Energy Management of a Battery Storage System Considering Variable Load and Controllable Renewable Generation (Solar Study Case) to Keep the Grid's Frequency Stability

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Abstract: - This paper presents the research of analytical functions related to the energy generation of photovoltaic systems and the residential and commercial load demanded by end users, concerning a statistical function. To test this model, a linear cost function was considered to compute its overestimation and underestimation due to its maximum and minimum production limits, where energy consumption is obtained at each instant of time, within the established production ranges, through the analytical equations that determine solar energy generation and demand load. The result obtained by applying the Uncertainty Quantification (UCF) theory in these equations, in the same way through the Monte Carlo (MC) simulation for comparison, is the expected value of energy for a hypothetical storage system E (C_u, C_o). Better accuracy of results via this model can be improved upon when the energy generation parameters are structured as analytical functions each instant of time associated with probability distributions based on the uncertainty costs of controllable sources, instead of statistical functions.

Key-Words: - energy management, frequency, mathematical modeling, Montecarlo simulation, overestimation cost, solar photovoltaic, Uncertainty Cost Function, underestimation cost.

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1 Introduction

The main objective of energy management is to ensure the safe, reliable, and efficient operation of power systems. Reducing peak demand where there is greater consumption by end users is one of several approaches that contribute to the stabilization of a system. Another method is the production of energy through renewable sources in microgrids, as they provide a means to stabilize the grid's frequency, [1].

Microgrids are defined as a group of distributed loads and generators that operate as a controllable unit that provides power to its area either in isolation or connected to the conventional power network, [2], In paper [3], a comprehensive review of the current status of microgrids is presented, which discusses design trends, challenges and research efforts towards their implementation in power systems.

Energy generation in microgrids depends on the stochastic behavior of the renewable sources that comprise them, which might affect various parameters, including frequency. To address the issue of frequency deviation in microgrid control, various control strategies and methods have been proposed in recent research. For instance, the authors in [4], introduce a fractional order proportional-integral-derivative (FOPID) controller for islanded microgrids using intelligent optimization algorithms, which demonstrated effective frequency control. Additionally, in [5], the necessity of load shedding control schemes to maintain power balance and frequency stability in islanded microgrids is emphasized.

Frequency stability refers to the system's ability to maintain a constant nominal electrical frequency within acceptable limits, even in the face of disturbances or changes in load. To maintain system stability regarding frequency, it is fundamental to balance energy supply (generation) and demand in real time, [6].

In this context, the authors in [7], present Uncertainty Cost Functions (UCF) to model and evaluate stochasticity in power systems with high penetration of renewable energy sources, where the functions of uncertainty costs have analytically calculated minimum cost values and the marginal derived cost functions (MUCF) can be used as inputs for economic dispatch and optimal power flow (OPF) calculations, which support frequency stability.

Related research focusing on the OPF problem formulation has considered restrictions dealing with the secure operation of power systems in order to keep a balance between generation and demand in post-contingency states, [8], [9]. Specifically, the methodology to solve a probabilistic Security-Constrained Optimal Power Flow (SCOPF) to assess *N-k* contingencies is detailed in [8]. In [9], an iterative algorithm for solving realistic SCOPF problems in large-scale power systems is presented and its main features are discussed, i.e., consideration of nonlinear AC network models in both pre-contingency and post-contingency states, and optimization of active/reactive power flows jointly.

The before mentioned contingency analyses have an application in the framework of short-term asset management, also known as real-time asset management, [10], [11]. This is a detailed assessment of the possible impacts an unexpected outage might have on a certain asset's condition and performance. Its results support grid operators in the decision-making process concerning the definition of post-contingency states.

As the participation of renewable energy sources (e.g., solar and wind) in the generation mix of power systems has increased steadily in the last years, different approaches have been proposed to update the formulation of OPF problems. One such proposal is the adaptive geometry estimation-based multi-objective differential evolution (AGE-MODE) method for multi-objective OPF in hybrid power systems, which considers the stochastic behavior of solar photovoltaic (PV) and wind through probability distribution functions to compute direct costs, penalty costs for underestimation, and reserve costs for overestimation, [12].

Regarding the costs (i.e., under- and overestimation costs) associated with the intermittency and variability over time of generation based on renewable energy sources, different papers have analyzed the potential of UCF to enhance the mathematical formulation of OPF problems. For example, the authors in [13], propose the application of UCF in the economic dispatch of power systems with a penetration of small hydroelectric plants (SHPs). To this end, the analytical development of the UCF based on the power injected by a SHP is presented, as well as the validation procedure of the computed under- and overestimation costs via a Monte Carlo (MC) simulation.

Similar research has developed UCF for the power consumed by electric vehicles and the power output of solar PV and wind plants, [14], [15]. The detailed mathematical approach to compute the under- and overestimation costs was also validated using a MC simulation.

As it has been explained, different studies have analyzed the enhancement of OPF problems and, particularly, the ability of UCF to model the stochastic behavior inherent to the power output of renewable energy sources as a means to improve the formulation of the before mentioned problems. However, for the authors' best knowledge, any of these studies have analyzed the potential of UCF to support the frequency control of power systems in a context of increased solar PV generation.

For this reason, this article introduces the use of UCF to estimate an expected energy value that should be stored or released in a Battery Storage System (BSS) to control the stability of the grid's frequency. This methodology has two parts, i.e., an analytical development to calculate the expected energy value and a MC simulation. The obtained quantities are compared and the percentage error is computed to validate the accuracy of the analytical proposed UCF.

The structure of the remaining part of the paper is as follows: section 2 explains the selected methodology; section 3 covers the data analysis, study case, and application of results; and section 4 deals with the discussion of results and concluding remarks.

2 Problem Formulation

Renewable energy sources like wind and solar exhibit variable behaviors due to their dependence on weather conditions. This variability can lead to fluctuations in electrical grid frequency, causing instability and equipment damage. Frequency variation, $\Delta f(t)$, is linked to the power system's demand and generation, $D(t)$ and $G(t)$, respectively, as indicated by the following equation:

$$D(t) - G(t) = K\Delta f(t), \tag{1}$$

where K is a constant that represents the power system's inertia. If an ideal power system is considered, i.e., losses in conductors are not disregarded, the total demand must match the output of all available generators at each time instant. This ensures a stable frequency, i.e., $\Delta f(t) = 0$, and Equation 2 is obtained if it is assumed the generation of electrical energy is provided just by solar PV, $G_{sun}(t)$, and wind plants, $G_{wind}(t)$.

$$D(t) = G_{sun}(t) + G_{wind}(t) \tag{2}$$

As it is mentioned previously, renewable energy sources have a stochastic or variable output and a Battery Storage System (BSS) is required to ensure frequency stability. The amount of electrical energy (E_b) that should be stored or released from the BSS within a time range (t_1, t_2) is computed by solving Equation 3.

$$E_b = \int_{t_1}^{t_2} [D(t) - G_{sun}(t) - G_{wind}(t)]\, dt \tag{3}$$

The proposed methodology requires an analytical function with sinusoidal behavior that represents the energy output of a PV-system as a function of time, referenced to the time of sunrise (t_{rise}) and sunset (t_{set}) during the day. Another function represents the power demanded by a residential and industrial load, considering the before mentioned time variables and a change concerning the peak demand during the morning and afternoon. The energy in MWh for both functions could be determined calculating the area below the curve, i.e., calculating the integral.

2.1 Power Supplied by a PV-Plant as a Function of Time

The daily power output of a PV-plant as a function of time can be expressed analytically as:

$$P(t) = P_s * sin^2\left(\frac{\pi(t - t_{rise})}{t_{set} - t_{rise}}\right) \tag{4}$$

where the variation in the intensity of sunlight is modeled during the period between t_{rise} and t_{set}. The equation follows the radiation curve, which is modeled as a sinusoidal function, having some variation during the day. This variation for practical purposes and for the development of the paper, a P_{max} and P_{min} will be analyzed, reaching their maximum powers around noon and being minimum at dawn and dusk, respectively, in their established ranges.

$$P_{max}(t) = P_{max} * sin^2\left(\frac{\pi\left(t - t_{rise\_max}\right)}{t_{set\_max} - t_{rise\_max}}\right) \tag{5}$$

$$P_{min}(t) = P_{min} * sin^2\left(\frac{\pi\left(t - t_{rise\_min}\right)}{t_{set\_min} - t_{rise\_min}}\right) \tag{6}$$

These functions are normalized so that the power of each function varies from 0 to a maximum within allowable ranges. The power generated by a solar panel or solar system depends on many factors, such as geographical location, panel inclination, weather conditions, among others. However, for this analysis it was simplified by providing random values.

2.2 Power Required by the Selected Load as a Function of Time

The power demanded in a residential or industrial load can vary throughout the day, and its load profile typically follows predictable patterns. The analytical expression of the power demanded as a function of time is represented as:

$$P_D(t) = P_{peak\_to} * sin\left(\frac{2\pi\left(t - t_{start\_to}\right)}{t_{end\_to} - t_{start\_to}}\right) + P_{peak\_af} * sin\left(\frac{2\pi\left(t - t_{start\_af}\right)}{t_{end\_af} - t_{start\_af}}\right) \tag{7}$$

This function considers a daily variation with different patterns during the day, where the equation models the electrical demand with a constant base component and two sinusoidal components that represent the demand peaks in the morning and afternoon. It is necessary to adjust the parameters of the equation depending on the specific consumption patterns of the residential or industrial load being modeled.

2.3 Uncertainty Quantification

The mathematical development obtained using the uncertainty quantification theory, considering in each time instant D and G_{sun}, which have associated some probability distributions, would provide an expected value of E.

$$E[C_u(P)] = \frac{C_u}{P_{max} - P_{min}}\left(\frac{P_s^2}{2} - P_s P_{max} + \frac{P_{max}^2}{2}\right) \tag{8}$$

$$E[C_o(P)] = \frac{C_o}{P_{max} - P_{min}}\left(\frac{P_s^2}{2} - P_s P_{min} + \frac{P_{min}^2}{2}\right) \tag{9}$$

The previous results make it possible to calculate the expected uncertainty cost function (UCF), which describes a remarkable quadratic pattern, something useful for conventional economic dispatch software.

$$E[UCF] = E[C_u(P)] + E[C_o(P)] \tag{10}$$

The uncertainty cost can be modeled as a function of time performing simple calculations.

3 Study Case and Simulations

3.1 Monte Carlo simulation

Monte Carlo (MC) simulation uses random sampling and statistical modeling to estimate mathematical functions and mimic the operations of complex systems. When applied in physical models, this method generates data from fixed probability distribution functions of stochastic variables such as solar irradiance, customer demands, etc., [16], [17], and it has gained widespread acceptance to validate their accuracy, [15], [18].

For this reason, this research considers MC simulation to study the behavior of overestimation and underestimation instances for a predetermined power value (P_s), within a set of power values uniformly distributed over a 24-hour range. The test values initially set for analysis were the variables P_s (average power), P_{max} (maximum power), and P_{min} (minimum power) at 100, 110, and 90 watts, respectively. The uncertainty costs of underestimation and overestimation were adopted from reference [4], with C_u=300 and C_o=700 values, respectively.

Equations 4, 5, and 6 represent the demanded powers of a residential or industrial load, wherein the sunrise time (t_{rise}) was considered at 6 AM, while the sunset time (t_{set}) was taken as 6 PM. These values were considered for practical purposes; however, they can be analytically obtained by considering various factors such as incidence angle, extraterrestrial radiation, climate type, solar declination, among others. Figure 1 illustrates the power values derived from Equations 4, 5, and 6 concerning the predetermined time.

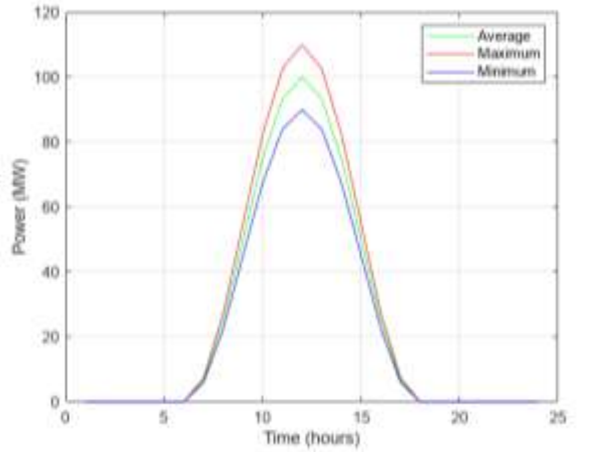


Fig. 1: Solar power

Equation 11 will generate random values within the interval (P_{min}, P_{max}) following a uniform distribution.

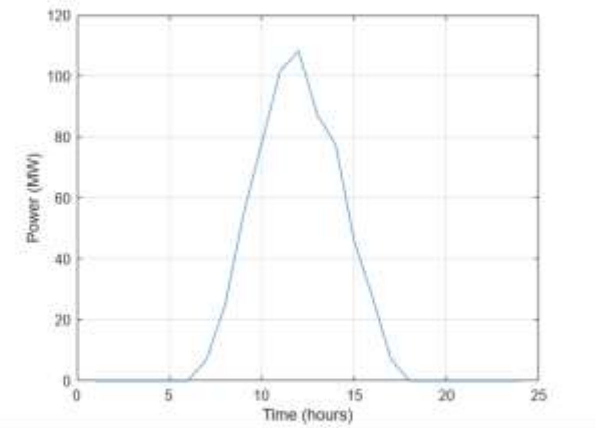
$$P(random) = P_{min} + (P_{max} - P_{min}) * rand() \tag{11}$$

The outcome will establish values within the generated scenarios (N=1000) for the Overestimation Cost (C_o) and Underestimation Cost (C_u), depending on the average power value (P_s), as depicted in Figure 2.

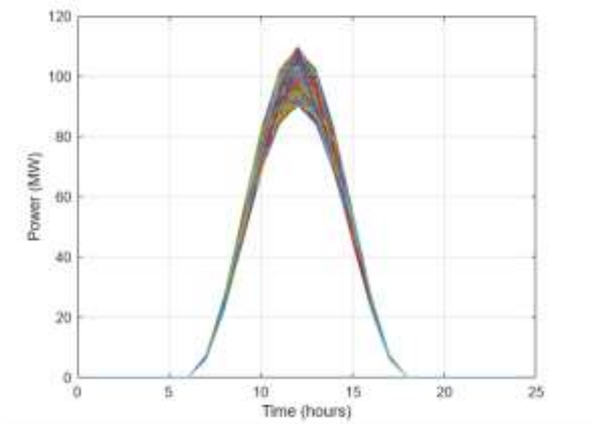
$$E[C_{o,i}(P_{s,i}, P_{r,i})] = C_{o,i} * (P_{s,i} - P_{r,i}) \tag{12}$$

$$E[C_{u,i}(P_{s,i}, P_{r,i})] = C_{u,i} * (P_{r,i} - P_{s,i}) \tag{13}$$

Following an elapsed simulation time of approximately 0.18 seconds, multiple statistical parameters were obtained.



a)



b)

Fig. 2: Behavioral curve of solar generation throughout the day, including: a) random scenario of solar generation and b) Monte Carlo simulation curves in scenarios with maximum and minimum values.

The histogram in Figure 3 represents the sum of all generated powers across the N scenarios, exhibiting a high frequency around 600 MW. The estimated energy output resulted in 599.82 MWh.

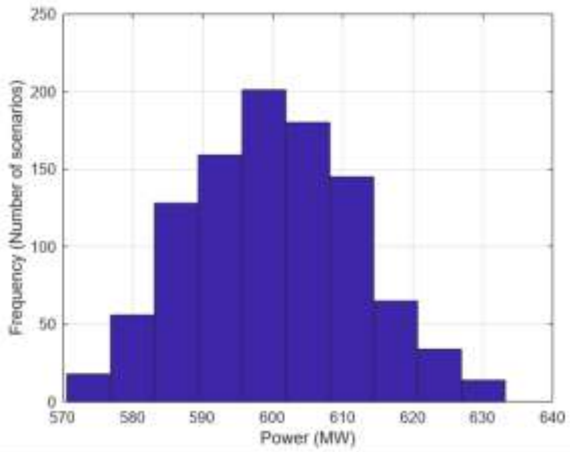


Fig. 3: Expected energy from MC scenarios

3.2 Uncertainty Cost Functions

MC simulation was employed to derive underestimation and overestimation penalty values for the Uncertainty Cost (UC) of photovoltaic generation at a specific time instance. Under a uniform distribution model, the validation for the Uncertainty Cost Function (UCF) was presented and compared favorably with MC simulation, showcasing minimal error.

$$UCF_{PAH} = \frac{C_u\,(\sigma_1) + C_o\,(\sigma_2)}{(P_{max,i} - P_{min,i})}$$

where,

$$\sigma_1 = \frac{{P_{s,i}}^2}{2} - P_{s.i}P_{max,i} + \frac{{P_{max,i}}^2}{2} \tag{14}$$

$$\sigma_2 = \frac{{P_{s,i}}^2}{2} - P_{s.i}P_{min,i} + \frac{{P_{min,i}}^2}{2}$$

The average of the sum of $E[C_{u,i}, C_{o,i}\,(P_{s,i}, P_{r,i})]$ and the result from the Analytical Hourly Uncertainty Cost Function (UCF_{PAH}) in Equation 14 is illustrated in Table 1, demonstrating minimal error percentage.

Table 1. Comparison of results between the analytical method and the Montecarlo method

Time (Hour)	UCF $_{MEAN}$ (MW/\$)	UCF$_{PAH}$ (MW/\$)	%error
7	0.1725	0.1674	0.2953
8	0.6165	0.6250	0.1367
9	1.2657	1.2499	0.1246
10	1.8341	1.8749	0.2228
11	2.4129	2.3325	0.3331
12	2.5283	2.5000	0.1121
13	2.4040	2.3325	0.2974
14	1.8958	1.8750	0.1102
15	1.2838	1.2500	0.2640
16	0.6149	0.6250	0.1632
17	0.1673	0.1674	0.0045

Given text already adheres to the principles. Considering that it is photovoltaic solar generation, the other hours of the series have a value of zero.

On the other hand, the variable k is associated with the uncertainty cost function, either hourly estimated costs or analytical hourly costs, within the 24-hour time range.

$$K_{PAH} = \frac{P_{s,i}}{UCF_{PAH}} \tag{15}$$

The average $K_{PAHprom}$, shown in Figure 4, serves as a link for MWh energy estimation in an analytical model, affirming its similarity. It is noteworthy that only non-zero values are taken into consideration.

$$K_{PAH_{prom}} = mean\left(K_{PAH}(7:17)\right) = 0.04\ (MW/\$) \tag{16}$$

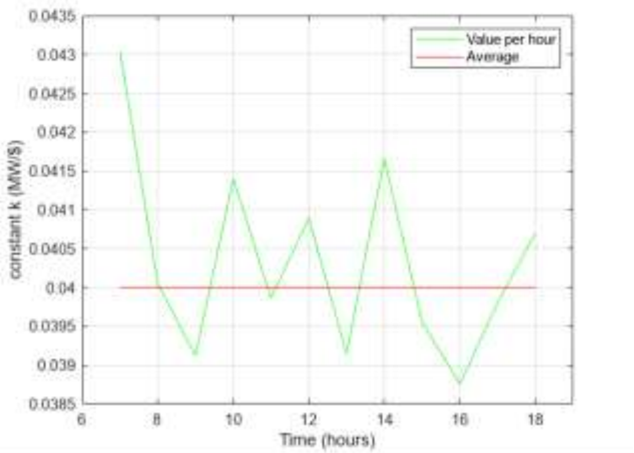


Fig. 4: Constant $K_{PAHprom}$

Figure 5 shows the values from Table 1, comparing the analytical and Monte Carlo methods graphically, with a minimum error observed.

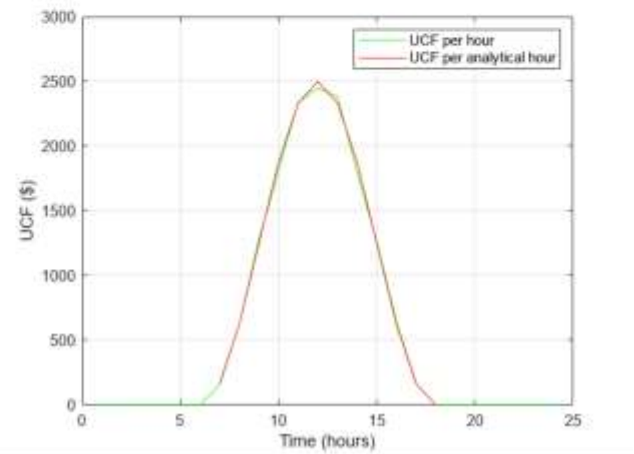


Fig. 5: Comparison of UCF, analytical and Monte Carlo simulation

3.3 Analytical Method

An analytical method represents a systematic approach employed to comprehend, explain, or solve problems by utilizing analysis, logical reasoning, and, often, mathematical formulas or existing theories. It is characterized by its emphasis on breaking down a problem into smaller, more manageable parts for detailed examination. These methods enable the dissection of complex issues into simpler components, facilitating their comprehension and resolution.

The necessity of providing a model for load and generation with variability in behavior becomes evident when estimating costs. Therefore, an analytical proposal will be developed to estimate the energy in MWh that the photovoltaic system will produce over 24 hours.

For a linear function representing the cost of underestimation penalty, determining the corresponding expected penalty cost function can be achieved as follows:

$$E[C_u(P)] = \frac{C_u\ (\sigma_3)}{P_{max,i}\ \sigma_5 - P_{min,i}\ \sigma_5}$$

where,

$$\sigma_3 = \frac{{P_{max,i}}^2 * \sigma_4}{2} - P_{s.i}\ P_{max,i}\sigma_4 + \frac{{P_{s,i}}^2\sigma_4}{2} \tag{17}$$

$$\sigma_4 = sin\left(\frac{\pi\ (t - t_{rise})}{t_{rise} - t_{set}}\right)^4$$

$$\sigma_5 = sin\left(\frac{\pi\ (t - t_{rise})}{t_{rise} - t_{set}}\right)^2$$

To obtain the energy produced over time, the function is integrated to find the area under the curve within the established range (6, 18), denoting sunrise and sunset hours.

$$E[C_u(P(t))] = \int_6^{18} \frac{C_u\ (\sigma_3)}{P_{max,i}\ \sigma_4 - P_{min,i}\ \sigma_5} \tag{18}$$

$$E[C_u(P(t))] = \frac{C_u(P_{max,i} - P_s)^2(\sigma_6 - \sigma_7 + 6)}{2\left(P_{max,i} - P_{min,i}\right)}$$

where,

$$\sigma_6 = \frac{sin\left(\frac{2\pi\ (t-18)}{t_{rise} - t_{set}}\right)(t_{rise} - t_{set})}{4\pi} \tag{19}$$

$$\sigma_7 = \frac{sin\left(\frac{2\pi\ (t-6)}{t_{rise} - t_{set}}\right)(t_{rise} - t_{set})}{4\pi}$$

Similarly, the expected cost function for overestimation with $E[C_o(P)]$ can be derived:

$$E[C_o(P)] = \frac{C_o\ (\sigma_8)}{P_{max,i}\ \sigma_{10} - P_{min,i}\ \sigma_{10}}$$

where,

$$\sigma_8 = \frac{{P_{min,i}}^2 * \sigma_9}{2} - P_{s.i}\ P_{min,i}\sigma_9 + \frac{{P_{s,i}}^2\sigma_9}{2} \tag{20}$$

$$\sigma_9 = sin\left(\frac{\pi\ (t - t_{rise})}{t_{rise} - t_{set}}\right)^4$$

$$\sigma_{10} = sin\left(\frac{\pi\ (t - t_{rise})}{t_{rise} - t_{set}}\right)^2$$

$$E[C_u(P(t))] = \int_6^{18} \frac{C_u\ (\sigma_8)}{P_{max,i}\ \sigma_{10} - P_{min,i}\ \sigma_{10}} \tag{21}$$

$$E[C_u(P(t))] = \frac{C_u(P_{min,i} - P_s)^2(\sigma_{11} - \sigma_{12} + 6)}{2(P_{max,i} - P_{min,i})}$$

where,

$$\sigma_{11} = \frac{sin\left(\frac{2\pi\ (t-18)}{t_{rise} - t_{set}}\right)(t_{rise} - t_{set})}{4\pi} \tag{22}$$

$$\sigma_{12} = \frac{sin\left(\frac{2\pi\ (t-6)}{t_{rise} - t_{set}}\right)(t_{rise} - t_{set})}{4\pi}$$

The results enable the calculation of the expected UCF for both overestimation and underestimation, whose outcome, multiplied by the variable K_{prom} obtained from Monte Carlo simulation, allows us to calculate the energy in MWh. The result from the analytical function is 600 MWh, which is like the result obtained with the Monte Carlo simulation 599.85 MWh.

4 Discussion of Results and Conclusion

The results of the previous sections, where the Monte Carlo simulations and the analytical results shown in Table 1 clearly show that the results are equivalent with estimation errors of less than 0.34%, demonstrating the possibility of using the analytical method for energy estimation.

This result makes it possible to consider the implementation of algorithms for calculating energy to manage storage in batteries in scenarios where there are variable loads.

On the contrary, regarding the estimation of variable $K_{PAHprom}$ that relates to the cost function of uncertainty, forthcoming research could explore the use of a polynomial function approximation capable of capturing changes in uncertainty magnitude in difference time instances.

Among the conclusions, the following are highlighted:

- The analytical equations for estimating the energy in loads and in solar photovoltaic generation are equivalent to the log-normal statistical function considered.
- The finding of equivalence makes it possible to apply this new method for energy management in hybrid systems where there is solar generation and batteries for storage.
- The initial hypothesis about the possibility of maintaining the frequency from the energy equivalence is fulfilled, leading to improvements in the response of the algorithms.

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