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Customer Selection in the Conversion Program of LPG Stove to Induction Stove

Abstract: - The oversupply condition is due to differences in the current electricity supply which is higher than actual electricity demand. One option to increase demand is by converting LPG stoves into induction stoves. To achieve the conversion goal successfully, a customer selection process must be carried out to determine the conversion targets, aiming for a significant increase in electricity demand with the lowest investment costs. The main problem is the absence of a standard for determining conversion targets. The combination of clustering techniques and Multiple Criteria Decision Making (MCDM) analysis provides the best ideal solution to overcome these problems. The research included several main criteria for selecting customers that support the success factors of implementing a conversion program. The initial analysis involved clustering customers based on coordinates using the k-means method. By using the clustered customer data, the TOPSIS (Technique for Ordering Preference by Similarity to an Ideal Solution) method identified the best cluster based on general criteria. Additionally, using detailed customer data, the TOPSIS method also identified the ranking of customer priorities for each selected cluster. The recommended priority target customers are those with the greatest potential for additional kWh, the best level of electricity reliability, shortest distance to the cluster centroid, and supplied by feeders and distribution transformers with the largest reserve margin. The results indicated the difference in revenue improvement compared to the current method was US$ 16,291.31 per month. Investment costs were also reduced by US$ 166,084.80 compared to the current method. The other results were a reduction in operational costs, improvement in average reliability according to the SAIDI SAIFI, improvement in the average operation-hours, and an improvement in the distribution transformer average reserve margins.

Keywords: Induction Stove, K-means, Oversupply, TOPSIS

I. INTRODUCTION

The oversupply condition is one of the inhibiting factors for the development of new power plants [1]. The generation of the power system should consider the balance between supply and demand. Electricity demand improvement to overcome oversupply is focused on the conversion program of LPG stoves into induction stoves. The number of PLN (Perusahaan Listrik Negara) customers throughout Indonesia as of the end of 2022 is 85.27 million customers [2]. With a very large number of customers, it is a challenge to determine the customers selection of the LPG stove to induction stove conversion program. Various criteria need to be applied to achieve maximum conversion results, including the average monthly kWh usage, monthly operation-hours, tariffs, wattage, System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), feeder load, distribution transformer reserve margin, and the coordinates of the customer's location.

The conversion program for LPG stoves to induction stoves will be implemented in all regions in Indonesia, with pilot projects being carried out in the cities of Solo and Bali. To ensure the effectiveness of the induction stove conversion program, various analyses and studies are conducted to determine the eligible target customers for the conversion program. As part of this research, a customer selection analysis was conducted as a pilot project at the Binjai area which had 483,226 customers.

Energy consumption on the induction stoves conversion program specifically for cooking purposes needs to be monitored regularly. To support this, each induction stove is equipped with a kWh metering. As a result, additional costs will increase due to the meter reading for the monitoring process. To minimize the addition costs, a customer clustering program was carried out based on the customer's location coordinates using the k-means method. It is most useful for forming a small number of groups from a large number of observations [3]. Clustering is a method for finding cluster structure in a data set that is characterized by the greatest similarity within the same

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cluster and the greatest dissimilarity between different clusters [4].

The TOPSIS method is then utilized to rank the established clusters. Within the Multiple Attribute Decision Making (MADM) domain, TOPSIS is highly regarded, applied, and adopted MADM method due to its simplicity and underlying concept that the best solution is the one closest to the positive ideal solution and furthest from the negative ideal solution [5]. Further analysis for the selected clusters is to determine the customer conversion targets on each selected cluster. Consequently, TOPSIS method is also conducted for the analysis by using more specific criteria. The expected customer criteria are the customers who have a high average monthly kWh usage, customer who have a lower wattage, customers who have high average monthly operation-hours, customers who are supplied by feeders and distribution transformers that still have high reserve margins, and customers who located in areas with a high level of reliability.

To estimate the impact of the additional kWh, a sampling technique needs to be conducted across several different strata. Stratified sampling is a sampling scheme in which the original data is divided into a homogeneous disjoint set of groups (strata); from each group (stratum) a random sample is drawn, and these are combined to build the sample of the original data [6]. Stratified sampling is used to determine the estimated increase in induction stove kWh consumption based on the average monthly household kWh consumption.

II. RESEARCH METHOD

The customer category used for the research was single-phase customers with household or business tariffs. Out of a total of 483,226 customers in the Binjai area, 469,504 customers met these criteria [7].

A. K-means clustering

The next step involved clustering the customers based on their location coordinates, resulting in a total of 2,000 clusters. This clustering process aimed to group customers with similar location coordinates. The clustering was performed using SPSS software which includes a k-means clustering feature. The first step in k-means clustering was to determine the desired number of clusters according to management criteria. After determining the desired number of clusters, the next step involved performing calculations using the k-means method, resulting in centroid points for each cluster. These centroid points represented the central point of each customer in the same cluster. Furthermore, the distance for each cluster to the specified point was obtained by using the haversine method. The haversine formula is an important form of equation in the field of navigation, used to find the arc distance between two points on a sphere from longitude and latitude [8] as can be seen in eq. (1) and eq. (2).

$$haversine\ (\tfrac{d}{R}) = haversine\ (\theta_1 - \theta_2) + cos\ (\theta_1)\ x\ cos\ (\theta_2)\ x\ haversine\ (\lambda_2 - \lambda_1) \quad (1)$$

$$haversine\ (\theta) = sin^2(\tfrac{\theta}{2}) = \frac{1 - cos\ \ (\theta)}{2} \quad (2)$$

θ_1 = latitude from point 1
θ_2 = latitude from point 2
λ_1 = longitude from point 1
λ_2 = longitude from point 2
d = distance between 2 points (km)
R = earth's radius (6371 km)

In this case, the specified point was the location of the ULP (Unit Layanan Pelanggan) office. This distance calculation provided valuable insights into the location distribution of the clusters and helps to identify which areas were closer or farther from the ULP office.

The k-means cluster analysis method uses the following algorithm [9]:

- Determine *k* as the number of cluster.
- Determine the initial cluster centroid randomly then calculate the next cluster centroid by using the eq. (3):

$$v = \frac{\sum_{i=1}^{n} x_i}{n} \quad (3)$$

where *v* is the cluster centroid, x_i is the i^{th} object, and *n* is the number of object in a cluster.

- Calculate each object distance to the appropriate cluster using the euclidian distance in eq. (4):

$$d(x, y) = |x - y| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (4)$$

where y_i is the cluster centroid.

- Allocate each object to the nearest cluster centroid and determine the new cluster centroid using eq. (3).
- Iterate the calculation using eq. (4) until the new cluster centroid do not change.

B. TOPSIS method

The results of the clustering that had been determined previously produce several clusters. Each cluster was then analyzed using several general criteria, namely the distance from the cluster centroid to the ULP office, cumulative kWh per month per cluster, and cumulative wattage per month per cluster. By using the TOPSIS method according to these criteria, a cluster ranking was produced from the best to the worst. TOPSIS method helps rank alternatives closeness which based on optimum ideal solution and obtained the maximum level from available alternatives [10]. Furthermore, management determined about 105 clusters that will be taken for further analysis. The stages of the TOPSIS algorithm are as follows [10]:

- Construct decision matrix by using eq. (5):

$$DM = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_p \end{array} \begin{array}{c} \begin{array}{cccc} R_1 & R_2 & \dots & R_q \end{array} \\ \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1q} \\ C_{21} & C_{22} & \cdots & C_{2q} \\ \cdots & \cdots & \cdots & \cdots \\ C_{p1} & C_{p2} & \cdots & C_{pq} \end{bmatrix} \end{array} \quad (5)$$

where *R* is the criteria with the number of *q* and *A* is the alternatives with the number of *p*.

- Calculate a normalized decision matrix (NDM) by using eq. (6):

$$NDM = L_{lm} = \frac{c_{lm}}{\sqrt{\sum_{l=1}^{q} c_{lm}^2}} \quad (6)$$

where *l* is the alternative index and *m* is the criteria index.
$l = 1,2,\dots,q;\ m = 1,2,\dots,p$

- Calculate weighted normalized decision matrix by multiplying the criteria weight matrix $W_m$with the matrix L_{lm} as given by eq. (7):

$$V_{lm} = W_m \times L_{lm} \quad (7)$$

- Calculate the positive ideal solution I^+ and the negative ideal solution I^- by using eq. (8) and (9).

$$I^- = v_1^-, v_2^-, v_3^-, \dots, v_q^- \quad (8)$$
$$I^+ = v_1^+, v_2^+, v_3^+, \dots, v_q^+ \quad (9)$$

where:

$$v_m^- = \{(min(V_{lm}) if m \in J); (max(V_{lm}) if m \in J')\} \quad (10)$$
$$v_m^+ = \{(max(V_{lm}) if m \in J); (min(V_{lm}) if m \in J')\} \quad (11)$$

J is associated with beneficial attributes and *J'* is associated with non-beneficial attributes.

- Calculate the distance of each alternative from the ideal solution by using the eq. (12):

$$S_l^+ = \sqrt{\sum_{m=1}^{p} (V_m^+ - V_{lm})^2}$$
$$S_l^- = \sqrt{\sum_{m=1}^{p} (V_m^- - V_{lm})^2} \quad (12)$$

where *l* = 1,2, ..., *q*
l = alternative index
m = criteria index

- The relative closeness to the ideal solution is determined by using the eq. (13):

$$C_l = \frac{S_l^-}{S_l^+ + S_l^-} \tag{13}$$

where $0 \leq C_l \leq 1$

Each cluster was sorted based on its ranking, and the top 105 clusters were selected, while the other clusters were ignored.

The next step involved conducting a deeper analysis down to the characteristic level of each customer using several criteria: average customer kWh consumption per month, average customer monthly operation-hours, customer wattage contract, customer SAIDI, customer SAIFI, and customer distance to the appropriate cluster centroid. At this stage, further analysis was carried out using the TOPSIS method again to produce customer ranking for each selected cluster. The same process was carried out for every customer that is included in the selected cluster. Furthermore, management determined up to 100 customers in each selected cluster that will be targeted for the induction stove conversion program.

C. Stratified sampling

In stratified sampling design, sampling in one stratum is independent of that in others [11]. This technique enabled strata differentiation of a customer's kWh consumption for the cooking purpose based on their monthly household kWh consumption as shown in Table I. Moreover, utilizing the findings of the conducted survey allows for the calculation of the projected additional kWh improvement for this program. In this research, the sampling technique used was Slovin formula as shown in eq. (14) [12].

$$n = \frac{N}{1+N(e)^2} \tag{14}$$

where *n* is the number of samples; *N* is the number of populations; and *e* is margin of error.

Table I
Strata Based on Monthly Energy Consumption (kWh)

0-50	50-100	100-150	150-200	200-250
250-300	300-350	350-400	400-450	450-500
500-550	550-600	600-650	650-700	700-750
750-800	800-850	850-900	900-950	950-1000
1000-1050	1050-1100	1100-1150	1150-1200	1200-1250
1250-1300	1300-1350	1350-1400	1400-1450	1450-1500
1500-1550	1550-1600	1600-1650	1650-1700	1700-1750
1750-1800	1800-1850	1850-1900	1900-1950	1950-2000
> 2000				

To allocate the size of each stratum by proportional distribution, that is, to allocate the sample size according to the weight of each stratum, the sample size of the h^{th} stratum is shown in eq. (15) [13]:

$$n_h = \frac{N_h}{N}\ x\ n\ ; (h = 1,2, \ldots, n) \tag{15}$$

Strata determination was also carried out based on the customer's distance to the appropriate cluster centroid. Subsequently, each selected customer was grouped into 10 strata as shown in Table II.

Table II
Strata Based on Customer Distance to Centroid (meters)

0-100	100-200	200-300	300-400	400-500
500-600	600-700	700-800	800-900	> 900

D. Data and research diagram

In this research, the evaluation of potential additional kWh was carried out through a comparison with the existing technique. Furthermore, another comparison with the existing technique was also conducted for each criterion. This comparison involved the cumulative distance of each customer to its centroid, average operation-hours, average SAIDI, average SAIFI, average feeder load, average distribution transformer reserve margin, and cumulative wattage.

Fig. 1 shows the flowchart of the research method for determining induction stove conversion targets.

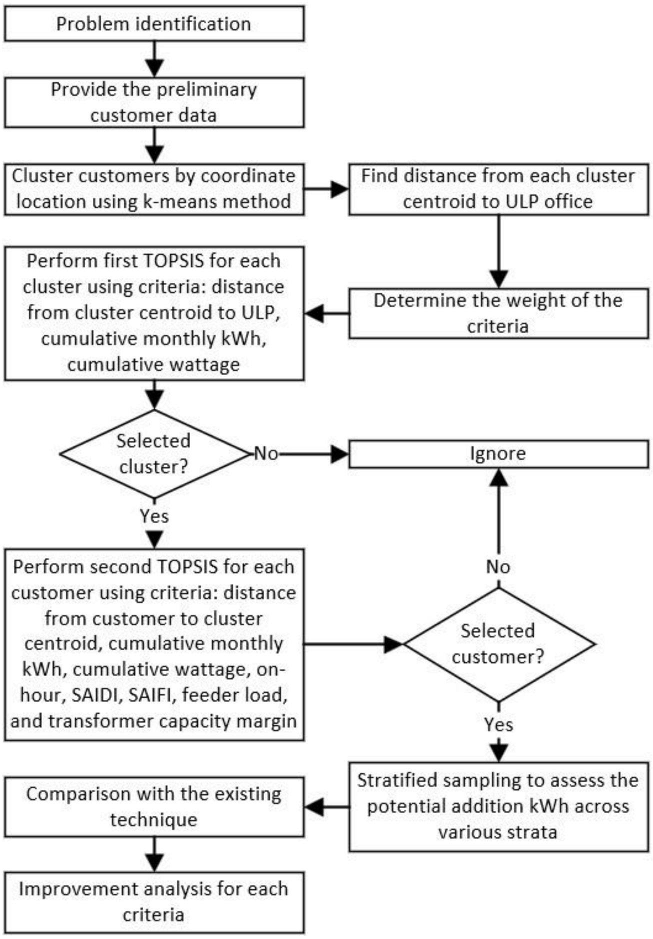

Fig. 1 Research Flowchart

The investment cost calculated in this research included the capital expense required for adding a distribution transformer due to insufficient reserve margin of the existing distribution transformer. The maximum transformer loading is 100%, consequently, if a customer was served by a distribution transformer operating over the maximum capacity, investment cost on distribution transformers became necessary.

III. RESULTS AND DISCUSSIONS

Stage 1. Collecting preliminary customer data.

The collected data comprised customer parameter data, which served as criteria for determining customer selection. Some of the customer data used as criteria were as follows:

- Customer coordinate location
- Monthly kWh consumption
- Customer wattage contract
- SAIDI SAIFI
- Feeder load
- Distribution transformer reserve margin

Stage 2. Cluster customer location.

In this research, the clustering values employed were customer coordinates, specifically latitude and longitude. The utilization of this data aligns with prior research, which applied the k-means clustering method based on GPS location [14]. The total number of clusters provided was 2,000 clusters with the cumulative monthly kWh, cumulative wattage, and the distance of cluster centroid to the ULP office as shown in Table III.

Table III
Clustering Output Data

Cluster	kWh	Wattage	Distance (km)
1	1088.4	13050	14.70

2	93220.4	758900	1.39
3	9203.8	72150	13.94
4	45.1	900	26.07
5	266216.8	1629700	2.72
6	1009.2	18900	24.80
7	633876.3	4537750	0.43
8	38762.5	358200	9.01
1999	6503.4	34600	2.02
2000	7068.6	79500	44.79

Stage 3. Determine the weighting of the criteria.

The weights of the criteria in the first TOPSIS corresponded to the criteria for each formed cluster. The cumulative kWh and cumulative wattage criteria possessed a beneficial effect, where higher values indicated greater opportunities. In contrast, the distance value exhibited a non-beneficial effect, where smaller values indicated higher chances as given in Table IV.

The weight of the criteria in the second TOPSIS corresponded to the criteria for each customer in the same cluster. In these stages, the criteria were more complex for each customer as can be seen in Table IV.

Table IV
Weighting Criteria

Cluster weighting			**Customer weighting**		
criteria	**weight (%)**	**effect**	**criteria**	**weight (%)**	**effect**
kWh	40	beneficial	kWh	20	beneficial
wattage	20	beneficial	wattage	20	non-beneficial
distance	40	non-beneficial	distance	20	non-beneficial
			operation-hour	5	beneficial
			transformer margin	10	beneficial
			feeder load	5	non-beneficial
			SAIDI	10	non-beneficial
			SAIFI	10	non-beneficial

Stage 4. Calculate the ranking of clusters.

The first TOPSIS analyzed each cluster that has been formed previously. The value of I^{+} and I^{-} for each criterion that was shown in Table V were calculated using eq. (9) and eq. (8) after the calculation of the normalized decision matrix using eq. (6) and weighted normalized decision matrix using eq. (7).

Table V
Ideal Solution for Each Cluster

Ideal solution	**kWh**	**Wattage**	**Distance**
I^{+}	10.123619	6.491166	0.000964
I^{-}	0	0.000340	13.670966

The distance of each alternative from the ideal solution and the ranking for each alternative were calculated using eq. (12) and eq. (13) as can be seen in Table VI.

The next step involved determining the number of selected clusters. In this research, a total of 105 clusters were chosen for further analysis, while the remaining 1895 clusters were disregarded. Subsequently, all selected clusters were analyzed separately by using the characteristics of each customer within the same cluster.

Table VI

Positive and Negative Distance to Ideal Solution
and Ranking of Each Cluster

Cluster	S^+	S^-	C_I	Rank
1	12.0107	13.4640	0.528	1278
2	10.7241	13.7142	0.561	154
3	11.9000	13.4752	0.531	950
4	12.0306	13.3040	0.525	1565
5	8.5603	14.0967	0.622	34
6	12.0125	13.3218	0.525	1529
7	3.7125	16.2129	0.813	5
8	11.4675	13.5557	0.541	350
1999	11.9425	13.6427	0.533	715
2000	11.9347	13.0409	0.522	1667

Stage 5. Calculate the ranking of customers.

The purpose of the second TOPSIS analysis was to identify the top 100 customers within each selected cluster, showcasing the highest potential for the conversion program. Consequently, the cumulative result presented a ranking of 100 customers in 105 clusters, ultimately equating to 10,500 customers target for the conversion program.

The second TOPSIS analysis was applied to all selected clusters separately. As an example, cluster number 88 calculation was provided, with the understanding that the same steps can be equally applied to the other selected clusters.

The value of I^+ and I^- for each criterion that was shown in Table VII were calculated using eq. (9) and eq. (8) after the calculation of the normalized decision matrix using eq. (6) and weighted normalized decision matrix using eq. (7).

Table VII
Ideal Solution for Each Customer in Cluster Number 88

Ideal solution	kWh	Wattage	Distance	Operation-hour
I^+	5.0444	0.2232	0.0047	1.1480
I^-	0	5.4577	1.6502	0
Ideal solution	**Transformer margin**	**Feeder load**	**SAIDI**	**SAIFI**
I^+	0.8480	0.0053	0.0009	0.0225
I^-	-0.0244	0.3137	0.5606	1.1789

The distance of each alternative from the ideal solution and the ranking for each alternative were calculated using eq. (12) and eq. (13) as can be seen in Table VIII.

Table VIII
Positive and Negative Distance to Ideal Solution
and Ranking of Each Customer for Cluster Number 88

Customer	D^+	D^-	C_I	Rank
1	5.2144	5.2512	0.501	1029
2	4.1736	4.8642	0.538	173
3	5.1259	5.3238	0.509	831
4	5.1808	5.4194	0.511	780
5	4.4244	5.2920	0.544	118
6	5.3045	4.6397	0.466	1192
7	4.9902	5.2393	0.512	752
8	5.2888	5.2182	0.496	1106
1217	5.3092	5.1544	0.492	1138
1218	5.2168	5.3188	0.504	966

Stage 6. Define stratified sampling.

A total of 41 strata from Table I were used to determine the expected additional kWh for each stratum. Subsequently, the sampling of each stratum was collected from the existing customers who had been actively using induction stove. By adhering to a sample error criterion of 5%, the sample size was calculated using eq. (14) and eq. (15). Using the sample data provided, the expected additional kWh for each stratum can be seen in Fig. 2.

Fig. 3 illustrates the expected cumulative additional kWh for a total of 10,500 selected customers. The highest potential for additional kWh was observed within the strata with a monthly kWh consumption range of 300-350 kWh.

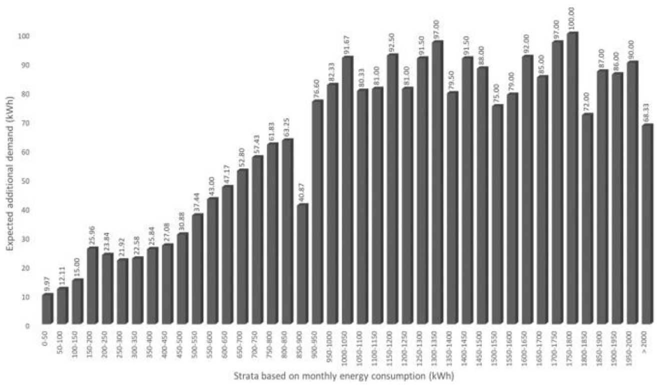

Fig. 2 Expected Additional kWh per Strata

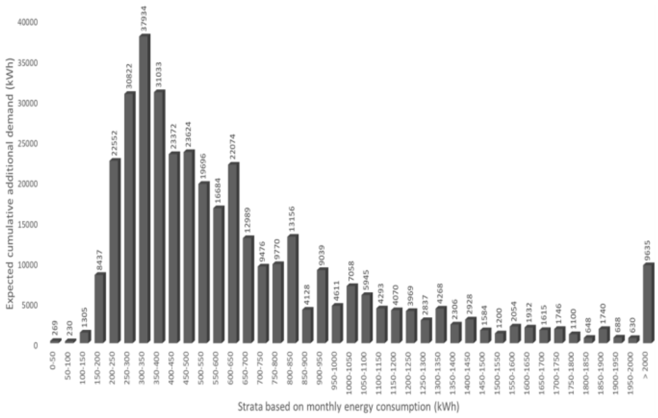

Fig. 3 Total Expected Additional kWh per Strata

Stage 7. Comparison with random technique

Random selection was performed two times, referred to as Random A and Random B, to establish consistency. The comparison between the estimated cumulative additional kWh from the research results and the random technique can be seen in Fig. 4.

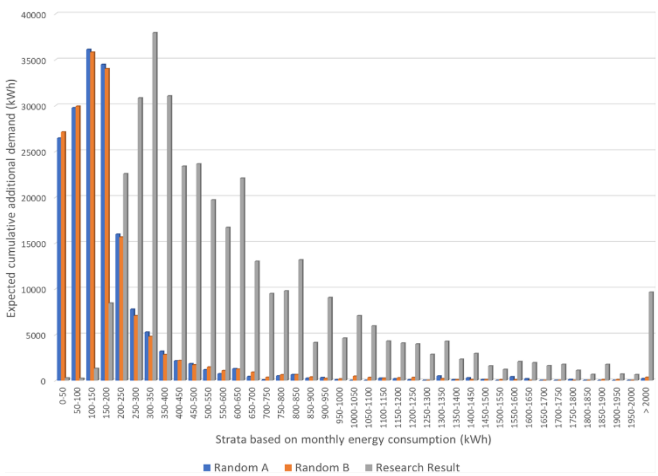

Fig. 4 Comparison to the Random Technique

The distribution of expected additional kWh in the research results demonstrated better outcomes when compared to the random technique. Random technique predominantly selected customers with low electricity consumption, while the research result revealed higher electricity consumption. By utilizing the electricity rates according to Permen ESDM number 28 year 2016 [15], adjustment tariff in July – September 2023 [16], and the currency rate on 1st August 2023, the expected additional monthly revenue can be seen in Table IX.

Table IX
Additional Monthly Revenue

Method	kWh	Revenue
Random A	170,592	US$ 11,276.77
Random B	170,755	US$ 11,402.65
Research Result	363,445	US$ 27,631.02

Either for electricity or LPG, the rates consist of subsidized (S) and non-subsidized (N) prices. The energy utilization of 1 kg LPG on an LPG stove is equivalent to 7.9 kWh on an 1800 watt induction stove [17]. LPG stove subsidized tariff is US$ 1.52/3 kg cylinder at the retail point and non-subsidized tariff is US$ 3.14/3 kg cylinder at the retail point [17]. Assuming that the LPG consumption is similar with the estimated additional kWh for each stratum in Fig. 2, the detailed cost comparison can be seen in Table X. In addition, customers with subsidized electricity tariffs were assumed to use subsidized LPG, while customers with non-subsidized tariffs were assumed to use non-subsidized LPG.

Table X
Cost Comparison Between Induction Stove and LPG Stove

no	tariff	wattage	rate (US$)	kWh	electricity cost (US$)	equivalent (kg)	type	LPG cost (US$)
1	R3T	7700	0.112	68	7.69	8.65	N	9.04
2	R2T	3500	0.112	81	9.11	10.25	N	10.72
3	B1T	5500	0.072	81	5.90	10.25	N	10.72
4	R1T	2200	0.095	77	7.32	9.69	N	10.14
5	B1T	5500	0.072	93	6.73	11.70	N	12.24
6	R1T	2200	0.095	77	7.32	9.69	N	10.14
7	R2T	3500	0.112	82	9.26	10.42	N	10.90
8	R1T	2200	0.095	77	7.32	9.69	N	10.14
10499	R1MT	900	0.089	26	2.32	3.28	N	3.43
10500	R1	450	0.032	26	0.85	3.28	S	1.66

The additional revenue for both subsidized and non-subsidized customers was compared to the existing customer expenses due to LPG consumption. According to Table XI, electricity consumption by induction stove is more economical than gas consumption on LPG stove.

Table XI
Additional Monthly Electricity Consumption Compared to the
Existing Gas Consumption for LPG Stove

Method	Subsidized cost		Non-subsidized cost	
	electricity	LPG	electricity	LPG
Random A	US$ 2,538	US$ 4,822	US$ 8,737	US$ 12,631
Random B	US$ 2,480	US$ 4,706	US$ 8,921	US$ 12,891
Research Result	US$ 3,368	US$ 6,441	US$ 24,263	US$ 34,822

Additionally, cumulative distance analysis was conducted based on the distance from each selected customer to its centroid by using eq. (1) and eq. (2). The same calculation method was also carried out for the selected customers using random A and random B technique. In accordance with Table II, the distance criteria were divided into 10 strata. Additionally, according to Fig. 5, the random method generally has a higher cumulative distance value compared to the research results.

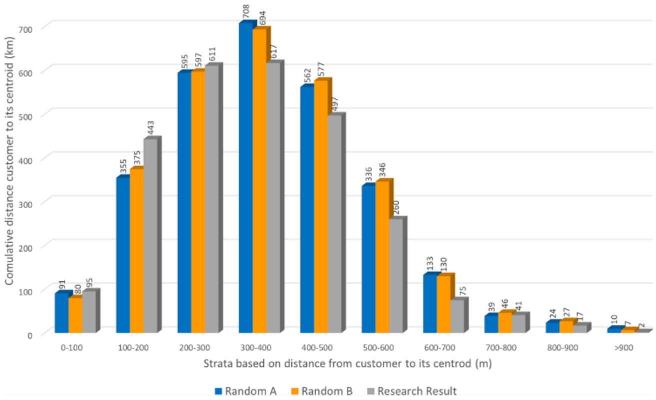

Fig. 5 Cumulative Customer Distance to Its Centroid

Further analysis was conducted for each criterion. The nominal values in Table XII are the average of SAIDI, average of SAIFI, average of operation-hour, average of distribution transformer reserve margin, and average of feeder load.

Table XII
Comparison of Results for Each Criteria

Method	SAIDI	SAIFI	operation-hour	transformer margin	feeder load
Random A	6.61	7.34	153.03	53.25	135.88
Random B	6.75	7.46	149.99	53.72	136.98
Research result	4.77	6.77	438.88	69.14	150.17

Fig. 6 illustrates the percentage of improvement from research results compared to the random techniques. The improvements were quite significant in most of the categories that had been determined. Lower results were obtained for the criteria of feeder load and wattage. Feeder load criteria has a non-beneficial effect where the smaller value is better. However, feeder load was not a top priority criterion in the conversion program with a weighting of only 5%. Besides, the number of 450 VA and 900 VA wattage value were not better compared to the random technique. However, the number of 450 VA and 900 VA wattage still dominated when compared to the other wattage level in the research results.

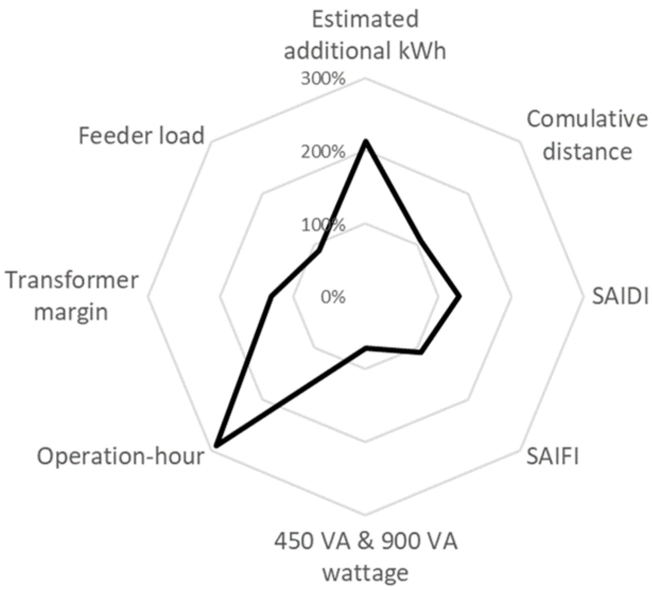

Fig. 6 Improvement on Each Criteria

The value of distribution transformer reserve margin determined the necessity of a new transformer. A zero or negative reserve margin identified the requirement for additional transformer. For the analysis of additional cost requirement, the assumption for adding a 50 kVA distribution transformer about US$ 5,190.15 was appointed.

The research results indicated that the research process considering the technical constraints and avoided the customer which is in the areas with the technical limitations. As a result, the investment cost was minimized as can be seen in Table XIII.

Table XIII
Additional Investment Cost on Distribution Transformer

Method	**Customer supplied by transformer margin ≤ 0 VA**	**Transformer margin ≤ 0 VA**	**Additional investment cost**
Random A	216	39	US$ 202,415.85
Random B	202	37	US$ 192,035.55
Research Result	21	6	US$ 31,140.90

IV. CONCLUSION

Clustering using the k-means method resulted in a total of 2000 clusters, which were subsequently analyzed using the first TOPSIS method to identify the best 105 clusters based on criteria including kWh consumption, wattage, and distance from cluster centroid to ULP office. The customers on 105 selected clusters were then analyzed by second TOPSIS analysis, considering kWh consumption, wattage, distance from customer to its centroid, operation-hours, distribution transformer reserve margin, feeder load, SAIDI, and SAIFI. This process led to the selection of 10,500 customers.

A comparison with the random technique yielded the following outcomes:

- The estimated monthly additional kWh, based on research results, stands at 363,445 kWh or US$ 27,631.02, whereas the average random technique indicated 170,673 kWh or US$ 11,339.71.
- The cumulative customer to centroid distance from research result was 2,658 km, while the average random method results was 2,865 km.
- The average SAIDI value from the research result was 4.77, while the average random method value was 6.68.
- The average SAIFI value from the research outcomes was 6.77, while the average random method value was 7.40.
- Selected customers in the research result were predominantly with wattage of 450 VA and 900 VA, in alignment with the established weighting criteria.
- The average operation-hour for the selected customers within the research results was 438.8 hours, while the average random method value was 151.51 hours.
- The average distribution transformer reserve margin for the selected customers based on research findings amounted to 69.14 kVA, while the average random method value was 53.49 kVA. The investment cost of adding the required transformers in the research result was US$ 31,140.90, while the average random method cost was US$ 197,225.70.
- The average feeder load for selected customers from the research findings was 150.17 A, while the random method value was 136.43 A. This discrepancy could be attributed to the relatively low weighting of 5%.

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