An efficient EMS for aggregated energy systems including renewables, storages, CHP units and heat pumps

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Abstract

The need to reduce man-made greenhouse gas emissions leads to the ever larger importance of exploiting operational synergies of Aggregated Energy Systems. Mixed Integer Linear Programming (MILP) based Energy Management Systems (EMS) are state-of-the-art tools for exploiting these synergies by determining the optimal operation of different units over the desired time horizon. This work presents two EMSs evaluated through a two-month case study. The performance of these two EMSs is compared against the ideal operation of the system assuming perfect forecasts, as well as heuristic strategies. Results showed that using EMS can yield monthly cost savings of up to 14.7% compared to heuristic strategies. The EMS shows also a very good robustness to the uncertainty of input forecasts. The solutions derived remain feasible, with only 1.1% suboptimality compared to the scheduling solution obtained under perfect forecast conditions.

**Keywords**: energy management systems, energy districts, MILP, microgrids, rolling-horizon.

* 1. Introduction

Improvements in energy efficiency have been identified as one of the key actions for achieving required emission reductions that will put the energy sector on the pathway to limit the global average surface temperature increase below 1.5 °C above pre-industrial levels (IEA, 2023). One of the ways to achieve an increase in energy efficiency is to leverage synergies between energy sources. They can be exploited by including different energy sources in an Aggregated Energy System (AES) that can use different techniques for determining their operation that allows the system to satisfy user’s energy demand. HOMER (Lambert et al., 2005) is a widely known commercial software used for determining the design and operation of off-grid microgrids. For determining the operation of the system, it uses two heuristic strategies, Load Following (LF) and Cycle Charging (CC), as described in Barley & Winn, 1996. However, due to their inability to see the future, these approaches provide suboptimal solutions. This problem can be solved by means of adopting an Energy Management System (EMS) that uses systematic optimization approaches and forecasts of the energy demand, production of intermittent renewables, and ambient conditions, to determine the optimal operation of the system.

There are numerous works in literature adopting MILP models for the EMS of Combined Heat and Power (CHP) systems, multi-energy systems and microgrids. For example, Bischi et al., 2014 developed a detailed MILP model for the short-term operational optimization of CHP units, that was later extended to optimize the long-term yearly operation (Bischi et al., 2019), and uncertainty of the input forecasts (Moretti et al., 2020, Castelli et al., 2023). Further examples include work by Fang & Lahdelma, 2016 in which they developed an EMS that optimizes the operation of a CHP plant, coupled with the heat storage, under inaccurate forecast, and work by Hellmers et al., 2016 in which the operation of the AES, consisting of CHP plant and wind farm, was optimized on the day-ahead and balancing markets.

This work presents two EMSs developed by Politecnico di Milano throughout the years, tailored specifically for AES featuring CHP units, energy storages, and intermittent renewables. These EMSs are applied in collaboration with Yanmar R&D to determine the optimal operation of AES that incorporates their products, in particular CHP engines and Heat Pumps (HPs). The EMSs employ a rolling-horizon approach, utilizing forecasts of the energy demand, intermittent renewables production (PV and ST), and ambient conditions (ambient temperature and irradiation) to determine optimal unit commitment, loads of dispatchable generators (CHP engines, HPs, boilers, etc.), storage management, and electricity import/export from/to the grid. The EMSs are based on a rigorous and accurate formulation of the optimization problem as a MILP that is solved using Gurobi.

* 1. Methodology

Both EMSs are an adaption of the one originally proposed by Moretti et al., 2020 for off-grid microgrids. They are implemented using the rolling horizon framework with an optimization horizon of 24 hours. Moreover, the performance maps of the units are linearized using the convex hull approach considering the effect of the ambient temperature. EMS 1 is a single-layer rolling-horizon approach which uses a forecast correction strategy for the transition from the current measured data to the forecasted ones. EMS 2 consists of two layers, its first layer employs only the forecasts and therefore its time resolution is equal to one hour. Meanwhile, the second layer works only with the measured data resulting in a time resolution of 15 minutes. Figure 1 shows a schematic representation of the two EMSs (i.e., EMS 1 and EMS 2) proposed in this work.

* + 1. EMS 1: Single-layer EMS

EMS 1 combines both measurements and forecasts by taking the measured values in the first timestep of the optimization horizon, while taking the forecasted values for the rest. It is formulated as a MILP, where the real variables are used to characterize the production and consumption of the machines, renewables production, storage charge/discharge and State of Charge (SOC), and import/export from/to the grid. On the other hand, binary variables are used to define the machines on/off state, and machine start-up.



Figure 1: Schematic representation of EMS 1 and EMS 2



Figure 2: Example of forecast correction and variable time discretization.

Forcing a value of storage SOC at the end of the day might lead to suboptimal solutions for tomorrow. Therefore, to improve the management of the storage system, it is decided to impose SOC value after two days to reduce its impact on the scheduling solutions during the first day. In the case that forecasts are available only for the first 24 hours, the proposed approach can be realized by repeating the same forecast. If the fine time discretization, required to include measured values results in MILP being too large, it is possible to adopt an adaptive time mesh. It consists of adopting finer discretization in the timesteps close to the present, while coarser time resolution is used for the future. Finally, as the forecasts can have a significant impact on the results of the EMS, this work applies a forecast correction strategy. The idea is to make the weighted average between the average of the measured values in the last two timesteps and forecasted values. To ensure that the correction made is more significant in the timesteps closer to the present, a weight vector that starts from a defined value at the current timestep and then linearly reduces to zero, is considered. Figure 2 shows a schematic representation of adaptive time mesh and forecast correction.

* + 1. EMS 2: Two-layer EMS

It is a two-layer EMS in which each of the two layers is formulated as a MILP. The role of the first layer is to determine the optimal operation of the system across a day using the forecasts of energy demands, ambient temperature (which influence the efficiency of the engines, refrigeration cycles and heat pumps) and renewables productions. It is formulated exactly as the single layer of the EMS 1, with the only difference being that it uses forecasts also in the first timestep. The second layer is used on a real-time basis to correct the solution of the first layer in light of the actual energy demands and renewables production. Since it carries out optimization only in the present timestep, without considering the future, without an additional constraint it would shut down the machines and discharge the storage to meet energy demands. Therefore, an additional cost term, that imposes the desired behavior of the storage, is added to the objective function as shown in Eq. (1). It includes a fictitious revenue ($\tilde{c}\_{st}^{surplus}E\_{st}^{surplus})$ obtained by charging the storage above the setpoint indicated by the first layer, and a fictitious cost ($\tilde{c}\_{st}^{deficit}E\_{st}^{deficit})$ associated with discharging the storage below it.

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| --- | --- |
| $$OF=OF+\sum\_{st\in S}^{}\left(\tilde{c}\_{st}^{deficit}E\_{st}^{deficit}-\tilde{c}\_{st}^{surplus}E\_{st}^{surplus}\right)+\sum\_{m\in M}^{}\tilde{c}\_{m}^{dispatch}δ\_{m}^{dispatch}$$ | (1) |

Unmet demand, that can arise due to the error in the forecasts, is avoided by including a binary variable in the second layer that allows it to turn on the machines. However, this allows the second layer to turn off the machines if the demand is lower than expected, which can result in frequent on/off of the machines. Therefore, an additional cost term ($\tilde{c}\_{m}^{dispatch}δ\_{m}^{dispatch})$ is added to the objective function that penalizes the divergence in the dispatching decisions of the first and second layers that is expressed through a binary variable $δ\_{m}^{dispatch}$ defined for every machine.

* + 1. Benchmark Control Strategies

In addition to the widely adopted heuristic strategies such as LF and CC, this work also proposes the single timestep MILP (here called LF-MILP) as the benchmark for the EMS performance (for each timestep, the LF-MILP minimizes the operational cost without taking into account the future timesteps). While the LF-MILP uses the units that minimize the current operational cost, the LF case uses the units according to an efficiency priority order (set by the user).

* 1. Case Study and Computational Results

To assess the effectiveness of the two EMSs, they are used for optimizing the operation of the case study shown in Figure 3 for the months of January and March of 2017. The case study consists of the following components: TESS, 2 CHP engines, boiler, HP, ST panels, and PV panels. Its hourly demand values for electricity and heating are taken from the National Renewable Energy Laboratory, 2014 data set for a full-service restaurant, while ambient condition data are taken from the TMY provided by PVGIS (Huld et al., 2012). Values for the forecast are obtained using the persistence method on the aforementioned data, where for the demand, weekends are forecasted using the data of the previous weekend. In the case of electricity demand forecast, Mean Average Percentage Error (MAPE) and Mean Average Deviation (MAD) are equal to 5.6 % and 1.7 kW, respectively. On the other hand, the forecast for the heat demand is much less reliable, with MAPE and MAD equal to 200.4 % and 19.1 kW, respectively. Table 1 reports the performance of the two EMSs and the comparison with the two heuristic strategies and LF-MILP. Moreover, the table reports the minimum possible operating cost (lower bound) which could be achieved with perfect forecasts (no forecast uncertainty) and optimizing the operation with a single large-scale MILP. Such an ideal case is referred to as “omniscient EMS”. It is evident that management of the AES using two proposed EMSs is not far away from the perfect operation described by the omniscient. As expected, EMS 1 provides the best performance as it can avoid suboptimal second-layer corrections and its operating cost is only 1.1 % higher compared to that of the lower bound. This also indicates that the EMS is very robust to the uncertainty of the forecasts.



Figure 3: Configuration of the AES used in the test case.

Table 1: Performance summary of the different EMSs.

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|  | Total cost [€] | Cost increase [%] | Average run time [s] |
| Lower bound (Omniscient EMS) | 7,792 | / | 1.87 |
| EMS 1 | 7,881 | 1.1 | 2.29 |
| EMS 2 | 7,993 | 2.6 | 0.61 |
| LF-MILP | 8,264 | 6.1 | 0.02 |
| LF | 8,477 | 8.8 | <10-5 |
| CC | 9,239 | 18.6 | <10-5 |

On the other hand, LF-MILP and heuristic strategies are extremely fast, however, this comes at the expense of their performance, having significant deviation from the omniscient. For the sake of brevity and easier interpretation, only plots presenting the results of EMS 1 and omniscient in the case of thermal energy demand for the first day of January are reported in Figure 4. Before commenting on the differences in the results, it is important to note that the forecast for January 1st significantly underestimates thermal demand during the largest part of the day, especially in the morning. However, for January 2nd the situation is the other way around, with the forecast that significantly overestimates actual thermal demand. These two factors are a driving force behind the differences in EMS 1 and omniscient operation which can be seen in Figure 4. Omniscient, due to its perfect knowledge, is aware that the load is significantly higher than forecasted and therefore dispatches both CHP 2 and HP during the morning to fill the storage that, together with the HP, will be used during morning hours to meet the demand. On the other hand, EMS 1 is unaware of the forecast error and therefore is not able to prepare the storage and instead uses CHP 2 to cover most of the demand during early morning. The second main difference is the energy content of the storage at the end of the day. EMS 1 sees high demand for the following day and therefore completely fills the storage. On the contrary, as omniscient is aware that the forecast is overestimating actual demand, it fills storage only up to 60 % of its maximum energy content.

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| 1. EMS 1
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| 1. Omniscient
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Figure 4: Comparison between operation of EMS 1 and omniscient for January 1st

In terms of cost savings, EMS 1 performs better than EMS2 because the second layer corrections of EMS2 are made without knowledge of the future.

* 1. Conclusions

This work presented two different EMSs developed by Politecnico di Milano used for determining optimal operation of the AESs with combined heat and power units, heat pumps, energy storages, and intermittent renewables. These two EMSs were employed in collaboration with Yanmar R&D for a case study considering the AES employing their CHP engines along with other machines (i.e., HP and boiler) and renewable energy generators (i.e., PV and ST panels). Operation of the AES was simulated during the months of January and March and the results showed that the single-layer EMS is particularly effective, with a total operating cost of only 1.1 % higher than the perfect operation. Compared to benchmark heuristic algorithms, it allows reducing the operational cost in the range 5-15 %. Therefore, the proposed EMS is very promising for the optimal operation of aggregated energy systems.

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