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Article

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

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Abstract: Optimal planning and design of microgrids is a priority for electrification of off-grid areas. Indeed, according to one of the Sustainable Development Goals (SDG) 7, the UN recommends universal access to electricity for all but, at the lowest cost. To achieve this goal, several optimization methods with different strategies have been proposed in the literature. This paper proposes a microgrid installation and planning model based on a combination of several techniques. Python 3.10, the programming language, has been 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: onset. The results obtained enabled us to simulate the model obtained, with a cluster considered as a case study, based on the elbow and k-means clustering method; then, in a second phase, to size the microgrid with a capacity of 40 kW, by optimizing all the resources available on the site: the example of the various resources in the case of Togo was considered (solar, wind, hydropower). This study therefore highlighted the optimal resources obtained by integrating battery systems by the optimization model formulated on the basis of the various technology costs, such as investment, maintenance and operating costs, based on the technical limits of the various technologies. For 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. Next, an optimal microgrid connection model was proposed, based on the constraints of a voltage stability limit estimated at 10% of the maximum voltage drop. The substation capacity limit was also taken into account. The results obtained from the case studied enabled us again, to present selective results for load nodes in relation to the substation node. And finally, the spatial technology planning tool made it possible to obtain results on the different strategies for the various technologies required for the electrification planning study of the Togo case. The various results obtained from the different techniques provide the leads needed for a feasibility study for optimal electrification of off-grid areas, using microgrid systems.

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

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, small technologies for supplying electrical energy, are solutions for which the various forms of renewable energy are favored. Fernando Antonanzas-Torres and al. [1] recommend mini-grid systems for the electrification of countries whose electrification rate has not yet reached 100%, as recommended by the United Nations Sustainable Development Goal (SDG7): access to electricity for all [2,3] while respecting environmental constraints[4,5]. Furthermore, according to Sedzro et al. [6], microgrids, or mini-grids, are a potential solution to macrogrids for restoring electricity networks after disasters. In short, microgrids make it possible, on the one hand, to reduce losses on supply lines and improve local power supply reliability and energy efficiency, while offering a sustainable and efficient system [7], and on the other hand, 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] ; intermittent weather conditions that sometimes affect reliable and economic behavior. Among these challenges, the modeling of microgrids is an important factor. Indeed, according to FAHAD SALEH AL-ISMAIL [10], to overcome the challenges associated with microgrids, they 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 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 based, firstly, on the cluster consideration of the microgrid and the minimization of the centroid distance from the loads. Secondly, it 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, an optimal model based on its optimal load connections following the definition proposed in [11] by the US Department of Energy and finally, in a fourth step, an optimal microgrid planning is proposed for the particular case of Togo using the onset method.

The different electrical models of the various microgrid components are presented.

2. Theoretical Background

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 formula [12,13]:

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

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

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

Hydroelectricity production, which depends on the average water flow (m³/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/s², the density of the water and the yield [13,15,16], is expressed by:

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

Battery state of charge and power [18–21] at each simulation time is formulated as follows:

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

Storage at a given time t is formulated as follows:

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

$$E(t) = S_i \times t \quad (6)$$

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

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

The bi-directional converter is given by:

$$P_{conv} \geq \alpha_u \times P_s \quad (9)$$

A part from the technological models of microgrids, the electrical load models of the microgrid are formulated by [21–23]:

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

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

2.2. Scientific Methods for Microgrid Deployment

2.2.1. Clustering Techniques

2.2.1.1. k-means Clustering Model

The clustering technique refers to the notion of measuring similarity between two vectors. In fact, 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 kmeans clustering technique first, groups the different variables x_i in a certain set (cluster formation), and then, in a second step, minimizes the distance between the centroid and the clusters formed.

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

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

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

For

$$1 \leq k \leq c \quad (13)$$

Minimizing the distance between centroids and their respective clusters consists in assigning each nearest centroid to clusters such that:

$$\min \sum_{i=0}^n \|v_i - \mu_k\|^2 \quad (14)$$

2.2.1.2. Elbow Method

The elbow method is a method for determining 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 and normalized to [0 ;1] in [25,26].

2.2.2 Haversine Method

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

$$D = R \times c \quad (15)$$

$$c = 2 \arctan \left(\frac{\sqrt{a}}{\sqrt{1-a}} \right) \quad (16)$$

$$a = \sin^2 \left(\frac{\varphi_B - \varphi_A}{2} \right) + \cos \varphi_A \cdot \cos \varphi_B \times \sin^2 \left(\frac{\lambda_B - \lambda_A}{2} \right) \quad (17)$$

$$R = 6371 \text{ Km} \quad (18)$$

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

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

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 different scenarios (4), taking into account the costs and availability of these resources not far from localities. The electrification planning model therefore takes into account: the minimization of system costs (operating costs, investment costs, maintenance costs), the evolution and level of the population, and the different technology configurations according to resource availability. The mathematical formulation of the model, inspired by [29] and the global study for all of the four scenarios for the case of Togo is obtained in [30]. In effect, this model informs the general planning of a country's overall electrification.

In this study, the developed microgrid model makes it possible to specifically define the technologies to be implemented according to their cost and annual availability for a given site, then with onset, a general configuration of the implementation of these technologies is 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 research. [31]. However, several studies have been carried out in the literature using different methods.

Indeed, Li Bei et al. [32] have exploited evolutionary algorithm methods and mixed integer linear programming, for optimal sizing of microgrids; Alessandra Parisio and al. [33] present 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 is formulated using integer linear programming with Matlab as the solution tool; Li Guo and al. [34] present 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 propose a microgrid optimization based on a hybridization system of renewable energy resources; Mah AXY et al. present an optimization for the 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, are proposed in [37,38]. Aiswariya L. and al. [39] propose optimal battery sizing using the simulated annealing method actually based on the probabilistic method [39,40] ; stochastic methods for the planning, operation and economic control of microgrids are presented in [41].

Various microgrid optimization techniques can be used, including probabilistic techniques [41,42], artificial intelligence techniques [43,44], iterative techniques [45,46], and deterministic techniques [47–49].

Among all these different methods, there is the linear programming [50,51] and mixed integer linear (PLNEM) solver (PLNEM) [32,33], which provides a suitable framework for obtaining high-quality solutions [52] with acceptable computational effort and good convergence properties. The mixed integer linear programming solution method, therefore, is one that is widely employed for HRES (Hybrid Renewable Energy Systems) and is characterized by good convergence [53,54].

In this work, the mixed integer linear programming method is widely exploited.

3. Materials and Method

3.1. Materials

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

3.2. Method

3.2.1. Microgrid System Model

The proposal for a microgrid model, inspired by existing models [55–58], is presented.

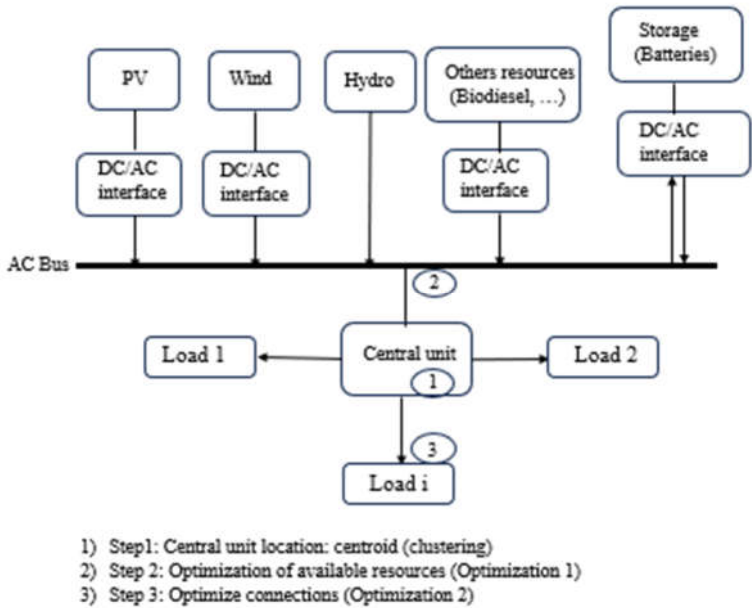


Figure 1. Microgrid model.

Three different methods were used. The first is an optimization formulation which initially consists in 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 that minimizes not only the microgrid connection distance, but also the load shedding or supply of the loads to be connected. 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 onset (described in 1.33), 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. Optimization Problem Formulation

Objective function 1: minimization of deviation between centroid and loads (k-means clustering method)

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

Subject to:

$$\mu_k > v_i^{\min} \quad (19)$$

$$\mu_k < v_i^{\max} \quad (20)$$

Objective function 2: minimizing the total cost of technology (microgrid sizing)

$$\min: C_{inv}^T = \left\{ C_{inv}^i + \sum_{t=1}^{n-1} \frac{C_{o\alpha M} + C_r}{(1+r)^t} \right\} \quad (21)$$

$$C_{inv}^i = \sum_{i=1}^5 \sum \sum \alpha_i c_i P_i \quad (22)$$

$$C_{o\alpha M} = \sum_{i=1}^5 \sum \sum \alpha_i c_{\alpha} P_i \quad (23)$$

$$s_j = \sum_{j=1}^5 \sum \alpha_j P_j = \alpha_6 P_{bat} + \sum_i p_i \quad (24)$$

$$\alpha_j = \begin{cases} 1 & \text{if the resource is available} \\ 0 & \text{if not} \end{cases} \quad (25)$$

$$j = \begin{cases} 1, \text{solar (s)} \\ 2, \text{wind (e)} \\ 3, \text{hydraulic (h)} \\ 4, \text{biomass (bio)/biodiesel} \\ 5, \text{batteries (bat)} \end{cases} \quad (26)$$

$$\begin{bmatrix} p_s^{\min} \\ p_e^{\min} \\ p_h^{\min} \\ p_{bio}^{\min} \\ p_{bat}^{\min} \\ soct^{\min} \end{bmatrix} \leq \begin{bmatrix} p_s \\ p_e \\ p_h \\ p_{bio} \\ p_{bat} \\ soct \end{bmatrix} \leq \begin{bmatrix} p_s^{\max} \\ p_e^{\max} \\ p_h^{\max} \\ p_{bio}^{\max} \\ p_{bat}^{\max} \\ soct^{\max} \end{bmatrix} \quad (27)$$

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

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

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

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

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

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

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

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

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

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

$$s_i = \frac{\sum_i p_i}{\cos\phi}$$

Objective function 3: minimization of load connection distances and selectivity of loads according to their capacities

$$\min: \sum_i x_{ij} d_{ij} \quad (28)$$

For a fixed j

Subject to:

$$x_{ij} = \begin{cases} 1 & \text{if } i \text{ is connected at } j \\ 0 & \text{if not} \end{cases} \quad (29)$$

$$\sum_i x_{ij} s_i \leq 0.8 \times s_j \quad (30)$$

$$\tau \times 100 < 10 \quad (31)$$

$$\tau = \sqrt{3} \frac{I_n^i}{U_n} x_{ij} \times d_{ij} \left(r \cos\theta + z \sqrt{1 - (\cos\theta)^2} \right) \times 1000 \quad (32)$$

$$\sum_i I_n^i \leq I_n \quad (33)$$

$$s^i = \sqrt{3} U_n \times I_n^i \quad (34)$$

$$d = 6371 \times c$$

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

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

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

$$i \in I = \{\text{charges}\} \quad (35)$$

$$j \in J = \{postes\} \quad (36)$$

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

The clustering algorithm is presented:

- 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:

$$\mu_k = [\mu_k^1, \mu_k^2, \dots, \mu_k^j, \dots, \mu_k^p], \quad 1 \leq k \leq c$$

- Calculate mk averages of vectors in cluster k
 - Until there are no more changes in the mk
 - Do Each Vi point is assigned 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.

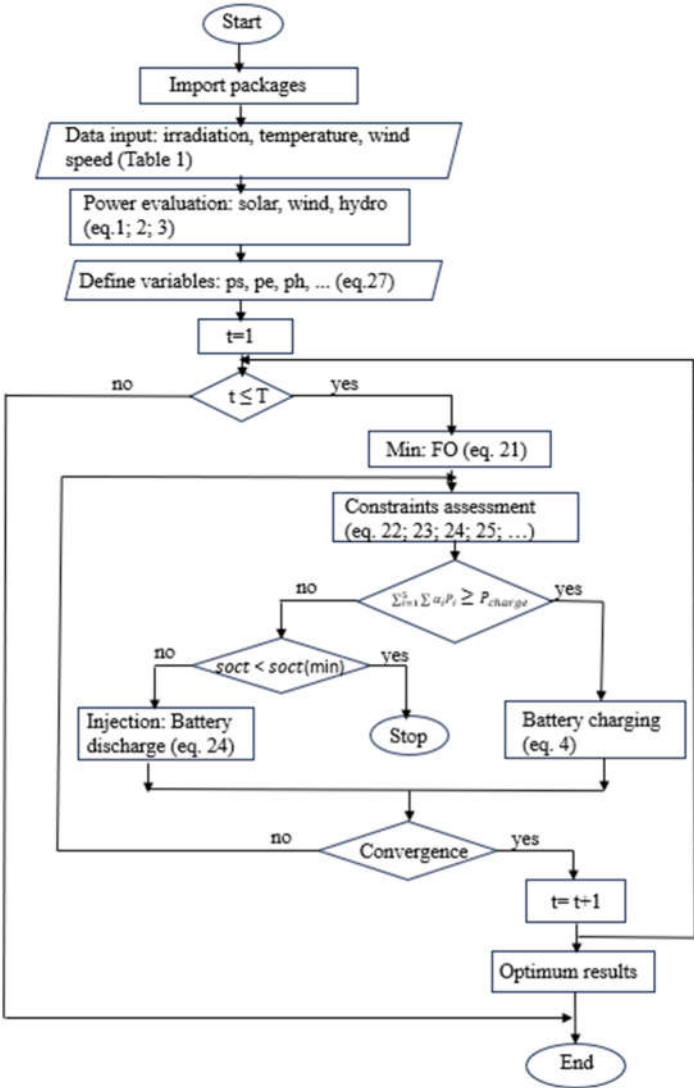


Figure 2. Renewable resources optimization flowchart.

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

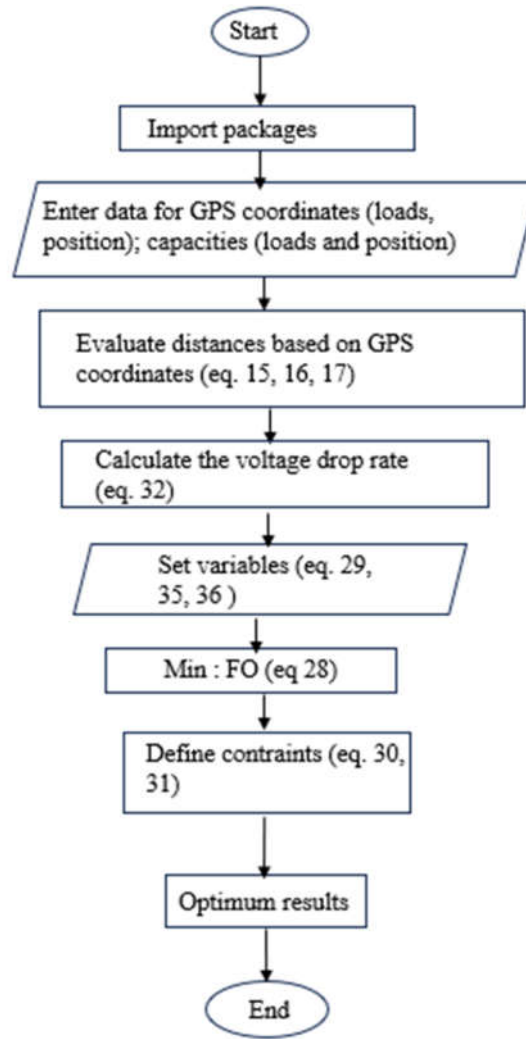


Figure 3. Optimal connection optimization flowchart.

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, the mean, the standard deviation:

$$\min = \min(x_i) ; \max = \max(x_i) : i = 1, \dots, N \quad (35)$$

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N x_i \quad (36)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{X})^2} \quad (37)$$

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

Mon ths	Solar radiation (W/m²)				Temperature (degree)				Humidity (%)				relative Wind speed (m/s)			
	Min	Ma	$\bar{X}$	σ	Mi	Ma	$\bar{X}$	σ	Mi	Ma	$\bar{X}$	σ	Mi	M	$\bar{X}$	σ
	x				n				n				n			
J	85.4	115.	99.0	5.	26.	28.	27.	0.	60.	85.	75.	6.	2.0	4.4	3.	0.
	6	71	1	87	12	41	59	59	56	62	25	92	4	5	27	68
F	85.9	113.	103.	6.	27.	28.	28.	0.	69.	85.	80.	2.	2.2	5.1	3.	0.
	8	63	63	95	58	57	05	23	75	19	92	97	1	7	94	76
M	84.9	122.	108.	9.	27.	28.	28.	0.	78.	86.	81.	1.	3.9	6.1	4.	0.
	8	43	85	69	83	96	38	23	44	31	99	89	9	1	78	57
A	109.	137.	127.	7.	26.	28.	27.	0.	78.	88.	83.	2.	1.8	5.4	3.	0.
	64	14	32	0	95	38	67	46	31	31	72	35	6	9	7	91
M	108.	132.	126.	4.	26.	28.	27.	0.	76.	88.	85.	2.	1.9	4.4	3.	0.
	89	91	36	72	49	11	41	41	19	62	21	59	1	7	41	56
J	112.	128.	121.	3.	25.	27.	26.	0.	79.	92.	87.	3.	1.9	5.6	3.	0.
	42	5	95	63	09	42	25	73	0	88	34	28			69	85
J	117.	129.	123.	2.	24.	25.	25.	0.	82.	90.	87.	2.	3.4	6.5	5.	0.
	48	11	56	93	44	9	10	36	19	81	35	33	2	5	06	66
A	117.	134.	127.	3.	23.	25.	24.	0.	82.	92.	87.	2.	2.4	7.8	5.	1.
	97	07	02	74	64	35	34	46	62	31	89	0		2	29	36
S	125.	140.	134.	3.	24.	25.	25.	0.	82.	91.	87.	2.	3.2	6.5	4.	0.
	77	23	24	19	95	87	45	24	88	5	28	18	6	5	85	88
O	113.	133.	125.	4.	25.	27.	26.	0.	84.	90.	87.	1.	2.1	5.5	3.	0.
	06	61	49	72	17	4	32	63	62	69	60	55	6	5	19	89
N	106.	122.	114.	4.	26.	27.	27.	0.	79.	87.	83.	1.	1.6	4.7	3.	0.
	05	58	64	22	64	83	24	3	44	0	24	78	5	7	03	71
D	90.7	111.	103.	4.	25.	27.	27.	0.	61.	86.	78.	6.	1.6	4.3	2.	0.
	2	33	36	46	9	8	01	35	62	62	24	64	2		94	61

J=January; F= February; ...; D= December.

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

Table 2. Random statistical data.

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

Table 3. Parameters [59,60].

Costs /systems	PV (USD /kW)	Batteries/6V (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/an	20/an
Replacement cost	700	1300	-	-	-

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

4. Results and Discussions

4.1. Optimization Results

4.1.1. Results on Cluster Formation

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

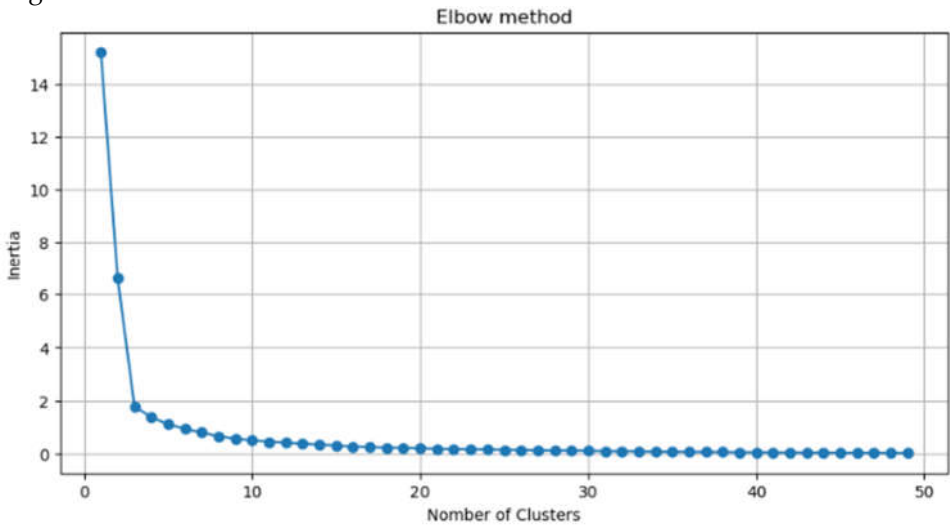


Figure 4. Elbow method for determining cluster numbers.

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

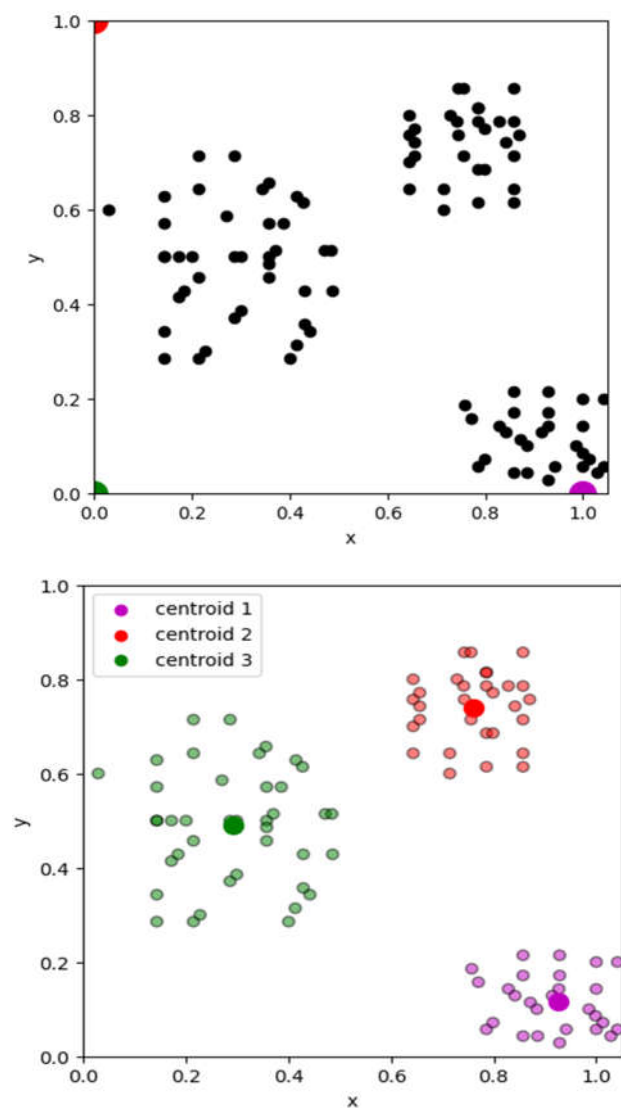


Figure 5. (a) K-means technique; (b) Centroids formation.

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

Table 4. Summary of cluster centroid values.

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

With the clusters and their centroids formed, a special case study based on cluster 3 is carried out.

Figure 6 shows the corresponding cluster 3. Two nodes of centroid 1 are also shown for study.

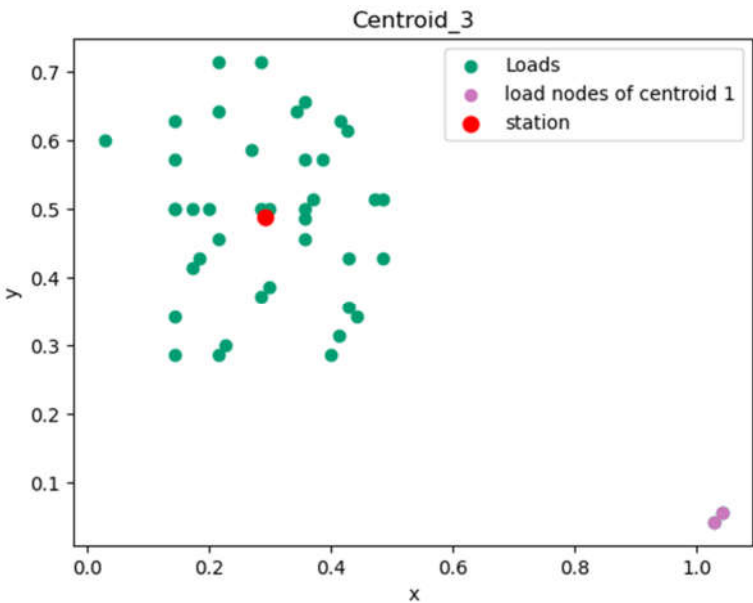


Figure 6. Cluster 3 considered.

The number of load nodes defined for this centroid 3 is 40. For these load nodes, the total capacity defined for study is assumed to be 40,000W or 40 kW.
The results of the optimal simulations are presented.

4.1.2. Renewable Energy Resources 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 potential is shown. According to Rafat Al Afif et al. [61], there would be no specific impacts from extreme events that could 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.

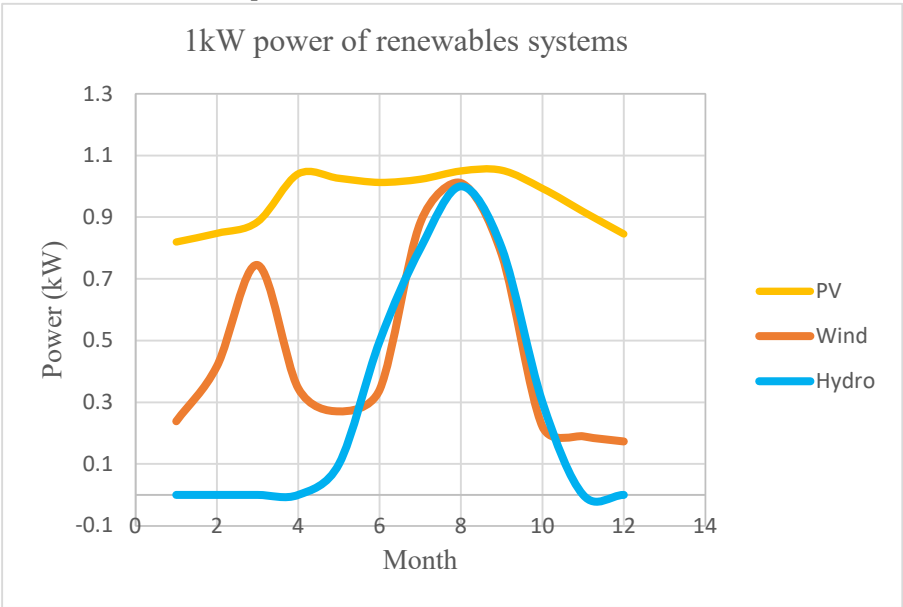


Figure 7. Energy resources of 1 kW in power.

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 9 respectively.

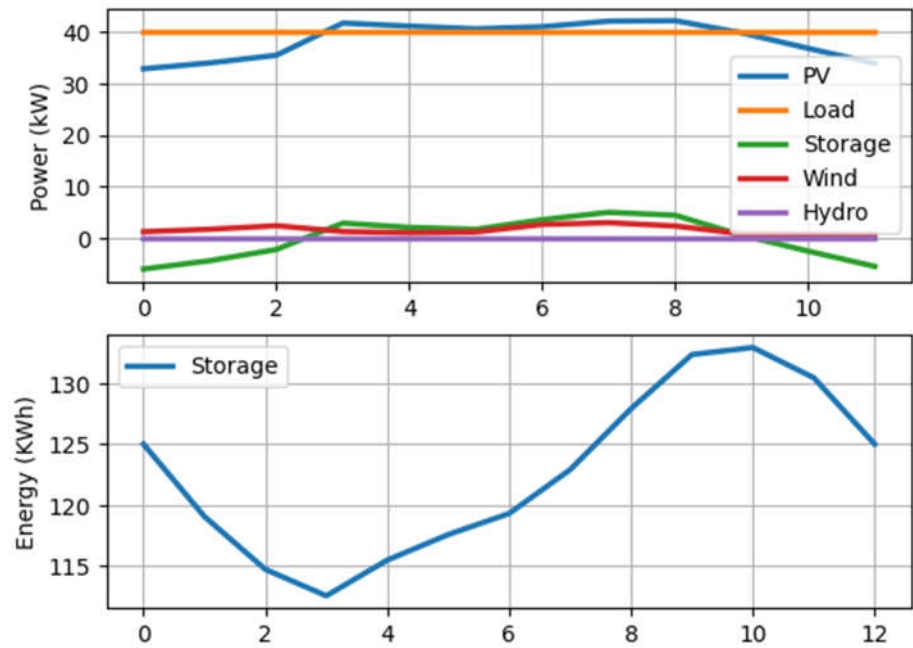


Figure 8. Optimal profile of renewable resources and energy storage.

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, whose annual variation would allow optimal choices of technologies depending on the period. The wind resource is not neglected either.

In fact, this optimization of resources makes it possible to define the appropriate technologies for each month when installing the microgrid.

The maximum capacity of the storage system is estimated at 135 kWh. Details of the power of the various resources, which may be small or large depending on the period, are shown in Figure 9.

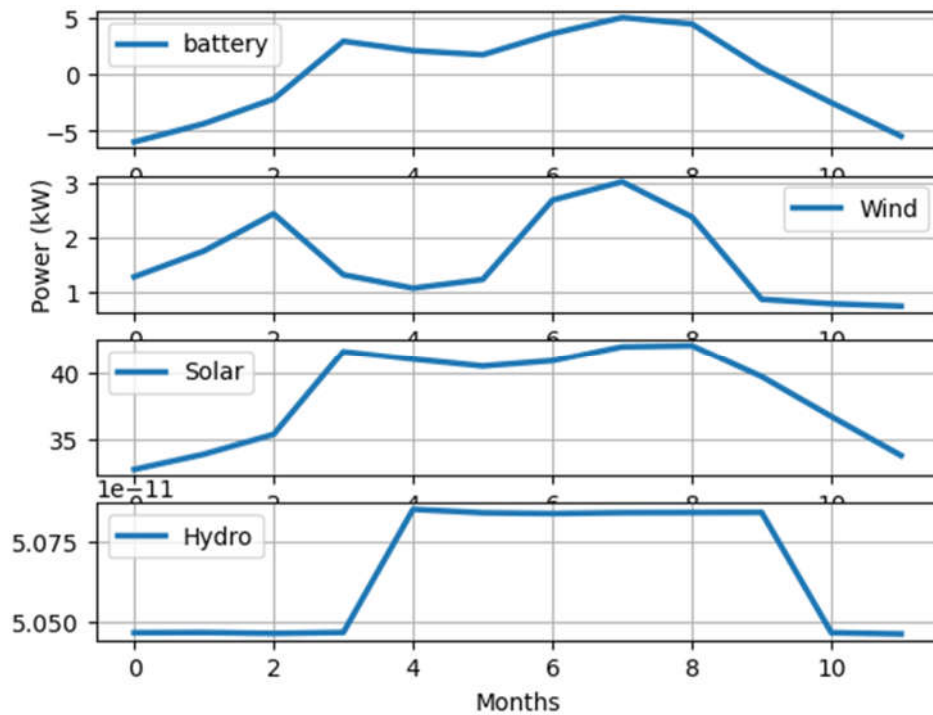


Figure 9. Optimum performance of renewable resources.

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

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 at around 50 kVA.

4.1.4. Capacity and Connection Optimization Results

To evaluate the optimization results formulated on the microgrid study, two scenarios were carried out. The first scenario was based on the influence of the distance of the load nodes for their connection; and the second scenario, on the influence of the variation in the capacity of the load nodes.

a) Scenario 1: results on voltage rate profile/distance

Simulation results on the influence of load distance from the substation (centroid) and on the influence of the satisfaction rate are shown in Figure 10. The following equation translates the satisfaction rate equation:

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

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.

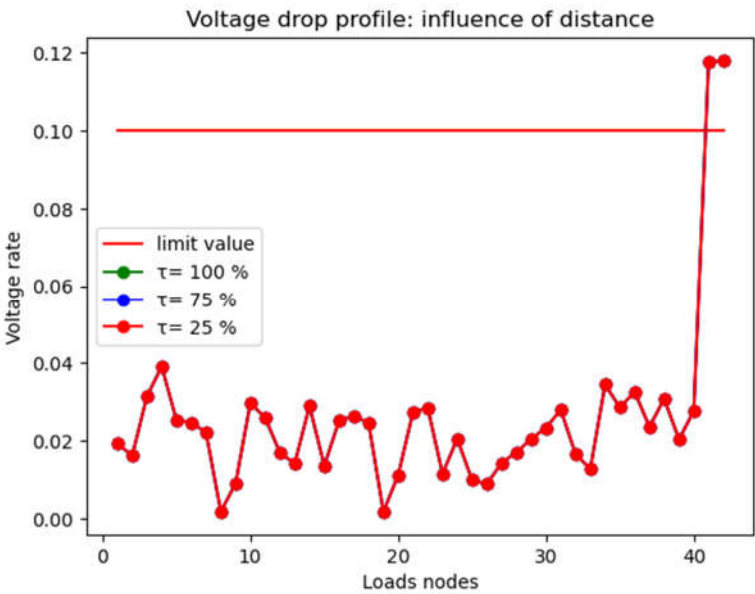


Figure 10. Voltage drop profile as a function of satisfaction rate and distance.

This figure shows the variation in voltage ratio as a function of load node location. 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 11 shows the total connection of centroid 3 load nodes when substation and load capacities are in balance. Unlike the load nodes of centroid 1, which are switched off.

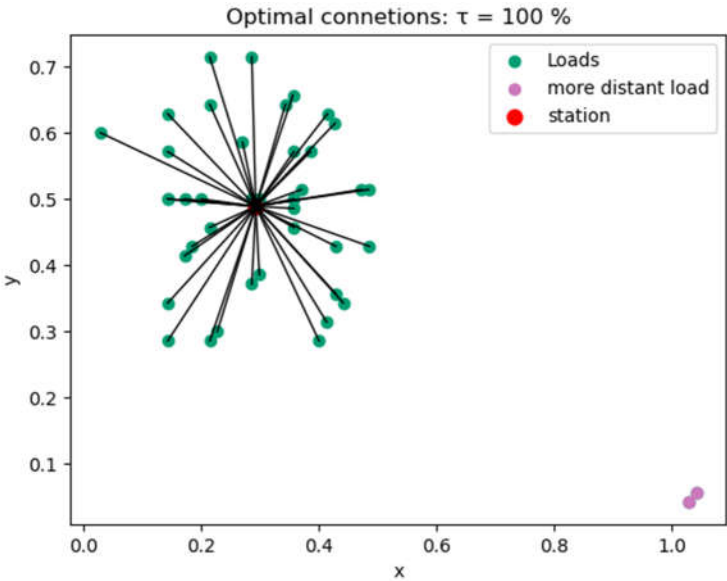


Figure 11. Optimum connection for $\tau_s = 100\%$.

However, the variation in the satisfaction rate does not influence the voltage rate, but influences their connection. Figure 12 (a and b) shows the results obtained.

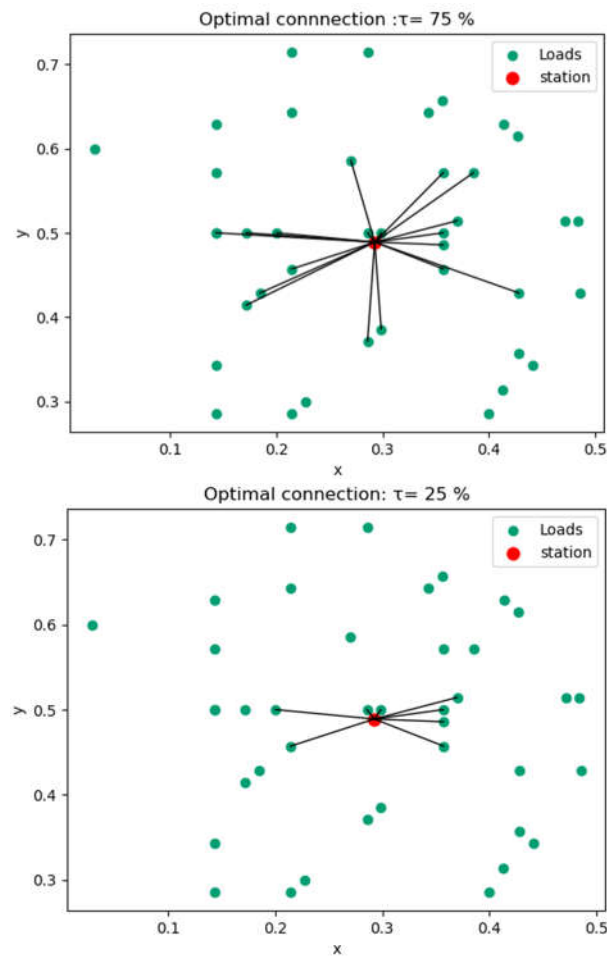


Figure 12. Load shedding a) $\tau_s=75\%$; b) $\tau_s=25\%$.

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. 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 $\tau_s=100\%$), and loads that are too far away will not be connected, whatever 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 13

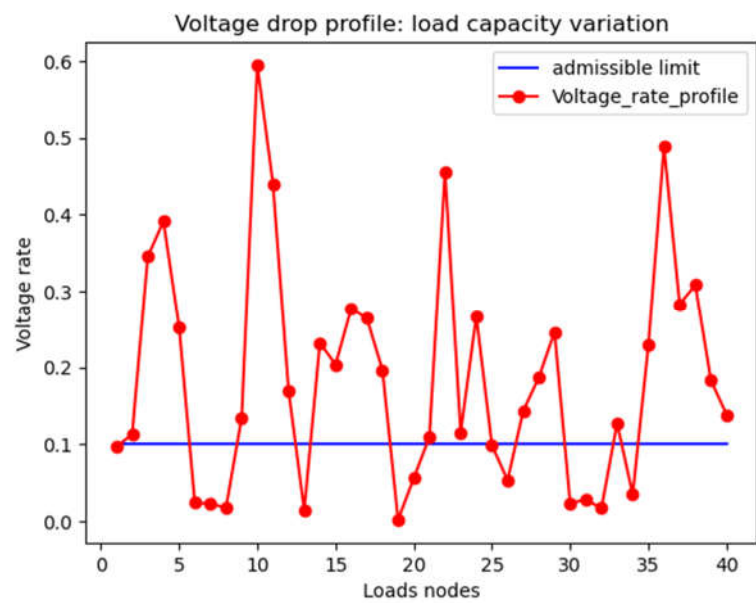


Figure 13. Voltage rate profile as a function of load capacity.

If the 40 load nodes in the initial study satisfied the voltage ratio condition, it’s obvious that their load variations would cause them to dysfunction. Figure 13 actually illustrates the influence of load capacity on voltage ratio. In fact, as loads increase in capacity, the voltage drop rate also increases, making them ineligible for the admissible voltage drop rate limit.

In response to this fault, loads are disconnected whatever their proximity to the substation. Figure 14 illustrates optimal load shedding.

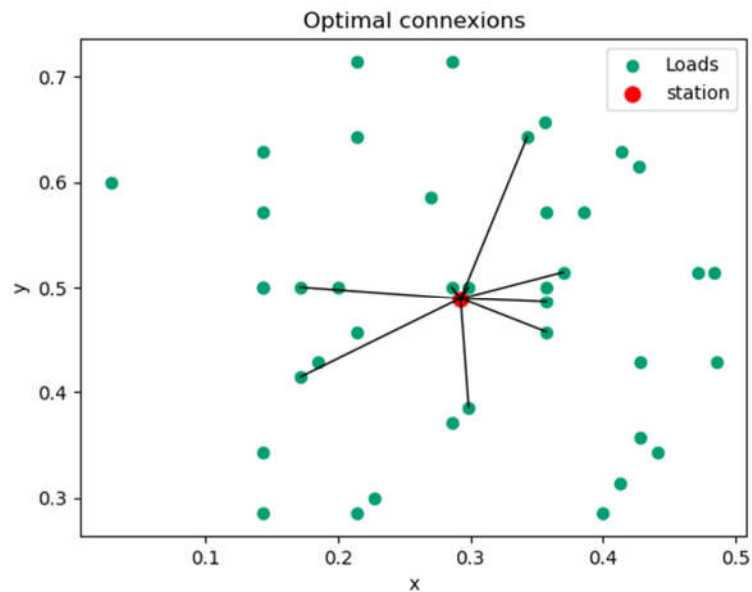


Figure 14. Load shedding: optimal load selectivity.

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

A comparative study of the variation in load capacity is shown in Figure 15.

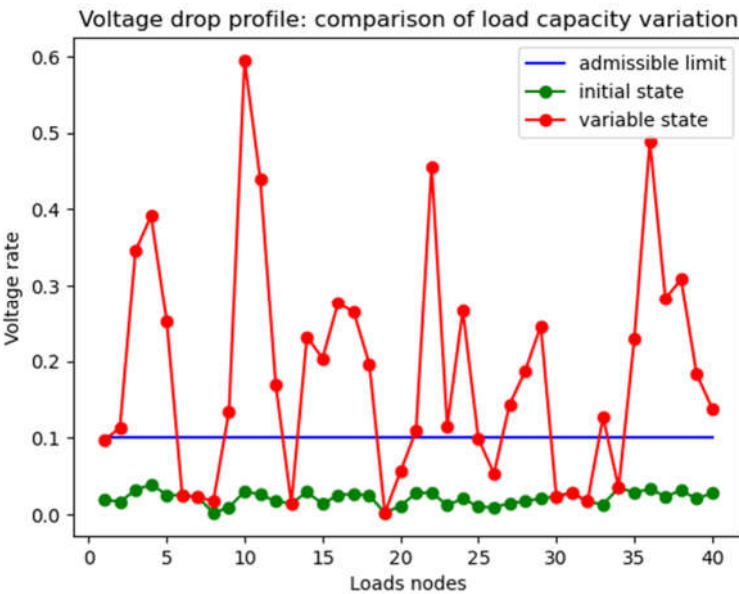


Figure 15. Comparative study: initial state and transitional state of load capacity.

The comparative study 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.

4.1.4 Results of Microgrid Formation Evaluation Studies in Togo

The results of the open-source spatial planning tool, onsets, have been used to optimize the planning of general electrification in Togo, based on the various technologies, such as stand-alone photovoltaic systems and microgrids. Figures 16 a and b, illustrate the following planning process.

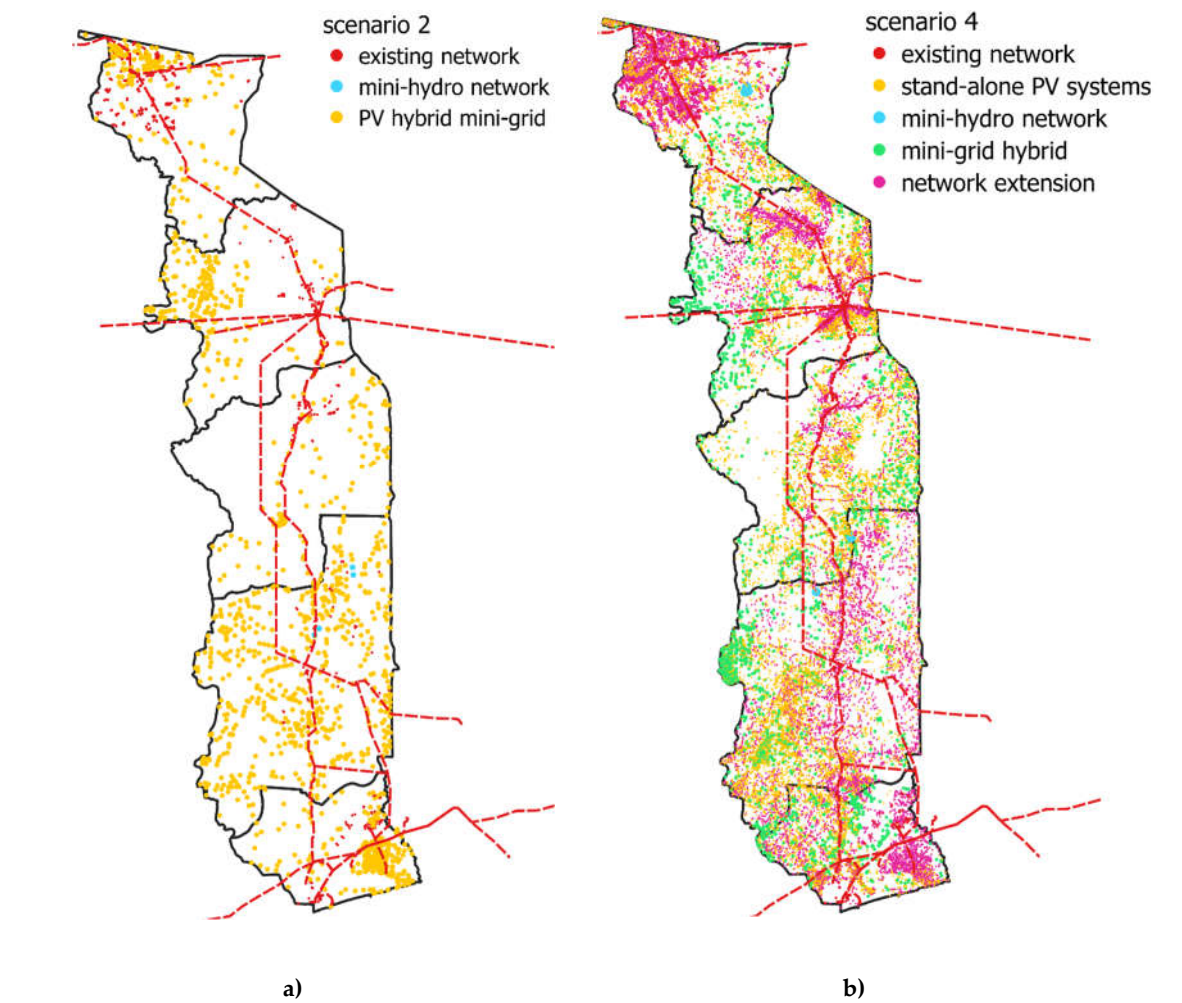


Figure 16. (a) Onset: short term; (b) Onset: long term.

The results in Figure 16 a) 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 16 b). Indeed, for the long term, in addition to the microgrid systems considered, stand-alone photovoltaic systems are also recommended if electrification is to be total throughout the country.

Table 5 presents the results of the different costs according to the scenario.

Table 5. summary of results for short- and long-term scenarios.

Horizon/Year	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	320	564	720	1371
PV hybrid				
Mini-grid	< 1	1.12	1	4.42
hydraulic				
Mini-grid	0	0	0	0
wind, biodiesel				
Extension	-	-	274	964
PV Systems	-	-	62	280
stand-alone				

Table 5 shows the results of two different scenarios. For the short term, i.e., scenario 2, stand-alone photovoltaic systems are recommended with a capacity of 20 MW, estimated at 184 million USD. Scenario 2 also opts for hybrid PV mini-grids with a capacity of 320 MW at a cost of 564 million USD, versus hydraulic mini-grids estimated at 1.12 million USD. On the other hand, for the long term (scenario 4), PV systems are proposed with a capacity of 62 MW at an investment of 280 million USD. Mini-grids are also recommended, at an estimated total cost of 1,374 million USD, for a capacity of 721 MW. However, scenario 4 shows the possibility to achieve total electrification of the country, by estimating a global capacity of 1.06 GW for an investment of 2.6 billion USD.

4.2. Discussion

Microgrid installation requires not only optimization methods to minimize investment costs, but also automated voltage stability methods to keep it more stable and resilient in accordance with connections. In this study, the elbow and kmeans clustering methods were used respectively to determine the number of clusters required for autonomous microgrid management and to determine the coordinates of the corresponding centroid; this strategy being necessary in 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 at 40 kW. It resulted that the solar resource was the most favored, with a rate of 80% compared with 7.5 % for the wind resource and 12.5% of battery capacity, to satisfy these electrical loads. 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 the open-source spatial optimal electrification planning system, onnsset. 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. In fact, the optimal investment costs for the short and long term are estimated at around 567 million USD for an energy production capacity of around 321 MW, compared with 2.6 billion USD 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 too, 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, as the stability of the microgrid is very important, this study enabled us to limit load connections either according to their capacity or their position relative to the microgrid substation.

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 a long way from the substation has an impact on the voltage stability of the network, which also results in load shedding. In fact, the variation in load capacity in a microgrid, and their positioning in relation to their 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 the 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 management the implementation of all the components of this system and to ensure its stability. As a first step, this study has therefore enabled us to carry out feasibility studies on the availability of the country's annual renewable energy resources. Secondly, an 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. Finally, a study of optimal load selectivity according to their 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 567 million USD for a capacity of 321 MW of the short time, and 1374 million USD for a capacity of 721 MW for the long time.

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, for the case of South Togo. However, the biodiesel system is not taken into account in this simulation. All in all, the results obtained are satisfactory and highly conclusive, having enabled us to optimally simulate 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.

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Conflicts of Interest: "The authors declare no conflicts of interest."

Nomenclature

$P_s(t)$ = puissance solaire variable	S_i = power of loads i
τ, τ' = charging (80%) and discharging (20%) rates	i = index
η = performance	P_{conv} = converter power
ε = performance rate	α_u = utilization factor
S = area	P_s = solar power
Δt = temperature differential	V = load vector matrix
X_s^d = decision variable	v_i = vector i
$T_{c,ref}$ = standard temperature	μ_k = clusters
$soct(t + 1)$ = battery storage at $t+1$	D = distance
$soct(t)$ = battery storage at t	R = earth radius
$p_{bat}(t)$ = battery power	c = constant
N_{bat} = number of batteries	φ_A, φ_B : latitudes
C_{bat} = battery capacity	λ_A, λ_B : longitudes

V_{bat} = battery volatge	C_{inv}^T = total investment cost
η_{bat} = battery efficiency	C_{inv}^i = investment cost
$P_e(t)$ = wind power	$C_{o\propto M}$ = maintenance and operating costs
ρ_e = air density	r = discount rate
S_w = area swept by the turbine	t = year
η_e = wind power efficiency	P_i = load i power
X_e^d = wind decision variable	P_j = substation j power
$f(v)$ = probability density	α_j = coefficient
c = scale factor	j = substation index
v = wind speed	C_r = replacement cost
k = shape factor	x_{ij} = binary variable load – substation $\{0;1\}$
σ = standard deviation	S_j = substation j power
$\bar{v}$ = average speed	τ = voltage drop rate
$\bar{P}$ = average power	d_{ij} = distance load – substation
Γ = gamma fuction	I_n = nominal current
$P_h(t)$ = hydroelectric power	I_n^i = nominal current of load i
ρ_h = density of water	U_n = nominal voltage
g = acceleration	r = linear resistance
Q = water flow rate	z = reactance
h = waterfall height	$\bar{X}$ = average
η_h = hydroelectric efficiency	S_i = power of loads i
μ = average solar irradiance	
σ = variance of solar irradiance	
P_{ch} = load power	
$f(P_{ch})$ = load modeling function	

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