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# Optimal operation of Distributed Battery Energy Storage System

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**Abstract.** This paper presents an algorithm for the optimal-operable dispatch of distributed battery banks in systems with high integration of variable renewable energies. As a test case, the application of the algorithm is presented in a possible expansion of the Colombian system 2024-2039, subdivided into five regions each with its DBESS. The novelty lies in how to integrate a set of technologies such as stochastic dynamic programming, with reinforcement learning and optimization of the marginal benefit of an agent to obtain an operable operation policy close to the achievable optimum.

**Key words.** operation, distributed battery banks, operation policy, energy dispatch.

## 1. Introduction

With the high incorporation of renewable energy with hourly variability (VRE), such as wind and solar, the incorporation of Distributed Battery Energy Storage System (DBESS) energy storage systems that allow energy to be moved in terms of hours within the same day becomes an important element that avoids the need to install new thermal power plants to cover power balance requirements at transmission level, as well as the need to expand transformation or transmission capacity to cover peak hours at distribution level (see [1]).

These storage elements will be installed in a distributed manner, both at the residential level and at the transmission station level of the National Interconnected System (NIS).

Given the time constants involved, with storage capacities in the order of hours, these storage elements deserve a different treatment than longer-term energy reservoirs such as the lakes of hydroelectric plants.

In hydroelectric generating systems, with reservoirs capable of storing the energy that can be generated over periods of months to years, optimization techniques are used to calculate what is known as an Operating Policy. Traditionally, to obtain an Optimal Operating Policy (the one that leads to the lowest expected value of the future operation) a Stochastic Dynamic Optimization problem is used to solve. In 1957 Richard Bellman [2] published the algorithm that is now known as the Bellman Recursion and that is the conceptual basis of most current implementations. In the same publication Bellman warned that his solution suffered from the Curse of Dimensionality, commonly referred to as the Bellman Curse. The optimal operation of energy dispatch has been and will continue to be a constant battle against the Bellman curse. In this battle different weapons have emerged such as Stochastic Dual Dynamic Programming (SDDP) [3] or Rolling Horizon [4] or Reinforcement Learning techniques [5]. A good compendium of different solutions and systematic approaches to the problem can be found in books [6] and [7].

An operating policy is ultimately a mapping between available information and control actions. Available information can be classified between that which represents the State of the System and that which is exogenous to the system. The State of the System can be represented as a vector X that captures all relevant information from the system's past and the exogenous information as a vector that reports, for example, whether it is raining or not, whether there is good solar radiation, the price of a barrel of oil, etc. As a system status, it is common to consider the volume of water stored in the different reservoirs and the availability of the equipment.

Bellman's Curse implies that as the number of variables to be considered grows, Bellman's recursion involves solving subproblems that grow exponentially with the dimension of the variable space. Just as an example, if we consider a space of $N_v$ variables that are discretized in $N_d$ positions to create the Operation Policy in $N_t$ time steps, $N_t \times N_v^{N_d}$ dispatch subproblems must be solved.

The incorporation of VRE, along with an unquestionable advance in the speed and security of communications and control elements, means that reservoirs of hydroelectric plants with a storage capacity of a few days can be considered as state variables in new systems, since in the new systems, these energy stores undoubtedly allow the management of the variability of the new energies. In the same sense, the incorporation of DBESS in the different areas of the NIS must be considered for the optimal operation of the system.

The increase in the variables to be considered reinforces the need for new strategies to combat the Bellman curse.

## 2. Operable policy

An important aspect to consider is the way of programming the actual operation. In different systems, dispatching agencies must program in advance, applying an operating policy, how the operation will be carried out in real time. From this programming, a dispatch order is set to be followed by the real-time operators and for the automatic generation controls (AGC). This way of operating the systems imposes a certain temporal parsimony that must be respected in the proposed solutions to achieve operating policies close to the optimum. In other words, an optimal operating policy is one that minimizes the expected value of the future operation subject to the real operation constrains. These constrains include the programming and reaction times of human operators, AGC and the automated systems and protections that ensure the safe operation of the system.

In addition to the control actions, the programming of the use of the different resources and of the subsequent operation must be such that it allows the generation of price signals that make the operation of the energy block supply markets with price viable. All this imposes the need not to exaggerate the granularity of the temporal representation, given that a certain parsimony is required for the operation of the dispatch and the markets to be feasible.

From our point of view, solutions such as those proposed [8], could be encapsulated within a system-wide dispatch resolution problem, in a similar way to what is proposed in the rest of this work for the proposed algorithm, but they can hardly be incorporated directly into the actual dispatch programming stages.

## 3. The proposed operation policy for integrating DBESS

This paper presents a novel model for SimSEE that allows optimizing the use of DBESS in different regions of a system.

As already mentioned, the incorporation of faster dynamics in the systems implies that state variables associated with energy storage elements, which were not necessary before, become relevant for the formation of the operating policy. This policy must be operable. It must allow its application to the real programming of the operation and to the generation of price signals, with sufficient temporal stability that make the operation of the real markets viable.

The time necessary for the start-up and shutdown of the thermal generation plants imposes a daily or higher dispatch horizon (or programming time step). As an example, for the management of steam cycle plants, programming times of the order of 48 to 72 hours are necessary, while for motor generators and gas turbines programming times of hours are enough.

In addition to this, it might be included as part of the DBESS also the capacity of electric vehicle of providing manageable energy to the system (V2G) within the day. In line with the previous consideration, this work presents a strategy to represent and manage DBESS.

In [9] the result of an optimal generation expansion is presented, in which the competition between batteries and flexible thermal plants is analyzed. To calculate the operating policy, the using the classic Bellman recursion. The system already had three hydroelectric plants with reservoirs, so the representation had to be limited to using a single battery bank in order to perform the analysis in a reasonable time.

In [5] we presented the application of reinforcement learning to obtain the optimal policy of what the Uruguayan system could be in 2050 with 100% renewable energy supply and with the incorporation of 4 large battery banks. This work showed the feasibility of obtaining the Operation Policy by increasing the dimension of the state space by 4.

In this paper we propose an alternative approach that does not involve increasing the dimension of the state space. The proposal is applicable to systems with relevant hydroelectric generation components on which it is necessary to build an Operation Policy. This methodology consists of: a) representing as state variables the stored volumes (or the stored energy) in those reservoirs capable of storing for periods longer than the programming time-step, b) representing the DBESS not with state variables but as market agents that optimize their profit based on buying or selling their energy at marginal cost, and c) iterating the dispatch resolution in such a way that the market takes into consideration the participation of the DBESS in the formation of the marginal cost.

The optimal dispatch solution at each time step using the SimSEE [10] platform is performed by posing an optimization problem that minimizes the cost of supplying the energy demand of the time step plus the expected value of the cost of the future operation from the state in which the system will be at the end of the time step. It is normally used as a simulation step in SimSEE of equal duration to the scheduling horizon (for example daily). To better represent the dispatchable power requirements, SimSEE subdivides the time step into different hourly blocks in which it groups the hours of similar Net Demand value.

The developed model allows defining a DBESS in a SimSEE Region, thus representing the set of small energy storage systems, distributed in the different Buses (of the real network) associated with the represented SimSEE Region.

The resolution of the dispatch at each time step using SimSEE poses an optimization problem that is solved collaboratively between the different Actors (generators, demands, interconnectors, etc.) including the instances of the DBESS model that is the object of this work. At the beginning of the resolution, the Actors are required to add their energy offers and prices to the dispatch problem that will be solved centrally. After the dispatch is resolved (hour by hour of the programming/simulation horizon), the Actors are given the opportunity to request a new iteration. For example, hydroelectric plants present their offers based on an energy coefficient that they calculate assuming a disbursed flow. If once the dispatch is resolved the disbursed flow differs substantially from the assumption, they will require a new iteration (resolution round).

In the resolution of each time step, iterations are performed in the resolution of the dispatch of each Region. In the first iteration, the Net Demand (ND, for a definition of see [11]) is known, but there is still no information on the marginal cost ( $cmg_h$ ) of the hours of the time step. In this first iteration, the DBESS does not intervene in the dispatch and thus the marginal cost of generation in each hour of the time step is obtained. For the second iteration, once the $cmg_h$ is known, the

$$\max_{G_h, D_h, B_h} \sum_{h=1}^{h=N} (G_h cmg_h - D_h cmg_h) + B_n vfe - \alpha (G_h + D_h)$$

$$@\left| \begin{array}{l} B_h = \rho B_{h-1} - \frac{1}{\eta_G} G_h + \eta_D D_h \\ B_{hLB} \leq B_h \leq B_{hUB} \\ G_{hLB} \leq G_h \leq G_{hUB} \\ G_{hLB} \leq D_h \leq D_{hUB} \end{array} \right. \quad (1)$$

DBESS solves the optimization problem (1).

Where:

- $h = 1, 2, \ldots N$ identify the hour inside the time-step,
- $B_h$ is the amount of energy stored at the end of the hour $h$ .
- $G_h$ It is the power injected by the DBESS to the NIS, acting as a generator and reducing the amount of stored energy.
- $D_h$ It is the power extracted from the DBESS from the NIS, acting as a demand and increasing the amount of stored energy.
- $B_{hLB}$ , $G_{hLB}$ and $D_{hLB}$ are the minimum storage capacity and the minimum powers as a generator and as a demand at $h$ .
- $B_{hUB}$ , $G_{hUB}$ and $D_{hUB}$ are the maximum storage capacity and the maximum powers as a generator and as a demand at $h$ .
- $\rho$ is the factor that takes into consideration the battery losses in one hour.
- $\eta_G$ and $\eta_D$ are the charge and discharge performance of the battery banks.
- $cmg_h$ is the marginal cost seen by the DBESS, and represents the cost or savings for the NIS of extracting or injecting an additional MW in that hour by the DBESS.
- $\alpha$ is the variable cost associated with the passage of power through the DBESS. In the case where the storage is a battery bank, this factor can be directly associated with the degradation of the battery due to its use.
- $vfe$ is the future value of the stored energy. This value must be set for the resolution of the problem (1). Different strategies can be used, such as setting that value equal to the $vfe = cmg_1$ , which would imply assuming that the next time step is expected to start with a marginal cost equal to the current one, or considering that the stored energy is worth the average of the marginal costs of the step. $vfe = \frac{1}{N} \sum_h cmg_h$ . Or more sophisticated strategies, such as including $B_1$ (energy at the start of the time step) as another state variable of the SIN and allow to form an Operation Policy valuing it, or to build a stochastic model that represents the expected distribution of $cmg_1, cmg_2, \ldots cmg_N$ of the next step knowing that of the current step and based on it create an operation policy of the DBESS valuing the value of $B_1$ .

### *A. Iterations in the resolution of the dispatch of a time step*

In this way, based on the hourly marginal costs of the previous iteration, the powers injected or extracted in each hour of the NIS that maximize the benefit are defined, charging the battery in the hours of lowest cost and discharging in the highest cost hours. With this decision of hourly injections and extractions, the dispatch problem is raised again and the variation of the marginal costs caused by the operation of the DBESS is calculated and with the new series of hourly marginal costs, the iteration is started again.

In each iteration, the new hourly values of $G_h$ and $D_h$ are obtained based on the hourly values of the marginal cost $cmg_h$ of the previous iteration by solving the optimization problem (1) and re-posing and solving the time step dispatch problem (standard SimSEE algorithm) in which the series of contributions $G_h$ and withdrawals $D_h$ by the DBESS are considered.

Generally, $B_{hLB}$ and $B_{hUB}$ , limits of the battery capacity, will be constant over the ours of the same time-step. They vary over the simulation horizon due to accidental breakage, degradation, decommissioning or installation of new battery banks.

The $G_{hLB}$ , $G_{hUB}$ , $D_{hLB}$ and $D_{hUB}$ power limits of the DBESS, as well as the capacity limits, are subject throughout the simulation horizon to the random and scheduled availability and installation or decommissioning of the DBESS units. But also, as explained in the next section, their values during the hours of the time step under resolution are modified to ensure the convergence of the iterations.

### *B. Controlling convergence*

As mentioned before, the proposed algorithm implies that the DBESSs of each region request that the dispatch resolution be iterated. They do not participate in the first iteration from which they take the information on hourly marginal costs and offer for the second iteration the result of $G_h$ and $D_h$ from the solution of problem (1).

To control the convergence of this loop of iterations, the limits of the boxes of the variables $G_h$ and $D_h$ are adjusted in a dichotomous way.

Note that since (1) is a linear optimization problem, its solution is on the border of the polyhedron that defines the domain of said problem. Note also that the domain is formed by the box-restrictions of the optimization variables plus an equality restriction that takes into account the loading and unloading dynamics during the hours of the step. It is therefore to be expected that given a marginal cost hourly-sequence, the solution of (1) will try to maximise the purchase of energy in the hours of low marginal costs and maximise the sale in the hours of high marginal costs, reaching, if possible, the limits of the box of the respective variables in each hour. After the resolution of each iteration in which the DBESS participates, the marginal costs of the system may change, associated with the action of the DBESS themselves, increasing in the hours of greatest extraction and decreasing in those of greatest injection. These changes are expected if the magnitude of the extractions and injections produces changes in the generators that marginalise in the resolution of the dispatch.

In order to control that in the successive iterations for the resolution of the same time step no oscillations occur, a modification is made at the beginning of each iteration of the limits of the power boxes in order to bring the non-active limit closer to the active limit, dividing the interval of the box in half.

Assuming that the cost curve of the entire system is convex, with respect to power injections and extractions, it can be demonstrated that the described power adjustment mechanism leads the global optimization problem (SimSEE + DBESS iterations) to the optimum. It is not worth going into this demonstration in depth, since real systems, although from a global perspective have this convexity (the greater the extraction, the higher the production costs) in the hourly dispatch, the effect on the efficiency of partial loads of the thermal power plants, makes this hypothesis (when the cost function is examined with a magnifying glass) present non-convex sections. For this reason we say that the proposed solution is optimal-operable, since in mathematical purism the true-optimal could be in some dispatches somewhat different from the optimal-operable obtained.

## 4. Test case and results

As a first test case, the Colombian five DBESS system model of 40 MWh and with charging and discharging powers of 10 MW was incorporated. As a starting model for Colombia for SimSEE, the one available at: https://sourceforge.net/projects/simsee/files/Modelo_Colombia/ was used.

A new operating policy was obtained, using the SimSEE reinforcement learning facility, on the set of hydroelectric plants having reservoirs, without and with the DBESS added according to the proposed model. Then, simulations of 1000 realizations of the stochastic processes of both systems were carried out and the expected reduction in the system cost due to the inclusion of the DBESS was calculated.

Table I shows the valuation of the DBESS, in each of the five modelled regions, calculated as the expected reduction in the operating cost of the system and distributed by the marginal contribution of each DBESS to it.

As can be seen from Table I, in this case, there are no significant differences between the valuation of the different regions, which would indicate that they are sufficiently well interconnected so that the location of the DBESS is not very relevant. Surely, as the system grows and the incorporation of renewables also grows, if the transport capacity between the regions is not expanded, differences will appear.

Table I: Valuation of a 40 MWh battery bank with 10 MW charging and discharging power. (9% discount rate and 10-year life)

| | Oriental | Suroccident | Nordeste | Caribe | Antioquia |
|---|---|---|---|---|---|
| | [US$/kW] | [US$/kW] | [US$/kW] | [US$/kW] | [US$/kW] |
| 2024 | 112 | 112 | 111 | 112 | 114 |
| 2025 | 129 | 132 | 130 | 131 | 134 |
| 2026 | 154 | 150 | 148 | 150 | 151 |
| 2027 | 96 | 96 | 94 | 95 | 96 |
| 2028 | 87 | 87 | 86 | 87 | 88 |
| 2029 | 95 | 96 | 94 | 96 | 96 |
| 2030 | 97 | 98 | 96 | 98 | 99 |
| 2031 | 96 | 96 | 94 | 96 | 97 |
| 2032 | 101 | 102 | 100 | 102 | 102 |
| 2033 | 118 | 119 | 117 | 119 | 120 |
| 2034 | 131 | 132 | 130 | 132 | 133 |
| 2035 | 144 | 146 | 143 | 145 | 147 |
| 2036 | 175 | 177 | 173 | 176 | 177 |
| 2037 | 188 | 190 | 187 | 190 | 191 |
| 2038 | 223 | 226 | 222 | 225 | 227 |
| 2039 | 255 | 258 | 253 | 257 | 259 |

According to the IEA report [12] the value of the cost of battery banks will drop from approximately 250 USD/kWh in 2025 to approximately 150 USD/kWh by 2040, which would imply, according to the results in Table I, that if only the benefits of reduced dispatch costs are considered, their installation would be justified in the Colombian system from approximately 2034.

## 5. Conclusion and future work

The proposed algorithm was implemented in SimSEE and the test case was executed without a significant increase in the calculation time. Possibly the iterations imposed by the DBESS overlap those already requested by the hydraulic generators or other actors in the system.

The work [13], concludes that none of the Approximate Stochastic Dynamic Programming algorithms they tested satisfactorily fulfills the task of solving problems with many distributed energy storages. Perhaps the crux of the matter is to separate the state variables associated with processes slower than the dispatch scheduling step from those associated with faster processes (including the state of the battery banks). The Approximate Operation Policy is learned on the slow variables, considered as state variables of the system. On the other hand, at each time step, the use of the fast variables is optimized, within the hours of the time step as proposed in this work.

As a future work, it could be attempted that problem (1) involves considering an estimation of the nodal marginal costs of the real electrical network within the DBESS area. This would imply increasing the complexity of solving (1) without increasing the complexity of solving the global dispatch. This possible improvement would allow a better assessment of the contribution of the battery banks installed in the sub-transmission and distribution network bars, while maintaining the possibility of taking into consideration their contribution to the energy dispatch of the region (market node). Something similar to what was proposed in [14] but implemented in direct connection with an energy dispatch programming tool such as SimSEE and allowing the aggregation of distributed batteries via DBESS

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