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Hybrid storage system control for real-time power balancing in a hybrid renewable energy system

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Abstract : Hybrid renewable energy systems (HRES), which co-locate two or more renewable energy sources, have proven to be promising frameworks for harnessing complementarity among different renewable resources. However, the inherent uncertainty within these systems require the recourse to potential flexibility sources such as storage. This paper proposes a data-driven control scheme for scheduling the operation of a hybrid energy storage system (ESS) within a HRES comprising PV, wind and hydro generation. The objective is to maintain the generation-demand balance in real time while maximizing renewable generation intake. Multi-agent deep reinforcement learning is investigated as a decision-making tool for real-time scheduling. Its performance is compared with common state-of-the art approaches, namely model predictive control and rule-based control. The comparison is based on a set of diverse and rigorous criteria to evaluate the trade-offs of each approach. These criteria include reliability of supply, environmental impact, uncertainty handling, battery lifetime preservation, computational tractability, communication requirements, anticipative control behavior, and adaptability. The analysis highlights as well the benefits of hybrid ESS integration within a HRES. Results show that data-driven approaches can be executed with similar levels of performance as conventional control approaches. Furthermore, depending on the system characteristics and operation priorities, the selection of an appropriate scheduling scheme is a compromise between different criteria, which need to be jointly taken into account.

Keywords: Hybrid renewable energy system, hybrid storage, model predictive control, power balancing, reinforcement learning, rule-based control

Résumé : Les systèmes de production d'énergie renouvelables hybrides (SPERH), oú l'on peut trouver deux ou plusieurs moyens de production d'énergie renouvelables co-localisées, sont prometteurs car ils permettent de mettre en commun les aspects complémentaires de différentes sources d'énergie. En revanche, l'incertitude associée au niveau de production de ces systèmes requiert qu'ils aient recours à des ressources, tels les systèmes de stockage d'énergie (SSE), afin de contrôler l'équilibre entre la production et la charge. Cet article propose une approche de commande basée sur les données d'un SSE hybride—c'est à dire un SSE possèdant plusieurs médiums de stockage—dans le contexte d'un SPERH. Son objectif est de maintenir l'équilibre entre la production et la charge du SPERH en temps réel tout en maximisant l'apport de production renouvelable. L'approche de commande proposée est basée sur l'apprentissage par renforcement multi-agent profond. En comparant cette approche aux autres méthodes utilisées en pratique, c'est-à-dire la commande par modèle prédictif et la commande à base de règles, on constate sa performance selon une gamme de critères rigoureux afin d'y voir les compromis associés pour chaque approche. Parmi ces critères on retrouve la fiabilité de service, l'impact environnemental, la gestion de l'incertitude, la durée de vie des systèmes de stockage par batteries, l'effort de calcul, les besoins de moyens de télécommunication, les habiletés adaptatives et les capacités d'anticipation. L'analyse met en lumière les bénéfices des SSE hybrides au sein d'un SPERH et les résultats expérimentaux démontrent comment notre approche basée sur les données peut performer au même niveaux que les méthodes de pointe. De plus, dépendamment des caractéristiques des systèmes et des priorités d'exploitation, la sélection d'une approche de commande présente un compromis entre différents critères qui doivent être pris en compte de manière conjointe.

Mots clés : Système de production d'énergie renouvelables hybrides, Stockage d'énergie hybride, Commande par modèle prédictif, Équilibrage de puissance, Apprentissage par renforcement, Commande à base de règles.

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1 Introduction

To meet climate targets, there is an urgent need for swiftly decarbonizing energy systems and reaching carbon neutrality by 2050 [1, 2]. Achieving this objective requires the integration of high shares of renewable energy sources to reduce the reliance on pollutant fossil fuel-based generation. Over the last decade, the world has been witnessing a rapidly increasing participation of renewable generation, namely wind and PV, with new records of penetration levels [3]. The participation of renewable generation in the energy mix has grown from 20% in 2010 to around 28% in 2020, and is expected to rise at a higher pace in the coming decades in order to meet climate targets [1]. In this regard, hybrid renewable energy systems (HRES), defined as settings that co-locate two or more renewable energy sources, are receiving increasing attention. Such interest is motivated first by the urgent need for swiftly decarbonizing energy systems and reaching carbon neutrality. Furthermore, a HRES has proven to be a promising framework for harnessing complementarity among different renewable resources. Some of the most common combinations include PV-wind, PV-hydro, wind-hydro, PV-wind-hydro [4], etc. With the rapid technological progress in renewable generation, the co-location of diverse renewable energy sources is becoming an effective solution for reduced emissions, optimal operation cost and enhanced system reliability [5].

Renewable energy sources are known to be intermittent, non-controllable and stochastic. The diversification of renewable generation resources within the same location can enhance reliability and reduce the overall intermittency through leveraging their temporal-spatial energy complementarity [6]. However, this comes with increased levels of uncertainty that make the balancing of generation and demand at every instant more and more challenging [5, 7]. Loads as well are subject to various uncertainties due to stochastic user behavior [3]. Furthermore, a higher share of renewable generation would put pressure on the grid as it has proven to be paired with network congestion, which has, in turn, resulted in increased curtailment levels [2]. Suitable actions are therefore needed to foster the integration of renewable generation and minimize the wasted energy in the form of curtailments.

To confront the aforementioned challenges, flexibility sources are becoming increasingly crucial. Energy storage systems in particular, viable flexibility providers, have proven to be effective in dealing with such issues. Various studies have shown that in hybrid systems where renewable resources may have low tendency to complement each other on a short time scale, battery banks can effectively address this issue by a proper charging/discharging. It has been also proven that the integration of ESS technologies can effectively reduce the reliance on fossil fuel-based generation leading to less emissions while fostering the participation of clean energy and enhance overall system reliability [6, 8]. Acknowledging the potential of energy storage integration within a HRES, various projects–namely co-locating storage, PV, wind and other renewable sources– have been implemented in the last few years, while the planned projects to be put in service in the near future are on the rise (see [9, 10, 11]).

Recent attention has focused on a particular configuration of energy storage, which is a dual storage system or hybrid ESS. Such a system is usually composed of two (or more) different types of storage systems: a fast-response ESS (e.g., a supercapacitor) and a slow (long-term) ESS (e.g., a battery) with high energy capacity [12, 13]. The fast-response storage handles high-frequency and transient power fluctuations while the high-capacity storage tackles low-frequency fluctuations and supplies/absorbs energy over relatively long periods of time [7]. Such configuration is of great interest as it has proven to be economically viable and is shown to extend the service life of its sub-component ESS [14, 15]. Various scheduling approaches have been proposed in the literature to optimize the operation of a hybrid ESS [16, 17, 18, 19, 20, 21]. For instance, [18] proposes an operation scheme for a dual storage system that allowed to achieve a reduction in operation and maintenance costs while preserving the life of the high-capacity storage bank namely. Reference [20] employs a model predictive control (MPC)-based approach for scheduling the operation of a dual storage system on an hourly-basis. The objective is to smooth power fluctuations resulting from wind-generation integration.

In this study, we mainly focus on the integration of a hybrid ESS within a HRES to maintain the generation-demand balance in real time (in the scale of seconds to a few minutes). The problem of optimally coordinating a hybrid ESS in real time within a highly uncertain environment is challenging as it involves the coordination of storage systems with different speeds within an environment featuring high volatility with both fast and slow dynamics [22]. Furthermore, as the focus is on real-time dispatch, the coordination scheme should be highly reliable and computationally tractable. Although a variety of control methods for dispatching a single ESS have been proposed in the literature, research work on hybrid storage systems is still in its early stages. As have been reviewed in many surveys such as [23], existing approaches (e.g., [16, 17, 18, 19, 20, 21]) are limited to either droop-based, rule-based or optimization-based scheduling schemes. Droop-based control is the simplest, however, it usually results in sub-optimal solutions as it does not consider other operational aspects such as the operation cost or battery lifetime. Rule-based control consists of a set of dispatch rules that are implemented on a controller. The controller features a feedback loop for controlling each ESS based on sensor information or control states and pre-defined set-points. Although very common, the performance of rule-based control is conditioned on its pre-defined set-points, which are difficult to set up and may require expert knowledge or other approaches for their setting (e.g., fuzzy logic as in [24]). It may therefore result in sub-optimal and inflexible control decisions, especially in environments featuring high levels of uncertainties as in a HRES. As for optimization-based approaches (e.g., MPC), they require reliable predictions and accurate system models to generate meaningful control decisions. These are increasingly difficult and costly to obtain, especially in a rapidly changing HRES that is co-locating various stochastic energy sources and loads. Moreover, existing optimization-based approaches neglect real-time requirements in terms of computational burden, and generate decisions on relatively long time intervals which is not enough to cater for both fast and slow supply and demand dynamics. Here, we recall that optimization-based approaches require the re-iteration of all computations whenever a decision is to be made. In addition, in the majority of dispatch control proposals, dispatch actions are determined for relatively long time intervals (e.g., typically one hour), which may not be enough for managing the rapid fluctuations of renewable energy sources and load in a HRES.

The existing scheduling schemes consider the integration of a hybrid ESS in a framework comprising only one type of renewable generation (e.g., tidal, wind, hydro or PV generation) or, more recently, two sources that are mainly PV and wind as in [21]. Increasing the sources of uncertainty by co-locating various types of renewable generation can make the scheduling problem more challenging with increasingly complex and interdependent power flows. Furthermore, performance evaluation are carried out over short periods (i.e., some selected days) which is not sufficient for evaluating global performance under different operation conditions. In particular, the effectiveness of proposed approaches need to be tested over longer time periods (e.g., one or more years) to verify whether they are able to cope with a broader range of cases and operation conditions.

Another challenge that has not been taken into account is reliability. Existing approaches for hybrid ESS control are fully centralized; therefore, they rely on dispatch signals coming from a central coordinator, and real-time exchange of information among resources and the central controller. In this case, any issue that affects the central controller results in malfunctioning of the whole system. In addition, if communication links between each ESS and the central controller or between the different ESS are jeopardized, the hybrid ESS becomes inoperable, as each ESS would always wait for a dispatch signal for taking decisions. In such a case, autonomous and decentralized approaches could present viable alternatives to effectively handle these concerns.

To overcome the limitations of existing studies, this work proposes a real-time multi-agent deep reinforcement learning (MADRL)-based control scheme for scheduling the operation of a hybrid-ESS within a HRES comprising multiple classes of renewable generation (PV, wind and variable flow run-of-the-river hydro here). The aim is to reliably match generation and demand in real time while leveraging synergies among renewable energy sources. The reliance on fossil fuel-based generation is also to be abridged in order to limit its resulting emissions and optimize the overall operation cost. Besides the investigation of MADRL for HRES control, this study also looks at performing a thorough comparison between scheduling approaches from different categories (i.e., rule-based, optimization-based and model-free). The comparison should be founded on diverse criteria so that different aspects are thoroughly evaluated.

The main contributions of this study are summarized as follows:

- The main objective is to develop a real-time dispatch scheme for scheduling the operation of a hybrid ESS within a HRES comprising several types of renewable generation (e.g., PV+wind +hydro). The aim is to reliably match generation and demand in real time while leveraging synergies among renewable energy sources. The reliance on fossil-fuel based generation is also to be abridged in order to limit its resulting emissions and optimize the overall operation cost.
- Scheduling schemes emanating from three different control categories are implemented for real-time power balancing: rule-based, model-based and model-free control. The model-based approach relies on a receding horizon-based optimization for coping with uncertainties and generating farseeing control decisions.

  Model-free control, investigated here for the first time for hybrid ESS scheduling, relies on a multi-agent deep deterministic policy gradient (MADDPG)-based approach for real-time decision-making. A thorough analysis and comparison of different control approaches is provided to better assess the trade-offs of each method and guide the selection of the most appropriate approach for real-time power balancing. The approaches are compared based on the ability to supply load and reduce reliance on conventional generation sources. Criteria of interest also include uncertainty handling, battery lifetime preservation, tractability, communication requirements, and adaptability. The control schemes are assessed over one year to capture all variations' pattern (ranging from short to long time scales), and evaluate the performance under different operating conditions.
- The ability of the MADDPG-based algorithm to overcome non-stationarity and partial observability is investigated. In particular, its performance is compared with an independent learning-based algorithm.
- The energy transfer between the two storage systems composing the hybrid ESS is analyzed extensively under different scheduling schemes and operation conditions.
- A methodology for estimating the average remaining lifetime of battery-based ESS is proposed. The aim is to compare the proposed control strategies in terms of battery service life preservation.

The rest of the paper is organized as follows: Section 2 presents the control framework. Section 3 provides an overview of each control method and introduces basic performance metrics. Experimental results are exhibited in Section 4 with a detailed discussion of the obtained results and potential trade-offs of each approach. Finally, the paper is concluded in Section 5.

2 System description

A HRES is a framework co-locating various types of renewable generation sources. A typical hybrid renewable microgrid with PV, wind and hydro generation is shown in Figure 1. The system is composed of a hybrid ESS and a diesel generator. The hybrid ESS consists of two types of energy storage: a fast-charging storage with low capacity (i.e., low rated energy to rated power ratio) and a slow-charging storage with high capacity (i.e., high rated energy to rated power ratio). The major role of such a system is to feed load while taking full advantage of potential synergies between different renewable generation sources, and those of the load itself. The operation of the diesel generator, which is used as a back-up, needs to be minimized in order to reduce its resulting emissions and running cost.

To simulate a HRES, we consider real data of load, PV, wind and hydropower (run-of-the-river with variable inflow) generation with 5-minute time resolution for three successive years (2018, 2019 and 2020) [25].

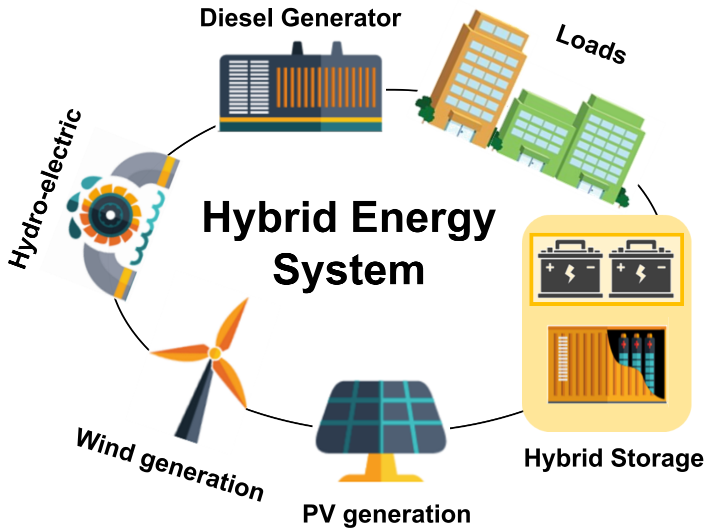

Figure 1: An illustration of a typical hybrid energy system.

3 Control methods and performance metrics for HRES

Section 3.1 provides a general overview of control methods that will be implemented for scheduling the operation of a hybrid ESS within a HRES. To compare these three control approaches, Section 3.2 defines some performance metrics that will be used for performance assessment.

3.1 Overview of control methods

3.1.1 Rule-based control

Rule-based control, known also as logical threshold control, is a simple, widely-used and easy-to-implement approach. It consists of a set of predefined rules and instructions that describe how certain controllable units react when particular cases occur or when specific conditions are met. In the context of energy storage scheduling, a rule-based strategy instructs the ESS when to charge, discharge or remain idle. Rules vary depending upon the intended use of the ESS. The performance of a rule-based control approach strongly depends on the pre-defined parameters and thresholds, which require expert knowledge for its setting. Furthermore, it lacks generalization and adaptability as it is designed for reaching specific objectives in particular systems [26, 27].

3.1.2 Model predictive control

MPC is a receding horizon-based optimization approach that is commonly used in power system operation. The main advantage of MPC is its ability to cope with uncertainties affecting system operation through rolling forecasts. Furthermore, its generated control actions optimize the system's current and future states. A general illustration of a classical MPC process for HRES control is shown in Figure 2. In particular, at a given decision time-step, forecasts of uncontrollable variables such as load and renewable generation are generated. The storage scheduling problem is cast as an optimization problem that minimizes an objective function subject to system constraints. MPC takes advantage of the generated forecasts and system model in order to predict and optimize the system behavior over the coming horizon of H forward time steps. The control input (i.e., control actions) obtained upon solving the problem is a sequence of actions for the length of the forward horizon H. This control sequence minimizes the objective function while satisfying all system constraints at any time step of the time horizon. However, only the first element of the sequence of actions, which is the current time control action, is implemented and applied to the controlled system. At the next decision time step, the system's state (such as the storage systems' state of charge) is received and the same process is re-iterated, however using new generated forecasts at the current time step [22, 28].

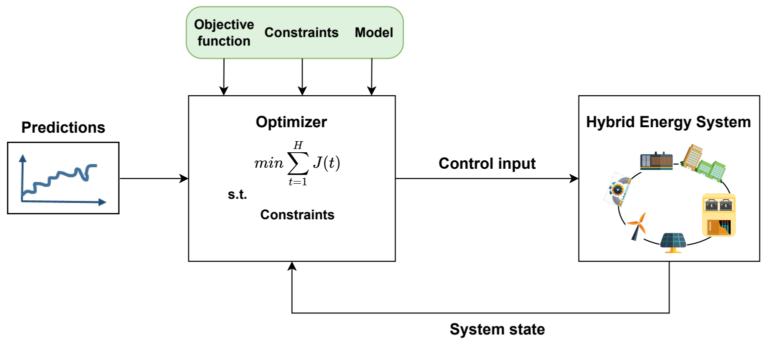

Figure 2: An illustration of MPC for HRES control.

3.1.3 Multi-agent deep reinforcement learning

In general, reinforcement learning (RL) is a decision-making approach in which a decision maker called *agent* learns, through interaction with the external control environment, a control policy which is a mapping that generates an action given the controlled-system's state. Here the focus is on model-free RL which does not necessitate a control environment model, but rather can learn by interacting with the control environment. The case in which two or more agents interact with the environment is referred to as multi-agent RL. In this case, each agent should learn a unique control policy that differentiates it and allows it to efficiently coordinate with other agents to reach the desired objectives.

In the context of a hybrid ESS scheduling task, two or even more ESS with completely different characteristics are involved. The decision to be taken by each ESS at a given time step concerns the amount of power to charge or discharge. In this regard, MADRL appears to be a good candidate for learning sufficiently optimal control policies by modeling each ESS as a separate agent. Various categories of MADRL exist in the literature as it is an active research area and the choice depends on the application. The most straightforward category of MADRL is independent learning which is based on the incorporation of single agent-based RL. In particular, each agent learns individually, and treats other agents as part of the environment. Although such approach is simple, it suffers from environment non-stationarity, and it does not perform well in environments where agents are required to reach a complex coordination task. To overcome these limitations, approaches based on centralized training decentralized execution (CTDE) have been proposed in the literature. The CTDE allows to use shared information among agents during the training phase only, while the execution phase is fully decentralized and relies on local observations of each agent. For this particular application, we choose to implement the MADDPG algorithm, proposed initially in [29], which is based on CTDE. An illustration of MADDPG is shown in Figure 3.

The application of MADDPG for hybrid ESS scheduling in particular has various advantages that motivate its selection. In particular, each ESS becomes able to generate decisions autonomously in real time without the need of receiving external dispatch commands or exchanging information, which can result in an enhanced system reliability against cyber-attacks or communication issues. Moreover, MADDPG allows to reach an adequate coordination between the decision-making units even if featuring different characteristics. Furthermore, the adaptability feature of RL enables each ESS to be in preparation for unprecedented system changes and adjust to its changing dynamics. Such a feature is of great interest in storage scheduling problems within a HRES including a mix of uncertain and interdependent variables. Furthermore, with the rapid race towards decarbonisation, the

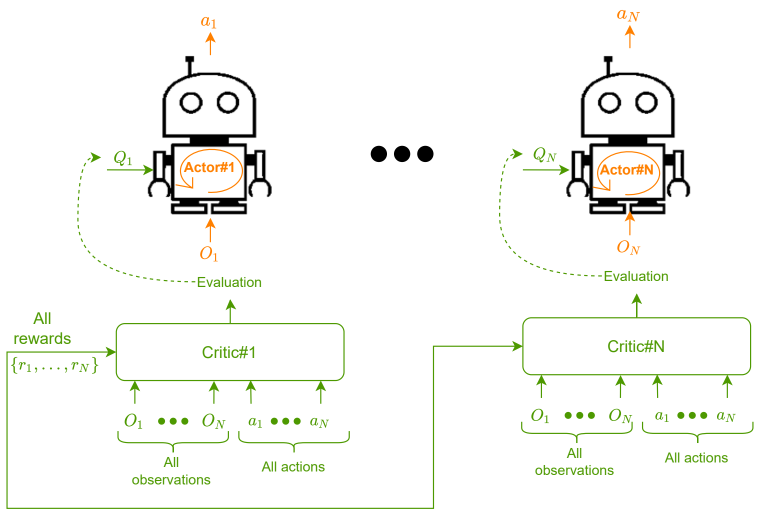

Figure 3: MADDPG: Centralized training decentralized execution.

structure of energy systems is rapidly and constantly changing, which makes the calibration of system models temporally and economically inefficient. The application of model-free control approaches in such rapidly varying frameworks provides a flexible alternative.

3.2 Metrics and performance evaluation

3.2.1 Diesel generator energy and cost

As the scheduling approaches are compared on the scale of one year, the annual diesel generator energy can be calculated

$$E_{dsl} = \sum_{k=1}^{T} P_{dsl}(k)\Delta k \tag{1}$$

where E_{dsl} is the annual energy of the diesel generator and $P_{dsl}(k)$ represents the average diesel's power-consumption during k^{th} time step. The length of the operation period is T which corresponds to the number of control time steps in one year. The length of each time step is denoted with Δk which is set to 5 minutes in this study.

The operation cost of a diesel generator at a given time step k can be calculated as follows

$$C_{dsl}(k) = c_0 u_d(k) + c_1 P_{dsl}(k) + c_2 P_{dsl}(k)^2 \tag{2}$$

where c_0, c_1 and c_2 are the cost coefficients of the diesel generator. The ON/OFF status of the diesel generator at k^{th} time step is denoted by $u_d(k)$ (1 if ON; 0 if OFF).

The annual cost is therefore determined by

$$C_{dsl} = \sum_{k=1}^{T} C_{dsl}(k) \tag{3}$$

3.2.2 Loss of load probability

The loss of load probability (LOLP) is a measure of system reliability in terms of supplying load. It reflects the percentage of non-served load with respect to the total load [30, 31]. On a daily basis, the

LOLP can be defined using [5, 31]

$$LOLP_d = \frac{\sum_{k=1}^{T_d} P_{nsl}(k)\Delta k}{\sum_{k=1}^{T_d} P_{load}(k)\Delta k} \tag{4}$$

where $LOLP_d$ is the daily LOLP. The non-served load and total load at k^{th} time step are denoted with $P_{nsl}(k)$ and $P_{load}(k)$, respectively. For a daily LOLP, the horizon T_d corresponds to one day.

3.2.3 Battery lifetime estimation

Battery degradation is an essential component that needs to be taken into account when managing battery-based ESSs. Either extra charging cycles or inversely deep discharging can negatively affect the lifetime of a battery. A scheduling approach should minimize at best these two effects to extend battery lifetime and thus push costly battery replacements further into the future. The approach proposed in [32] is implemented for estimating the lifetime of a battery-based ESS in an environment featuring renewable generation. The cycle life against depth of discharge characteristic is shown in Figure 4 [32, 33].

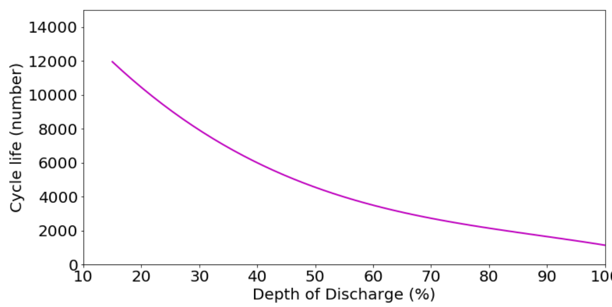

Figure 4: Cycle life against depth of discharge characteristic of storage battery [32, 33].

4 Experiments

This section investigates the HRES introduced in Section 2, and analyzes the performance of each control method when applied for scheduling the operation of the hybrid ESS. A detailed comparison is also drawn between different control schemes to highlight the trade-offs of each approach.

4.1 Control environment

The parameters of the HRES (of Figure 1) components can be found in Tables 1 and 2. More specifically, Table 1 includes diesel generator maximum power output $P_{dsl}^{\max}$ and cost coefficients c_0, c_1 and c_2, while Table 2 presents the parameters of the hybrid storage system. It is noted that subscript "1" denotes ESS #1 (the storage with high energy to power ratio), while subscript "2" designates the fast ESS with low energy to power ratio (i.e. ESS #2). $P_{bi}^{\max}$ and $S_{bi}^{\max}$ denote the maximum charge/discharge power in kW and energy capacity in kWh of ESS #i ($i \in \{1, 2\}$). The charging efficiencies for ESS #1 and ESS #2 are designated by η_{ch1} and η_{ch2}, respectively. Similarly, charging efficiencies are designated by η_{dch1} and η_{dch2}.

4.2 Real-time storage scheduling implementation

4.2.1 Rule-based scheduling

Figure 5 illustrates the flowchart describing the rule-based real-time scheduling scheme of the hybrid ESS. At a given time step, if renewable generation exceeds the demand, the ESS with larger energy

Table 1: Diesel generator parameters.

c_0 (€/kWh)	c_1 (€/kWh)	c_2 (€/kWh)	$P_{dsl}^{\max}$ (kW)
0.0157	0.108	0.31	1.5

Table 2: Hybrid storage system parameters.

$P_{b1}^{\max}$ (kW)	$P_{b2}^{\max}$ (kW)	$S_{b1}^{\max}$ (kWh)	$S_{b2}^{\max}$ (kWh)	η_{ch1}	η_{ch2}	η_{dch1}	η_{dch2}
1.5	1.5	4	0.4	0.95	0.95	0.95	0.95

to power ratio (ESS #1) has the priority to be charged if its SOC is less than a given threshold value ($\tau_{b1}^{\max}$). Afterwards, the second ESS (fast with low energy to power ratio) is charged if the remaining generation excess is still sufficient and if its current stored energy is less than a specific threshold ($\tau_{b2}^{\max}$). In the opposite case when renewable generation is less than demand, the difference needs to be supplied by other means. The first line of action in this case is the hybrid ESS. More specifically, ESS #1 discharges if its stored energy is more than a certain fixed threshold ($\tau_{b1}^{\min}$). If load is still uncovered, ESS #2 intervenes if it satisfies the minimum threshold constraint ($\tau_{b2}^{\min}$). If load is still unmet, the diesel generator picks up the remaining demand, however within its admissible operation range. The last recourse is to curtail the load if all the aforementioned generation and storage resources are insufficient [34]. In all experiments, $\tau_{b1}^{\max}$ and $\tau_{b2}^{\max}$ are set equal to the energy capacity of ESS #1 and ESS #2, respectively, whereas $\tau_{b1}^{\min}$ and $\tau_{b2}^{\min}$ are both set equal to zero.

4.2.2 Model predictive control

As MPC is a particular form of optimization, an objective function and constraints need to be defined for the scheduling problem. The problem to be solved is subject to establishing the load-generation balance, each ESS operation constraints, and the diesel generator constraint in terms of maximum allowable power production. The objective of load supply and reduced operation cost can be translated into a sum of terms as follows:

$$C_{HRES}(t) = c_0 u_d(t) + c_1 P_{dsl}(t) + c_2 P_{dsl}^2(t) + \alpha_l P_{nsl}(t) \tag{5}$$

The first three terms describe the diesel generator operation cost, while the fourth term penalizes curtailed load. The weight α_l can be interpreted as the cost of curtailed load (i.e., through load shedding). If meeting the demand has the highest priority, then the weight α_l takes a value larger than the diesel generator cost components. The value of α_l in all experiments is set to 0.31 €/kWh. It is of interest to note here that although renewables curtailment cost does not appear in the objective function, it is implicitely accounted for. That is, the way to reduce the reliance on diesel generation and load shedding necessitates harnessing the renewable generation whenever it is available. An approach that succeeds in reaching a trade-off between these two objectives is a one that has taken advantage of its renewable generation by avoiding unnecessary curtailments.

Many variants of MPC exist in the literature. In this study, two variants of MPC are implemented for the real-time scheduling of the hybrid ESS, namely classical MPC and two-time-scale MPC. Classical MPC is based on a single time scale where the control inputs for all controllable units are determined over the time horizon H, with the same time resolution (set to 5 minutes in this study) [22]. In a two-time-scale MPC, as the name suggests, actions of dispatchable units can have different horizons and time resolutions depending on the characteristics of the controllable units [22]. Similar to [22], two time scales can be considered in the receding horizon-based optimization problem: a "coarse-grained time scale" for ESS #1 and a "fine-grained time scale" for ESS #2. In particular, the time resolution for the "coarse-grained time scale" is set to half an hour with a horizon H. As for the "fine-grained time scale", the time resolution is 5 minutes with a horizon of half an hour.

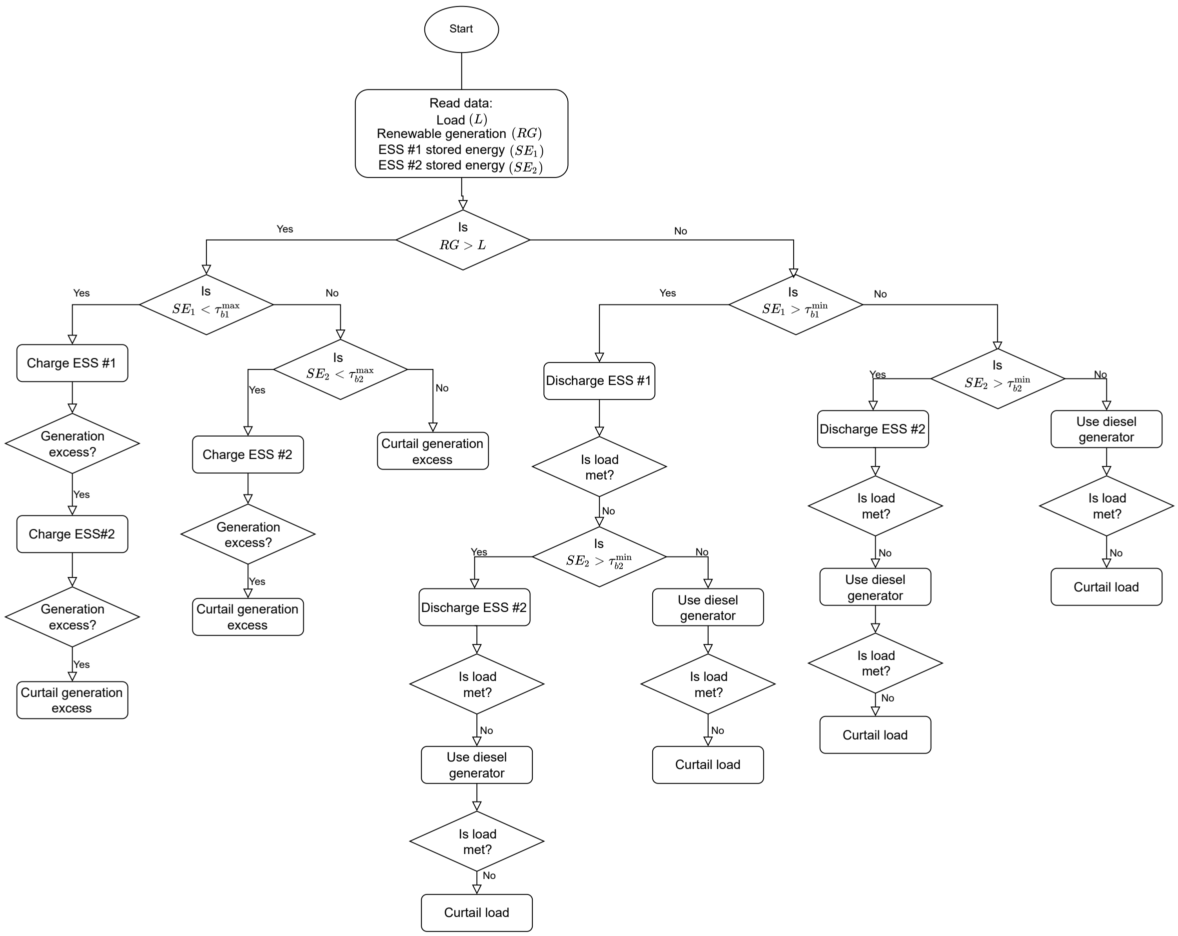

Figure 5: Rule-based control flowchart.

For MPC, predictions of load and renewable generation are obtained by a neural network-based time series forecasting approach. Given the last T_s time steps, the predictor delivers forecasts of the coming horizon H.

4.2.3 Multi-agent deep reinforcement learning

In a multi-agent framework, each ESS of the hybrid storage system is modeled as an agent: agent #1 represents ESS #1 while agent #2 represents ESS #2. The observation space groups the state of charge of the ESS at the current time step plus the history of net load (consumption minus renewable generation) in the last n (n is a hyperparameter) time steps. The action space of each agent is the interval between the minimum charging power and maximum discharging power of the ESS. The reward is simply the negative of the cost previously defined in (5). For the purpose of this study, two categories of MADRL are implemented: MADDPG and independent learning.

For the implementation of MADDPG, the same actor network architecture is selected for the two agents. Details about model architectures are omitted due to space limit.

To investigate whether MADDPG is able to adapt to the changing environment, it is trained based on load and most importantly the combined generation of hydro and wind power generation only. In other words, RL agents learn in an environment that assumes that no PV system is installed, and then its performance is tested in an environment comprising all renewable sources (i.e., PV, wind and hydro).

The Independent learning algorithm is based on deep deterministic policy gradient (DDPG) [35]. In particular, each agent learns independently based on the DDPG algorithm and treats other agents as part of the control environment. Therefore, both training and execution phases are fully decentralized. For a fair comparison, the architecture of the actor network is kept the same as in MADDPG. The critic network associated to a given agent has also the same structure as in MADDPG except for the input layer, which receives only the local observation of the agent and its action.

4.3 Experimental results

Two main cases are simulated:

Case *"No-Storage"*: The HRES consists of load, renewable generation and the diesel generator with no storage systems.

Case "*Hybrid-ESS*": The HRES comprises load, the diesel generator serving as a back-up generator, and the hybrid ESS described previously.

Characteristics of the diesel generator and hybrid ESS were already illustrated in Tables 1 and 2. It is noted that the case *"No-Storage"* will serve as a benchmark to highlight the effect of installing a hybrid ESS. In the case "*Hybrid-ESS*", the following control methods are implemented for scheduling the hybrid ESS:

- "*RB*": The rule-based controller shown in the flowchart of Figure 5.
- "*MPC-8H-prf*": A single-time-scale MPC controller with an 8-hour horizon and perfect predictions.
- "*MPC-6H-prf*": A single-time-scale MPC controller with a 6-hour horizon and perfect predictions.
- "*MPC-3H-prf*": A single-time-scale MPC controller with a 3-hour horizon and perfect predictions.
- "*2step-MPC*": A two-time-scale MPC controller with a 6-hour horizon and perfect predictions.
- "*MPC-6H-pred*": A single-time-scale MPC controller with a 6-hour horizon and time-series based neural network predictions.
- "*MADDPG*": An MADDPG-based controller.
- "*Independent learning (DDPG)*": An independent learning (DDPG)-based controller.

4.3.1 "No-Storage" case

Performance metrics for the case "*No-Storage*" are presented in Table 3. The distribution of LOLP for each month over one year is illustrated in Figure 6, whereas Figure 7 shows variation of diesel generator power output over the same year.

Table 3: Case "No-Storage": Diesel generator energy and cost, non served load (i.e., load shedding) and average LOLP over one year obtained with the operation of diesel generator only (no storage).

E_{dsl} (kWh)	C_{dsl} (€)	E_{nsl} (kWh)	Yearly LOLP
2348.70	1079.65	234.25	1.04%

As can be seen in Table 3, energy consumption and cumulative operation cost of the diesel generator are relatively high. Still, the diesel generator is unable to cover the load on its own as there is a residual cumulative amount of non-served load as seen in Table 3. Although the average yearly LOLP is around 1.04%, it does not reflect the variations of LOLP in different periods of the year. These variations are depicted in the boxplot of Figure 6, where the LOLP can reach percentages higher than 15%.

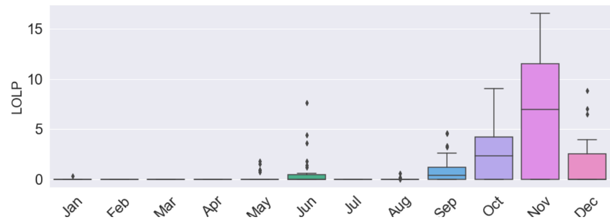

Figure 6: Case "No-Storage": Distribution of LOLP for each month obtained with the operation of diesel generator only.

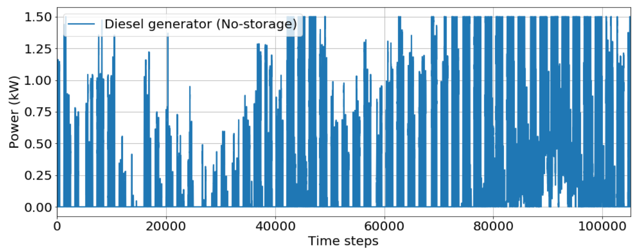

Figure 7: Case "No-Storage": Variation of diesel generator power output.

In the following parts, the effect of integrating a hybrid ESS in conjunction with the diesel generator is investigated. In this study, the ESS power was sized to be on par with the diesel generator.

4.3.2 "Hybrid-ESS": Strategy and performance analysis

General performance metrics in terms of load serving and operation cost obtained with each control approach (excluding "*Independent learning (DDPG)*") are demonstrated in Table 4. Note that the total cost in the table represents the yearly yield, which is calculated based on (5) and groups both diesel running cost and load shedding cost.

Table 4: Case "Hybrid-ESS": Diesel generator energy and cost, curtailed load energy and average LOLP over one year obtained with different scheduling approaches.

Method	*RB*	*MPC-8H-prf*	*MPC-6H-prf*	*MPC-3H-prf*	*2step-MPC*	*MPC-6H-pred*	*MADDPG*
E_{dsl} (kWh)	1755.32	2018.10	2075.60	2289.26	2287.24	1926.89	2040.12
C_{dsl} (€)	851.81	846.82	896.56	1023.20	1037.84	829.45	866.68
E_{nsl} (kWh)	233.00	57.75	84.40	166.68	201.48	144.81	133.75
LOLP	1.03%	0.24%	0.36%	0.72%	0.88%	0.84%	0.57%
Total cost (€)	1317.81	962.33	1065.36	1356.56	1440.00	1119.07	1134.18

A comparison between the recorded validation scores throughout the training phase of "*MADDPG*" and "*Independent learning (DDPG)*" is depicted in Figure 8. It is noted that the total cost, defined in equation (5), combines the diesel generator cost and the cost of curtailed load. Note also that the reward indicated on the vertical axis of Figure 8 is simply the negative of the total cost.

Furthermore, to better see the difference between RL and MPC strategies, Figure 16 and 17 show the histogram of SOC for each ESS over one year (i.e. the validation year) obtained with "*MADDPG*" and "*MPC-8H-prf*", respectively.

To better analyze the strategy embraced by each control approach to reach the objectives, Figure 9, 10, 11, 12 and 13 illustrate a sample of control actions taken by "*MADDPG*", "*MPC-3H-prf*", "*MPC-8H-prf*", "*2step-MPC*" and "*RB*" approaches during 10 random days of the validation year. It is noted that the ESS power is positive for charging mode and negative for discharging. To emphasize the effect of the hybrid ESS integration on the LOLP compared with the "*No-Storage*" case,

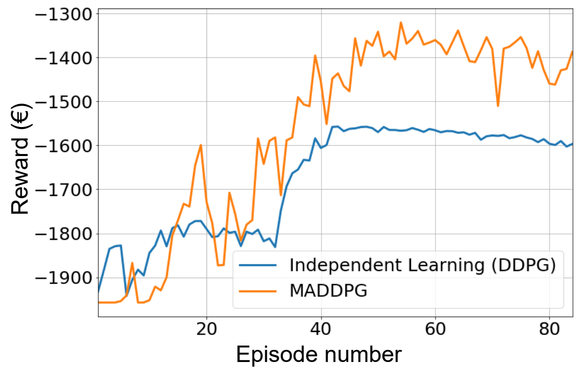

Figure 8: Case "Hybrid-ESS": Comparison of reported validation scores of "MADDPG" and "Independent learning (DDPG)" throughout the training phase.

Figure 14 and Figure 15 illustrate the daily LOLP variation over one year for the cases "*Hybrid-ESS*" and "*No-Storage*", respectively.

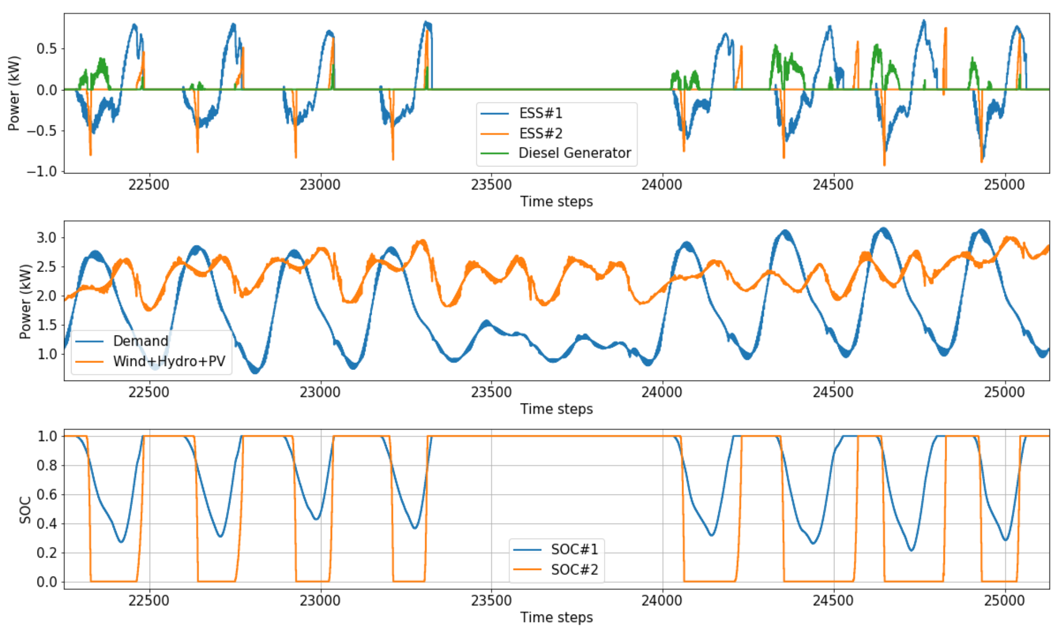

Figure 9: Case "Hybrid-ESS": Experimental results obtained with MADDPG for 10 random days from the validation year: 1^{st} plot: Variation of the charge/discharge power of each ESS and diesel generator power output; 2^{nd} plot: Variation of demand and total renewable generation; 3^{rd} plot: SOC variation of each ESS.

Although the problem studied here is the same, experimental results demonstrate that each control method adopts its own strategy for taking decisions. In the following, we discuss and compare particularities and characteristics of each scheduling approach.

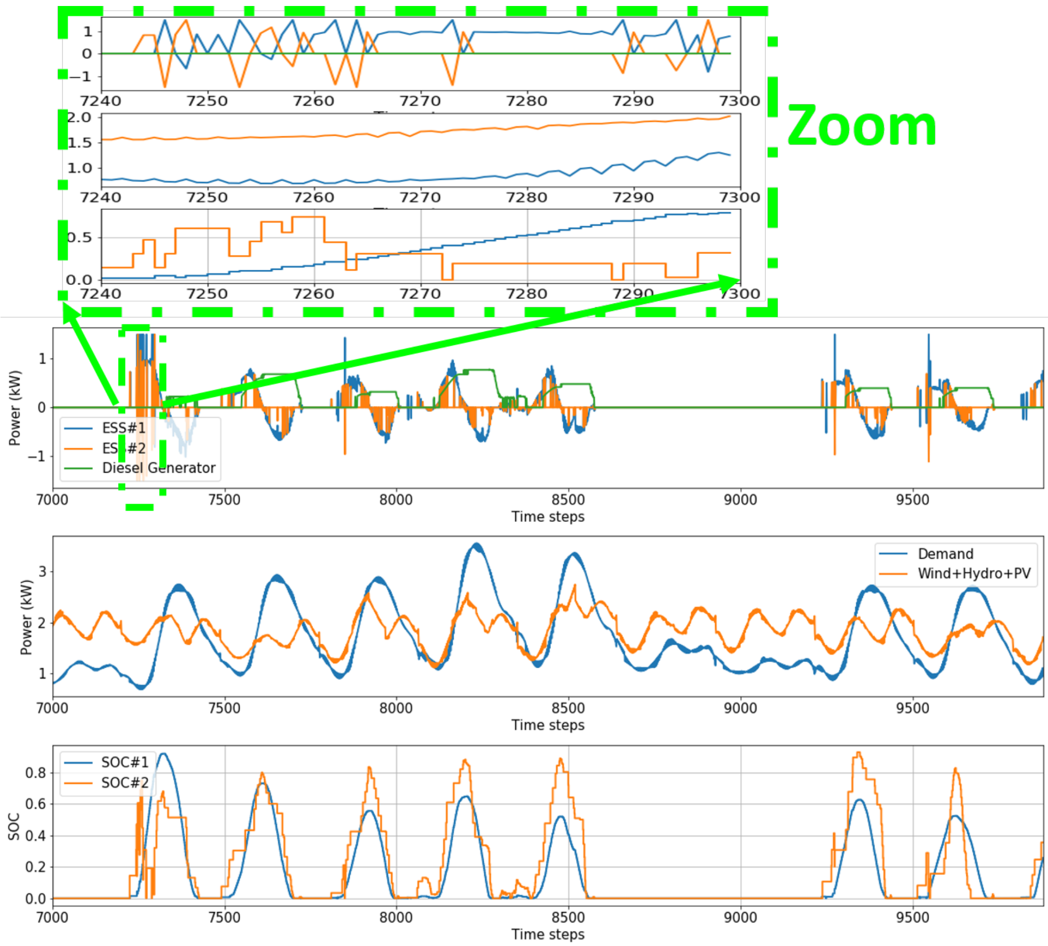

Figure 10: Case "Hybrid-ESS": Experimental results obtained with "MPC-8H-prf"-based approach for 10 random days from the validation year: 1^{st} plot: Variation of the charge/discharge power of each ESS and diesel generator power output; 2^{nd} plot: Variation of demand and total renewable generation; 3^{rd} plot: SOC variation of each ESS.

Experimental results indicate that the strategy adopted by "*MADDPG*" is based on committing ESS #1 for meeting slower variations of the load, while ESS #2 is reserved for fast load variations with high ramping (i.e. near load-peak periods). As can be seen in Figure 9, "*MADDPG*" anticipates, hours ahead, periods of negative net load, and consequently prioritizes the charging of the storage with higher energy-to-power-ratio (i.e. ESS #1) as it is able to cover load over a longer period of time. Therefore, the renewable generation excess during low demand periods (mainly during the night) is harnessed to properly charge ESS #1 in preparation for the coming hours of high demand (around noon). If the generation excess is still sufficient, ESS #2 has the second priority and is usually charged right after ESS #1. Otherwise, "*MADDPG*" may delay the charging of the fast storage ESS #2 until the few hours preceding the anticipated peak where it can benefit from the renewable generation excess, if available, or can get assistance from the diesel generator. "*MADDPG*" has recognized the importance of notably having ESS #1 well charged before high-demand periods in order to avoid curtailing load as the operation of diesel generator alone is not enough. Furthermore, "*MADDPG*" fosters the participation of ESS #2 exactly around the peak in order to accommodate the fast-increasing demand but also to reduce the reliance on diesel generator during these stress periods.

Figure 16 confirms the strategy adopted by "*MADDPG*" in terms of charging and discharging the hybrid ESS. It is clear that the SOC reached by ESS #1 covers a wider range of values. This is because "*MADDPG*" tends to slowly and gradually charge/discharge ESS #1 as its main purpose is handling

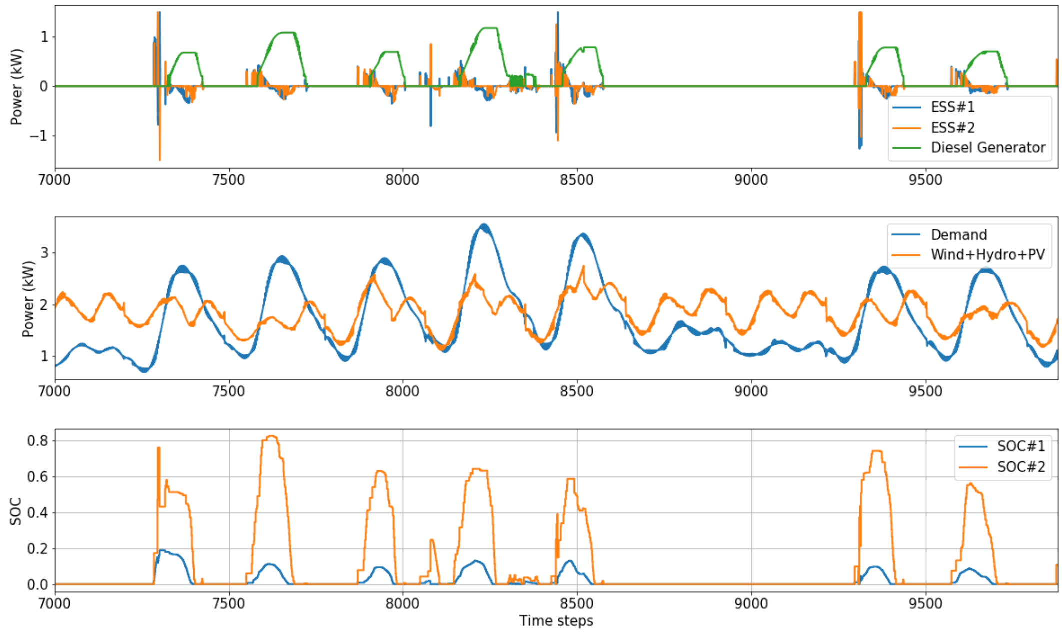

Figure 11: Case "Hybrid-ESS": Experimental results obtained with "MPC-3H-prf"-based approach for 10 random days from the validation year: 1^{st} plot: Variation of the charge/discharge power of each ESS and diesel generator power output; 2^{nd} plot: Variation of demand and total renewable generation; 3^{rd} plot: SOC variation of each ESS.

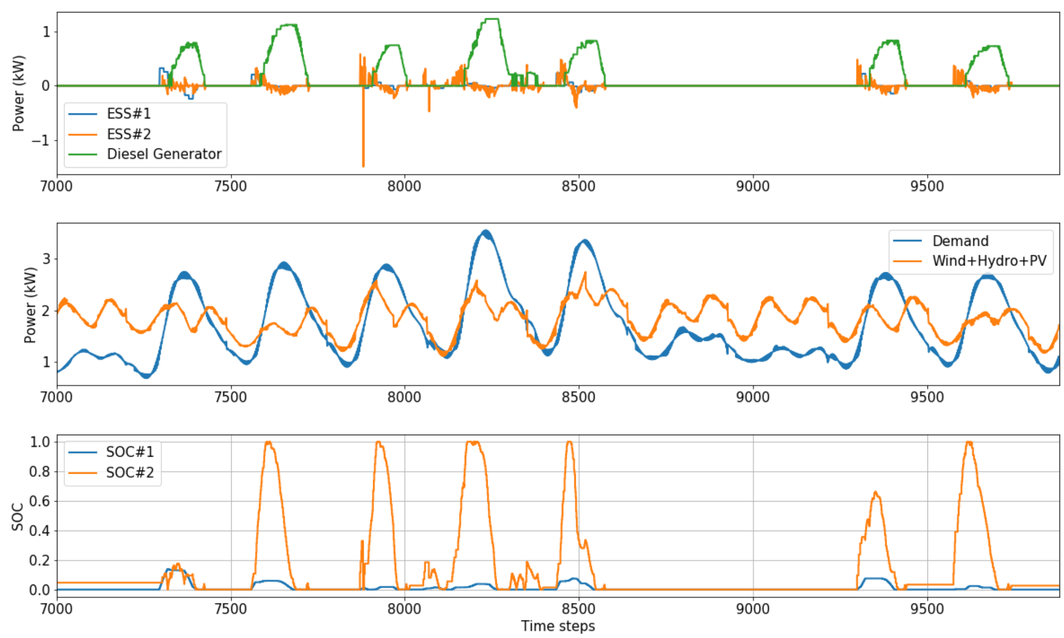

Figure 12: Case "Hybrid-ESS": Experimental results obtained with "2step-MPC"-based approach for 10 random days from the validation year: 1^{st} plot: Variation of the charge/discharge power of each ESS and diesel generator power output; 2^{nd} plot: Variation of demand and total renewable generation; 3^{rd} plot: SOC variation of each ESS.

slower variations of load over relatively long periods. Another interesting pattern is that "*MADDPG*" tends to keep the SOC of ESS #1 at relatively high values. This effect can be observed in detail in Figure 9 where the assistance of the fast-charging storage ESS #2 hinders ESS #1 from getting fully discharged, hence keeping the SOC of ESS #1 at values approximately higher than 30%. Such regime of operation has the potential of preserving the lifespan of ESS #1 and delaying its degradation, as will

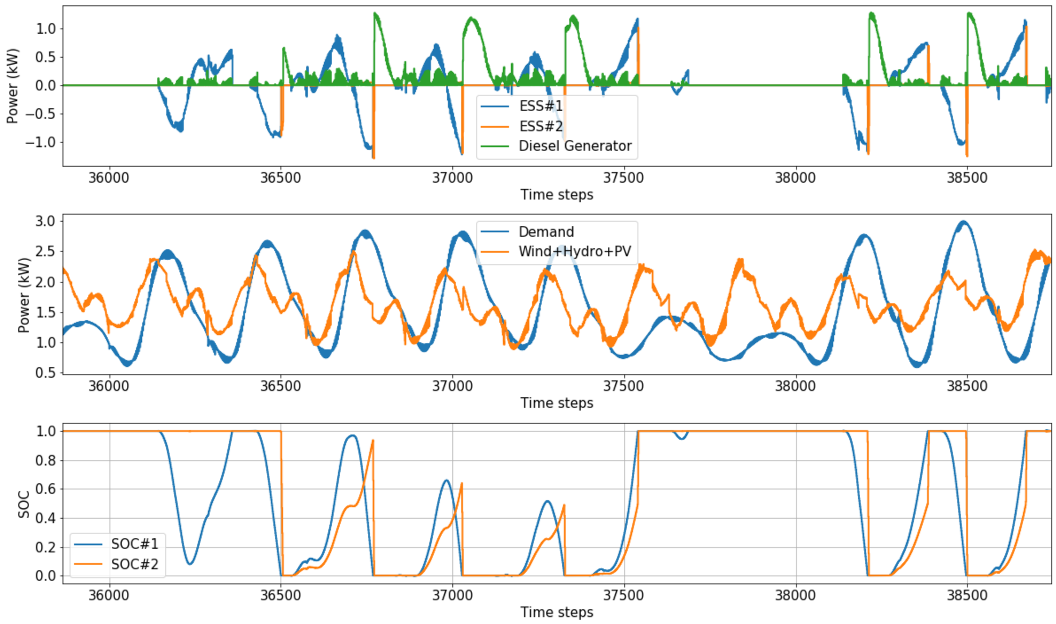

Figure 13: Case "Hybrid-ESS": Experimental results obtained with "RB" approach for 10 random days from the validation year: 1^{st} plot: Variation of the charge/discharge power of each ESS and diesel generator power output; 2^{nd} plot: Variation of demand and total renewable generation; 3^{rd} plot: SOC variation of each ESS.

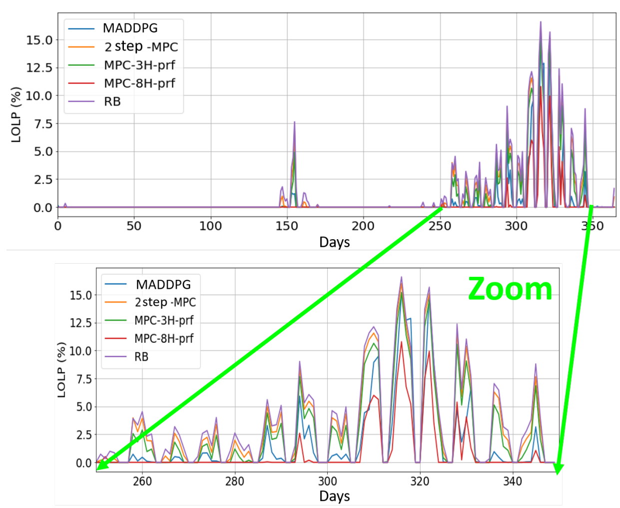

Figure 14: Case "Hybrid-ESS": Variation of daily LOLP over one year obtained with different scheduling approaches.

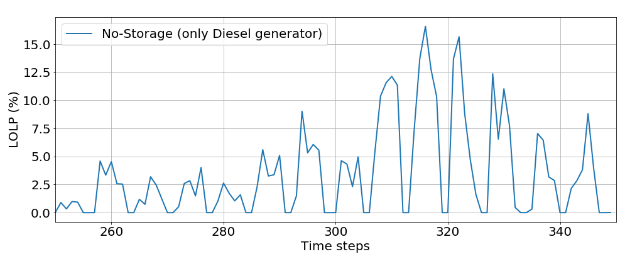

Figure 15: Case "No-Storage": Variation of daily LOLP over one year obtained with the operation of diesel generator only (no storage).

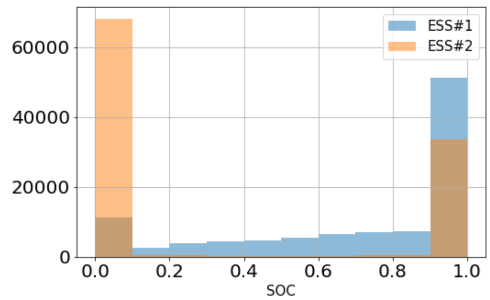

Figure 16: Case "Hybrid-ESS": Histogram of SOC obtained with "MADDPG".

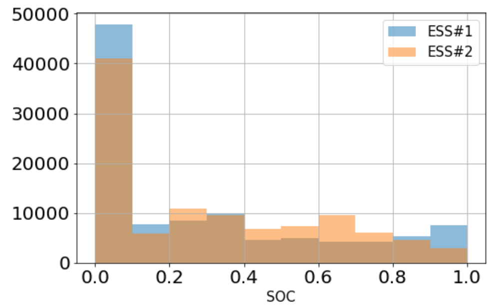

Figure 17: Case "Hybrid-ESS": Histogram of SOC obtained with "MPC-8H-prf"-based approach.

be discussed in more detail later in Section 4.3.3. Figure 16 confirms also that ESS #1 is reserved for meeting fast load peaks as it is more likely to occupy SOC values that are either close to 0 (i.e., fully discharged) or close to 1 (i.e. fully charged). According to Table 4, "*MADDPG*" has allowed reducing the yearly non-served energy and average LOLP by around 43% and 45%, respectively compared with the "*No-Storage*" case. Meanwhile, substantial savings in terms of diesel generator's yearly produced energy and cost are achieved as these two have declined by around 13% and 20%, respectively.

Figure 8 compares the performance of "*MADDPG*" with "*Independent learning (DDPG)*". It clearly shows that "*MADDPG*" allows to reach a much higher score than "*Independent learning (DDPG)*". Although the number of agents is limited, the task of hybrid ESS scheduling requires complex coordination between two heterogeneous decision-making units in a partially observable environment. Such a control framework is challenging for independent learning, as it is unable to reason over the joint information of the two agents being controlled [36]. "*MADDPG*" was able to learn more powerful control policies as its centralized learning phase allows to reason over the joint information of agents, thereby limiting the effect of non-stationarity and partial observability.

Overall, it can be concluded that "*MADDPG*" is deploying ESS #1 as an energy buffer while the role that it attributes to ESS #2 replaces the need for quick starting units (in standby) that usually intervene only during peak demand periods to assist the operation of the diesel generator. Furthermore, to cope with uncertainties, "*MADDPG*" avoids the full discharge of the storage with higher energy to power ratio, and rather tends to always keep an amount of reserve in the form of stored energy in ESS #1.

Turning now to MPC results, Figure 10 shows a sample of control actions decided by "*MPC-8H-prf*" over 10 random days. It can be inferred that an 8-hour horizon with perfect predictions is sufficiently long to anticipate periods of high demand and have the storage systems ready at the required times. In particular, "*MPC-8H-prf*" knows in advance the exact amounts of both generation and demand in the next 8 hours, and accordingly plans the charging of the two storage systems so that they are properly charged exactly at the moment when the demand starts to exceed the renewable generation. Unlike RL, "*MPC-8H-prf*" uses the two ESS simultaneously and alternatively for meeting the load during high-demand periods. This is further confirmed by the SOC distribution in Figure 17 where ESS #1 and ESS #2 occupy analogous SOC values with similar probabilities. In case the stored energy is not sufficient for supplying the load, the diesel generator intervenes to assist the operation of the hybrid ESS. Another point of dissimilarity with "*MADDPG*" is that "*MPC-8H-prf*" tends to use the storage systems until they are fully discharged as it knows exactly that in the coming few hours there will be no need for stored energy as the net load will become negative. Therefore, "*MPC-8H-prf*" tends to fully utilize the hybrid ESS for reaching its objectives.

Owing to the receding horizon principle of MPC, "*MPC-8H-prf*" is able to identify high demand periods eight hours in advance, which is early enough for the two ESS to get prepared. Awaiting for the anticipated period of high demand, the two ESS get charged in advance by one of three means: the first and obvious means is to leverage the excess of renewable generation. Another interesting means is through an energy exchange between the two storage systems as seen in the zoomed part of Figure 10, where the uppermost plot shows how ESS powers are out of phase by 180 degrees. In particular, it is ESS #2, which has a fast-charging pattern, that alternatively and repetitively charges and discharges to foster the charging of ESS #1. Alternatively, the diesel generator may participate in charging the storage systems during periods of low demand and low renewable generation so that, in return, the hybrid ESS becomes able to assist the diesel generator during high demand periods. Obviously, this mode of operation may increase running costs, but in counterpart minimizes the non-served load.

The approach "*MPC-3H-prf*" is clearly myopic as can be seen from the control actions in Figure 11. It is noted that Figure 10 and Figure 11 are extended over the same 10-day period to better evaluate the effect of the prediction horizon. It can be observed that the knowledge of both demand and generation profiles three hours in advance is not enough to get the storage systems well prepared for high-demand periods. This is mostly problematic for ESS #1 because of its slow-charging pattern. Figure 11 shows that ESS #1 can only reach around 20% of stored energy at the beginning of the peak period, while it was able to reach around 60% with "*MPC-8H-prf*" because of the early enough notice (i.e. 8 hours in advance). These results demonstrate that a relatively long prediction horizon is needed to reach an acceptable optimization performance. This is further confirmed by analyzing the performance metrics in Table 4. In general, results suggest that the performance is improved with an increase in the prediction horizon as deduced by comparing 3, 6 and 8-hour prediction horizons. A longer horizon is equivalent to a wider insight, and therefore an ability to schedule the storage systems at suitable times and early enough, in order to be ready at the occurrence of positive net-load periods.

Although the control decisions for "*MPC-6H-prf*" are not presented to avoid redundancy, we found that "*MPC-6H-prf*" has a similar strategy to that adopted by "*MPC-8H-prf*". Moreover, based on Table 4, both approaches have sufficiently close performance metrics in terms of load supply and operation cost. Compared with the case "*No-Storage*", "*MPC-6H-prf*" allows a reduction by 64% and 12% in yearly curtailed load and diesel energy, respectively. The approach has resulted in an average yearly LOLP of 0.36% which is 65% less than that obtained by the operation of diesel generator only in the "*No-Storage*" case.

To investigate the effect of prediction accuracy on the performance of MPC, Table 4 shows that "*MPC-6H-pred*" has a comparable performance to "*MPC-6H-prf*" (case with perfect predictions). The total operation cost has increased by only 5% when considering neural network-based time series predictions. This minor discrepancy is mainly due to the difference between the actual and predicted variations in terms of either an overestimation of renewable generation and/or an underestimation of the load in some periods.

As for the "*2step-MPC*", it tends to negligibly employ the storage ESS #1 which has higher energy to power ratio, while it charges/discharges ESS #2 more frequently as illustrated in Figure 12. Such effect is due to the two-time-scale principle which relies on using ESS #1 for meeting the coarse-grained average variation of demand, while ESS #2 is reserved for meeting the small and rapid fluctuations of the load. Such choice of operation does not allow the full use of ESS #1 as the net load is highly fluctuating in a HRES, while the reliance on storage ESS #2 with low energy to power ratio is not sufficient for covering the demand over a relatively long period. Overall, Table 4 shows that an improved performance in terms of load supply and reduced reliance on the diesel generator are attained; however, the other control approaches have a better performance in this regard. It is interesting to note here that the reduced reliance on the storage with higher energy to power ratio has the potential of reducing the pressure on ESS #1, which may delay the degradation of the battery and preserve its lifespan. This is claim will be confirmed by concrete proofs later in Section 4.3.3.

Now we move on to analyze the experimental results corresponding to "*RB*" control. Figure 13 shows a sample of control actions decided by the "*RB*" approach over 10 random days. Overall, it can be observed that the strategy adopted by "*RB*" is based on reacting to the net-load changes rather than anticipating them. Storage systems are charged whenever a generation excess is available. When facing high demand periods, "*RB*" control gives the priority of reaction to ESS #1 (as can be seen in Figure 13) that discharges accordingly. However, the problem with the adopted strategy is that the stored energy of ESS #1 depletes at the peak, where the "*RB*" control decides to initiate ESS #2 which in turn depletes fast because of its small capacity. To supply demand during the second half of the high demand period, the "*RB*" approach initiates the diesel generator. Unlike RL and MPC (with an acceptable forward-looking horizon), which strategically schedule the two storage systems so that they cover the whole period of high demand, the "*RB*" control is extremely myopic as it has no knowledge about the duration of the high-demand period. Hence, it depletes its stored energy before the end of the period. Furthermore, "*RB*" control lacks flexibility in its control decisions regarding how/when to charge the hybrid ESS.

In terms of demand covering ability, Figure 14 presents the daily LOLP obtained with different control approaches over one year. In parallel, Figure 15 shows variations of daily LOLP obtained with the operation of the diesel generator only. Overall, RL and single-time-step MPC with an appropriate prediction horizon have the most effective strategies in terms of LOLP reduction. In particular, the performance of "*MADDPG*" approaches that of MPC with an 8-hour horizon. Although "*RB*" has the minimal diesel generator operation cost (see Table 4), it does not perform well in terms of LOLP minimization because of its myopic character.

4.3.3 Hybrid-ESS": Effect on battery lifetime

Table 5 reports the estimated average battery lifetime (in years) obtained with different scheduling approaches. It can be seen that "*MADDPG*", "*2step-MPC*" and "*MPC-3H-prf*" have resulted in a more prolonged battery's service life in years. As discussed previously, "*MADDPG*" avoids deep and full discharge of the storage with larger energy to power ratio, while maintaining a minimum SOC as a reserve. Furthermore, it gradually and slowly discharges/charges the storage system for coping with the slower variations of the load. Such characteristics justify the high average battery lifetime obtained with the operation of "*MADDPG*". As for "*2step-MPC*", it tends to marginally use the storage with large energy to power ratio, thereby inferring a slower degradation process which directly explains its high expected lifetime. In the category of single-time-step MPC, as discussed earlier, a 3-hour horizon is not enough for getting the large battery well prepared prior to a high-load period, therefore "*MPC-3H-prf*" is unable to charge the battery well beyond 30%. Cycles characterized by deep discharge are therefore avoided, which in turn results in slower degradation effects.

Table 5: Case Hybrid-ESS: Estimated average battery lifetime (years) obtained with different scheduling approaches.

Method	*RB*	*MPC-8H-prf*	*MPC-6H-prf*	*MPC-3H-prf*	*2step-MPC*	*MPC-6H-pred*	*MADDPG*
Average battery lifetime (in years)	15.44	12.21	11.62	26.34	27.42	12.95	24.54

In contrast, as explained earlier, "*MPC-6H-prf*","*MPC-6H-pred*", "*MPC-8H-prf*" and "*RB*" control are approaches that frequently charge/discharge battery at high rates. Such overuse puts a pressure on the storage with high energy to power ratio, which in turn accelerates its degradation and results in a reduced average service life. According to Table 5, a simple comparison shows that the "*MADDPG*" approach results in an average battery lifetime that is nearly double that of "*RB*" and MPC (with more than 6-hour horizon). It should be noted here that to reduce the negative effect of MPC or "*RB*" on the battery lifespan, a constraint on the minimum and maximum stored energy can be added, which is expected to yield a higher operation cost as it hinders the full utilization of the storage systems. However, the objective of this study was to investigate the natural impact of each control strategy on the hybrid ESS scheduling without adding any constraint on the storage system charging/discharging patterns.

4.3.4 Hybrid-ESS: Tractability analysis

For MPC, the computational complexity is directly related to the complexity of the problem (e.g., if many decision-making units are involved), but also to the selected prediction horizon. Our previous results have shown that an increase in the prediction horizon, results in better cost reductions. However, a longer horizon implies a higher number of variables, which infers a higher computational burden.

To better see such effect, Figure 18 shows a comparison between "*MPC-3H-prf*" and "*MPC-8H-prf*" in terms of execution time over 15 random days. The execution time here denotes the time required to solve the receding horizon-based optimization problem at a given decision time step.

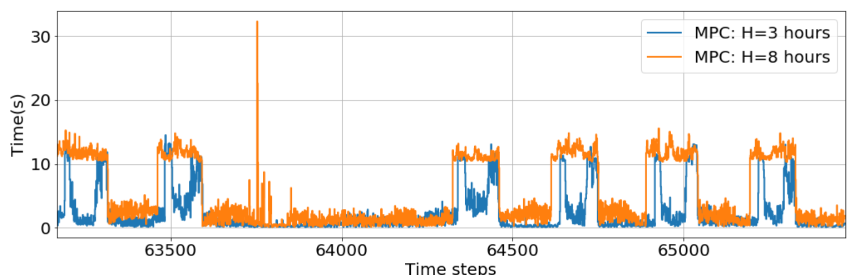

Figure 18: Case "Hybrid-ESS": Comparison of execution time at each time step obtained with "MPC-3H-prf" and "MPC-8H-prf" approaches for 15 random days from the validation year.

Simulations were performed on an Intel Core i7-8550U CPU @ 1.8GHz∼1.99GHz. It can be seen that although the execution time is highly fluctuating, "*MPC-8H-prf*" takes, in general, as much or longer time for problem solving compared with "*MPC-3H-prf*". In many periods, the "*MPC-8H-prf*" solution can take approximately nine times the time required by "*MPC-3H-prf*". Furthermore, although not shown in Figure 18, we have identified some time steps where the solution of "*MPC-8H-prf*" exceeded one minute which is not suitable for a decision time interval of 5 minutes. It is noted that, practically, a real MPC implementation includes other delicate time-dependent requirements that need to be taken into account such as the time required for receiving or sending control signals, and the possibility of communication signal delays or errors. All these elements need to be taken into account besides the selection of the prediction horizon length.

The time required for "*RB*" approach to take a decision is negligible as it is rule-based and does not require any problem solving. Similarly,"*MADDPG*" has an evident advantage over optimization-based approaches in this regard as every agent generates its own action instantaneously by performing a simple policy-evaluation step. This characteristic makes "*MADDPG*" a perfect fit for applications involving real-time decision making.

4.3.5 Hybrid-ESS: Adaptability analysis

In this part, we investigate the ability of a given control approach to react and adapt to control environment changes. An example of such changes include new asset addition or modification, installation of extra renewable energy capacity, unpredictable load changes, etc. In this regard, MPC and "*RB*" control are clearly unadaptable. "*RB*" control requires expert knowledge for manually tuning parameters and thresholds in response to large system upgrades or changes. As for MPC, it needs an updated system model to cope with the environment changes and may need to re-adjust its prediction models. It is interesting to recall here that accurate system models and predictions are becoming difficult to obtain with the increasing complexity of energy systems. Such inaccuracies may result in set points that do not match the actual system state and dynamics.

In contrast, "*MADDPG*" is a model-free decision-making approach; therefore, it does not necessitate a system model. Note that "*MADDPG*" can benefit from existing system models as a good initial solution, then potentially improve its performance via its learning capability. Furthermore, previously obtained results have implicitly proved that "*MADDPG*" is adaptable to control environment variations. More specifically, we recall that "*MADDPG*" is trained with a scenario in which the generation mix includes only wind and hydropower generation. However, "*MADDPG*" performance was trained on an environment comprising two renewable resources (i.e., wind+hydro), and a new source of generation (i.e., PV) was integrated during testing. As reported previously, "*MADDPG*" was able to achieve an acceptable performance in terms of load supply and reduced operation cost although it had not seen the PV generation pattern during its training phase.

To further support our point about adaptability feature, cases of increase/decrease in the demand side are simulated. The aim is to investigate whether "*MADDPG*" is able to adapt to such changes. Figure 19 reports the total yearly operation cost obtained with the case "*No-Storage*" and with the "*MADDPG*"-based approach for load variations ranging from -20% (decrease) to $+20\%$ (increase). It is noted that the percentages shown in red denote the decrease in total operation cost that "*MADDPG*" was able to achieve compared with the "*No-Storage*" case. The results confirm that "*MADDPG*" can adapt to the load variations and maintain a reduction by between 25% and 30% for all scenarios. Therefore, in reaction to the control environment changes,"*MADDPG*" was able to generate adequate scheduling decisions that resulted in acceptable operation costs.

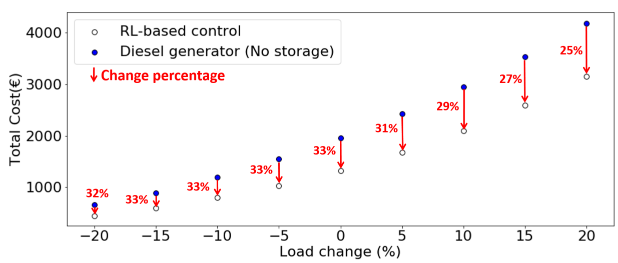

Figure 19: Comparison of total yearly operation cost obtained with the case "No-Storage" (only diesel generator) and with "MADDPG" for load variations ranging from -20% (decrease) to 20% (increase).

4.3.6 Hybrid-ESS: Communication requirements

Both "*RB*" and the classical MPC-based categories are based on the principle of direct "control and command" of controllable devices. Therefore, a communication infrastructure is required for dispatching control decisions from a central processing unit to the controllable devices. Such centralized approach has the potential of generating adequate set points as the central unit oversees the control environment, and therefore can generate decisions that jointly take into account all environment components. However, the reliance on a central unit for dispatching decisions tends to be unreliable as any problem affecting the central unit may easily result in single-point operation failure and a malfunctioning of the two ESS. Moreover, it is subject to cyber-attacks and is unable to strategically react in cases of communication shortage, as the controllable resources would always need an external dispatch signal prior to taking any action.

Conversely, "*MADDPG*", which is based on CTDE, does not necessitate any communication link between the agents as each agent acts in a fully decentralized way. Moreover, each agent acts autonomously without the need for any external dispatch signal. "*MADDPG*" joins the merits of both centralized and decentralized approaches. It is known that the main limitation of a purely decentralized approach is that it is difficult to reach a higher coordination level among the controllable resources. "*MADDPG*" overcomes such issue through its centralized training phase where agents learn to cooperate and coordinate their actions for reaching the desired objectives. By the end of the training phase, each agent has acquired the skill of achieving the required tasks while collaborating with the other agent. The learned skills allow each agent to take appropriate decisions even when operating in a decentralized way. Autonomous decision making and no reliance on real-time exchange of information of "*MADDPG*" can be seen as an advantage over centralized approaches. Any issue that may disturb the operation of one ESS agent, does not, at all, affect the other ESS operation, which results in a highly reliable operation.

5 Conclusion

In this study, the effect of integrating a hybrid ESS within a HRES comprising different renewable generation sources is investigated. The aim is to maintain the generation-demand balance in real time while harnessing renewbale generation. Three different scheduling schemes for the real-time dispatch of the hybrid ESS are implemented and compared, namely rule-based, model-based and model-free. In the category of model-based control, MPC with single and two time scales was implemented. The category of model-free RL focused on implementing an MADDPG-based scheme as the control environment involves the coordination of two heterogeneous storage systems with different characteristics and time scales.

A typical HRES with a hybrid ESS was simulated based on real data. Through the simulation of a no-storage case purely relying on diesel generation, results show that the integration of a hybrid ESS within a HRES allows leveraging renewable generation for increasing overall reliability, optimizing operation cost and abridging the reliance on a diesel generator.

Different control schemes were implemented for scheduling the operation of the hybrid ESS. Our study focused on evaluating the performance of each approach based on experiments performed over one year with a 5-minute dispatch interval. Results indicate that control methods adopt different behaviors and strategies for reaching the objectives. A performance evaluation based on diverse criteria was conducted for investigating the trade-offs of each approach.

Results show that a rule-based approach takes inflexible and myopic decisions resulting in longer periods of supply shortage. A model-based approach based on MPC, results in an improved reliability and operation cost, however needs a relatively long prediction horizon to properly anticipate high-demand periods and have the storage systems well prepared at the required times. Still, an increase in the prediction horizon implies longer computational time, which may be an issue for real-time decision making. Predictions' accuracy of load and renewable generation can also influence the overall performance due to overestimation/underestimation of generation/demand. The MADDPG-based approach have learned to solve the power-balancing task through interaction with the controlled system. Experimental results show that MADDPG can generate flexible, adaptable and farseeing control decisions for dispatching the hybrid ESS. To handle uncertainties, MADDPG tends to maintain a reserve of stored energy and avoids full discharge of the storage with higher energy to power ratio. A comparison between MADDPG and independent learning-based control shows a superior performance of MADDPG because of its centralized training phase that allowed reaching complex coordination among the two ESS with different characteristics and time scales. Unlike MPC, MADDPG and rule-based approaches can generate decisions instantaneously, as they do not require a problem-solving task. In terms of communication requirements, both classical MPC and rule-based control rely on dispatch signals coming from a central coordinator, which tends to limit the reliability of these approaches. In contrast, MADDPG-based control is fully autonomous and decentralized wherein each ESS takes decisions with no reliance on dispatch signals from a central coordinator or exchange of information with other units as each ESS only needs the history of net load variations.

The effect of each approach on the storage's lifetime preservation is evaluated. Results show that a single time-step MPC without constraints on the minimum/maximum stored energy limit results in faster degradation, whereas MADDPG and two-time-scale MPC resulted in a more prolonged storage's service life. In terms of adaptability to variations in the system's architecture or components, MPC would need an updated system model and potentially updated predictors, whereas rule-based control needs an adjustment of pre-defined thresholds and parameters based on expert knowledge. MADDPG, however, flexibly adapts to environment changes. This point was justified by considering the case of new renewable generation installation and through simulating various changes in overall system demand.

Taken together, these results suggest that the choice of the control method is a compromise between different criteria, which need to be jointly taken into account depending on the characteristics of a given system and its operation priorities.

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