energies

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Optimal Electrification Using Renewable Energies: Microgrid Installation Model with Combined Mixture k-Means Clustering Algorithm, Mixed Integer Linear Programming, and Onsset Method

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Abstract: Optimal planning and design of microgrids are priorities in the electrification of off-grid areas. Indeed, in one of the Sustainable Development Goals (SDG 7), the UN recommends universal access to electricity for all at the lowest cost. Several optimization methods with different strategies have been proposed in the literature as ways to achieve this goal. This paper proposes a microgrid installation and planning model based on a combination of several techniques. The programming language Python 3.10 was used in conjunction with machine learning techniques such as unsupervised learning based on K-means clustering and deterministic optimization methods based on mixed linear programming. These methods were complemented by the open-source spatial method for optimal electrification planning: onsset. Four levels of study were carried out. The first level consisted of simulating the model obtained with a cluster, which is considered based on the elbow and k-means clustering method as a case study. The second level involved sizing the microgrid with a capacity of 40 kW and optimizing all the resources available on site. The example of the different resources in the Togo case was considered. At the third level, the work consisted of proposing an optimal connection model for the microgrid based on voltage stability constraints and considering, above all, the capacity limit of the source substation. Finally, the fourth level involved a planning study of electrification strategies based mainly on microgrids according to the study scenario. The results of the first level of study enabled us to obtain an optimal location for the centroid of the cluster under consideration, according to the different load positions of this cluster. Then, the results of the second level of study were used to highlight the optimal resources obtained and proposed by the optimization model formulated based on the various technology costs, such as investment, maintenance, and operating costs, which were based on the technical limits of the various technologies. In these results, solar systems account for 80% of the maximum load considered, compared to 7.5% for wind systems and 12.5% for battery systems. Next, an optimal microgrid connection model was proposed based on the constraints of a voltage stability limit estimated to be 10% of the maximum voltage drop. The results obtained for the third level of study enabled us to present selective results for load nodes in relation to the source station node. Finally, the last results made it possible to plan electrification using different network technologies and systems in the short and long term. The case study of Togo was taken into account. The various results obtained from the different techniques provide the necessary leads for a feasibility study for optimal electrification of off-grid areas using microgrid systems.

Keywords: microgrids; optimization; k-means clustering; mixed integer linear programming; onsset

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1. Introduction

Controlling today's global warming is, on the one hand, a subject of common interest worldwide and one in which all sectors are involved. On the other hand, the need to supply people with electricity off-grid necessitates the development of small-scale technologies for supplying renewable electrical energy. Fernando Antonanzas-Torres et al. [1] recommend mini-grid systems for the electrification of countries where the electrification rate has not yet reached 100%, in line with the United Nations Sustainable Development Goal 7 (SDG7): access to electricity for all [2,3]. Such systems should be implemented with the consideration of environmental constraints [4,5]. Furthermore, according to Sedzro et al. [6], microgrids, or mini-grids, are a potential solution to macro-grids for restoring electricity networks after disasters. In short, microgrids make it possible to reduce losses on supply lines and improve local power supply reliability and energy efficiency while offering a sustainable and efficient system [7]. They can also be utilized to avoid blackouts of the entire power grid (macro-grid) when it is split into mini-grids. The classification of microgrids, therefore, depends on their configuration and applicability [8,9].

However, microgrids present challenges related to stochastic variation in demand and fluctuations in voltage and frequency [7] and intermittent weather conditions that sometimes affect reliability and economic behavior. Among these challenges, the modeling of microgrids is an important factor. The optimization of microgrids is one of the most important research objectives. These methods are often limited to a single objective: optimizing the various systems to exploit various resources such as solar systems, wind systems, hydro systems, battery systems, and biodiesel systems. The aim of these studies is to find the best compromise in the optimal choice of these different technologies, using a number of different problem-solving methods. Among these challenges, the modeling of microgrids is an important factor. Indeed, according to Fahad Saleh Al-Ismail [10], to overcome these challenges, microgrids need to be studied and modeled before being implemented and applied.

According to the U.S. Department of Energy's Microgrid Exchange Group [11], microgrids are electrical energy systems composed of one or more energy resources with a group of loads interconnected within clearly defined electrical boundaries and are able to act as single controllable entities. Referring to the definition of microgrids and their classifications [8,11], this paper proposes an optimal microgrid model that first considers microgrid clustering and the minimization of the centroid distance from the loads. Secondly, this work proposes the optimal management of energy resources as a function of the average levelized cost according to the different technologies [7]. Then, in a third step, this paper presents an optimal model based on optimal load connections, following the definition proposed in [11] by the US Department of Energy. Finally, in a fourth step, optimal microgrid planning using the onsset method is proposed for the particular case of Togo. This study is an optimization study of the installation of a microgrid that would reduce losses and costs as much as possible, in technical and economic terms, for power grid operators.

This work is not limited to a single objective, as previously mentioned, but is the result of a combination of several objectives. The paper, therefore, proposes to define the electrification strategy in four steps: step 1, physical allocation of microgrid centers to obtain the coordinates of the centroid; step 2, definition of the optimal choice of technologies depending on the availability of resources; step 3, definition of optimal load connections points to the electrical microgrid available in the study area; and in step 4, planning electrification strategies.

The remainder of the paper is structured into four sections: the state of the art in Section 2; materials and methods in Section 3; results and discussion in Section 4; and, finally, conclusions in Section 5.

2. Theoretical Background

This section describes the theoretical background of the various technologies that can constitute the microgrid and the different scientific methods applied for its optimal installation.

2.1. Scientific Models of Microgrid Technologies

Models of the various components of microgrids, such as solar photovoltaic systems, wind systems, hydroelectric systems, battery systems, biodiesel systems, and load modeling are expressed:

The maximum power produced by a photovoltaic solar panel can be directly calculated as a function of irradiation using the following formula [12,13]:

$$P_s(t) = \eta \times \varepsilon \times S \times I(t) \times (1 - k\Delta t) \times N_s \tag{1}$$

With direct measurement of wind speed, we can express the wind power of the site under consideration using the following equation [12,14]:

$$P_e(t) = \frac{1}{2} \times \rho_e \times S_w \times v^3(t) \times \eta_e \times N_e \tag{2}$$

Hydroelectricity production, which depends on the average water flow (m^3/s) over a period of time t, the difference in height between the entry and exit points (h) in m, the acceleration due to gravity (g) in m/s^2 and the density of the water and the yield [13,15,16], is expressed by

$$P_h(t) = \rho_h \times g \times Q \times h \times \eta_h \times X_h^d \tag{3}$$

Battery state of charge and power [17–20] at each simulation time are formulated as follows:

$$soct(t+1) = soct(t) + \frac{p_{bat}(t) \times \Delta t}{N_{bat} \times C_{bat} \times V_{bat}} \eta_{bat} \tag{4}$$

Storage at a given time t is formulated as follows:

$$soct(t) = \frac{E_{bat}(t)}{E_{bat}^{nom}} \tag{5}$$

$$E(t) = S_i \times t \tag{6}$$

$$C_{bat}(t) = \frac{E(t)}{V} \tag{7}$$

$$N_{bat} = \frac{C_{bat}(t)}{C_{bat}^{nom}} \tag{8}$$

The bi-directional converter is given by

$$P_{conv} \geq \alpha_u \times P_s \tag{9}$$

Aside from the technological models of microgrids, the electrical load models of the microgrid are formulated as follows [21–23]:

$$f(P_{ch}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(P_{ch}-\mu)^2}{2\sigma^2}} \tag{10}$$

In this work, the deployment of microgrid technologies required a number of measures, such as methods using machine learning techniques based on unsupervised learning, the method for determining the number of clusters (elbow method), the calculation of distance between the centroid and the various loads, the haversine method and the onset method for optimal national planning of the various technologies. These methods are described below.

2.2. Scientific Methods for Microgrid Deployment

The various techniques applied, such as the k-means clustering technique, the elbow method, and the haversine method, are presented.

2.2.1. Clustering Techniques

k-Means Clustering Model

The clustering technique refers to the notion of measuring similarity between two vectors. This method makes it possible to recognize and group sets called clusters. The clustering technique is presented in [24,25]. The most commonly used measures of similarity are distance measures. The k-means clustering technique first groups the different variables xi in a certain set (cluster formation) and then, in a second step, minimizes the distance between the centroid and the clusters formed.

Assume the following space of n vector points of dimension p with $j \subset p$:

$$V = \begin{bmatrix} v_1^1 & \dots & v_1^j & \dots & v_1^p \\ \dots & \dots & \dots & \dots & \dots \\ v_i^1 & \dots & v_i^j & \dots & v_i^p \\ \dots & \dots & \dots & \dots & \dots \\ v_n^1 & \dots & v_n^j & \dots & v_n^p \end{bmatrix} \tag{11}$$

These n points can be grouped into c- clusters such that $c < n$ with the vectors.
For

$$1 \leq k \leq c \tag{12}$$

minimizing the distance between centroids and their respective clusters consists of assigning each nearest centroid to clusters such that

$$min \sum_{i=0}^{n} \|v_i - \mu_k\|^2 \tag{13}$$

Elbow Method

The elbow method is used to determine the number of clusters in a given data set. It allows us to plot the variation explained as a function of the number of clusters and to choose the elbow of the curve as the number of clusters to exploit. It is formulated and simulated using 100 data points and normalized to [0; 1] in [25,26].

2.2.2. Haversine Method

The haversine method [26,27] is used to calculate distances (in km) between two nodes with different geographical coordinates (latitude; longitude) [28].

$$D = R \times c \tag{14}$$

$$c = 2\arctan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right) \tag{15}$$

$$a = sin^2\left(\frac{\varphi_B - \varphi_A}{2}\right) + cos\varphi_A.cos\varphi_B \times sin^2\left(\frac{\lambda_B - \lambda_A}{2}\right) \tag{16}$$

$$R = 6371 \text{ Km} \tag{17}$$

φ_A, φ_B: latitudes; λ_A, λ_B: longitudes (in degrees).

2.2.3. Open-Source Spatial Planning for Electrification Method: Onsset

The Open-Source Spatial Planning Model (onsset) is a free programming algorithm that uses spatial information data to propose a particular model for a given case study. It is, therefore, a model that enables the selection of different technologies according to four different scenarios, taking into account the costs and availability of these resources not far from localities. The electrification planning model, therefore, considers the minimization of system costs (operating costs, investment costs, and maintenance costs), the evolution and level of the population, and the different technology configurations according to resource availability. The mathematical formulation of the model is given by [29], and a global study for all of the four scenarios for the case of Togo was conducted in [30]. In effect, this model informs the general planning of a country's overall electrification.

In this study, the developed microgrid model made it possible to specifically define the technologies to be implemented according to their cost and annual availability for a given site. Then, with onsset, a general configuration of the implementation of these technologies was obtained according to the locality for the whole country.

2.3. Bibliographical Reviews

Optimizing microgrids is one of the most important and challenging objectives in this field of research [31]. Several studies have been carried out in the literature using different methods.

Li Bei et al. [32] exploited evolutionary algorithm methods and mixed integer linear programming for the optimal sizing of microgrids. Alessandra Parisio et al. [33] presented a study on the application of a model predictive control approach to the problem of efficiently optimizing microgrid operations while satisfying time-varying demand and operating constraints; the overall problem was formulated using integer linear programming with MATLAB as the solution tool. Li Guo et al. [34] presented a two-stage optimal planning and design method for a combined cooling, heat, and power microgrid system to simultaneously minimize total net present cost and carbon dioxide emission. In [35], the authors proposed microgrid optimization based on a hybridization system of renewable energy resources. Mah AXY et al. presented the optimized design and operation of an autonomous microgrid with electric and hydrogen loads, showing a significant reduction in load costs [36]. Moreover, a strategy for controlling and managing the energy supply of a microgrid in order to achieve higher efficiency, reliability, and economy was proposed in [37,38]. Aiswariya L. et al. [39] proposed optimal battery sizing using the simulated annealing method based on the probabilistic method [39,40], and stochastic methods for the planning, operation, and economic control of microgrids were presented in [41].

Various microgrid optimization techniques can be used, including probabilistic [41,42], artificial intelligence [43,44], iterative [45,46], and deterministic techniques [47–49]. Luigi Rubino et al. [50] use linear programming method-based power management for a multi-feeder ultra-fast DC charging station.

Among all these different methods are linear programming [51,52] and the mixed integer linear (PLNEM) solver (PLNEM) [32,33], which provide a suitable framework for obtaining high-quality solutions [53] with acceptable computational effort and good convergence properties. The mixed integer linear programming solution method is, therefore, widely employed for HRESs (Hybrid Renewable Energy Systems) and is characterized by good convergence [54,55].

In this work, the mixed integer linear programming method was extensively utilized.

3. Materials and Methods

The material used and the methodology are described in the following sections.

3.1. Materials

Python programming language version 3.10 was used. The optimization problem was formulated as a mixed integer linear instance.

3.2. Methods

The model of the microgrid with the different optimized parts is presented. The mathematical formulations of the different optimization problems are also presented.

3.2.1. Microgrid System Model

The proposal for a microgrid model, inspired by existing models [56–59], is presented. Different technologies such as PV, wind, hydraulic, storage and others (biodiesel, etc.) are shown first. Secondly, the positions of the unit central and the loads (Figure 1) are presented.

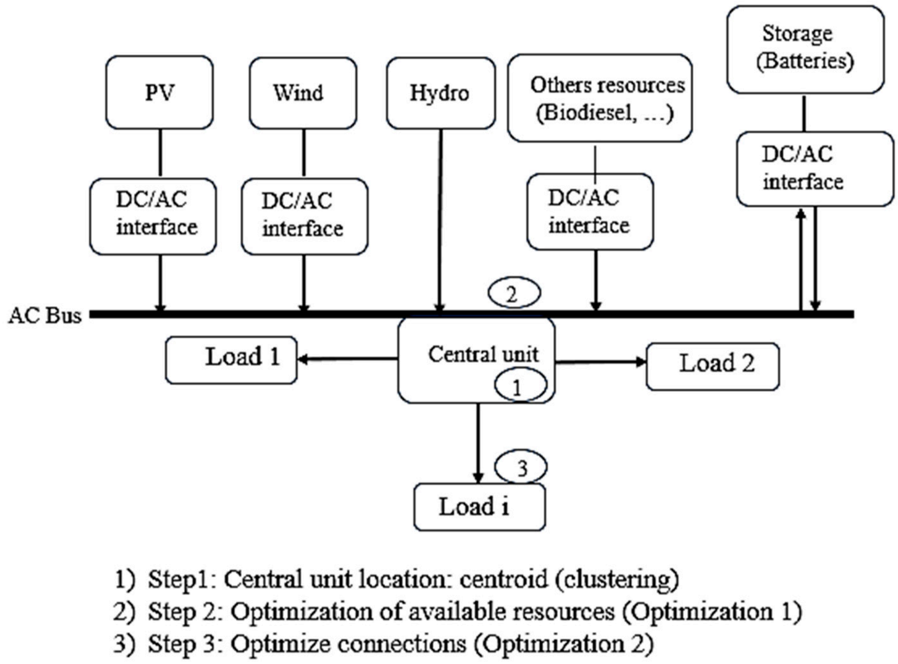


Figure 1. Microgrid model.

Three different methods were used. The first is an optimization formulation, which initially consists of minimizing the distance between the centroid, considered as the substation, and the various nodes representing the different electrical loads. The second is an optimal microgrid sizing method based on technology selection, minimization of overall cost, and availability of energy resources. In this method, a function is performed, which minimizes not only the microgrid connection distance but also the load shedding or supply of the loads to be connected (Step 3). In the second method formulated using mixed integer programming, two objective functions are presented. One function minimizes the investment cost for technology selection, and the other optimizes connections. Finally, the third method, based on onsset (described in Section 2.2.3), enables us to model the planning of national electrification spatially and optimally by implementing different technologies according to their cost and availability in each locality. Two scenarios are considered: short and long term.

3.2.2. Optimizations Problem Formulation

Three objective functions with constraints are clearly identified. First, a formulation of the optimization problem of minimizing the distance between the centroid and the various vectors that constitute the loads; then, a formulation of the optimization problem of selecting technologies as a function not only of the annual availability of natural resources but also of the various related costs, is presented; and finally, the minimization of the distance between the centroid considered as the substation and its various loads is formulated.

The various formulations described are presented.

In step 1: minimization of deviation between centroid and loads (*k*-means clustering method)

Objective function

$$min \sum_{i=0}^{n} \|v_i - \mu_k\|^2$$

This is subject to the following:

$$\mu_k > v_i^{min} \quad (18)$$

$$\mu_k < v_i^{max} \quad (19)$$

In fact, the distance of each vector point from the centroid is evaluated in such a way that the minimization of this distance is total. The coordinates of the centroid of the cluster obtained will allow an optimal physical localization of the centroid. After this step, the formulation of the technology selection is necessary.

Step 2: technologies selection (microgrid sizing)

Objective function:

$$min: \ C_{inv}^{T} = \left\{ C_{inv}^{i} + \sum_{t=1}^{n-1} \frac{C_{o\propto M} + C_r}{(1+r)^t} \right\} \quad (20)$$

$$C_{inv}^{i} = \sum_{i=1}^{5} \sum \sum \alpha_i c_i P_i \quad (21)$$

$$C_{o\propto M} = \sum_{i=1}^{5} \sum \sum \alpha_i c_{\propto} P_i \quad (22)$$

$$s_j = \sum_{j=1}^{5} \sum \alpha_j P_j = \alpha_6 P_{bat} + \sum_i p_i \quad (23)$$

$$\alpha_j = \left\{ \begin{matrix} 1 \ if \ the \ resource \ is \ available \\ 0 \ if \ not \end{matrix} \right\} \quad (24)$$

$$j = \left\{ \begin{matrix} 1, \ solar \ (s) \\ 2, \ wind \ (e) \\ 3, \ hydraulic \ (h) \\ 4, \ biomass \ (bio)/biodiesel \\ 5, \ batteries \ (bat) \end{matrix} \right. \quad (25)$$

$$\begin{bmatrix} P_s^{min} \\ P_e^{min} \\ P_h^{min} \\ P_{bio}^{min} \\ P_{bat}^{min} \\ soct^{min} \end{bmatrix} \leq \begin{bmatrix} p_s \\ p_e \\ p_h \\ p_{bio} \\ p_{bat} \\ soct \end{bmatrix} \leq \begin{bmatrix} P_s^{max} \\ P_e^{max} \\ P_h^{max} \\ P_{bio}^{max} \\ P_{bat}^{max} \\ soct^{max} \end{bmatrix} \quad (26)$$

$$P_s(t) = \eta \times \varepsilon \times S \times I(t) \times (1 - k\Delta t) \times N_s$$

$$P_e(t) = \frac{1}{2} \times \rho_e \times S_w \times v^3(t) \times \eta_e \times N_e$$

$$P_h(t) = \rho_h \times g \times Q \times h \times \eta_h \times X_h^d$$

$$soct(t) = \frac{E_{bat}(t)}{E_{bat}^{nom}}$$

$$E(t) = S_i \times t$$

$$C_{bat}(t) = \frac{E(t)}{V}$$

$$N_{bat} = \frac{C_{bat}(t)}{C_{bat}^{nom}}$$

$$soct(t+1) = soct(t) + \frac{p_{bat}(t) \times \Delta t}{N_{bat} \times C_{bat} \times V_{bat}} \eta_{bat}$$

$$P_{conv} \geq \alpha_u \times P_s$$

$$cos\varnothing \times \sum_i s_i = \sum_i p_{ch,i}$$

$$S_i = \frac{\sum_i p_i}{cos\varnothing}$$

The problem formulated is an optimization problem, which consists of minimizing the various technology costs as a function of the annual availability of existing resources. If the resource exists, the coefficient j is equal to 1; otherwise, it is zero. The formulation of the problem is, therefore, seen under different constraints linked to the different production and storage limits.

Once the optimal technologies have been selected, a further step in solving the optimization problem is carried out, linked to the optimal load connections.

Step 3: Optimal load selection based on distances and substation capacity

Objective function:

$$\begin{gathered} min : \sum_i x_{ij} d_{ij} \\ \text{For a fixed j} \end{gathered} \tag{27}$$

This is subject to the following:

$$x_{ij} = \begin{Bmatrix} 1\ if\ i\ is\ connected\ at\ j \\ 0\ if\ not \end{Bmatrix} \tag{28}$$

$$\sum_i x_{ij} s_i \leq c^{limit} \times s_j \tag{29}$$

$$\tau \times 100 < \tau^{limit} \tag{30}$$

$$\tau = \sqrt{3} \frac{I_n^i}{U_n} x_{ij} \times d_{ij} \left(r\ cos\theta + z\sqrt{1 - (cos\theta)^2} \right) \times 1000 \tag{31}$$

$$\sum_i I_n^i \leq I_n \tag{32}$$

$$s^i = \sqrt{3} U_n \times I_n^i \tag{33}$$

$$d = 6371 \times c$$

$$c = 2\ \text{arctan}\left(\frac{\sqrt{a}}{\sqrt{1-a}} \right)$$

$$a = sin^2\left(\frac{\varphi_B - \varphi_A}{2} \right) + cos\varphi_A . cos\varphi_B \times sin^2\left(\frac{\lambda_B - \lambda_A}{2} \right)$$

$$d > 0,\ c > 0,\ U_n > 0$$

$$\tau^{limit} = 10$$

$$c^{limit} = 0.8$$

$$i\ \epsilon\ I = \{loads\} \tag{34}$$

$$\epsilon\ J = \{substations/j,\ fixed\} \tag{35}$$

Knowing that the optimal connection of loads to the source substation is a function not only of their distance but also of the substation's available capacity, objective function 3 should minimize this distance. For a fixed j corresponding to the substation, the various loads i will be optimally selected under the various constraints mentioned above.

The various detailed flowcharts for implementing the resolutions of the different optimization problem formulations are presented.

The clustering algorithm is presented (step 1):

- Enter data for each vector

$$V = \begin{bmatrix} v_1^1 & \dots & v_1^j & \dots & v_1^p \\ \dots & \dots & \dots & \dots & \dots \\ v_i^1 & \dots & v_i^j & \dots & v_i^p \\ \dots & \dots & \dots & \dots & \dots \\ v_n^1 & \dots & v_n^j & \dots & v_n^p \end{bmatrix}$$

- Initialize the position of the centers:

$$\mu_k = \left[\mu_k^1, \mu_k^2, .., \mu_k^j, \dots, \mu_k^p\right], 1 \le k \le c$$

- Calculate mk averages of vectors in cluster k

- Until there are no more changes in the mk
- Assign each Vi point to the nearest cluster
- Calculate new mk
- End As long as

The flowchart for the formulation of objective function 2, resource optimization, is shown in Figure 2 below (step 2):

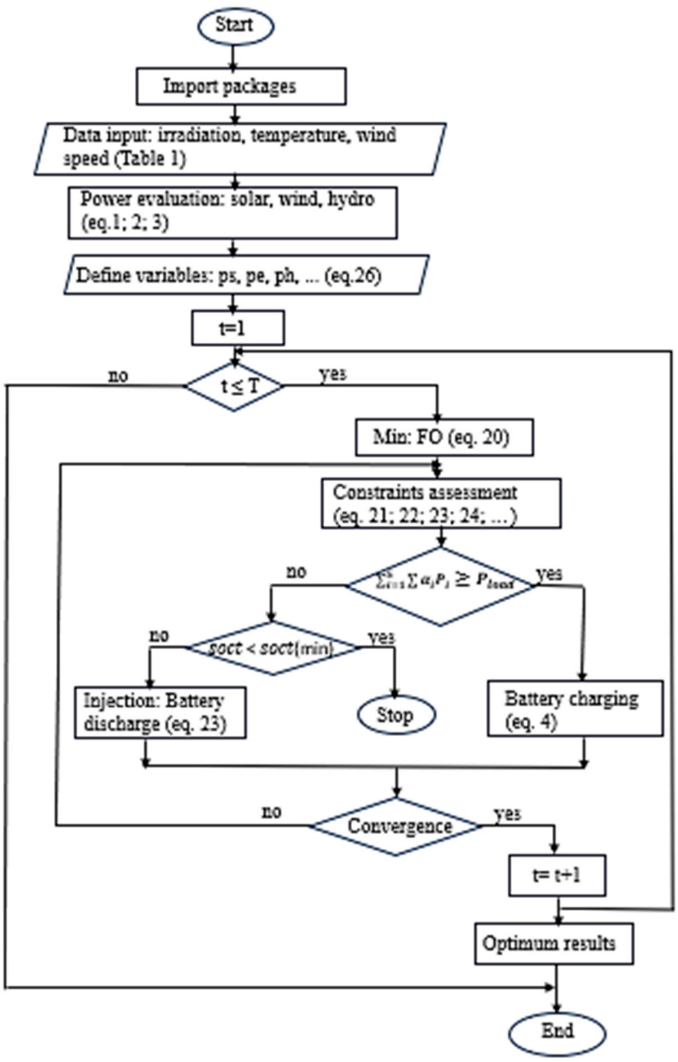


Figure 2. Renewable resources optimization flowchart.

T is set to 12 for the twelve months of the year.

Figure 3 shows the flowchart for the formulation of objective function 3: connection optimization (step 3).

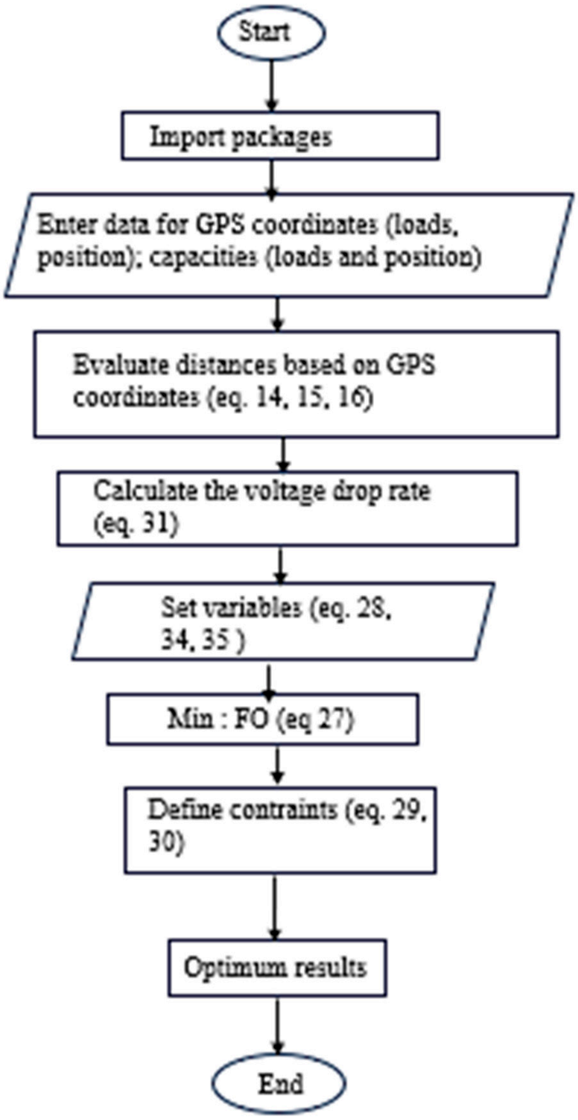


Figure 3. Optimal connection optimization flowchart.

3.2.3. Data

Only average and annual variations in the various energy resources of South Togo are presented. In fact, this area contains all the country's available resources.

Statistical analyses of the data presented are based on the minimum value of the data used, the maximum value (36), the mean (37) and the standard deviation (38):

$$min = \min(x_i); max = \max(x_i) : \mathrm{i} = 1, \ldots.\mathrm{N} \tag{36}$$

$$\overline{\mathrm{X}} = \frac{1}{\mathrm{N}}\sum_{i=1}^{N} x_i \tag{37}$$

$$\sigma = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N}\left(x_i - \overline{\mathrm{X}}\right)^2} \tag{38}$$

The statistical data on energy resources in South Togo are shown in Table 1.

Table 1. Statistical data on energy resources in South Togo.

Months	Solar Radiation (W/m^2)				Temperature (Degrees)				Relative Humidity (%)				Wind Speed (m/s)			
	Min	Max	$\overline{X}$	σ	Min	Max	$\overline{X}$	σ	Min	Max	$\overline{X}$	σ	Min	Max	$\overline{X}$	σ
Jan	85.46	115.71	99.01	5.87	26.12	28.41	27.59	0.59	60.56	85.62	75.25	6.92	2.04	4.45	3.27	0.68
Fev	85.98	113.63	103.63	6.95	27.58	28.57	28.05	0.23	69.75	85.19	80.92	2.97	2.21	5.17	3.94	0.76
Mar	84.98	122.43	108.85	9.69	27.83	28.96	28.38	0.23	78.44	86.31	81.99	1.89	3.99	6.11	4.78	0.57
Apr	109.64	137.14	127.32	7.0	26.95	28.38	27.67	0.46	78.31	88.31	83.72	2.35	1.86	5.49	3.7	0.91
May	108.89	132.91	126.36	4.72	26.49	28.11	27.41	0.41	76.19	88.62	85.21	2.59	1.91	4.47	3.41	0.56
June	112.42	128.5	121.95	3.63	25.09	27.42	26.25	0.73	79.0	92.88	87.34	3.28	1.9	5.6	3.69	0.85
Jul	117.48	129.11	123.56	2.93	24.44	25.9	25.10	0.36	82.19	90.81	87.35	2.33	3.42	6.55	5.06	0.66
Aug	117.97	134.07	127.02	3.74	23.64	25.35	24.34	0.46	82.62	92.31	87.89	2.0	2.4	7.82	5.29	1.36
Sep	125.77	140.23	134.24	3.19	24.95	25.87	25.45	0.24	82.88	91.5	87.28	2.18	3.26	6.55	4.85	0.88
Oct	113.06	133.61	125.49	4.72	25.17	27.4	26.32	0.63	84.62	90.69	87.60	1.55	2.16	5.55	3.19	0.89
Nov	106.05	122.58	114.64	4.22	26.64	27.83	27.24	0.3	79.44	87.0	83.24	1.78	1.65	4.77	3.03	0.71
Dec	90.72	111.33	103.36	4.46	25.9	27.8	27.01	0.35	61.62	86.62	78.24	6.64	1.62	4.3	2.94	0.61

Table 1 presents data linking the various renewable resources. The table shows monthly solar irradiation, temperature, relative humidity, and wind data. These data are, in effect, inputs for the power extraction of different technologies, such as solar panels (solar irradiation and temperature), hydro-generators (dependent on relative humidity), and wind turbines (dependent on wind speed).

Tables 2 and 3 below show the random statistical data for the load positions considered in the simulations and the parameters used in the simulations, respectively.

Table 2. Random statistical data.

Indicators	x_i	Min	Max	$\overline{X}$	σ
Data	100	0.028	0.9	0.455	0.25

Table 3. Parameters [13,60].

Costs/Systems	PV (USD/kW)	Batteries/6 V (USD/Unit)	Wind (USD/kW)	Hydraulic (USD/kW)	Biodiesel (USD/kW)
Installation cost	800–2000	900–1300	1800	2000	650
Maintenance and operating costs	8–200	9–14	700–1000	100/year	20/year
Replacement cost	700	1300	-	-	-

The different results obtained following the formulation of the various optimization problems are presented.

4. Results and Discussion

4.1. Optimization Results

4.1.1. Results for Cluster Formation: Physical Allocation of Microgrid Centers

The results of the elbow method applied to the xi data to determine the number of clusters are shown in Figure 4.

The number of clusters obtained, as shown in Figure 4, is 3. The graphical representation of these clusters is shown in Figure 5a,b using the k-means clustering technique.

This clustering technique was used to determine the coordinates of the various centroids (3). Table 4 shows the coordinates obtained.

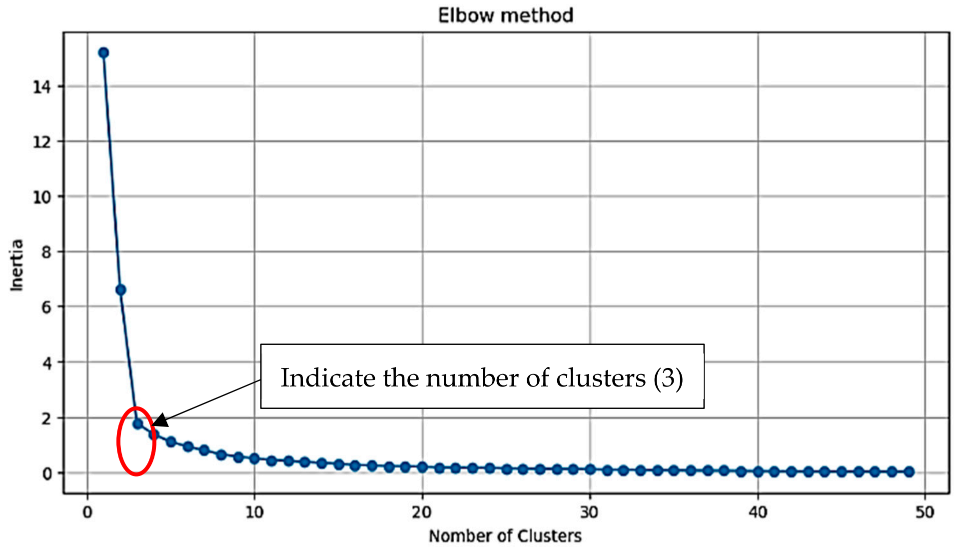
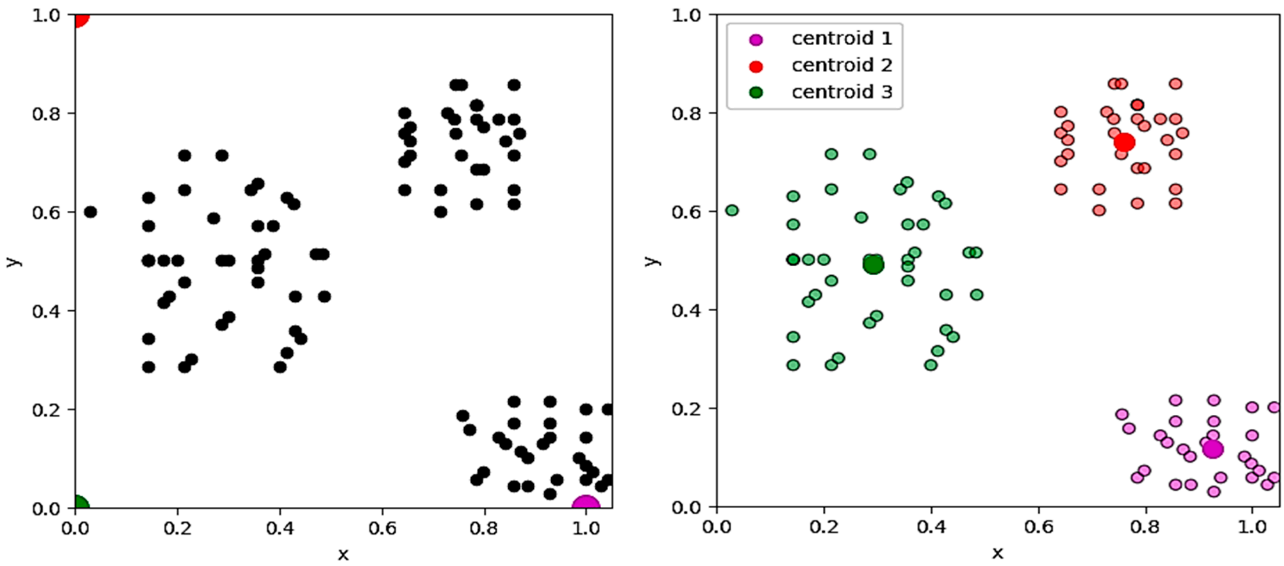


Figure 4. Elbow method for determining the number of clusters.



(**a**) (**b**)

Figure 5. (**a**) K-means technique. (**b**) Centroid formation.

Table 4. Summary of cluster centroid values.

Centroid/Axis	x	y
Centroid 1	0.92463054	0.11527094
Centroid 2	0.75952381	0.74047619
Centroid 3	0.29246429	0.48892857

Subsequently, a special study was carried out on cluster 3. Table 3 shows a centroid for this cluster with the coordinates (x; y): (0.29246429; 0.48892857).

Figure 6 shows the corresponding cluster 3. Two nodes of centroid 1 are also shown for reference (connection).

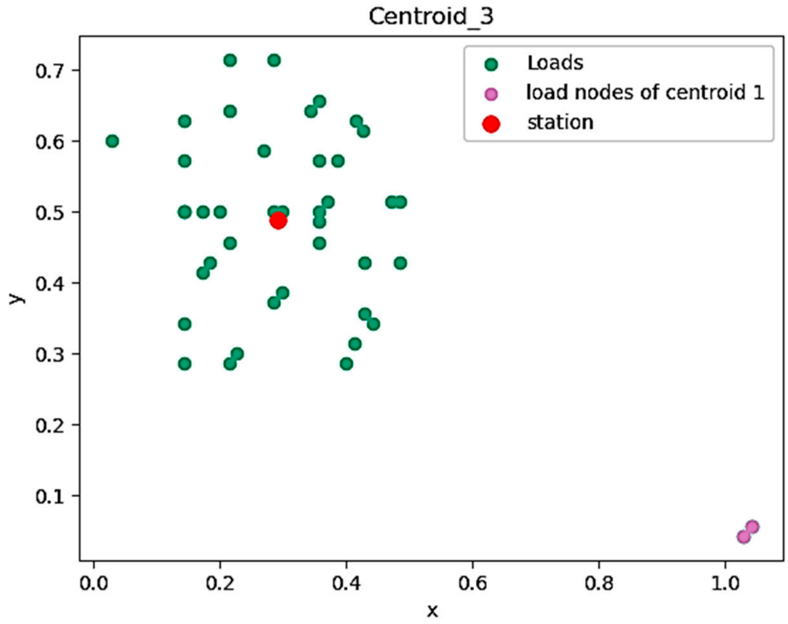


Figure 6. Cluster 3 considered.

The number of load nodes defined for this centroid 3 is 40. The total capacity defined for study for these load nodes is assumed to be 40,000 W or 40 kW.

The results of the optimal simulations are presented.

4.1.2. Renewable Energy Resource Availability Results

To define energy potential, the case of Togo is taken into account. A previous study of the availability and mapping of the country's renewable resources is presented by Kabe et al. [30]. The various intermittent energy potentials are presented for a capacity of around 1 kW. Only solar, wind, and hydraulic potentials are shown. According to Rafat Al Afif et al. [61], specific impacts from extreme events would not affect biomass power generation; it follows that biomass power generation is possible at any desired period and is therefore not taken into account in the simulation.

Figure 7 below shows these potentialities.

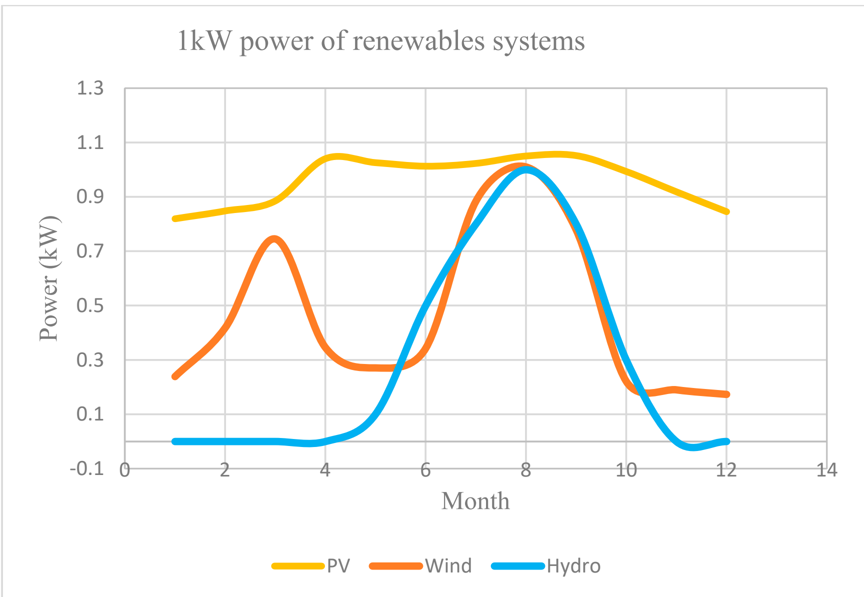


Figure 7. Energy resources of 1 kW in power.

This figure shows the unequal annual distribution of Togo's potential energy mix. This unequal distribution requires an optimal combination of these resources. Optimal management of these resources is only possible with optimal management optimization models, hence this study.

Data from different variations of these resources are considered for the study.

4.1.3. Optimization Results for Technology Selection

The results of the optimum selection of renewable resources and the optimum power ratings obtained are shown in Figure 8 and Figure 10, respectively.

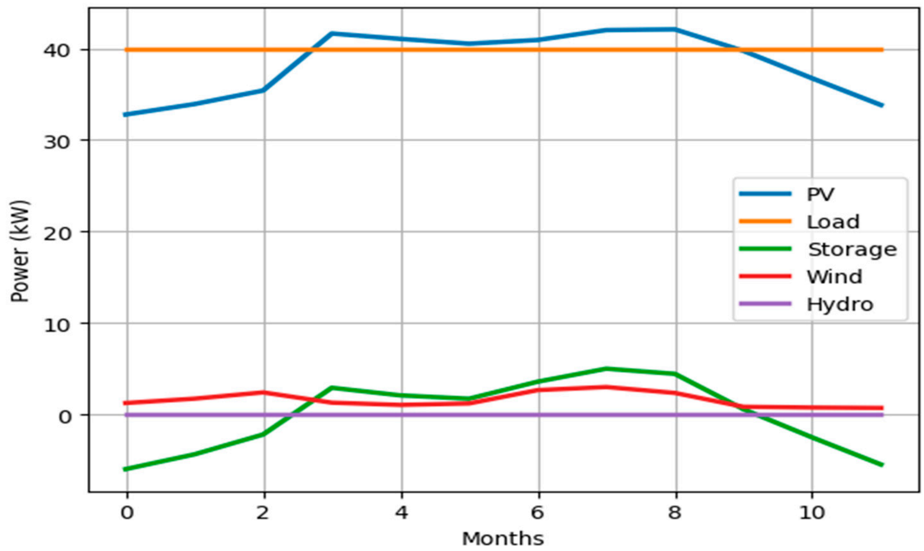


Figure 8. Optimal profile of renewable resources.

Figure 8 shows the optimal annual variation in renewable energy resource profiles for the microgrid under consideration. It can be seen from this figure that only photovoltaic, storage, and wind power systems are considered and, therefore, recommended. The hydraulic resource is neglected. In addition, the most available resource is the solar resource, the annual variation of which would allow optimal choices of technologies depending on the period. The wind resource is not neglected either. Figure 9 shows the energy storage.

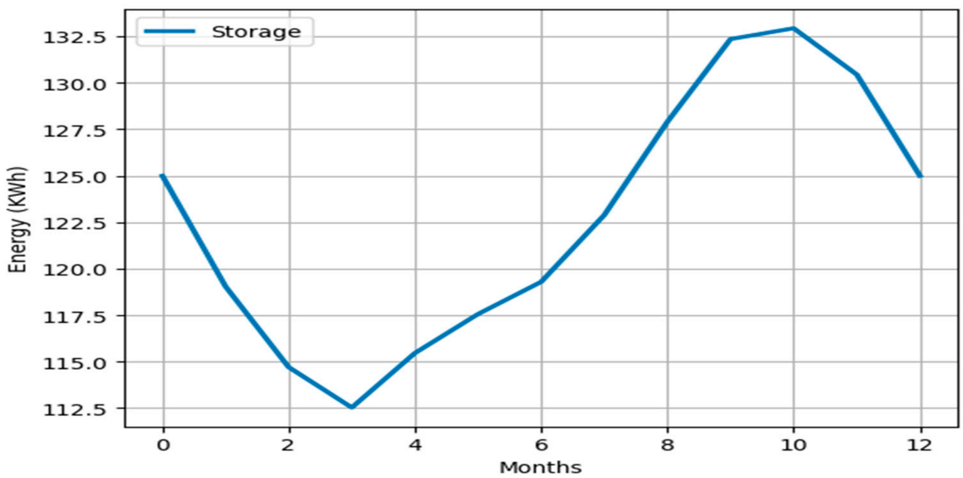


Figure 9. Energy storage.

This optimization of resources makes it possible to define the appropriate technologies for each month when installing the microgrid.

Now, the maximum capacity of the storage system is estimated to be 135 kWh. Details of the power of the various resources, which may be low or high depending on the period, are shown in Figure 10.

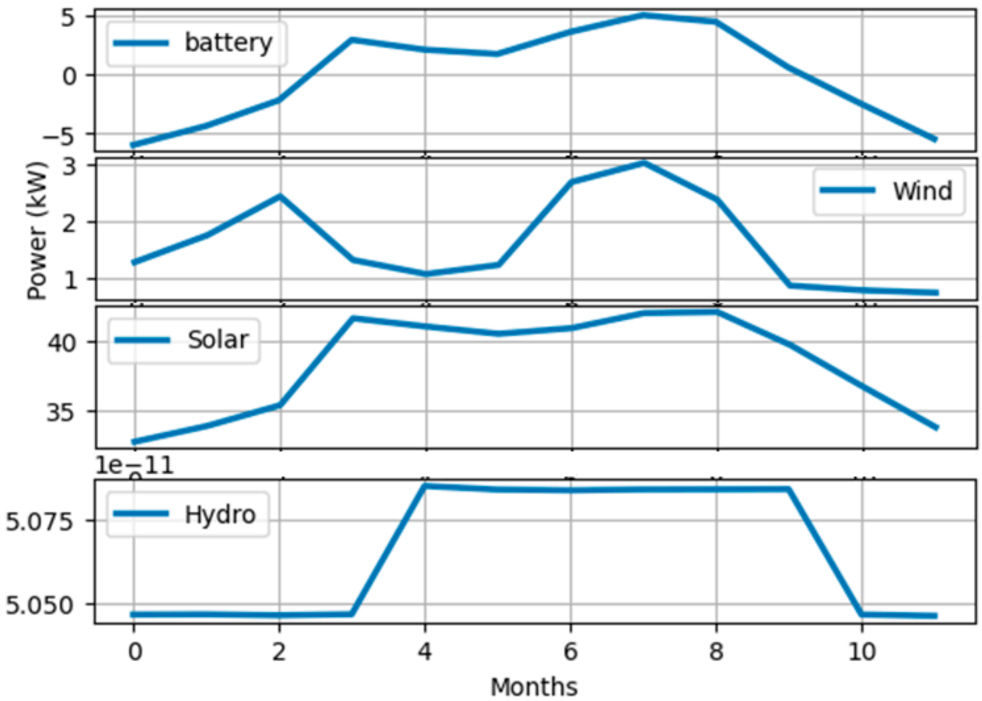


Figure 10. Optimum performance of renewable resources.

The solar capacity considered ranges from 30 to 42 kW, while the maximum wind capacity is estimated to be 3 kW. Solar capacity represents 80% of the total load of the microgrid under consideration against 7.5% for wind power. Solar is the most favored resource, but wind can also be considered for its exploitation. The battery system capacity is 5 kW (12.5% of the total load capacity).

The total annual optimal value of the objective function is USD 1,389,578.75999646. The maximum optimal value is obtained in August and is equal to USD 177,942.34. The various power and energy values are shown in Table 5.

Table 5. Optimal values per month for different resources.

Month/Resources	Objective Function	Batteries (Injection/Consumption)	Storage	Solar	Wind	Hydro
	Cost (USD)	P (kW)	E (kWh)	P (kW)	P (kW)	P (kW)
January	86,993.372	−5.9521873	125	32.78232	1.2654927	5.05×10^{-11}
February	107,862.57	−4.3408207	119.04781	33.91956	1.7396193	5.05×10^{-11}
March	137,518.88	−2.1732186	114.70699	35.40348	2.4233014	5.05×10^{-11}
April	113,170.6	2.9308321	112.53377	41.62752	1.3033121	5.05×10^{-11}
May	102,321.29	2.0975483	115.46461	41.04108	1.0564683	5.05×10^{-11}
Jun	106,827.33	1.7328749	117.56215	40.5162	1.2166749	5.05×10^{-11}
Jully	162,312.84	3.5950199	119.29503	40.9212	2.6738199	5.05×10^{-11}
August	177,942.34	5.0149667	122.89005	42.00336	3.0116067	5.05×10^{-11}
September	154,083.06	4.4502273	127.90502	42.08436	2.3658673	5.05×10^{-11}
October	91,055.383	0.5818162	132.35524	39.72888	0.8529362	5.05×10^{-11}
November	79,623.893	−2.4906887	132.93706	36.73836	0.7709513	5.05×10^{-11}
December	69,867.2	−5.44637	130.44637	33.8256	0.72803	5.05×10^{-11}

Table 5 shows monthly data for a year of optimization of renewable energy systems with battery energy storage. According to the results, the battery systems were first injected into the mini-grid in January, February, and March, then in November and December, in order to compensate for electrical loads. The maximum injection is 5.95 kW. From April to October, the battery system acts as a load, consuming electrical energy for storage. Total storage energy is estimated to be 133 kWh. These injection and storage periods for the battery system depend on the availability of renewable resources: solar and wind power. Hydro resources are neglected. Maximum solar power is estimated to be 42 kW, and maximum wind power is estimated to be 3 kW. The maximum cost of all technologies is estimated to be USD 177,942.34.

It should also be noted that in Togo [30], the main resource is solar power. However, other renewable energy resources, such as wind power in the south of the country, hydropower, and biomass, depending on the study area, are not neglected.

The transformer capacity of the microgrid under consideration is estimated to be around 50 kVA.

4.1.4. Capacity and Connection Optimization Results

To evaluate the optimization results of the microgrid study, two scenarios were considered. The first scenario was based on the influence of the distance of the load node connection, and the second scenario was based on the influence of the variation in the capacity of the load nodes.

(a) Scenario 1: results for voltage rate profile/distance

Simulation results for the influence of load distance from the substation (centroid) and for the influence of the satisfaction rate are shown in Figure 11. The following equation translates the satisfaction rate equation:

$$\frac{P_{station}}{P_{load}} \times 100 = \tau_s$$

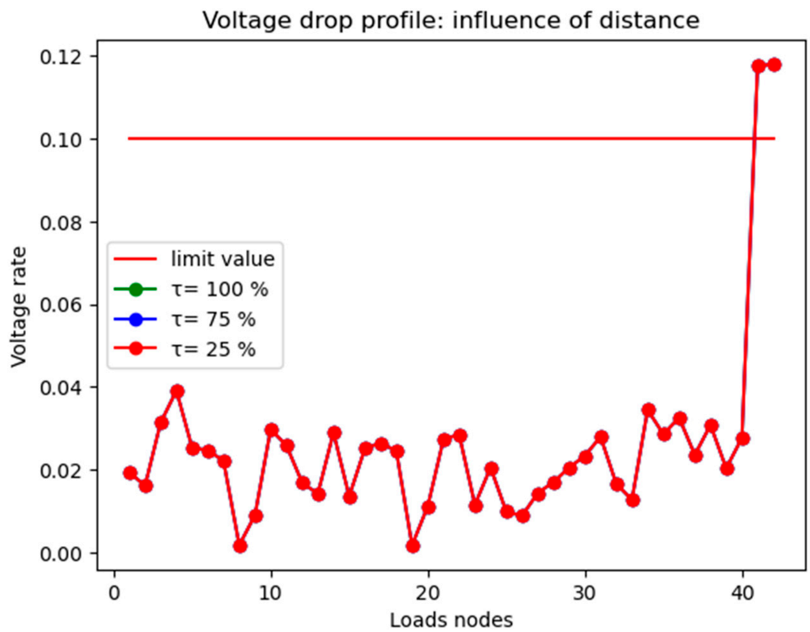


Figure 11. Voltage drop profile as a function of satisfaction rate and distance.

This equation expresses, in percentage terms, the satisfaction rate due to the availability of substation capacity in relation to load capacity. It expresses energy satisfaction due either to a balance between supply and demand or to a lack of energy at the substation due to an imbalance between supply and demand.

This figure shows the variation in voltage ratio as a function of load node location. This figure shows a perfect correlation between the satisfaction rates. Indeed, in this figure, the location of the loads in relation to the substation demonstrates the non-homogeneous trend of the voltage ratio. As the admissible limit value is 0.1, nodes 41 and 42 are outside the voltage ratio limit, as their distance influences the defined limits.

Figure 12 shows the total connection of centroid three load nodes when substation and load capacities are in balance. These nodes are unlike the load nodes of centroid 1, which are switched off.

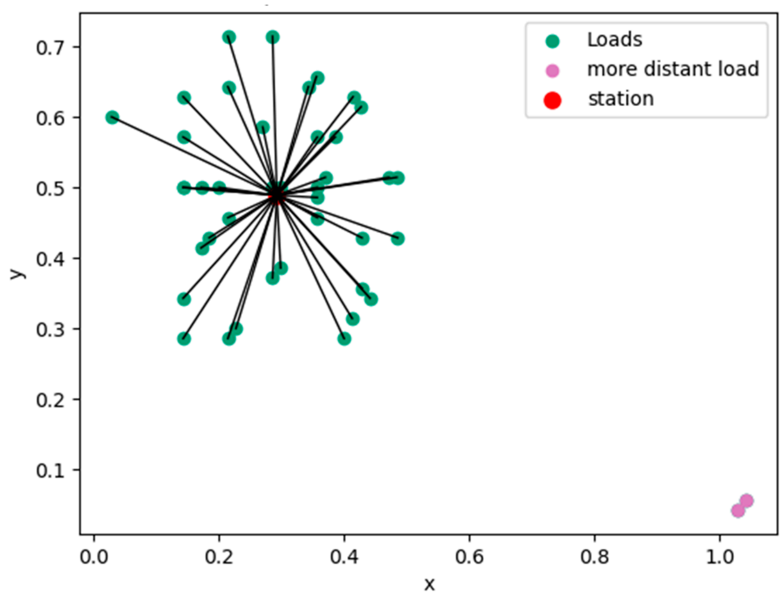


Figure 12. Optimum connection for $\tau_s = 100\%$.

However, the variation in the satisfaction rate does not influence the voltage rate but influences the connection. Figure 13a,b show the results obtained.

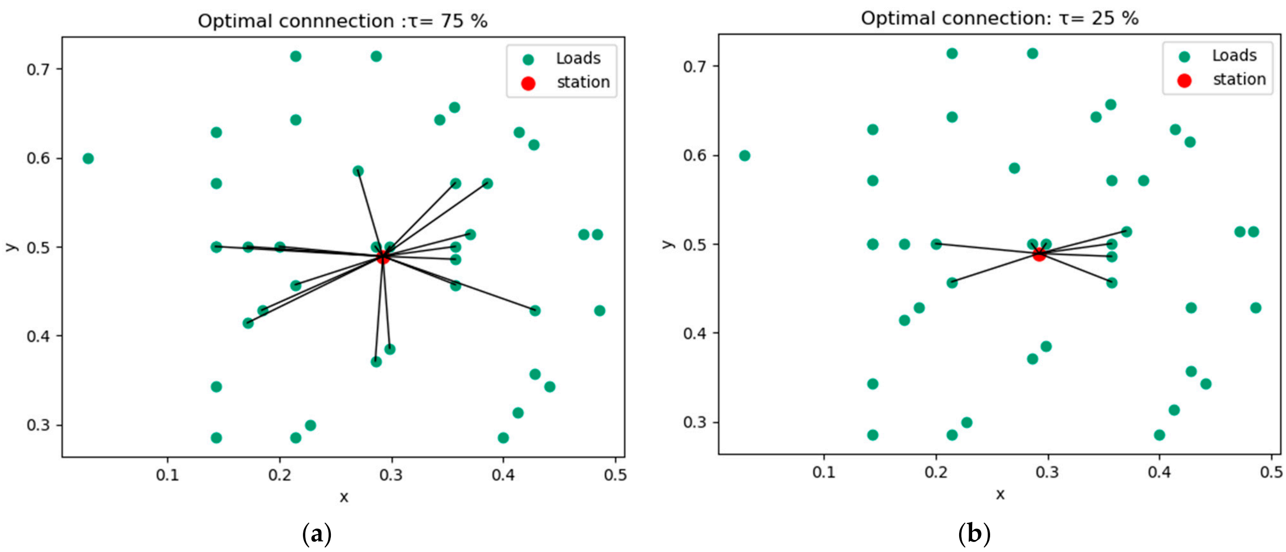


Figure 13. Load shedding. (**a**) τ_s = 75%; (**b**) τ_s = 25%.

Depending on the satisfaction rate, certain load nodes are not connected (in reality, these loads are switched off). This satisfaction rate reflects the energy insufficiency of the substation and would lead to optimal load shedding according to load capacity. The greater the energy shortfall, the fewer loads are connected (as shown in Figure b, where load shedding is higher).

However, if energy is injected into the microgrids, the loads will be connected back initially (as in the previous figure, where τ_s = 100%), and loads that are too far away will not be connected, regardless of the substation's capacity (as in the case of the two load nodes of centroid 1).

(b) Scenario 2: influence of load capacity

Variations in load capacity have a significant influence on the voltage ratio profile. The results are shown in Figure 14.

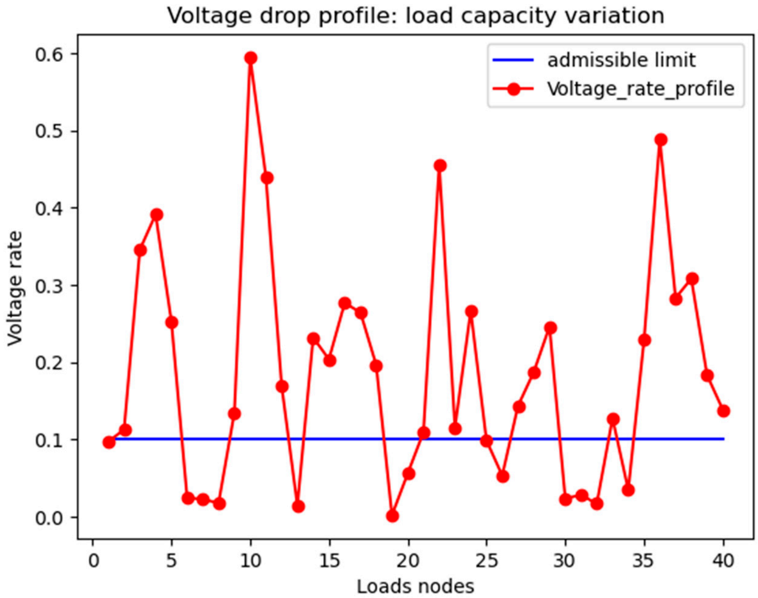


Figure 14. Voltage rate profile as a function of load capacity.

If the 40 load nodes in the initial study satisfied the voltage ratio condition, it is obvious that their load variations would cause them to malfunction. Figure 14 illustrates the influence of load capacity on voltage ratio. In fact, as loads increase in capacity, the voltage drop rate also increases and surpasses the admissible limit.

In response to this fault, loads are disconnected regardless of their proximity to the substation. Figure 15 illustrates optimal load shedding.

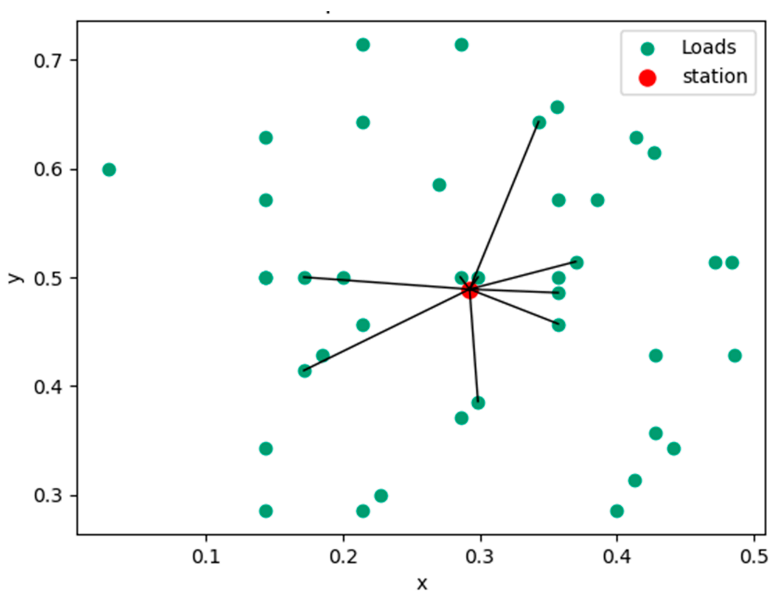


Figure 15. Load shedding: optimal load selectivity.

Although some load nodes are closer than others, and because they are more heavily loaded, they will be less connected than less heavily loaded load nodes located at a reasonable distance but further away. In Figure 15, some closer load nodes are unloaded, while some more distant, less-loaded load nodes are supplied (while still complying with the voltage drop rate condition).

A comparison of the variation in load capacity is shown in Figure 16.

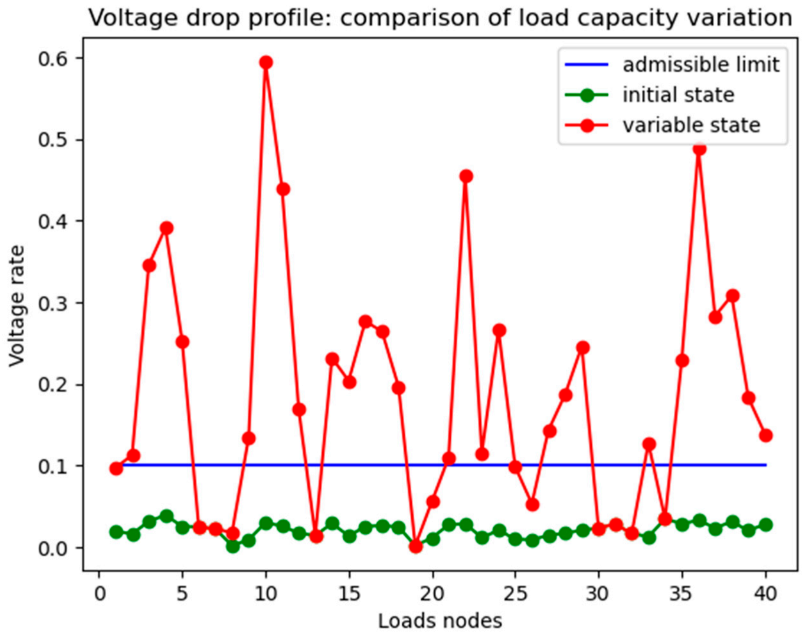


Figure 16. Comparison of initial state and transitional state of load capacity.

The comparison of the initial state, where load capacities are lower than in the variable state, shows the impact of load capacity on the microgrid.

The optimal national planning of microgrid systems and stand-alone photovoltaic systems in the short and long term is presented.

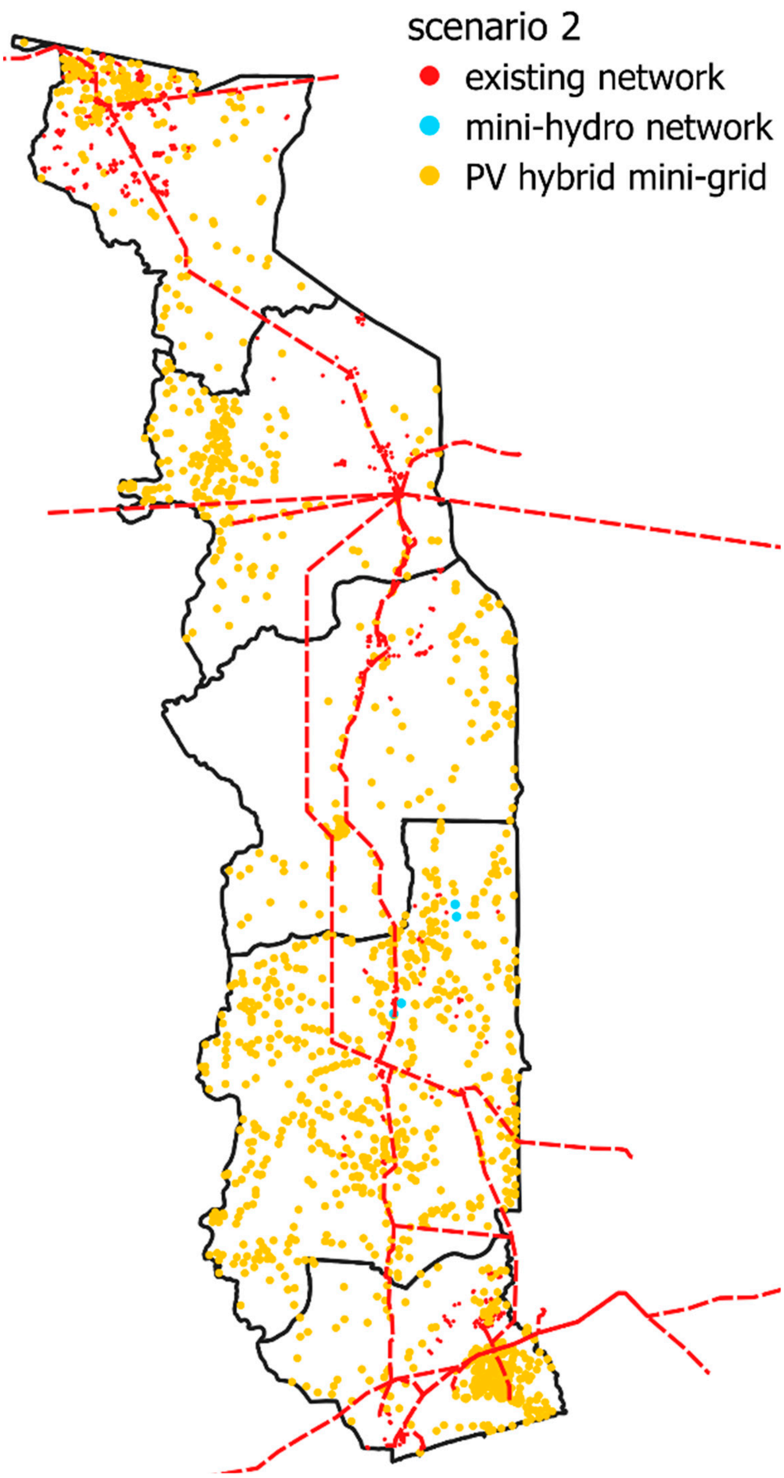
4.1.5. Results of Microgrid Formation Evaluation Studies in Togo

The results of the open-source spatial planning tool onsset were used to optimize the planning of general electrification in Togo based on various technologies, such as stand-alone photovoltaic systems and microgrids. Figure 17a,b illustrate the planning process.

The results in Figure 16a for the short term suggest microgrid systems with an electrification rate of 70%, compared with an electrification rate of 100% for the long term (Figure 17b). For the long term, in addition to the microgrid systems considered, stand-alone photovoltaic systems are also recommended if electrification is to be achieved throughout the country.

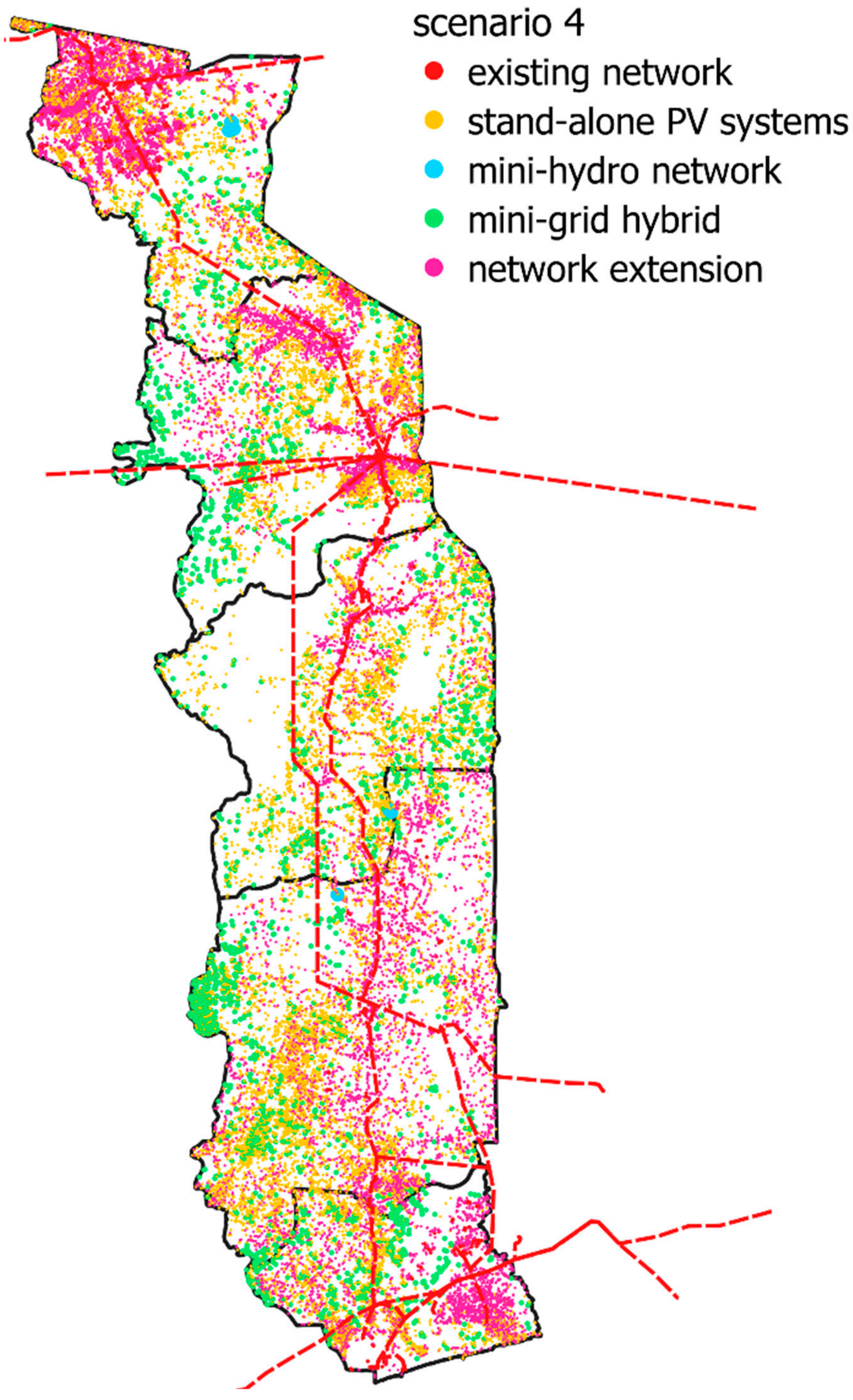
Table 6 presents the results of the different costs according to the scenario.

Table 5 shows the results of two different scenarios. For the short term, i.e., scenario 2, stand-alone photovoltaic systems with a capacity of 20 MW are recommended and are estimated to cost USD 184 million. Scenario 2 also opts for hybrid PV mini-grids with a capacity of 320 MW at a cost of USD 564 million versus hydraulic mini-grids with an estimated cost of USD 1.12 million. On the other hand, for the long term (scenario 4), PV systems are proposed with a capacity of 62 MW and an investment of 280 million. Mini-grids are also recommended at an estimated total cost of USD 1374 million for a capacity of 721 MW. However, scenario 4 shows the possibility of achieving total electrification of the country by estimating a global capacity of 1.06 GW for an investment of USD 2.6 billion.



(a)

Figure 17. *Cont.*



(**b**)

Figure 17. (**a**) Onsset: short term. (**b**) Onsset: long term.

Table 6. Summary of results for short- and long-term scenarios.

Horizon/Years	2024–2030		2030–2050	
Population	8,095,498		>12,000,000	
Scenarios	Scenario 2		Scenario 4	
Technologies/costs	Capacity (MW)	Investment (In million USD)	Capacity (MW)	Investment (In million USD)
Mini-grid PV hybrid	320	564	720	1371
Mini-grid hydraulic	<1	1.12	1	4.42
Mini-grid wind, biodiesel	0	0	0	0
Extension	-	-	274	964
Stand-alone PV systems	-	-	62	280

4.2. Discussion

Microgrid installation requires not only optimization methods to minimize investment costs but also automated voltage stability methods to ensure stability and resilience in accordance with connections. In this study, the elbow and k-means clustering methods were used to determine the number of clusters required for autonomous microgrid management and to determine the coordinates of the corresponding centroid, respectively; this strategy is necessary for the initial steps of a microgrid installation. Secondly, the intermittency of renewable resources led us to optimize the complementary management of these resources in order to contribute to the total energy satisfaction of electrical loads estimated to be 40 kW. This resulted in the solar resource being the most favored for satisfying these electrical loads, with a rate of 80% compared with 7.5% for the wind resource and 12.5% for battery capacity. In areas with very low wind and water resources, solar power and battery systems may be the preferred option. Nevertheless, a careful study is needed before a microgrid can be installed in a given locality; hence, the results that enabled us to evaluate the formation of microgrids using an open-source spatial optimal electrification planning system: onsset. In this study for Togo, two types of isolated or hybrid mini-grid systems were recommended: solar mini-grid systems and hydraulic mini-grid systems. Stand-alone photovoltaic systems were also proposed. The optimal investment costs for the short and long term are estimated to be around USD 567 million for an energy production capacity of around 321 MW, compared with USD 2.6 billion for a capacity of around 1 GW. However, it should be pointed out that wind systems based on mini-aerogenerators and biodiesel are not negligible, as their feasibility studies are essential for any microgrid installation project. In this study, the case of the wind mini-grid is proposed and is therefore not neglected.

In addition, a technical proposal for one of the options for installing a microgrid based on photovoltaic systems would be to exploit either the roofs of houses or to consider other methods, such as agri-photovoltaics (photovoltaics combined with agriculture).

Finally, this study enabled us to limit load connections according either to their capacity or their position relative to the microgrid substation, crucially ensuring the stability of the microgrid. On the one hand, it was found that high load capacity leads to network instability and, therefore, to the shedding of higher loads in favor of lower ones in order to keep the microgrid more stable. On the other hand, the fact that the loads are located far from the substation has an impact on the voltage stability of the network, which also results in load shedding. The variation in load capacity in a microgrid and its positioning in relation to its connection can have a significant impact on grid performance, resulting in voltage instability, hence the need for pre-feasibility studies when installing a microgrid.

The study also showed that a substation's energy deficiency would optimally lead to the shedding of certain loads.

5. Conclusions

The study of the installation of microgrids is important because it allows us to optimally manage the implementation of all the components of a system and to ensure the system's stability. As a first step, we, therefore, carried out feasibility studies on the availability of the country's annual renewable energy resources. Secondly, optimal management of these resources is proposed for the optimal sizing of the microgrid energy systems to be installed, taking into account their costs and availability according to their intermittency. In the optimum results obtained, solar systems account for 80% of the maximum load considered, compared with 7.5% for wind systems and 12.5% for battery systems. Finally, a study of optimal load selectivity according to its effect on the voltage stability (connections or load shedding) of the mini-grid was carried out. The results of this study were conclusive and enabled us to obtain the optimal model required for the installation of the microgrid being considered. In addition, a specific study of the overall planning of Togo's electrification using the spatial optimal planning tool generated solar, hydraulic, and hybrid mini-grid systems. The estimated overall cost for the short and long term during the planning phase is in the order of USD 567 million for a capacity of 321 MW in the short term and USD 1374 million for a capacity of 721 MW in the long term.

However, in this sizing study, the application of wind mini-systems was demonstrated as the feasibility study showed that wind-based hybrid systems were not neglected in the case of South Togo. However, the biodiesel system was not taken into account in this simulation. In summary, the results obtained are satisfactory and highly conclusive, indicating that we optimally simulated the dimensioning of a microgrid through the optimal management of energy resources, the optimal connection or load shedding of its loads, and the optimal planning of electrification. This study is an optimization study of the installation of a microgrid that would reduce losses and costs as much as possible, in technical and economic terms, for power grid operators.

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Conflicts of Interest: Author Pidéname Takouda was employed by the Electrical Energy Company of Togo. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Nomenclature

$P_s(t)$	solar power variable
τ, τ'	charging (80%) and discharging (20%) rates
η	performance
ε	performance rate
S	area
Δt	temperature differential
X_s^d	decision variable

$T_{c,ref}$	standard temperature
$soct(t+1)$	battery storage at t + 1
$soct(t)$	battery storage at t
$p_{bat}(t)$	battery power
N_{bat}	number of batteries
C_{bat}	battery capacity
V_{bat}	battery volatge
η_{bat}	battery efficiency
$P_e(t)$	wind power
ρ_e	air density
S_w	area swept by the turbine
η_e	wind power efficiency
X_e^d	wind decision variable
$f(v)$	probability density
c	scale factor
v	wind speed
k	shape factor
σ	standard deviation
$\overline{v}$	average speed
$\overline{P}$	average power
Γ	gamma function
$P_h(t)$	hydroelectric power
ρ_h	density of water
g	acceleration
Q	water flow rate
h	waterfall height
η_h	hydroelectric efficiency
μ	average solar irradiance
σ	variance of solar irradiance
P_{ch}	load power
$f(P_{ch})$	load modeling function
S_i	power of loads i
i	index
P_{conv}	converter power
α_u	utilization factor
P_s	solar power
V	load vector matrix
v_i	vector i
μ_k	clusters
D	distance
R	Earth radius
c	constant
φ_A, φ_B	latitudes
λ_A, λ_B	longitudes
C_{inv}^T	total investment cost
C_{inv}^i	investment cost
$C_{o\propto M}$	maintenance and operating costs
r	discount rate
t	year
P_i	load i power
P_j	substation j power
α_j	coefficient
j	substation index
C_r	replacement cost
x_{ij}	binary variable load $-$ substation $\{0;1\}$
S_j	substation j power
τ	voltage drop rate
d_{ij}	distance load $-$ substation

I_n	nominal current
I_n^i	nominal currentof load i
U_n	nominal voltage
r	linearr esistance
z	reactance
$\overline{X}$	average

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