



MODULAR APPROACH FOR THE OPTIMIZATION OF DISTRIBUTION NETWORKS WITH DYNAMIC RECONFIGURATION AND BESS OPERATION WITH STATIC NETWORK RECONFIGURATION UNDER RENEWABLE GENERATION VARIABILITY

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ABSTRACT

This work presents a modular approach for the optimization of distribution networks through Dynamic Reconfiguration (DR) and the static operation of Battery Energy Storage Systems (BESS), considering the variability of Distributed Generation (DG) from solar and wind sources. The methodology combines the Differential Evolution (DE) metaheuristic for DR and optimization models in AMPL, solved by KNITRO, for the static operation of BESS. The main objective is to minimize technical losses, mitigate reverse power flow, improve voltage profiles, and manage DG injection over a 24-hour operation horizon. Tests conducted on a 33-bus system demonstrated that the modular integration of DR and BESS significantly contributes to the modernization and resilience of distribution networks, especially in scenarios with high penetration of renewable energy sources. The results show that both the isolated application and the combined use of these strategies are effective in promoting a safer, more efficient, and sustainable energy transition.

Palavras-chave: Battery Energy Storage Systems; Renewable Energy; Distribution Network Reconfiguration; Losses; Slack

1 INTRODUCTION

The increasing penetration of intermittent renewable sources, such as photovoltaic solar and wind energy, has challenged the traditional operation of electrical distribution systems (Lund et al., 2015; IRENA, 2024). The variable and uncertain nature of these sources affects the network's stability, predictability, and efficiency, requiring advanced solutions that provide greater flexibility and operational intelligence (Siano, 2014). In this context, two approaches stand out as promising: Dynamic Distribution Network Reconfiguration (DNR), which involves real-time topological changes in the network through the opening and closing of switches (Civanlar et al., 1988; Baran & Wu, 1989), and Battery Energy Storage Systems (BESS), which enable the compensation of generation and demand fluctuations over time, promoting local energy balance (Gomes(a) et al., 2023). While many studies address these solutions in isolation, the modular approach proposed in this work aims to integrate them complementarily, allowing greater adaptability to the dynamic conditions imposed by renewable generation. The modularity enables the analysis, implementation, and expansion of each component, dynamic DNR, BESS, and control, independently yet in a coordinated manner (Gomes(b) et al., 2023) and Gomes(c) et al., 2021).

Thus, this study proposes a methodology for optimizing distribution network operation that combines DNR with static BESS integration, aiming to minimize technical losses, improve voltage profiles, manage distributed generation, and enhance system resilience under different renewable generation scenarios.



2. APPROACHES USED

In this work, metaheuristic approaches are employed to solve the DR problem. The main technique used was Differential Evolution (DE). However, to evaluate its relative performance and explore alternatives for improving convergence, PSO and GWO techniques were also implemented for comparison purposes.

2.1 Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a metaheuristic algorithm inspired by the social behavior and hunting hierarchy of grey wolves in nature. Proposed by Mirjalili et al. (2014), GWO models the social roles of alpha, beta, delta, and omega wolves to guide the search toward optimal solutions, balancing exploration and exploitation of the objective function. Its simplicity, efficient convergence, and ability to avoid local minima make it suitable for complex optimization problems, such as distribution network reconfiguration studies.

2.2 Differential Evolution Algorithm

Differential Evolution (DE) is a population-based metaheuristic optimization technique that relies on simple mutation, crossover, and selection operations, widely used for solving complex and nonlinear problems (Storn & Price, 1997). DE stands out for its efficiency, ease of implementation, and ability to quickly converge toward near-global optimal solutions (Das & Suganthan, 2011). Its core feature is the generation of new candidate solutions through the combination of differential vectors, promoting a balance between exploration and exploitation in the search process. Table 1 presents the ten mutation and crossover strategies of the DE algorithm employed and tested in this study. After a comparative evaluation, the strategy that demonstrated the best performance was adapted specifically to the problem under analysis, ensuring higher solution quality and faster convergence.

Table 1 – Mutation and Crossover Strategies in Differential Evolution

Strategy	Mutation	Explanatory Notation
S1	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)})$	DE/rand/1/bin
S2	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)})$	DE/rand/1/exp
S3	$V^{(q+1)} = X_{best}^{(q)} + F(X_b^{(q)} - X_c^{(q)})$	DE/best/1/bin
S4	$V^{(q+1)} = X_{best}^{(q)} + F(X_b^{(q)} - X_c^{(q)})$	DE/rand/1/exp
S5	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)})$	DE/rand/2/bin
S6	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)})$	DE/rand/2/exp
S7	$V^{(q+1)} = X_{best}^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)})$	DE/best/2/bin
S8	$V^{(q+1)} = X_{best}^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)})$	DE/best/2/exp
S9	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)}) + F(X_f^{(q)} - X_g^{(q)})$	DE/best/3/bin
S10	$V^{(q+1)} = X_a^{(q)} + F(X_b^{(q)} - X_c^{(q)}) + F(X_d^{(q)} - X_e^{(q)}) + F(X_f^{(q)} - X_g^{(q)})$	DE/best/3/exp



2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a method inspired by the collective behavior of swarms, such as fish schools or bird flocks, developed by Kennedy and Eberhart (1995). In PSO, particles represent candidate solutions that adjust their positions in the search space based on their own experience and that of their neighbors, promoting convergence toward local and global optima. Due to its simplicity and efficiency, PSO is widely applied to both continuous and combinatorial optimization problems, including electric power network reconfiguration.

3 PROPOSED SOLUTION METHODOLOGY

This section provides a detailed description of the methods, mathematical models, and computational procedures used to solve the proposed problem. The adopted approach combines DNR with the integration of BESS, taking into account the variability of renewable generation. The main objective of the methodology is to minimize technical losses and/or operational costs, manage DGs effectively, and ensure the safe and efficient operation of the system.

$$\min \sum_{(i,j) \in \Omega_i} R_{ij} I_{ij}^2 \quad (1)$$

Where I_{ij}^2 is the current in branch (i,j) , which depends on the active and reactive powers of the network, affected both by the RRD topology and by the operation of the BESS. The following constraints apply.

3.1 Power Flow

The power flow equations describe the balance of active and reactive power at each bus in the distribution network. For any bus i , the active power balance is given by Eq. (2)

$$P_i^G + P_i^{BESS} - P_i^D = \sum_{j \in \Omega_i} P_{ij} \quad (2)$$

And the reactive power balance is given by Eq. (3)

$$Q_i^G - Q_i^D = \sum_{j \in \Omega_i} Q_{ij} \quad (3)$$

In these equations, $P_i^G - Q_i^G$ represent the active and reactive power generated at bus i , respectively, while; P_i^D and Q_i^D denote the active and reactive load demands. The term P_i^{BESS} accounts for the active power contribution from a battery energy storage system at bus i . On the right-hand side, the summations represent the total active and reactive power flows from bus i to all downstream buses j within the set Ω_i .

These equations ensure that the network maintains power balance under normal operating conditions, considering both conventional generation and distributed energy resources, such as BESS. They form the basis for analyzing voltage profiles, losses, and overall system performance in radial distribution networks.

3.2 Voltage Magnitude Constraint

According to ANEEL, through PRODIST – Module 8, the admissible steady-state voltage limits for medium-voltage networks are within the range of 0.93 to 1.05 p.u., as presented in Eq. (4).

$$V_i^{min} \leq V_i \leq V_i^{max}, \quad \forall i \in \Omega_b \quad (4)$$

3.3 Radiality Constraint

The distribution network must operate in a radial configuration, without loops, ensuring a single path between the substation and each bus. This simplifies system protection, control, and operation.



$$\sum x_{ij} = |N| - 1, \quad x_{ij} \in \{1, 0\} \quad (5)$$

Where x_{ij} is a binary variable indicating whether branch (i, j) is closed (1) or open (0), and $|N|$ is the total number of buses in the system. The value $|N|-1$ represents the exact number of active branches required to form a tree (radial structure) with $|N|$ nodes.

3.4 Charging and Discharging Constraint

To prevent simultaneous charging and discharging of the battery, the following constraint is imposed. The energy storage system charges when there is an excess of renewable generation (and low demand) and discharges when the demand is high (and little or no renewable generation is available). Thus, the operation follows the logic by Eq. (6).

$$\begin{cases} P_{i,t}^{carga} > 0, P_{i,t}^{descarga} = 0 & \text{se } P_{GD}(t) > P_{carga}(t) \\ P_{i,t}^{carga} = 0, P_{i,t}^{descarga} > 0 & \text{se } P_{GD}(t) < P_{carga}(t) \end{cases} \quad (6)$$

4 RESULTS AND DISCUSSION

For obtaining the results of this study, the simulations were carried out on a Dell computer equipped with an 11th-generation Intel Core i7 processor, 1 TB HDD, 256 GB SSD, 8 GB of RAM, and the Windows 11 operating system. The tests were conducted at the Energy Systems Optimization Laboratory (LOSE). The distribution system used consists of 33 buses and 37 branches, as shown in Figure x. This system was originally described by Baran (1989), with the complete dataset available, and its main characteristics are summarized in Table 2.

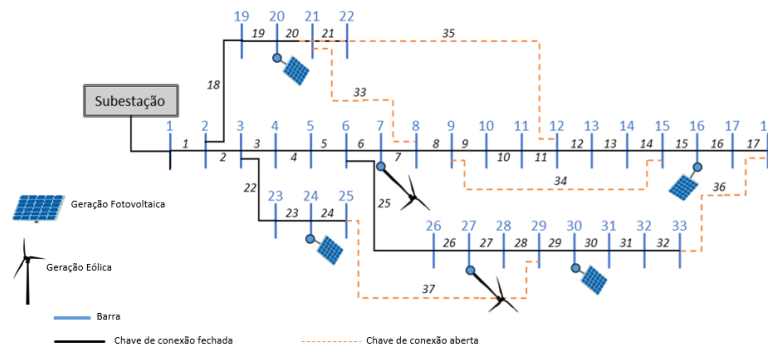
Table 2 – Initial and Optimal Configuration of the 33-Bus System

33-Bus System	Initial Configuration	Optimal Configuration
Open Switches	33-34-35-36-37	7-9-14-32-37
Losses (kW)	208.09	139.55
Minimum Voltage (p.u)	0.9120	0.9435
Total Active Load (MWh)	89.2714	
Total Reactive Load (MVar)	55.2690	

The study was structured into three main stages. In the first stage, the DE metaheuristic was compared with PSO and GWO, demonstrating superior performance in terms of accuracy, execution time, and computational effort. After analyzing ten mutation strategies, E9 was selected for presenting the best results. With the addition of the Mesh Search (MS) technique, the DE-MS/S9 version was obtained, which showed faster convergence and more consistent solutions, and was therefore defined as the basis of this study. In the second stage, DE-MS/S9 was applied to two scenarios: (1) a system with DG and (2) a system with DG and DNR, considering dynamic reconfiguration analysis in Matlab. In the third stage, additional scenarios were evaluated: (3) a system with only BESS and (4) a system with BESS and static RRD, modeled in AMPL, allowing the assessment of the proposed approach under different conditions.



Figure 1 – 33-Bus, 37-Branch System



(Adapted from Silva, 2016)

4.1 Results for Different Scenarios

Table 3 presents the results obtained for four distinct scenarios: Scenario I – system with DGs; Scenario II – system with DGs and RRD; Scenario III – system with BESS; and Scenario IV – system with BESS and RRD. The analysis of these scenarios allows evaluating the impact of different network modernization strategies on technical losses and slack bus dispatch over a 24-hour period.

4.1.1 Scenarios I

In Scenario I, the highest total losses throughout the day are observed, totaling 3.1546 MWh. Even with the presence of DGs, the absence of control strategies and network RRD limits operational efficiency.

Figure 2 – Power and Voltage Curves of the System with DGs in Scenario - I

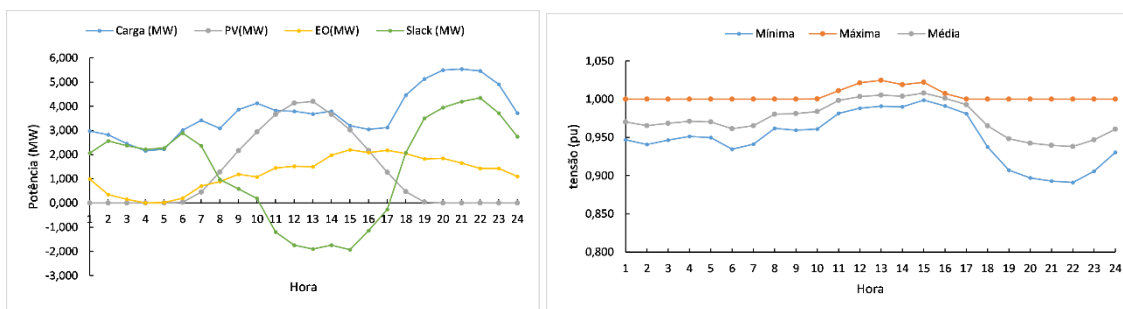


Figure 2A – Power Curves

Figure 2B – Voltage curves

Losses are particularly pronounced during peak load hours, especially between hours 18 and 22, which is also reflected in the high values of power supplied by the slack bus.

4.1.2 Scenarios II

Scenario II, which incorporates RRD together with DGs, shows a significant improvement, with total losses reduced to 2.2117 MWh, representing a reduction of approximately 29.9% compared to the base scenario. The reconfiguration of the network topology contributes to the redistribution of power flows, relieving overloaded branches and reducing the need for additional supply from the slack bus. However, reverse power flow at the slack bus was not mitigated.



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Figure 3 – Power and Voltage Curves of the System with DGs in Scenario II

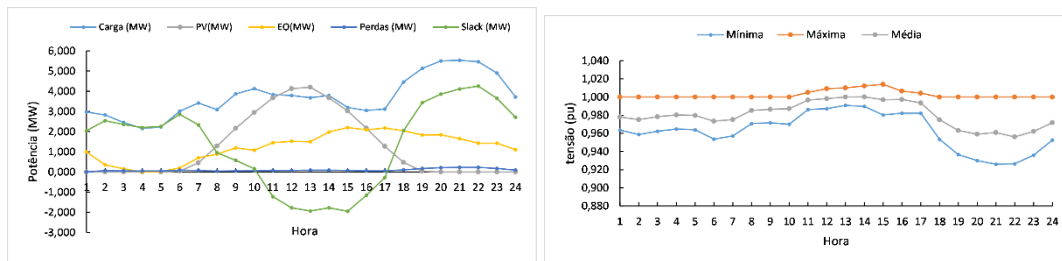


Figure 3A – Power Curves

Figura 3B – Voltage curves

4.1.3 Scenarios III

In Scenario III, the inclusion of BESS, without RRD, results in total losses of 2.5137 MWh. This configuration proves to be more efficient than Scenario I in terms of losses, with a reduction of approximately 20.3%, indicating that energy storage contributes significantly to load compensation and demand curve smoothing. However, without RRD, this strategy is not as effective as that adopted in Scenario II regarding losses, but in terms of reverse power flow, the mitigation was better when compared to Scenarios I and II.

Figure 4 – Power and Voltage Curves of the System with DGs and BESS in Scenario III

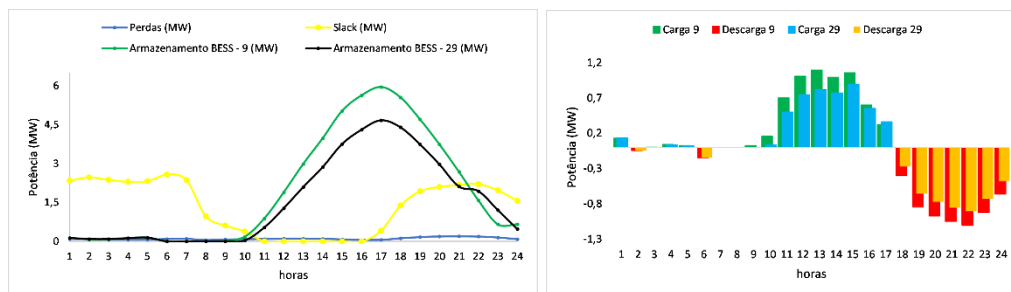


Figure 4A – Power Curves

Figure 4B – Charging and Discharging Profiles

4.1.4 Scenarios IV

Finally, Scenario IV, which combines BESS and RRD, exhibits the best performance among the four cases, with total losses of only 2.1279 MWh, corresponding to a 32.6% reduction compared to Scenario I. In addition, the power supplied by the slack bus

Figure 5 – Power and Voltage Curves of the System with DG, DNR and BESS in Scenario - IV

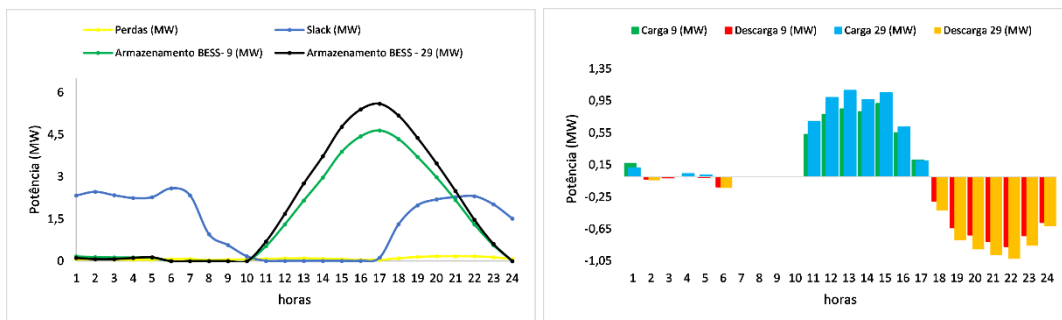


Figure 5A – Power Curves

Figure 5B – Charging and Discharging Profiles



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Table 3 - Results from different scenarios

Hours	Scenarios I		Scenarios II		Scenarios III		Scenarios IV	
	Losses (MW)	Slack (MW)	Losses (MW)	Slack (MW)	Losses (MW)	Slack (MW)	Losses (MW)	Slack (MW)
1	0.0784	2.0604	0.0576	2.0396	0.092693	2.3400	0.0698	2.3340
2	0.0934	2.5648	0.0672	2.5386	0.0878	2.4692	0.0660	2.4661
3	0.0763	2.3742	0.0543	2.3522	0.0763	2.3751	0.0554	2.3437
4	0.0640	2.2187	0.0451	2.1998	0.0684	2.2983	0.0482	2.2446
5	0.0677	2.2747	0.0477	2.2547	0.0704	2.3224	0.0500	2.2746
6	0.1148	2.8924	0.0812	2.8587	0.0947	2.5759	0.0724	2.5895
7	0.1014	2.3658	0.0730	2.3374	0.1014	2.3658	0.0748	2.3391
8	0.0518	0.9701	0.0385	0.9567	0.0518	0.9701	0.0385	0.9567
9	0.0752	0.5878	0.0561	0.5714	0.0754	0.6121	0.0562	0.5688
10	0.0865	0.1921	0.0609	0.1665	0.0878	0.3850	0.0655	0.1712
11	0.0969	-1.1952	0.0675	-1.2246	0.0914	0.0000	0.0794	0.0100
12	0.1152	-1.7421	0.0794	-1.7779	0.1056	0.0000	0.0980	0.0100
13	0.1173	-1.9009	0.0808	-1.9373	0.1065	0.0000	0.1014	0.0100
14	0.1152	-1.7421	0.0814	-1.7759	0.0996	0.0000	0.0894	0.0100
15	0.1023	-1.9268	0.0748	-1.9543	0.0791	0.0000	0.0728	0.0100
16	0.0706	-1.1403	0.0555	-1.1554	0.0582	0.0000	0.0488	0.0100
17	0.0603	-0.2697	0.0495	-0.2805	0.0595	0.4136	0.0464	0.1246
181	0.1390	2.0764	0.1044	2.0418	0.1200	1.3837	0.1018	1.3118
19	0.2405	3.5034	0.1735	3.4364	0.1673	1.9322	0.1504	1.9850
20	0.2907	3.9409	0.2077	3.8579	0.1939	2.1008	0.1755	2.1936
21	0.3099	4.1953	0.2238	4.1092	0.1959	2.1755	0.1778	2.2771
22	0.3161	4.3472	0.2229	4.2540	0.1903	2.2092	0.1731	2.3094
23	0.2397	3.7135	0.1712	3.6450	0.1526	1.9721	0.1382	2.0192
24	0.1313	2.7463	0.0952	2.7102	0.0869	1.5649	0.0780	1.5111
Total (MWh)	3.1546	---	2.2117		2.5137		2.1279	---

becomes more stable and lower throughout the day, demonstrating a more efficient operation of the network. Overall, the comparative analysis of the scenarios shows that the combination of strategies, such as network reconfiguration and energy storage, provides significant operational benefits, optimizing the use of existing infrastructure and reducing technical losses.



4 CONCLUSIONS

The static integration of BESS and DR proved essential for enhancing the operational reliability of distribution networks in scenarios with high penetration of renewable DGs. In Scenario IV, the system exhibited the lowest total energy losses over the 24-hour period, along with a significant reduction in reverse power flow, as shown in Table 3. This configuration demonstrated the most robust performance, ensuring greater stability and consistency despite the inherent variability of solar and wind generation. Thus, the results confirm that the proposed approach represents an efficient and robust strategy to address the challenges of modernizing distribution networks. However, further work on dynamic optimization analyses and economic feasibility assessments is recommended to maximize the application potential and ensure the long-term sustainability of the solutions.

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REFERÊNCIAS

- Baran, M. E.; Wu, F. F.** *Network reconfiguration in distribution systems for loss reduction and load balancing*. IEEE Transactions on Power Delivery, v. 4, n. 2, p. 1401–1407, 1989.
- Civanlar, S. et al.** *Distribution feeder reconfiguration for loss reduction*. IEEE Transactions on Power Delivery, v. 3, n. 3, p. 1217–1223, 1988.
- Gomes(a), Y. R. et al.** *Daily and weekly operation of battery energy storage systems in networks with high photovoltaic generation penetration: a comprehensive analysis*. International Symposium on Energy: Energy Transition, Green Hydrogen and Sustainable Industry – ISE, 2023. p. 1–5. Disponível em: <https://doi.org/10.55592/ISE.2023.2515747>. Acesso em: 29 ago. 2025.
- Gomes(b), Y. R. et al.** *Analysis of SOS and PSO metaheuristics applied to the distribution network reconfiguration problem*. In: IEEE INTERNATIONAL CONFERENCE ON INDUSTRY APPLICATIONS (INDUSCON), 15., 2023. Anais [...]. p. 997–1004.
- Gomes(c), Y. R.; Belati, E. A.; Vargas, R.** *Flower pollination algorithm for distribution system reconfiguration problem*. In: IEEE PES INNOVATIVE SMART GRID TECHNOLOGIES CONFERENCE – LATIN AMERICA (ISGT Latin America), 2021. Anais [...]. p. 1–5.
- INTERNATIONAL RENEWABLE ENERGY AGENCY – IRENA.** *Innovation landscape for a renewable-powered future: Solutions to integrate variable renewables*. Abu Dhabi: IRENA, 2020. Disponível em: <https://www.irena.org/publications/2020>. Acesso em: 4 ago. 2025.
- Kennedy, J.; Eberhart, R.** *Particle swarm optimization*. In: PROCEEDINGS OF THE IEEE INTERNATIONAL CONFERENCE ON NEURAL NETWORKS, 1995, Perth, Austrália. IEEE, 1995. p. 1942–1948.
- Lund, P. D. et al.** *Review of energy system flexibility measures to enable high levels of variable renewable electricity*. Renewable and Sustainable Energy Reviews, v. 45, p. 785–807, 2015. DOI: 10.1016/j.rser.2015.01.057.
- Mirjalili, S. Lewis, A.** *Grey Wolf Optimizer*. Advances in Engineering Software, v. 69, p. 46–61, 2014.
- Siano, P.** *Demand response and smart grids: A survey*. Renewable and Sustainable Energy Reviews, v. 30, p. 461–478, 2014.
- Silva, L. I.; Belati, E. A.; Junior, I. C. S.** *Heuristic algorithm for electrical distribution systems reconfiguration based on firefly movement equation*. IEEE Latin America Transactions, v. 14, n. 2, 2016
- Storn, R.; Price, K.** *Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces*. Journal of Global Optimization, v. 11, p. 341–359, 1997.