Intelligent Data-Driven Energy Flow Controllers for Renewable Energy and Electrified Transportation Systems

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INTELLIGENT DATA-DRIVEN ENERGY FLOW CONTROLLERS FOR RENEWABLE ENERGY AND ELECTRIFIED TRANSPORTATION SYSTEMS

A Thesis
Submitted to the Graduate Faculty of the
Louisiana State University and
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Doctor of Philosophy

in
The Division of Electrical & Computer Engineering

by
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ABSTRACT

In recent years, large scale deployments of electrical energy generation using renewable sources (RES) such as wind, solar and ocean wave power, along with more sustainable means of transformation have emerged in response to different initiatives oriented toward reducing greenhouse gas emissions. Strategies facilitating the integration of renewable generation into the grid and electric propulsion in transportation systems are proposed in this work.

Chapter 2 investigates the grid-connected operation of a wave energy converter (WEC) along with a hybrid supercapacitor/undersea energy storage system (HESS). A combined sizing and energy management strategy (EMS) based on reinforcement learning (RL) is proposed. Comparisons in terms of power and energy capacity between the HESS sized with the proposed approach, and SC-only and UESS-only cases are performed. To facilitate fair comparisons a similar WEC output power profile is employed, and it is assumed that the storage components, as hybrid or individually, counteract the power variations. The adaptability of the RL-based EMS is verified using different power profiles in the learning and testing phases. Real-time simulation results corroborate that the capacity of the HESS components is notably reduced when EMS is considered in the sizing stage. Furthermore, RL-based EMS is able to regulate WEC output power, even in presence of serious imbalances between harvested and dispatched wave energy.

In the marine sector, new shipboard power system architectures are been proposed in response to the increasing use of electric propulsion, e.g. medium-voltage dc (MVDC) topologies. Due to interactions of the ship and the propeller with sea waves, large thrust/torque variations are translated into steep power fluctuations on the MVDC bus of the ship, affecting the stability and quality of the onboard power grid. A method to joint sizing/EMS a HESS
comprising battery and supercapacitor to mitigate power fluctuations on the medium-voltage dc bus associated to propulsion system thrust/torque variations is studied in chapter 3. A deep reinforcement learning framework is employed for the joint sizing/EMS problem. The proposed strategy avoids the requirement for knowledge of the ship propulsion power profile, and it features adaptability to varying sea states and feasibility of real-time implementation. A comparative analysis between the HESS designed with the proposed methodology and the cases where battery-only, and SC-only, mitigate power fluctuations caused by propulsion system variations demonstrates the efficacy of the joint sizing/EMS on reducing the size of the energy storage system. Furthermore, real-time implementation feasibility and adaptability to different ship propulsion power profiles is validated through real-time simulations.

In chapter 4, a control method for grid-side power electronic converters in grid-connected renewable energy generators (REG) is presented. The scheme, known as hybrid data-model predictive direct power control (HD-MPDPC), employs long-prediction horizons to provide more reliable REG output power dispatch. Computational load of classical MPDPC is mitigated by reducing the number of candidate voltage vectors to be examined in the cost function. Candidate voltage vector reduction is accomplished by using data-driven forecast of REG output power and the principle of direct power control (DPC). REG power is forecasted using recurrent neural networks. In DPC, active and reactive power hysteresis controllers along with the sector in which grid voltage vector lies are used to determine the switching states of the grid-side power electronic converter. Thanks to reduced computational burden offered by the hybrid structure, the proposed strategy is able to dispatch REG power more reliably over long horizons. This in turn enables REG as a regulating reserves service provider in power systems. Real-time simulation studies of a grid-connected wave energy conversion system demonstrate the reduced
computational toll of HD-MPDPC and its effectiveness in regulating REG output power over long horizons.
CHAPTER 1
INTRODUCTION

Global concern for climate change has led to different efforts to minimize greenhouse gas emissions. The use of fossil fuels for electric energy generation and transportation is considered one of the main contributors to greenhouse gas emissions. In order to reduce the consumption of fossil fuels, local authorities and government entities are pushing towards more environmentally friendly means of production and use of energy in the aforementioned areas. As a result, large scale deployments of electrical energy generation using renewable sources (RES) such as wind, solar and ocean wave power, along with more sustainable means of transformation have emerged in recent years.

Due to strong dependency on environmental conditions, the output power of RES is highly variable, making their integration into the grid complex [1]. The use of hybrid energy storage systems (HESS), where multiple energy sources with complimentary features operate in parallel with the RES, has been proposed as viable solution to address the issue associated to the availability and intermittency of RES [2]. HESSs have also found a niche in transportation systems, where their major function is to contribute towards reducing fuel consumption and extending all-electric driving range. Several energy storage technologies for electric vehicles (EV), hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV) are presented in [3]. Recently, the use of HESS in the marine sector has gained interest as a potential solution to mitigate issues associated to shipboard power grid stability, efficiency and quality, when electric propulsion systems and dedicated high power loads are integrated into the onboard grid [4].
The design of HESS consists of three major components: 1) selection of the energy storage technology, 2) sizing the HESS elements, and 3) controlling the energy flow between the storage elements and the system [5]. Batteries, supercapacitors (SC), and fuel cells (FC) are among the well-known energy storage technologies that are widely employed in HESS [2], [3]. Recently, a novel concept known as undersea energy storage system (UESS) has been presented as an alternative to standard energy storage technologies, particularly for offshore RES applications [6]. In UESS, a hollow concrete sphere equipped with a pump-turbine is deployed onto sea bed, and similar to the physical principle of pumped-hydro storage plants, electrical energy is generated with inflowing water while electrical energy is stored by pumping the water out of the sphere [1].

Among the objectives followed in obtaining the optimal size of HESS elements are the reduction of cost, weight, fuel consumption, and in the case for transportation systems, extending the lifetime of the HESS and driving range. While reaching these goals, certain group of constraints in each application, such as, state of charge, voltage, current and frequency ratings, must be satisfied. Sizing the HESS elements in utility oriented and electrified transportation applications has been extensively studied in the literature [7]-[9].

The energy management strategy (EMS) in HESS is of great importance for increasing operational performance and system efficiency. In the literature, EMSs for HESS are split into two major classes: 1) Rule-based and 2) Optimization-based [10]. Rule-based EMSs are simple to implement and present reduced computational burden [11]. However, since these methods involve the use of heuristics and engineering criteria, optimality of results is not warranted. EMSs employing optimization-based strategies can be divided into global optimal and real-time near-optimal. Global optimal EMSs, e.g. dynamic programming, present high computational
complexity, making their real-time implementation unfeasible. Real-time EMSs, such as model predictive control, generally provide high performance control of the system, but in terms of complexity and amount of calculations at each time step, they are costly [12]. In order to find a tradeoff between performance, complexity and real-time implementation, EMSs employing fuzzy logic, machine learning techniques and Markov chain models have been proposed in the literature [13]-[15].

Recent studies have shown the correlation that exists between component sizing and the EMS in HESS [16]. Since each component of the HESS presents different characteristics in terms of power and energy densities, the operating point must be considered in the sizing phase. The operating point, in turn, depends on the EMS. Thus, approaches combining the sizing and EMS must be conceived. Most studies devise methods that combine sizing and EMS for HESS in wind and electrified transportation systems involving road vehicles, [17], [18]. However, literature devoted to this subject for wave energy conversion systems and electric ship applications does not exist. Lack of such studies constitutes the major motivation for the first part of this work, i.e. chapters 2 and 3.

As the integration of renewable energy generation (REG) into power grids grows, grid codes are been adjusted to include regulations requiring REG to provide essential reliability services (ERS) i.e. services that are vital to ensure the reliability and stability of the grid. In the literature, forecast methods involving statistical and machine learning techniques have been developed to better manage and dispatch the output power of RES. In [19], a forecasting method for wind power ramps, which combines orthogonal test and support vector machines, is presented. A Solar generation forecasting approach based on cluster analysis and ensemble model is proposed in [20]. Despite the good performance, some degree of prediction uncertainty
is nevertheless present, and its impact can be further mitigated, e.g. using energy storage systems (ESS) [21].

In scenarios where the application of energy storage systems to mitigate the impact of variable output power from REG is not viable, strategies to integrate RES into the grid must be devised, such that operation requirements set by the grid are fully satisfied. The use of reliable forecast information in combination with proper control strategies to dispatch the output power of RES is crucial to maintain the grid stability. Model predictive control (MPC), which features ability to handle constraints, non-linearities, multiple inputs and outputs, and long prediction horizons in the optimization process has been considered in applications where REG provides ESR [22]. In majority of the existing literature, REGs employing MPC participate in fast and/or primary frequency response service. However, MPC’s potential for enabling REGs participation in a subclass of ESR know as Regulating Reserves (RR) service is not exploited. This is mainly associated to the longer prediction horizons (required for RR) in the grid-side power electronic converter control strategies add to the computational burden of MPC, making it almost infeasible for real time implementation.

Motivated by the lack of studies on grid-integration of RES providing RR service, chapter 4 presents a hybrid data-driven model predictive control with long prediction horizon methodology for grid-side PECs. Conclusions and future study plans are provided in Chapter 5.
CHAPTER 2
INTEGRATIVE SIZING/REAL-TIME ENERGY MANAGEMENT OF A HYBRID SUPERCAPACITOR/UNDERSEA ENERGY STORAGE SYSTEM FOR GRID INTEGRATION OF WAVE ENERGY CONVERSION SYSTEMS

2.1. Introduction

Wind, solar and ocean wave energy conversion systems (WECS) offer clean energy. However, due to strong dependency on environmental conditions, their output power fluctuates widely, making their integration into the grid challenging [1], [2]. Schemes comprising multiple energy storage technologies with complementary characteristics, where the hybrid energy storage system (HESS) and the renewable energy source (RES) operate in parallel, have been proposed as a viable solution to mitigate power fluctuations. An assessment of several utility oriented energy storage technologies is presented in [3]. HESSs have also found applications in transportation systems, where their major role is to contribute towards reducing fuel consumption and extending all-electric driving range. Different energy storage technologies for electric vehicles (EV), hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV) are discussed in [4].

HESS design can be broken down into three major tasks: 1) selection of the energy storage technology, 2) determining the power and energy capacity (sizing) of the HESS components, and 3) managing the energy flow between the storage components and the system [5]. Batteries, supercapacitors (SC), and fuel cells (FC) are among the well-known energy storage technologies that are widely employed in HESS [6], [7]. Recently, the concept of

undersea energy storage system (UESS) has been proposed as a potential alternative to standard energy storage technologies, particularly for offshore RES applications [8]. The UESS, which is placed at the seabed, consists of a concrete sphere, a reversible pump-turbine unit (RPT), a permanent-magnet synchronous machine (PMSM), and a steel pipe through which water flows into/out of the sphere from/to the deep ocean. The RPT and the PMSM are placed on one shaft. When there is surplus in the generated electricity, it is used to pump the water out of the device and when the demand is higher than generation, water is allowed to flow back in through the turbine to generate electricity [9], [10].

The objectives pursued in determining the optimal size of HESS components are, but not limited to, reducing the cost, weight, fuel consumption and losses as well as extending the lifetime and driving range (for transportation systems). While achieving these goals, specific set of constraints in each application, such as, state of charge (SOC), voltage, current and frequency ratings, must be satisfied. Sizing the HESS components in utility oriented and electrified transportation applications has been widely studied in the literature [11]-[13]. For HESS sizing when employed in RESs, the majority of studies are devoted to wind and solar applications [14]-[16] and a very few cover those involving WECSs. In [14], a frequency-based method employing the Fourier transformation is proposed for sizing a battery-SC HESS in order to maintain the power balance in an isolated system with high penetration of wind generation. An HESS sizing approach using pinch analysis in a photovoltaic-based isolated power system, where generation is always higher than the load, is presented in [15]. A search-based optimization method is proposed in [16], where the probability distribution function of the stochastic RES generation is used to obtain the optimal size of the energy storage system and to analyze the reliability of a hybrid wind-solar power system. In [17], batteries and SC modules are employed for smoothing
output power from a wave energy park. The power exchanged with the grid is set as the average of the WECS output power profile throughout a designated time period. Power imbalance between WECS generation and power delivered to the grid is used for sizing the HESS as a whole in terms of power and energy capacity. However, details of individual battery and SC sizing is not discussed. A methodology for sizing HESS operating with autonomous WECS, which supply power to on-board loads, is presented in [18]. Location of the wave energy harvesting devices is assumed to be known and used to obtain the probability and amplitude of each component in the WECS output power spectrum. Next, the generated output power profile with its probability of occurrence is employed for sizing the HESS in the short, medium, and long term horizons. HESS size is extracted from the long term operation analysis and a load energy demand compromise is considered for avoiding oversizing.

The energy management strategy (EMS) in HESS is of paramount importance for enhancing operational performance and system efficiency. In the literature, EMSs for HESS are divided into two major categories: 1) Rule-based and 2) Optimization-based [19]. Rule-based
EMS are featured by simplicity, ease of implementation and reduced computational burden [20], [21]. However, since heuristics and engineering criteria are employed, optimality is not warrantied. Optimization-based EMSs can be categorized into global optimal and real-time near-optimal. Dynamic programming (DP) and Pontryagin’s minimum principle (PMP) are among the global optimal EMSs [22], [23]. However, these methods are not suitable for real-time implementation due to computational complexity. Model predictive control (MPC), meta-heuristics strategies and adaptive PMP fall into the real-time EMS category. The performance of the control system is, in general, high when these EMSs are employed, but in terms of complexity and volume of calculations at each sample time, they are costly [22]. In search for a tradeoff between performance and complexity, other proposed alternatives for real-time EMS, particularly for HEV and PHEV applications, involve fuzzy logic, artificial neural networks, Markov chain models, radial basis functions, and reinforcement learning (RL) [24]-[28]. In [29], a reinforcement learning based EMS (RLEMS) is presented for effective power allocation to the battery and internal combustion engine in an HEV. RLEMS offers advantages over stochastic dynamic programming in terms of adaptability, optimality, and computational simplicity.

Recent studies have revealed the interdependency between component sizing and the EMS in HESS [30], [31]. Since each component of the HESS is featured with distinctive power and energy densities, proper sizing requires knowledge of their operating point. The operating point, in turn, is dependent on the energy management approach. In [32]-[34], combined sizing and EMS methods for HESS in wind and electrified transportation systems are analyzed. However, literature on this issue in WECS applications does not exist. Lack of such studies constitutes the major motivation for this work. In [35], which originates this chapter, a technical comparison between batteries, SCs and UESS in terms of lifetime and efficiency for applications
in WECSs is conducted. It is concluded that a HESS comprised of SC and UESS is a viable solution for smoothing the WECSs output power fluctuations.

This chapter proposes a novel integrative sizing/EMS of an HESS, comprising UESS and SC, operating along with a direct-drive linear generator-based WECS. The goal is to regulate the WECS output power fluctuations and dispatch it to the grid. RL is employed for developing the integrative sizing/EMS approach. It features adaptability and optimality is slightly compromised to facilitate real-time implementation feasibility. A general scheme of the proposed method is shown in Figure 2.1. In the sizing stage, the agent first interacts with the environment to learn actions that maximize the received reward. For this, an RL-based model-free technique known as Q-learning is employed. The reward measures how “good” the agent is performing in terms of power allocation between the UESS and SC, while satisfying the system constraints within a time window. When the learning process is concluded, relevant information, e.g. rewards and Q-table, is extracted and stored. This process is repeated for different UESS and SC sizes, and the combination that produces the highest reward is selected. The sizing stage is carried out for a random WECS output power profile generated at a high sea state. Once the sizing phase is completed, the effectiveness of the EMS is evaluated during the application phase. The obtained HESS capacity and the experience gained by the agent, i.e. the Q-table, are used in real-time simulation studies. To validate the adaptability of the proposed method, a different random WECS power profile is used in the simulations.

The major contributions of this chapter can be summarized as: 1) introducing an intelligent and model-free approach for integrative sizing/real-time EMS of HESS in WECS applications, 2) comparisons of the UESS/SC and SC-only power and energy density obtained
from the proposed method with those obtained in [35], and 3) assessing the real-time adaptability and implementation feasibility of the proposed EMS.

The chapter is structured as follows: Section 2.2. introduces the model of the HESS and formulation of the power-allocation problem. Application of the RL algorithm to solve the power-allocation problem is discussed in section 2.3. In section 2.4., the operation scheme of the WECS and HESS is explained. Sizing and real-time EMS simulation results are presented in section 2.5.

2.2. Hybrid UESS/SC model and Power-Allocation Formulation

2.2.1. WECS Model

A generic scheme of a grid-connected WECS operating in parallel with an HESS is shown in Figure 2.2. The WECS is mainly composed of two components: buoy and linear generator. The state space model of the WECS along with the linear generator model in $d$-$q$ reference frame [10] are employed to obtain the WECS output power. Parameters of the WECS are given in [36]. Real-time simulations of a random irregular wave profile, the resulting force acting on the buoy for a sea state with a significant wave height (SWH) of 6 m and an average period of 9 s, and the power generated by the WECS, $P_{WECS}$, are presented in [35]. In this work the same WECS output power profile will be used in the sizing stage of the HESS to facilitate fair comparisons. The power of the HESS and its energy can be calculated as

$$P_{HESS} = P_{WECS} - P_{grid}$$  \hspace{1cm} (1)

$$E_{HESS} = \int_{0}^{T_{opr}} (P_{HESS}) \, dt$$  \hspace{1cm} (2)
where the constant power delivered to the grid, $P_{\text{grid}}$, is the average of $P_{\text{WECS}}$ over a designated time period, $T_{\text{opr}}$.

### 2.2.2. UESS Model

The UESS model is described in [35] based on the following governing hydraulic equations for discharge (Eq. (3)) and charge (Eq. (4)) modes of operation

\begin{align*}
  z_1(t) = & \quad z_2(t) - P_{\text{UES}}/(A_{\text{pipe}}v_{\text{pipe}}\eta_{tg}g) - \frac{[A_{\text{pipe}}/(2\pi r_i z_1(t)-\pi z_1^2(t))]^2 v_{\text{pipe}}^2(t)}{2g} - \frac{f l v_{\text{pipe}}^2(t)}{2gd} - \sum K_L \frac{v_{\text{pipe}}^2(t)}{2g} \\
  z_1(t) = & \quad z_2(t) - \eta_{pm} P_{\text{UES}}/\rho A_{\text{pipe}} v_{\text{pipe}} g - \frac{[A_{\text{pipe}}/(2\pi r_i z_1(t)-\pi z_1^2(t))]^2 v_{\text{pipe}}^2(t)}{2g} + \frac{f l v_{\text{pipe}}^2(t)}{2gd} + \sum K_L \frac{v_{\text{pipe}}^2(t)}{2g} 
\end{align*}

where $P_{\text{UES}}$ is the power absorbed/delivered by the UESS, $z_1(t)$ is the elevation of water inside the sphere with respect to seabed, $z_2(t)$ is the installation depth of the UESS, $A_{\text{pipe}}$ is the cross sectional area of the pipe, $v_{\text{pipe}}$ is the water velocity in the pipe, $l$ is the pipe length, $r_i$ is the sphere internal radius, $d$ is the pipe diameter, $K_L$ is the loss coefficient, $g$ is the gravity constant, $f$ is the friction factor which is calculated using (5) and (6), and $\eta_{tg}$ and $\eta_{pm}$ are the combined turbine-generator and pump-motor efficiencies, respectively.

\begin{align*}
  \frac{1}{f} = & \quad -1.8 \ast \log \left[ \left( \frac{\varepsilon}{3.7d} \right)^{1.11} + \frac{6.9}{Re} \right] \\
  Re = & \quad \rho \ast d \ast v_{\text{pipe}}(t)/\mu
\end{align*}

Here, $\varepsilon$ is the pipe equivalent roughness, $\rho$ is the sea water density, $Re$ is the Reynolds number and $\mu$ is the viscosity of the fluid. The UESS parameters are listed in Table 2.1. [35].
2.2.3. Supercapacitor Model

Featuring a good tradeoff between simplicity and accuracy, SC dynamics can be modeled through an equivalent circuit formed by a capacitor connected in series with a resistance. Based on the SC model, the terminal voltage, $V_{sc}$, and the cell voltage are calculated as

$$V_{sc} = V_{osc}(t) - R_{sc}I_{sc}(t)$$ \hspace{1cm} (7)

$$V_{osc} = V_{osc,0} - \left(\frac{1}{C_{sc}}\right) \int_0^t I_{sc} \, d\zeta$$ \hspace{1cm} (8)

where $C_{sc}$ is the capacitance of the SC cell, $V_{osc,0}$ is the initial cell voltage, and $\zeta$ is a dummy variable of integration.

The SC cell current, $I_{sc}$, in terms of total absorbed/delivered power, $P_{sc}$, cell voltage, $V_{osc}$, cell resistance, $R_{sc}$, and the total number of cells, $n_{sc}$, can be obtained from [12]

$$I_{sc} = \frac{V_{osc}(t)}{2R_{sc}} - \frac{\sqrt{V_{osc}^2(t) - 4R_{sc}P_{sc}(t)/n_{sc}}}{2R_{sc}}$$ \hspace{1cm} (9)
The state of charge of the SC, $SOC_{sc}$, reflects the percentage of the rated energy capacity [37]. The state of charge can be expressed as the ratio of the SC terminal voltage to its rated voltage, $V_{nsc}$

$$SOC_{sc} = \frac{V_{sc}(t)}{V_{nsc}}$$

(10)

The lower bound of $SOC_{sc}$ is normally set to 25% based on the minimum terminal voltage required to supply energy [31]. In order to keep $SOC_{sc}$ at an appropriate level for possible future demands, the lower bound of $SOC_{sc}$ is selected at 50% in this work. The upper bound is set to 90%. The parameters of the considered SC cell are listed in Table 2.2. [35].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>BCAP3000</td>
</tr>
<tr>
<td>Manufacturer</td>
<td>MAXWELL</td>
</tr>
<tr>
<td>Rated Voltage [V]</td>
<td>2.7</td>
</tr>
<tr>
<td>Rated continuous current [A]</td>
<td>1900</td>
</tr>
<tr>
<td>Capacitance [F]</td>
<td>3000</td>
</tr>
<tr>
<td>ESRdc initial [mΩ]</td>
<td>0.29</td>
</tr>
<tr>
<td>Specific energy [Wh/Kg]</td>
<td>6</td>
</tr>
<tr>
<td>Weight [Kg/cell]</td>
<td>0.51</td>
</tr>
<tr>
<td>$C_{ESC}$ [$/Wh]$</td>
<td>25.06</td>
</tr>
</tbody>
</table>

2.2.4. Power Allocation Formulation

The integrative sizing/real-time EMS is developed based on a frequency allocation policy for the power blending among the two sources comprising the HESS. In general, the frequency allocation policy is considered as follows

$$P_{HESS} = L_f[P_{HESS}(t)] + H_f[P_{HESS}(t)]$$

(11)
where $L_f$ and $H_f$ are the low and high frequency operators respectively. $L_f[P_{\text{HESS}(t)}]$ and $H_f[P_{\text{HESS}(t)}]$ are obtained from

$$L_f[P_{\text{HESS}}] = \frac{1}{\tau s + 1} P_{\text{HESS}}(t) \quad (12)$$

$$H_f[P_{\text{HESS}}] = P_{\text{HESS}}(t) - L_f[P_{\text{HESS}}] \quad (13)$$

Here, $\tau$ is the time constant of the low-pass filter. Due to the power and energy characteristics of each storage device, the low and high frequency power components will be allocated to the UESS and the SC, respectively. Proper selection of the time constant $\tau$ plays a major role in the HESS sizing and is one of the main focuses of this work. Detailed discussions on this subject are provided in section 2.3.

The integrative HESS sizing and control problem can be regarded as taking a control action $u(t) \in \mathbf{u}$ at time $t$ that minimizes certain objective criteria without violating some operational constraints. This control action takes the HESS design from a given state $x(t)$ to a new state $x(t+\Delta t)$, $\Delta t>0$. Here, $x$ and $u$ are the state and control action vectors, respectively. In general, the design problem can be formulated as [32]

$$\min_x \int_0^{\text{Topr}} J(x)$$

$$J(x) = \sum_{m=1}^{M} w_m f_m(x) + \sum_{n=1}^{N} \varphi_n$$

$$\varphi_n = \max\{0, c_n(x)\} \quad (14)$$

where $J(x)$ is the objective function formed by a weighted sum of individual objectives, $f(x)$, and a sum of penalty factors, $\varphi$, associated with operational constraints, $c(x)$. $w_m$ is the $m$ positive weighting factor that denotes the importance of the individual objective $f_m(x)$ with respect to the other objectives. Multiple individual objectives, including lifetime of the components, charge...
sustainability, and cost can be included in the objective function. For this particular case of the HESS comprising the UESS and the SC, the following objective function is employed

$$J = \int_0^{T_{opr}} (w_1 \text{RMS}[P_{UESS}(t)] + w_2 \Delta z_1(t) + w_3 \Delta SOC_{sc}(t) + w_4 \sum_j C_E j E_j + \sum_{i=1}^t \phi_i) dt$$

(15)

Here, \( \text{RMS}[] \) = \( \sqrt{1/(t_f - t_0) \int_{t_0}^{t_f} x^2 dt} \), \( P_{UESS}(t) \) is the power absorbed/delivered by the UESS. The first term, \( \text{RMS}[P_{UESS}(t)] \), is included to prolong the lifetime of the RPT unit and PMSM by reducing the electrical and mechanical stresses due to power fluctuations. \( \Delta z_1(t) \) and \( \Delta SOC_{sc}(t) \), given in (16) and (17), ensure the charge sustainability of the SC and UESS, respectively. The term \( \sum_j C_E j E_j \), where \( C_E j \) are capital energy costs for the UESS and SC and \( E_j \) is given in (18), reflects the capital cost per unit energy for possible combinations of the SC and UESS sizes. The UESS and SC capital energy costs are obtained from [3] and [38] and provided in Tables 2.1 and 2.2, respectively. The last term, \( \sum \phi_i \), penalizes the agents in the learning phase to avoid taking actions which result in violations of the operational constraints.

$$\Delta z_1 = |z_1(t) - z_1(0)|$$

(16)

$$\Delta SOC_{sc} = |SOC_{sc}(t) - SOC_{sc}(0)|$$

(17)

$$E_j = \int_0^{T_{opr}} P_j(t) dt$$

(18)

As opposed to the SC, the UESS is a novel storage technology. Thus, detailed economical information about it is very limited. As a consequence, in the cost function, energy costs are used instead of the capital costs. Regarding the energy cost value associated with the UESS, the value reported in [3] for pump hydro generation is adopted here. This is due to the fact that, to good extend, similarities exist between pump hydro generation and the UESS principle of operation.
To complete the design problem, constraints imposed by the HESS model, (1)-(10), along with essential operational constraints to prolong the lifetime of the HESS components, (19)-(24), need to be satisfied.

\[
SOC_{sc} \leq SOC_{sc} \leq SOC_{sc} \tag{19}
\]
\[
I_{sc} \leq I_{sc} \leq I_{sc} \tag{20}
\]
\[
N_{zc} \leq N_{zc} \leq N_{zc} \tag{21}
\]
\[
|\Delta P_{UESS}| \leq \xi \tag{22}
\]
\[
n_{sc} \leq n_{sc} \leq n_{sc} \tag{23}
\]
\[
r_{l} \leq r_{l} \leq r_{l} \tag{24}
\]
\[
d \leq d \leq d \tag{25}
\]

Constraints in (19) and (20) ensure safe operation of the SC within the specifications of the cell and leaving enough charge to meet demand in the next \( T_{opr} \). Restrictions for the UESS operation are considered in constraints (21) and (22), which are discussed in details in the following paragraphs. Constraints (23)-(25) limit the search space of the number of SC cells, pipe radius and internal sphere diameter in the sizing stage.

During the operation of the UESS, the RPT unit has to switch modes according to the power requirements of the systems, i.e. in charging mode the unit works as a pump, while in discharging mode it operates as a turbine. Since the RPT is coupled to an electric machine, a combined mechanical inertia is present, which imposes physical limitations on instantaneous transitions from pump to turbine mode and vice versa. Figure 2.3. depicts real-time simulations
of a typical WECS operating in parallel with a UESS. The UESS is controlled to counteract the WECS output power fluctuations. As seen, the storage device is not able to absorb/deliver power within short transition periods. To take this issue into account, two constraints are imposed through (21) and (22). First, during the learning process, (21) encourages the agent to take actions that restrict the number of times $P_{UESS}$ alternates from positive to negative values and vice versa. In other words, the number of zero crossings, $N_{zc}$, is restricted. The objective of this constraint is to provide enough time for the machine to respond by prolonging the time periods between the transitions. If not restricted, the number of charge/discharge cycles allocated to the SC in order to supply constant $P_{grid}$ will be excessively high. Furthermore, reducing the number of machine transitions benefits its lifetime due to reduced stress on the shaft. The upper and lower bounds of $N_{zc}$ can be selected based on the machine maximum number of start/stop cycles within a time period allowed by the manufacturer. The constraint in (22) provides a measure in the learning stage to limit the depth of discharge (DOD) of the UESS. This constraint dissuades the agent from taking actions that can lead to very deep charge/discharge cycles within a sampling time, which in turn can impose sharp transitions on the machine. This measure also contributes to preserving the safety and lifetime of the machine. Transient response of the RPT unit will be discussed in section 2.4.

Figure 2.3. Real-time simulation results of $P_{WECS}$ and $P_{grid}$ including RPT transient response (left), (top right) zoomed-in of the circled area, (bottom right), zoom-in of the area in brackets.
2.3. RL-Based Integrative sizing/real-time EMS

2.3.1. Background on RL and Q-learning algorithm

In RL, an agent learns how to behave when interacting with the surrounding environment, while receiving back only a numerical indicator called reward from the environment. The agent’s main purpose is to choose actions that eventually maximize the cumulative reward ($R$). RL employs finite Markov decision processes (MDP) to model agent-environment interactions, as can be seen in Figure 2.1. A finite MDP can be described by a tuple $(S, A, P, R, \gamma)$, where $S$ is a set of states, $A$ denotes a set of actions, $P = \mathbb{P}[S_{t+1} = s' | S_t = s, A_t = a]$ is the probability of transitioning from the current state, $s$, to a new state, $s'$, after taking an action $a$, $R$ is a reward function defined as $R = \mathbb{E}[R_t | S_t = s, A_t = a, S_{t+1} = s']$ which provides the expected reward after the state transition, and $\gamma \in [0,1]$ is a discount rate [39], [40].

Majority of RL algorithms evaluate the agent’s performance in terms of future $R$ through state value functions, or action-value functions. Since the value functions are strongly linked to the way the agent behaves, or to the policy, the goal of the agent is to determine an action-selection policy that generates the maximum reward in the long run. Several RL methods exist for value function estimation, and consequently to obtain the required action-selection policy. DP, Monte Carlo method, and temporal-difference learning (TD) are among the well-known methods [40].

TD algorithms blend DP and Monte Carlo methods, offering a good combination of optimality and low computational burden, making them an attractive solution for real-time implementation. A class of model-free TD algorithm, called $Q$-learning, has been used in different applications, such as maximum power point tracking (MPPT) in WECS and power
systems restoration [41], [42]. Q-learning uses action-value functions, $Q(s,a)$, to assess the agent’s performance. The one-step update rule for $Q(s,a)$ is given by

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{b \in A} Q(s', b) - Q(s, a)]$$ (26)

where $r$ is the immediate received reward and $\alpha \in (0,1]$ is the learning rate which governs the level of update between the actual and new $Q$-value. The discount rate $\gamma$ was previously defined, and it controls whether the agent is more concerned with immediate or future rewards. Note that $P$ is not needed in (26); hence this algorithm is characterized as model free [40]. The pseudo-code of the Q-learning algorithm is shown in Table 2.3.

Table 2.3. Q-learning Pseudo-code

<table>
<thead>
<tr>
<th>Algorithm: Q-learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Initialize $Q$ arbitrarily for all $s \in S$ and $a \in A$</td>
</tr>
<tr>
<td>2. For each episode do</td>
</tr>
<tr>
<td>3. Initialize $s$</td>
</tr>
<tr>
<td>4. For each step of episode:</td>
</tr>
<tr>
<td>5. Choose action $a$, based on $Q(s, _)$ and an exploratory strategy ($\epsilon$-greedy)</td>
</tr>
<tr>
<td>6. Perform action $a$, observe $s'$ and $r$</td>
</tr>
<tr>
<td>7. $Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{b \in A} Q(s', b) - Q(s, a)]$</td>
</tr>
<tr>
<td>8. $s \leftarrow s'$</td>
</tr>
<tr>
<td>9. until $s$ is terminal</td>
</tr>
</tbody>
</table>

Table 2.4. Q-learning Parameters for Performance Study

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\tau$</th>
<th>$\beta$</th>
<th>$w_{1,2,3,4}$</th>
<th>$\xi$</th>
<th>Number of episodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time constant</td>
<td>-</td>
<td>0.008</td>
<td>0.35-0.45-0.1-0.1</td>
<td>0.3</td>
<td>10</td>
</tr>
<tr>
<td>Exploration rate</td>
<td>15:5:75</td>
<td>-</td>
<td>0.35-0.45-0.1-0.1</td>
<td>0.3</td>
<td>10</td>
</tr>
<tr>
<td>Weighting factors</td>
<td>15:5:75</td>
<td>0.008</td>
<td>-</td>
<td>0.3</td>
<td>10</td>
</tr>
<tr>
<td>DOD restriction</td>
<td>15:5:75</td>
<td>0.008</td>
<td>0.35-0.45-0.1-0.1</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>
2.3.2. Application of Q-learning algorithm in integrative sizing/real-time EMS of HESS

The operation of the HESS within $T_{opr}$ is considered as a MDP involving a discrete set of state variables: $s_k \in S = \{(P_{UESS}[k],SOC_{sc}[k]) \mid (P_{UESS} \leq P_{UESS}[k] \leq P_{UESS \_s}), (SOC_{sc} \leq SOC_{sc}[k] \leq SOC_{sc})\}$, a discrete set of actions: $a_k \in A = \{\tau[k] \mid \tau \leq \tau[k] \leq \bar{\tau}\}$, and a reward function associated with minimizing $J$ (maximizing the reward), which can be expressed as

$$R = 1/J$$ (27)

Several factors need to be taken into account when applying the Q-learning algorithm. Selection of bounds for the state and action spaces requires a tradeoff between speed of convergence and learning accuracy: a large number of states and actions might adversely impact the learning time period, whereas validity of the learning results might be reduced if a small number of states and actions is used [41]. The exploration strategy affects the agent behavior during the learning process: in order to maximize the reward, the agent has to exploit its current knowledge, but in order to learn, the agent has to explore actions that might produce higher than already selected reward values. Weighting factors and $\zeta$ selection in (15) influences the received reward, and $\alpha$ and $\gamma$ in (26) affect the execution of the algorithm in terms of learning convergence and importance of immediate received reward, respectively. Discussions on selection of these factors are presented in marks 1-4 in the following. To support these discussions, simulations using the Q-learning algorithm were carried out for two different tuples $(n_{sc}, r_i, d)$: tuple\_1 = (400, 1, 0.1) and tuple\_2 = (600, 1, 0.2). Table 2.4. lists the parameters used in the algorithm during the study. Simulations results for maximum value of $P_{UESS}, P_{UESS\_max}$, the
mismatch between initial and final $SO\!C_{sc}$ values, $SO\!C_{sc\_error}$, and initial and final $z_1$ values, $z_1\_error$, and $\mathcal{R}$ are shown in Figure 2.4.

1) **State space:** The state variables, $P_{UES\!S}$ and $SO\!C_{sc}$, are bounded by the highest and lowest values of $P_{HES\!S}$, as well as the operation limits imposed by the SC cell. Thus, $P_{UES\!S} = [-70:10:540]$ Kw and $SO\!C_{sc} = [0.25:0.0164:1]$. It should be noted that the range of $SO\!C_{sc}$ in this case is different than the one introduced in subsection 2.2.3. This is to cover possible values of $SO\!C_{sc}$ that might fall outside the limits of (19) during the sizing stage.

2) **Action space:** The low-pass filter time constant dictates the power split between the HESS components: bulk of power is allocated to the UESS when very low values of $\tau$ are used, whereas with very high $\tau$ values almost all the power is allocated to the SC. Thus, a combination of $\tau$ values that provide an effective split of power between the UESS and SC is needed. Four sets of $\tau$ were considered for the analysis: set_1 = {2:5:40}, set_2 = {10:5:50}, set_3 = {50:5:100}, and set_4 = {100:5:150}. In Figure 2.4(a), the lowest value of $P_{UES\!S\_max}$ for both tuples is obtained with set_4. This is because basically almost all the energy is absorbed/delivered by the SC, which impacts the size of the SC. For $SO\!C_{sc\_error}$ and $z_1\_error$, set_2 results in the lowest values for tuples_1 and 2. The highest $\mathcal{R}$ is achieved with set_3, which suggests to select this set as the set of actions to be employed in the algorithm. However, to avoid oversizing the SC, a combination of values from set_2 and set_3 is used. Thus, $\tau \in \{10:5:60\}$ is considered.

3) **Learning rate, exploration rate, and discount factor:** For learning convergence, a learning rate with a high initial value and a proper decaying law are needed. In the literature, different decaying laws for $\alpha$ have been analyzed. In this work, a decaying rule that does not rely on parameters (hence, does not require tuning) is considered.
Figure 2.4. Simulation results showing influence of (a) time constant, (b) exploration decaying-rate, (c) weighting factors, and (d) DOD constraint on the UESS peak power, charge sustainability and received reward.

\[
\alpha = \ln(k)/k
\]  

where \(k\) denotes the iteration number during the episode.

In order to maximize the reward received by the agent in the long run, a balance between exploration and exploitation should exist. The exploration strategy employed in the \(Q\)-learning algorithm for the power-allocation problem is called \(\epsilon\)-greedy. This strategy can be formulated as

\[
a_k = \begin{cases} 
\arg \max_{b \in A} Q(s', b) & \text{with } p_k = (1 - \epsilon_k) \\
\text{random action} & \text{with } p_k = \epsilon_k
\end{cases}
\]  

\(\epsilon_k = \epsilon_f + (\epsilon_i - \epsilon_f)e^{-\beta k}\quad (30)\)
where at iteration $k$, $a_k$ is the action taken by the agent, $\epsilon_k$ is the exploration rate, and $p_k$ is the probability of selecting a particular action given the current state, $s$. $\beta$ is a positive scalar value that controls the decaying speed of $\epsilon_k$, $\epsilon_f = 0.01$ and $\epsilon_i = 1$ [43]. The impact of $\beta \in \{0.0002:0.0002:0.001\}$ on $P_{UESS_{max}}$, $SOC_{sc_error}$, $z_{l_error}$, and $\Re$ is shown in Figure 2.4(b). Analysis of the results as a whole suggests that values of $\beta$ between 0.0006 and 0.0008 provide a relatively good tradeoff between exploration and exploitation; thereby a value of 0.0007 is adopted in the algorithm.

The discount factor governs the importance that the agent assigns to the immediate received reward after an action has been taken. In this work, a farsighted perspective in terms of cumulative reward is given to the agent through a value of $\gamma = 0.95$. This implies that an immediate reward is less important for the agent than the total reward that can be obtained in the future.

4) Weighting factors and DOD restriction: Multiple objectives are merged in (15) by employing weighting factors. Proper tuning of these factors is needed for achieving a desired performance. Impact of six different combinations of weighting factors on $P_{UESS_{max}}$, $SOC_{sc_error}$, $z_{l_error}$, and $\Re$ is investigated and the results are shown in Figure 2.4(c). The combinations, from 1 to 6 are respectively: (0.4,0.4,0.1,0.1), (0.2,0.6,0.1,0.1), (0.6,0.2,0.1,0.1), (0.1,0.1,0.6,0.2), (0.1,0.1,0.2,0.6), and (0.1,0.4,0.4,0.1). As seen in Figure 2.4(c), the combinations that prioritize the cost of energy, i.e., combinations 4 and 5, show degraded performance in terms of charge sustainability, $P_{EUSS}$ peak and cumulative reward, while combinations 1 and 2 result in the best performance (from the same perspective). Thus, the combination (0.3,0.5,0.1,0.1) is employed when implementing the algorithm.
Figure 2.5. Flow chart of the proposed integrative sizing/EMS method

As explained in Section 2.2, a measure to limit the DOD of the UESS is taken by imposing the constraint in (22). The objective of this constraint is to reduce the number of sudden machine transitions and preserve its safety and lifetime. In Figure 2.4(d), the highest value of \( P_{UESS, max} \) and \( \xi \) are produced for \( \xi = 0.9 \). This is due to the fact that \( J \) is less penalized in this scenario. For \( SOC_{sc, error} \) and \( z_{L, error} \), values of \( \xi \) between 0.3 and 0.5 offer the lowest mismatch between the initial and final values. Therefore, the value of \( \xi = 0.4 \) is adopted.
A flow chart illustrating the process of adapting the $Q$-learning algorithm into the proposed integrative sizing/real-time EMS approach is given in Figure 2.5. The sizing process starts by selecting a tuple $(n_{sc}, r_i, d)$ from each particular set of values. In the next step, the number of episodes, $N_e$, is defined, and the $Q$-table, reward vector $R$ and power vector $P$ are initialized. Matrix $Q$-table has a dimension of $l \times m \times n$, where $l$ and $m$ are the number of elements of each state, and $n$ is the total number of actions. Vectors $R$ and $P$ have dimensions of $y \times 1$, where $y$ is the number of steps in each episode. In order to set the number of episodes, simulations were carried out to determine the convergence of the $Q(s,a)$ values based on both the number of episodes and number of discrete steps in each episode. The number of steps is related to the time duration of the $P_{HESS}$ profile and sampling time, $T_s$. A power profile with a duration of 1 h and $T_s = 1$ sec is considered in the sizing stage. The difference between two $Q(s,a)$ values was calculated for 100 steps. Simulations results shown in Figure 2.6. conclude that with $N_e = 10$, $Q(s,a)$ convergences.

At the beginning of each episode, all the states $s = (P_{UESS} [k], SOC_{sc} [k])$ are initialized. In the episode, the agent picks an action $\tau$ at each discrete step based on the exploration strategy,
and the power split is performed using (12) and (13). Solving (3)-(10) situates the agent in a new state, \( s' = (P_{UESS}[k+1], SOC_{sc}[k+1]) \), while receiving an immediate reward \( r \) obtained from (15)-(22) and (27). With \( s, s', \tau, \) and (26) the \( Q \)-value is updated and stored in the \textit{Q-table}; \( P_{UESS} \) is stored in \( P \), and \( r \) is stored in \( R \). Once the episode terminates, the cumulative reward is calculated and the maximum \( P_{UESS} \) is extracted. This process is repeated for each episode until \( N_e \) is reached and the learning period ends. Following this, the cumulative reward \( \mathcal{R} \) is calculated and the highest value of \( P_{UESS} \) among all episodes as well as the \textit{Q-table} are stored. The previous steps are repeated for each tuple \((n_{sc}, r_i, d)\) until the sizing stage is completed. Then, the tuple \((n_{sc}, r_i, d, \text{max}[P_{UESS}])\) with the highest \( \mathcal{R} \) is picked as the best solution. The \textit{Q-table} corresponding to the selected tuple is extracted as the action-selection policy for the agent to follow during the energy management phase.

2.4. Grid-connected operation of WECS

The WECS output power quality is enhanced using the HESS as well as the proposed RL-based power-allocation control scheme. As seen in Figure 2.7, each source is interfaced with a power electronics converter (PEC). Brief discussions about the control of each source-PEC pair are provided in the following subsections.

2.4.1. WECS-side converter control

The WECS model was discussed in subsection 2.2.1. The WECS-side converter interfaces the linear generator with the dc-link capacitor. This converter is a three-phase, two-level ac/dc rectifier, which allows the WECS to deliver power to the dc link. The inverter controller’s objective is to extract the maximum power from the ocean waves to realize MPPT operation [10].
2.4.2. Grid-side converter control

The grid-side converter, which is a three-phase, two-level grid-tied inverter, regulates the dc-link voltage, \(v_{dc}\), and the active and reactive power injected to the grid. In this work, classical direct power control (DPC) [44] is used for the grid-side converter control. In DPC, the grid active power, \(P_g\), is adjusted to keep \(v_{dc}\) constant, while the terminal voltage is regulated by controlling the grid reactive power, \(Q_g\). The grid active and reactive power are given by

\[
P_g = \frac{3}{2}(v_{\alpha}i_{\alpha} + v_{\beta}i_{\beta})
\]

\[
Q_g = \frac{3}{2}(v_{\beta}i_{\alpha} - v_{\alpha}i_{\beta})
\]

where \(v_{\alpha\beta}\) and \(i_{\alpha\beta}\) are the voltage and current in the stationary \(\alpha-\beta\) reference frame.
2.4.3. HESS control

A two-level controller for the storage side converter is proposed: at the upper level, the reference power, $P_{SC}^*$ and $P_{UESS}^*$, for the SC and UESS controllers is provided; at the lower level, the PECS interfacing the SC and UESS with the dc-link capacitor are controlled to follow the reference power. The power that the HESS needs to deliver/absorb is obtained from the balance of power at the dc link

$$P_{HESS} = P_{WECs} - P_{dc} - P_{grid}$$  \hspace{1cm} (33)

where $P_{dc}$ is the dc-link power (see Figure 2.7.). Several factors impact the reference dc-link voltage, $v_{dc}^*$, value. The rated line-to-line voltage of the UESS PMSM which must be available from the inverter feeding the machine, peak of the WEC output voltage, and the power level transmitted from the offshore WEC to the onshore grid are among them. Based on these factors, 900 V is selected as the reference dc-link voltage value in this work.

At the upper level, which is referred to RL controller in Figure 2.7, the **Q-table** obtained in the sizing phase is employed as the action-selection policy, i.e., at each time step, a $\tau$ based on the actual values of $P_{UESS}$ and $SOC_{sc}$ is selected. With $P_{HESS}$ obtained from (33), and the adopted $\tau$, $P_{UESS}^*$ and $P_{SC}^*$ are calculated using (12) and (13), respectively.

As can be seen in Figure 2.7, the load torque $T_L$ and the reference speed, $\omega_m^*$, of the PMSM are derived from $P_{UESS}^*$. In subsection 2.2.4., measures that must be taken in the sizing stage to reduce the number of machine transitions (due to its rotary inertia) were stated. This issue is also contemplated in obtaining $\omega_m^*$ by taking the mechanical time constant of the machine into account. The mechanical time constant is given as [45]

$$\tau_m = J \omega_n^2 / P_n$$  \hspace{1cm} (34)
where $J_t$ is the combined inertia of the RPT and the rotor, and $\omega_n$ and $P_n$ are the rated speed and power of the RPT unit, respectively. $\tau_m$ can be physically interpreted as the time required by the machine to reach $\omega_n$ from rest, when a mechanical torque of $P_n/\omega_n$ is applied (assuming a generator) [46]. Thus, it is used for safe ramping up/down of the machine until $+\omega_m^*/-\omega_m^*$ is reached. Classical field oriented control (FOC) strategy is employed to control the PMSM of the UESS. The $q$-axis reference current $i_{qs}^*$ in the rotor reference frame is obtained from the speed PI controller, while the $d$-axis reference current $i_{ds}^*$ is set to zero for realizing maximum torque per ampere (MTPA) operation.

It is noteworthy to mention that the mode of operation of the RPT unit is determined based on the sign of $P_{UESS}^*$ as follows

\[
\begin{cases} 
if \ P_{UESS}^* > 0 & \text{pump mode} \\
if \ P_{UESS}^* < 0 & \text{turbine mode}
\end{cases}
\]  

(35)

The PEC interfacing the SC pack with the dc-link capacitor is a bi-directional boost/buck dc/dc converter, which allows the SC to deliver/absorb power to/from the dc link. The SC reference current $i_{sc}^*$, which is calculated from $P_{sc}^*$ and $v_{dc}$, is compared with the actual current to obtain the duty cycle of the dc/dc converter switch.

2.5. **Sizing and real-time implementation results**

2.5.1. **Sizing results**

The RL-based sizing algorithm described in section 2.3. is applied to obtain the HESS power and energy capacity. For the sake of comparison, the same $P_{WECS}$ power profile used for sizing the SC and UESS for sea state 6 in [35] is used here. The power profile has a time window of 1 h with $T_s = 1$s. The following set of values and ranges have been considered in the sizing
stage: $n_{sc} \in \{111:20:888\}$, $r_i \in \{0.8:0.05:3.2\}$ m, and $d \in \{0.1:0.05:0.4\}$ m. The lower and upper bounds are set based on the results obtained in [35] for WECs operation with SC only, and UESS only.

Two outputs of the RL-based sizing algorithm are shown in Figure 2.8(c) and (d). Figure 2.8(c) corresponds to the case where only the SC is used for smoothing $P_{WECS}$. For this case, a set of actions with large time constants allocated the whole delivered/absorbed power to the SC. The number of SC cells that generates the highest reward is $n_{sc} = 731$. Compared with $n_{sc} = N_{ser} * N_{par} = 111*8 = 888$ in Figure 2.8(a) for sea state 6, a significant reduction in the number of SC cells is achieved with the proposed algorithm. In Figure 2.8(a), $N_{ser}$ and $N_{par}$ are the number of SC cells connected in series and parallel, respectively.

Figure 2.8(d) depicts the sizing results when both the SC and UESS are considered. Note the steep slope on the leftmost side of the figure. This can be attributed to the constraints on $SOC_{sc}$ and requirement of charge sustainability for both SC and UESS: with low number of SC cells, $SOC_{sc}$ bounds are violated and charge is not sustained. Consequently, the UESS counteracts the power fluctuations that the SC is not able to provide/absorb, imposing sharp transients on the electric machine and/or high DODs, some of which may not be tracked due to the rotary inertia. This, in turn, adversely affects the UESS charge sustainability. As the number of SC cells increases, these issues occur less frequently or not at all, and it is the middle region of the figure that suggests a tradeoff between HESS performance and the capital cost. The highest reward is obtained in this region, as well. Increasing $n_{sc}$ further, enhances the HESS performance; however, the combined capital cost of its components rises.
Figure 2.8. Sizing results: (a) SC only and (b) UESS only [35]. (c) RL-based SC only and (d) RL-based hybrid SC/UESS.

Table 2.5. Parameters of the UESS PMSM [47]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stator resistance [Ω]</td>
<td>0.012</td>
</tr>
<tr>
<td>Armature inductance [H]</td>
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</tr>
<tr>
<td>Flux linkage $\lambda_f$ [V.s]</td>
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</tr>
<tr>
<td>Inertia $J_t$ [Kg.m²]</td>
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</tr>
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<td>Pole pairs $p$</td>
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<td>Rated power [kW]</td>
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<tr>
<td>Rated current [A]</td>
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<tr>
<td>Rated voltage [V]</td>
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</tr>
<tr>
<td>Rated frequency [Hz]</td>
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</tr>
</tbody>
</table>

**Remark 1:** The tuple $(n_{sc}, r_i, d, \text{max}[P_{UESS}])$ with the highest reward is $(531, 1.4515, 0.4, 156.6)$. Note that the number of SC cells in this case (531) is less than the ones obtained for SC
only operation (731). This is a testament to the effectiveness of the proposed power-allocation algorithm.

*Remark 2:* The obtained inner radius of the sphere (1.4515 m) following the proposed sizing approach is close to the value in Figure 2.8(b), 1.5 m. The energy storage capacity of the UESS is directly proportional to the sphere volume [35]. Since at sea state 6 the energy requirement is relatively low, bulk of energy demand is provided by the UESS based on the frequency allocation policy. Thus, almost similar values of $r_i$ are obtained following the two sizing approaches.

*Remark 3:* In [35], where only the UESS operates in parallel with the WECS, the rated power of the PMSM required for handling the power variations is obtained as 700 hp. Following the proposed method, however, the power rating of the PMSM is obtained as 210 hp. Thanks to the effectiveness of the algorithm in splitting the power between the SC and UESS, a power rating reduction of about ~70% is achieved for the electric machine.

### 2.5.2. Real-time implementation results

Real-time simulations are carried out to evaluate the performance of the energy management strategy in enhancing the output power quality of the WECS. The WECS, including the buoy and the linear generator, the HESS, the grid, and the interfacing PECs are modeled on an OP4510 real-time simulator from Opal-RT Technologies Inc. operating with Kintex7 FPGA. The simulation is run for 300 s. The sampling frequency is set to 20 kHz. Parameters of the UESS PMSM are listed in Table 2.5.

A random wave power profile generated with a SWH of 6 m and average period of 9 s is generated. It is then used along with the tuple $(n_{sc}, r_i, d)$ obtained in subsection 2.4.1. to determine the action-selection policy that the agent will follow in the real-time simulations. This
is the learning phase. In order to examine the adaptability of the EMS, a different wave power profile from the one used in the learning stage is employed in the simulations. This profile is extracted from a random wave profile generated with a SWH of 5.3 m and average period of 8.9 s. At $t = 0$, $P_{\text{grid}}$ is set to 40 kW. The power to be delivered to the grid is then increased by a step of 10 kW at $t = 105$ s, and decreased by a step of -5 kW at $t = 205$ s. The WECS output power and the power absorbed/delivered by the HESS are shown in Figure 2.9(a). The power split between the SC and UESS is shown in Figure 2.9(b); the high-frequency power component is allocated to the SC, while the low-frequency component is allocated to the UESS. Figure 2.9(c) depicts the load torque and the electromagnetic torque developed by the UESS PMSM. Note that the torque and the UESS power profile follow a similar form. This is due to obtaining the load torque from $P_{UESS}^*$ in the HESS control scheme (see Figure 2.7.). The $d$-$q$ axis components of the PMSM stator current in the rotor reference frame are shown in Figure 2.9(d). The $d$-$axis$ component follows $i_{ds}^* = 0$ to realize MTPA, and the $q$-$axis$ component contributes to developing the electromagnetic torque to follow the load torque. Two modes of operation of the RPT, i.e. charging and discharging mode, are shown in Figure 2.9(e). In the charging mode, the RPT unit works as a pump and the speed of the UESS PMSM is positive. The machine operates in the motoring mode and surplus of the generated power is used to pump the water out of the UESS. As seen in Figure 2.9(f), the water level inside the sphere drops during charging mode. In the discharge mode, the controller provides the speed reversal command. The speed of the machine is negative and the RPT unit works as a turbine. Water flows into the UESS through the turbine to generate electricity. A corresponding increase in the water level can be seen in Figure 2.9(f).
Figure 2.9. Real-time results. a) WECS and HESS power, b) SC and UESS power, c) electromagnetic and load torque, d) PMSM $d$-$q$ stator current components, e) reference and actual PMSM speed, f) water level inside the UESS and the SC state of charge, g) actual and reference grid active power, h) actual and reference grid reactive power, i) actual and reference dc-link voltage, j) the SC and the UESS efficiencies.
It is noteworthy to mention that only two transitions from charging mode to discharging mode and vice versa take place. This is thanks to the constraints imposed by (21) and (22) in the learning phase. Considering $\tau_m$ in the upper level of the storage side controller and the learning phase allows the PMSM to follow the speed transitions. Further, state of charge of the SC is maintained at the imposed lower bound, i.e., $SOC_{sc} = 0.5$. Also, it is clear from Figure 2.9(f) that the charge sustainability is accomplished for both the SC and UESS as the initial and final values of $SOC_{sc}$ and $z_f$ are the same at the beginning and end of the designated time period.

The dynamic response to power changes is shown in Figure 2.9(g). The active and reactive power injected to the grid follow reference set points. The reference reactive power $Q_g^*$ is set to zero (see Figure 2.9(h)). As shown in Figure 2.9(i), the dc-link voltage is maintained at its reference value $v_{dc}^* = 900$ V, showing the effectiveness of the control strategy in regulating the WECS output power in presence of imbalances between generation and demand.

Efficiencies of the SC and the UESS are shown in Figure 2.9(j). The efficiencies are obtained following the approach presented in [35]. The UESS shows efficiencies between 69% and 76%. The efficiency is mainly associated with the operation point in terms of dynamic head and flow rate and the UESS PMSM’s rated values. As discussed in [35], when the UESS is subject to very deep charge/discharge cycles, the overall efficiency raises since the PMSM operates closer to the rated point where efficiency is optimum. Markers 2 and 3 in the figure show the instants when the UESS changes its mode of operation from the charging mode to the discharging mode (see Figure 2.9(e)). The SC efficiency varies approximately between 94% and 99%. It can be noticed that when the SC is subject to very deep charge/discharge cycles (marker 1), the internal losses increase; thus, its efficiency drops.
3.1. Introduction

Transportation electrification is considered as a viable solution in response to environmental protection policies pushing towards the reduction of hydrocarbon consumption [1]. In the marine sector, the application of electric propulsion and power electronic converters (PEC) has provided new shipboard power system architectures, such as the medium voltage dc (MVDC) shipboard power system [2], [3]. Due to wave encounter frequency fluctuations, propeller blade passing frequency fluctuations, and fluctuations from propeller emergence, the propulsion system of the ship is subject to large thrust/torque variations [4], [5]. These variations translate into steep power fluctuations on the MVDC bus, adversely impacting the stability, efficiency and quality of the power network; thus, making the integration of electric propulsion into the shipboard power system challenging.

Strategies involving application and control of the thrusters have been proposed in the literature to reduce the power fluctuations [6]. Hybrid energy storage system (HESS), comprising multiple energy storage devices with complementary power and energy densities, is a promising solution to this problem [5], [7], and [8]. HESS design involves selecting the energy storage devices and determining their power and energy capacity (sizing) [9]. The most popular energy...
storage technologies employed in HESS are batteries, supercapacitors (SCs), and fuel cells (FCs) [10], [11].

The majority of studies on HESS sizing for electrified transportation applications are devoted to road vehicles [12]-[14], and very few cover those involving ships. In [12], a sample-based oriented dividing rectangles algorithm is used to solve a multi-objective optimization problem, involving minimization of a battery/SC HESS size, while maximizing the lifetime of the battery in a midsize electric vehicle. A battery/SC/FC HESS sizing approach for FC hybrid electric vehicles based on the multi-objective grey wolf optimizer and a frequency split-based analysis is presented in [13]. The Pontryagin's minimum principle is used in [14] to obtain the optimal size of the battery/SC HESS considering the fuel, electricity, and battery degradation costs for a plug-in hybrid bus. In [15], an approach to determine the optimal size of the diesel and photovoltaic generation systems and the energy storage system (ESS) for an oil tanker is proposed. The method employs particle swarm optimization along with the elitist nondominated sorting genetic algorithm to minimize multiple objectives, such as, the investment cost, fuel cost and the CO2 emissions.

The EMS of the HESS plays a vital role in improving the system operation and efficiency. EMSs for the HESS are either rule-based or optimization-based [16]. The rule-based EMSs are less complex, but do not warranty optimality [17]. Optimization-based EMSs can be categorized into global-optimal and real-time near-optimal. Global optimal EMSs yield a global-optimal solution, but are complex and not suitable for real-time implementation [18, 19]. EMSs proposed in [20]-[23] for hybrid and plug-in hybrid electric vehicle applications are based on fuzzy logic, artificial neural networks, Markov chain models, and radial basis functions. These EMSs slightly compromise the optimality, but are implementable in real time. In [24], a
reinforcement learning (RL)-based EMS is proposed and used for allocating power to the battery and internal combustion engine of a hybrid electric vehicle. This method features adaptability, optimality, and reduced computational complexity. In [5], the integration of a battery/SC HESS into the shipboard power grid is investigated. An EMS based on model predictive control (MPC), which falls into the subcategory of real-time near-optimal EMSs, is proposed to mitigate the power fluctuations. However, the effectiveness of the proposed method is evaluated using the regular wave model, which is not a realistic scenario. Furthermore, the computational burden of the model predictive-based EMS is high.

The power and energy that the HESS components must deliver/absorb are dependent on the EMS; thus, the size/capacity of the HESS is impacted by the EMS [25], [26]. Therefore, methods that integrate the HESS sizing and EMS must be devised. In [27]-[30], such methods for the HESS employed in wind and wave energy conversion systems, and electric/hybrid electric/FC vehicles are presented. However, studies of this nature for electric ship applications are scarce. A methodology to sizing and EMS of a battery pack for a ferry and a supply platform vessel is proposed in [31]. A two-phase approach, where in the first phase the battery sizing is carried out, and in the second phase the EMS for both generation and the battery is selected, is proposed. In [7], a combined sizing and EMS for the integration of a battery/SC HESS into the power system of an excursion ship is developed. The HESS component selection and power allocation is performed through a frequency split-based analysis. However, in both studies it is assumed that the ship propulsion power profile is known.

In this chapter, a data-driven joint sizing/energy management approach for integration of a HESS into the MVDC shipboard power system is proposed. A HESS comprising the battery and SC is sized and energy flow between its components and the shipboard power system is such
managed that the power fluctuations caused by thrust/torque variations are mitigated. The proposed approach is developed based on deep reinforcement learning (DRL). Thus, unlike rule-based methods, it yields a near-optimal solution, and unlike optimization-based methods, is implementable in real time. Furthermore, the proposed method is adaptable to varying sea states and does not require the knowledge of the ship propulsion power profile.

Figure 3.1. depicts the outline of the proposed method. In the learning phase, several power profiles are used to train the agent with the actions that generate maximum rewards $R$. The reward is an indicator of the effectiveness of the action selection policy (that is the power allocation strategy), and whether the system constraints are satisfied. After repeating this process for various battery and SC sizes, the learning phase is concluded by selecting the battery-SC combination with the maximum cumulative reward, along with the action selection policies that produce the highest rewards. In the testing phase, propulsion power profiles different than those used in the learning phase are employed and the adaptability of the joint sizing/EMS is validated.

![Figure 3.1. Scheme of the proposed joint sizing and energy management approach](image-url)
The contributions of this chapter are twofold: (i) proposing a novel approach for joint sizing and energy flow control of HESS in MVDC shipboard power systems, which features optimality, real-time implementation feasibility while obviating the requirement for knowledge of the ship propulsion power profile, and (ii) obtaining and comparing the hybrid battery/SC, battery-only and SC-only power and energy densities for MVDC electric ship applications by the proposed approach.

The structure of the chapter is organized as follows: The models of the ship and its propulsion system, and the HESS are introduced in Section 3.2. The formulation of the power-allocation problem is presented in Section 3.3. In Section 3.4, the DRL algorithm is employed to solve the power-allocation problem. In Section 3.5, the operation scheme of the ship propulsion system and the HESS is discussed. The real-time simulation results and discussions are provided in Section 3.6.
3.2. **Ship and hybrid battery/SC models**

Since real data of power fluctuations are not available, a comprehensive model of a ship interacting with the waves is employed in extended simulations to generate the required data for DRL. Irregular wave profiles generated by the modified Pierson-Moskowitz spectrum are employed in the simulations to attain more realistic scenarios.

Figure 3.2 illustrates the interactions between the ship and its propulsion system, including the electric motor, shaft and propeller [32]. Propeller thrust and torque are calculated from the propeller model employing the wake field and shaft speed information. The thrust produced by the propeller is the input to the ship model, and the speed of the ship is the output. The shaft speed is obtained from the shaft model using the propeller torque and actual motor torque. The shaft speed is employed by the motor speed controller to generate the input to the motor model and consequently, develop the torque demanded by the propeller.

### 3.2.1. Ship model

Propeller thrust, $T_a$, torque, $Q_a$, and power, $P_a$, are commonly given in terms of the shaft speed, $n$, propeller diameter, $D$, water density, $\rho$, and thrust and torque coefficients, $K_T$, and $K_Q$, as follows [5]:

$$T_a = \text{sign}(n)K_T \rho D^4 n^2 \beta_T$$

$$Q_a = \text{sign}(n)K_Q \rho D^5 n^2 \beta_Q$$

$$P_a = 2\pi \text{sign}(n)K_Q \rho D^5 n^3 \beta_Q$$

Here $K_T = f(J_A, \text{Pitch}/D, A_e/A_o, Z, R_n)$, $K_Q = g(J_A, \text{Pitch}/D, A_e/A_o, Z, R_n)$, and $\beta_T$ and $\beta_Q$ are the thrust and torque loss factors, respectively. In this study, a unique loss factor is considered, i.e. $\beta$. 

41
\[ \beta_T = \beta_Q. \] Pitch/D is the propeller pitch ratio, \( Z \) is the number of propeller blades, \( J_A \) is the advance coefficient, \( A_e/A_o \) is the expanded blade-area ratio, and \( R_n \) is the Reynolds number. The shaft speed unit is in revolution per second (rps). The advance coefficient is expressed as \( J_A = V_A/nD \), where \( V_A \) is the propeller advance velocity and in most cases is less than the speed of the ship, \( U \). The difference between the ship speed and the advance speed with respect to the ship speed is defined as the wake fraction: \( w_h = (U - V_A)/U \) [33]. The calculation of the advance coefficient requires knowledge of the wake field given by \( w_h \). The wake field model assumed in this study involves mean wake along with wake fluctuations [34], and is expressed by

\[
w_h = \frac{1}{Z} \sum_{j=0}^{Z-1} \left[ 0.173 + 0.1388 \cos \left( \theta - \frac{j}{2} \pi \right) + 0.1417 \cos \left( 2\theta - \frac{2j}{2} \pi \right) + 0.0187 \cos \left( 3\theta - \frac{3j}{2} \pi \right) + 0.02137 \cos \left( 4\theta - \frac{4j}{2} \pi \right) - 0.0162 \cos \left( 5\theta - \frac{5j}{2} \pi \right) \right]
\]

where \( \theta \in [0, 2\pi] \) is the angular position of the blade. In order to capture the effect of waves on the ship propulsion system, thrust and torque losses associated with the propeller emergence, free surface and Wagner effects must be considered. These effects are accounted for through the parameter \( \beta \), given below [32]:

\[
\beta = \begin{cases} 
1 - 0.675 \left[ 1 - 0.769 \left( \frac{h}{R} \right) \right]^{1.258} & \text{if } h/R < 1.3 \\
1 & \text{if } h/R \geq 1.3
\end{cases}
\]

where \( h \) is the propeller shaft submergence and \( R \) is the propeller radius. The parameters of the considered propeller are listed in Table 3.1. In this work, the propeller shaft is assumed to be coupled to a squirrel-cage induction motor (SCIM) in the ship propulsion system. Parameters of the motor are listed in Table 3.2.
In the shaft model, which includes a gearbox coupling the motor and propeller shafts, the torque balance equation can be written as

\[ J'p \omega_m = T_e - Q'_a - B \omega_m \]  

where \( J' \) and \( Q'_a \) are the referred moment of inertia and torque of the propeller, respectively, \( \omega_m \) is the rotor mechanical speed, \( T_e \) is the electromagnetic torque developed by the SCIM, \( B \) is the damping coefficient, and \( p = d/dt \).

Dynamics of the ship motion through the ocean waves can be modelled as follows [32]:

\[ (m + m_x)pU = (1 - t')T_a - (0.5\rho K_{ship}U^2 + F_{wave}) \]  

Here \( m \) is the ship mass, \( m_x \) is the surge added mass of the ship and \( t' \) is the thrust deduction coefficient. \( K_{ship} \) is a constant that depends on the ship wetted surface area, the drag resistance coefficient, the ship advance facing area in the air, and the wind resistance coefficient. \( F_{wave} \) is the first-order wave excitation force. These parameters are listed in Table 3.1. Thrust deduction is assumed constant; thus, \( t' \) is equal to the calm water value given in Table 3.1. In (7), only \( T_a \) and \( F_{wave} \) are time dependent parameters, and they mainly determine the ship speed in terms of its average and fluctuating components, respectively.

### 3.2.2. SC model

The SC cell dynamics are commonly modelled by an equivalent circuit comprising a capacitor, \( C_{sc} \), connected in series with a resistance, \( R_{sc} \). Based on Kirchhoff's voltage law, the SC terminal voltage, \( V_{sc} \), and the cell voltage, \( V_{osc} \), can be calculated as

\[ V_{sc}(t) = V_{osc}(t) - R_{sc}I_{sc}(t) \]  

\[ V_{osc}(t) = V_{osc,0} - (1/C_{sc}) \int I_{sc} dt \]
Table 3.1. Ship Particulars [35]-[37]

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length between perpendiculars</td>
<td>L&lt;sub&gt;pp&lt;/sub&gt;</td>
<td>51.5 m</td>
</tr>
<tr>
<td>Length of the water line</td>
<td>L&lt;sub&gt;WL&lt;/sub&gt;</td>
<td>47.702 m</td>
</tr>
<tr>
<td>Breadth of the water line</td>
<td>B&lt;sub&gt;WL&lt;/sub&gt;</td>
<td>7.726 m</td>
</tr>
<tr>
<td>Draft at L&lt;sub&gt;pp/2&lt;/sub&gt;</td>
<td>T&lt;sub&gt;pp/2&lt;/sub&gt;</td>
<td>2.29 m</td>
</tr>
<tr>
<td>Ship Mass</td>
<td>m</td>
<td>364.78 t</td>
</tr>
<tr>
<td>Surge added mass</td>
<td>m&lt;sub&gt;x&lt;/sub&gt;</td>
<td>17.4 t</td>
</tr>
<tr>
<td>Density of sea water</td>
<td>ρ</td>
<td>1025 Kg/m&lt;sup&gt;3&lt;/sup&gt;</td>
</tr>
<tr>
<td>Design speed</td>
<td>U</td>
<td>15 kt</td>
</tr>
<tr>
<td>Propeller diameter</td>
<td>D</td>
<td>1.6 m</td>
</tr>
<tr>
<td>Number of blades</td>
<td>Z</td>
<td>4</td>
</tr>
<tr>
<td>Expanded blade-area ratio</td>
<td>A&lt;sub&gt;e&lt;/sub&gt;/A&lt;sub&gt;o&lt;/sub&gt;</td>
<td>0.7</td>
</tr>
<tr>
<td>Propeller pitch ratio</td>
<td>Pitch/D</td>
<td>1</td>
</tr>
<tr>
<td>Thrust deduction coefficient</td>
<td>t’</td>
<td>0.1754</td>
</tr>
<tr>
<td></td>
<td>K&lt;sub&gt;ship&lt;/sub&gt;</td>
<td>54.65 m&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

Table 3.2. Induction Motor Parameters [38]

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stator resistance</td>
<td>r&lt;sub&gt;s&lt;/sub&gt;</td>
<td>0.112 Ω</td>
</tr>
<tr>
<td>Rotor resistance</td>
<td>r&lt;sub&gt;r’&lt;/sub&gt;</td>
<td>0.074 Ω</td>
</tr>
<tr>
<td>Stator inductance</td>
<td>L&lt;sub&gt;s&lt;/sub&gt;</td>
<td>0.1452 H</td>
</tr>
<tr>
<td>Rotor inductance</td>
<td>L&lt;sub&gt;r’&lt;/sub&gt;</td>
<td>0.1452 H</td>
</tr>
<tr>
<td>Magnetizing inductance</td>
<td>L&lt;sub&gt;m&lt;/sub&gt;</td>
<td>0.1436 H</td>
</tr>
<tr>
<td>Rated voltage</td>
<td>V&lt;sub&gt;n&lt;/sub&gt;</td>
<td>2300 V</td>
</tr>
<tr>
<td>Rated speed</td>
<td>n&lt;sub&gt;n&lt;/sub&gt;</td>
<td>1778 rpm</td>
</tr>
<tr>
<td>Rated Power</td>
<td>P&lt;sub&gt;n&lt;/sub&gt;</td>
<td>1000 hp</td>
</tr>
<tr>
<td>Combined inertia</td>
<td>J&lt;sub&gt;m&lt;/sub&gt;</td>
<td>29.871 Kg.m&lt;sup&gt;2&lt;/sup&gt;</td>
</tr>
<tr>
<td>Damping coefficient</td>
<td>D</td>
<td>0.786 N.m.s</td>
</tr>
<tr>
<td>Gear ratio</td>
<td>a</td>
<td>4.42</td>
</tr>
</tbody>
</table>

where \( V_{osc,0} \) is the cell initial voltage. The SC cell current, \( I_{sc} \), can be obtained from

\[
I_{sc}(t) = \frac{V_{osc}(t)}{2R_{sc}} - \frac{\sqrt{V_{osc}(t)^2 - 4R_{sc}P_{sc}(t)/n_{sc}}}{2R_{sc}}
\]  

(10)

where \( P_{sc} \) is the SC power, and \( n_{sc} \) denotes the total number of the SC cells
The state-of-charge (SOC) can be obtained as [30]

$$SOC_{sc}(t) = \frac{V_{sc}(t)}{V_{nsc}}$$  \hspace{1cm} (11)

where \( V_{nsc} \) is the SC rated voltage. The lower and upper bounds of \( SOC_{sc} \) are set to 30 and 90%, respectively. Table 3.3. lists the SC cell parameters. The SC efficiency is calculated as [40]

$$\begin{cases} 
\eta_{sc}^{ch}(t) = \frac{2}{P_{sc} < 0} 
\left( 1 + \sqrt{1 - \frac{4R_{sc}^{eq} P_{sc}(t)}{(V_{osc}^{eq}(t))^2}} \right) \\
\eta_{sc}^{dis}(t) = \frac{1}{2} \left( 1 + \sqrt{1 - \frac{4R_{sc}^{eq} P_{sc}(t)}{(V_{osc}^{eq}(t))^2}} \right) P_{sc} \geq 0 
\end{cases}$$  \hspace{1cm} (12)

where \( \eta_{sc}^{ch} \) and \( \eta_{sc}^{dis} \) are the SC efficiencies during charge and discharge, respectively, and \( R_{sc}^{eq} \) and \( V_{osc}^{eq} \) are the equivalent internal resistance and internal voltage of the SC pack, respectively.

<table>
<thead>
<tr>
<th>Table 3.3. Parameters of the SC cell [39]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>----------------------</td>
</tr>
<tr>
<td>Type</td>
</tr>
<tr>
<td>Manufacturer</td>
</tr>
<tr>
<td>Rated Voltage [V]</td>
</tr>
<tr>
<td>Rated continuous current [A]</td>
</tr>
<tr>
<td>Capacitance [F]</td>
</tr>
<tr>
<td>ESRdc initial [mΩ]</td>
</tr>
<tr>
<td>( C_{sc} ) [$/cell]</td>
</tr>
</tbody>
</table>

### 3.2.3. Battery model

The battery is modelled by an ideal voltage source connected in series with an internal resistance, with both the voltage and resistance considered as nonlinear functions of the SOC, \( SOC_{bat} \). The battery cell parameters listed in Table 3.4. as well as the plots of internal cell voltage and internal resistance as functions of the SOC are taken from [29].
The battery cell current, $I_{bat}$, in terms of cell voltage, $V_{obat}$, total absorbed/injected power, $P_{bat}$, cell resistance, $R_{bat}$, and number of cells, $n_{bat}$, can be calculated as

$$I_{bat}(t) = \frac{V_{obat}(t)}{2R_{bat}} - \sqrt{\frac{V_{obat}^2(t) - 4R_{bat}P_{bat}(t)/n_{bat}}{2R_{bat}}}$$  \hspace{1cm} (13)

The SOC is defined as the ratio of the battery electric charge, $Q_{bat}(t)$, to the battery rated capacity, $Q_o$ [17]

$$SOC_{bat}(t) = \frac{Q_{bat}(t)}{Q_o}$$  \hspace{1cm} (14)

Since a direct measurement of $Q_{bat}$ is not feasible in most cases, time rate change of the SOC is calculated as below:

$$pSOC_{bat} = -\frac{I_{bat}(t)}{Q_o}$$  \hspace{1cm} (15)

where $p$ is the time derivative operator. The lower and upper bounds of $SOC_{bat}$ are set to 20 and 90%, respectively. Cycling and calendar ageing contribute to degradation of the battery capacity. An indicator for the battery capacity loss is the battery's state of health, $SOH_{bat}$, which is defined as the ratio between the actual battery discharge capacity and its nominal value [42]. During discharge period, i.e. $I_{bat} \geq 0$, $SOH_{bat}$ can be expressed in terms of $SOC_{bat}$ as [43]

$$SOH_{bat}(t) = SOH_{bat}(t - \Delta t) - Z_{lac}[SOC_{bat}(t - \Delta t) - SOC_{bat}(t)]$$  \hspace{1cm} (16)

where $Z_{lac}$ is the linear ageing coefficient. Since the battery capacity degrades with cycling, a more accurate estimation of $SOC_{bat}$ can be obtained by considering the capacity loss reflected by $SOH_{bat}$ in (15) as follows [41]:

$$pSOC_{bat} = -\frac{I_{bat}(t)}{(SOH_{bat}(t) * Q_o)}$$  \hspace{1cm} (17)
Remark 1: Compared with cycling, calendar ageing has less of an impact on battery capacity degradation. Therefore, only the latter is taken into account for calculating $SOH_{bat}$ [41].

Remark 2: The upper bound (new battery) and lower bound (end of life) of $SOH_{bat}$, are 1 and 0.8, respectively. The lower bound considers the end-of-life of the battery when the actual discharge capacity reaches to 80% of the initial value [42].

Remark 3: Battery and SC models adopted in this work assume the battery and SC cells operate at the room temperature, i.e. 25°C, and this temperature is maintained during the operation of the HESS. Therefore, dependence of parameters such as $R_{bat}$, $V_{obat}$, $R_{sc}$ and $C_{sc}$ to temperature is neglected.

Table 3.4. Parameters of the Battery [29], [43]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>SCIB</td>
</tr>
<tr>
<td>Manufacturer</td>
<td>TOSHIBA</td>
</tr>
<tr>
<td>Rated Voltage [V]</td>
<td>2.3</td>
</tr>
<tr>
<td>Rated capacity [Ah]</td>
<td>20</td>
</tr>
<tr>
<td>Max C-rate for charging/discharging</td>
<td>3.5/3.5</td>
</tr>
<tr>
<td>$C_{bat}$ [S/cell]</td>
<td>51.6</td>
</tr>
<tr>
<td>$Z_{lac}$ [%]</td>
<td>0.017</td>
</tr>
</tbody>
</table>

The efficiency of the battery is obtained by employing the zeroth-order battery efficiency model [44]

\[
\eta_{bat}^{ch}(t) = \frac{1}{2} \left( 1 + \sqrt{1 - \frac{4R_{bat}^eq P_{bat}(t)}{V_{obat}(t)^2}} \right) \quad P_{bat} < 0
\]

\[
\eta_{bat}^{dis}(t) = \frac{1}{2} \left( 1 + \sqrt{1 - \frac{4R_{bat}^eq P_{bat}(t)}{V_{obat}(t)^2}} \right) \quad P_{bat} \geq 0
\]

(18)
Here $\eta_{bat}^{ch}$ and $\eta_{bat}^{dis}$ are the battery efficiencies during charge and discharge, respectively, and $V_{obat}^{eq}$ and $R_{bat}^{eq}$ are the internal voltage and equivalent internal resistance of the battery pack, respectively.

### 3.3. Joint sizing and energy management

The HESS joint sizing and EMS is accomplished based on the following power allocation strategy:

$$P_{HESS}(k) = P_{HESS}^L(k) + P_{HESS}^H(k)$$

(19)

Here $P_{HESS}^L(k) = (1 - \phi)P_{HESS}^L(k - 1) + \phi P_{HESS}(k)$ and $P_{HESS}^H(k) = P_{HESS}(k) - P_{HESS}^L(k)$ are the low and high frequency components of the HESS power, $P_{HESS}(k)$, and $\phi = T_s/(\tau + T_s)$. $\tau$ denotes the time constant of the low-pass filter. The battery features high energy density, while the SC is characterized by high power density. Thus, $P_{HESS}^L(k)$ and $P_{HESS}^H(k)$ will be allotted to the battery and the SC, respectively. With determining $\tau$ being regarded as the action-selection policy, the proposed method will maximize the reward (minimize the objective function) by appropriately allocating power to the battery and SC. The details of selecting $\tau$ are provided in Section IV.

The joint sizing and control of HESS can be formulated as a multi-objective optimization problem with penalty factors associated to operational constraints. In general, the design problem can be expressed as [30]

$$\min_x \sum_{k=k_0}^{k_f} G(x)$$

$$G(x) = \sum_{m=1}^{M} w_m \psi_m(x) + \sum_{n=1}^{N} \phi_n$$

$$\phi_n = \max\{0, \varphi_n(x)\}$$

(20)
where \( \mathbf{x} \) is the state variables vector, \( G(\mathbf{x}) \) is the objective function formed by a weighted sum of individual objectives, \( \psi(\mathbf{x}) \), and a sum of penalty factors, \( \phi \), associated with operational constraints, \( \varphi(\mathbf{x}) \). \( w_m \) is the \( m \) positive weighting factor that indicates the importance of \( \psi_m(\mathbf{x}) \) with respect to the other objectives. \( k_0 \) and \( k_f \), respectively, correspond to the initial and final time steps within the designated time period, \( T_{opr} \). In this work, the following objective function is employed

\[
\min_{\mathbf{x}} \sum_{k=k_0}^{k_f-1} G(\mathbf{x})
\]

\[
G(\mathbf{x}) = w_1 \left( \Delta I_{bat}^{eq}(k) \right)^2 + w_2 \left( \Delta SOC_{bat}(k) \right)^2 + w_3 \left( \Delta SOC_{sc}(k) \right)^2 + w_4 \sum_{j=1}^{2} \left( C_{Cj} x_j \right)^2 + w_5 \sum_{j=1}^{2} \left( P_{lossj}(k) \right)^2 + \sum_{n=1}^{4} \phi_n
\]

\[
\phi_n = \max\{0, \varphi_n(\mathbf{x})\}, n \in \{1,2,3,4\}
\]

Here \( \mathbf{x} = (x_1, x_2) \). \( x_1 \) and \( x_2 \) correspond to \( n_{bat} \) and \( n_{sc} \), respectively. \( \Delta I_{bat}^{eq}(k) \) is the battery pack current variation, which is included to ensure that the battery current fluctuations (due to power fluctuations) are restricted, and the battery lifetime is preserved \[19\]. \( \Delta SOC_{bat}(k) \) and \( \Delta SOC_{sc}(k) \) objectives, given in (22) and (23), ensure charge sustainability, i.e. the battery and SC SOC are the same at \( k_0 \) and \( k_f \)

\[
\Delta SOC_{bat}(k) = |SOC_{bat}(k) - SOC_{bat}(k_0)|
\]

\[
\Delta SOC_{sc}(k) = |SOC_{sc}(k) - SOC_{sc}(k_0)|
\]

\( \sum_j C_{Cj} n_j \) is considered to ensure the economic viability of the battery and SC sizes. Here, \( C_{Cj} \) is the capital cost of the battery and SC cells. \( \sum_j P_{lossj} \), defined in (24), ensures that the internal losses of the HESS components are reduced and the efficiency is not adversely impacted

\[
\sum_j P_{lossj} = \left( i_{bat}^{eq}(k) \right)^2 R_{bat}^{eq} + \left( i_{sc}^{eq}(k) \right)^2 R_{sc}^{eq}
\]

49
Here $i_{sc}^{eq}$ is the SC pack current.

As it will be explained in the next section, the DRL-based sizing/energy management method will minimize the cost function in (21) by following proper power allocation policies. The constraints to be satisfied are those imposed by the HESS model, given in (8)–(18), and those related to state of charge and current ratings of the battery and SC, given in the following equations:

\[
SOC_{sc} \leq SOC_{sc}(k) \leq \overline{SOC}_{sc} \tag{25}
\]

\[
l_{sc} \leq l_{sc}(k) \leq \overline{l}_{sc} \tag{26}
\]

\[
SOC_{bat} \leq SOC_{bat}(k) \leq \overline{SOC}_{bat} \tag{27}
\]

\[
l_{bat} \leq l_{bat}(k) \leq \overline{l}_{bat} \tag{28}
\]

In order to restrict the search space in the sizing stage, the number of battery and SC cells need to be bounded, as well

\[
n_{sc} \leq n_{sc} \leq \overline{n}_{sc} \tag{29}
\]

\[
n_{bat} \leq n_{bat} \leq \overline{n}_{bat} \tag{30}
\]

### 3.4. Application of DRL to joint sizing/energy management problem

In RL, an agent interacts with the environment and receives a numerical indicator, $r$, known as reward. The major goal is to select actions that produce maximum cumulative reward, $\mathcal{R}$. Agent environment interactions in RL are modelled as finite Markov decision processes (MDP), which can be described by a tuple $(S, A, P, R, \gamma)$, where $S$ is a set of states, $A$ is a set of
actions, $P$ is the probability of moving from the current state, $s$, to a new state, $s'$, after action $a$ has been taken, $R$ is a reward function that generates the expected reward following a state transition, and $\gamma \in [0,1]$ is the discount rate that weights the importance the agent designates to the immediate reward received following an action.

State-value functions are commonly used to appraise the agent’s performance in terms of $\Re$. Among the available RL algorithms for estimating the value function and consequently, obtaining the required action-selection policy, temporal-difference learning (TD) algorithm features optimality and low computational burden. Therefore, it is a suitable choice for real-time application. A model-free TD algorithm, known as $Q$-learning, has been employed in wave energy conversion systems [30] and for power system restoration [45]. However, both studies use the tabular version of the $Q$-learning algorithm. For large state-action sets, application of the tabular $Q$-learning algorithm is not practical since all actions need to be repeatedly sampled in all states in order to ensure adequate exploration, and consequently obtaining the optimal $Q$-value function [46]. Furthermore, applications demanding more precise control call for finer discretization of the action set. Thus, the number of discrete actions increases [47]. In addition, storing the $Q$-values can impose issues associated with memory limitations.

In this work, a DRL algorithm known as deep deterministic policy gradient (DDPG) is employed. DDPG does not require discretization of both state and action sets and is a model-free, online, off-policy algorithm that uses deep function approximators to learn action selection policies in large continuous action sets [47]. A scheme of DDPG algorithm is shown in Figure 3.3.
An actor–critic architecture with deep neural networks (DNNs) is adopted. The actor network is employed to estimate the action selection policy, $\mu(s|\theta^\mu)$, parameterized by $\theta^\mu$, and the critic network estimates the value function, $Q(s,a|\theta^Q)$, parameterized by $Q$. An actor–critic architecture with deep neural networks (DNNs) is adopted. The actor network is employed to estimate the action selection policy, $\mu(s|\theta^\mu)$, parameterized by $\theta^\mu$, and the critic network estimates the value function, $Q(s,a|\theta^Q)$, parameterized by $Q$. In order to increase the learning efficiency and avoid divergence of parameters, an experience replay buffer is employed during the learning phase [48]. From the environment, transitions are sampled based on the exploration policy, $\mu' = \mu(s|\theta^\mu) + \mathcal{N}$, where $\mathcal{N}$ is a noise process, and the tuple $(s_i, a_i, r_i, s_{i+1})$ is stored in the replay buffer, $\mathcal{R}$. At each time step, a minibatch of $M$ tuples is uniformly sampled from $\mathcal{R}$ and the actor and critic are updated. Parameters of the critic and actor networks are updated by minimizing the loss function $L$ in (30), and using the sampled policy gradient given in (31),
respectively. The target network parameters for the actor are updated with (32), while the target critic parameters are updated employing (33) [47]

\[
L = \frac{1}{M} \sum_i \left( \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^\mu)|\theta^Q) - Q(s_i, a_i|\theta^Q) \right)^2
\]

(31)

\[
\nabla_{\theta^J} J \approx \frac{1}{M} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}
\]

(32)

\[
\theta^\mu = \varphi \theta^\mu + (1 - \varphi) \theta^\mu
\]

(33)

\[
\theta^Q = \varphi \theta^Q + (1 - \varphi) \theta^Q
\]

(34)

In (33) and (34), \( \varphi \ll 1 \) is the target smooth factor.

The joint sizing/EMS of the HESS can be considered as a finite MDP, with a set of state variables, \( s_k \in S = \{ (SOC_{bat}(k), SOC_{sc}(k)) : (SOC_{bat} \leq SOC_{bat}(k) \leq \overline{SOC_{bat}}), (SOC_{sc} \leq SOC_{sc}(k) \leq \overline{SOC_{sc}}) \} \), a continuous set of actions, \( a_k \in A = \{ \tau_t : \mathbb{R}^+ \} \), and a reward function associated with minimizing \( G \) (maximizing the cumulative reward \( R \)). In order to employ deep reinforcement learning to solve the joint sizing and control problem of HESS, (21) is reformulated as a reward function and is given in (35).

At the beginning of each episode, all the states \( s_1 = (SOC_{bat}(k_0), SOC_{sc}(k_0)) \) are initialized. At each time step \( k \) during the episode, the agent selects an action \( a_k = \tau \) based on \( \mu' \), and the power is allotted to the battery and SC using \( P^{lf}_{HESS}(k) \) and \( P^{hf}_{HESS}(k) \), respectively. Solving (8)–(18) transitions the agent to a new state, \( s_{k+1} = (SOC_{bat}(k+1), SOC_{sc}(k+1)) \), and an immediate reward \( R_k \) (obtained from (35)) is received. The experience described by the tuple \( (s_k, a_k, R_k, s_{k+1}) \) is stored in \( \mathcal{R} \), and a minibatch of \( M \) tuples is sampled from \( \mathcal{R} \) in order to update the parameters of the actor and critic networks through (31)–(34). This process is repeated for...
each episode until the maximum number of episodes, \( N_e \), is reached and the learning stage is completed. Later, the cumulative reward \( \mathcal{R} \) and the learned policy, \( \mu \), are extracted and stored. This process is carried out for each tuple \((n_{bat}, n_{sc})\) to complete the sizing stage. Then, the tuple corresponding to the highest \( \mathcal{R} \) is selected as the optimal solution and is followed by the agent in the energy management phase.

\[
\begin{align*}
    r_1 &= \begin{cases} 
        10 & \text{if } |SOC_j(k) - SOC_j(k_0)| \leq \epsilon \\
        -1 & \text{otherwise}
    \end{cases} \\
    r_2 &= \begin{cases} 
        -100 & \text{if any } j \left\{ \begin{array}{l}
            \text{SOC}_j < \bar{SOC}_j \\
            \text{SOC}_j(k) > \bar{SOC}_j \\
            -l_{eq}^j < l_{eq}^j(k) \\
            l_{eq}^j(k) > l_{eq}^j \\
            SOH(k) < SOH
        \end{array} \right. \\
        0 & \text{otherwise}
    \end{cases}
\end{align*}
\tag{35}
\]

\[
r_3 = -\left( w_1 \Delta l_{bat}^{eq}(k) \right)^2 + w_2 \sum_j \left( C_{c_j} n_j \right)^2 + w_3 \sum_j \left( P_{loss_j}(k) \right)^2 \\
R = r_1 + r_2 + r_3
\]

where \( j \in \{bat, sc\} \) and \( \epsilon \) is a small positive value.

**Remark:** The model of the noise process \( \mathcal{N} \) is taken from [49], with a variance of 0.3 and a variance decaying rate of \( 1 \times 10^{-5} \). Weighting factors in (35) emphasize the importance of a certain objective with respect to the others. Thus, their selection is made based on the desired goal. The weighting factors are obtained through empirical procedures since analytical methods do not exist [50].

In order to examine effect of the weighting factors on \( \max(\Delta l_{bat}^{eq}), \sum_j P_{loss_j}, \) and cumulative reward, simulations were carried out with three different combinations of weighting factors. The combinations, from 1 to 3, respectively, are \((0.1, 0.7, 0.2), (0.7, 0.1, 0.2), (0.1, 0.2, 0.7)\).
The analyses are carried out for two different tuples of \((n_{\text{bat}}, n_{\text{sc}})\): tuple_1 = (1800, 800) and tuple_2 = (800, 1800).

As seen in Figure 3.4, combination 1 which prioritize the cost of battery and SC cells, results in the highest \(\Delta t_{\text{bat}}^{eq}, \Sigma_j P_{\text{lossj}},\) and the lowest cumulative reward. Combinations 2 and 3 produce better results, with combination 2 leading to the lowest variation of the battery pack current as well as HESS losses, and the highest cumulative reward. Thus, combination 2 is used as the base. In this work, a slight adjustment is applied to combination 2 in order to increase the weight of the battery and SC cells cost. Therefore, the combination \((0.6, 0.2, 0.2)\) is employed.

![Simulation results showing the impact of weighting factors on (a) Maximum variation of the battery pack current, (b) Total battery and SC losses, (c) Cumulative reward](image)

Figure 3.4. Simulation results showing the impact of weighting factors on (a) Maximum variation of the battery pack current, (b) Total battery and SC losses, (c) Cumulative reward

3.5. Energy flow control

As seen in Figure 3.5, PECs are used to interface the generator, HESS, and the propulsion motor with the MVDC bus. Brief discussions on the generator and propulsion motor PECs control are provided. The novel DRL-based control of the PECs interfacing the HESS with the MVDC bus, through which power fluctuations are mitigated, is elaborated in detail.

3.5.1. Prime mover-generator control

The prime mover-generator controller's goal is to adjust the generator's power, \(P_{\text{gen}}\), based on the speed and power set points. Here, it is assumed that the set points are adjusted such that
throughout a designated time period, the generator delivers average of the power fluctuations caused by the propulsion system. This average is basically equivalent to the propulsion system power consumption in calm sea states.

3.5.2. Generator-side converter control

The dc-link voltage, \( v_{dc} \), and the power delivered by the generator to the shipboard power system are controlled by the generator-side converter, which interfaces the synchronous generator with the MVDC bus. The reference dc-link voltage value, \( v_{dc}^* = 3 \) kV, is determined based on the generator voltage, converter design, load considerations, cable ratings, efficiency and arc fault energy [2]. The generator-side converter is controlled through the classical direct power control scheme. The active power injected to the shipboard power system, \( P_g \), is adjusted to keep the dc-link voltage constant, while the injected reactive power, \( Q_g \), is kept at zero for unity power factor.

3.5.3. Propulsion motor-side converter control

Speed of the SCIM coupled to the propeller is controlled through classical field-oriented control (FOC). The \( q \)-axis reference current, \( i_{qs}^* \), is obtained from the speed PI controller, while the \( d \)-axis reference current, speed of the SCIM coupled to the propeller is controlled \( i_{ds}^* \), is determined from the flux model of the machine in the rotor-flux oriented reference.

3.5.4. HESS control

The HESS delivers/absorbs power to/from the dc link to balance the generated power, \( P_{gen} \), propulsion load, \( Pa \), and the dc-link power, \( P_{dc} \)

\[
P_{HESS} = P_{gen} - P_{dc} - P_{a}
\]  

(36)
Here, the propulsion load demand, $P_a$, is obtained from (3).

The HESS power obtained from (35) is passed through a lowpass filter. The DRL controller in Figure 3.4. employs the actions-election policy derived earlier in the sizing stage to determine the low-pass filter's time constant ($\tau$) at each time step and split $P_{\text{HESS}}$ between the battery and SC. Current-controlled bi-directional boost/buck dc/dc converters are used to interface the HESS components with the MVDC bus. Once the SC, $P_ {sc}^*$, and battery, $P_{bat}^*$, reference powers are determined, the PECs interfacing them with the MVDC bus regulate their current accordingly: the SC, $i_{sc}^*$, and battery, $i_{bat}^*$, reference currents, which are calculated by dividing the corresponding reference power with the dc-link voltage, are compared with the measured currents. The current errors are passed through PI controllers and pulse width modulators are used to generate the gating signals for the dc/dc converters switches.

3.6. Real-time simulation results and discussion

3.6.1. Sizing results

The DDPG-based algorithm discussed in Section 4 is used to size the battery/SC HESS. The propulsion system power profiles employed in the sizing stage, which are randomly selected at the beginning of each episode, are obtained by assuming that the ship navigates in rough seas with constant propeller rotational speed. Table 3.5. summarizes the parameters used in the simulations in the sizing stage. The lower bounds for the number of the battery, $n_{bat}$, and SC, $n_{sc}$, cells are set based on the rated voltage of the battery and SC packs considered for the HESS operation, i.e. 800 V, as well as the individual battery and SC cell rated voltages.

As the first case study, the battery and SC storage are used individually for mitigating the power fluctuations. The obtained results from the DDPG-based sizing algorithm are shown in
Figures 3.6(a) and (b). Both the figures illustrate similar patterns with three distinctive regions. The leftmost region shows a positive slope with reward values increasing as the number of cells grow. Due to low number of cells, \( \Delta SOC_{bat} \) and \( \Delta SOC_{SC} \) are large and predominant in the cost.

Figure 3.5. Energy flow control block diagram

function. As a result, low reward values are gained. As the number of cells grow, a balance between the charge sustainability, internal losses and cell cost is achieved, and the maximum reward is obtained in the middle region. In the rightmost region, although the high number of cells result in good charge sustainability, almost all the weight in the objective function is shifted towards the cell cost and internal losses; thus, the obtained reward is low. The number of battery and SC cells that generate the highest reward are \( n_{bat} = 3048 \) and \( n_{sc} = 3097 \), respectively.

The sizing results for the battery/SC HESS are shown in Figures 3.6(c) and (d). Note that the shape of the surface is similar to those obtained for the SC-only and battery-only cases. In the leftmost region, where the SC absorbs/delivers high frequency power fluctuations, the bounds on
the SC SOC are not respected due to low number of cells. Therefore, the battery delivers/absorbs the power deficit/surplus that the SC is not able to counteract. This will adversely affect the battery's SOH if $n_{bat}$ is small. In addition, some of these power fluctuations may not be even counteracted by the battery due to its low power density.

Table 3.5. Parameters for the Sizing Stage

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave type</td>
<td>Irregular</td>
</tr>
<tr>
<td>Wave spectrum</td>
<td>Modified Pierson-Moskowitz-Sea state 6</td>
</tr>
<tr>
<td>Sailing condition</td>
<td>Head seas</td>
</tr>
<tr>
<td>Significant wave height</td>
<td>6 [m]</td>
</tr>
<tr>
<td>Average wave period</td>
<td>9.5 [s]</td>
</tr>
<tr>
<td>Propeller speed $n$</td>
<td>300 [rpm]</td>
</tr>
<tr>
<td>Simulation time</td>
<td>1 [h]</td>
</tr>
<tr>
<td>Sampling period $T_s$</td>
<td>1 [s]</td>
</tr>
<tr>
<td>$n_{sc}$</td>
<td>${297:10:5000}$</td>
</tr>
<tr>
<td>$n_{bat}$</td>
<td>${348:10:5000}$</td>
</tr>
<tr>
<td>Critic learning rate</td>
<td>1e-3</td>
</tr>
<tr>
<td>Actor learning rate</td>
<td>1e-4</td>
</tr>
<tr>
<td>Target smooth factor</td>
<td>1e-3</td>
</tr>
<tr>
<td>Discount factor</td>
<td>0.98</td>
</tr>
<tr>
<td>Max number of episodes</td>
<td>500</td>
</tr>
<tr>
<td>$w_1$</td>
<td>0.6</td>
</tr>
<tr>
<td>$w_2, w_3$</td>
<td>0.2</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>0.05</td>
</tr>
</tbody>
</table>

With growing number of cells, the bounds on the battery and SC SOC are not violated any longer and the charge sustainability is achieved for both. Presenting a trade-off between HESS charge sustainability, internal losses and the capital cost, the middle region is where the highest rewards are gained. Further increase in the number of battery and SC cells lead to increased capital cost and internal losses. Although charge sustainability is achieved, high cost and losses result in a low cumulative reward. To better visualize the tuple that produces the highest reward, Figure 3.6(c) is rotated and shown in Figure 3.6(d). It is clear that the number of
battery and SC cells that produce the highest reward are $n_{bat} = 1824$ and $n_{sc} = 1835$, respectively. Comparing these numbers with those obtained for the SC-only and battery only cases, confirms the effectiveness of the proposed joint sizing/ energy management strategy in enhancing the size of the HESS.

![Graphs and diagrams](image)

**Figure 3.6.** Sizing results (a) Battery only, (b) SC only, (c) Hybrid battery/SC, (d) Hybrid battery/SC (rotated)
3.6.2. Real-time implementation results

The efficacy of the EMS in mitigating the power fluctuations is validated through real-time simulations. The shipboard power system, including the propulsion system and the HESS, and the interfacing PECs are modelled on an OP4510 real-time simulator from Opal-RT Technologies Inc. Simulations are executed for 200 s with a sampling frequency of 20 kHz.

In the learning phase, the DRL-based EMS is trained with the action-selection policies that generate the highest reward. The adaptability of the EMS is validated in the real-time simulations by employing a different propulsion power profile than that used in the learning phase. This power profile is generated at sea state 6 with a significant wave height (SWH) of 4 m, and average period of 7.8 s. Head seas sailing condition is assumed.

At \( t = 0 \), \( P_{\text{gen}} \) is set to 242 kW, and the propulsion motor is accelerated from 0 to 1326 rpm in 2 s. The motor reference speed along with \( P_{\text{gen}} \) are then decreased by steps of \(-371 \text{ rpm}\) and \(-189.7 \text{ kW}\) at \( t = 40 \text{ s} \), respectively, and increased by steps of \(+371 \text{ rpm}\) and \(+277.8 \text{ kW}\) at \( t = 100 \text{ s} \), respectively. Subsequent \( P_{\text{gen}} \) steps of \(-82.5 \text{ and } -55 \text{ kW}\) occur at \( t = 140 \) and \( t = 190 \text{ s} \), respectively. \( P_{\text{gen}} \), dc-link power, and propeller power profiles are shown in Figure 3.7(a). Steep fluctuations are present in the propeller power profile, particularly when the propeller emergence occurs, and the propeller thrust/torque undergoes sharp transients. The power absorbed/delivered by the HESS is shown in Figure 3.7(b). As it can be seen from the HESS power split between the SC and battery, the SC counteracts the high-frequency power fluctuations, while the battery delivers/absorbs the low-frequency power component. Figure 3.7(c) depicts the state of charge of the SC and battery along with the battery's state of health. For both the SC and battery, the
Figure 3.7. Real-time simulation results (a) Generator power, dc-link power, and propeller power profile, (b) HESS, SC and battery power, (c) battery SOH, battery SOC, and SC SOC, (d) SC and battery efficiencies

Figure 3.8. Real-time simulation results (a) SCIM stator currents and dc-link voltage, (b) SCIM stator currents and dc-link voltage zoomed-in, (c) Actual and reference SCIM speed
charge is sustained during the designated time period. Furthermore, from Figure 3.7(c) it can be confirmed that the lower bounds imposed on the SC and battery SOC, i.e. 30 and 20%, are not violated as the lowest SOC values measured for the SC and battery are 53 and 74%, respectively.

The propulsion motor three-phase stator currents are shown in Figures 3.8(a) and (b). The variations in the current amplitude reflect the propeller torque fluctuations. Despite these large fluctuations, the motor speed controller is capable of tracking the reference, as shown in Figure 3.8(c). Figure 3.8(b) depicts the dc-link voltage, which follows the reference value. This confirms the effectiveness of the energy flow control in mitigating the power fluctuations on the MVDC bus, even in the presence of sharp propulsion thrust/torque transients.
4.1. Introduction

As penetration of renewable energy in power grid grows, power grid operators (PGO) are developing regulations requiring renewable energy generators (REG) to provide essential reliability services (ERS) for grid flexibility and stability. ERSs can be divided into operating reserves (OR), which are critical for maintaining the frequency of the grid within operational bounds, voltage support, power factor regulation, black start, etc. [1]. For instance, ESRs for wind power integration in Europe, China and United States are discussed in [2], [3].

The capacity of REG to provide a specific OR is influenced by three factors: (i) the margin between the REG’s actual and maximum output power; (ii) the time period required to bring REG’s output power up/down to a desired setpoint, and (iii) the time period through which REG is required to maintain its output at a specific setpoint [1]. The first factor is associated to generator derating, which is the reduction in the amount of generated power with respect to available maximum power at a given operating condition [4]. The second factor concerns with the speed of response of REG to power commands. The third factor involves the period through which a specific OR service is expected form REGs. Due to inherent variability and uncertainty of renewable energy, determining this period constitutes a critical challenge [7]. Figure 4.1 shows a general classification of OR services, including subclasses and their respective temporal scales. For the purpose of this work, the subclass regulating reserves (RR) will be discussed in more details.
The RR service deals with active power imbalances that exist between the scheduled generation and load under normal grid operation [8]. Economic dispatch problem, through which a day ahead power system dispatch is planned, is solved by relying on the RR service and balance of the active power mismatches caused by either varying load/generation or forecasting errors [1], [7]. Since REGs employ power electronic converters (PEC), their output power can be adjusted faster than traditional synchronous generators [5], [6]. Therefore, REGs can be considered as promising candidates for providing the RR service. However, utilizing REGs for this purpose poses serious challenges due to intermittency and uncertainty of renewable energy. If large errors between the very short-term forecasted power and actual output power of REGs exist, more RR would be needed to reduce the load-generation mismatch. Therefore, strategies enabling reliable participation of REGs as RR service providers must be devised.

The accuracy of short-term REG power forecasting is a critical factor in power systems operation as it can adversely impact the reliability and stability of the system, its operating costs, reserves requirement, and load management [9], [10]. In the literature, forecasting techniques employing physical, statistical, machine learning, fuzzy logic and hybrid methods have been extensively studied [11]-[16]. Despite good performance, some degree of prediction uncertainty is nevertheless present. Energy storage systems (ESS), if utilized, can resolve this problem by mitigating unpredicted power fluctuations [17].

In scenarios where utilizing an ESS is not a viable option, devising approaches with the ability to (i) predict future system behavior, (ii) accommodate constraints and nonlinearities, (iii) anticipate violation of bounds, and (iv) provide fast dynamic and good steady state performance becomes essential. Model predictive control (MPC), which offers these features, is proposed in applications where REG provides OR services [18], [19]. In [20], a controller that combines
centralized-local Kalman filters with MPC is proposed to generate power reference signals for participation of individual wind turbine units in frequency regulation. In [21], a three-layer nonlinear MPC scheme is presented, where the upper-layer sends overall wind farm power command for frequency support to the middle-layer, power references are then distributed among the wind units and are sent to the bottom-layer for local control execution. A control scheme for emergency frequency support among ac asynchronous areas connected through multi-terminal dc grid is studied in [22]. The model predictive controller produces power setpoints and provides a balance between dc voltage and ac frequency deviations. In majority of the existing papers, including the above referenced ones, REGs employing MPC participate in fast and/or primary frequency response service. However, MPC’s potential for enabling REGs participation in RR service is not exploited. This is because longer prediction horizons (required for RR service) in the grid-side PECs control scheme add to the computational complexity of MPC, making it almost infeasible to implement in real time.

Most recent strategies on reducing computational complexity of MPC for grid-connected PECs are discussed in [23]-[30]. Majority of those studies are focused on either multi-vector MPC [23], [24], [27], where multiple voltage vectors are applied in one control period to improve current and power quality, or multi-level converters [25], [28], [30] where the number of candidate voltage vectors is high due to multiple switching devices in the converter topology. Only few papers aim at extending the prediction horizon of single-vector model predictive algorithms for commonly used two-level PECs. In [26], computational load is alleviated by offline optimization. Drawback of such generalized predictive control algorithm is that all the operational, dynamic constraints may not be satisfied when the cost function is optimized offline. A receding horizon MPC strategy for a grid-connected voltage-source inverter with an LCL filter
is proposed in [29]. Computational burden is reduced by employing a reduced model of the converter. However, the capacitor effect of LCL tank is neglected and only a single equivalent inductor is considered.

In this chapter, a novel hybrid data-model predictive direct power control (HD-MPDPC) for grid-side PECs is presented. The main feature of the proposed method is long prediction horizon, which is achieved through a two-stage process. In the first stage, forecast of REG’s output power (based on historical data) along with some measurements are used to generate a set of candidate voltage vectors, where in the second stage they are fed to a model predictive direct power controller to select the voltage vector that minimizes the power tracking error. Each stage has distinctive objectives. The main goal of the first stage is to exploit forecasted REG power and reduce the number of candidate voltage vectors to be examined by the model predictive direct power controller in the second stage. The purpose of the second stage is realization of multiple-step model predictive direct power control (MPDPC) for enabling more reliable dispatch of REG power, a necessity for regulating reserves in power systems.

![Figure 4.1. General classification of operating reserve services [1]](image)

Since HD-MPDPC is proposed for the grid-side dc-ac PEC in grid-connected REGs, it can be employed in PV systems with two-stage dc-dc-ac power conversion, and wind and wave energy conversion systems with back-to-back ac-dc-ac power conversion. Here, the real-time implementation feasibility of HD-MPDPC is verified by real-time simulations of a grid-connected wave energy conversion system (WECS). Comparatives studies are carried out to show effectiveness of the proposed HD-MPDPC in enabling participation of WECS in RR service. In the first case study, the grid-connected WECS is controlled such that the generator-side PEC extracts maximum wave power and the model predictive direct power-controlled grid-side PEC injects the harvested power to the grid. In the second case study, a modified generator-side controller along with the proposed grid-side hybrid predictive controller successfully curtail the WECS output power to the grid reference power set by PGO. Computational time of both conventional MPDPC and proposed HD-MPDPC are extracted. It is shown that for long prediction horizons, complexity of conventional MPDPC raises exponentially, whereas HD-MPDPC maintains its digital implementation feasibility.

The chapter is organized as follows: Section 4.2. overviews the WECS model, conventional MPDPC and REG power forecast method. Section 4.3. describes the proposed long-horizon HD-MPDPC. Real-time simulation results and discussions are presented in section 4.4.

4.2. Overview of WECS model, MPDPC and REG power forecast

4.2.1. WECS model

Direct-drive WECSs, which comprise a buoy and a linear generator, are considered in this chapter. A simplified motion equation of the WECS, given in (1), along with the model of
the linear permanent magnet generator (LPMG) in $d$-$q$ coordinates, given in (2) and (3) are used to estimate the WECS output power, $P_{WEC}$ [31].

\[
 F_{wave} = m_{tot} \ddot{x} + (\gamma_d + \beta_b) \dot{x} + K_g x
\]  

(1)

\[
 L_{ss} \frac{\omega}{|\omega|} p_{i_ds} = -R_{ss} i_{ds} + X_{ss} i_{qs} - v_{ds}
\]  

(2)

\[
 L_{ss} \frac{\omega}{|\omega|} p_{i_{qs}} = -R_{ss} i_{qs} - X_{ss} i_{ds} - v_{qs} + \omega \psi_{PM}
\]  

(3)

\[
 P_{WEC} = \frac{3}{2} \omega \psi_{PM} i_{qs}
\]  

(4)

Here, $F_{wave}$ is the wave-induced force acting on the buoy, $m_{tot}$ is the total mass of the buoy and translator of the LPMG, $\gamma_d$ is the LPMG damping coefficient, $\beta_d$ is the buoy damping coefficient, $K_g$ is spring coefficient of the power take-off, $x$ is the buoy position, and $\dot{x}$ is the buoy speed. $P_{WEC}$ is the active power of the LPMG, $L_{ss}$ and $R_{ss}$ are the stator inductance and resistance of the LPMG, respectively, $\psi_{PM}$ is the flux linkage of the permanent magnet, $i_{ds}$ and $i_{qs}$ are the LPMG stator current components in the $d$- and $q$-axis, respectively, $v_{ds}$ and $v_{qs}$ are the LPMG stator voltage components in the $d$- and $q$-axis, respectively, $X_{ss} = |\omega| L_{ss}$, $\omega = 2\pi \dot{x}/\lambda$, where $\lambda$ corresponds to the pole width of the LPMG, and $p = d/dt$. Parameters of the WECS considered in this chapter are provided in Table 4.2.

4.2.2. MPDPC

MPC requires a model of the system to estimate future behavior of its states over a specific time horizon. In space vector notation, the output current dynamics of the grid-side PEC with an L-filter is expressed as [32]

\[
 L_s p i_{sgr} = v_{conv} - v_{sgr} - R_s i_{sgr}
\]  

(5)
where, $\mathbf{v}_{sgr}$ and $\mathbf{i}_{sgr}$ are the grid voltage and converter output current space vectors respectively, $R_s$ and $L_s$ are the filter resistance and inductance, respectively, $p$ is the derivative operator, and $\mathbf{v}_{conv}$ is the voltage generated by the converter, which is a function of the converter’s switching states and the dc-link voltage.

Using the first-order forward Euler approximation to discretize (5) with sampling time $T_s$, the predicted converter current at time step $k + 1$ can be given by

$$
\mathbf{i}_{sgr}(k + 1) = \left(1 - R_s \frac{T_s}{L_s}\right) \mathbf{i}_{sgr}(k) + \frac{T_s}{L_s} [\mathbf{v}_{conv}(k) - \mathbf{v}_{sgr}(k)]
$$

(6)

The converter active and reactive powers are then predicted as

$$
P_{gr}(k + 1) = \frac{3}{2} \Re\{\mathbf{v}_{sgr}(k + 1) \mathbf{i}^{\text{conj}}_{sgr}(k + 1)\}
$$

(7)

$$
Q_{gr}(k + 1) = \frac{3}{2} \Im\{\mathbf{v}_{sgr}(k + 1) \mathbf{i}^{\text{conj}}_{sgr}(k + 1)\}
$$

(8)

where $\mathbf{i}^{\text{conj}}_{sgr}$ is the conjugate of $\mathbf{i}_{sgr}$. The future grid voltage, $\mathbf{v}_{sgr}(k + 1)$, can be estimated as

$$
\mathbf{v}_{sgr}(k + 1) = \mathbf{v}_{sgr}(k)e^{j\omega_{gr}T_s}
$$

(9)

where $\omega_{gr}$ is the angular frequency of $\mathbf{v}_{sgr}$.

The objective of MPDPC is to select the converter voltage vector that minimizes the error between the reference and predicted active and reactive powers, formulated as the following cost function

$$
J = [P^*_{gr}(k + 1) - P_{gr}(k + 1)]^2 + [Q^*_{gr}(k + 1) - Q_{gr}(k + 1)]^2
$$

(10)

It is worth noting that a two-level grid-side PEC can produce eight voltage vectors; six active and two zero. Therefore, in conventional MPDPC, eight possible voltage vectors are examined in
each sampling period and the voltage vector that minimizes (10) is selected and applied in the next period.

### 4.2.3. Forecasting REG power

Proper selection of the forecasting technique is directly associated to type of REG, as each resource, i.e., solar irradiance, wind and ocean waves, has its own characteristics. Several prediction techniques using past time-series data for short-term wave parameters forecasting, including cyclical models, extended Kalman filters, and regression models have been studied in the literature [33]. Recently, prediction methods employing Neural Networks (NN) have gained attention due to their ability to model nonlinearities and robustness to noise [34]. Recurrent neural networks (RNN) are a class of NNs with internal feedback connection and capable of capturing the dynamic temporal behavior of time-series data [35]. A type of RNN called nonlinear autoregressive with exogenous inputs (NARX) has been applied for short-term prediction of wave surface elevation and WECS output power in [34] and [36], respectively. The results verify NARX suitability for these purposes and thus, it is considered for forecasting WECS power in this chapter. In NARX networks, the predicted output \( \hat{y} \in \mathbb{R}^{N_y} \) is obtained from the NARX model equation given by

\[
\hat{y}(k) = f(\hat{y}(k-1), \hat{y}(k-2), ..., \hat{y}(k-n_y), x_{et}(k-1), x_{et}(k-2), ..., x_{et}(k-n_x), \theta)
\]

(11)

where \( f, x_{et} \in \mathbb{R}^{N_x}, n_x, n_y, \) and \( \Theta = \{ \theta_{in}, \theta_o, ..., \theta_{h_{N_l}} \} \) are the mapping function, exogenous input, input time delay, output time delay, and trainable parameters of the network, respectively. 

\[
\theta_{in} = \{ W_{in}^{h_1} \in \mathbb{R}^{N_x \times (N_y N_x + N_y N_h_1)} , b_{h_1} \in \mathbb{R}^{N_h_1} \} \quad \theta_o = \{ W_{h_{N_l}}^{o} \in \mathbb{R}^{N_N_l \times N_y} , b_o \in \mathbb{R}^{N_y} \} , \quad \theta_{h_{l-1}} =
\]
\[ \{W_{h_{l-1}}^{h_l} \in \mathbb{R}^{N_{h_{l-1}} \times N_{h_l}}, b_{h_l} \in \mathbb{R}^{N_{h_l}} \} \] are sets of weight factors corresponding to the input layer, output layer, and the \( l^{th} \) hidden layer, respectively.

The architecture of a NARX network is depicted in Figure 4.2. In the training stage (position 1 of the switch), the network has a feedforward architecture, and both exogenous input \( x_ei \) and true output \( y^* \) are used to train the network parameters through static backpropagation. Once the training stage is completed (position 2 of the switch), true output \( y^* \) is removed and the predicted output \( \hat{y} \) is fed back to the input of the network.

![Figure 4.2. NARX network architecture [35]](image)

4.3. Hybrid data-model predictive direct power control

A scheme of HD-MPDPC is shown in Figure 4.3. As described earlier, in the first stage, REG output power prediction combined with a novel methodology facilitate reducing the number of candidate voltage vectors. In the second stage, based on the desired power set by PGO, a multi-step model predictive direct power controller selects appropriate voltage vectors (from candidate voltage vectors) to be applied by the grid-side PEC. The following subsections provide details of the proposed hybrid control scheme.
4.3.1. WECS output power prediction

The proposed prediction model is shown in Figure 4.4, where \( P_{\text{mech}} = F_{LPMG} \dot{x} \), and \( F_{LPMG} = y_g \dot{x} + K_g x \) is the force acting on the LPMG. At each time step, actual values of wave height \( \zeta_{WAVE} \) are fed into the position and speed prediction blocks along with their respective feedback vector signals of predicted values, i.e. \( \dot{\hat{x}} \) and \( \ddot{\hat{x}} \). Elements of these two vectors are later combined to generate the vector of predicted mechanical power, \( \hat{P}_{\text{mech}} \). Finally, this vector is fed into the prediction block as the exogenous input along with the \( \hat{P}_{WEC} \) feedback signal to yield new estimates of generated wave power. Each neural network consists of 3 hidden layers with 5 neurons per layer. The activation function between layers is the Sigmoid function.

Figure 4.3. Block diagram of the proposed HD-MPDPC
A data set, containing buoy position and speed, and WECS output power profiles is generated. Parameters of the considered WECS are listed in Table 4.2. The WECS output power profiles are produced using the model given by (1)-(4) for a period of 6000 s with a sampling frequency of 100 Hz. Wave time-series are obtained using the modified Pierson-Moskovitz wave spectrum with a SWH of 4 m, and dominant wave period (DPD) of 10.1 s. For training, 70% of the data points are employed, and the remaining 30% are employed for validation and testing. The forecasting accuracy is assessed using the mean squared error (MSE), normalized mean squared error (NMSE) and correlation coefficient (CC) indexes expressed as

\[
MSE = \frac{1}{N_y} \| \hat{y} - y^* \|^2 \\
NMSE = \frac{\| \hat{y} - y^* \|^2}{\| (y^* - \mu_{y^*}) \|^2} \\
CC = \frac{(y^* - \mu_{y^*})^T (\hat{y} - \mu_{\hat{y}})}{\| (y^* - \mu_{y^*}) \| \| (\hat{y} - \mu_{\hat{y}}) \|}
\]

where \( \mu_{\hat{y}} \) and \( \mu_{y^*} \) are the mean of vectors \( \hat{y} \) and \( y^* \) respectively, \( 1 \in \mathbb{R}^{N_y} \) is the vector of all ones, and \( \| \cdot \| \) is the Euclidean norm.

Figure 4.4. Model for WECS output power prediction
Position and speed NARX networks are trained and tested individually for different prediction horizons. Table 4.1 provides forecasting performance of both NARX networks. It is seen that the networks have good accuracy in the short-term, i.e. prediction horizons between 1 and 10 s, where the CCs are greater than 0.9 (highly correlated). It is worth noting that the future estimated values of position and speed, including their respective prediction errors, are mathematically combined to obtain WECS power (see Figure 4.4.). Therefore, performance of the power NARX network is slightly degraded when compared to the other two networks for the same prediction horizon.

![Figure 4.5. Prediction results for WEC output power (top), marker zoomed-in section (bottom)](image)

<table>
<thead>
<tr>
<th>NARX</th>
<th>Index</th>
<th>horizon [s]</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
<td>5</td>
<td>10</td>
<td>25</td>
</tr>
<tr>
<td>Position</td>
<td>MSE</td>
<td>5.23e-5</td>
<td>3.17e-4</td>
<td>0.0019</td>
<td>0.0057</td>
<td>0.0119</td>
</tr>
<tr>
<td></td>
<td>CC</td>
<td>0.9991</td>
<td>0.9953</td>
<td>0.9364</td>
<td>0.9113</td>
<td>0.7233</td>
</tr>
<tr>
<td>Speed</td>
<td>MSE</td>
<td>2.54e-4</td>
<td>0.0011</td>
<td>0.0031</td>
<td>0.0062</td>
<td>0.0113</td>
</tr>
<tr>
<td></td>
<td>CC</td>
<td>0.9994</td>
<td>0.9931</td>
<td>0.9669</td>
<td>0.9143</td>
<td>0.6719</td>
</tr>
<tr>
<td>Power</td>
<td>NMSE</td>
<td>0.0715</td>
<td>0.0902</td>
<td>0.1152</td>
<td>0.3125</td>
<td>0.7246</td>
</tr>
<tr>
<td></td>
<td>CC</td>
<td>0.9842</td>
<td>0.9613</td>
<td>0.9506</td>
<td>0.8972</td>
<td>0.6315</td>
</tr>
</tbody>
</table>
As another comparison, real WECS power and forecasted power (with a prediction horizon of 5 s) are shown in Figure 4.5. The WECS power time series is obtained by using a wave profile with SWH of 3.8 m and DPD of 8.7 s. The zoomed-in figure (marker) verifies that the proposed prediction model is capable of producing accurate future estimates of WECS power.

4.3.2. Reducing the number of candidate voltage vectors

As already mentioned, in conventional MPDPC with one step ahead prediction horizon, eight possible voltage vectors are examined in each sampling period. The number of candidate voltage vectors increases exponentially as the prediction horizon increases, imposing computational burden and complexity.

In this work, a methodology inspired from direct power control (DPC) [37] is proposed for reducing the number of candidate voltage vectors. As seen in Figure 4.3, at each sampling time, forecasted REG power $P_{REG}$, reference dc-link voltage $v_{dc}^*$, actual converter output powers $P_{gr}(k)$ and $Q_{gr}(k)$, reference powers $P_{gr}^*(k)$ and $Q_{gr}^*(k)$, grid-side currents $i_{a\beta gr}(k)$ and voltages $v_{a\beta gr}(k)$ in $a\beta$ coordinates, and dc-link voltage $v_{dc}(k)$ are the inputs to the proposed methodology.

First, active and reactive power errors, $e_p(k)$ and $e_q(k)$, are calculated and fed to corresponding hysteresis controllers. Also, the sector in which $v_{sgr}(k)$ lies, i.e., $s_N(k)$, is identified. Next, sector information along with the output of hysteresis controllers $K_p$ and $K_q$ are used as inputs to a predefined switching table, where appropriate voltage vector to counteract power errors is selected. The selected voltage vector is stored and later employed along with forecasted REG output power to calculate converter output current and dc-link voltage at time
step $k + 1$. In addition, future grid voltage is computed, and new predicted and reference grid

![Diagram of grid voltage](image)

powers are obtained. This process is repeated for all the time steps within the designated prediction horizon $N_p$, i.e. $N_p + k - 1$. All the voltage vectors are stored in the set of candidate voltage vectors $U_v$, and will be evaluated by model predictive direct power controller in the next stage. It is noteworthy to mention that thanks to the proposed method, the number of candidate voltage vectors in $U_v$ grows linearly with the number of prediction steps. This drastically reduces the computational complexity in stage two.

To calculate power errors at time step $k + 1$, corresponding reference powers must be determined. As shown in Figure 4.3, the reference active power $P_{gr}^*$ is obtained from the dc-link controller, while reference reactive $Q_{gr}^*$ is set by PGO. Here, dc-voltage droop control is adopted to regulate the dc-link voltage by correcting power imbalances between generation and power

![Diagram of sector location strategy](image)
delivered to the grid

\[ P_{gr}^*(k + 1) = P_{so}^*(k) - K_D(v_{dc}(k + 1) - v_{dc}^*) \]  

where \( P_{so}^* \) is the active power set by PGO, \( v_{dc}^* \) is the reference dc-link voltage, and \( K_D \) is the droop constant. In (15), predicted value of \( v_{dc} \) at time step \( k + 1 \) is required for calculating \( P_{gr}^*(k + 1) \).

The dc-link capacitor dynamics can be determined by applying Kirchhoff’s current law at the dc-link node

\[ C_{dc}p v_{dc} = i_{ge} - i_{conv} \]  

where \( C_{dc} \) is the capacitance of the dc-link capacitor, and \( i_{ge} \) and \( i_{conv} \) are the currents of REG and converter on the dc-link side, respectively. By discretizing (16), \( v_{dc}(k + 1) \) may be written as

\[ v_{dc}(k + 1) = v_{dc}(k) + \frac{T_s}{C_{dc}}[i_{ge}(k) - i_{conv}(k)] \]  

where

\[ i_{ge}(n) = P_{REG}(k)/v_{dc}(k) \]  

\[ i_{conv}(k) = i_{sa}(k)(S_1(k) - S_3(k)) + i_{sb}(k)(S_2(k) - S_3(k)) \]  

In (19), \( i_{sa}(k) = \Re\{i_{s gr}(k)\}, \)  \( i_{sb}(k) = -1/2 \Re\{i_{s gr}(k)\} + \sqrt{3}/2 \Im\{i_{s gr}(k)\}, \) and \( S_i \in \{0, 1\} \) with \( i \in \{1, 2, 3\} \) are the switching states of each converter leg.

As mentioned, in addition to power errors, the sector in which the grid voltage space vector lies must be determined. In DPC, \( s_N \) is determined by obtaining the angle of \( v_{s gr}, \theta_s \).
This involves trigonometric functions, e.g., arctangent operator. Keeping in mind that digital processing of trigonometric functions imposes high computational burden, and the fact that \( s_N \), and not \( \theta_s \) is required for realizing the proposed method, a novel scheme employing only logic and arithmetic operators is proposed.

The method employs two auxiliary voltage vectors that are collinear with sectors boundaries and their projections on the \( \alpha \)-axis are equal to \( \alpha \)-component of \( \mathbf{v}_{\text{sgr}} \), \( v_{agr} \). To visualize these voltage vectors, consider Figure 4.6(a) for instance, where \( \mathbf{v}_{\text{sgr}} \) lies in sector V. The auxiliary voltage vectors \( \mathbf{v}'_{\text{sgr}} \) and \( \mathbf{v}''_{\text{sgr}} \) share the same \( \alpha \)-component with \( \mathbf{v}_{\text{sgr}} \) and are collinear with boundaries between sectors IV-V and V-VI. The \( \beta \)-component of the auxiliary voltage vectors are \( v'_{\beta gr} = \frac{\sqrt{3}}{3} \left| v_{agr} \right| \) and \( v''_{\beta gr} = \sqrt{3} \left| v_{agr} \right| \). It is clear that \( v_{agr} < 0 \), \( v_{\beta gr} > 0 \), \( v_{\beta gr} - v'_{\beta gr} > 0 \) and \( v_{\beta gr} - v''_{\beta gr} < 0 \). Sign of each of these inequalities is used to form vector \( \mathbf{z} = [-1 \ 1 \ 1 \ -1] \). Following similar steps, sign combinations associated with every 12 sectors are obtained and \( \mathbf{z}^T \) is stored as a column in matrix \( \mathbf{D} \), given in (21). It should be mentioned that for sectors I, IV, VII and X two \( \mathbf{z} \) vectors exist. Thus, matrix \( \mathbf{D} \) is a \( 4 \times 16 \) matrix. Finally, an indexing process is carried out to determine the column of \( \mathbf{D} \) that shares the same elements of \( \mathbf{z} \). The column number corresponds to the sector in which \( \mathbf{v}_{\text{sgr}} \) lies. Figure 4.6(b) depicts the block diagram of the proposed sector selection method, where \( \text{sgn} \) is the sign function, and \( G_1 = \sqrt{3} \) and \( G_2 = 1/3 \). Inside the logical expression and indexing block, the following rules are employed

\[
\xi = i \\
\text{such that} \\
\mathbf{d}_{i,*} = \mathbf{z} \quad \text{for } i = 1, \ldots, 16
\]

\[
s_N = r_{1,\xi}
\]
Table 4.2. Real-Time Simulation Parameters

<table>
<thead>
<tr>
<th>Grid</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Line Voltage (rms)</td>
<td>480 [V]</td>
</tr>
<tr>
<td>Frequency</td>
<td>60 [Hz]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Converter and filter</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power</td>
<td>70 [KVA]</td>
</tr>
<tr>
<td>L_s</td>
<td>10.3 [mH]</td>
</tr>
<tr>
<td>R_s</td>
<td>0.12 [Ω]</td>
</tr>
<tr>
<td>DC-link voltage</td>
<td>1200 [V]</td>
</tr>
<tr>
<td>C_{dc}</td>
<td>50 [mF]</td>
</tr>
<tr>
<td>Droop constant</td>
<td>2 %</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>WECS [31]</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>m_{tot}</td>
<td>0.6 x 10^6 [Kg]</td>
</tr>
<tr>
<td>K_g</td>
<td>0.56 x 10^6 [N/m]</td>
</tr>
<tr>
<td>γ_g</td>
<td>27 x 10^3 [Ns/m]</td>
</tr>
<tr>
<td>β_b</td>
<td>1.42 x 10^6 [Ns/m]</td>
</tr>
<tr>
<td>L_{ss}</td>
<td>31 [mH]</td>
</tr>
<tr>
<td>R_{ss}</td>
<td>0.29 [Ω]</td>
</tr>
<tr>
<td>Ψ_{PM}</td>
<td>23 [Wb]</td>
</tr>
<tr>
<td>λ</td>
<td>0.1 [m]</td>
</tr>
</tbody>
</table>

Here, \( d_{i,*} \) is a vector that contains the \( i^{th} \) row of matrix \( D \), and \( r_{1,ξ} \) is the \( ξ^{th} \) element of vector \( r \).

It is noteworthy that \( z_1, ..., z_4 \) in Figure 4.6(b) form \( z = [z_1, z_2, z_3, z_4] \).

Matrix \( D \) and vector \( r \) are defined as follows

\[
D = \begin{bmatrix}
1 & 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 & 1 & 0 & -1 & 0 \\
1 & 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 & -1 & 0 & 1 & 0 & -1 \\
-1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & -1 & 1 & -1 & 1 & 1 \\
-1 & -1 & 1 & 1 & -1 & -1 & -1 & 1 & 1 & -1 & -1 & -1 & 1 & 1 & 1
\end{bmatrix}^T
\]

\[
r = [1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 10 \ 11 \ 12 \ 14 \ 7 \ 10]
\]  \( (22) \)

Following the proposed indexing process, for the example shown in Figure 4.6(a), \( ξ = 5 \) and \( s_N = r_{1,5} = 5 \), which gives sector V as the location of \( v_{sgr} \).
4.3.3. Multi-step MPDPC

REG output power prediction affects selection of the candidate voltage vectors stored in $U_v$, thus some degree of uncertainty in terms of counteracting power deviations is inherently present. As a result, applying those voltage vectors directly by the grid-side PEC could undermine reliability of the RR service that REG can provide. Model predictive control can anticipate and handle violation of bounds. Therefore, MPDPC is considered to address this issue.

As described earlier, the control objective of MPDPC is power tracking, formulated as the cost function in (10). Evaluating (10) for each voltage vector $v_{conv} \in U_v$ results in a set of different values of the cost function. The vector that produces minimum power deviations, i.e. lowest value of $J$, is selected and applied in the next sampling time. With classical MPDPC and prediction horizon of $N_p$, $O(N^3)$ number of voltage vector sequences must be evaluated within one sampling period. However, hybrid structure of the proposed method enables the model predictive controller to evaluate only $N_p$ voltage vectors.

4.4. Real-time simulation results and discussions

Real-time simulations are carried out to, 1) compare the computational complexity of the proposed HD-MPDPC versus MPDPC proposed in [32], and 2) verify efficacy of multi-step HD-MPDPC in adjusting the REG output power when it operates as an RR service provider.

The real-time setup consists of an OP4510 real-time simulator from Opal-RT Technologies Inc with a 4-core Intel Xeon® 3.2 GHz CPU, and Kintex-7 XILINX FPGA. One core is devoted to grid, WECS, and interfacing PECs modeling and generator-side PEC controller implementation, and another core is devoted to implementing the grid-side PEC
controller. This is done so that an accurate digital implementation time of the grid-side PEC controllers is obtained.

Table 4.2 lists parameters of the real-time simulations. Simulations are carried out with a sampling frequency of 20 kHz. A wave profile with SWH of 4.2 m and DPD of 10 s is used to obtain the WECS output power time-series. Trained NARX networks from section III are employed to forecast the WECS output power. The generator-side PEC controller follows the maximum power point tracking (MPPT) approach presented in [31]. However, when WECS operates as RR service provider, generator derating is achieved by directly adjusting the $d$- and $q$-axis current setpoints of the generator-side PEC.

Real-time simulations of the system are carried out when grid-side PEC is controlled under MPDPC and HD-MPDPC with $N_p = 1, 2$ and 3. The computation time for each controller and time step is summarized in Table 4.3. For one prediction step, MPDPC shows marginally less computational burden (0.04 µs) than HD-MPDPC. For two prediction steps, however, MPDPC exhibits an increment of 270% in computational effort when compared to 183% of HD-MPDPC. As shown in Figure 4.7, when the prediction horizon is further increased to three steps, the computational burden of MPDPC rises drastically, spiking to 1015% from 270%, showing 745% increase. The computation time for three-step HD-MPDPC though, increases by only 63% (increasing from 183% to 246%). This demonstrates the exponential increase in computational time of MPDPC with longer prediction horizons and confirms efficacy of the hybrid data-model predictive control scheme in significantly alleviating the computational burden. Thanks to reduced computational complexity, it is possible to achieve a prediction horizon of $N_p = 25$ in real-time simulations when HD-MPDPC is implemented on only one core. It can be noticed from
Table 4.3. Computational Time (Real-Time Implementation)

<table>
<thead>
<tr>
<th>Method</th>
<th>Horizon N_p</th>
<th>Computation time</th>
<th>Increment* %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min (µs)</td>
<td>Max (µs)</td>
</tr>
<tr>
<td>MPDPC</td>
<td>1</td>
<td>0.18</td>
<td>0.30</td>
</tr>
<tr>
<td>HDMPDPC</td>
<td>0.21</td>
<td>0.30</td>
<td>0.24</td>
</tr>
<tr>
<td>MPDPC</td>
<td>2</td>
<td>0.51</td>
<td>0.59</td>
</tr>
<tr>
<td>HDMPDPC</td>
<td>0.40</td>
<td>0.53</td>
<td>0.44</td>
</tr>
<tr>
<td>MPDPC</td>
<td>3</td>
<td>1.98</td>
<td>2.10</td>
</tr>
<tr>
<td>HDMPDPC</td>
<td>25</td>
<td>0.55</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.28</td>
<td>4.58</td>
</tr>
</tbody>
</table>

*% increment = 100*[(ave compt time (Np) - ave compt time (Np=1))/ ave compt time (Np=1)]

Figure 4.7. Implementation time for one-, two- and three-step horizon

Table 4.3. that computational time for 25-step ahead prediction horizon is very close to the sampling period (50 µs) and thus, further increase of $N_p$ would have produced simulation overruns. With higher performance computational resources, the proposed HD-MPDPC could potentially pave the way for enabling participation of REGs in RR services thanks to very long prediction horizons.
In order to demonstrate how the proposed HD-MPDPC can regulate the output power of a REG in a long horizon, two scenarios are simulated in real time. In the first scenario, the generator-side PEC operates under MPPT mode and MPDPC with one prediction step is employed to control the grid-side PEC. Figure 4.8(a) shows WECS generated power and dc-link voltage under MPPT mode. It is seen that MPDPC is able to adjust the reactive power and voltage at the dc link to their respective reference values. However, the injected active power to the grid exhibits large fluctuations associated to inherit variability of WECS generation. Thus, the PGO will not be able to rely on REG as RR service provider.

In the second scenario, as shown in Figures 4.8 (d)-(f), WECS generation capacity is pre-curtailled, and the proposed HD-MPDPC with 25 prediction steps is employed to control the grid-side PEC. Initially, under pre-curtailment regime, WECS is delivering 15 KW of active power, while the reactive power is kept at 0 KVAR. At \( t = 40 \) s, a power step of 25 KW is commanded by the PGO, increasing injected power to the grid from 15 KW to 40 KW, while maintaining \( Q_{gr}^* = 0 \). At \( t = 82 \) s, a further increase of 20 KW in active power is applied, adjusting the delivered active power to the grid to 60 KW. Despite the variable nature of WECS generation, the proposed multi-step HMPDPC is capable of tracking the reference values of active and reactive powers, as well as keeping the dc-link voltage constant. Thanks to the long prediction horizon offered by HD-MPDPC, the PGO can rely on promised output power from REG, allowing its participation in RR service.
Figure 4.8. Real-time simulations of MPPT case. a) DC-link voltage, grid-side active and reactive power, b) grid-side currents, and c) grid-side currents zoomed-in. RR service case. d) DC-link voltage, grid-side active and reactive power, e) grid-side currents, and f) grid-side currents zoomed-in.
CHAPTER 5
CONCLUSIONS AND FURTHER WORK

The major contribution of this work is developing machine learning-based control techniques to facilitate grid integration of renewable energy systems as well as energy management in electrified transportation systems.

In chapter 2, a combined sizing and energy management method for an UESS-SC HESS based on RL is presented. The objective of regulating a direct-drive linear generator-based WECS output power variations is successfully accomplished. Comparisons are carried out in terms of required component capacity between the cases where SC-only, UESS-only, and HESS regulate WECS output power fluctuations. The obtained results show the proposed strategy significantly reduces the number of SC cells and rated power of UESS PMSM. Real-time simulations demonstrate the effectiveness of the proposed sizing/EMS method in facilitating the integration of a WECS into the grid.

Chapter 3 proposes an integrative sizing and control strategy of a HESS comprising battery/SC for reducing the impact of power variations in a MVDC shipboard power system. Deep reinforcement learning is employed for the derivation of the combined sizing/EMS strategy. Unlike optimization-based EMSs, which carry high computational toll, and rule-based EMSs, where optimality of solution is not warrantied, the proposed approach is implementable in real time and provides near-optimal solutions. A comparative analysis shows a reduction of $\sim 40\%$ in the component capacity of the HESS designed with the proposed methodology, in comparison to the cases where battery-only and SC-only ESSs mitigate the power fluctuations. Real-time simulation results verify the adaptability of the proposed method to different sea states without previous knowledge of propulsion power profiles.
A hybrid data-model predictive direct power control is presented in chapter 4. Compared to classical MPDPC, computational complexity is significantly alleviated by reducing the number of voltage vector sequences evaluated within a prediction horizon $N_p$. Real-time simulation results demonstrated the ability of HD-MPDPC to achieve very long prediction horizons, and to successfully regulate WECS output power variations without the use of ESSs. Provision of more reliable REG output power dispatch over long prediction horizons allows power system operators to 1) avoid excessive reserves, and 2) contemplate REGs as regulating reserve service providers.

Following subjects are proposed for further studies

**Chapter 2**

- Developing an integrative sizing/energy management strategy of HESS for grid integration of WECS arrays.
- Developing a more detailed economic analysis of the UESS-SC HESS.

**Chapter 3**

- Developing an integrative sizing/energy management strategy of HESS in MVDC shipboard power system with high-ramp power loads, e.g. rail guns.

**Chapter 4**

- Investigating the extension of HD-MPDPC for
  - voltage support service.
  - Combined fast frequency support and regulating reserves services
• Investigating application of deep NN prediction algorithms and comparing performance results with recurrent NN architecture in terms of number of prediction horizons steps, computational load, and power quality.
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Chapter 4


VITA

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