Energy management and techno-economic assessment of a predictive battery storage system applying a load levelling operational strategy in island systems

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Summary
In the present study, a predictive battery energy storage system (BESS) for application in geographical non-interconnected islands with high renewable energy penetration is proposed, capable of performing load levelling. The system under consideration is composed of diesel and heavy oil generators, a photovoltaic farm, and a small wind turbine. The proposed solution integrates machine learning (ML) methods for the forecasting of load and intermittent solar and wind power productions, alongside a custom scheduling algorithm, which calculates the necessary BESS setpoints that accomplish the desired levelling effect. An important feature of the scheduling algorithm is that the charge and discharge energy amounts of each day are by design equal and independent of the forecasts' accuracy. This aspect enables economic investigations to identify the appropriate BESS capacity for the particular system, also taking into account the battery's capacity degradation. The overall system is modelled and simulated utilizing the open-source languages Python and Modelica. Simulations presented a 9.8% peak-to-mean ratio (PMR) reduction of the thermal plant's load. Furthermore, economic investigations estimated a marginal BESS cost of 287.1 €/kWh revealing the financial viability of the proposed integrated system, in at least the case of geographical islands.

Keywords
battery energy storage system, BESS, load forecasting, load levelling, peak shaving, RES forecasting

1 | INTRODUCTION

The electric power sector is currently undergoing several important transitions, which individually and collectively have the potential to transform the design, operation, and characteristics of electricity systems. Defossilization of the non-interconnected island systems, in particular, is one of the most challenging goals for the transition into a low carbon era. The main driving force in this direction...
is the considerably higher energy production costs in islands compared to the mainland. The European Union has a leading role on this strategy, encouraging the development of cutting-edge technologies and initiatives that are accelerating the transition to a clean energy era for all European islands.\textsuperscript{3,4}

While variable renewable energy sources (vRESs) such as photovoltaic (PV) and wind turbine (WT) technologies are critical drivers towards sustainability and energy conservation,\textsuperscript{5} high shares of vRESs introduce several technical challenges that are associated with their stochastic and intermittent nature. One of the challenges relates to the “net load curve”, which is defined as the load minus the non-dispatchable generation and forms the basis of operation planning in the day-to-day delivery of electricity to the consumers.\textsuperscript{6} The intermittency of the solar and wind power resources results in a high variation of the net load that has to be served by the conventional generation units. Moreover, fluctuations associated with both the plug-in electric vehicles consumption profiles and the electricity price bring new challenges to the power engineers nature and aiming to achieve demand-supply balance.\textsuperscript{7} In the meantime, rapid fluctuations should be minimized, as may lead to load imbalance, instability, and damages to the system components.\textsuperscript{8} Utilities have to address these issues by ensuring that the generation fleet is able to meet seamlessly the load requirements at all times.\textsuperscript{9}

Traditionally, utilities meet these challenges through the formation and solution of a scheduling problem known as economic dispatch (ED). In this approach, the allocation of the total demand among generating units is performed, so that the production cost is minimized while satisfying all system constraints.\textsuperscript{10} This problem is tackled using dynamic programming, mixed integer programming, or evolutionary/heuristic optimization algorithms.\textsuperscript{11,12} A comprehensive review of the different optimization methods for the deployment and operation of RESs has been provided by Iqbal et al.\textsuperscript{13} Moreover, a general form of the resource allocation problem has been proposed, dividing it into four parts, that is, input, output, objectives, and constraints, as well as specifying different options for each part. Shi et al\textsuperscript{14} formulated a distributed energy management system for a microgrid as an optimal power flow problem, taking into consideration the underlying power distribution network and the associated constrains. Di Piazza et al\textsuperscript{15} proposed a method for improved integration of hybrid PV-storage systems into the grid. The focus was given on the minimization of the peak-to-mean ratio (PMR) of the grid-injected power profile, avoiding any possible energy curtailment and enabling better participation of PV producers in the energy market.

The case of the smaller, non-interconnected island systems presents specific peculiarities, compared to mainland systems. On the one hand, the scheduling challenges being faced can be considered as easier to handle, since there is only a limited number of generation units available at any time, compared to those of a mainland; nevertheless, the need for fast and highly flexible generation units is more essential than in mainland, for the exact same reason. The net load curve has to be served by the conventional thermal power generation units, which in the case of small island systems are usually reciprocating internal combustion engines operating with diesel and heavy fuel oil. Such machines are highly versatile, as they are easy to commit and are capable of responding rapidly to stiff load changes. Within the context of mixed RES and fossil-based power generation in islands, the requirement for as maximum as possible RES penetration usually results in a sub-optimal operation of the fossil-based power units, which in turn translates in higher fuel consumption and increases of the NOx and SOx emissions, mainly due to partial load operation and frequent transient responses.\textsuperscript{16}

To cope with these challenges, battery energy storage systems (BESSs) are considered a promising solution for the case of small island systems, since their cost has been reduced significantly during the recent years.\textsuperscript{9,17} The International Energy Agency reports a battery cost reduction of 45% from 2012 to 2018.\textsuperscript{18} Depending on the type, a BESS can provide a variety of services to the grid, such as primary and secondary ancillary services, virtual inertia as well as voltage control in the distribution grid.\textsuperscript{19,20} BESSs are also essential for energy management,\textsuperscript{21} peak shaving, load levelling, seasonal storage, and standby generation during a fault.\textsuperscript{22}

Load levelling, in particular, involves storing power during periods of light loading, and its delivery during periods of high demand, reducing the load on less economical peak-load generating engines. Furthermore, load levelling allows for the postponement of investments in necessary grid infrastructure upgrades or in the addition of new generating capacity, to confront with the continuous uprisings for energy. An economic analysis of load levelling using BESS in the Korean electricity market has been examined by Kerestes et al,\textsuperscript{23} in which the authors underlined that a large cumulative capacity of BESS should not be assumed economically beneficial, as it may actually increase the total cost of electricity. Hameer and van Niekerk\textsuperscript{24} presented a comprehensive techno-economic evaluation of large-scale energy storage technologies, highlighting also the key differences among various chemistries of the batteries. Liao et al\textsuperscript{25} performed a focused cost-benefit analysis for load shifting using a sodium-sulphur BESS installed in a university. Agamah and
Ekonomou\textsuperscript{26} successfully applied heuristic combinatorial optimization algorithms in BESS scheduling. In particular, the bin packing and subset sum algorithms were combined to perform peak shaving and load levelling. Barzak and Hosseini\textsuperscript{27} modelled peak load shaving for residential building using the shortest path optimization method, followed by a method for real-time scheduling of the storage system.

A novel, decision-tree-based peak-shaving algorithm was proposed by Uddin et al.,\textsuperscript{28} tested in a real islanded microgrid system, for various load conditions. The cost-benefit analysis showed that the overall revenue from the proposed system is 1.84 times of the capital investment. Garcia-Plaza et al.\textsuperscript{29} proposed a new algorithm for peak shaving by categorizing the states of a microgrid power balance and implemented the appropriate response of the BESS. As main drawbacks of the aforementioned approaches, can be considered the high levels of complexity in their implementation, and the heavy computational burdens that are often required. Furthermore, in almost all studies examined, the battery degradation mechanism was neglected, albeit its major role on the system's economic feasibility.

The main scope of this study is to propose a methodology for the design and operation of a predictive BESS, which applies a flexible and economically feasible load levelling approach for geographical island systems that include both diesel and heavy fuel oil generation units. The system operation is based on forecasting methodologies for the next day's hourly load consumption and vRESs production, along with a custom scheduling algorithm that calculates the next day's BESS setpoints. The outcome of the proposed strategy is an almost flattened net load curve, shifting load from the more expensive diesel generation during the peak hours to the cheap heavy fuel oil generation during the night, rendering the overall operation of the coupled vRES and fossil-based energy mixture, economically more viable, than it currently is. Novel aspects of the present work include:

- The proposition for a load levelling algorithm, with the assumption that the battery's charge and discharge amounts for each day are by design equal and independent of the forecasts' accuracy. The corollary of this feature is that the battery supports each day's scheduling, offering grid flexibility by reducing extremes in the variability of vRES, while taking advantage of stored energy when consumption load profile requires that.
- The exploitation of the battery operation in the system's sizing procedure, considering also the battery's degradation effect.
- Besides the theoretical methodology description, the approach is examined for the case of a small island system. The proposed system decreases the associated operational costs by reducing the capacity factor of the costly diesel generators (DGs), while enhances the smoothing of the power generation, decreasing substantially the successive ramp-ups and downs of the generation units.

The proposed BESS strategy has been developed and integrated into the energy system model using non-proprietary tools (Python and Modelica). Simulations have been carried out for the reference case of a small Southern European insular system and proved that an implementation of this algorithm can result in a smoother operation of the conventional power plants. Thanks to the effective prediction of near-future power production and consumption, better programming on the operation of the conventional thermal plants can be achieved, eliminating the operation factor of the high-cost diesel-fuelled engines, and achieving lower marginal system prices (MSPs).

2 | METHODOLOGY DESCRIPTION

Contemporary BESSs consist of numerous modules, the combination of which is crucial for the performance and robustness of the overall system. The proposed methodology is composed of predictive modules that can accurately estimate next day's load and vRESs power production, followed by a scheduling algorithm capable of calculating the battery setpoints that lead to an optimised operation of the conventional power generation units. A conceptual diagram of the overall system is presented in Figure 1.

The basic components can be identified in this figure, namely the forecasting and scheduling modules developed in Python, and the simulation environment in Modelica. The forecasting and scheduling procedures are performed once a day (at midnight) in the current implementation, but further development is planned, in which the algorithms will run at frequent timesteps, for example, every 15 minutes, in a model predictive control (MPC) scheme.

2.1 | Reference island power system

The power system under consideration in this study can be considered as a representative, in terms of capacity at least, of a typical southern European island with high vRES penetration. The system presents a yearly load peak of approximately 1.5 MW, and is composed of 1 thermal power plant (TPP) with 1 DG and 2 heavy fuel oil generators (HFOG) rated at 700 kW\textsubscript{e} output each, a 300 kW\textsubscript{p} PV
farm and a WT of 450 kW. A typical year of the system operation is presented in Figure 2.

The highly intermittent vRESs introduce several challenges to the grid operator and lead to high variability of the TPP's load. In Figure 3, the resulted net load curve is presented for the selected typical year. The TPP output has to rapidly fluctuate within the day to cover this load, involving successive stiff ramp-ups and downs. This non-optimal operation imposes additional stress on the generation units.

In the following sections, the design and sizing of a predictive BESS are presented for this system, which aims to serve as a guide for the replication on other island systems.

2.2 | Forecasting methods

Forecasting constitutes the foundation of modern power system operation and is an integral component of every energy or power scheduling procedure. In the proposed BESS, accurate forecasts are needed for both the demand and generation sides, as the system calculates the next day's battery schedule based on the forecasted values of the load as well as the PV and WT production. Therefore, it is evident that accurate forecasts play a vital role in the overall system performance.

In this framework, three supervised machine learning (ML) methods for forecasting are explored, namely the a) multilayer perceptron (MLP), b) support vector machine (SVM) and c) long short-term memory (LSTM). A benchmarking procedure was followed to identify the most suitable method in terms of accuracy for each forecasting task, that is, a) load, b) PV production, and c) WT production. Each of the three methods was applied for each of the three forecasting tasks, and the selected evaluation metric (mean absolute error (MAE)) was calculated for each case and is presented in Section 3.1. In the following paragraphs, a short description of each module’s main structure, along with the most significant implementation choices, is presented.

Following the above-mentioned trials, the load forecasting module was selected to be developed on the basis of the MLP network utilizing the open-source ML framework “scikit-learn”. The network included 79 input neurons, one hidden layer with 20 neurons and an output layer of 24 neurons, that yield the next day's load curve. The two previous days' load vectors were used as inputs, alongside the previous day's temperature vector and a "one-hot" binary vector which encodes the days of the week. The features were pre-processed using the min-max normalization function which scales them down to [0, 1] interval. The load forecasting data structure is presented in Figure 4A.

For the PV production forecasting module, an SVM model was finally selected to be used among the three available options, also utilizing the scikit-learn framework. After conducting several tests regarding the appropriate data input, the selected ones to feed in were the irradiation and temperature, which, after the necessary normalization, provided acceptable enough predictions for the power production of the PV plant. The RBF was used as the kernel function. An important requirement for the model is to produce a 24-valued vector for the next day's PV production. However, as the mathematical formulation of SVM permits only scalar output, a common workaround approach was adopted. Multiple vector machines (24 in our case) were trained, one for each target-hour within the day, and the results of each machine were combined as the output vector. An abstract structure of the overall PV forecasting module is depicted in Figure 4B.

For the WT forecasting, the Keras framework is utilized, which implements a high-level API capable of running on top of the deep learning libraries TensorFlow, CNTK and Theano. The implemented LSTM network has 40 units with the rectified linear unit, acting as the activation function. The LSTM layer is followed by a dense
layer (which in the Keras context refers to the regular densely connected network layer) with 24 units and no activation function that serves as an output layer. The selected features, namely wind speed and direction, were also normalized in the [0, 1] interval, and the models were trained for 1500 epochs. The complete structure is presented in Figure 4C.

The data used for the load forecasting procedure consisted of hourly time series for the load and vRESs production, for four subsequent years (2014-2017). Furthermore, the necessary historical meteorological data, that is, hourly time series of temperature, wind speed, and irradiation, were obtained from the ERA5 climate reanalysis data set produced by the European Centre for Medium-Range Weather Forecasts.32 The modules were trained using data of the years 2014, 2015, and 2016 and produced forecasts for the year 2017, which were evaluated against the actual year’s values. The hyperparameters of each module were tuned with the “grid search” approach.33

Although the presented forecasting techniques of this section can be considered well known in the literature, the included short description regarding the implementation details is crucial for the evaluation of the proposed system. The forecasting errors are combined in the calculation of the net load curve (net_load = load − pv − wt) and are propagated to the load levelling algorithm, resulting in a sub-optimal scheduling as it will be presented in Section 3.2. The focus of the present work is paid more on the energy management and integration of the different

FIGURE 2  One-year operation (hourly resolution) for the system under consideration [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 3  Thermal power plant’s yearly operation (net load curve) [Colour figure can be viewed at wileyonlinelibrary.com]
modules and less on the forecasting performance. This is acceptable as forecasts are modular in their nature, in the sense that they are easily interchangeable.

2.3 Load levelling algorithm

The proposed load levelling algorithm implements a flexible and easily applicable approach that results in lower PMRs and consequently in a smoother operation of the TPP. It accomplishes this task by the calculation of the appropriate BESS setpoints, based on the energy predictions provided by the forecasting modules. The algorithm is schematically depicted in Figure 5 in a flow chart form.

Initially, the three forecasted 24-value vectors representing the next day’s a) load, b) PV, and c) WT production profiles are inserted into the algorithm. The algorithm works on the difference between the load and the vRESSs production curves (net_load), which refers to the TPP production in the case of no battery installation (net_load = load - pv - wt). Additional inputs of the algorithm are the available capacity and power rating of the battery (cap and pwr, respectively).

The subroutine’s mechanism is depicted at the right side of Figure 5, and although a single chart has been used for both the charge and discharge procedure, it has been appropriately colour-coded to highlight the differences among them. Before the while loop entrance, the corresponding level curve (ch_lvl, dis_lvl) is initialized with its extreme value; the minimum of the net_load for the ch_lvl and the maximum for the dis_lvl. The while loop that follows calculates the shape of these curves, ensuring that the battery’s power rating will not be exceeded at all times.

The main body of the algorithm is presented on the left side of Figure 5 and is formed by two successive subroutines enclosed within a main outer one. The subroutines are entirely independent of each other, in the sense that there is no requirement for any particular order of appearance for each of them. Their task is to calculate the shape of the corresponding level curves, namely charge level (ch_lvl) and discharge level (dis_lvl). These lines express the upper and lower limits of the range, within which the resulted TPP curve will lie. The outer while loop ensures that the resulted charge and discharge areas (I_ch and I_dis) will be almost equal. To achieve this, a variable that expresses the amount of energy that will be shifted from the peak to the low demand hours (I) is initialized, according to the entire available battery capacity. In the rare case that the available capacity is higher than the necessary capacity to entirely flatten the curve, this amount is iteratively reduced by a small step (ext_step). The resulted I is equal to the area above (or below) the mean line.

The subroutine’s mechanism is depicted at the right side of Figure 5, and although a single chart has been used for both the charge and discharge procedure, it has been appropriately colour-coded to highlight the differences among them. Before the while loop entrance, the corresponding level curve (ch_lvl, dis_lvl) is initialized with its extreme value; the minimum of the net_load for the ch_lvl and the maximum for the dis_lvl. The while loop that follows calculates the shape of these curves, ensuring that the battery’s power rating will not be exceeded at all times.
The final phase of the algorithm includes the extraction of the battery’s setpoints (bess_setpt) from the already calculated level curves. This is accomplished by a short script that follows the while loop in the algorithm’s main body. The result is a 24-value vector of the battery’s hourly setpoints, which can be directly imported in the dynamic simulation environment for further analysis.

Figure 6 focuses on a single winter day and schematically presents the load levelling effect, comparing the difference between the daily peak and valley points in both the reference and advanced scenarios of operation. The charge and discharge amounts of energy are selected by design to be equal and independent of the forecasts’ accuracy (load, PV, and WT). This design selection is made to allow the grid operator be assured that the system will complete a full battery cycle for each day. This strategy offers the advantage that the batteries cycling ageing can be controlled, allowing the batteries being utilized as optimum as possible through their whole lifecycle, since their degradation rates can be quite accurately predicted, compared to less uniform charging/discharging cycle periods.

Furthermore, albeit its simple structure, the algorithm manages to achieve all the benefits of load levelling approaches, namely a) avoidance of high variations of...
the conventional generation units, and b) avoidance or reduction of vRES curtailment during the night. At the same time, it is easily applicable and customizable by the small power system operators, enabling them to tailor it, according to the specific needs of their system. All aforementioned arguments are supported by the simulation results presented in Section 3.2.

2.4 Power system modelling in Modelica

Dynamic simulations are a cost-effective and efficient tool for designers, in aiding the development of more efficient and sustainable energy systems. As mentioned in a previous section, the island system under consideration includes a fossil fuel-based TPP, a PV plant, and a WT. The deployment of a BESS is under examination, from both technical and economic standpoints. In this section, a brief description of the developed system model alongside its components is given.

As a first step, a lithium-ion battery pack module was developed in order to simulate the BESS operation and calculate important BESS variables such as state of charge (SOC), terminal voltage, and capacity degradation. The battery was modelled with its equivalent electrical circuit, consisting of a voltage source in series with its internal impedance, represented by two resistors and two RC networks in series. An important aspect of the present study, compared to others, is that the capacity degradation (also called capacity fading) is taken into consideration, as it is directly coupled with the economic feasibility of the proposed system. The causes of this phenomenon in the literature are 2-fold and referred to as calendar and cycling ageing. The equations that describe this behaviour are the following:

\[
C_{\text{max}} = C_{\text{nom}} \cdot CCF;
\]
\[
CCF = 1 - (f_{\text{sl}} + f_{\text{cl}}),
\]

where \(C_{\text{max}}\) is the remaining useable capacity at each moment, \(C_{\text{nom}}\) is the initial nominal capacity, \(CCF\) is the multiplier that represents the ageing of the battery (capacity correction factor), and \(f_{\text{sl}}\) and \(f_{\text{cl}}\) are the fractions for the lifetime storage and cycle losses, respectively. The equations that perform the calculation of these two fractions are:

\[
f_{\text{sl}} = \int s_{\text{l}1} \cdot e^{s_{\text{l}2} \cdot \frac{t}{100 \cdot 259200}} \cdot dt,
\]
\[
f_{\text{cl}} = \left( k_1 \cdot N_{\text{eqv}} + k_2 \right) \cdot \left( N_{\text{eqv}} \cdot dt \right) \cdot dt,
\]
\[
N_{\text{eqv}} = \int \frac{1}{3600} \cdot \frac{1}{C_{\text{max}}} \cdot dt,
\]

where \(s_{\text{l}1}\) and \(s_{\text{l}2}\) are constants, \(R_\text{gas}\) is the gas constant (8314 J/kmol K), \(T\) is the temperature of the cell in K, \(N_{\text{eqv}}\) represents BESS equivalent cycles, and \(k_1\) \(k_2\) are temperature-dependent coefficients. For the purpose of our study, a constant temperature is assumed (25°C). This is reasonable, as stationary battery systems are temperature-controlled utilizing air or fluid cooling systems. The battery modules are arranged in series forming stacks and then in parallel forming the BESS module.

The BESS model is interfaced with the three-phase AC grid through the consideration of an ideal average inverter model, as being assumed as well in similar works. The vRESs plants are considered to always operate at maximum power point tracking (MPPT) mode, thus allowing, with an acceptable accuracy, the WT and the PV forms to be modelled as PQ sources. The aggregated load has also been represented as a steady-state PQ load, and finally, the TPP is represented by an infinite bus.

Utilizing the described model, several simulations have been conducted with different BESS capacities and setpoints, allowing for the technical assessment of the battery’s performance and degradation, under the proposed load levelling operation strategy.

3 RESULTS AND DISCUSSION

In this section, the results of all parts of the present study are presented and discussed. First, the benchmarking of the implemented forecasting modules is presented,
followed by the dynamic simulations being conducted. These simulations aim at assessing the benefits presented by the load levelling control strategy because although the battery setpoints are calculated beforehand based on the forecasted values from the forecasting modules, the simulations run against the actual values for each asset. In this way, the behaviour of the system can be investigated, and useful conclusions regarding its performance can be extracted. Last, the battery sizing procedure that has been followed is described, while also considering technical and economic aspects.

### 3.1 Forecasting methods benchmarking

As mentioned in Section 2.2, the selection of the appropriate method for each of the forecasting tasks was investigated through numerical experiments. The chosen evaluation metric for this benchmark is the MAE which expresses the deviation of the forecasted values from the actual (true) values and is described by the following equation.

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |W_{\text{forecasted}} - W_{\text{true}}|,
\]

The output of the conducted numerical experiments is summarized in Table 1, which includes the resulted metrics for each method-task combination. It is seen that the lowest MAE values for the load, PV, and WT forecasting were achieved when MLP, SVM, and LSTM methodologies were used, respectively.

| Forecasting Task | MLP  | SVM  | LSTM |
|------------------|------|------|------|
| load             | 0.0168 | 0.0172 | 0.0229 |
| PV               | 0.0128 | 0.0120 | 0.0137 |
| WT               | 0.0705 | 0.0674 | 0.0522 |

Abbreviations: LSTM, long short-term memory; MAE, mean absolute error; MLP, multilayer perceptron; PV, photovoltaic; SVM, support vector machine; WT, wind turbine.

It is worth pointing out that all error results are within an acceptable interval (<5.3% MAE) and none of the examined methods performed poorly in our implementations.

It is also worth noting that benchmark results like the ones presented here can only be interpreted as informative and do not aim to produce a generalized suggestion on the preferable method per task. There are several parameters that affect the performance of methods in all implementation stages, that is, pre-processing, training, evaluation, testing, and data quality. The implementations that have been described in Section 2.2 in detail aimed more at exploring the extensive subject of the load and vRES production power forecasting, and less on proving that a method outmatching another.

A proper (possibly dedicated) investigation study regarding energy forecasting should have incorporated more methods, followed by an extensive benchmarking procedure with multiple metric indicators. We purposely limited the discussion for the three selected forecasting methods and evaluated them based on just one metric indicator, that is, the MAE, already presented.

### 3.2 Simulation results

In Figure 8, the 1-year operation of the TPP units is presented for both the reference and advanced scenario. The advanced scenario includes a BESS of a 500 kWh capacity with a 200 kW maximum power rate. The sizing procedure that has been followed is described in Section 3.4. The improvement in the overall TPP operation can be noticed by the change of colours in the peaks and valleys of the yearly curve. From the presented results, it can be deduced that the implantation of the selected control strategy can considerably improve the overall system behaviour; rendering it less fluctuating compared to the reference one.

To highlight the impact that the forecasting accuracy has on the resulted system performance, we perform a comparative analysis using as a reference an indicative week of operation. Figure 9A presents the scheduled operation of the TPP (red curve) produced by the load levelling algorithm, which is drawn based on the forecasted net load curve (blue curve). On the contrary, Figure 9B depicts the resulted operation that has been occurred. An important point to remark is that the battery setpoints are the same in both figures, although they result in different TPP profiles. As the net load curve differs from the forecasted one, the resulted TPP operation (red curve) does not perform as scheduled in Figure 9A. Another way to interpret this effect is to assume 0% forecasting error in the first figure and >0% error in the
second one. Nevertheless, the load flattening effect on the TPP load is achieved albeit the expected forecasting inaccuracies.

Though the BESS improves the system’s behaviour from a technical perspective, the associated key economic performance indicators must be well taken into consideration, to assess this integration from a cost-effectiveness perspective, and examine its applicability in similar sized real operating systems.

3.3 | Comparison with a rule-based approach

The benefits of the proposed load levelling algorithm over other standard ones can be depicted, using at least a simple rule-based approach, as a reference point. These systems are based on two thresholds, namely low_lvl and up_lvl. The BESS charging is starting when the net load curve becomes lower than low_lvl. Correspondingly, the discharging is initiated when the net load curve overcomes the up_lvl. The rest of the time the battery remains in idle mode, as the net load curve lies between low_lvl and up_lvl. Besides the two thresholds, some additional logic assertions are required that refer to the SOC. The major difficulty of this approach is the proper determination of the two levels. Herein, we utilized the forecasted net load curves, in order to calculate the extrema of each day. The difference between the highest and lowest point of each day expresses the range of the net curve’s values. By segmenting this range into equal distributed segments (seg), in our case 4, the required levels can be identified as

![Linear regression plots for the yearly forecasted and actual values of A, load-MLP; B, PV-SVM; C, WT-LSTM, and D, the combination of A, B, and C, which refers to the TPP’s load (TPP = load-PV-WT). LSTM, long short-term memory; MLP, multilayer perceptron; PV, photovoltaic; SVM, support vector machine; TPP, thermal power plant; WT, wind turbine [Colour figure can be viewed at wileyonlinelibrary.com](A) R=0.99067 (B) R=0.93993 (C) R=0.78405 (D) R=0.92525]
**FIGURE 8** Yearly TPP operation before (blue) and after (red) the predictive BESS installation. TPP, thermal power plant; BESS, battery energy storage system [Colour figure can be viewed at wileyonlinelibrary.com]

**FIGURE 9** Comparison of the A) scheduled operation with B) the resulted one for an indicative week [Colour figure can be viewed at wileyonlinelibrary.com]
up lvl = max – seg and low lvl = min + seg. The overall scheme is presented in Figure 10 in a flow chart form.

Figure 11 presents the resulted operation for the same indicative week examined in Figure 9. Although the algorithm shaves successfully the peaks of some days, this is not always the case. This is due to the significance of the two thresholds, that is, the low lvl and up lvl. For instance, in the sixth day, it can be noticed that the threshold has been overcome in the morning hours and the battery has been discharged, leaving the evening peaks unaffected. In comparison to the forecasting based approach, the load in the same day in Figure 9 has been appropriately flattened, even though both methods have utilised the same forecasts.

Another important point to remark is that in this approach, the charge and discharge amounts are not equal to each other, introducing additional load to the batteries and preventing the operator from long-term economic considerations in respect to the profitability of the system.

Regarding the PMR, the rule-based approach fails to properly identify each day's lowest points (valleys) in the net load curve, resulting in a 63% less PMR reduction for 1-year operation compared to the proposed operation strategy.

3.4 Sizing procedure

To identify the optimal BESS capacity with respect to the proposed load levelling operation, a sizing procedure was performed for the particular system under consideration. Herein, the technical metrics are discussed, as the corresponding economic ones are analysed in more detail as part of the overall economic evaluation in Section 3.5. Besides the sizing procedure, these metrics contribute in the quantification of the overall improvement. The general approach that has been followed is a 5-year simulation under varying storage capacities, taking into account the battery degradation effect, as described in Section 2.4. For each case, 80% of the total battery capacity was assumed to be available for the load levelling algorithm, to avoid high depths of discharge. Table 2 presents the resulted indicators for the simulated 5-year operation of all examined cases. The technical indicators include a) the total amount of energy that was shifted, b) the cumulative PMRs, and c) the standard deviations of the net load, while the economic indicators to be discussed in Section 3.5 included) the electricity cost savings at the end of the 5-year operation along with e) the marginal capital costs of the BESS.

The delta-cumulative PMR presents decreasing values, with an increasing BESS capacity, confirming the expected asymptotic behaviour of the cumulative PMR curve. In essence, any additional battery capacity results in lower marginal improvement of the yearly PMR until the absolute flattening of the net load curve is achieved. These results were combined with the economic considerations in Section 3.5, suggesting the installation of a BESS with a 500 kWh capacity and 250 kWe power rating, as the most operational and cost-efficient choice, among those being examined for the current under investigation power system. The results revealed an average of 9.8% PMR reduction on the net load.

A more comprehensive depiction of the impact that the load levelling approach using BESS has on the

FIGURE 10 Rule-based load levelling algorithm

FIGURE 11 Rule-based approach for the same indicative week of Figure 10 [Colour figure can be viewed at wileyonlinelibrary.com]
operation of the thermal units is shown at Figure 12. On the one hand, the HFOG operates fewer hours in very low loads when the BESS is employed, a fact that improves the average performance of the engines, leading to less specific fuel consumption than in the reference case. The average operation load of the HFOG increases by 1% to 1.4% at the cases of BESS with capacity 500 kWh and 875 kWh, respectively. On the other hand, the operation of DG, which serves as a “peaker” for the overall system, decreases considerably. It is evident that the main objectives of the proposed strategy, that is, the levelling of the thermal units’ load and the mitigation of diesel fuel consumption, have been met.

### 3.5 Economic considerations

Apart from the analysis on the purely technical aspects of the proposed concept, a techno-economic assessment was carried out aiming to identify the conditions under which the proposed use of BESS with the specific operation strategy is financially beneficial. At the same time, the methodology for the BESS sizing is described in this section and can serve as the guide for other similar studies. The methodology takes advantage of the fully controllable degradation rate of the BESS, which is a property of the load levelling algorithm, as described in Section 2.3.

As already mentioned, the island system under consideration includes 1 DG and 2 HFOG with an installed capacity of 0.7 MW_e each. Since heavy fuel oil consumption is cheaper than diesel fuel consumption, it is preferable for HFOG to operate and DG to be used only when the load is high and cannot be covered by the HFOG. The general approach that is followed by the operators can be expressed by the following equation:

\[
N(\text{net\_load}) = \left(\text{net\_load} \div \left(\text{max} \cdot P_{\text{nom}}\right)\right) + 1,
\]

where \( N \) represents the number of the committed generating units, the \( \text{net\_load} \) has already been defined as the difference between the total load and vRES production, \( P_{\text{nom}} \) is the rated power capacity of the units, and last,
$c_{\text{max}}$ is the coefficient that expresses the maximum admissible utilization of each committed machine, which in the current case is equal to 80%. Utilising this equation in conjunction with the aforementioned commitment priority (heavy fuel oil is preferable compared to diesel), the dispatch of the TPP under consideration can be approximated.

The main economic parameters that were considered in this analysis are presented in Table 3. The calculation of the cost of electricity (COE) of the thermal engines was based on a simplified approach where no depreciation cost is taken into account (it is assumed that the oil engines are old enough and the capital cost has already been depreciated) and only the fuel cost and the CO$_2$ emissions are considered. A 35% net efficiency of both units$^{38}$ and a 25 €/t cost of CO$_2$ are assumed. The resulting electricity cost of the DG and the HFOG engines are 363.0 €/MWh$_{th}$ and 145.9 €/MWh$_{th}$, respectively.$^{39}$ The levelized COE for the two renewable units is obtained from Kost et al.$^{42}$ The MSP is calculated as the sum of the electricity cost from the four power production units using the following formula:

$$\text{MSP} = \frac{P_{\text{DG}} \cdot \text{COE}_{\text{DG}} + P_{\text{HFOG}} \cdot \text{COE}_{\text{HFOG}} + P_{\text{PV}} \cdot \text{COE}_{\text{PV}} + P_{\text{WT}} \cdot \text{COE}_{\text{WT}}}{P_{\text{DG}} + P_{\text{HFOG}} + P_{\text{PV}} + P_{\text{WT}}}.$$  

The marginal specific capital cost of the BESS (including the inverter) is set as the breakeven point. The economic analysis is performed for a period of 5 years.

It should be underlined that the present methodology is developed considering a specific installed capacity of the conventional and renewable units. Its main goal is the improvement of the energy management of the island system towards a smoother operation of the oil engines, and the lowering of the MSP through the reduction of diesel contribution to the power generation. Thus, the expected revenues come from fuel savings and the reduction of the electricity cost.

Table 4 presents the results of the economic analysis described above. The minimum BESS price is estimated at 287.1 €/kWh which is within the range of expected capital cost for lithium-ion batteries according to relevant studies.$^{18,43}$ Moreover, it is revealed that significant fuel cost savings can be achieved, as the maximum load of the thermal plant is reduced and thus, the DG operates for fewer hours. According to the calculations, the savings in the electricity production cost for the first year is 38.3 k€ or 2.8%. The total production cost in a 5-year period is reduced by 169.2 k€, which is a considerable amount for a small-scale island energy system.

Figure 13A presents the fluctuations of system demand, whereas Figure 13B presents the number of oil engines that are in operation for the two scenarios in a random week (in the current case, the 10th week of the year). It can be observed that in the reference scenario, during the night hours when the system load demand is maximizing, there is a necessity to operate the diesel engine, which has the highest COE of all the power production units, thus, rendering the need of the total engines in operation at three. However, in the advanced scenario with the BESS installation, thanks to the developed algorithm, the DG engine contribution during these periods is reduced, and in some days entirely avoided. As seen in Figure 13C, when the operation of the diesel engine is avoided, the MSP can be

### TABLE 3 Assumed parameters for the economic analysis

| Parameter          | Value          |
|--------------------|----------------|
| Diesel fuel price  | 1.2 €/l or 121.0 €/MWh$_{th}$ |
| Heavy fuel oil price | 0.48 €/l or 44.2 €/MWh$_{th}$ |
| TPP engines efficiency | 35%          |
| CO$_2$ emissions price | 25 €/t        |
| Rate of Interest   | 6%             |
| DG COE             | 365.9 €/MWh$_{th}$ |
| HFOG COE           | 147.1 €/MWh$_{th}$ |
| PV LCOE            | 50.0 €/MWh$_{th}$ |
| WT LCOE            | 60.0 €/MWh$_{th}$ |
| BESS installed capacity | 500 kWh      |

**Abbreviations:** BESS, battery energy storage system; COE, cost of electricity; DG, diesel generator; HFOG, heavy fuel oil generators; PV, photovoltaic; TPP, thermal power plant; WT, wind turbine.

### TABLE 4 Economic analysis results

| Examined Scenario | No BESS | With BESS |
|-------------------|---------|-----------|
| Maximum marginal system price (€/MWh) | 322.4 | 296.0 |
| Average marginal system price (€/MWh) | 157.4 | 153.1 |
| Minimum marginal system price (€/MWh) | 83.3 | 87.0 |
| Diesel annual production (MWh$_{th}$) | 540 | 364 |
| HVO annual production (MWh$_{th}$) | 7322 | 7498 |
| Annual electricity production cost (k€) | 1379 | 1341 |
| Annual savings at first year (€) | - | 38.25 |
| Annual savings (%) | - | 2.8% |
| Marginal BESS price (€/kWh) | - | 287.1 |

**Abbreviation:** BESS, battery energy storage system.
reduced up to 50%, especially during the night (see day 1 and day 4). On the other hand, the increase of oil engines contribution is observed in the daytime due to the battery charging, but the increase of the MSP at the same period is insignificant.

The evolution of the annual revenue and the investment profit are depicted in Figure 14. The revenue drops by 6% per year, due to the battery’s capacity degradation which results in a lower peak shaving per day. It should be mentioned that taking into account the present energy system situation (ie, no new renewables are installed, and no additional restrictions in oil engines penetration to the system are imposed), the 20-year revenue can reach the amount of 14 000 €.

It is also worth mentioning that this is a rather conservative analysis, as various other parameters that increase the oil engine electricity cost, such as the fuel consumption increase due to the rapid ramp-ups and the workload shift when more engines are in operation, have not been taken into consideration. For that reason, a sensitivity analysis of the key parameters is performed to assess the impact of their change on the economic feasibility of the investment (Figure 15).

At first, the hypothesis of constant TPP efficiency at various load is further investigated. According to relative data, the thermal efficiency of a typical DG with capacity <1 MWe does not change at 70% to 100% load but drops 2.4% when operates at 50% of the nominal design point. Similarly, the thermal efficiency of HFOG in 50% load is 1.4% less than those in 100%. Taking into account this information and making a more precise estimation of the electricity cost of the conventional units, the
marginal BESS price for the case of BESS with 500 kWh nominal capacity is calculated at 327.7 €/kWh. It is thus inferred that a more realistic techno-economic approach can reach to even more promising results in terms of the expected profitability of the investment.

The selection of the appropriate BESS capacity has a small impact on the profitability of the investment, since for the specific economic parameters values, the marginal BESS price ranges between 260 and 287 €/kWh (see also Table 2). The highest value is observed for the case that the battery size is 500kWh. It should be mentioned that in case the battery specific capital cost is 200 €/kWh or lower, the higher the BESS capacity is, the more profitable the investment is as the electricity cost savings increase when a larger BESS is installed (see Table 2). Another factor that enhances the feasibility of the concept is the low efficiency of the existing TPP. In other words, it is more beneficial to seek investment in islands with old engines (ie, net efficiency <30%), in which the TPP electricity cost is high (higher than 420 €/MWh and 170 €/MWh for DG and HFOG, respectively) than in cases with more efficient thermal plants like in the base case that is investigated in this study. Moreover, the increase in diesel price leads to higher marginal BESS cost, because the proposed methodology minimizes the diesel oil consumption. On the other hand, the increase in HFO price does not have a beneficial effect on the investment, as the fuel cost savings and consequently the savings from the electricity cost reduction decrease.

Summing up, taking into account a) the aforementioned results from the economic analysis, b) the future trends for the diesel fuel price, c) the battery installation falling cost, and d) the increase of TPP electricity cost as a result of their efficiency deterioration, the profitability prospects of the proposed concept are quite promising.
As in most small-scale islands, the further development of RES is retained by the current legislation framework, this methodology can enable the increase of RES penetration and guarantee a well-balanced coexistence of dispatchable and vRES in the isolated energy system. Under a technical configuration, as the one proposed by this study, not only will the oil engines operate more smoothly and any rapid ramp ups/downs will be avoided, but also cheap renewables will lower the electricity cost. Thus, the present methodology can make the local authorities allow the installation of more vRES in the islands and open the way for new RES-based investments there.

3.6 | Environmental impact

Although no modification in the energy mix of the island in terms of the installed capacity of the power production units is performed, the differentiation of thermal plants operation brings about some environmental benefits. Firstly, the NOx emissions are reduced by 1% or 1.7% when a 500 kWh or 875 kWh BESS is employed, respectively. The NOx reduction calculations were based on experimental data at partial load from the study of Oh et al. 16

Considering a CO2 emissions factor of 0.24 tn/MWhth and 0.28 tn/MWhth for diesel and HFO, respectively, it is estimated that the proposed peak shaving strategy will contribute to the reduction of 11 tn CO2 after a 5-year operation, when a BESS with 500 kWh nominal capacity is used. The GHG emissions reduction is small even though the HFO consumption increases at the peak shaving cases. If a fuel with less specific emissions that diesel was used instead of HFO, the CO2 emissions reduction would be higher.

4 | CONCLUSIONS

The present study proposes an end-to-end approach for the mitigation of the challenges that vRESs evoke in small non-interconnected island systems. The adopted approach addresses both technical and economic concerns by combining the sizing and operation of a BESS and aims to flatten the load of the fossil-based thermal plants, resulting in reliable operation and enabling higher renewable penetration levels.

The devised predictive BESS consists of forecasting and scheduling algorithms that calculate the appropriate battery setpoints that implement the load levelling effect. The forecasting modules estimate the next day’s hourly load and vRES power production with sufficient accuracy (<5.3% MAE), which are combined to result in the forecasted net load curve, representing the TPP’s load. Based on this curve, the scheduling algorithm draws the BESS operation strategy. The economic study presented a marginal BESS cost of 287.1 €/kWh, while in case that the cost is 200 €/kWh or lower, the higher the BESS capacity is, the more profitable the investment is, as the electricity cost savings increase when a larger BESS is installed. A BESS of 500 kWh capacity (and of 250 kWp power rating) has been selected, capable of shaving the peaks and reducing by 9.8% the PMR of the TPP’s load.

Results showed that the introduction of such a predictive BESS can drastically improve the performance of the conventional units, contribute to the electricity cost reduction, and pave the way for additional RES installations. Furthermore, the BESS installations in small island systems prevent TPP units from operating close to their technical limits, avoid possible renewable energy curtailment, and achieve greater RES penetration.

Even though the overall analysis presented in this study concerns a small island with particular energy mix, there are many islands in the world with similar characteristics, in which the proposed algorithm can be easily adapted and implemented. For instance, in Greece, there are 8 islands (excluding Crete) which operate using almost the same energy mixture (DG, HFOG, and RES) with 730 MWe total installed capacity. In most Greek island cases, where the size of them is at the same scale or slightly bigger than the island under examination in this study, the algorithm can be applied with minor modifications. In bigger, non-interconnected islands as Cecily (IT), Crete, and Rhodes (GR) and other similar ones, additional challenges that need to be overcome lie on the most efficient scheduling of operation for a large number of thermal engines existing, well-orchestrated in conjunction with the strongly varying vRES power generation profiles available, as a result of their distribution in different locations on the same island; rendering the selection of the number of associated batteries and their sizing is even more difficult to solve the problem, than in the case of a small island. The sizing of an electrical storage system, while considering the numerous available and varying dispatchable and non-dispatchable units influence both the grid stability and its power quality offer, with
the consideration of the associated batteries’ degradation being one key economic design decision parameter. In view of these multi-parameter scalable tough problem, from small to big islands, the proposed algorithm can support this type of decision-making, while smoothing the power production profiles, maintaining the balance between generation and load under uncertainty.

To generalize, the approach can be applied on any island system scale that includes more than one dispatchable and non-dispatchable unit either RES or non-RES based one, that is, oil, natural gas, biomass, PV, etc. The main system-specific parameters that have to be set, include the load and vRES (if any) production profiles, and the corresponding operational costs of the fossil-based power generation.

The next planned step in the development of the proposed concept is the incorporation of the proposed BESS in a MPC scheme. In that case, the algorithm would be able to run periodically within the day, instead of once a day as in the current implementation, enabling more accurate forecasts and permitting intra-day corrections on the BESS schedule that will result in performance improvements.

Concluding, the present study proposed an economically feasible operating approach that contributes to the sound operation of the grid, and tackles the challenges introduced by the variable intermittent sources.

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