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Load Profile Analysis for Mitigating Load-Shedding in Central Africa: Case of Kinshasa

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Abstract

Load shedding is a major problem in Central Africa, with negative consequences for both society and the economy. However, load profile analysis can help to alleviate this problem by providing valuable information about consumer demand. This information can be used by power utilities to forecast and reduce power cuts effectively. In this study, the direct method was used to create load profiles for residential feeders in Kinshasa. The results showed that load shedding on weekends results in significant financial losses and changes in people's behavior. In November 2022 alone, load shedding was responsible for \$ 23,4 08,984 and \$ 2 80,9 07,808 for all year in losses. The study also found that the SAIDI index for the southern direction of the Kinshasa distribution network was 122.49 hours per feeder, on average. This means that each feeder experienced an average of 5 days of load shedding in November 2022. The SAIFI index was 20 interruptions per feeder, on average, and the CAIDI index was 6 hours, on average, before power was restored. This study also proposes ten strategies for the reduction of load shedding in the Kinshasa and central Africa power distribution network and for the improvement of its reliability, namely: Improved load forecasting, Improvement of the grid infrastructure, Scheduling of load shedding, Demand management programs, Energy efficiency initiatives, Distributed Generation, Automation and Monitoring of the Grid, Education and engagement of the consumer, Policy and regulatory assistance, and Updated load profile analysis.

Keywords

Statistical Analysis, Load Profile, Load Shedding, Kinshasa Distribution Network, Distribution Reliability Indices

1. Introduction

In many developing regions of the world, including Central Africa, load shedding the controlled and temporary reduction of electricity supply to consumers during periods of peak demand, is a persistent problem. A prominent example of this challenge is the city of Kinshasa, the capital of the Democratic Republic of Congo (DRC) [1]-[3]. As well as disrupting daily life, power cuts have negative economic and social consequences, hampering progress and development in the region [4]-[6]. With its rapidly growing population and industrialization, Central Africa faces a growing electricity demand. The problem of load shedding has been exacerbated by the inadequacy of the existing electricity infrastructure to meet this ever-increasing demand [2] [7]. This paper addresses the challenge of load shedding in Kinshasa through load profile analysis. This will shed light on potential solutions and strategies that can mitigate the problem.

Load Profile Analysis involves taking a comprehensive look at the patterns and behavior of how electricity gets used and consumed over time. It provides valuable insights into when and how electricity is used, allowing for the identification of peak demand periods, the categorization of different types of consumers, and the formulation of effective load management strategies [8]-[10]. In the context of Kinshasa and Central Africa, understanding the load profiles of different sectors, from residential to industrial, is essential for optimizing the allocation of limited resources and improving overall grid performance [8] [11] [12]. In addition, the integration of renewable energy sources, such as solar panels, into the energy mix provides an opportunity to mitigate load shedding and improve the reliability of the energy supply [10] [13]-[16].

Electricity in Central Africa presents several specific challenges, including widespread informal settlements, intermittent supply, and a lack of historical consumption data. As a result, this study aims to provide insight into the specific load profile of Kinshasa and to make recommendations for targeted improvements to the energy infrastructure and demand-side management. It will also consider the role of renewable energy integration, the impact of electrification programs, and the potential for demand response mechanisms to address load shedding in Central Africa [17] [18].

To address these challenges, it is essential to analyze subscriber load profiles and calculate relevant reliability indices such as System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI). These indices are used to measure network reliability and the effectiveness of load-shedding measures [19]-[21].

The main problem with electrical energy is that it has to be consumed at the same time as it is produced because it cannot be stored. Hence a need for a balance between the energy produced and the energy consumed through a network [22]-[24].

This paper aims to contribute to the development of strategies that can alleviate load shedding and promote sustainable energy management in Central Africa by studying load profiles in Kinshasa.

2. Overview of Kinshasa Distribution Electrical Networks

2.1. Outline of the Electricity Distribution Network in the City of Kinshasa

The city of Kinshasa is currently supplied with electricity from the Inga and Zongo hydroelectric power stations in Central Kongo (**Figure 1**). **Table 1** shows that even supplied by two central there is a huge lack of energy in Kinshasa. Energy is transported from the production centers to Kinshasa by [25]:

A 220 kV double-circuit line between Inga and Kinshasa, 262 km long, operated without n-1 safety.

A 132 kV Zongo-Badiadingi line, 59 km long, with a transit capacity of 90 MW operated without n-1 security.

A 70 kV Zongo-Gombe line, 80 km long, with a transit capacity of 23 MW, operated without security n-1. The energy situation in the city of Kinshasa is shown in **Table 1** below.

Table 1. Kinshasa's energy situation [25].

	Estimated power [MW]	%
Estimated demand	1158 - 1210	100
Current peak	490	49
Unmet demand	668 - 720	51

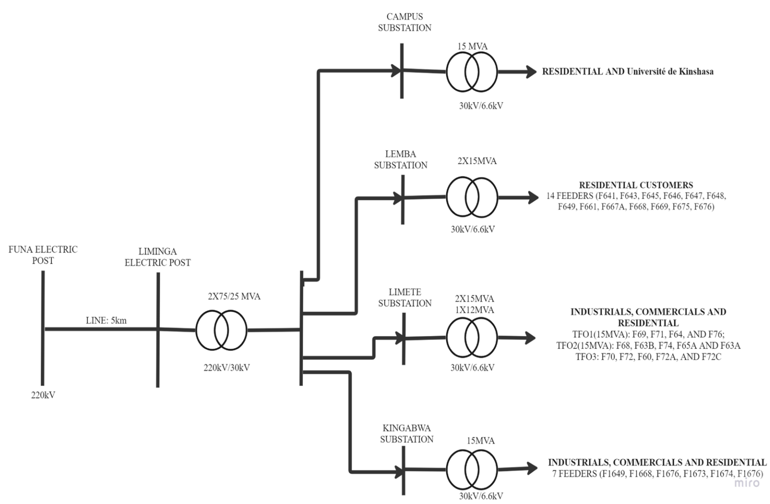

Figure 1. Single-line diagram of the distribution network of the Kinshasa South Regional Division (DKS).

2.2. Load Shedding in Kinshasa

The main causes of load shedding in the Kinshasa distribution network and the energy deficit in the city of Kinshasa are due to the following reasons [26]-[28].

- The obsolescence of installations or the absence of standard maintenance leading to machine stoppages.
- The strangulation of energy evacuation routes, through the saturation of transmission lines or distribution networks that do not cover all the needs of the growing customer base, and through the expansion of urban centers.
- The aggressive nature of distribution networks, mainly low voltage, contributes to the premature deterioration of equipment subjected to excessive load rates. This mainly concerns distribution transformers, electrical cables, etc.

While the installations are being rehabilitated, the logical outcome of this situation is to rotate load shedding among certain installations to protect them and ensure a fair distribution of electrical energy [29] [30].

3. Materials and Methods

In carrying out this study, it was necessary to use statistics to analyze and process the data collected at SNEL. Two approaches were required: The documentary approach and the Survey approach or data collection in the field.

3.1. The Documentary Approach

The documentary approach involved reviewing existing records and documents related to electricity consumption and load shedding in Kinshasa. This included historical data from SNEL, reports on electricity distribution, and previous studies on load profiles and energy management in Central Africa. This approach provided a foundational understanding of the current state of electricity supply and demand, as well as the factors contributing to load shedding.

3.2. Load Measurement

For our study, the energy was measured every hour or half hour, depending on the accuracy required which is the case in the various substations and sub-stations of the Société Nationale d'Électrique (SNEL).

3.3. Sampling

3.3.1. Determining the Sample Size

The main objective is to evaluate SNEL's network feeders in the city of Kinshasa to help it achieve its economic and social plan. However, our approach consisted of identifying the SNEL/Kinshasa branches, including Regional Management East (DKE), Regional Management North (DKN), Regional Management West (DKO), Regional Management Centre (DKC), and Regional Management South (DKS). These five directions/areas formed the basis of our survey.

3.3.2. Data Collection Instrument

The 30 days of November were divided into three groups, as follows:

- Working days without load shedding;
- Working days with load shedding;

- Weekends without load shedding.

3.3.3. Southern Regional Division (DKS)

The Direction Regional Sud (DKS) is part of the Department de Distribution de Kinshasa (DDK). It is located in the commune of Limete, at 12th Street Industrial. It manages 5 sub-stations and 1 substation (**Figure 1**): Liminga substation, Lemba substation, Campus substation, Kingabwa substation, and Limete substation.

- DKS was chosen for its industrial, port, administrative, academic, and tourist activities.
- The study was cross-sectional, focusing on November 2022.

3.4. Descriptive Statistics Calculation

3.4.1. Mean

The mean (average) is calculated by summing all the data points and dividing by the number of data points as follows [31] [32]:

$$Mean(\mu)\frac{\sum_{=1}^{in} x_i}{n} \tag{1}$$

3.4.2. Standard Deviation

The standard deviation measures the variation or dispersion in a set of values. The mathematical Formula [33] [34]:

$$\text{Standard Deviation}(\sigma)=\sqrt{\frac{\sum_{=1}^{in}(x_i-\mu)^2}{n-1}} \tag{2}$$

3.4.3. Median

The median is the middle value of a dataset when it is ordered in ascending or descending order. If there is an even number of observations, the median is the average of the two middle numbers.

3.4.4. Quartiles

Quartiles divide the data into four equal parts. The first quartile (Q_1) is the 25th percentile, the second quartile (Q_2) is the median, and the third quartile (Q_3) is the 75th percentile [31] [33] [34].

3.4.5. Interquartile Range (IQR)

The IQR is the range between the first quartile (Q_1) and the third quartile (Q_3). The mathematical expression is [31] [32]:

$$I_{QR}=Q_3-Q_1 \tag{3}$$

3.5. Comparison Test

3.5.1. ANOVA (Analysis of Variance) [32]

a) Objective

To determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups.

b) Steps

(1) Assumptions Check

The samples are independent.

The data in each group are normally distributed.

Homogeneity of variances.

(2) Hypotheses

Null hypothesis (H_0): All group means are equal.

Alternative hypothesis (H_1): At least one group mean is different.

(3) ANOVA Test

Calculate the between-group variability (sum of squares between).

Calculate the within-group variability (sum of squares within).

Compute the F-statistic.

Compare the F-statistic to the critical value from the F-distribution table to determine the p-value.

(4) Decision:

If p-value < alpha level (commonly 0.05), reject the null hypothesis.

3.5.2. T-Student Test

a) Objective

To compare the means of two groups and determine if they are significantly different from each other.

b) Steps

(1) Assumptions Check

The samples are independent.

The data in each group are normally distributed.

The variances of the two groups are equal (for a two-sample t-test).

(2) Hypotheses

Null hypothesis (H0): The means of the two groups are equal.

Alternative hypothesis (H1): The means of the two groups are different.

(3) T-Test Calculation

Calculate the t-statistic and p-value [32].

$$t = \frac{\left(\overline{X_1} - \overline{X\,2}\right)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

(4) Decision

If p-value < alpha level (commonly 0.05), reject the null hypothesis.

3.6. Power Loss Ratings

Neglecting the contribution of harmonics, a power factor equal to $\cos\varphi = 0.8$ was considered. The total power lost (Pp) during load shedding for each of the substation feeders is calculated as follows:

1) Calculation of the arithmetic mean for each working day with load shedding. The formula 5 is the average which corresponds to the power loss for the

day with only one load shedding and is given by the following expression:

$$p = \frac{\sum_{i=1}^{24} Pi}{n} \tag{5}$$

where *Pp* is the power loss due to load shedding, *Pi* is active power per hour, and $n = 24$.

1) For a day with several load-shedding events, add up these averages. To determine the total power lost for that day.

2) Add up the power losses for each working day of the month, which corresponds to the total power loss for the feeder.

3.7. Load Shedding Ratio

The load-shedding ratio (formula 6) is the ratio between the power in hours without load-shedding and the power in hours with load-shedding. It will enable us to classify the different feeders in order of priority.

$$Ratio = \frac{\sum \text{load-shedding power per hour}}{\sum \text{power without load shedding per hour}} \tag{6}$$

The load-shedding power is the average power for the whole day, or what would be delivered on average if there were no load-shedding (*Pp*).

The power without load shedding corresponds to the power delivered without any interruption (normal).

3.8. Cost of Lost Energy

The Table 2 below presents the sales tariffs of electricity by the National Society in charge of electricity, which is:

Table 2. SNEL sales tariffs.

	Selling price USD/kWh
High voltage (transmission)	0.0659
Medium voltage (MV)	0.0980
Residential	0.070

3.9. The SAIDI, SAIFI, and CAIDI Indices

Two main sets of indices are used to characterize voltage continuity: 1) "system" indices and 2) "connection point" indices (connection point of a neighboring network or a generation or consumption installation). The "system" indices provide more global information, making it possible to characterize the system as a whole or a subset of it. The IEEE has defined a series of indices of both types [35] [36]:

- SAIDI (the system average interruption duration index): The average system outage duration index generally used as a reliability indicator by electric power utilities is measured in units of time, often minutes or hours. SAIDI is the average outage duration for each customer served and is calculated as:

$$SAIDI = \frac{\text{the sum of all customer interruption duration}}{\text{and total number of customers served}} \quad (7)$$

- *SAIFI* (the system average interruption frequency index): The system Average Interruption Frequency Index (*SAIFI*) measured in units of interruptions per customer: is generally used as a reliability indicator by electric power utilities. *SAIFI* is the average number of interruptions a customer would experience and is calculated as:

$$SAIFI = \frac{\text{total number of interruptions per customer}}{\text{and total number of customers served}} \quad (8)$$

- *CAIDI*: Customer Average Interruption Duration Index, which represents the average time required to restore service.

$$CAIDI = \frac{\dfrac{\text{the sum of all customer interruption duration}}{\text{total number of customers served}}}{\dfrac{\text{number of interruptions per customer}}{\text{total number of customers served}}} = \frac{SAIDI}{SAIFI} \quad (9)$$

3.10. Load Factor

The load factor for a feeder is the ratio between the rated power and the maximum power. It is given by the relationship below.

$$\delta_i = \frac{S_{i,n}[MVA]}{S_{i,\max}[MVA]} \quad (10)$$

where δ_i represents the feeder *i* factor, $S_{i,n}$ is the feeder *i* power rating, and $S_{i,\max}$ is the feeder *i* maximum power.

3.11. Software

MATLAB software was employed for the analysis and visualization of the collected data. This software provided a robust platform for performing complex analyses and ensuring accurate results, which were essential for developing strategies to mitigate load shedding in Kinshasa.

4. Results

4.1. Analysis of Load Profile

Figures 2-3 show the power averages for days with load shedding, days without load shedding, and weekends without load shedding for the various feeders in the southern distribution direction.

Figure 4 represents the probability of occurrence of load shedding and no load shedding.

4.2. Comparison Test

4.2.1. Anova Test

Figure 5 and Table 3 show the results of the ANOVA test used to compare load shedding and non-load shedding.

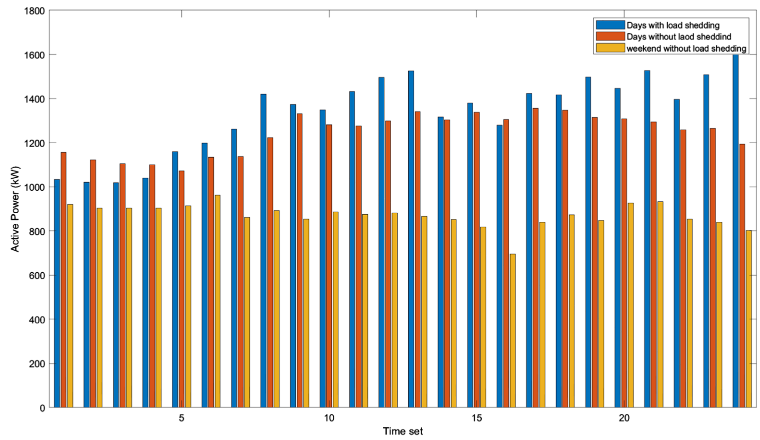

Figure 2. Presentation of days without load, days with load shedding, and weekends without load shedding in Kinshasa.

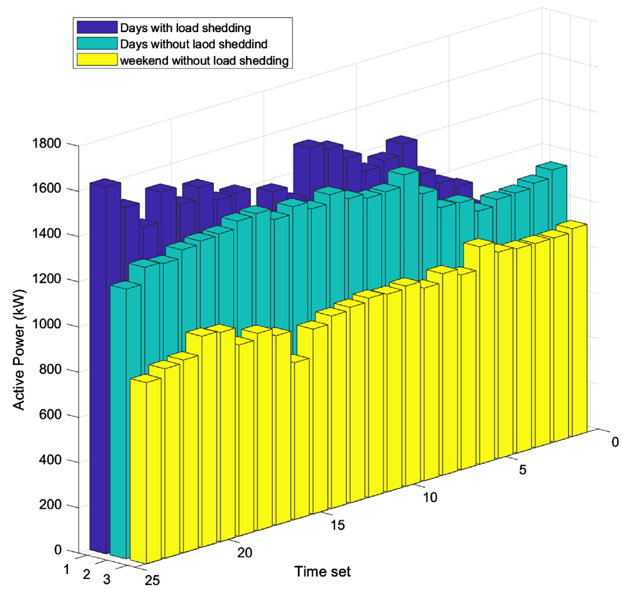

Figure 3. 3D presentation.

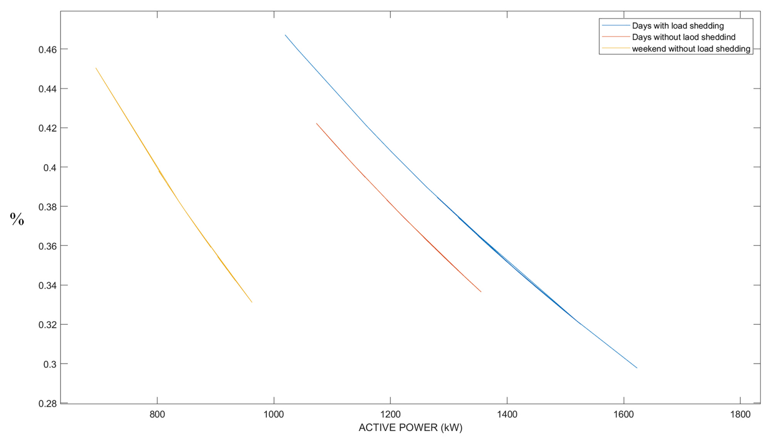

Figure 4. Probability density of shedding and no shedding.

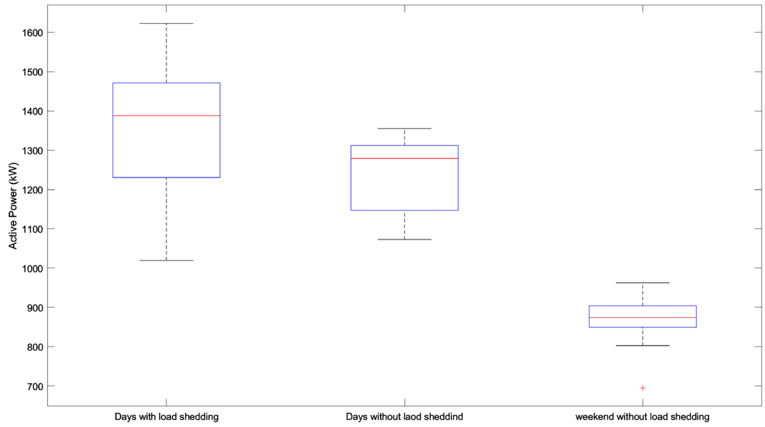

Figure 5. Anova test figure.

Table 3. ANOVA test.

Source	ss	df	MS	F	Prob > F
Columns	2943292.5	2	1471646.3	103.42	1.72692e-21
Rows	0	0	NaN	NaN	NaN
Interaction	0	0	Inf	Inf	NaN
Error	981826.2	69	14229.4		
Total	3925118.7	71			

4.2.2. T-Student Test

To confirm the results on the disparity between load shedding and non-load shedding, we added the t-student test shown in Figure 6.

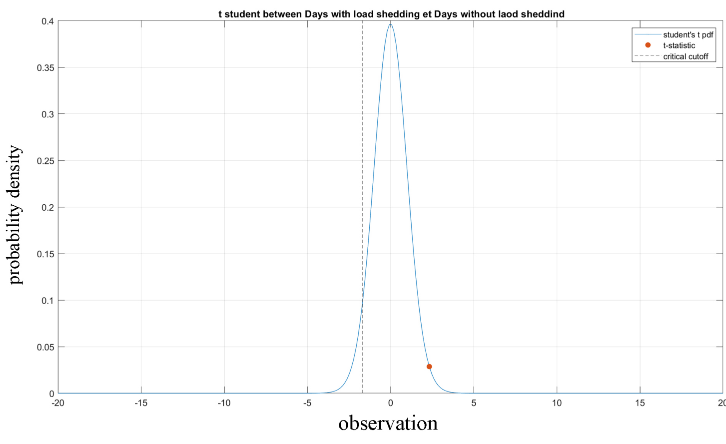

Figure 6. t-student test results.

4.3. Interpretation

Analyzing the first two figures, we see that load shedding is a major factor in the distribution of electrical energy.

There is a high probability density of load shedding in the city of Kinshasa, as shown in the figure Based on the information in the table above, since the p-value (Prob > F) is extremely small, less than 0.00000000000000000001, we can conclude that there is a statistically significant difference between the means of the three groups (days with load shedding, days without load shedding, and weekends without load shedding).

This indicates that it is implausible that the observed differences in the group means could have occurred by chance, and we can reject the null hypothesis that there is no difference between the group means. The key features from the t-student test figure are:

The red curve represents the t-student PDF for the "Days with load shedding" scenario. This curve appears to be centered around a t-statistic value close to 0, indicating that the mean difference between the two groups (days with vs. without load shedding) is not statistically significant. The blue curve represents the t-student PDF for the "Days without load shedding" scenario. This curve is also centered around 0, similar to the red point. The green curve represents the t-student PDF for the "Weekends without load shedding" scenario. This curve appears to be shifted to the right, indicating a larger t-statistic value compared to the other two scenarios. The dashed vertical line represents the critical cutoff value for the t-student distribution. This cutoff value is likely used to determine statistical significance, with values beyond the cutoff considered statistically significant.

Overall, this figure suggests that there is no statistically significant difference between the "Days with load shedding" and "Days without load shedding" scenarios, as their t-statistic values are close to 0. However, the "Weekends without load shedding" scenario appears to have a larger t-statistic value, potentially indicating a significant difference compared to the other two scenarios.

4.4. System Reliability Analysis (DKS)

The SAIDI, SAIFI, and CAIDI indices: For our system (DKS), the various corresponding indices are shown in **Table 4** below. The customers represent the various feeders of the major DKS substations, namely: Limete, Kingabwa, and Lemba. These indices give:

Table 4. Reliability indices.

Substation	Number of interruptions	Interruption time (h)	Number of subscribers	SAIFI	SAIDI	CAIDI
Limete	203	1289	16	20.2	122.49	6.06
Kingabwa	163	953	7			
Lemba	382	2290	14			
Total	748	4532	37			

Limete substation feeder load factor: **Table 5** shows the load factor for the various feeders at the Limete substation.

Table 5. Load factor for the limited sub-station.

Feeder	P_n [MW]	$P_{i,\max}$[MW]	Load factor (%)
F60	1.92	2.56	75.49
F61	2.608	1.68	154.054
F63A	1.92	1.6	122.222
F63B	2.61	1.68	152.308
F64	1.92	2.24	86.087
F65A	1.92	0.56	350
F68	1.92	2.24	86.194
F69	1.92	2.08	91.667
F70	1.92	1.44	131.25
F71	1.92	1.84	103.433
F72A	2.61	2.64	98.276
F72B	1.92	2.16	90.234
F72C	1.92	1.52	127.273
F73	1.92	1.52	125.43
F74	1.92	2	94.77
F76	2.61	2.72	95

4.5. Reliability Analysis

Our calculations demonstrate that the load-shedding ratio shows that a significant amount of energy is lost throughout the various load-shedding activities. According to the calculations above, nearly $ 23,4 08,984 was lost due to load shedding in November 2022 alone. This is a common practice that should only be used in extreme emergencies, but it has become commonplace in the operation of our electricity network.

- As for the reliability of our system, our calculations above (Table 5) give the following results for November 2022 alone:
- A SAIDI index equals 122.49 h on average per feeder, which corresponds to the hours of interruptions or load shedding for the month. In terms of days, we have 5 days of load shedding per feeder.
- A SAIFI index equals around 20 interruptions on average per feeder.
- A CAIDI index equals approximately 6 hours on average before power is restored.

The load factors as seen in Table 5 are above 100%, which means that our feeders are operating almost at overload.

5. Strategies to Mitigate Load Shedding in Central Africa

In light of the foregoing, several strategies have been proposed for reducing blackouts in the Kinshasa distribution network, and in Central Africa in general, and for improving the reliability of the network.

5.1. Improved Load Forecasting

- Phase 1: Research and Development (0 - 6 months).
- Conduct a comprehensive study on current load forecasting techniques.
- Collaborate with academic institutions and industry experts to identify advanced forecasting models.
- Phase 2: Pilot Implementation (6 - 12 months)
- Implement pilot projects using advanced forecasting models in select areas.
- Collect and analyze data to assess the effectiveness of these models.
- Phase 3: Full-Scale Implementation (12 - 24 months)
- Implement pilot projects using advanced forecasting models in select areas.
- Continuously monitor and adjust models based on real-time data.

5.2. Improvement of Grid Infrastructure

- Phase 1: Infrastructure Assessment (0 - 6 months)
- Conduct a thorough assessment of the existing grid infrastructure.
- Identify critical areas requiring upgrades.
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- Identify critical areas requiring upgrades.
- Phase 2: Planning and Budgeting (6 - 12 months)
- Develop a detailed plan and budget for the necessary upgrades.
- Secure funding from government and international donors.
- Phase 3: Infrastructure Upgrades (12 - 36 months)
- Implement infrastructure upgrades, including replacing aging equipment and expanding the network.
- Prioritize areas with the highest load factors and frequent outages.

5.3. Scheduling of Load Shedding

- Phase 1: Development of Load Shedding Schedules (0 - 3 months)
- Develop structured and predictable load-shedding schedules.
- Communicate schedules to the public through multiple channels.
- Phase 2: Implementation and Monitoring (3 - 12 months)
- Implement the schedules and monitor compliance.
- Gather feedback from consumers to refine schedules as needed.

5.4. Demand Management Programs

- Phase 1: Program Design (0 - 6 months)
- Design demand response programs that incentivize reduced consumption during peak hours.
- Include time-of-use pricing and other mechanisms.
- Phase 2: Pilot Programs (6 - 12 months)

Launch pilot programs in select areas to test the effectiveness of the designed programs.

- Phase 3: Full-Scale Rollout (12 - 24 months)
- Implement successful programs across Kinshasa.
- Continuously monitor and adjust based on program performance.

5.5. Energy Efficiency Initiatives

- Phase 1: Awareness Campaigns (0 - 6 months)

launch public awareness campaigns on energy-efficient technologies and practices.

- Phase 2: Incentive Programs (6 - 12 months)

Develop and implement incentive programs for adopting energy-efficient appliances.

- Phase 3: Long-Term Monitoring (12 - 36 months)

Monitor energy consumption patterns and adjust initiatives as necessary.

5.6. Distributed Generation

- Phase 1: Policy Development (0 - 6 months)

Develop policies to promote distributed energy resources like solar panels and small generators.

- Phase 2: Incentive Programs (6 - 12 months)

Implement incentives for the adoption of distributed generation technologies.

- Phase 3: Integration and Monitoring (12 - 36 months)

Integrate distributed generation into the grid and monitor its impact.

5.7. Automation and Monitoring of the Grid

- Phase 1: Technology Assessment (0 - 6 months)

Assess available smart grid technologies and real-time monitoring systems.

- Phase 2: Pilot Projects (6 - 12 months)

Implement pilot projects in select areas to test these technologies.

- Phase 3: Full-Scale Implementation (12 - 36 months)
- Roll out successful technologies across the entire grid.
- Continuously monitor and adjust based on performance data.

5.8. Education and Engagement of Consumers

- Phase 1: Development of Educational Materials (0 - 3 months)

Develop educational materials on load shedding and energy conservation.

- Phase 2: Public Engagement Campaigns (3 - 12 months)

Launch campaigns to educate consumers on the importance of reducing peak demand.

- Phase 3: Continuous Engagement (12 - 36 months)

Maintain ongoing engagement with consumers through regular updates and workshops.

5.9. Policy and Regulatory Assistance

- Phase 1: Policy Review (0 - 6 months)

Review existing policies and regulations related to grid reliability and infrastructure investment.

- Phase 2: Policy Development (6 - 12 months)

Develop new policies that support grid reliability and infrastructure investment.

- Phase 3: Implementation and Monitoring (12 - 36 months)

Implement new policies and continuously monitor their impact on grid performance.

5.10. Updated Load Profile Analysis

- Phase 1: Data Collection and Analysis (0 - 6 months)

Collect and analyze load profiles to identify trends and issues.

- Phase 2: Strategy Adjustment (6 - 12 months)

Adjust mitigation strategies based on updated load profiles.

- Phase 3: Continuous Monitoring (12 - 36 months)

Continuously monitor load profiles and make necessary adjustments to strategies.

6. Feasibility Analysis

6.1. Technical Feasibility

Implementation of advanced forecasting models, smart grid technologies, and distributed generation systems is technically feasible and aligns with global best practices.

6.2. Economic Feasibility

While the initial investment for infrastructure upgrades and technology implementation is significant, the long-term economic benefits outweigh the costs. Reducing load shedding will enhance economic productivity, reduce financial losses, and attract investments. Funding can be sourced from government budgets, international donors, and private sector investments.

6.3. Operational Feasibility

The phased approach ensures manageable implementation and minimal disruption to current operations. Pilot projects will help refine strategies and address potential operational challenges before full-scale rollout.

6.4. Social Feasibility

Public awareness campaigns and consumer engagement will ensure community support for the initiatives. Educating consumers on the benefits of reduced load shedding and energy efficiency will enhance acceptance and cooperation.

6.5. Environmental Feasibility

Promoting energy-efficient technologies and distributed generation (e.g., solar panels, waste to energy) supports environmental sustainability. These initiatives will reduce greenhouse gas emissions and reliance on fossil fuels.

7. Conclusions

This article focuses on the issue of load shedding in Kinshasa, the capital of the Democratic Republic of Congo, and its impact on society and the economy. The study highlights the importance of load profile analysis to address this issue and provide insight into consumer demand and electricity consumption patterns.

The study results indicate that load shedding in November 2022 alone resulted in financial losses of $ 23,4 08,984 and $ 2 80,9 07,808 for all year. Also, we found the *SAIDI* index for the southern direction of the Kinshasa distribution network averaged 122.49 hours per feeder, which means each feeder experienced an average of 5 days of load shedding in November 2022. For the *SAIFI* and *CAIDI* indexes, we found an average of 20 interruptions per feeder and, an average of 6 hours before power was restored.

The study recommends ten strategies to reduce load shedding and improve electricity distribution network reliability, including better load forecasting, improving network infrastructure, and load shedding scheduled loads, load management program needs, energy efficiency initiatives, distributed generation, automation and grid monitoring consumer education and engagement, policy and regulatory support, and updated load profile analysis. By analyzing subscriber load profiles and reliability indices, this study provides the basis for data-driven decision-making to action load shedding and promote sustainable energy management in Central Africa, thereby contributing to economic growth, energy security, and overall development of the region.

Author Contributions

Ngondo Otshwe Josue: analysis, writing original draft preparation, writing review & methodology, Bin Li: validation, research coordination, Ngouokoua Jaime Chabrol: simulation, data collection, Nawaraj Kumar Mahato, editing and visualization.

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Conflicts of Interest

The authors declare no conflicts of interest.

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