $Q_{L,Th}$ and $P_{L,Th}$, first a uniform random sampling is performed to determine the value of Q_S^n. The value of P_S^n is then uniformly sampled within the resulting range.

Evolution process

The evolution process is implemented according to the three algorithms tested. For the EDA, the EMNA algorithm proposed by Teytaud and Teytaud (2009) was implemented. It consists in re-weighting to remove bias, which is aimed at limiting premature convergence. The main hyperparameter is the λ which is the number of individuals retained at each generation.

For the DE, the original algorithm from Storn and Price (1997) has been implemented where vectors are recombined based on the trial vector that is a linear recombination of random vectors of the population. The main hyperparameter is the scaling factor β which determines the weight of the selected vectors compared to the individual that is being evolved.

The GA implements a Gaussian mutation of mean $\mu = 0$ and deviation σ and a uniform crossover which is a commonly used implementation according to the review of GA by Katoch et al. (2021).

As for the initial generation of the population, the evolution process might generate invalid individuals. Several approaches exist to address this problem: 1) Define a specialized operators so that the evolution process only produces valid solutions; 2) Include a penalty for invalid solutions in the fitness function. One limitation of this approach is that the algorithm then works on reducing the penalty and might not focus as much on the optimization objective; 3) Introduce a repair operator that transforms invalid solutions into valid solutions.

Approach (3) was implemented using Equations 19 and 20. When the value at n violates one of the constraints, the individual is repaired sequentially at all the time steps between n and N. This enables to keep diversity in the population despite the reparation process.
The fitness of the generated individuals is evaluated using the cost function defined in Equations 6. It is used to build a ranking of individuals and select among them which ones progress to the next generation.

Baseline definition

To assess the performance of the optimization strategy, a static control strategy was defined using a set of rules. This strategy consists in a basic sequence that, in case where there is a PV surplus, it is stored in the battery, and once this is full, the system starts filling the thermal storage through the heat pump. Once both storage are full, it sends the surplus to the electricity grid. In the case there is no PV surplus, the system uses, if possible, the energy available both at the battery and the storage, and if they are empty, it will use electricity from the grid. This control strategy is evaluated for each individual in the optimization process, to compare to the evolutionary algorithms' results.

Implementation

This section describes the implementation of the MPC descried in the previous section and the test case that was used to test it. The mathematical model was implemented in Python, and the DEAP python library was used to implement the evolutionary algorithms.

Test case

The test case is based on a real multi-family building located in Pasaia, Spain. The energy system to be controlled has two central air-to-water heat pumps with a total heating power of 34 kW at nominal conditions with a thermal storage of 2.000 litres located in the building garage. From this centralized system, a low temperature (30º C) distribution loop runs through the building to the individual water-to-water heat pumps located at each of the dwellings to provide heating and Domestic Hot Water (DHW). Besides, there is a 6 kWp PV system on the roof and an electrical battery for storage.
The controlled system does not include the storage for the DHW linked with the water-to-water heat pumps at each of the dwellings. They offer limited flexibility potential (less than 2 kWh compared to close to 70 kWh for the central storage) while including them would significantly add to the computational complexity. This means an increased computational effort, poorer performance, more expenses in monitoring and control and in general, a less robust implementation.

Heat pump and water tank models

The *COP* and the thermal losses of the tank use equations specific to the use case. Those are characterized by a correlation that is a function of the tank temperature and the ambient temperature. For the COP, the following function was used:

$$COP = 10.168 - 2.716\cdot10^{-1} \cdot T_{Tank} + 4.331\cdot10^{-2} \cdot T_{amb} + 2.372\cdot10^{-3} \cdot T_{Tank}^2 - 6.623\cdot10^{-4} \cdot T_{amb}^2 \quad (21)$$

This correlation was obtained from data generated by a simulation of the system in TRNSYS, where the heat pump was modeled by a performance map obtained from the manufacturer data. This correlation could be updated by monitoring data from the system if available.
$G(T_{Tank})$ is a function that characterizes the thermal losses of the water tank. To obtain it, a thermal storage with cylindrical geometry and insulated according to the regulatory specifications was modeled in TRNSYS. The function was obtained preforming a correlation of the results of simulations of this model:

$$G(T_{Tank}) = (3.6 + 1.9 \cdot Vol) \cdot (T_{Tank} - 15) \cdot 10^{-3} \quad (22)$$

Where Vol is the tank volume in m³ and T_{Tank} is the tank temperature in °C.

Test case parameters

The optimization horizon N was selected to be 24 hours with time steps Δt of 1 hour.
In the cost function, the value of α_1 was set to $0.9 \cdot \psi$, and the value of α_2 to 0.9/3.5, where 3.5 is a proxy of the heat pump average COP. The motivation for the 0.9 value was to give a slightly higher value to the energy already consumed than the one stored for the next day.
The values of the physical parameters of the system are summarized in Table 1. The value of the heat storage capacity was calculated from the sensible heat capacity of water as:

$$cap_{max,Th} = \frac{4.18 \cdot Vol \cdot (T_{Tank,max} - T_{Tank,min})}{3.6} [kWh] \quad (23)$$

Optimization inputs

To test the validity of the developed MPC, one year of synthetic input data were generated. The hourly production were generated with PVGis for the location of the building. The TMY weather file generated by PVGis was used as well for generating the ambient temperature, to ensure consistency between radiation and temperature data. The hourly thermal load data were generated based on the historical natural gas invoices of the occupants. From these invoices, the summer consumption was accounted as representative of the DHW load, and the rest of the consumption was accounted as space heating. To generate hourly values of DHW load, the software DHWCalc 2.0 was used, imposing that the yearly load fits the value estimated from the invoices. For the space heating, the generation of hourly loads from annual values was done by allocating the operation of the thermostat in a minute basis based mainly on ambient temperature, hour of the day, a setpoint temperature and radiator capacity. The profile is subject to fit the amount of energy derived from the natural gas invoices.

Table 1: System parameters of the test case

Parameter	Value
Battery capacity (cap_{max})	6 kWh
Valid SoC range for the battery (ΔSoC)	0.8
Battery minimum SoC (SoC_{min})	0.2
Battery charge/discharge efficiency (Ψ)	0.95
Maximum storage temperature ($T_{Tank,max}$)	55 ºC
Minimum storage temperature ($T_{Tank,min}$)	25 ºC
Accumulator volume (Vol)	2 m³
Storage capacity ($cap_{max,Th}$)	70 kWh
Heat pump maximum capacity ($Q_{th,max}$)	18 kW
Maximum electricity consumption (pow_{max})	18 kW

Table 2: Days selected for the evaluation of the optimizer

Quantile	Date	PV/Load ratio	Total load (kWh)
0	16/01/2022	0.04	46.12
0.1	07/03/2022	0.32	24.85
0.2	15/11/2021	0.59	15.97
0.3	09/12/2021	0.77	36.22
0.4	25/04/2022	1.06	18.19
0.5	06/05/2022	1.74	9.03
0.6	01/07/2022	2.03	8.68
0.7	01/08/2022	3.22	8.12
0.8	07/05/2022	2.59	12.99
0.9	06/09/2021	4.29	6.41
1	06/07/2022	4.45	7.83

The initial daily SoC were set to 0.6 for SoC_{ini} and 0.5 for $SoC_{ini,Th}$, so as to be in the middle of the range between minimum and maximum charge.

Test days

To select the best algorithm, a set of days representative of the different boundary conditions were selected. Since the optimization potential is strongly affected by the PV production and the thermal and electrical loads, the ratio between the PV production and the system load was used. After evaluating the metric for all the days in the test data, the days were ordered and days on the quantiles were sampled in increments of 0.1 (Table 2).

The days with a low PV/Load ratio have a high demand compared to the PV production, when the days with a high PV/Load ratio have a lot of production compared to the demand. The days with the most optimization potential are the ones where the PV/Load ratio is more balanced. The optimization results of the best algorithm were then evaluated on the full year.

Discussion and result analysis

Evolutionary algorithm selection

Several configuration were tested on the 10 reference days for the different algorithms. For the EDA, several values of λ between 300 and 1200 were tested. They were found to have a very small influence on the final results. Although the EDA gave acceptable results some days, there were days when it did not manage to improve on the baseline, mostly in days with a low PV/Load ratio. For the DE, different values of the scaling factor β were tested. Lower values of β performed better, but the DE got stuck in a local minimum and complexity would need to be added to the algorithm to increase its exploration rate, in order to have satisfactory results. For this reason and although the EDA and the DE could be improved to palliate their initial limitations, the GA was selected as the best algorithm as a basic implementation would give better results than the baseline.

For the GA, the main hyperparamters tested were the selection method and the σ value. The most important factor for the GA to find better solutions than the baseline is the selection of individuals that pass to the next generation. With the roulette method the GA converges in a local minimum and fails to improve the baseline, whether the tournament selection method enables to improve the baseline. Finally, σ was found to have a small influence on the results, and only affect the optimization outcome on the days with more solar production than demand. The final value selected is 0.5.

Once the GA algorithm was selected, some experiments have also been carried out to determine the best population size and optimal number of generations. It was found that 200 was generally a good number for both. Table 3 shows that the best individual is generally identified between generations 157 and 200. Even in the cases where the best individual was generated in the generation 200, it was found that running the optimization longer would only marginally improve the result.

Optimization results

This section summaries the optimization results obtained with the MPC with GA optimization. Table 3 shows the

Table 3: Results of the genetic algorithm for the test case

Date	PV/Load ratio	Total load (kWh)	Cost GA	Cost baseline	Absolute savings	Relative savings %	Best individual's generation
16/01/2022	0.04	46.12	30.47	30.12	-0.35	-1.17 %	179
07/03/2022	0.32	24.85	4.27	4.66	0.39	8.39 %	165
15/11/2021	0.59	15.97	-5.19	-3.56	1.64	46.00 %	191
09/12/2021	0.77	36.22	0.78	3.14	2.36	75.14 %	199
25/04/2022	1.06	18.19	-8.21	-8.10	0.11	1.31 %	198
06/05/2022	1.74	9.03	-15.59	-13.76	1.83	13.33 %	178
01/07/2022	2.03	8.68	-17.59	-17.39	0.21	1.20 %	187
01/08/2022	3.22	8.12	-21.69	-19.88	1.81	9.10 %	198
07/05/2022	2.59	12.99	-23.04	-18.99	4.06	21.36 %	200
06/09/2021	4.29	6.41	-23.39	-19.57	3.82	19.52 %	157
06/07/2022	4.45	7.83	-20.90	-21.21	-0.31	-1.48 %	199

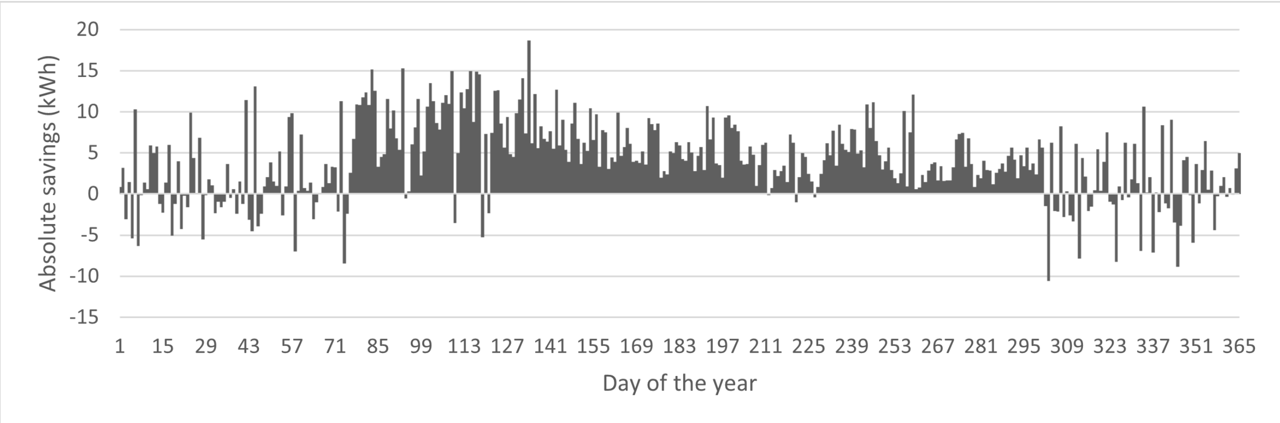

Figure 3: Daily absolute saving over one year

savings achieved for the 10 representative days. The absolute savings are difficult to interpret due to the additional term added to the cost function which makes it lose its physical meaning. Relative savings were thus calculated as the percentage of absolute saving compared to the cost of the baseline.

It can be seen that for two of the selected reference days, the MPC yields a performance under the baseline definition. Those days correspond to the limit cases. The 16/01, there is almost not PV production while the load is high. The 06/07, the demand is limited while the PV production is high. In both cases, there is no potential for optimization and the baseline provide the optimal solution. In those cases the GA failed to converge to the baseline. This can be solved in practice by implementing a control rule that does only run the MPC when there is optimization potential.

Two of the representative days have savings that are lower than 2 %. The 25/04 the demand during the hours with PV production is very close to the production, meaning the optimal solution is to consume the PV energy as it is produced leaving little room for optimization. The 01/07, the lack of optimization reserve comes from the fact that the pick of demand is before the period of PV production and the rest of the days then corresponds to a case with high solar production and no demand.

For the rest of the days (7 out of 11), the MPC is able to leverage the combined electrical and thermal storage much better than the rule base system.

Figure 3 shows the daily saving (without the additional term) that the MPC achieves compared to the rule base control. It can be seen that the MPC yealds less interesting saving in the winter month (beginning and end of the year) where there is statistically less solar production, but provides good results the rest of the year. Over the year 1454.23 kWh less is imported from the grid, which represents an average of 38.7 % of daily saving compared to the baseline. This could be further improved by using the baseline when it yields better results.

The MPC has been developed with PV in mind because of the test case at hand, but the mathematical formulation remains valid for any other electrical production (e.g. micro wind generation). The optimization results would need to be validated as the pattern between production and consumption would be different. Similarly, the formulation stays valid for a case where there is only one of the two storage types. In this case, the values of the system that is not present can simply be put to be zero.

Conclusions

In this paper, an evolutionary algorithm-based MPC optimizing the operation of both electrical and thermal renewable energy storage was proposed. A parametrisable mathematical formulation of the optimization problem was presented. Three evolutionary algorithms were tested to solve the optimization problem and a methodology to address physical restrictions was proposed. A genetic algorithm with tournament selection was shown to give the best results. The average daily saving of the MPC compared to a traditional rule-base control was found to be 38.7 %.

As future work, it would be interesting to test the results with variable energy prices, which enable to take even more advantage of the thermal and electrical storage.

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